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Impact of Microclimate on People Flows in Dense Urban Space

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Impact of Microclimate on People Flows in Dense Urban Space

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Abstract

Walking in dense urban environments is influenced by microclimatic variations, which result from urban morphology, materiality and vegetation, co-shaping the quality of public space, determining its use and fruition.

In a multidisciplinary and novel approach, this dissertation combines methods with digital tools to put into evidence the interdependencies between outdoor thermal comfort and pedestrian movement in dense urban environments. By employing data collected by mobile phone applications, the proposed data-based methodology complements previous studies that investigate the relationship between environmental conditions and the use of public space. In this way, it distinguishes itself from existing research that relies on subjective perceptions and direct observations.

The methodological framework provided in this dissertation enables the connection and interrelation of different dynamic datasets. Constructing the STOCA (Spatio Temporal Outdoor Comfort Availability) metric, based on the biometeorological UTCI index, introduces a new method to quantify outdoor comfort availability at the human scale and relating it to the dynamic pedestrian trajectories dataset. By developing the methodology and testing it at the case study of a selected section in the Boston Back Bay area, the interdependencies between microclimatic conditions and individual pedestrian navigation are presented.

The results from applying the methodology confirm the existing relationship between people flows and microclimate, indicating the spatial and temporal conditions under which the impact becomes particularly relevant: under heat stress conditions, comfort navigation is evident. As such, the employed metrics are shown to be useful to reveal human sensory experience and to depict microclimatic characteristics of urban space, defined as the microclimatic genius loci. The evidence-based insights contribute to formulate indications to re-negotiate public space in the context of reconfiguring urban mobility, shaping its design for facilitating walking, health and inclusion.

Zusammenfassung

In dichten städtischen Umgebungen wird das Gehen durch mikroklimatische Variationen beeinflusst, die aus der städtischen Morphologie, Materialität und Vegetation resultieren und die Qualität des öffentlichen Raums mitgestalten und seine Nutzung und Umsetzung bestimmen.

In einem multidisziplinären und neuem Ansatz kombiniert diese Dissertation Methoden mit digitalen Werkzeugen, um die Interdependenzen zwischen thermischem Komfort und der Bewegung von Fußgängern in dichten städtischen Umgebungen zu belegen. Durch die Verwendung von Daten, die mit mobilen Telefonanwendungen gesammelt wurden, ergänzt die vorgeschlagene datenbasierte Methodik frühere Studien, die die Relation zwischen Umweltbedingungen und der Nutzung des öffentlichen Raums untersuchen. Auf diese Weise unterscheidet sie sich von bestehenden Untersuchungen, die sich auf subjektive Wahrnehmungen und direkte Beobachtungen stützen.

Der methodische Rahmen, der in dieser Dissertation präsentiert wird, ermöglicht die Verbindung und Gegenüberstellung verschiedener dynamischer Datensätze. Durch die Konstruktion der STOCA-Metrik (Spatio Temporal Outdoor Comfort Availability), die auf dem biometeorologischen UTCI-Index basiert, wird eine neue Methode zur Quantifizierung der Verfügbarkeit von Komfort im Außenraum auf menschlicher Ebene eingeführt und mit dem dynamischen Datensatz der Fußgängerpfade in Bezug gesetzt. Durch die Entwicklung der Methodik und ihrer Erprobung an der Fallstudie eines ausgewählten Abschnitts im Bostoner Stadtteil Back Bay werden die Abhängigkeiten zwischen mikroklimatischen Bedingungen und individueller Fußgängernavigation dargestellt.

Die Ergebnisse aus der Anwendung der Methodik bestätigen den bestehenden Zusammenhang zwischen Personenströmen und Mikroklima und zeigen auf, unter welchen räumlichen und zeitlichen Bedingungen der Einfluss besonders relevant wird: unter Hitzestressbedingungen zeigt sich eine Komfortnavigation. Als solche erweisen sich die verwendeten Metriken als nützlich, menschliche Sinneserfahrungen aufzuzeigen und mikroklimatische Charakteristika des urbanen Raums, definiert als mikroklimatischer Genius Loci, darzustellen. Die evidenzbasierten Erkenntnisse tragen dazu bei, Hinweise für die Neuverhandlung des öffentlichen Raums im Kontext der städtischen Mobilitätswende zu formulieren und dessen Gestaltung so zu prägen, dass sie das Gehen, die Gesundheit und die Inklusion fördert.

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Inspired by my curiosity as an architect and fascinated by the potential of digital technologies, this work started in 2016 when I was a research associate at the Chair of Building Technology and Climate Responsive Design at the Technical University of Munich (TUM). A few months before, Carlo Ratti, founder of the Senseable City Lab (SCL) at Massachusetts Institute of Technology (MIT) was appointed Rudolf Diesel Industry Fellow at the Institute of Advanced Studies of TUM and was affiliated at our chair. I was asked to give support to his fellowship when he required to develop a doctoral thesis out of the research project we were starting. Combining his expertise and background in data science applied to the built environment with our specific focus on environmental qualities, he proposed different topics to me. All of them were located at the intersection of urban microclimate and data science, but what immediately captured my deep interest was the idea of understanding the influence of thermal comfort on people's use of public space.

The proposal contained *in nuce* what is presented in this dissertation. Besides the overwhelming opportunity of being invited at the SCL for a research stay, I was humbled by the idea of merging the domain of data science with environmental studies, fusing information gathered through data collection with the immaterial qualities of our built environment as well as addressing the topic of the use of public space in dense urban systems in relation to crucial issues of our time. This represented a big challenge and an even bigger opportunity that I developed and deeply engaged with over the past five years.

As such, this dissertation has been a long journey, during which I have encountered many people.

First, I would like to thank Thomas Auer, my supervisor, for his encouraging support and the numerous opportunities and challenges he has offered me, which I have accepted with enthusiasm.

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List of Abbreviations

API Application Programming Interface AOMA Activity-Oriented Mobile Application CFD Computational Fluid Dynamics CSV Comma Separated Value DBT Dry Bulb Temperature EPW EnergyPlus Weather Data File ET Equivalent Temperature FAR Floor Area Ratio GPS Global Positioning System GSV Google Street View IMEM Instationary Munich Energy-Balance Model IPCC Intergovernmental Panel on Climate Change LAS Local Access Score LES Large Eddy Simulation MAPC Metropolitan Area Planning Council MIT Massachusetts Institute of Technology MRT Mean Radiant Temperature NSE Navier-Stokes Equations OSM Open Street Map OSM_ID Open Street Map Identification OTC Outdoor Thermal Comfort **RH** Relative Humidity SCL Senseable City Lab STOCA Spatiotemporal Outdoor Thermal Comfort Availability SVF SkyView Factor TMY Typical Meteorological Year TUM Technical University of Munich UHI Urban Heat Island UTCI Universal Thermal Climate Index **UN United Nations** UN, SDG United Nations Sustainable Development Goals.

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I. INTRODUCTION

Topic

Creating vibrant urban spaces is one of the most demanding tasks for architects, designers, administrators and urban planners. Attractive, liveable and salubrious urban space is the result of a huge array of parameters that converge and intersect inducing an immense complexity that has been increasingly investigated in the past centuries of urban and health studies. This work focuses on the relation of environmental conditions in urban space, human mobility and individual experiences of city life, providing innovative approaches to understand the influences of the environmental conditions on human activity and people's use of outdoor space as well as to the implications of creating more liveable public spaces.

Moreover, the most urgent issues of our time, as declared by the United Nations with the formulation of the Sustainable Development Goals, impose to frame the significance of the quality of public space: from climate change's radical alteration of architecture's basics to the deep transformations that data science and technology are causing, the built environment is essential to every challenge and opportunity our planet is facing (United Nations, SDG).

The impacts of climate change result in a high amount of challenges for public space, manifested in urban systems in a variety of direct and subtle ways, by more extreme and frequent weather events, exacerbated by the Urban Heat Island (UHI) effect (Stone, 2012). Posing severe health hazards for urban populations, in particular to some of the poorest and most vulnerable and placing extreme stress causing serious impacts on the everyday lives and well-being of hundreds of millions of people around the globe (Hasan et. al, 2012). In his book, *The City and the Coming Climate*, Brian Stone states: "the world's largest cities are warming much more rapidly than the planet as a whole" (Stone, 2012).

Besides increasing temperatures, growing urban population determines densification with a subsequent need of resources and space. In particular the environmental qualities of public space are heavily affected by urban density and morphology. Outdoor spaces accommodate daily pedestrian traffic and enable more outdoor activities for people on city streets under various physical, economic and social aspects (Hakim et al., 1998; Hass-Klau, 1993; Jacobs, 1961; Whyte, 1980).

In our era, digitalisation accelerates processes by enabling traceability of people and devices, which generates a new source of knowledge to understand the dynamics of urban systems: besides cyclical phenomena, structural needs such as human health and well-being represent a great challenge for planners, designers and public authorities that needs a multidisciplinary approach to obtain optimal results in terms of spatial quality, ecology and respectful dealing with the built environment and the social domain. Cities develop in relation to urban society, cultural characteristics and local climate. Therefore, the use of public space, is shaped by specific socio-economic developments, mutating habits and local cultural identities.

Beyond these structural phenomena and the increasing presence of digital space, conjunctures such as the 2020 COVID-19 pandemic enhance the awareness of the relevance of public space, once its use is limited or forbidden. During the COVID-19 pandemic, empty public space was considered as one the strongest indicators for isolation and missing human exchange, despite the fully digitalised dimension that allows people to communicate through social media and other digital means (NYT, 2020). It once again elevates public space to its intrinsic significance of the physical representation of a community and belonging to a healthy society. Despite the increasing presence of different means of digital communication that facilitate communication without physical proximity, cities continue growing also due to the constant human need of social exchange.

Fostered by these relations, public space represents the place for social inclusion, diversity, environmental justice and equal access, throwing in sharp relief the *sui generis* relation between its use and its environmental qualities, since it is co-shaped by environmental and socio-technical conditions. Guaranteeing environmental quality is essential for an equal distribution of health: microclimatic conditions are part of a wider range of a set of qualities that are fundamental for creating social justice since vulnerable populations are more exposed to the environment than wealthier ones. For millions of people on earth, the (outdoor) environment is the living habitat.

Outdoor thermal comfort in an urban environment is a complex issue with multiple layers of concern. The environmental stimulus (i.e., the local microclimatic condition) is the most important factor affecting the thermal sensations and comfort assessments of people. Thus, people's sensation of thermal comfort is greatly affected by the local microclimate, particularly pedestrians are directly exposed to their immediate environment in terms of variations of sun and shade, changes in wind speed and other climatic characteristics.

In his primary work *Life Between Buildings: Using Public Space*, Jan Gehl studied the influence of microclimate on outdoor activities by counting people sitting on sunny and shady benches: he showed that local sunny or shady conditions significantly impact the desire of people to either stay or leave (Gehl, 1971). Even 50 years after his pioneering work, good evidence and objective measures remain lacking to answer on how environmental aspects really impact individual behaviour. Assuming that walkable cities are an advantage for society because they provide more social and environmental justice, a deep understanding of the underlying mechanisms by which urban planning and design actions and policies interfere with health and well being is paramount, as this knowledge is critical for decision-makers and urban practitioners to generate a city for the people.

Analysing and assessing these conditions demands not only innovative computational methodologies and metrics but also the exploration of new sources of information. Especially in cities, it seems that research data for socio-environmental scientific inquiry are widely available from public transport, demographics, education, public health figures, crime statistic, weather stations, social media, etc.. The challenge is thus not only how to collect, process or interpret such enormous arrays of heterogeneous information, but how to exploit it in a methodological setting.

Large-scale urban sensing data such as mobile phone traces are emerging as an important data source for urban modelling (Barbour et al., 2019; Calabrese et al. 2012). These data sources offer the unique opportunity to understand and characterise the use of the public realm as the centre of human social activity and as an indicator for quality of life. Models of human mobility already have a wide range of applications; in this dissertation, they are employed to investigate the relation between individual pedestrian mobility and its interdependencies with microclimatic conditions. Through the quantification of spatiotemporal human comfort in dense urban environment, people flows in urban space can be evaluated by putting into evidence its rules.

Based on this analysis, the dissertation aims furthermore to evaluate how microclimatic manipulation can reshape urban space and how to enhance the quality of public space to counteract extreme climate conditions in cities. To respond to the needs, demands, and desires of all of its citizens and for understanding the complex, interconnected, imperfect and very human realities of urban existence (Greenfield, 2013).

1. Research Questions and Hypothesis

The premise of this dissertation is that outdoor thermal comfort can influence human individual mobility, particularly in dense urban space. Because of its material diversity and complex morphology, urban space is characterised by continuously varying microclimates across very small spatial and temporal scales. Pedestrian movement across this labyrinth of microclimates experiences a complex sequence of transient exposures, including step changes, temperature drifts and cyclic variations. This urban microclimatic texture induces thermal experiences that are vastly more complex than it would be under steady-state microclimatic exposures. Thermal comfort dynamics have been widely discussed in indoor studies, but such understandings in outdoor environments where the transients are even more pronounced are generally lacking. Höppe highlighted the fundamental differences between steady- and non-steady-state conditions of outdoor thermal comfort (Höppe, 2002). Although numerous studies demonstrate that pedestrians' routing decisions prioritise thermal comfort and pleasure expectations over simplistic trip minimisation criteria, a deeper investigation on how these complex subjective constructs operate is necessary. The lack of internationally accepted non-steady state indices for outdoor thermal comfort assessment underscores the technical challenges posed by this complex multidisciplinary research problem.

The general topic of urban climate can be addressed from two different scales; one focuses on the physical environment and how architecture, urban morphology, materiality and vegetation affect the climate of cities in meso- and micro-scales. The second approach focuses on the human experience of urban climate, meaning how humans perceive and react to the varying climatic conditions in urban environments and to what extent the physiological and behavioural response mechanisms adapt to this thermal environmental diversity. While the bigger climatic picture at meso-scale is an important driver, its transformation down at the human scale of urban microclimates is necessary to properly interpret biometeorological effects on perception and behaviour.

Furthermore, one of the crucial topics in microclimate analysis is the assessment and forecast of the outdoor thermal environment. The importance is due to the need for human beings to balance their heat budget in order to optimise their comfort, performance and health during daily activities. In parallel to the increasing public awareness about the effects of the natural and built environment on wellbeing and health that we have witnessed in the last few decades, research in the field of human comfort provides clear evidence through objective measures and data based methods, how environmental aspects impact individual behaviour (Reinhart et al., 2017). In fact, robust and integrative evidence is required to empower the community to reshape the urban microclimates' quality. Unlike the visual aesthetic dimensions of urban outdoor and semi-outdoor spaces, their thermal quality has largely been ignored in the urban design processes. This is not because our thermal sense of a place is inconsequential or superfluous, but simply because our scientific understanding of human thermal perception in the outdoor context is at the beginning stage where it can be purposively engineered and managed. Powered by the application of data science strategies to describe subjective human behaviour and combined with urban microclimate modelling, the framework could lead to a comfort navigation model, contextualised in its specific climate zone.

1.1. Research Questions

Consequent to the outlined state of research, this dissertation poses the following research questions:

1.) Can a systematic relation between microclimatic conditions and people's spatiotemporal walking patterns in public space be confirmed, when employing data collected from mobile phone applications?

2.) Which are the relevant metrics to evaluate these relations and how can they be used to express results?

3.) Under which spatial and thermal conditions does human thermal comfort influence people flows in public space?

4.) Can the results generated by applying the proposed data-based methodology be employed to formulate indications for facilitating walking in cities?

5.) Can these findings be instrumental for design, urban planning and governance of public spaces?

1.2 Research Subquestions

The multidisciplinary nature of this work also requires additional investigation, condensed in the following research subquestions:

1.) Which are the most accurate tools to model microclimate basing on mesoclimatic data (air temperature and humidity, solar radiation, and wind speed) to quantify how the urban physical environment (urban morphology and materiality) shapes the climate?

2.) Does microclimate create the nexus between spatial configuration and pedestrian's movement?

3.) If so, can we predict people's presence according to microclimatic forecasts?

4.) Can we categorise defined measurable variables affecting outdoor thermal comfort to generate manipulation and design guidelines?

1.3 Hypothesis

Hence, the following hypothesis is formulated:

Particularly in dense urban environments, microclimatic conditions determine people's walking trajectories. Large urban georeferenced datasets collected by mobile phone applications provide evidence to pedestrian comfort navigation.

To test this hypothesis, this research develops a methodology, using a theoretical framework and a data based empirical case study.

1.4 Research Objectives

The objective of this doctoral thesis is to provide robust scientific evidence of an existing relation between outdoor thermal comfort and people flows in dense urban space. Determining the metrics to evaluate the effects of the built environment on human thermal comfort and using a data based method, this work aims at generating a deeper understanding of the spatiotemporal dynamics of pedestrian behaviour in cities, providing a novel approach for upscaling to the urban scale those relations that generally occur at the human scale. In order to determine the relevance and to quantify the influence of microclimate and, consequently, of outdoor comfort on peoples' mobility patterns, this work investigates how to quantify outdoor comfort in time and space and defines methods to relate it to spatiotemporal individual human mobility. The methodology proposed will be validated using a case study.

The research presents digital workflows for characterising outdoor thermal comfort-based mobility evaluation of cities, combined with a theoretical framework that conceptualises topics and relations that are embedded in its dynamic complexity.

The objectives of this research are:

- to develop and validate simulation workflows to assess spatiotemporal outdoor thermal comfort, by using a digital model for generating microclimatic maps at a high spatiotemporal resolution to evaluate and eventually predict microclimatic conditions;
- to differentiate between temporal, seasonal and spatial walking patterns;
- to develop a strategy to filter and quantify human activity extracted from individual travel survey analysis;
- to identify indices and metrics to predict and evaluate environmental quality and the performance of urban space for guaranteeing comfort availability in time;
- to prove the value of analytic capacities of digital tools to evaluate and predict the effects of urban systems on well-being and health;
- to integrate the information gathered into design and planning decisions for city planning.

1.5 Thesis' Structure

This work draws from many fields, such as data science, geographic information systems and science, environmental modelling, urban climatology and social sciences, combining qualitative and quantitative methods. This interdisciplinary approach is articulated in the following chapters:

Chapter I, the introduction, outlines the general scope and vision of this work, with regard to the scientific relevance and the previous work supporting the employed methods and tools. Chapter II presents the theoretical framework that connects topics and research domains: this chapter has a particular relevance because it describes the unique relations that this work is addressing, giving definitions and a theoretical ground to its interdisciplinary nature. Chapter III lays out the methodological framework, the research design and the tools to be employed, setting the stage for the empirical part presented in chapter IV, that presents the applied workflow and analyses how the previously introduced method has been applied and tested on the case study, showing and discussing its results that lead to the conclusions that are summarised in chapter V.

2. Relevance

Since the 1990s, publications such as research on global cities has abounded in several fields of urban studies (Sassen, 1991; Castell, 1996). Urban space can be regarded as agglomeration of multiple distinct networks in a mutual influence of network dynamics, providing specificity for each urban point of interest (Pflieger & Rozenblat, 2010). In that regard, cities are dynamic and highly mutable entities, city creation and living in cities is in constant flux (Hommels, 2005), change of urban structure is closely linked to social circumstances such as material properties and social structure, but also shared values. From then, the challenge seemed to be explaining the relative stability of urban environments. The citizen's perspective on livability and comfort, its local variation and "social micro-climates" is captured in several phenomenological approaches in the field of human geography (Cutchin, 2008).

This research develops a methodology and tests it to fill a research gap between microclimatology and urban studies, employing data science to integrate knowledge about urban space and its dynamics in high spatiotemporal resolution. In fact, despite the large body of research on urban (micro)climate, we have not come across a coherent systematic and synthesised assessment of the effects of microclimatic conditions on people's walking patterns.

To answer the research question, it is necessary to further investigate the question of individual and intersubjective outdoor comfort not only to develop a multilayered analysis, but also to identify the relevance of data and the quality of information. In addition to climatic aspects of outdoor thermal comfort, a variety of physical and social factors that influence perceptions of urban space come into play when people are outdoors.

The methodological framework provides evidence to the nexus between the local microclimatic condition and the human sensations as well as the use of space in both spatial and temporal terms. In other words, static and objective aspects (i.e., physical and physiological characteristics) need to be measured and modelled effectively to provide "climatic knowledge", and combined with dynamic and subjective aspects (i.e., psychological and social/behavioural characteristics) to provide "human knowledge".

Employing digital technology and data tools enables designers and researchers to provide a platform for integrating knowledge from various perspectives and comparisons of various design scenarios. These technologies are used as predicting tools to generate metrics that measure performance.

In urban studies, the most evident measure of the public realm's performance is its use, and yet most cities rely on vague estimates to understand how many people are using their public spaces and under which conditions. All the involved stakeholders, such as city dwellers, administrators or policy-makers are interested in understanding the environmental conditions in cities to estimate the threat posed by urban climatic phenomena such as the urban heat island effect, which makes hyperlocal thermal measures all the more important, not only for pedestrians who might choose to take the cooler route, but also for researchers studying long-term trends on health.

The thermal quality of public space is decisive during extreme climatic conditions and health crises: on July 17. 1995, a heat wave hit Chicago causing 739 casualties during one week. The absence of urban community spaces increased mortality for those vulnerable groups who couldn't leave their unconditioned homes. Saving them would have required "little more than a cold bath or exposure to air-conditioning. There was plenty of water and artificial cooling available in the city that week. For the truly disadvantaged, however, social contact was in short supply. In that event, as in so many other American disasters, social isolation was a leading risk factor and social connections made the difference between life and death." (Klinenberg, 2020). This example emphasises the strength of the connection between microclimate, social exclusion, and accessibility.

Evaluating and forecasting thermal comfort in urban space will empower cities to improve their public spaces, making them more pleasant, productive, and healthy. The COVID-19 pandemic that has emerged in 2020 shows extremely clearly the immense value of public life and space in cities and the strong impact of seclusion and social distance for people: the highest fulfilment of urban space is the prevalence of physical interactions (Lewnard and Lo, 2020).

In order to address the complex connections between different disciplines, the following subchapters present the state of research of the three main topics to contextualise the relevance of the adopted approach.

2.1 Outdoor Thermal Comfort in the Context of Climate Change

Urban climatic studies are often conducted at three scales: mesoscale, local scale and microscale in descending order (Oke 1997). However, mapping the spatial distribution of meteorological parameters at the microscale is even more important because urban microclimate mapping reveals how microclimate behaves within urban districts and between buildings (Oke 1988; Erell, Pearlmutter and Williamson 2011), which contributes to a better understanding of its impacts on the outdoor thermal environment (Kántor and Unger 2010). Mapping microclimatic spatial variations provides useful information for public health research and management, identifying the hotspots of thermal discomfort so that individual thermal impacts can be evaluated. Increasing efforts are being made to generate spatially continuous data that is essential to explore the intra-urban variations of microclimatic conditions. However, acquiring these data through large-scale field measurements and long-term monitoring is time-consuming and expensive (Oke 2004; Li and Heap 2008).

In the past decades, broad applications in urban studies of concepts and equipment used in biometeorology and urban climatology have provided a large number of research projects on outdoor thermal comfort in various climates around the world (Ahmed, 2003; Ali-Toudert & Mayer, 2006; Cheng & Ng, 2006; Cheng, Ng, Chan, & Givoni, 2010; Givoni et al., 2003; Gulyas, Unger, & Matzarakis, 2006; Höppe, 2002; Nikolopoulou & Lykoudis, 2006; Spagnolo & De Dear, 2003; Stathopoulos, Wu, & Zacharias, 2004; Tseliou, Tsiros, Lykoudis, & Nikolopoulou, 2009). Some studies have focused on modelling and assessment methods from a thermo-physiological perspective (Gulyas et al., 2006; Höppe, 2002), whereas others have conducted detailed investigations of climatic parameters that determine thermal comfort level of humans (Cheng & Ng, 2006; Spagnolo & De Dear, 2003).

In the literature reviewed above, all scholars agree that outdoor spaces are important in promoting the quality of life in cities. However, all these studies have enabled a more powerful analyses of the dependency between urban boundary layer climate and architecture, urban morphology and materiality, despite the limited spatial resolution. This dependency between the built environment and its microclimate is a key determinant of the livability of cities: outdoor space can be regarded as an important public health resource.

Recently, the UN has issued new population projections for 2100, reflecting data up to 2015 (World Population Prospects, 2015). According to the UN's predictive distribution, probabilistic projections based on a Bayesian model, the world population in 2100 has a median of 11.2 billion and a 90% interval from 9.7 to 12.9 billion. Besides the growth of urban systems, this increase in population "raises the question of the impact of the higher projected future population on climate. The likely range of temperature increase is 2.0–4.9° C, with a median of 3.2°C. There is a 5% chance of less than 2°C warming, and a 1% chance of less than 1.5° C. This takes account of uncertainty in future population growth, economic growth, carbon intensity and climate sensitivity" (Raftery et al., 2017). The report also acknowledges that adaptation of societies to a new climate context is of prime importance.

In fact, the projected global-scale changes can be exacerbated by city-scale phenomena, such as the formation of heat islands (UHI). Since the 1960s, the field of urban climatology has illustrated the character and intensity of urban heat island (UHI) formation (Chandler, 1962;

Oke, 1982; Taha, 1997). While the phenomenon differs in magnitude by city size (Oke, 1973), and urban morphology (Kobayashi & Takamura, 1994; Nunez & Oke, 1977), the maximum intensity of the effect has been measured between 2 and 12° C (Oke, 1987), suggesting that most large cities have already experienced a magnitude of warming roughly equivalent to that projected to occur through the global greenhouse effect this century (Stone et. al, 2012). Besides the size, as Stone et al. suggest to further investigate, "is the rate at which heat islands have intensified over the last several decades. If the planet as a whole is expected to experience an increase in globally averaged surface temperatures of 2–12° F by 2100, what rate of warming is to be expected in urbanized regions?" (Stone et. al, 2012).

The UHI is considered as one of the most serious urban environmental problems in the world, resulting in many deaths, specifically during heat wave events (Gabriel and Endlicher, 2011; Johnson and Wilson, 2009) (in Masson et al., 2014). The contributing factors of UHI include less vegetation in city areas, absorption of solar energy input by concrete and paved surfaces, multiple heat reflections from canyon structures of high-rise buildings, anthropogenic heat releases from air-conditioning systems, automobiles, etc. (Mochida and Lun, 2008).

The issue has particular relevance to urban areas where more than half the world's population resides and will be growing enormously with the predicted impacts, causing densification and urban sprawl. The modes of regulating and organising urban population growth in its system is crucial. If densification can be regarded as a successful way to reduce the environmental footprint per resident by lowering the mean floor area per person and increasing the use of individual and public transportation, new constructions "increase the pressure on the remaining spaces between buildings from public plazas to parks and streets, creating shade, blocking or redirecting wind and contributing to the urban heat island effect" (Reinhart et al., 2017). Urban sprawl, on the other hand, requires massive use of individual transport and aggravates the balance of sealed surfaces. The resulting spatiotemporal microclimatic effects can decisively impact OTC levels in urban space, affecting activities, the use of recreational space and the means of transport.

The UHI phenomenon, contextualised in the increasing heat waves intensity originated by the climate change, has thrown in sharp relief the topic of outdoor thermal comfort, beyond the concept of thermal acceptability and pleasure, rather as an indicator for heat stress.

Early studies of thermal comfort involved evaluating indoor spaces (De Dear, G.S. and Brager, 1998: 2002; Nicol and Humphreys, 2002) and widely assumed that indoor thermal comfort theory generalises to outdoor settings (Spagnolo and De Dear, 2003). Nonetheless, transferring these assumptions on outdoor spaces has generated a wide body of research that helps to understand subjective perceptions and responses to the urban environment.

The unique complexity of each built environment, combined with the specific climatic conditions of each place and the transient behaviour of people generates a complex combination of physiological and psychological states of each individual that are difficult to depict. Despite this complexity, over the last two decades, various studies with different approaches have deepened knowledge, combining biometeorological and thermo-physiological aspects (Ali-Toudert and Mayer 2006: Chow et al., 2016: Lai et al., 2014; Lin, Matzarakis, and Hwang, 2010: Spagnolo and De Dear, 2003).

In their synesthetic mode of capturing, humans are unable to sense each individual meteorological quantity. Indeed, they feel the thermal effect of their environment caused by several meteorological parameters integrally through the skin and the blood temperature in the thermoregulatory system of the hypothalamus (Tromp, 1980; Höppe, 1993 in Fröhlich and Matzarakis, 2020). Therefore, thermal comfort cannot fully be described by individual parameters but needs to be approximated through thermal comfort indices considering all relevant conditions. The more sophisticated indices are based on the approach of equivalent temperatures and are relying on the evaluation of the human energy balance or heat flux models (e.g., Fanger, 1972; Gagge et al., 1986; Höppe, 1993; Błazejczyk et al., 2012). Thermal indices require input for the meteorological parameters air temperature (Ta), vapor pressure (VP), wind speed (WS) and the mean radiant temperature (Tmrt), defined as the temperature of a perfectly black environment causing thermal radiation only, that leads to the same radiational gain or loss as the actual environment (Fanger, 1972; Thorsson et al., 2007). All input conditions are required at the very location the index is calculated for at a height of 1.1 m, representing the gravimetric center of an average human body (Fanger, 1972, in Fröhlich and Matzarakis, 2020)

The dynamic character of outdoor comfort diverges from the thermal homogeneity that indoor environments have to guarantee. Dynamic in the sense that adaptation to an ambient thermal condition is progressive, and that thermal sensation is primarily affected by previous experience, and subjective in the sense that the evaluation of a thermal comfort condition is not always consistent with the objective climatic or biometeorological condition. While the afore mentioned models can accurately simulate thermo-physiology, the realm of thermal perception is inadequately understood (Parkinson et al., 2012). The transient states that the urban context generates can be addressed also from the perspective of thermal pleasure, that rather provides insights about the thermal attractiveness of places. Since thermal pleasure can only be experienced in transient states (Cabanac 1992), the dynamic character of travelling through different thermal exposures can be synthesised with the concept of Allisthesia (Parkinson et al., 2012).

This work employs a data driven approach, combining simulation and data analysis tools for modelling thermally induced human behaviour employing mobility signals collected due to the increasing availability of big data sources from human activity.

The contribution of this thesis in the field of OTC, is primarily focused on assessing spatiotemporal OTC conditions to relate it to pedestrian mobility in urban space. To do so, this work simulates microclimatic conditions with tools and methods presented in chapter III.

Due to their complex geometries that vary over large scales, urban environments are rather simulated through numerical models than measured. Most of the cited research in fact employs simulation tools to generate information about microclimatic conditions at the human level. These numerical models also allow to predict conditions using historical weather data projecting them into wider spatiotemporal domains.

Building upon research by Tarek Rakha (Rakha, 2015) and Negin Nazarian, Juan A. Acero and Leslie Norford, (2019) this dissertation develops a spatiotemporal comfort metric that illustrates variations in time and space.

Tarek Rakha proposes the concept of *Thermal Autonomy* for Indoor spaces , defined as "the percent of occupied time over a year where a thermal zone meets or exceeds a given set of thermal comfort acceptability criteria through passive means only" (Rakha, 2016). In his dissertation, Rakha expands this concept to three measures: 1) Thermal Comfort Autonomy, which is defined as the percentage of active time of a year that a specific space is within thermal comfort zone. 2) Heat Sensation Hours (HSH), which measures the exposure to heat stress during a designated time series and 3) Cold Sensation Hours (CSH), which conversely measures the exposure to cold stress during a designated time series. Both HSH and CSH are hourly aggregations of thermal sensation, based on ASHRAE's 7-point thermal sensation scale. These metrics converge into the Annual Thermal Comfort Percentage (TCPa), which is defined as "The percentage of active time of a year that a person in a certain space is experiencing thermal comfort, with linear partial credit as comfort decreases. TCPa allows a direct interpretations of outdoor thermal comfort annually" (ibidem).

Negin Nazarian, Juan A. Acero and Leslie Norford, (2019) have recently presented the Outdoor Thermal Comfort Autonomy (OTCA) as a temporal metric to evaluate comfort levels (Nazarian et al., 2019). The aim of their study is to introduce and define performance metrics that capture the site-specific and dynamic interaction between buildings and the surrounding climate on an annual basis. The OTCA metric describes "the percentage of occupied time over a year, or a prescribed period of use, where a designated area meets a given set of thermal comfort acceptability criteria." (ibidem). The calculation of OTCA is based on a time series of the prescribed thermal comfort metric within outdoor space.

Both approaches are based on the concept of autonomy through year-long simulation workflows. Autonomy refers to specific conditions defined by the use of biometeorological indices. The afore mentioned indices use a mono-dimensional descriptive scale, the equivalent temperature, because they still rely on indoor experiments where temperature is "the main contributor to human comfort" (Liu et al., 2020).

In summary, these approaches allow to confront different conditions in space over the year, indicating the frequency of a certain condition in space.

In contrast to the notion of "autonomy", the proposed methodology requires to employ an index that can be used to compare different street segments or streets, being adaptive to any spatiotemporal domain. Going beyond predetermined schedules, it allows taking into account seasonal specificity and provide meaningful results in terms of comfort availability within a specific spatiotemporal domain.

What is still to be investigated, is the interpretation of what is considered comfortable in dynamic settings such as walking, the adaptation to the thermal environment includes adjustments, in terms of clothing or "physiological responses, or an altered perception / psychological reaction mean that in an uncomfortable situation, humans react". These reactions extend the "range of what we consider to be discomfortable" (de Dear & Brager, 1998).

2.2 Data from and for the City

The digital world has provided a new perspective to the observation and understanding of cities: through sensors that enable tracking with a high spatiotemporal resolution, it has enabled a prospect "of an entirely different way of thinking about cities" (Batty, 2018). In the field of urban studies and planning, it has allowed to measure how the physical characteristics of public spaces generate social interaction providing urban designers with metrics to design better public spaces (Carr et al., 1992; Mehta, 2014).

In the second half of the 20th century, the shift to motorised mass mobility and the subsequent loss of social interaction in the public realm inspired the use of data to understand this phenomenon, especially in North America. The aim of creating vibrant urban spaces is paramount in Jane Jacob's seminal work *The Death and Life of Great American Cities* (1961), where she was one of the first to employ data generated by observation techniques to analyse neighbourhoods. Jacob's observations provided important insights for planners, setting up a link between the socio-spatial behaviours of citizens with the economies of cities.

Developing this modus operandi, other researchers of urban studies such as Lynch (1960), Gehl (2011), and Whyte (1980) developed similar frameworks for qualitative and quantitative measures to observe public space. As pointed out by Sarah Williams, "Kevin Lynch, for example, left a rich legacy by developing methods such as cognitive mapping and mixed-medium observations that aid in understanding public space from the eyes of members of the public." (Williams et. al, 2019) In his study *The View from the Road*, Lynch combined tape recordings, films, photographs, and sketches to understand the public's visual impression of urban highways (Appleyard et al., 1964).

In 1970 William H. Whyte formed a small research group, *The Street Life Project*, and began to study New York City's urban spaces including parks, playgrounds and city blocks. His book summarises the findings about plazas in New York City. A NOVA film was also made from this work (*City Spaces: People Places*). Whyte's work on the characteristics of public spaces in New York City is composed of a mixed methods study of time-lapse photography and interviews. However, direct observations emerged as the most effective technique. Time-lapse

photography was used to quantify people's usage of public space and reveals the spatial and non-spatial elements that lead to active use of specific urban plazas. His approach identifies healthy places in cities, those that people like and that contribute to happiness. He states: "I am going to show you some film of people walking the streets of Manhattan, and I want you to look for what these people have in common. Feet. Shoes. Legs. Pants. Shirts. Blouses. Skirts. Arms. Hats. Hard Hats. Faces. Smiles. Smiles? Why should people on New York streets be smiling?" (Whyte, 1980). Whyte's contribution is valuable because it unfolds the dynamics of fine grained sociological behaviour through direct, first hand observation, showing rituals in street encounters, chance meetings, reciprocal gestures, trying to put into evidence the qualities of urban spaces that make them attractive.

Attempting to define measures for public life, numerous design manuals have used Lynch' and Whyte's studies as supporting evidence for their design recommendations (Childs, 2006; Kaplan et al., 1998; Lennard et al., 1987; Marcus and Francis, 1997). In particular, Jan Gehl's public space measurement methods, detailed in *How to Study Public Life* (Gehl and Svarre, 2013), have been applied to numerous cities through the Gehl Architecture practice (Williams et. al, 2019). Employing direct observations of public space documented through maps, counts, and photographs, Gehl's pioneering method combines qualitative and quantitative data. Through the Gehl Institute (2017) this approach converged into the *Public Life Data Protocol*, then defined as the *Gehl Method*, to generate a systematic public life data collection protocol. The *Gehl Method* has been applied for a project in Melbourne to measure walkability with a 24-hour pedestrian counting system. 44 sensors measured human activity at strategic locations throughout the city, collecting data as a good proxy for walkability, which, in turn, reflects the city's liveability and vibrancy (Doan et al., 2015).

In analogy to these studies, this dissertation employs different datasets and combines them in order to generate knowledge about the attractiveness of urban space in relation to microclimatic qualities. To achieve this target, climate data is combined with individual mobility data in order to expose interdependencies that allow formulating design indications.

Besides the analogies, however, this dissertation bases on anonymised collected dynamic data and evaluates the dynamic interaction between walkers and microclimate. Whyte's studies observe rather static human behaviour without quantifying it through objective measures: how people occupy space and how they behave within it. In this sense, he also considers the "role of natural elements (sun, wind, trees and water)", reflecting on behavioural changes in relation to direct solar radiation, wind speed, presence of greenery and water features. While he differentiates between these elements, this dissertation synthesises them into the concept of thermal quality. Whyte's observations indicate that "sun was important but did not explain the difference in the popularity of plazas" (Whyte, 1980, p. 24). In fact, he notes "what simple figures don't measure, however, is the quality of the experience, which can be much greater when there is sun" (Whyte, 1980, p. 42). In contrast to Whyte's work, this dissertation utilises collected individual walking data, and provides new methods to explore the nexus between people flows and thermal quality.

In this framework dynamic data can extend the relevance of direct observations to a wider scalar and temporal domain, putting into evidence the thermal quality of spaces to understand its continuous influence in people flows in public space.

Another important difference that needs to be pointed out is the definition of public space: Whyte's observations are directed to small plazas in New York City's dense urban space. As such, these are often private spaces that are freely accessible as a result of the commercialisation of public space, considered as a rare opportunity.

Data availability is crucial for generating knowledge and developing subsequent guidelines and policies. In fact, urban data and software-enabled technologies have become essential to the functioning of many cities.

As observed by Rob Kitchin,

"consequently, urban operational governance and city services are becoming highly responsive to a form of data-driven urbanism. At the heart of data-driven urbanism is a computational understanding of city systems that reduces urban life to logic and calculative rules and procedures, which is underpinned by an instrumental rationality and realist epistemology. This rationality and epistemology are informed by and sustains urban science and urban informatics, which seek to make cities more knowable and controllable" (Kitchin, 2016).

Driven by the need of managing complex urban systems, municipalities have begun to develop sensor networks in conjunction with private technology companies that help measure and manage public spaces (Heath, 2016; Reichert, n.d.; Sauter, 2018; Singer, 2012).

Since Manuel Castells presented the concept of the network society, a new emerging society that is connected by ubiquitous information and communication technologies (Castells, 1996), data has created multiple applications for civic action and policy change.

As observed by Kitchin, "for as long as data have been generated about cities, various kinds of data-informed urbanism have been occurring; that is, data have been used as the evidence base for formulating urban policies, programmes and plans, to track their effectiveness and to model and simulate future development. Such data include censuses, household, transport, environment and mapping surveys, and commissioned interviews and focus groups, complemented with various forms of public administration records. In general, these data are analysed at the aggregate level and provide snapshots of cities at particular moments. Increasingly, these datasets are being supplemented with new forms of data, generating what has been defined as urban big data" (Kitchin, 2016).

The term *Big Data* is relatively new, with fundamentally different properties to traditional 'small' datasets, being generated and processed in real time, exhaustive in scope and having fine resolution (Kitchin, 2014). Rather than data being derived from a travel survey with a handful of city dwellers during a specific time period, transport big data consist of a continual survey of every traveller: for example, collecting all the tap-ins and tap-outs of Oyster Cards on the London Underground, or using automatic number plate recognition (ANPR)-enabled cameras to track all vehicles, or using sensors to monitor the mobile phone MAC addresses to track all pedestrians with a phone (Kitchin, 2016).

Driven by the pervasive enthusiasm of data usage, in 2010, the *Economist* magazine developed a series of stories called the *Data Deluge*, which explained the possibilities of using data to develop strategies for almost anything, including cities (Economist, 2010).

Big data implies a "transformation from slow and sampled data to fast and exhaustive data has been enabled by the roll-out of a raft of new networked, digital technologies embedded into the fabric of urban environments. As the data are digital and organized and stored in digital databases, they are easily conjoined and shared and highly suited to examination using data analytics" (Kitchin, 2016).

The result is a vast deluge of real-time, fine-grained, contextual and actionable data, which are routinely generated about cities and their citizens by a range of public and private organizations, including: utility companies (use of electricity, gas and water), transport providers (location/movement, travel flow), mobile phone operators (location/movement, app use and behaviour), travel and accommodation websites (reviews, location/movement and consumption); social media sites (opinions, photos, personal information and location/movement), crowdsourcing and citizen science (maps, e.g. OpenStreetMap;; local knowledge, e.g. Wikipedia; weather, e.g. Wunderground), government bodies and public administration (services, performance and surveys), financial institutions and retail chains (consumption and location); private surveillance and security firms (location and behaviour),; emergency services (security, crime, policing and response), and home appliances and entertainment systems (behaviour and consumption). While some of these data are generated by local authorities and state agencies, much of the data are considered a private asset. The latter are generally closed in nature, though they might be shared with third party vendors (such as city authorities, often for a fee) or researchers (using a licence). In some cases, they are open in nature, often on a limited basis (through data infrastructures or APIs) (Kitchin, 2016).

Opening data to a wider group of interests and stakeholders has been considered an opportunity by governments in North American and Europe, that have begun the experiment of sharing their data. The result has been an explosion of civic-based applications, the forging of new partnerships between civic organisations, and an increased involvement in civics by the technology community (Goldstein and Dyson, 2013). Open data allows governments to generate city infrastructure outside formal governmental structures, creating new possibilities for innovation (Rojas, 2012). Overall, open data has increased information sharing, which in turn helps to generate new partnerships, innovation, and civic action (Williams, 2015). These urban big data, it is contended, produces a highly granular, longitudinal and holistic understanding of a city system or service and enable city systems to be managed in real time (Kitchin, 2016). The interest in using data to analyse and determine city policies is not new: Shannon Mattern, a cultural theorist, traces curiosity about using data for urban planning to modernist notions of "cities-as-machine" and the fascination with the development of cities as efficient systems (Mattern, 2013). One of the first developments of grounding urban planning on environmental data analysis occurred during the early 1910s and 1920s with the 1916 Manhattan zoning ordinance (Fig. I.1) being one of the first success stories of technocratic planning (Williams, 2015). These ordinances have introduced a systematic definition of requirements in the stipulation between public and private actors involved in urban development processes.

But not all data-driven planning experiences have generated successful results: "inaccurate models became the key failure of data driven planning policies in the 60s. The construction of these models was flawed because of the lack appropriate data to develop them, the use of biased information, and not testing whether the data results fit people's experiences (Townsend, 2013). A great example of this is the 1970s era model developed by the RAND Corporation for the New York City Fire Department, to determine the efficiency of its fire house net-work" (Williams, 2015).

As Lewis Mumford writes in The City in History,

"Through its concentration of physical and cultural power, the city heightened the tempo of human intercourse and translated its products into forms that could be stored and reproduced. [...] By means of its storage facilities (buildings, vaults, archives, monuments, tablets, books), the city became capable of transmitting a complex culture from generation to generation, for it marshalled together not only the physical means but the human agents needed to pass on and enlarge this heritage. That remains the greatest of the city's gifts. As compared with the complex human order of the city, our present ingenious electronic mechanisms for storing and transmitting information are crude and limited." (Mumford, 1961)

The limitations of data usage is not only referable to the lack of sources that Mumford alludes to. Also more recent approaches based on a huge amount of available data "wilfully ignored the metaphysical aspects of human life and the role of politics, ideology, social structures, capital and culture in shaping urban relations, governance and development (Harvey, 1973). Consequently, they fail to recognise that cities are complex, multifaceted, contingent, relational systems, full of contestation and wicked problems that are not easily captured or steered, and that urban issues are often best solved through political or social solutions and citizen-centred deliberative democracy, rather than technocratic forms of governance (Kitchin et al., 2015, Greenfield, 2013).

Addressing these limitations and taking advantage of a multidisciplinary approach, this research combines qualitative observations and field measurements for data collection with analytics, as it helps to verify quantitative data analysis, as data is not solely quantitative in nature.

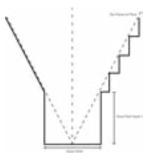


Figure I.1:NewYork City 1916 Zoning Ordinance.Own image based on Lighting Design and Application: LD and A. 16(6), Bryan, H. & Stuebing, S., Natural light as an urban amenity, 44-48, 1986.

2.3 Urban Dynamics

Beyond the opportunity that ubiquitous data collection has opened for the understanding and optimisation of processes in complex urban systems, it has introduced the possibility of unpacking the city through its dynamics (Batty, 2018).

Although dynamics have always been hard to measure, in particular the 19th century was dominated by the idea of a city as a machine and analogies between urban systems and bodies with blood flows and a nervous system were widely prevalent, referring to Leonardo da Vinci's view. Traffic, movements and activities articulated in time and space — Michael Batty defines them as the pulse of the city — was a central topic of Victor Gruen's *The Heart of Our Cities* (Gruen, 1965), in which he develops the idea of flows that Benton Mackaye introduces, using the city of Boston as an example in his work *The New Exploration* (Mackaye, 1928).

As the title of this dissertation suggests, flows are the core of our analysis and exploration. Flows and fluxes are broad definitions to describe the rhythmic sequence of varying patterns that create intensity in public life (Gruen, 1967). These forces are fundamental in understanding urban phenomena in the symbiotic relationship between static physical artefacts and dynamic patterns, how they are experienced and how they influence each other.

In fact, ever since the establishment of urban planning in the early 20th century and increasingly after its institutionalisation from the mid-1950s onwards, there has been growing interest in quantitative approaches to urban phenomena (Michael Batty, 2013b; Hall, 1988). Methods and tools were incrementally imported from social sciences, such as urban and quantitative geography, as well as economics, social physics, and mathematics, among others, and integrated into urban studies. The goal was to model spatial flows to support planners to effectively comprehend and subsequently tackle the challenges facing cities.

In the 21st century, rapid urbanisation processes have resulted in a demographic outburst that has not been experienced so far, in both developed and developing countries (Townsend, 2013; World Population Prospects, 2015). The subsequent tip in the ratio of urban-to-rural global populations poses additional challenges not only to cities, but also for planners and policy makers. Economic growth, social segregation, human migration, accessibility to services, ageing populations and transportation optimisation, among others, continue to constitute the key problems. In addition, urban issues emerge, relating to energy consumption, environmental sustainability, shrinking cities, and deindustrialisation. Present-day planners and policy makers are, thus, confronted with a multiplicity of complex urban problems that change rapidly over time and, therefore, need to address demands in shorter time spans than in the past decades. Subsequently, the primary concern is not only on the physical structure of cities, but also on the dynamic interactions between the various components that coexist in urban systems.

Following up on the previous observations, a contemporary notion of urban dynamics does not only concern economic interactions and growth processes of cities, but also refers to human mobility, flows of individuals and goods, and the distribution of social activity over space and time: simultaneously addressing spatial, social, and temporal aspects of the urban environment. Understanding the dynamics of human activity in cities is essential to urban planning, policy making, and transportation planning. Quantitative measures of flows and the distribution of social activity over space and time have potential to facilitate the characterisation of urban areas and the development of urban models (e.g. land-use transportation models, mobility models etc.) to simulate and, possibly, predict the use of urban space by individuals. In achieving this, conventional urban data such as census records and travel surveys, though reliable and accurate, have limited capacities to give insights into the spatiotemporal dynamics of cities, primarily due to their infrequent update rate. Therefore, emerging sources such as sensors, mobile phones, and social media could be used as proxies for human activity and mobility dynamics, in combination with traditional sources of urban data.

The systematic use of urban data to understand morphological and functional aspects of cities has its roots already in the late 1950s, when quantitative methods started to be applied to urban and regional studies (Kwan & Schwanen, 2009). Early attempts in modelling cities using

mathematical abstractions employed data from population censuses, individual or household travel surveys and economic surveys, which comprised the only available sources to calibrate model parameters. Drawing on location theory, one of the first systems to be mathematically represented were transportation networks and their relation to land uses (Michael Batty, 2009; Forrester, 1969; Hunt, Kriger, & Miller, 2005; Lowry, 1965). More recent models addressed spatial interactions (e.g. gravity models, spatial interaction models etc.), and the correlation between vegetation and urban coverage (e.g. Land Use/Land Cover Change models (LUCC)) (Michael Batty, 2007; Button, Haynes, Stopher, & Hensher, 2004; Fotheringham, Brunsdon, & Charlton, 2000). Gradually, dynamic simulation methods were developed, based on Cellular Automata (CAs), Agent-Based Models (ABM), and Multi-Agent Systems (MAS) (Michael Batty, 2009; Michael Batty & Torrens, 2005). Overall, the aforementioned attempts constituted the fundamental means to simulate and quantitatively assess the way cities function (Psyllidis, 2016).

In recent years though, the increasing penetration of sensor resources (e.g. GPS trackers, RFID cards etc.) that are embedded in physical space or in handheld devices (i.e. cellphones), in combination with geo-enabled social media (e.g. Twitter, Instagram etc.) and location-based social networks (LBSNs) (e.g. Foursquare) provides an emerging set of data sources about cities. The majority of data that are generated from these new sources are tagged to space and time, have frequent update rates, therefore addressing short time spans and allowing for disaggregation at the level of individual location or person (Psyllidis, 2016).

Such technologies generate a range of real-time location, movement and activity data that is, a radical expansion in the volume, range and granularity of the data being generated about people and places (Kitchin, 2014; Crawford and Schultz, 2014).

Although the data generated from these sources usually serve different purposes than those pertaining traditionally to urban and regional studies, they have potential to be used as proxies for studying urban phenomena. More specifically, owing to the inclusion of spatial, social, and temporal dimensions, they offer new possibilities to the exploration of urban dynamics (Psyllidis, 2016).

Particularly in the field of individual mobility, the availability of large urban datasets has generated a significant body of research. Andres Sevtsuk's work addresses research on walking in cities through computational models for evaluating pedestrian accessibility, daily routines and publicly accessible private space in Singapore (Sevtsuk & Ratti, 2010; Sevtsuk, 2014; Sevtsuk et al., 2016).

In her research, Marta Gonzales integrates new data sources into existing urban and transportation planning frameworks for estimating travel demand and infrastructure usage. Her work brings together numerous existing and new algorithms to generate representative origin–destination matrices, route trips through road networks constructed using open and crowd-sourced data repositories, and perform analytics on the system's output (Toole et al., 2015).

The data employed in this doctoral thesis is produced from portable devices, that are spatially and temporally referenced and is related to locally high grained microclimatic data generated by modelling more traditional weather data. In this sense, the novelty of this work consists in combining different datasets with inherent granularities, related to the same spatial and temporal domain.

In this doctoral thesis, the author avoids using the term *Big Data* for several reasons. First, because it lacks a univocal definition and it refers rather to the volume of data. Second, it constitutes a generic concept that is insufficient when it comes to addressing the inherent diversities of emerging urban data types (Psyllidis, 2016).

To summarise, this dissertation is incorporating heterogeneous data from a variety of sources and with a diversity of purposes they usually serve. Furthermore, the multidimensionality of the information they contain simultaneously addresses spatial, social, temporal, and topical features of people and places. In fact, the methodological framework illustrated in chapter III combines:

- dynamic data from mobile tracking applications;
- open source spatially static but temporally dynamic data from weather stations;
- open source static data of urban morphologies.

The data is either analysed and filtered or used to generate new data through modelling techniques, providing insights into the dynamics of human activity in cities and offering new perspectives on how complex phenomena in cities change over short time intervals, compared to the sparsely updated conventional urban data (Psyllidis, 2016).

3. Previous Own Work

Combining combinations of datasets and proposing a new methodological framework required some preliminary work at the intersection of human thermal comfort and individual mobility.

The following section presents four research projects that have been developed at the Technical University of Munich (TUM) and at the Senseable City Lab (SCL) of the Massachusetts Institute of Technology (MIT) as preliminary research for this dissertation. Behind the general topic of relating individual movement to microclimatic conditions, there was a need to collect a small sample data to test the methodological setup that this work proposes. The Elytra Filament Pavilion Survey, introduced in section 3.1., has been taken as a case study to apply the first draft of the applied methodology.

Section 3.2 illustrates the results of the first attempts to compare datasets on a wide urban scale. This study employs the same dataset that this doctoral thesis is based upon and consists of a preliminary filtering to become familiar with the quality and resolution of the data. The datasets employed in this study are geo-referenced, creating a spatial alignment to highlight interdependencies.

The work presented in section 3.3, addresses the topic of individual mobility flows in urban space in relation to weather conditions. More specifically, walking behaviour is put into relationship to bike sharing systems' use, considering the density of urban morphology.

All the presented research has been already published in conference proceedings or in peer reviewed journal articles, as indicated above each subsection.

3.1 Climateflows

This section is based upon the findings published in the following papers:

Santucci, D., Auer, T., Chokhachian, A. (2017) Impact of environmental quality in outdoor spaces: dependency study between outdoor comfort and people's presence. *S.ARCH 2017 I Sustainable Architecture Conference Proceedings*.

Santucci, D., Mildenberger, E., Plotnikov, B. (2017) An investigation on the relation between outdoor comfort and people's mobility: the Elytra Filament Pavilion survey. *PowerSkin Conference Proceedings*.

In the Elytra Filament Pavilion, an experimental pavilion which consists of a modular robotically constructed canopy commissioned by the Victoria & Albert Museum in London and a collaborative work between the ICD (Institute for Computational Design, University of Stuttgart), the ITKE (Institute of Building Structures and Structural Design, University of Stuttgart) and Transsolar KlimaEngineering GmbH, we explored new ways to combine real time on site measurements and simulations to estimate the microclimate effects of the canopy and seek correlations between people's movement and thermal comfort.

To achieve this target, we combined two data levels of information:

An outdoor comfort model which generated outdoor comfort mapping, modelling recorded weather data available from weather stations. In order to access the thermal comfort conditions, we have used the UTCI (Universal Thermal Climate Index, cfr. Chapter II.) UTCI values were calculated for every canopy element to visualise the microclimatic conditions that the structure generates. Air temperature, wind speed and relative humidity were retrieved from a nearby weather station in five-minute intervals. The process of estimating the mean radiant temperature required a radiation simulation using Honeybee and Daysim (Reinhart, 2011) for a five minute interval between May and November, the time frame of the pavilion exhibition. Once we calculated the radiation values, we estimated the mean radiant temperature using the "Human Bio-Meteorological Chart" (Kessling, et al. 2013).

An occupancy information model through sensing; in this case, several limitations involving the museum's regulations led to seeking solutions that would be as transparent as possible for the occupants without storing any personal information. The use of infrared cameras, thermal imaging or Wi-Fi tracking was abandoned and instead we have adopted the Modcam (Modcam, 2016), a device that tracks occupancy patterns. For the pavilion, we installed 11 modcam devices seamlessly integrated in the canopy that have been collecting data from May 2016 for a period of several months in 15-minute intervals.

Both occupancy and thermal comfort information have been stored in databases for further analysis and post processing of the results. In addition, a web application to document the project (http://elytra-pavilion.com) offered a visual representation of the results and an interface to choose and move between different times.

We carried out the data evaluation using two different methods: a tabular and a graphical method. In the tabular analysis, we confronted the single values composing the UTCI – solar radiation, air temperature, relative humidity and wind velocity – using day average resulting from the recorded data.

Furthermore, we added detailed observation based on graphical observation. With the information gathered from the tabular evaluation, we defined single frames of a specific day. The graphical analysis allowed a more detailed spatiotemporal distribution of information and a more effective visual representation.

To filter the consistent amount of frames, we selected six representative days corresponding to the criteria of a high, an average and a low UTCI score. The days corresponded to a hot sunny day, a cloudy dry day and to a cold, rainy day. Due to this differentiation, frequency, activity and behaviour have been evaluated, relating them to the UTCI score. For each reference day a visualisation of all movement patterns was done indicating peaks in movement frequency that allowed reading clear characteristics and tendencies. To each image, we associated a corresponding picture of the UTCI mapping.

The analysed data finds its correlation in a model that overlays data on two different temporal scales and with two layers of concern: a wider scale that gives general information about weather condition and people's presence, and a more detailed scale that focuses on typical days with specific climatic conditions, and visualising movement in a higher resolution.

The study was limited to an objective observation, excluding subjective factors and, due to data availability, it was limited to the summer period, referring only to museum visitors: these constraints were given by the project itself.

Besides the results that we have already published, the study highlighted the need of a consistent data format. Similarly to the case of this dissertation, in the Elytra Filament Survey, one dataset was collected in real time, the other was the result of a simulation.

3.2 Methodological Framework for Evaluating Liveability of Urban Spaces

This section is based upon the findings published in the following paper:

Santucci, D., Fugiglando, U., Li, X., Auer, T., Ratti, C. (2018) Methodological framework for evaluating liveability of urban spaces through a human centred approach. *Proceedings of 10th Windsor Conference Rethinking Comfort*, NCEUB 2018.

The novelty of this study is to evaluate the dependency between walking activity and climatic conditions at a micro-level using the SkyView Factor (SVF) as a fundamental indicator to identify spatiotemporal patterns of environmental diversity at the urban scale depending on seasonal climatic variations. SVF variability corresponds to the diversity of the built environment and therefore to diverse microclimatic conditions: variant urban environments generate varying comfort conditions in space at the street level. Since complex urban morphology generates environmental diversity, this correlates with freedom of choice and an overall expression of comfort (Steemers and Ramos, 2010).

Through data mining, individuals can become the main experimental subjects: using data of individuals allows developing a personal comfort model that predicts individual responses also on a large sample. Personal comfort models are usually based on a small number of individual surveys. In this study, we were using a data approach using signals collected from a sensed environment. Following this premise, this study used human response for predicting the quality of comfort conditions in public spaces, and not a simulation-based method. For reaching this aim, we used walking data collected over a period of one year – from May 2014 to May 2015 – in the Greater Boston area. The dataset, which consists of 250.000 anonymous pedestrian trajectories collected through smartphone applications, records human walking activity and is the same that was employed for this dissertation as well as in section 3.3.

The data reveal patterns of how people use public spaces for walking in a high spatiotemporal resolution. Presence is used as an indicator for walkability and, more in general, to estimate the quality and the characteristics of the urban environment. In order to relate walking behaviour to form and its effects, we use the SkyView Factor (SVF) as an indicator of the urban morphology. The SVF is an index that allows determining a variety of parameters such as density, typological variety, and the exposure to the environmental conditions (Carrasco-Hernandez et al., 2015).

Several studies have demonstrated the relevance of the SVF in characterising both microclimatic conditions, as peak temperature difference can be assessed in terms of height-to-width ratios or sky view factors (Oke, 1987), and comfort, as environmental stimulation is an issue of primary importance in external spaces (Nikoloupoulou et al., 2003).

As the largest city in Massachusetts, the city of Boston was chosen as the study area. Boston has land area of 106.7 km² and total population of 670,000 in 2016. Due to its compact structure, Boston is one of the most walkable cities in the United States (Vanky et al., 2017).

The datasets used in this study include anonymous human trace data, Google Street View (GSV) and Open Street Map (OSM) data.

The GSV data were used to measure and estimate the geometries of street canyons and the amount of street greenery. Since GSV panoramas are distributed discretely along streets, we first created samples every 100 m along the streets in the study area. Based on those created samples, we further downloaded the GSV images based on the Google Street View API (Google, 2016; Li et al., 2018).

The GSV images and the walking trajectories matched with the OSM street segments have a complete correspondence in space since they are both located at the street centreline. The datasets allow generating a georeferenced occupancy study in relation to the sky view factor (SVF) that quantifies the degree of sky visibility and therefore the proportions of street canyons. Previous studies have shown that the enclosure of street canyons is related to human perception of the environment (Asgarzadeh et al., 2014; Li et al., 2015) and the walkability of the streets (Yin and Wang, 2016).

Additionally, we analysed weather data for the same time period May 2014 until May 2015 using Weather Underground hourly data records retrieved from the KBOS station (Boston Logan Airport) to classify daily conditions and cluster them into typical days categories,.

After selecting the most representative days for each season in terms of air temperature, relative humidity, wind speed and wind direction that are considered typical in relation to the season's averages, we identified the highest concentration of hot days. This classification was used as a fundamental clustering of mesoclimatic conditions throughout the year corresponding to the available human trace data.

To illustrate people's response to microclimatic conditions and for finding correlations between varying weather conditions and trajectories' length and location, we selected a streetscape variable – street enclosure by buildings – to identify a parameter that corresponds to diverse outdoor comfort conditions. Numerous studies have already demonstrated that the sky view factor (SVF) can be a representative indicator for urban building density and layout. SVF is the ratio of the radiation received (or emitted) by a planar surface to the radiation emitted (or received) by the entire hemispheric environment and it affects urban radiation exchange and urban microclimate (Watson and Johnson, 1987). Several others have related the effects of SVF to thermal comfort in the urban environment (Mayer et al., 1987; Lin et al., 2008/2011; Bröde et al., 2012). Under this premise, the SVF is considered to be a fundamental parameter in order to evaluate microclimate in urban space as it has been demonstrated that the correlation between SVF and outdoor thermal comfort (mean radiant temperature) is particularly strong, in particular for dense urban environments (Wang et al., 2014).

SVF sampling points on the streets (obtained combining different GSV pictures) are uniformly distributed every 100 m in the urban environment. We therefore computed for each street segment the standard deviation of the corresponding SVFs, assigning a value equal to zero to the segments that contain only one SVF sample. The SVF variability (in terms of standard deviation) is then compared to the total frequency of the street segments. In order to investigate a possible relation between the street segment frequency and the SVF's variability, a linear regression model has been fitted to the data. The regression line shows a positive linear dependency between the SVF standard deviation and the street segment frequency. In fact, the null hypothesis on the regression line's coefficient equal to zero can be rejected through a t-test with a significance level of 1.6% and 3.8% for respectively February and September.

The present study provides a global mapping that illustrates to which extent pedestrians respond to the variability of the urban environment. The correlation between the SVF and the frequency of pedestrian activity along a street segment shows strong relations between the variability of urban spaces and their attractiveness for pedestrian use.

This result can be associated to the concept of diversity of cities that Jane Jacobs (Jacobs, 1961) considered one of the most important indicators for urban vitality. Furthermore, a higher variance of the SVF corresponds to a higher variability of the microclimatic conditions, producing frequent differences and variations in terms of outdoor comfort conditions: people preferably walk where the urban morphology determines variant microclimatic conditions. From a physiological point of view, sudden changes do not immediately provoke skin temperature shifts (Parkinson et al. 2012).

This tendency is valid under highly different climatic conditions, both for cold periods as well as for hot ones. The large number of trajectories and the urban scale allow considering this relation as an effective indicator for planners and policy makers with potentially extensive design implications.

3.3 Comparing Bicycling and Pedestrian Mobility in Greater Boston

This section is based upon the findings published in following paper:

Bongiorno, C., Santucci, D., Kon, F., Santi, P. and Ratti, C. (2019) Comparing bicycling and pedestrian mobility: Patterns of non-motorised human mobility in Greater Boston. *Journal of Transport Geography*, Volume 80, 2019, 102497.

Several studies have already illustrated potentials of bike use and walking (Pucher et al., 2011; Griffin et al., 2014). The novelty of the present study is to perform a quantitative comparison of bike use and walking mobility modes, in the same spatial and temporal domain. To this end, we employed datasets for the Greater Boston area covering the same period (May 2014 to May 2015). The analysed area consists of approximately of 200 km² and total population of approximately 900,000 in 2016.

The anonymised human trace data was collected from an activity-tracking mobile phone application. Boston's pioneering bike-sharing system, Hubway, was launched in 2011 and it has been growing since then. In 2018, its name changed to BlueBikes and it now has over 1800 bicycles and 308 dock stations across Boston, Brookline, Cambridge, and Somerville. For the analysis described in this study, we utilised open data from the Hubway system, which describes the origin, destination, and timestamps of each individual trip in the period under study, totalling nearly 800 thousand trips.

The novel data-driven analysis and comparison method between pedestrian and cycling mobility datasets is illustrated with two datasets covering the same area and the same one-year period. We discuss the similarities and differences between the two modes of transportation, showing that they serve different, complementary purposes. We identify and quantify how non-motorised mobility is affected by weather, time, distance, and duration and characterise its spatial mobility flows in terms of network metrics. These findings can serve both as evidence for public policy and as a basis for further research in the field.

Combining bike and pedestrian data offers the opportunity to evaluate non-motorised mobility in a wider perspective, considering not only the recreational character of these modes of transportation. Unlike most vigorous physical activities engaged in for health or recreational purposes, walking and cycling can be undertaken for multiple purposes. Walking and cycling can be done for leisure, recreation, or exercise; for occupational purposes; and for basic transportation, including shopping or going to work (Saelens et al., 2003).

In fact, besides increasing physical activity, biking and walking are basic modes of transportation, particularly in dense urban environments. Rietveld (2001) points out that "transport statistics are usually formulated in terms of 'main' transport mode. This leads to a systematic underestimation of non-motorised transport modes. Even in the case of car trips, walking to and from the parking place is an inevitable element of the chain. The same holds true for walking and biking to the bus stop or the railway station. A consequence of this complementarity is that when the various trip elements are considered, the share of bike and walking is much higher."

Still according to Rietveld (2001), in multimodal chains, pedestrians dominate the scene and bicycles are rather important in particular in train related public transport trips. Bike mobility is relevant for the activities at the end of train routes; non-motorised transport modes can be faster than bus or tram, especially when aspects like rescheduling costs and uncertainty costs are taken into account: because of their time-continuous character, these non-motorised modes do not give rise to the risk of missing a connection in a chain. Furthermore, individual characteristics such as age, income, and physical abilities play a role and income can be an essential feature to include in the evaluation.

Another frequently mentioned factor is infrastructure: bicycle paths may be essential to improve the convenience and safety of bicycle trips (Pucher et al., 1999) and could contribute to

the community as a whole over the longer term.

Despite their increasingly recognised potential as a solution to several pressing problems, walking and cycling remain the most understudied – and least understood – modes of travel. Complicating the study of walking and cycling as modes of transportation is their frequent use for exercise and recreation rather than for travel (Krizek et al., 2009), mainly in the past decades. Despite individual preferences, replacing motorised mobility by cycling and walk brings up the necessity of considering these modes as part of the complex network of urban mobility. Nevertheless, our studies help unveiling that, despite being non-motorised, cycling and walking present substantially different features and, as such, should be considered distinct transport modes.

To the best of our knowledge, no previous research has performed a comparative analysis of walking and cycling activity. Similar (non-comparative) analysis in the past were based on small datasets or questionnaire data while our research is based on mathematical analysis of large datasets collected with GPS from real trips. In our research, we not only identify the influence of multiple metrics on walking and cycling, but we also quantify it based on data analysis. Finally, our comparisons were derived from the analysed data using our flow-based method, which is also not prevalent in the literature.

One of the challenges of this study, was to compare the spatial flows of the two modes of mobility: we aggregated the bike sharing and pedestrian trips into flows connecting different regions of the city. As mentioned before, we divided the greater Boston area by using a 100×100 grid, each Grid cell being a square of side close to 300 m. For each pair of grid cells, we counted the number of trips connecting those two regions. We then plot the resulting flows on the map, with an arrow whose width and opacity is proportional to the number of trips represented by that flow, so that flows with more trips are more prominent and flows with very few trips tend to disappear in the visualisation. Finally, to better visualise different mobility patterns, we divided the trips in workday or weekend and according to the time of the day. The three rows present the patterns in the morning rush hour (7 am to 10 am), lunch-time (11 am to 2 pm), and afternoon rush hour (5 pm to 8 pm).

The resulting plots show that bike flows and pedestrian flows have different purposes. Both present a high concentration around the major subway and train stations. But bicycles are used mostly to connect the different cities in the Greater Boston and to connect neighbourhoods that are 2 to 5 km away from each other. Moreover, most pedestrian trips are shorter and are used to access locations in business and university districts. The bicycle trips are more concentrated on fewer flows while the pedestrian trips are more evenly distributed across all major business and university areas. we can observe a few commuting-style pedestrian trips in the morning and afternoon covering longer distances but most trips are short, within the same area of the city., most bike sharing trips in the morning and afternoon peaks present a commuting style (from a residential area to business/education area in the morning and vice versa in the afternoon) or are connected to the major subway and train stations.

We can conclude that the overall shape of the flows across the city demonstrate that pedestrian trips and bike trips serve a different purpose with regard to urban mobility. Although they overlap in trips between 600 m and 1 km, they mostly complement each other providing alternative mobility modes for shorter (under 600 m, normally on foot) and longer (from 1 km to 4 km, normally on a bike) trips. Combined, they represent a real alternative for decreasing the number of car trips in contemporary cities since, for instance, as much as 1/3 of car trips in the USA are shorter than 3.2 km (USDOT, 2018).

Looking at the sensitivity to variation of temperature, the external temperature has a strong influence on pedestrian and bike mobility. With regard to it, we aim to have a quantitative estimate of the impact on the number of trips per hour of an increase of temperature with respect to its average monthly value. It is important to consider variation of temperature with respect to the average temperature of each month and not the absolute value because the perception of what is a warm or a cool day varies a lot throughout the year. For instance, while

15 °C might be perceived cold for a summer day, it can be perceived as warm for a winter day. To do that, we estimate, from our dataset, the average temperature and the average number of trips for each weekday hour in each month (weekends show a very different pattern and were not considered in this analysis). Then, for a fixed month, we compute the Pearson correlation between the percentage increment of the number of trips per hour with respect to its average value and the increase in Celsius with respect to the average monthly value in the considered hour. To assess the statistical significance of the metric, we estimate a 95% bootstrap confidence interval (DiCiccio and Efron, 1996) on the Pearson correlation. As result, during the summer months, the increment of the number of trips of the pedestrian is negatively correlated with the increase of temperature, it means that a rise in temperature implies a decrease of trips; differently, the increment of the number of bike trips seems to be not significantly correlated with the temperature increment. During the autumn and until the beginning of the Spring, the increment of the number of bike trips is significantly correlated with the increment of temperature; it means that a rise in temperature implies an increase of cycling trips. It is worth noticing that only during the winter period we observed this clear correlation for pedestrians, whereas during autumn such association seams less robust.

In summary, these results show that, on the one hand, during hot months, people tend to walk less when the temperature increases but this change does not affect cycling. On the other hand, in colder months (October to April) people tend to use significantly more bike sharing when the temperature increases. During these colder months, there is also an increase, but of smaller magnitude, in pedestrian trips when the temperature increases.

4. Expected Impacts

This doctoral thesis attempts to verify and quantify microclimatic pedestrian navigation in urban space. To do so, it generates and tests a methodology employing a specifically developed workflow to create evidence from heterogeneous sources and data types (meteorological, urban geometry, material and georeferenced data) with the primary aim of addressing urban planning solutions that underscore a more human-centered urban environment and promote urban health, well-being and life quality. What distinguishes this work from previous studies that have typically relied on subjective measures, is its focus on objectively measured data. The data based methodology enables a bottom-up approach avoiding a merely technological response by including the very individual human component that the data can include.

This works also aims to address multiple societal challenges of our time, such as public health in the context of the climate change, whose complex relationships will be illustrated in chapter II. Indeed, the expected impacts of this work will reach different domains. In fact, this research develops a methodology to understand the relation between microclimates and pedestrian flows explicitly for predicting the implications of temperature increase for public space and pedestrian mobility. A robust adaptability for change can be considered as a collective response to climate changes and the emergency we are experiencing. In the disciplines of architecture and urban planning, the need for new politics of interventions and scale is of paramount importance. In fact, to address the urgent agenda, designers and planners, policy makers and administrators are required to think beyond the conventional spatial and temporal scales. The digital revolution also allows taking into consideration dynamics, enabling interconnected, interdisciplinary workflows. The combination of across scale thinking and digital tools enables new ways of approaching needs, from the local human scale to the entire planet, exploring engagement at all scales to activate vast resources and interdependencies.

One of the most essential impacts of this research is on mobility, since it attempts to measure and understand the effects of urban form, materiality and vegetation and their microclimatic genius loci on walking. Walking as an every day practice has an enormous impact on health, wellbeing and carbon emissions as well as societal implications on practices of inclusion and cohesion. The COVID-19 pandemic has exacerbated the interest in mobility, emphasising, in a short time, the importance of proximity and non-motorised individual mobility. In this context, models such as the "15-minute city" received a sudden, global attention. In her manifesto for the 2020 election, Paris' mayor Anne Hidalgo claims that Paris needs to become a "15-minute city." (O'Sullivan, 2020) A "15-minute city" offers its residents all their needs for work, shopping, health, or culture within 15 minutes from their home. On an urban scale, this requires a strong functional mix implying "deconstructing the city" as Hidalgo's adviser Carlos Moreno, a professor at Paris-Sorbonne University, puts it. "There are six things that make an urbanite happy" he told Liberation. "Dwelling in dignity, working in proper conditions, [being able to gain] provisions, well-being, education and leisure. To improve quality of life, you need to reduce the access radius for these functions."

The car centred city development during the 20th century has created a strong separation, both through a functional distinction and the immense networks of roads and parking infrastructure that are essential to serve motorised mobility. Redesigning mobility in cities would require to built a new generation of infrastructure, avoiding to segregate communities from economic centres. The shift in mobility and travel implies a reconfiguration of public space and a redefinition of domains. Out of the reconfiguration of both physical spaces, and our relationships with them, a new paradigm in urban density would resize the city, eventually with an inspiration from the city of the pre-car era, that provides less spatial inequalities as we know them from our contemporary cities. Understanding the influence of microclimate will assign to the thermal quality of urban space the role of one of the shaping parameters for density. In addition to these aspects, climatic knowledge is fundamental for improving urban health and well-being. Supported by a robust evidence, the insights could inspire policy making on improved urban health in urban areas.

Within the inherent limits of predicting scenarios, this contribution aims at creating a new dimensioning for future cities, addressing particularly the commitment for less spatial inequalities and inclusion in public space. In full recognition of the built world as a single and simultaneous practice, the next decade is asked to ensure models and specific local responses for differentiated necessities.

References

Ahmed, K. S. (2003). Comfort in urban spaces: Defining the boundaries of outdoor thermal comfort for the tropical urban environments. *Energy and Buildings*, 35, 103–110.

Ali-Toudert, F, Mayer, H. (2006) Numerical study on the effects of aspect ratio and orientation of an urban street canyon on outdoor thermal comfort in hot and dry climate, *Build. Environ.* 41 (2) 94–108.

Appleyard D, Lynch K, Myer JR, et al. (1964) *The View from the Road*. Joint Center for Urban Studies of the Massachusetts Institute of Technology and Harvard University. Massachusetts Institute of Technology: MIT Press.

Asgarzadeh, M., Lusk, A., Koga, T., & Hirate, K. (2012) Measuring oppressiveness of streetscapes. Landscape and Urban Planning, 107(1), 1–11.

Barbour, E., Davila, C.C., Gupta, S. et al. Planning for sustainable cities by estimating building occupancy with mobile phones. *Nat Commun* 10, 3736 (2019).

Batty, M. (2007). Spatial Interaction. In K. K. Kemp (Ed.), *Encyclopedia of Geographic Information Science* (pp. 416–419). Thousand Oaks, CA: Sage.

Batty, M. (2009). Urban Modeling. In R. Kitchin & N. Thrift (Eds.), International Encyclopedia of Human Geography (Vol. 12, pp. 51–58). Oxford, UK: Elsevier.

Batty M. (2013) The new science of cities. Cambridge, MA: MIT Press.

Batty, M (2018) Inventing Future Cities, MIT Press.

Batty, M., & Torrens, P. M. (2005). Modelling and prediction in a complex world. *Futures*, 37(7), 745-766. doi:10.1016/j.futures.2004.11.003

Blazejczyk, K., Epstein, Y., Jendritzky, G., Staiger, H., Tinz, B. (2012) Comparison of UTCI to selected thermal indices, *Int. J. Biometeorol.* 56 (2012) 515–535.

Bongiorno, C., Santucci, D., Kon, F., Santi, P. and Ratti, C. (2019) Comparing bicycling and pedestrian mobility: Patterns of non-motorized human mobility in Greater Boston. *Journal of Transport Geography*, Volume 80, 2019, 102497.

Bröde, P., Błazejczyk, K., Fiala, D., Havenith, G., Holmér, I., Jendritzky, G., Kuklane, K., Kampmann, B. (2013) The Universal Thermal Climate Index UTCI compared to ergonomics standards for assessing the thermal environment, *Industrial Health*, 51(1):16–24.

Button, K. J., Haynes, K. E., Stopher, P., & Hensher, D. A. E. (2004). Handbook of Transport Geography and Spatial Systems (Vol. 5 (Handbooks in Transport)). New York: Elsevier Science.

Calabrese, F., Diao, M., Di Lorenzo, G., Ferreira, J. Jr., Ratti, C. (2012) Understanding individual mobility patterns from urban sensing data. A mobile phone trace example. Transportation Research. Part C: *Emerging Technologies*, (2013). Volume 26, p. 301-313.

Carr, S., Stephen, C., Francis, M., et al. (1992) Public Space. Cambridge: Cambridge University Press.

Carrasco-Hernandez, R., Smedley, A.R.D., Webb, A. R. (2015) Using urban canyon geometries obtained from Google Street View for atmospheric studies: Potential applications in the calculation of street level total shortwave irradiances. *Energy and Buildings* 86 (2015) 340–348.

Castells, M. (1996). The network society. Oxford: Blackwell.

Chandler, T. J. (1962). London's urban climate. The Geographical Journal, 128(3), 279-298.

Cheng, V., & Ng, E. (2006). Thermal comfort in urban open spaces for Hong Kong. Architectural Science Re- view, 49(3), 236–242.

Cheng, V., Ng, E., Chan, C., & Givoni, B. (2010). Outdoor thermal comfort study in sub-tropical climate: A longitudinal study based in Hong Kong.

Childs, M.C. (2006) Squares: A Public Place Design Guide for Urbanists. Albuquerque, NM: UNM Press.

Chow, W., Akbar, S.N.B.A., Heng, S.L., Roth, M. (2016) Assessment of measured and per- ceived microclimates within a tropical urban forest, *Urban For. Urban Green.* 16, 62–75.

Crawford K, Schultz J. 2014 Big data and due process: toward a framework to redress predictive privacy harms. *Boston College Law Rev.* 55, 93–128.

Cutchin, M. P. (2008). John Dewey's metaphysical ground-map and its implications for geographical inquiry. *Geoforum*, 39(4), 1555-1569.

De Dear, R.J., Brager, G.S. (1998) Developing an adaptive model of thermal comfort and preference/discussion, *ASHRAE Transact.* 104 (1998) 145.

De Dear, R.J., Brager, G.S. (2002) Thermal comfort in naturally ventilated buildings: revi- sions to ashrae standard 55, *Energy Build.* 34 (6) 549–561.

DiCiccio, T.J., Efron, B., 1996. Bootstrap confidence intervals. Stat. Sci. 11 (3), 189-212.

Duncan, D.T., Aldstadt, J., Whalen, J., Melly, S.J., 2013. Validation of walk scores and transit scores for estimating neighborhood walkability and transit availability: a small-area analysis. *GeoJournal* 78 (2), 407–416.

Doan MT, Rajasegarar S, Salehi M, et al. (2015) Profiling pedestrian distribution and anomaly detection in a dynamic environment. *Proceedings of the 24th ACM international on conference on information and knowledge management, CIKM '15*, pp.1827–1830. New York: ACM.

Economist, The (2010) The data deluge. https://www.economist.com/weeklyedition/2010-02-27. (Accessed, March 2020)

Erell, E., Pearlmutter, D., & Williamson, T. (2011). Urban microclimate. Design the Spaces Between Buildings, London-Washington, DC: Earthscan.

Fanger, P. (1970) Thermal comfort, Danish Technical Press, Copenhagen.

Forrester, J.W. 1969 Urban dynamics. Encino, CA: Pegasus Communications.

Fotheringham, A. S., Brunsdon, C., & Charlton, M. (2002). Geographically Weighted Regression: The Analysis of Spatially Varying Relationships. Chichester: John Wiley and Sons.

Fröhlich, D., & Matzarakis, A. (2020). Calculating human thermal comfort and thermal stress in the PALM model system 6.0. *Geoscientific Model Development*, 13(7), 3055-3065.

Gagge, A.P. (1936) The linearity criterion as applied to partitional calorimetry, Am. J. Physiol. 116 656-668.

Gehl Institute (2016) The Public Life Diversity Toolkit. New York: Gehl Institute. Available at: https:// gehlinstitute. org/work/the-public-life-diversity-toolkit/ (accessed November 2018).

Gehl Institute (2017) Public Life Data Protocol. New York: Gehl Institute. Available at: https://gehlinstitute.org/work/public-life-data-protocol/ (accessed October 2018).

Gehl, J. (2011) Life Between Buildings: Using Public Space. Washington, DC: Island Press.

Gehl, J., and Svarre, B. (2013) How to Study Public Life. Washington, DC: Island Press.

Givoni, B., Noguchi, M., Saaroni, H., Pochter, O., Yaacov, Y., Feller, N., & Becker, S. (2003). Outdoor comfort research issues. *Energy and Buildings*, 35(1), 77-86.

Goldstein B., and Dyson, L, (eds.) (2013) Beyond Transparency: Open Data and the Future of Civic Innovation (San Francisco: Code for America Press, 2013).

Google, 2016. Google StreetView Image API. https://developers.google.com/maps/documentation/streetview/ (accessed October 2018).

Greenfield, A. (2013) Against the smart city. New York, NY: Do Publications.

Griffin, G., Nordback, K., Götschi, T., Stolz, E., Kothuri, S., March 2014. Monitoring Bicyclist and Pedestrian Travel and Behavior: Current Research and Practice. *Transportation Research Circular* E-C183.

Gruen, V. (1967) The heart of our cities. p. 28.

Gulyas, A., Unger, J., & Matzarakis, A. (2006). Assessment of the microclimatic and human comfort conditions in a complex urban environment: Modelling and measurements. *Building and Environment*, 41, 1713–1722.

Hasan, S., Schneider, C.M., Ukkusuri, S.V., Gonzalez, M.C. (2013). Spatiotemporal patterns of urban human mobility. In: Springer Science+Business Media. *Journal of Statistical Physics*, 2012, New York.Volume 151, Issue 1, S. 304-318.

Hakim, A. A., Petrovitch, H., Burchfiel, C. M., Ross, G. W., Rodriguez, B. L., White, L. R., et al. (1998). Effects of walking on mortality among nonsmoking retired men. *New England Journal of Medicine*, 338, 94–99.

Hall, P. (1988). Cities of Tomorrow: An Intellectual History of Urban Planning and Design in the Tiventieth Century. Oxford, UK: Basil Blackwell.

Hass-Klau, C. (1993). A review of the evidence from Germany and the UK. Transport Policy, 1(1), 21-31.

Harvey, D. (1973) Social justice and the city. London, UK: Edward Arnold.

Heath, A. (2016) Inside LinkNYC's free public gigabit WiFi plan – *Business Insider*. Available at: http://www.businessinsider.com/inside-linknycs-free-public-gigabit-wifi-plan-2016-2 (accessed October 2018).

Hommels, A. M. (2005). Unbuilding Cities. Obduracy in Urban Sociotechnical Change. MIT Press.

Höppe, P. R. (1993) Heat balance modelling. Experientia, 49(9), 741-746.

Höppe, P. (2002). Different aspects of assessing indoor and outdoor thermal comfort. *Energy and Buildings*, 34, 661–665.

Hunt, J. D., Kriger, D. S., & Miller, E. J. (2005). Current operational urban landuse-transport modelling frameworks: A review. *Transport Reviews*, 25(3), 329-376.

Jacobs, J. (1961) The Death and Life of Great American Cities. New York: Random House.

Kaplan, R., Kaplan, S. and Ryan, R.L. (1998) With People in Mind: Design and Management of Everyday Nature. Washington, DC: Island Press.

Klinenberg, E. (2020) We Need Social Solidarity, Not Just Social Distancing. *The New York Times*. Available at https://www.nytimes.com/2020/03/14/opinion/coronavirus-social-distancing.html (Accessed 17 March 2020)

Lowry, I. S. (1965). A Short Course in Model Design. Journal of the American Institute of Planners, 31, 53 - 64.

Lynch, K. (1960) The Image of the City. Cambridge: MIT Press.

Kántor, N., & Unger, J. (2010). Benefits and opportunities of adopting GIS in thermal comfort studies in resting places: an urban park as an example. *Landscape and Urban Planning*, 98(1), 36-46.

Kessling, W., Engelhardt, M., Kiehlmann, D. (2013) The Human Bio-Meteorological Chart - A design tool for outdoor thermal comfort. *PLEA 2013 Conference proceedings*.

Kitchin, R. (2016) The ethics of smart cities and urban science. Phil. Trans. R. Soc. A 374: 20160115.

Kitchin, R. (2014) The data revolution: big data, open data, data infrastructures and their consequences. London, UK: Sage.

Kitchin, R., Lauriault, T.P., McArdle, G. (2015) Knowing and governing cities through urban indicators, city benchmarking & real-time dashboards. *Reg. Stud. Reg. Sci.* 2, 1–28.

Kobayashi, T., & Takamura, T. (1994). Upward longwave radiation from a non-black urban canopy. *Boundary-Layer Meteorology*, 69(1), 201–213.

Krizek, K.J., Handy, S.L., Forsyth, A., 2009. Explaining changes in walking and bicycling behavior: challenges for transportation research. *Environ. Plan. B Plan. Des.* 36 (4), 725–740.

Kwan, M. P., & Schwanen, T. (2009). Quantitative revolution 2: The critical (re) turn. *The Professional Geographer*, 61(3), 283-291.

Lai, D., Guo, D., Hou, Y., Lin, C., Chen, Q. (2014) Studies of outdoor thermal comfort in northern China, *Build*. *Environ.* 77 110–118.

Lennard, S.H.C., Lennard, H.L. and Bert, P. (1987) Livable Cities: People and Places: Social and Design Principles for the Future of the City. Southampton, NY: Gondolier Press.

Lewnard, J.A., Lo, N.C. (2020) Scientific and ethical basis for social-distancing interventions against COVID-19 *The Lancet Infectious Diseases*, ISSN: 1473-3099, Vol: 0, Issue: 0.

Li, J., & Heap, A. D. (2008). A review of spatial interpolation methods for environmental scientists.

Li, X., Santi, P., Courtney, T., Verma, S., Ratti, C. (2018) Investigating the association between streetscape built environment and human walking activities using human trace data. *Transactions in GIS*.

Li, X., Zhang, C., Li, W., Ricard, R., Meng, Q., & Zhang, W. (2015) Assessing street-level urban greenery using Google StreetView and a modified green view index. *Urban Forestry & Urban Greening*, 14(3), 675-685.

Lin T-P, Matzarakis A (2008) Tourism climate and thermal comfort in Sun Moon Lake, Taiwan. Int J Biometeorol 52:281–290.

Lin, T.-P., Matzarakis, A., Hwang, R.-L. (2010) Shading effect on long-term outdoor thermal comfort, *Build. Environ.* 45 (1) 213–221.

Lin T.-P., Matzarakis A., (2011) Estimation of outdoor mean radiant temperature by filed experiment and modelling for human- biometeorology use. *Proceedings of the 11th annual meeting of the European Meteorological Society*, Berlin, Germany, 9.19–22 2011 European Meteorological Society, EMS2011–2089.

Liu, S., Nazarian, N., Niu, J., Hart, M., de Dear, R. (2020) From thermal sensation to thermal affect: A multi-dimensional semantic space to assess outdoor thermal comfort, *Building and Environment*.

Mackaye, B. (1928) The New Exploration: A Philosophy of Regional Planning

Marcus, C.C. and Francis, C. (1997) People Places: Design Guidelines for Urban Open Space. New York: John Wiley & Sons.

Mattern, S. (2013) Methodolatry and the Art of Measure: The New Wave of Urban Data Science. *Design Observer: Places*, November, 2013, accessed October 2019 https://placesjournal.org/article/methodolatry-and-the-art-of-measure/

Mayer, H., and P. Höppe (1987) Thermal Comfort of Man in Different Urban Environments. *Theoretical and Applied Climatology* 38 (1): 43–49.

Mehta, V. (2014) Evaluating public space. Journal of Urban Design 19: 53-88.

Modcam (2016-04-09). Retrieved 2016 from http://modcam.io/

Mumford, L. (1961) The City in History: Its Origins, Its Transformations, and Its Prospects (New York: Harcourt, 569)

Nazarian, N., Acero, J., Norford, L. (2019) Outdoor thermal comfort autonomy: Performance metrics for climate-conscious urban design. *Building and Environment* 155

Newson, P., & Krumm, J. (2009) Hidden Markov map matching through noise and sparseness. *Proceedings of the* 17th ACM SIGSPATIAL international conference on advances in geographic information systems (pp. 336–343). ACM.

Nicol, J.F., Humphreys, M.A. (2002) Adaptive thermal comfort and sustainable thermal standards for buildings, *Energy Build*. 34 (6) 563–572.

Nikolopoulou, M., & Lykoudis, S. (2006). Thermal comfort in outdoor urban spaces: Analysis across different European countries. *Building and Environment*, 41(11), 1455–1470.

Nunez, M., & Oke, T. R. (1977). The energy balance of an urban canyon. *Journal of Applied Meteorology*, 16(1), 11–19.

Oke, T. R. (1973). City size and the urban heat island. Atmospheric Environment (1967), 7(8), 769-779.

Oke, T. R. (1982). The energetic basis of the urban heat island. Quarterly Journal of the Royal Meteorological Society, 108(455), 1–24.

Oke, T. R. (1987) Boundary Layer Climates, Routledge, London

Oke T. R. (1988) Street design and urban canopy layer climate, *Energy Build*. 11 (1) (1988) 103–113.

Oke, T. R. (1997). Urban environments. The surface climates of Canada, 303-327.

Oke, T. R. (2004). Initial guidance to obtain representative meteorological observations at urban sites.

O'Sullivan, F. (2020) It's Time for a '15-Minute City' in Paris Mayor: https://www.citylab.com/environment/2020/02/paris-election-anne-hidalgo-city-planning-walks-stores-parks/606325/ (Accessed 18 February 2020)

Parkinson, T., de Dear, R., Candido, C. (2012) Perception of Transient Thermal Environments: pleasure and alliesthesia. *Proceedings of 7th Windsor Conference*, Windsor, UK, 2012.

Pflieger, G., & Rozenblat, C. (2010). Urban networks and network theory: the city as the connector of multiple networks. *Urban Studies*, 47(13), 2723-2735.

Psyllidis, A. (2016) Revisiting Urban Dynamics through Social Urban Data ISBN 978-94-92516-20-6 ISSN 2212-3202

Pucher, J., Buehler, R., Merom, D., Bauman, A. (2011) Walking and cycling in the United States, 20012009: evidence from the National Household Travel Surveys. *Am. J. Public Health* 101 (SUPPL. 1).

Raftery, A., Zimmer, A., Frierson, D. et al. Less than 2°C warming by 2100 unlikely. *Nature Clim Change* 7, 637–641 (2017).

Rakha, T. (2015) Towards comfortable and walkable cities: spatially resolved outdoor thermal comfort analysis linked to travel survey-based human activity schedules. Massachusetts Institute of Technology

Reichert, C. (n.d.) Cisco and AT&T partner on smart cities solutions. ZDNet. Available at: https://www.zdnet. com/article/cisco-and-at-t-partner-on-smart-cities-solutions/ (accessed October 2019).

Reinhart, C. F. (2011), Simulation-based Daylight Performance Predictions, Book chapter in *Building Performance Simulation for Design and Operation*, Editors J Hensen and R Lamberts, Taylor & Francis.

Reinhart, C. F., Dhariwal, J., Gero, K. (2017) Biometeorological indices explain outside dwelling patterns based on Wi-Fi data in support of sustainable urban planning. *Building and Environment* 126 (2017) 422–430.

Rietveld, P., (2001) Biking and Walking: The Position of Non-Motorized Transport Modes in Transport Systems. Tinbergen Institute, Tech. Rep.

Rojas, F (2012) Transit Transparency: Effective Disclosure through Open Data (Cambridge, MA: Transparency Policy Project, Harvard Kennedy School, 2012).

Saelens, B.E., Ph, D., Frank, L.D., Ph, D., Med, A.B., (2003)Environmental correlates of walking and cycling: findings from the transportation, urban design, and planning literatures. *Environ. Phys. Activity* 25 (2), 80–91.

Santucci, D., Auer, T., Chokhachian, A. (2017) Impact of environmental quality in outdoor spaces: dependency study between outdoor comfort and people's presence. S.ARCH 2017 I Sustainable Architecture Conference Proceedings.

Santucci, D., Mildenberger, E., Plotnikov, B. (2017) An investigation on the relation between outdoor comfort and people's mobility: the Elytra Filament Pavilion survey. *PowerSkin Conference Proceedings*.

Santucci, D., Fugiglando, U., Li, X., Auer, T., Ratti, C. (2018) Methodological framework for evaluating liveability of urban spaces through a human centred approach. *Proceedings of 10th Windsor Conference Rethinking Comfort*, NCEUB 2018.

Sauter, M. (2018) Google's Guinea-Pig City. The Atlantic. Available at: https://www.theatlantic.com/ technology/ archive/2018/02/googles-guinea-pig-city/552932/(accessed 13 February 2018).

Spagnolo, J., De Dear, R. (2003) A field study of thermal comfort in outdoor and semi- outdoor environments in subtropical Sydney Australia, *Building and Environment* 38 (5) (2003) 721–738.

Stathopoulos, T., Wu, H., & Zacharias, J. (2004). Outdoor human comfort in an urban climate. *Building and Environment*, 39(3), 297–305.

Steemers, K., Ramos, M. (2010) Urban Environment Diversity and Human Comfort, in *Designing High-Density Cities for Social and Environmental Sustainability*, Edited by Edward Ng, UK and USA in 2010

Stone, B. (2012). The City and the Coming Climate. Climate Change in the Places We Live. Cambridge University Press. New York.

Stone, B., Vargo, J., & Habeeb, D. (2012) Managing climate change in cities: Will climate action plans work? *Landscape and Urban Planning*, 107(3), 263-271.

Sassen, S. (1991) The global city: New York, London, Tokyo. Princeton University Press.

Sevtsuk, A., Ratti, C. (2010) Does urban mobility have a daily routine? Learning from the aggregate data of mobile networks. Journal of Urban Technology 17 (1), 41–60.

Sevtsuk, A. (2014). Mapping the elastic public realm. Accessed https://idc. sutd. edu. sg/wp-content/uploads/ sites/10/2014/07/2014-Mapping-the-Elastic.

Sevtsuk, A., Kalvo, R., & Ekmekci, O. (2016) Pedestrian accessibility in grid layouts: the role of block, plot and street dimensions. Urban Morphology, 20(2), 89-106.

Taha, H. (1997) Urban climates and heat islands: Albedo, evapotranspiration, and anthropogenic heat. *Energy and Buildings*, 25(2), 99–103.

Townsend, A. (2013) Smart cities: big data, civic hackers, and the quest for a new Utopia. New York, NY: W.W. Norton & Co.

Toole, J. L., Colak, S., Sturt, B., Alexander, L. P., Evsukoff, A., & González, M. C. (2015) The path most traveled: Travel demand estimation using big data resources. *Transportation Research Part C: Emerging Technologies*, 58, 162-177.

Tromp, S.W. (1980) Biometeorology-the impact of the weather and climate on humans and their environment (animals and plants). Heyden & Son Ltd..

Tseliou, A., Tsiros, I. X., Lykoudis, S., & Nikolopoulou, M. (2009) An evaluation of three biometeorological indices for human thermal comfort in urban outdoor areas under real climatic conditions. *Building and Environment*, 45(5), 1346–1352.

United Nations, Sustainable Development Goals (Accessed January 2020 https://www.un.org/sustainabledevelopment/) USDOT, 2018. U.S. Department of Transportation National Household Travel Survey. https://nhts.ornl.gov/vehicle-trips and https://nhts.ornl.gov/person-trips. (Accessed: March 2019). Washington, D.C.: USDOT.

Vanky, A.P., Verma, S. K., Courtney, T. K., Santi, P., Ratti, C. (2017) Effect of weather on pedestrian trip count and duration: City-scale evaluations using mobile phone application data, *Preventive Medicine Reports*, Volume 8, 2017, Pages 30-37, ISSN 2211-3355,

Wang Y., Akbari H. (2014) Effect of Sky View Factor on Outdoor Temperature and Comfort in Montreal. *Environmental Engineering Science*. June 2014, 31(6): 272–287.

Watson, I.D., and Johnson, G.T. (1987). Graphical estimation of sky view—factors in urban environments. J. Climatol. 7, 193.

Whyte W. H. (1980) The Social Life of Small Urban Spaces. Washington, DC: Conservation Foundation.

Whyte, W. H. (1988) City: Rediscovering the center. New York: Doubleday.

Williams, S., Marcello, E. and Klopp J.M. (2014) Toward Open Source Kenya: Creating and Sharing a GIS Database of Nairobi. *Annals of the Association of American Geographers* 104, no. 1 (2014): 114-130

Williams, S., Ahn, C., Gunc, H., Ozgirin, E., Pearce, M., & Xiong, Z. (2019). Evaluating sensors for the measurement of public life: A future in image processing. *Environment and Planning B: Urban Analytics and City Science*, 46(8), 1534–1548.

World Population Prospects: *The 2015 Revision* (United Nations, Department of Economic and Social Affairs, Population Division, 2015).

Yin, L., & Wang, Z. (2016) Measuring visual enclosure for street walkability: Using machine learning algorithms and Google Street View imagery. *Applied Geography*, 76, 147-153.

II. Literature and Methodological Context

Introduction

Owed to the fact that this dissertation views and relates different domains such as climate, health and public space, in the following, the quality of dynamic relations between the different domains addressed throughout this dissertation is critically reviewed: this chapter connects knowledge from climatology, urban studies, and sociology in a cross-disciplinary approach in order to depict the complexity of relations that this dissertation addresses. It describes the theoretical framework necessary for contextualising the interrelation of different domains across various scales, highlighting the uniqueness of relations that this work is addressing, since its implications are vast and manifold.

In order to view and better understand the quality of this dynamic relations, this chapter observes and contextualises the domains addressed and related in this dissertation: Climate, health and urban space in their declinations and interrelations. The first section is dedicated to the global scale of climate and its manifestations on the urban and human scale; the second illustrates the concept of health in relation to urban population, the metrics that are used to quantify it and its relation to the concept of thermal comfort. The third section explores the concept of public space, defining it by its complementarity to human flows. These relations are dynamic because each domain is *per se* of dynamic nature.

The innovation in methodology presented in chapter III is based on the combination of quantitative and qualitative approaches, correlational research and its application on an empirical study presented in chapter IV; thus the workflow drawn by this doctoral thesis requires solid definitions supported by an accurate literature review to fully depict socio-technological dynamics in urban space. This chapter draws a theoretical framework to describe the dynamic relations that are consistent beyond conjuncture phenomena.

In the past decades, numerous studies have tried to characterise the qualities of the built environment (Jacobs, 1961; Lynch, 1960; Milgram, 1970), fostered by the increasing presence of data and the unprecedented opportunities to visualise flows and fluxes by data. However, since urban systems resemble rather an ecosystem than a machine, the data-based approach fails at fully capturing the vast parameters and their interdependencies that generate that dynamic complexity. Michael Batty explains in his book *Inventing Future Cities* the limitations of a purely technological approach to understand the urban context (Batty 2018).

Urban data science has undertaken many efforts to detect the metrics to characterise cities, using numbers to facilitate urban planning and policy-making. One of the results of this approach is the so called *smart city* that, as Ben Green argues in his book *The Smart enough City*, falls short when constituting an attractive environment for people, using the argument, that the concept of *smart city* often confuses technology with innovation (Green, 2019).

When conceptualising and designing the city of the future, it is fundamental to determine what to prioritise. For assessing and improving performance, it is necessary to create a theoretical background before deploying data and algorithms. In 2008, Chris Anderson promised in an article published by the magazine *Wired*, that "the data deluge makes the scientific method obsolete" and declared "the end of theory" (Anderson, 2008). Ten years later, Ben Green summarises: "in todays age of endless data, theory matters more than ever" (Green, 2019).

Combining the empirical experiment presented in chapter IV with the theoretical body presented here, this dissertation aims at framing how to achieve a liveable urban environment using technology and the data that it generates, keeping a substantial attention to the human scale and its embodiment. Previous studies that define the human, its senses and its ability to walk as an inseparable dimension of design (Chokhachian et al., 2017), consider humans as the measure for framing fundamental relations and interdependencies.

Humans, in their continuous energy exchange to the environment, define this dimension:

"The layer of air within two meters of the ground, the noosphere, that is the most important of all in Earth's atmosphere. It is located in what meteorologists have come to call the anthroposphere, nestled in the "boundary layer," a turbulent, well-mixed zone at the very base of the sublunar realm. This is a space in which the "natural" atmosphere gets entangled with human energy. This is the anthropocentric layer is the interdisciplinary sphere of human affairs, the most influential layer of our planet's atmosphere. This layer has not been fully or even adequately explored, which is unusual, since it is so accessible to us—as intimately close as our next breath" (Rodger Fleming and Jankovic, 2011).

The 2 m high *anthroposphere* is the dimension of the symbiotic relationship with the environment where the indissoluble connection of human senses and the built environment becomes evident. Particularly in the individual navigation in urban space, the relation between humans and the artificial landscape generated by the city becomes crucial due to their energy exchange, shaped by the microclimate and its effects on human senses. Considered on a long term, these effects have a fundamental influence on health connecting to the more general question of how the urban environment affects life and how it interacts with humans. In this sense, the physical dimension influences social and spatial justice, affected by health, safety and mobility. Speculating on the future of cities, the *walkable city* has become a slogan in both popular and academic discourses. In fact, walking in the city has widely been recognised as a synthetic indicator for measuring the quality of urban space, not only in terms of mobility and health, but as the realm for social exchange.

Design solutions tend to underestimate the dynamic component of urban systems and its reflections on socio-geometric patterns. Therefore, following Michael Batty, who has pointed out the need for "good robust theory for making sense of an environment entirely dominated by computers, computation and networks" (Batty, 2019), the complexity of interrelations that are addressed in this chapter is targeted on identifying the fundamental criteria for a design and urban planning agenda for the next decades.

The urbanist and critical thinker Michael Mehaffy and the mathematician Nikos Salingaros describe the analogy between complexity of behaviours and interactions in cities and the complexity of ecosystems. Following their assumption, designing cities requires full recognition of the complex organisational relations without reducing them to work like giant machines.

"Distinguishing physical from metaphorical complexity clarifies a presently confused and unsustainable situation, and can help us out of it (the ultimate aim of any science, and any philosophy). The topics of urbanism, architecture, product design, environmental design, sustainability, and complexity in science are all tightly interrelated. Humans "design" with much the same aim toward which nature "designs" — both aim to increase the complexity of a system so that it works "better". "Better" in this sense means more stable, more diverse, and more capable of maintaining an organised state — like the health of an organism. We learn from the structures and processes by which nature designs, so that we can also create and sustain these more organised states" (Mehaffy & Salingaros, 2012).

Turning to the global agenda and the political arena, *The New Urban Agenda* is one of the most significant actions. The outcome document of the United Nations Habitat III conference in

2016 was adopted by consensus by all 193 member states of the United Nations, proclaiming that it represents a "new paradigm" in urban planning, reversing the "over-determined" model of 20th century Western-dominated planning and embracing more locally determined forms. Among the plethora of intellectuals contributing to the document, the sociologists Richard Sennett and Saskia Sassen co-authored the book *Toward an Open City: The Quito Papers and the New Urban Agenda* (2017), which offers a detailed exposition of the thinking behind the *New Urban Agenda*.

Sennett and Sassen draw on more recent intellectual influences in the late 20th Century, including criticisms of Western-led global development trends and their consequences (Sassen, 2014). The conference also featured extensive discussion of growing challenges for the Global South, including rapid urbanisation, informal settlements, loss of affordability and homelessness, gentrification, displacement, and challenges to the *right to the city* (Future of Places 2016).

For his part, Sennett argues that "we need to apply ideas about open systems currently animating the sciences to animate our understanding of the city" (Sennett, 2018). His *open city* draws on ideas of informal interaction described much earlier by Jane Jacobs (1961) in her powerful critique of the early 20th century architect Le Corbusier's conception of cities. "Against the over-determined vision of Le Corbusier," writes Sennett, "Jacobs argued that places should become both dense and diverse, either in the form of dense streets or packed squares; such physical conditions can prompt the unexpected encounter, the chance discovery, the innovation which is the *genius loci* of cities" (Sennett 2018, p. 7). In this sense, Sennett is underlining the fact that 20th century urban planning was oriented towards a standardisation of living, working and leisure conditions to guarantee basic requirements, reflecting the concept of an *Existenzminimum*. The challenge of the 21st century is to provide adaptable models that can be shaped according to the needs and the conditions of inhabitants.

In this respect, Richard Sennett is echoing the influential design theorist and polymath Herbert Simon, who described design as a process of "changing existing conditions into preferred ones" (Simon, 1988). As outlined by Michael Wet Mehaffy and Tigran Haas, "This view of design is in stark contrast with the over-determined *tabula rasa* approach of the Charter of Athens. Simon also pioneered describing the implications of the dawning age of complexity for design, notably in his paper *The Architecture of Complexity* (Simon, 1962). He noted that the structures treated by design are nearly decomposable hierarchies, but not necessarily so. Indeed, Simon saw clearly that the structures of the cybernetic age were *generative* — that is, they might proceed from a few simple rules that could produce considerable complexity as they interact within an environment over time. The same principle holds, he observed, for human beings: our own complex behaviours result from complex interactions with our environments and with one another, notably in an urban setting (Mehaffy and Haas 2018).

Simon also cautioned against over-planning too far in advance. Human beings are unable to anticipate all of the conditions that will occur because they are limited by what he termed "bounded rationality." This term referred to what he called "important constraints arising from the limitations on the actor himself as an information processor"—that is, our inability to know in advance all of the complex variables that will interact and determine a result (Simon, 1962). An obvious example is the inability to precisely predict the weather at a particular time next week (Mehaffy and Haas 2018). Simon's theory is strengthened by Yuval Noah Harari, the author of *Homo Deus: A Brief History of Tomorrow*, who acknowledges that predicting is "a waste of time" (Harari, 2016).

For designers, this implies the need for a more iterative kind of planning that is able to adjust and change paths to make the necessary transformation towards preferred conditions possible. Moreover, this is a kind of planning that creates a supportive framework within which the preferred changes may, with careful transformation, develop over time.

Data driven approaches can, in this sense, provide a deeper understanding of what the sociologist Bruno Latour (2005) defines as "actor-network theory", describing a shifting web of relationships in urban settings and not a rigid "determined" structure. Latour's socio-technological approach includes the interplay between human and non-human actors, echoing Henri Lefevbre "social production of space" and "right to the city" (Lefevbre, 1992), emphasising that the city is a "dynamic and emergent co-creation of many actors, not a static creation by a small group of technical specialists" (Mehaffy and Hass, 2018).

Projecting these ideas on design and planning approaches for reshaping cities to adapt them to the requirements of tomorrow, it seems crucial to re-orientate our view: rather than being "manageable systems that can be steered and controlled in mechanical, linear ways, cities need to be framed as fluid, open, complex, multi-level, contingent and relational systems that are full of culture, politics, competing interests and wicked problems and often unfold in unpredictable ways" (Kitchin, 2016).

For this reason, this chapter frames the dynamic relations between multiple actors that converge in the urban environment, assigning to city analytics and its instrumental rationality its scientific relevance without weakening reason and experience or other knowledge generated by qualitative analyses.

1. Climate

Today's understanding of climate still largely coincides with Alexander von Humboldt's definition of climate:

" all the changes in the atmosphere which sensibly affect our organs, as temperature, humidity, variations in the barometrical pressure, the calm state of the air or the action of opposite winds, the amount of electric tension, the purity of the atmosphere or its admixture with more or less noxious gaseous exhalations, and, finally, the degree of ordinary transparency and clearness of the sky, which is not only important with respect to the increased radiation from the Earth, the organic development of plants, and the ripening of fruits, but also with reference to its influence on the feelings and mental condition of men. The history of climatology "attempted to explain why certain species of grain grew in one region rather than another, why a textile was worn here rather than elsewhere, and why agricultural methods yielded better results in one place than in another." (Humboldt, 1848)

Climate defines the array of creatures — human, animal and vegetarian — according to the conditions they are able to adapt to. The relation between bodies and climate is not only a casual connection, it is, according to Michel Foucault, a classical episteme, not a mere "exterior relation between things, but the sign of relationship" (Foucault, 2004). They are not "simply contiguous to each other, but also co-constituted each other. In other words, when bodies and things were found in a particular place, their very placement became a warrant of ontological affinity between and among them" (Egan, 1999).

Since the industrial revolution, the attention of scientists and naturalists was addressed to develop theories on how atmospheric conditions affect human physiology, health, and everyday life. They linked climate and welfare to what has been defined as a socio-meteorological correspondence, giving a strong impetus for understanding the relationship between health and social conditions. Physicians recorded weather information to understand epidemics, urban planners accordingly developed theories and guidelines to create healthier cities. Such richness preceded the modern sense of climatology" (Jankovic, 2010).

The following subsections will frame climate using the outlined theoretical framework since its effects have been proven to potentially become a threat to human health and lives (WHO, 1994). In this sense, climatology has the power influence decision making with acts of paramount political magnitude and economic consequences (Rodger Fleming and Jankovic, 2011). Or, as stated by Jonathan Franzen in his article published in the *New Yorker* in September 2019, "any movement toward a more just and civil society can now be considered a meaningful climate action" (Franzen, 2019).

1.1 Climate in the Anthropocene

In 2002, the term *Anthropocene* was proposed by Paul Crutzen to describe a new geological periodisation n that had been initiated with industrialisation and the liberation of fossil fuels (Lahound, 2017).

According to Crutzen,

"For the past three centuries, the effects of humans on the global environment have escalated. Because of these anthropogenic emissions of carbon dioxide, global climate may depart significantly from natural behaviour for many millennia to come. It seems appropriate to assign the term 'Anthropocene' to the present, in many ways human-dominated, geological epoch, supplementing the Holocene—the warm period of the past 10–12 millennia. The Anthropocene could be said to have started in the latter part of the eighteenth century, when analyses of air trapped in polar ice showed the beginning of growing global concentrations of carbon dioxide and methane. This date also happens to coincide with James Watt's design of the steam engine in 1784 " (Crutzen, 2002).

In the Anthropocene, global climatic conditions change constantly, and extreme phenomena increase in frequency and intensity. These human-made conditions became well known as *climate change* or *global warming*. In the late 1980s, climate change became a public concern when scientists advised governments that "this was the biggest threat human civilisation had ever faced and that the threat came from our civilisation's dependence on the cheap and plentiful energy that fossil fuels provided" (Chakrabarty, 2015). Climate change is inherently anthropogenic and is affecting the poor population more than the rich: those "who were much more responsible for the emission of excessive greenhouse gases" (ibidem). The global scale of this phenomenon requires an interdisciplinary form of planetary thinking, combining the expertise of geologists, climatologists and economists, to clarify the relationships between the history of life, introducing "new questions of scale—astronomical scales for space, geological scales for time, and scales of evolutionary time for the history of life" (ibidem).

Climatic conditions and their effects on the anthroposphere, the microclimatic conditions, are fundamental factors for life: paraphrasing Vanderheiden, Venus would be too hot and Mars too cold for hosting human life (Vanderheiden, 2008). Looking at the human scale, the *anthropocentric layer* becomes "deeply significant for all human transactions. Although this layer remains out of sight, its very proximity rendering it invisible. And this invisibility means that the modern sense of *climate* has been eroded to an abstract three-dimensional geophysical system, rather than an intimate ground-level experience (Rodger Fleming and Jankovic, 2011).

1.2 Scales of Climate

In 2008, scientists from around the world launched the Urban Climate Change Research Network as a city-scale counterpart to the Intergovernmental Panel on Climate Change (IPCC) (Rosenzweig et al., 2011). Its first assessment report highlighted the need for high-resolution, high-frequency weather monitoring, including the full range of impact variables that relate to the scales of everyday life, such as frequency of power failures and transportation delays (Rosenzweig et al. 2011). Furthermore, urban anthropogenic weather modification is at last becoming recognised as a significant factor for carbon mitigation as well as for local adaptation to global warming's weather consequences. City weather cannot be modelled without detailed understanding of the urban landscape and cities cannot plan for climate change without knowledge of atmospheric hazards and potentials (Jankovic and Hebbert, 2012).

Cities create artificial climates, defined as urban climates that are shaped by morphologies and materials. Studying the urban microclimate, its anthropogenic origin emerges as fundamental in becoming meteorologically self-aware and in taking responsibility for their role as "co-patterners of their climate" (Kratzer, 1956). In fact, cities are cultural communities in which urban weather results form the interaction between morphology and atmospheric dynamics. The majority of the world population experiences weather phenomena in urban space, contributing to shape each cities' identity. Due to their morphological features, cities alter atmospheric phenomena, generating local phenomena that surpass global predictions: the three dimensional complexity generates microclimatic variations that have shaped local climatic knowledge, which is needed for being resilient towards the "contingencies of weather" (Hebbert and Jankovic, 2013).

Urban climatic change has lacked the public and political visibility that is given to its global counterpart. While scientists and policy makers acknowledge the role of human settlements in contributing to the global carbon metabolism, the local-scale impacts of urban weather have been relatively little studied and weakly managed. However, as forecasts of the human and economic risks of global warming have grown more precise, increasing attention has been focused upon the urban environments where the greatest vulnerability is concentrated; in turn, this has stimulated concern for street-level climates and the scale of real weather.

As such, cities are the most influential climate manipulators: while the effects of climate change are increasingly affecting existing urban structures, the existing policies seem to be underestimating these phenomena giving visibly weak responses to sclimate change. Also, the Kyoto Protocol is neither mentioning cities in their role of contributing to climate change nor as recipient of its effects. This attitude has been changing in more recent years: when the IPPC, for its Fifth Assessment, has commissioned "a new panel chaired by Arnulf Grubler from Yale University to investigate the overall relation between urban settlement patterns, energy and climate" (Hebbert and Jankovic, 2013).

Nevertheless, these policies are rather addressing the globality of weather instead of understanding its "local manifestation, the subjectivity of lived experience, and the specificity of urban/rural form. Small-scale phenomena such as urban weather remain below the threshold of visibility in representational tools and are thus rendered less relevant as meteorological events and building blocks of the environmental policy. This is surprising in the face of the fact that world cities account for of 75% of global energy consumption, 50% of population, 80% of GDP and 60% of luminosity. And while they comprise only 3% of land area, demographic growth of the twentieth-first is predicted to occur almost entirely in cities" (Jankovic, 2017).

In addition to that, the densification and the qualities of urban space have structural differences between cities of the Global North and South. Increasing urban population and worldwide urban growth have created cities that are no longer well adapted to the needs of citizens "largely because the rate of change is too fast for those involved in building to respond quickly enough to our changing needs and the innovations that seem to pile up and into other at an ever-faster pace" (Batty, 2018). Furthermore, diffused poverty, especially in the Global South, creates environmental degradation with the silent superintendency of the Global North.

The above-mentioned phenomenon of discontinuous and unstructured growth pace calls for developing knowledge outside traditional scalar categories precisely because the problems climate change makes visible "adhere to none and can be observed across all" (Graham & Blanchfield, 2016, p. 181). This complexity requires to surpass all so far considered spatial scales and boundaries to become conscious about the transscalarity of urbanisation.

The latter of scale reveals its limitations also in weather modelling: the grid resolution of weather forecast failed until recently to make major cities of the world visible. Also the highest weather modelling resolution of such models can hardly represent cities, since its scale is larger than the urban. The introduction of the "tiled-land surface models – which account for the sub-grid heterogeneity by calculating an energy balance for each element within a gridbox – has enabled modeling of subgrid land use and has given the opportunity to include cities within models. However, the progress is slow and with mixed results." (Jankovic, 2017) Seeing the urgency and the pressure of climate on people's lives, the agenda imposes to consider the human scale the pivot for inverting the process and proposing downscaling as one relevant way of approaching the issue.

1.3 Microclimate

The concept of *microclimate* was developed by and for meteorologists in the first half of the twentieth century and was increasingly taken up by architects and urban planners in the second half of the twentieth century. *Microclimatology* was established by systematically examining the relevance and autonomous behaviour of air layers above the ground, the *zone of disturbance* (Geiger, 1927) in that physical zone called boundary layer, where the global climate and manmade local conditions are superimposed on, and mutually impact one another — in other words, where, as the climate historians James Fleming and Vladimir Jankovic recently noted, the "abstract three-dimensional geophysical system" and "intimate ground-level experience" overlap (Rodger Fleming and Jankovic, 2011).

Human interactions and the energy exchange between the human body and its environment happen within this domain, raising the research question wether microclimate generates a *genius loci* that characterises places determining very specific and profound implications.

The modern foundation for research in microclimatology was developed in Germany when, in 1927, Rudolf Geiger published *Das Klima der bodennahen Luftschicht* (The Climate Near the Ground); followed by Albert Kratzer's 1937 research *Stadtklima* (Climate of Cities). These works created a basis for a scientific investigation of microclimatic conditions. In the words of Albert Kratzer, "man, like the other animals, avoids unfavourable habitats and seeks fa-vourable ones" (Kratzer, 1937). "Undisturbed nature", he says, has "an enormous number of microclimates", which humans, however, are destroying (Geiger, 1927). According to Geiger, a "rational search for the best climate" only takes place "with increasing civilization", however, architecture and urban development open up the chance to deliberately influence microclimates (Roesler, 2017).

Meteorological comparisons between city and countryside showed for the first time the stunning autonomy of the city climate. Kratzer formulated his research hypothesis that "the density of built-up areas, the heights of the houses, their distance from one another, the width of the streets and squares, their orientation and their plant life — all of these have their effect on the temperature picture of a city" (Kratzer, 1937). Microclimates "differ especially in the daily temperature curve, the vertical roughness (wind field disturbances), the topographic position and exposure and above all in the type of actual land use". Cities generate a variety of microclimates, subsequently "One may now speak not only of a specific city climate, but also of a specific climate of broad streets, avenues and squares, and narrow alleyways" (ibidem). The fundamental questions of early urban climate research were addressing the dichotomy of society's dependence on climate and the considerably more concrete question of the impact of the city on the climate "the manner in which these great concentrations of human beings influence their climate" (ibidem). Geiger thought that microclimatology first appeared in Germany due to the lack of living space and "the consequent necessity of getting the utmost out of the earth" (Geiger, 1927). Stemming from practicalities of agriculture and urban congestion, microclimatology helped to understand and reduce risks of industrial pollution and its impact on local land, property and human settlement.

More recently, the work of geographers and urban meteorologists got low levels of public attention and support, until a larger portion of human population became subject of dramatic climate change on local level and of a magnitude larger than has been predicted for the global atmosphere in the next several decades. Urban heat island, urban runoff island, air pollution, decreased sunlight, split thunderstorms, flash-floods, street canyon turbulence and carbon dioxide *dome* have all plagued metropolitan areas for longer than is usually acknowledged. Urban populations have suffered a climate change for at least a century, but their plight is becoming visible only because small-scale climates are now imagined as places where global climate change manifests itself" (Jankovich 2017).

As Sascha Roesler points out, "the interdisciplinary research into city climate and comfort of the first half of the twentieth century was still separate from the energy issues that were to determine the discourse so critically during the decades that followed" (Roesler, 2017). Con-

siderations about the relationship between climate and energy demand were not as crucial as the implications that outdoor climate had on thermal, sanitary and moral domains. Moreover, he states, "the generation of form — and thus the potential of *climate as a design factor* — was still ignored" (ibidem). It was not until the late 1960s that Reyner Banham coined the term *architecture of the well-tempered environment*, his trenchant phrase for the determining impact of artificial climate on architecture (Banham, 1965). However, only in the past few decades a rising attention towards the effects of urban climate has generated a vast number of studies and research activities, aiming at creating evidence for saving operational energy in buildings and improve microclimatic conditions in the urban environment.

Urban climatology has investigated the consequences of urban geometry for the alteration of the radiative energy balance and the reduction of heat loss by wind-driven turbulence in a city environment. The presence of urban structures and their surfaces lead to a radiative interaction that is absent in rural areas, where radiation is emitted into the atmosphere. The porosity that arises from the obstructive presence of buildings is also responsible for lowering the porosity of the city and limiting air flow through it (Britter & Hanna, 2003; Skote et al., 2005). The Urban Heat Island (UHI) effect, the most pithy definition that quantifies the urban-rural temperature difference, has been shown to display that more built up or denser cities have bigger heat island effects (Oke, 1981). However, a key difference between the surface energy budget at rural and urban sites is the ratio of the latent to sensible heat fluxes. In rural areas, the surface is dominated by vegetation, from which water evaporates (Smith & Levermore, 2008). In contrast, much of the surface in an urban environment has undergone waterproofing through the use of impervious materials, reducing the latent heat flux (Grimmond & Oke, 1999, 2002). Differences in land use, irrigation, wind speed and rainfall mean that evaporative cooling varies in urban environments. But even in densely populated areas the latent heat flux accounts for 20-40% of the net radiation balance (Grimmond & Oke, 2002; Grimmond et al., 2004). On a neighbourhood scale, the presence of a vegetated area or water body within a city can have a significant cooling effect on local temperatures (Spronken-Smith & Oke, 1999). As a matter of fact, beyond the mentioned phenomenon of the UHI, microclimates are affected by the full set of meteorological conditions that converge in urban structures, including anthropogenic heat and air quality. As man-made artefacts, however, microclimates are far more than purely thermodynamic phenomena, they are fabricated thermal places with varied meanings which require serious architectural, social, and cultural research (Heschong, 1979). Studies on microclimate include insights into everyday culture, social conditions and the political aspirations of energy-dependent and urbanised societies.

The *microclimatic genius loci* derives from distinctive artificial materialities as a result of the "microclimate as human artifact, even though it appears to be a natural, nonmaterial and physical phenomenon" (Roesler & Kobi, 2018). The dependency between artificial intervention and thermal characterisation with its effects on human activities is described by Reyner Banham:

"Societies who do not build substantial structures tend to group their activities around some central focus—a water hole, a shade tree, a fire, a great teacher—and inhabit a space whose external boundaries are vague, adjustable according to functional need, and rarely regular. The output of heat and light from a campfire is effectively zoned in concentric rings, brightest and hottest close to the fire, coolest and darkest away from it, so that sleeping is an outer-ring activity, and pursuits requiring vision belong to the inner rings. But at the same time, the distribution of heat is biased by the wind, and the trail of smoke renders the downwind side of the fire unappetising, so that the concentric zoning is interrupted by other considerations of comfort or need" (Banham, 1984).

Despite its trans-scalar nature, the microclimatic characterisation of places is still an object of observation for developing mapping techniques to create urban climate maps. Their use is addressing the correlation of climate data and spatial characteristics in order to understand the effects, interactions and predicting conditions. What is still a matter of research, is to highlight the various impacts of diverse microclimatic conditions in urban space, particularly addressing design solutions for facilitating its entire fruition. The microclimate at the pedestrian level, in fact, is the primary factor that allows the use of public space. As such, it has a fundamental in-

fluence on the quality of the urban experience. Facilitating access and creating the conditions for public health and safety, microclimate has tremendous impacts on the everyday lives and well-being of hundreds of millions of people around the globe.

2. Health

The relationship between climate and health has been studied since the earliest phases of meteorology research. Meanwhile, in the contemporary urbanised world, health is interpreted as the temporal psychological and physical condition of a human body. A permanent and holistic conception of well-being and its widened territory embracing the vitality of the entire nature are often neglected. Health in the urban environment is inscribed in infrastructures, rather than being a generative concept for a nurturing habitat. In some ways, having established that cities are the predominant circumstance of living in the twenty-first century, one can argue that cities are ubiquitous, and their impact so pervasive, that it is difficult to consider any aspect of health without thinking of the role of cities. Arguably, multiple academic disciplines produce research that is essentially premised on the existence and the importance of cities (Galea & Vlahov, 2005).

The author proposes urban health inquiry to include two principal aspects: the description of the health of urban populations, both as a whole and as particular subgroups within cities, and an understanding of the determinants of population health in cities, with particular attention to how characteristics of cities themselves may affect the health of urban populations. When thinking how cities may affect health, it is fundamental to recognise that cities are places where large numbers of people live in close proximity. Therefore, the impact of cities can be consider in two primary ways. First, as a growing proportion of the world's population lives in cities, the health of urban populations contributes increasingly to the overall population health worldwide. Therefore, factors that influence health in cities gain importance in influencing the health of global population. Second, as the largest part of the world's population already lives in urban areas, it becomes increasingly likely that aspects of the urban environment will affect people's health. The urban physical environment includes, among many other aspects, the built environment, air and water quality, noise levels, parks, and climate conditions in cities; all aspects of cities that citizens encounter on a daily basis and all with the potential to affect health.

One of the most valuable definitions of health is contained in the Constitution of the *World Health Organization* (WHO):

"Health is a state of complete physical, mental and social wellbeing and not merely the absence of disease or infirmity. The enjoyment of the highest attainable standard of health is one of the fundamental rights of every human being without distinction of race, religion, political belief or economic and social condition" (WHO, 1994).

This statement defines health, in terms of public health, beyond a medical model rather towards a social one. While the medical model focuses on the individual and on interventions that are used to treat disease, a social model considers health as an outcome of the effects of socioeconomic status, culture, environmental conditions, housing, employment and community influences (Duhl & Sanchez, 1999). In 1986, the First International Conference on Health Promotion in Ottawa declared that "the fundamental conditions and resources for health are peace, shelter, education, food, income, a stable ecosystem, sustainable resources, social justice and equity. Improvement in health requires a secure foundation in these basic prerequisites" (Ottawa Charter for Health Promotion, 1986). Following this definition, urban systems are the places that are "continually creating and improving those physical and social environments and expanding those community resources which enable people to support each other in performing all the functions of life and in developing themselves to their maximum potential" (Hancock & Duhl, 1988).

2.1 Public Health

The urban environment has a central role in generating the prerequisites for health, both for the physical and social constructs of communities. Studies confirm that significant numbers of diseases are caused by toxins in the environment and imply that disease prevention, instead of individual personal changes or medical treatments, rather demands changes in our surrounding environments (Tesh, 1990). Furthermore, the environmental hypothesis points not only to chemicals, but also to the physical environments and social organisation under which people live (Duhl & Sanchez, 1999).

In the light of the afore mentioned changes in climate, health in cities becomes more than ever a crucial topic. The links between the environment and health are not new to the field of public health. Even though human health is part of the larger global ecosystem and is sustained by this system, its effects are felt locally. The risk assessment of the effects of climate change on human health differs significantly from previous epidemiological research in environmental medicine. The main reasons for this diversification are the large spatial scale (regional/global compared to local effects), the temporal allocation and the long time frame, associated with the high complexity of the urban systems (Menne et al., 2000).

The hot summer of 2003 with about 70,000 additional heat-related deaths in Europe can serve as a drastic example that shows the vulnerability of society already under the current climatic conditions (Robine et al., 2008). Heat waves are statistically concentrated in urban areas, not just in line with increased population density, however it is due to urban form, materiality and urban metabolism as the force for the urban heat island effect (Chokhachian et al., 2017). In principle, the effects of climate change on health can be direct or indirect: possible direct effects result mainly from weather events such as heat waves or floods. In many cases, however, climate changes have indirect effects, e.g., by disturbing the ecology of pathogens and their vector organisms, food production or fresh water supply. Other health risks result from the increase in air pollution and air allergens, the increase in UV radiation due to stratospheric ozone depletion and socio-economic distortions (Jendritzky, 2009).

The afore mentioned concepts and theoretical orientations provide the foundation for a basic understanding of how public health and urban planning intersect. Since much of the planning professionals acknowledge that the focus of their activity is on the creation of vibrant places for people, design and public health professionals are not yet effectively linked. In fact, urban planning can and does serve as a form of primary prevention and contributor to health outcomes. Additionally, it highlights how a holistic approach to creating cities is pivotal.

As described in the previous subsection, the practice of studying health in urban populations started in the 19th century, fostered by the effects of industrialisation, urbanisation and social conditions of workers. Strengthened by reoccurring pandemics, the nexus between densely populated urban environments with their hygienic conditions and health was directly associated with the exposure to the agents of disease. New York City's urban development, for example, was strongly influenced by pandemics and by the resulting new requirements for urban health (Nevius, 2020). The emergence of epidemics brings forth the significance of health and wellbeing in relation to the built environment and beyond, particularly in relation to urban climate.

Increasing temperatures and changing weather patterns, together with heavily polluting industries, shift the vectors and spread of disease. In the US, during the COVID-19 pandemic, in three of the states with the highest number of cases — Illinois, Michigan and Louisiana — African-Americans made up 40 to 70 percent of deaths from the disease, exceeding consistently the percentage of black people. Many of the black communities ravaged by COVID-19 are "front-line communities" — where residents live adjacent to heavily polluting industries (Gunn-Wright, 2020). Similar correlations were found in polluted industrial areas in Italy. The combination of low income, poor environmental conditions and segregation highly influences mortality also in the Global North, making visible a wider global trend. As clearly outlined by Carleton at al. (2020), "the impact of climate change on mortality will be comparable globally to leading causes of death today, such as cancer and infections disease."

Concluding, the impacts of climatic conditions in cities, exacerbated by the artificial nature of urban systems and by the way they forge microclimate, are evident and seek for solutions in urban design. Strongly emphasised by the 2020 pandemic, the need for healthy urban environments is paramount and therefore developing innovative approaches and experiences from the pre-pandemic urban world to the post.

2.2. Thermal Comfort

The previous subsections have illustrated the nexus between climate, its manifestation on the micro scale and the consequences for public health. Going deeper into the human scale, this section draws a picture of the physiological implications on the human body and its thermoregulatory response while referring to a theoretic research framework in order to better understand the dynamic relations between climate and health.

A wide body of research has already demonstrated the of thermal stress on mortality (Carmona et al., 2016; De Bono et al., 2004; Haines et al., 2006; Kovats & Jendritzky, 2006) Opposite to thermal comfort, thermal stress, is originated by ambient temperatures that inhibit the physiological condition of thermal balance between the body and the surrounding environment (Givoni, 2010). Comfort, in its common understanding, is a subjective sensation and describes at first an absence of discomfort. Either from heat or from cold, it expresses the enjoyment of the thermal environment. The thermal regulation of the human body keeps the balance between the heat loss to the surrounding environment and the inner body temperature within a very narrow range, while "maintaining thermal balance is a pre-required, although not a sufficient, condition for feeling thermal comfort because thermal balance can also be maintained under uncomfortable thermal conditions" (ibidem).

The heat exchange process in the human body is regulated mainly by two types of heat flow, convection and radiation, and by heat loss through evaporation on the surface of the skin. The skin temperature is not homogeneous over the body, creating differences between various parts. Depending on the temperatures of the environments, these differences are small (in hot conditions) or large (in cold conditions). In cold conditions, the distal parts of the body tend to cool down quickly, creating these larger differences that humans perceive as local discomfort. The heat exchange between the skin and the surrounding air takes place through convection, either positive (heat gain) or negative (heat loss) in relation to the skin and air temperature difference. As the physical process suggests, convection is highly depending on air velocity and on the clothing factor. Its effects are non linear (ibidem). Convection is also regulating evaporation and subsequently sweating from the skin. While convection is highly depending on air velocity, that can be also very low or zero, the human body is in constant radiative exchange with the surrounding environment. Specifically in outdoor spaces, the influence of radiation is crucial since humans are exposed both to solar (short wave) as well as infrared (long wave) radiation. The surface temperatures in outdoor exposed environments are often higher than air temperature, creating local microclimatic conditions that are potentially perceived as discomfortable or stressful.

Originally, thermal comfort studies have been focused on indoor environments to assess the thermal quality of conditioned buildings (Fanger, 1970). The perception of comfort for indoor and outdoor spaces can differ in a wide range of tolerances due to different reasons. Besides different clothing and activities, the predominant divergence are the time ranges spent generally in these environments. Exposure to outdoor climate in many cases is in the range of minutes, while indoor exposure is in the range of several hours (Höppe, 2002). This difference results in different methods to assess comfort in indoor and outdoor environments. In his research based on the Instationary Munich Energy-Balance Model (IMEM), Peter Höppe concluded that thermal sensation outdoor is perceived differently from that of indoor and even postulated, that "indoor thermal comfort standards are not applicable to the outdoor settings" (ibidem). Höppe built up two scenarios for the winter and the summer case, concluding

that on a cold winter day it takes a long time to get close to steady state levels. After 1 hour of outdoor exposure, skin temperature has dropped from 33.5 °C to 27.3 °C which is still 5.9 K above the steady state level. This means, in real life conditions, thermal steady state is never reached even when people spend several hours outdoors (Höppe, 1997).

Besides behavioural adjustments that represent the most immediate feedback link to the thermal environment, humans develop different mechanisms such as acclimatisation or psychological processes to adapt (DeDear et al., 1997). Acclimatisation is an unconscious process of the autonomous nervous system that directly affects physiological thermoregulation and continuously occurs when people move through outdoor spaces. These varying environments consist of asymmetrical and transitional conditions, that are "pleasant sometimes, and distinct-ly unpleasant other times" (Parkinson et al., 2012). In fact, according to Parkinson, a thermal "stimulus can be perceived as either pleasant or unpleasant depending on its potential to restore the body to a normal thermal state." This assumption has set the basis for the concept of *allisthesia*, which bases on the idea that "displeasure must occur in order to experience pleasure" (ibidem).

Along with physical and physiological adaptation, different studies have attempted to put into evidence psychological adaptation, which largely depends on the information people have for a particular situation. (Nikolopoulos & Steemers, 2003). In this research domain, Griffiths et al. (1988) employ the term naturalness to describe an environment without artefacts in combination with the expectations people have for a specific environment. The expectations widely depend on seasonal conditions, where humans expect to encounter conditions they know, based on their experience. Experience, in fact, directly affects people's expectations both in short- and long-term. Supported by past exposure, people differentiate between seasonal scenarios where clothing and individual choices in terms of activities and time of exposure support the desire to reach comfortable conditions. These conditions have been considered as neutral. Nikolopoulos and Steemers underline the concept that "it is increasingly believed that a variable, rather than fixed, environment is preferred, whereas, a static environment becomes intolerable". The environmental stimulation that occurs in outdoor spaces, is the primary reason for people to go out of thermally stable environments, and to enjoy the variability of outdoor space, particularly in thermally pleasant conditions. Whereby, also under heat stress, people tend to adapt more easily to varying outdoor, conditions (Nikolopoulos & Steemers, 2003).

Unlike natural environments, urban spaces in fact present highly variable microclimatic conditions within small distances. Highly affected by lower wind speed, higher temperatures and irregular solar exposure, these spaces provide highly fluctuating conditions, additionally depending on seasonal scenarios. In this sense, thermal comfort results as a determining factor for the use and fruition of outdoor spaces, exhorting the emerging question of how far it is influencing specifically public space. For this reason, the next section illustrates different definitions of public space, to frame its significance within the investigated framework.

3. Urban Space

Urban space is the domain where climate and health dynamically interrelate and physically converge. Its definition is complex and manifold, due to its ambiguity and indetermination.

Amidst the many existing ones, the definition provided by the french philosopher Michel De Certeau is prominent: he stated that a city is defined by the "possibility of producing its own space (un espace propre)". He argues: "The *city*, like a proper name, thus provides a way of conceiving and constructing space on the basis of a finite number of stable, isolatable, and interconnected properties" (Certeau, 1984).

Beyond the definition of urban space, De Certeau's definition of space is relevant in the context of this research considering the dynamic nature of public space:

"A space exists when one takes into consideration vectors of direction, velocities, and time variables. Thus space is composed of intersections of mobile elements. It is in a sense actuated by the ensemble of movements deployed within it. Space occurs as the effect produced by the operations that orient it, situate it, temporalize it, and make it function in a polyvalent unity of conflictual programs or contractual proximities" (Certeau, 1984).

The simultaneity of movement, the flows, and networks, the infrastructure in public space, can be synthesised in the idea of a hidden face, an image containing patterns that can be perceived on a different way, depending on the circumstances and on the lens that are seen thorough. Based on this view, this section illustrates the concept of urban space in its duality as a geographical public space and in its complementarity to the flows that shape it.

3.1. Public Space

In 1958, Hannah Arendt published *The Human Condition*, her book about what she called *public space* (Arendt, 1958). What she meant by public space was not just the buildings and places that encourage people to come together in a good town square or market piazza. Public space, for Arendt, was also a metaphysical arena in which people realised their individual potential. (Knox Beran, 2009). Arendt drew her inspiration from the tradition of the Greek polis, a place designed "to multiply the chances for everybody to distinguish himself, to show in deed and word who he was in his unique distinctness" (Arendt, 1958). The Athenian polis also had to provide space for trade, an activity that gave the agora its vitality. To *go agora-ing* in Greek meant not only to seek distinction and honour in the public square but also to buy and sell things.

The polyhedric meaning of public space in its endless manifestations, from the Athenian agora to the Italian Piazza, reflects the idea of a common interest: even in the unequal societies of ancient Greece, the 16th century and the middle-age, these spaces embodied the idea of a shared interest for a peaceful, just and safe living. Ambrogio Lorenzetti's *Effects of Good Government in the City* from 1338, a fresco panel located in Siena's Palazzo Pubblico (Fig. II.1), depicts this aspiration, emphasising the temporal component, the effect on a long term — a characteristic that we, today, likely define as resiliency.

In *The City in History*, Lewis Mumford called the life of the old public spaces "many sided" (Mumford, 1961). He described the Piazza Navona as "a place for lovers to stroll, a market place, a playground for the children of the neighborhood with sidewalk restaurants on both sides of the place, where whole families can dine and gossip and drink, all three generations together." Typically, public space has an anchor institution that contributes to this complication of endeavour. The institution might be a church, as in the case of the Piazza Navona, a charitable foundation, like the hôtel-dieu in a French town a library, like the Library of Saint Mark on Venice's Piazzetta San Marco or a town hall, like the Palazzo Pubblico on Siena's Piazza del Campo. There is a close relation between the care with which a particular public space has been organised and the degree to which a feeling of community exists there. Visitors' experience shaped urban design, Goethe said, like a work of art. Venice itself was for him the "latest and best painting of the Venetian school" (Goethe, 1875 in Knox Beran, 2009).

Today, growing population is compressing urban spaces, leading the United Nations to include it into one of the Sustainable Development Goals (United Nations, Sustainable Development Goals). Public space is the place that serves society, where civic relations arise and an equitable society is created. Processes that cannot occur without the quality of urban space that enables its appropriation by users and citizens. Appropriation of public space allows citizens to take part in the production of urban space, in opposite to the commercialisation of the already formed urban space by giving citizens the right to completely manage and use their everyday life (Lefebvre, 1992, in Lara-Hernandez et al., 2019). Appropriation also characterises *Everyday*



Figure II.1: Ambrogio Lorenzetti (1338) "Effects of Good Government in the City" Palazzo Pubblico Siena. Source: Wikipedia.

Figure II.2: Detail of G.B. Nolli Nuova Topografia di Roma (1748) Source: https:// www.lib.berkeley.edu/EART/ maps/nolli.html



Urbanism (Santucci et al., 2020). Everyday Urbanism is referring to everyday life without the necessity of creating an ideal environment (Ahearne, 2010; Certeau, 1984; Mehrotra, 2005). This means day-to-day activities do not seek to transform physical structures and for that reason they take place in the already existing urban environment (Liabäck & Löwstett, 2018).

Referring to Ancient Greece, Hannah Arendt stated that the public realm requires plurality:

"The reality of the public realm relies on the simultaneous presence of innumerable perspectives and aspects in which the common world presents itself and for which no common measurement or denominator can ever be devised" (Arendt, 1958, p. 57) and specific locations, public spaces, – where this plurality gives way to action (Arendt 1968, p. 30), where what is said can be heard by others. This spatial differentiation is at the very basis of her opposition between the private and public space. Symmetrically, the private space in the polis of in Ancient Greece is said to correspond to a specific space devoted to labour, work and the "intimate life – the passions of the heart, the thoughts of the mind, the delights of the senses" (Arendt 1958, p. 50). Therefore, "the distinction between the private and public realms [...] equals the distinction between things that should be shown and things that should be hidden [...] each human activity points to its proper location in the world" (ibidem, pp. 72–73, in Debarbieux, 2017)

The Nolli Plan of Rome (Fig. II.2) clearly distinguishes between black and white domains, the black, built one is private, the white is empty and public. This representation of the 17th century equals Arendt's differentiation. One can observe, that our digitalised society has transcended physical boundaries in public space: our public experience is not limited to the time physically spent in public realm, it goes beyond, depending on the time people interact with the technologies that enable interactions, independently from their location. These fusing domains are fulfilling the two opposite properties cities are required to offer: being a place of otium, a place for human exchange, a shelter, and a place for developing *nec-otia*, businesses and economic exchanges (Cacciari, 2004). Public space has sequentially shifted from being a place of otium towards a fully equipped environment for negotia. The modern metropolis is the result of the pressure given by the market and the industry to transform the growing urban structures into a Grossstadt, affirming the spaces for economic exchange, as an expression of its mobility, its pulse or Nervenleben. Subsequently, public space has lost its role as a ritual space that every human society needs to celebrate its own foundational categories and values (Hantelmann, 2018). However, the value of public space is fundamental for place making, defined as the love for a place that makes the place more valuable and resilient, also in terms of life satisfaction (Glaeser, 2011).

Amidst many attempts to create a metric for measuring the quality of public space, an approach that reveals the relevance of this research has been presented by Richard Florida, referring to the spreading of the COVID-19 virus in cities. Florida relates the spreading rate to a particular kind of urban density, highlighting that it is "not density in and of itself that seems to make cities susceptible, but the kind of density and the way it impacts daily work and living" (Florida, 2020). Building upon this assumption, this density might be rather defined as urban intensity. This characteristic is underlying in every urban systems with different, varying strengths, in a non-linear phenomenon that relies on physical qualities (morphology, building density, population, etc.) and network connectivity. Describing this concept, Dovey & Pafka, observe that "a key problem with the production of knowledge about the city is that there are no controlled conditions - the city is the laboratory," (Dovey & Pafka, 2020) following Jane Jacobs, who referred to the city's form of logic as inductive "reasoning from particulars to the general; not the reverse" (Jacobs, 1961). According to Jacobs, "city processes in real life are always made up of interactions among unique combinations of particulars, and there is no substitute for knowing the particulars" (ibidem). She was critical of the ways that statistical averages can mislead and attuned to the ways that the atypical peculiarities of everyday urban life can be vital to understanding how cities work (Dovey & Pafka, 2020).

Having outlined the many requirements and qualities of public space, it becomes clear that understanding and exploring public space requires a dynamic and interconnected approach. The following section illustrates the flows that constitute urban life in its concentration of diverse encounters and interconnections.

3.2 Flows

Complex urban systems consist of flows and fluxes, whose dynamic confluences generate actions. The term flow refers not only to the physical interaction of humans with the built environment but also to the immaterial, thus fundamental, dimension of information and movement. In Michael Batty's words, "the city manifests a new liquidity of action: a place where physical desires, face-to-face contacts, and digital deliberations provide a new nexus of innovation" (Batty, 2019). The proposed term liquidity underpins Zygmunt Bauman's concept of *liquid modernity* (Palese, 2013) and refers to the transition "from a rural world into an urban world, from a world of highly local interactions to a world of global interactions, from a world based on physical technologies to a world based on information technologies" (Batty, 2019).

The debate around the relevance of physical proximity for interactions between people still presents highly controversial positions (Glaeser, 2011), however, looking at the city as a place for the people, their presence and their movement is of paramount interest and importance because their flows constitute the rhythm of the city. Victor Gruen's *The Heart of Our Cit*-*ies* (Gruen, 1965) asserts the concept of flows distributing energy to the city, that is seen as a living organism. These flows were mainly referring to the movement of people and goods through the networks that constitute urban systems: in fact, through their interdependency, networks and flows are complementary (Batty, 2019).

In the era of disruptive technologies and global connectivity, the existing digital technologies allow "to make visible that form is composed of flows. [...] Contemporary landscapes in populated places reflect not only physical flows but also human[...] presenting patterns in forms that are woven together by human and physical movements" (Batty, 2019). Movement, indeed, is the phenomenon that mostly characterises the complexity of urban systems, fundamentally through its transscalar nature. In this sense, analysing flows through digital technologies allows to design a new vocabulary for cities.

Focusing on human, individual flows, this section is differentiating between the topics of walking — as an activity, a basic mode of transport and a way of accessing space — and one of its metrics, walkability. While walking is envisioned as an elementary form of the urban experience, walkability is regarded as a metric for larger considerations of socioeconomic

conditions within the city, in terms of equal accessibility to places, services and opportunities, without societal divisions.

According to De Certeau, pedestrian movements form one of these "real systems whose existence in fact makes up the city.[...] They are not localized; it is rather they spatialize." (Certeau, 1984). Walking, in fact, has many levels of significance in the context of urban studies. Besides being the most elemental way of experiencing the urban environment, it is the basic mode of mobility. Walking speed has been considered as an indicator for city size and morphology (Batty, 2018 p. 102). In fact, till the beginnings of motorised mass mobility, the size of cities was highly related to the walkable distance, not necessarily in terms of path length but rather to the time people needed to get access to services and utilities. Studies have proven the different walking rhythm depending on the city size, as an indicator for the pace of life in cities (Bornstein and Bornstein, 1976; Walmsley and Lewis, 1989; Milgram, 1970). Furthermore, like other processes, walking speed intensifies as a consequence of increasing urban population (Batty, 2019).

In *The Practice of everyday life*, De Certeau dedicates a chapter to walking in the city as a *Spatial Practice*. He argues:

"The operation of walking, wandering, or 'window shopping,' that is, the activity of passersby, is transformed into points that draw a totalizing and reversible line on the map. They allow us to grasp only a relic set in the nowhen of a surface of projection. Itself visible, it has the effect of making invisible the operation that made it possible "(Certeau, 1984).

According to De Certeau, the act of walking is to the urban system what the speech act is to language. At the most elementary level, it has a triple *enunciative* function: first, it is a process of appropriation of the topographical system on the part of the pedestrian (just as the speaker appropriates and takes on the language); second, it is a spatial acting-out of the place (just as the speech act is an acoustic acting-out of language); and third, it implies relations among differentiated positions, that is, among pragmatic *contracts* in the form of movements (just as verbal enunciation is an *allocution*, posits another opposite the speaker and puts contracts between interlocutors into action). It thus seems possible to give a preliminary definition of walking as a space of enunciation (Santucci et al., 2020).

"The ordinary practitioners of the city live "down below," below the thresholds at which visibility begins. They walk—an elementary form of this experience of the city; they are walkers, Wandersmänner, whose bodies follow the thicks and thins of an urban "text" they write without being able to read it. These practitioners make use of spaces that cannot be seen; their knowledge of them is as blind as that of lovers in each other's arms. "(Certeau, 1984)

In the past two decades, a renewed interest in the connection between health and cities has arisen from concerns about obesity, physical inactivity, pollution, climate change and road traffic injuries, after the urban sanitarian movement in the mid-19th century, planning cities for health, seemed to have been forgotten (Corburn, 2007). Physical inactivity is one of the most important health challenges of the 21st century because of its influence on the most dead-ly chronic diseases. Therefore, transportation and planning policies promote active modes of transportation, such as walking and cycling as alternatives to private motor vehicles, since they can contribute to improve health, with the potential of gaining further co-benefits such as congestion mitigation (De Nazelle et al., 2011). Contemporary urban environments are highly affected by the consequences of car traffic: noise and air pollution, accidents and fatalities are the most frequent phenomena that are detrimental to the urban experience worldwide. Minimising individual motorised mobility in cities is an objective of many municipalities and policy makers, to improve health conditions for citizens and increase environmental quality in urban spaces (Bongiorno et al., 2019).

An interesting case is the city of Tucson, Arizona. Pedestrian traffic fatalities are increasing dramatically over the past years, despite all other traffic fatalities' decrease (Fig. II.3). This phenomenon is due to the social conditions of people who "lack access to a vehicle, live in

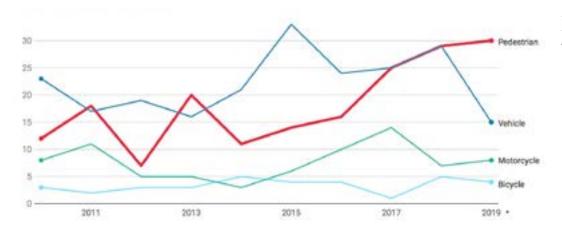
poor areas, are dependent on transit and walking" (O'Gara, 2019). The car oriented infrastructure does not provide, in Tucson as in many other places around the globe, enough safety for pedestrians. Furthermore, heat stress induces people to cross the wide unprotected lanes at any point of the streets to take shortcuts, regardless of traffic lights and pedestrian crosswalks.

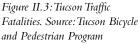
Before further elaborating the concept of walkability, the following paragraphs present a short review of the factors that contribute to the creation of the walkable city. Distinguishing between walking as an activity and walkability as a metric is crucial: while walkability describes a potential condition which does not predict the effect of its values, walking, as previously stated, is an activity that results from the status quo of urban space. Walking is primarily chosen for short distances and preferred over motorised transport modes due to its predictability in time. Time is often the parameter that encourages and limits the choice for walking. In fact, even in appropriate environments, walking is severely limited by the distance people can cover, mostly because of the required time. The advantages of a walkable public space are numerous and affect multiple domains: walkable environments promote social and cultural inclusion, guarantee accessibility and safety, are linked to a higher attractiveness of urban spaces and better environmental quality (Bongiorno et al., 2019).

In order to understand the parameters that facilitate walking, numerous studies have analysed correspondences between urban morphology and walking behaviour (Handy et al., 2002; Forsyth et al., 2008; Forsyth, 2015), in order to prove or disprove certain cause–effect relations between different morphologies and higher levels of walking and highlighting the influence of safety, vegetation, compactness and diversity. In these studies, researchers have attempted to reduce urban morphology to a measure, a quantifiable index (Cervero & Kockelman, 1997; Giles–Corti et al., 2003; Maghelal & Capp, 2011). As underpinned by Dovey & Pafka (2020), "such approaches often seek to the limits to aggregating complex factors that work in synergy".

In this sense, over the past century different approaches have attempted to characterise systematically the urban complexity clustering its synergetic-interconnected components. Ildefons Cerda', the Catalan urban planner who designed Barcelona's extension, produced an urban theory in the 19th century based on socio-spatial surveys, morphological analysis and observation of cities as complex movement economies with synergistic relations, where density, functional mix and street networks were the key components (Soria y Puig, 1999). The already mentioned studies by Jane Jacobs point out a "need for concentration" that results from *small blocks* and functional mix. Her principles were drawn from detailed observations of everyday urban life in her own neighbourhood of Greenwich Village, New York. Looking at that specific conditions that correspond to a walkable, lively urban environment, she formulated principles that can be applied almost in every city. According to her observations, urban density, access and functional mix are the three factors that facilitate walking (Jacobs, 1961).

Urban density is a fundamental property because it concentrates more people and places within walkable distances. The level of density literacy, however, is low and there is substantial confusion over what it means (Dovey & Pafka, 2014). Density is usually referred to building





density within given boundaries, however it could be related to inhabitants or pedestrians. As already illustrated by Walter Gropius, the same Floor Area Ratio (FAR) can be achieved with very different building types and height (Gropius, 1931), however, confusion persists because the "measure of dwellings/hectare is common but particularly blunt as it depends on the functional mix, household size and dwelling size for its relations to building or population densities." (Dovey & Pafka, 2020). Measures of the FAR can be highly misleading since they do not include population density, commuters, visitors, and even less indicating the level of urban vitality. Indeed, the nexus between walking and density persists, assuming that denser concentration of people, activities and utilities corresponds to shorter distances in space and therefore in time. Despite not having found yet the single density measure, urban density needs to be understood as a complex *assemblage* of relations and interdependencies (Dovey & Pafka, 2014).

The concept of functional mix was chosen by Jacobs (1961) against the modernist segregation of the city into mono-functional zones that limit close connections of living, working, education, recreation and leisure. This separation is a strong characteristic of North American Cities built during and for a car oriented mobility, and are therefore rather uncommon in historical cities where mixing functions is an intrinsic property due to walking activity of their inhabitants. Independently from their location, cities that developed before the era of motorised mobility embody the necessity of connecting functions and people by walking. Distances are shorter, people of different ages, abilities, ethnicities and social classes live and work close to each other, generating the unique quality of urban vitality. In this sense, access is a fundamental parameter to enhance urban life. It does not necessarily correspond to permeability or connectivity. Wider streets, for example, generate higher permeability but they don't promise any increase in terms of vitality. Access is rather crucial in terms of the quantity of interactions people encounter within a certain time frame. Isochrone maps enable to visualise and compare different scenarios, basing on the time factor.

New York City's pedestrian potential is the object of another study relevant for this doctoral research by Boris Pushkarev. In *Urban Space for Pedestrians* he provides urban policy makers with quantitative methods to proportion pedestrian space in North American downtown areas (Pushkarev, 1975). Besides the specificity of Manhattan's dense urban fabric, Pushkarev proposes a methodology that relies on people counting at the entrance of several buildings, combining it with transportation studies to put into evidence pedestrian density and the subsequent need of walking space. The study also includes the observation of environmental influences on people's presence, particularly in parks, soliciting the need for further research in flow analysis based on larger samples and including more specifically environmental factors.

More recently, at the end of the 1970's, the team of researchers behind Space Syntax developed theories for the spatial analysis of configurations that allow to correlate an urban indicator with statistical measures of the fluxes of people (Space Syntax, http://www.spacesyntax. com). These models were targeted to understanding the city by linking the physical and spatial patterns for finding dependencies between the form and use of spatial structure. In particular, they defined a method to measure natural movement by quantifying the level of connectedness of street segments by analysing their characteristics such as length, orientation, ends (node, cul-de-sac, multiple). These scientific approaches underpin the relevance of walking as an indicator for health and safety and its significance for creating vital urban space. What remains open, is the question of how to embed walking in design and planning strategies as well as in policies.

The possibility of walking has become an impelling agenda in academic and administration arenas. Subsequently, to facilitate walking in urban space, the previously mentioned studies have developed indices to evaluate this possibility, coining the term *walkability*. One of the most enlightening definitions has been given by Michael Southworth (2005) who states "walkability is the extent to which the built environment supports and encourages walking by providing for pedestrian comfort and safety, connecting people with varied destinations within a reasonable amount of time and effort, and offering visual interest in journeys throughout the network."

Jeff Speck's book *Walkable city rules: 101 steps to making better places* (Speck, 2018) elaborates all the relevant parameters that need to be considered when identifying the networks of walk-ability in cities. His work is targeted primarily to North American cities, where the transit experience is often associated with private motorised mobility.

Walkability has become a measure to evaluate and confront different urban environments also in terms of health, environmental and socioeconomic quality. It has also has also been recognised as a key to achieving equity between differences of social class, ethnicity, gender, age and ability (Massey, 2005; Sennett, 2018).

The term *walkability* is a Portmanteau word (Carroll, L. 1882), where a verb (walking) or adjective (walkable) is converted to an abstract noun that seems more objective but where the life of the concept referred to (the walkable city) has been depleted. While not suggesting any problem with using what is now a very common concept, the term *walkability* has been asked to capture an impossibly complex and abstract set of factors and interrelationships (Dovey & Pafka, 2014). The metrics adopted so far are mainly density, mix and access, whereas it is evident, that the concept is multi-dimensional (Talen and Koschinsky, 2013). In focusing on these dimensions, other potentially relevant parameters such as topography, micro-climate, safety and aesthetics have been excluded from these considerations. The oversimplification, has, on the one hand, promoted the inclusion of this metric in policies and urban planning regulations, on the other, it has reduced its complexity to a merely quantitative dimension. Particularly in the design and planning disciplines, the synthesis of qualitative and quantitative approaches is fundamental to avoid reducing these decision to numerical operations.

4. Summary and Conclusions

In the superordinate research question of finding systemic relations between microclimate and people's flows, this chapter has attempted to draw a picture of the dynamic relations between climate, health and public space, indicating approaches and metrics to understand their complex intersections and interactions. The literature and methodological context is essential to interpret the city as a living organism rather than a machine, deciphering the underlying mechanisms that regulate relations and exploring the synergies that occur and contribute creating a system that is more than the sum of its parts.

The influence of climate is pervasive and cannot be detached from other dynamic phenomena that regulate urban life. As such, the interdependencies that underpin a liveable public space are boundless, in continuous flow, generating reciprocal causalities. The applied methodology that will be presented in the following chapters, serves as a case study to address the question of how to shape public space to achieve health, vibrancy and inclusiveness. Through this lens, that data driven case study will indicate tendencies and prove the effect of certain features, being conscious that its results need to be considered in the light of the outlined theoretical framework. The case study is conceived following Michael Batty's concept of *bottom up* approach with a particular attention to the scale: the focus area has the highest possible resolution within a relatively small scale (Batty, 2018). This choice allows to analyse the specificity of a place by putting into evidence phenomena that might be true also elsewhere but are intrinsically related to that urban environment.

Looking at the case of Boston, this dissertation positions itself in a research line that started in the 19th century with the early work of thinkers such as Cerda, Sitte and Geddes through to the 20th century work of Jacobs, Whyte, Lynch, Pushkarev and others, that based on the detailed observation of particular cities and neighbourhoods. This dissertation ads to the described existing research by taking advantage of the availability of large datasets and combining it with simulation methods. ,This approach of using a sample that covers a large spatial and temporal domain, allows to upscale the findings of a specific area. In this set up, the mobile phone application data serves as basis for the creation of a high resolution combined with large scale observations. Despite the sample size, it is necessary to maintain awareness that we are not able to measure cities. According to Jacobs, most of the damage to cities was due to the tendency to reduce complex interrelations to *formulae* (Jacobs, 1961). Nevertheless the data based study facilitates answering the relevant questions that the afore mentioned studies addressed already in the past century, without neglecting the indispensable differentiation that the complex analysis requires.

For this reason, the approach of this doctoral thesis is not statistical, despite using statistical methods as part of a multidisciplinary approach to understanding rather than finding the rule that can be applied everywhere. City science remains a "proto-science with no monopoly on urban knowledge" because urban systems have not any controlled laboratory conditions that can be replicated by digital modelling (Dovey & Pafka, 2016). Depicting urban systems requires qualitative and quantitative approaches to be used contextually and in conjunction with each other, "across dichotomies between objective and subjective, materialities and representations, sciences and humanities" (Dovey & Pafka, 2020).

References

Ahearne, J. (2010) Michel de Certeau, The practice of everyday life. International Journal of Cultural Policy, 16(1), 2-3.

Anderson, C. (2008) The End of Theory: The Data Deluge Makes the Scientific Method Obsolete, *Wired* (Accessed March 2020 https://www.wired.com/2008/06/pb-theory/)

Arendt, H. (1958) TheHuman Condition. Chicago: The University of Chicago Press.

Banham, R. (1965) A home is not a house. Art in America, 2(4).

Banham, R. (1984) Architecture of the Well-tempered Environment. University of Chicago Press.

Batty, M (2018) Inventing Future Cities, MIT Press.

Bongiorno, C., Santucci, D., Kon, F., Santi, P. and Ratti, C. (2019) Comparing bicycling and pedestrian mobility: Patterns of non-motorized human mobility in Greater Boston. *Journal of Transport Geography*, Volume 80, 2019.

Bornstein, M. & Bornstein, H. (1976) The pace of Life, Nature 259, no. 19.

Britter, R. E., & Hanna, S. R. (2003). Flow and dispersion in urban areas. Annual review of fluid mechanics, 35(1), 469-496.

Cacciari, M. (2004) La città, Pazzini Editore.

Carleton, T. A., Jina, A., Delgado, M. T., Greenstone, M., Houser, T., Hsiang, S. M., & Rising, J. (2020) Valuing the global mortality consequences of climate change accounting for adaptation costs and benefits (No. w27599). National Bureau of Economic Research.

Carmona, R., Díaz, J., Mirón, I. J., Ortiz, C., Luna, M.Y., & Linares, C. (2016) Mortality attributable to extreme temperatures in Spain: A comparative analysis by city. *Environment International*, 91, 22-28.

Carroll, L. (1882) Mischmasch. Printed at the University Press.

Certeau, M. d. (1984) The practice of everyday life. Berkeley: CA: University of California Press.

Cervero, R., & Kockelman, K. (1997) Travel demand and the 3Ds: Density, diversity, and design. *Transportation research. Part D, Transport and environment*, 2(3), 199-219.

Chakrabarty, D. (2015) The Human Condition in the Anthropocene. *The Tanner Lectures in Human Values Delivered at Yale University*, February 18–19, 2015.

Chokhachian, A., Santucci, D., Auer, T. (2017) A Human-Centered Approach to Enhance Urban Resilience, Implications and Application to Improve Outdoor Comfort in Dense Urban Spaces. *Buildings* 2017/7, p. 113.

Corburn, J. (2007). Reconnecting with our roots: American urban planning and public health in the twenty-first century. *Urban affairs review*, 42(5), 688-713.

Crutzen, P.J. (2002) Geology of Mankind, Nature, vol. 415, p. 23.

Debarbieux, B. (2017) Hannah Arendt's spatial thinking: an introduction, Territory, Politics, Governance, 5:4, 351-367.

De Bono, A., Peduzzi, P., Kluser, S., & Giuliani, G. (2004) Impacts of summer 2003 heat wave in Europe.

de Dear, R.. Brager, G., Cooper, D. (1997) Developing an Adaptive Model of Thermal Comfort and Preference. *Final Report ASHRAE RP- 884*

de Nazelle, A., Nieuwenhuijsen, M. J., Anto, J. M., Brauer, M., Briggs, D., Braun-Fahrlander, C., Cavill, N., Cooper, AR., Desqueyroux, H., Fruin, S., Hoek, G., Panis, L. I., Janssen, N., Jerrett, M., Joffe, M., Anderson, Z. J., van Kempen, E., Kingham, S., Kubesch, N., ... Lebret, E. (2011). Improving health through policies that promote active travel: a review of evidence to support integrated health impact assessment. *Environment International*, 37, 766 - 777.

Dovey, K., & Pafka, E. (2014) The urban density assemblage: Modelling multiple measures. Urban Design International, 19(1): 66–76. Dovey, K., & Pafka, E. (2016). The science of urban design?. Urban Design International 21(1), 1-10.

Dovey, K., & Pafka, E. (2020). What is walkability? The urban DMA. Urban studies, 57(1), 93-108.

Duhl, L. J., Sanchez, A. K., & World Health Organization. (1999) *Healthy cities and the city planning process: a back-ground document on links between health and urban planning* (No. EUR/ICP/CHDV 03 04 03). Copenhagen: WHO Regional Office for Europe.

Egan, J. (1999) Authorizing Experience: Refigurations of the Body Politic in *Seventeenth-Century New England Writing*, 16.

Fanger, P. (1970) Thermal comfort, Danish Technical Press, Copenhagen.

Florida, R. (2020) The Geography of Coronavirus, https://www.citylab.com/equity/2020/04/coronavirus-spread-map-city-urban-density-suburbs-rural-data/609394/ (Accessed: April 2020)

Forsyth, A., Oakes, J. M., Lee, B., & Schmitz, K. H. (2009). The built environment, walking, and physical activity: Is the environment more important to some people than others? *Transportation research part D: transport and environment*, 14(1), 42-49.

Forsyth, A. (2015). What is a walkable place? The walkability debate in urban design. Urban Design International 20(4), 274-292.

Foucault, M. (2004) The Order of Things, 20.

Franzen, J. (2018) What If We Stopped Pretending? The climate apocalypse is coming. To prepare for it, we need to admit that we can't prevent it. *The New Yorker*, September 8, 2019.

Future of Places (2016) Future of Places: The global forum about public space. Accessed May 2020. http://future-ofplaces.com.

Galea, S., & Vlahov, D. (Eds.) (2006) Handbook of urban health: populations, methods, and practice. Springer Science & Business Media. Urban Health

Geiger, R. (1927) Das Klima der bodennahen Luftschicht, ein Lehrbuch der Mikroklimatologie, 2nd ed. (1927; repr., Braunschweig: F.Vieweg & Sohn Publisher, 1941), vi.

Giles-Corti, B., Macintyre, S., Clarkson, J. P., Pikora, T., & Donovan, R. J. (2003) Environmental and lifestyle factors associated with overweight and obesity in Perth, Australia. *American Journal of Health Promotion*, 18(1), 93-102.

Givoni, B. (2010) Thermal comfort issues and implications in high-density cities. Designing high-density cities for social and environmental sustainability, 87-106.

Glaeser, E. (2011) Triumph of the City. Pan.

Goethe, J.W. von (1875) Italienische Reise. Hempel.

Graham, James, (editor.) & Blanchfield, Caitlin, (editor.) & Anderson, Alissa, (editor.) & Carver, Jordan, (editor.) & Moore, Jacob, (Program coordinator), (editor.) 2016, *Climates : architecture and the planetary imaginary*, Columbia Books on Architecture and the City, New York, NY. p. 181

Grimmond, C. S. B., & Oke, T. R. (1999) Aerodynamic properties of urban areas derived from analysis of surface form. *Journal of Applied Meteorology*, 38(9), 1262–1292.

Grimmond, C. S. B., & Oke, T. R. (2002) Turbulent heat fluxes in urban areas: Observations and a local-scale urban meteorological parameterization scheme (LUMPS). *Journal of Applied Meteorology* 41(7), 792-810.

Grimmond, C. S. B., Salmond, J. A., Oke, T. R., Offerle, B., & Lemonsu, A. (2004) Flux and turbulence measurements at a densely built-up site in Marseille: Heat, mass (water and carbon dioxide), and momentum. *Journal of Geophysical Research: Atmospheres*, 109(D24).

Green, B. (2019) The smart enough city: putting technology in its place to reclaim our urban future. MIT Press.

Griffiths, R., Morphet, J. & Thornley, A. (1988) Editorials, Planning Practice & Research, 3:6, 3-4.

Gropius, W. (1931) Flach-, Mittel-oder Hochbau?.

Gruen, V. (1967) The heart of our cities.

Gunn-Wright, R. (2020) Think This Pandemic Is Bad? We Have Another Crisis Coming. https://www.nytimes. com/2020/04/15/opinion/sunday/climate-change-covid-economy.html (Accessed April 15, 2020)

Haines, A., Kovats, R. S., Campbell-Lendrum, D., & Corvalán, C. (2006). Climate change and human health: impacts, vulnerability, and mitigation. *The Lancet*, 367(9528), 2101-2109.

Hancock, T., & Duhl, L. (1988) Promoting Health in the Urban Context. FADL Publishers, Copenhagen.

Handy, S. L., Boarnet, M. G., Ewing, R., & Killingsworth, R. E. (2002). How the built environment affects physical activity: views from urban planning. *American journal of preventive medicine*, 23(2), 64–73.

Hantelmann, D. von (2018) What is the new Ritual Space of the 21st Century? https://theshed.org/program/se-ries/2-a-prelude-to-the-shed/new-ritual-space-21st-century (Accessed April 2020)

Harari, Y. N. (2016) Homo Deus: A brief history of tomorrow. Random House.

Hebbert, M., Jankovic, V. (2013) Cities and Climate Change: The Precedents and Why They Matter. Urban Studies, 50(7), 1332–1347.

Heschong, L. (1979) Thermal Delight in Architecture, Cambridge, MA: MIT Press.

Höppe, P. (1997) Aspects of human biometerology in past, present and future. *International journal of biometeorology*, 40(1), 19-23.

Höppe, P. (2002). Different aspects of assessing indoor and outdoor thermal comfort. *Energy and Buildings*, 34, 661–665.

Humboldt, A. (1848) Cosmos: a sketch of a physical description of the universe.

Jacobs, J. (1961) The Death and Life of Great American Cities. New York: Random House.

Jankovic, V. (2010) Confronting the Climate: British Airs and the Making of Environmental Medicine.

Jankovic, V (2017) Zone of Disturbance: Urban Weather and Climate Research during the Twentieth Century. *Proceedings of the Second Conference on the History of Meteorology*, CMATC: Beijing.

Jankovic, V., Hebbert, M. (2012) Hidden climate change – urban meteorology and the scales of real weather, *Climatic Change*, v.113, p.23-33

Jendritzky, G. (2009) Folgen des Klimawandels für die Gesundheit.

Kitchin, R. (2016) The ethics of smart cities and urban science. Phil. Trans. R. Soc. A 374: 20160115.

Knox Beran, M. (2009) Can the Polis Live Again? The modern world has withered public space and its virtues. *The Social Order; Arts and Culture* (Accessed March 2020 https://www.city-journal.org/html/can-polis-live-again-13238.html)

Kovats, R., Jendritzky, G. (2006) Heat-waves and human health. *Climate change and adaptation strategies for human health*, 63-97.

Kratzer. A. (1956) The Climate of Cities, American Meteorological Society, Boston.

Lahound, A. 2017 The Mediterranean: A New Imaginary retrieved on January 2020 https://www.internationa-leonline.org/research/politics_of_life_and_death/92_the_mediterranean_a_new_imaginary

Lara-Hernandez, J. A., Melis, A., & Lehmann, S. (2019). Temporary appropriation of public space as an emergence assemblage for the future urban landscape: The case of Mexico City. *Future Cities and Environment*, 5(1), 1–22.

Latour, B. (2005) Reassembling the social: An introduction to actor-network-theory. London: Oxford University Press.

Lefebvre, H. (1992) The Production of the Space. 1996th edn. Cambridge, Massachusetts: Blackwell Publishers Ltd.

Lynch, K. (1960) The Image of the City. Cambridge: MIT Press.

Maghelal, P.K., & Capp, C.J. (2011). Walkability: A Review of Existing Pedestrian Indices. Journal of the Urban & Regional Information Systems Association, 23(2).

Doreen, M. (2005) For space. London and Los Angeles: sage Publications.

Mehaffy, M. (2013) Medellín's remarkable renaissance. Urban Land. https://urbanland.uli.org/economy-mar-kets-trends/which-cities-are-worlds-most-innovative-winner/Press. 2015.

Mehaffy, M.W, & Haas, T. (2018) Engaging Informality in the New Urban Agenda. *Berkeley Planning Journal*, 30(1). Retrieved from https://escholarship.org/uc/item/53g7j9pn

Mehaffy, M., Salingaros, N. (2012) Science for Designers: The Meaning of Complexity. Complexity in nature and design, as well as how it differs from complication, is often misunderstood. (Accessed March 2019 https://www.metropolismag.com/author/sitestaff/)

Mehrotra, R. (Ed.) (2005) Everyday urbanism: Margaret Crawford vs. Michael Speaks (Vol. 1). University of Michigan College of.

Menne, B. et al. (2000): Methoden zur Erforschung der Auswirkungen von Klimaänderungen auf die Gesundheit. Umweltmedizin in Forschung und Praxis 5: 193 – 200.

Milgram, S. (1970) The Experience of Living in Cities, Science 167, no. 3924

Mumford, L. (1961). The city in history: Its origins, its transformations, and its prospects (Vol. 67). Houghton Mifflin Harcourt.

Nevius, J. (2020) New York's built environment was shaped by pandemics https://ny.curbed. com/2020/3/19/21186665/coronavirus-new-york-public-housing-outbreak-history (Accessed: April 2020)

Nikolopoulou, M., & Steemers, K. (2003). Thermal comfort and psychological adaptation as a guide for designing urban spaces. *Energy and Buildings*, 35(1), 95-101.

O'Gara, N. (2019) Tucson's pedestrian fatality problem https://news.azpm.org/p/news-articles/2019/11/1/161121-tucsons-pedestrian-fatality-problem/ (Accessed: February 2020)

Ottawa Charter for Health Promotion. Health promotion, 4: iii-v (1986).

Oke, T. R. (1981). Canyon geometry and the nocturnal urban heat island: comparison of scale model and field observations. *Journal of climatology*, 1(3), 237-254.

Palese, E. (2013) Zygmunt Bauman. Individual and society in the liquid modernity SpringerPlus 2013, 2:191 http:// www.springerplus.com/content/2/1/191

Parkinson, T., de Dear, R., Candido, C. (2012) Perception of Transient Thermal Environments: pleasure and alliesthesia. *Proceedings of 7th Windsor Conference*, Windsor, UK, 2012

Pushkarev, B., (1975.) Urban Space for Pedestrians

Spronken-Smith, R.A., & Oke, T.R. (1999) Scale modelling of nocturnal cooling in urban parks. *Boundary-Layer Meteorology*, 93(2), 287-312.

Robine, J.M.; Cheung, S.L.K.; Le Roy, S.; Van Oyen, H.; Griffiths, C.; Michel, J.P.; Herrmann, F.R. Death toll exceeded 70,000 in Europe during the summer of 2003. *C. R. Biol.* 2008, 331, 171–178.

Rodger Fleming, J., Jankovic, V. (2011) Revisiting Klima, Osiris, Vol. 26, No. 1, pp. 1-15.

Roesler, S. (2017). The Urban Microclimate as Artefact: Reassessing Climate and Culture Studies in Architecture and Anthropology. *Architectural Theory Review*, 21(1), 73-88.

Roesler, S., & Kobi, M. (2018). Microclimates and the City, Towards an Architectural Theory of Thermal Diversity. In S. Roesler & M. Kobi (Eds.) *The Urban Microclimate as Artifact*. Basel: Birkhäuser.

Rosenzweig, C., Solecki, W.D., Hammer, S.A., Mehrotra, S. (eds) (2011) *Climate change and cities*. Cambridge University Press.

Santucci, D., Chokhachian, A., Auer, T. (2020) Temporary Appropriation of Public Spaces: The Influence of Outdoor Comfort. *Temporary Appropriation in Cities: Human Spatialisation in Public Spaces and Community Resilience*. Melis, A., Lara-Hernandez, J. A., Thompson, J. (eds.) Springer International Publishing, Cham

Sassen, S. (2014) Expulsions: Brutality and complexity in the global economy. Cambridge: Harvard University Press.

Sennett, R., Burdett, R., Clos, J. (2017). Toward an Open City: The Quito Papers and the New Urban Agenda. New York: New York University. https://infoscience.epfl.ch/record/226637/files/Quito-Papers-Preview-Version2.3.pdf

Sennett, R. (2018) The Open City. The Post-Urban World: Emergent Transformation of Cities and Regions in the Innovative Global Economy, edited by Tigran Haas and Hans Westlund, 97–106. Cambridge: Routledge.

Simon, H.A. (1962) The architecture of complexity. Proceedings of the American philosophical society, 106(6), 467-482.

Simon, H.A. (1988) The science of design: Creating the artificial. Design Issues, 67-82.

Skote, M., Sandberg, M., Westerberg, U., Claesson, L., & Johansson, A.V. (2005) Numerical and experimental studies of wind environment in an urban morphology. *Atmospheric Environment*, 39(33), 6147-6158.

Smith, C., & Levermore, G. (2008) Designing urban spaces and buildings to improve sustainability and quality of life in a warmer world. *Energy policy*, 36(12), 4558-4562.

Soria y Puig, A., & Cerdá, I. (1999) Cerdá: The five bases of the general theory of urbanization. Barcelona, Spain: Electa.

Southworth, M. (2005) Designing the walkable city. Journal of urban planning and development, 131(4), 246-257.

Space Syntax, http://www.spacesyntax.com (Accessed: March 2020)

Speck, J. (2018) Walkable city rules: 101 steps to making better places. Island Press.

Talen, E., & Koschinsky, J. (2013). The walkable neighborhood: A literature review. *International Journal of Sustainable Land Use and Urban Planning*, 1(1).

UN-HABITAT (2011) Cities and Climate Change: Global Report on Human Settlements 2011. London: Earthscan.

United Nations, Sustainable Development Goals (Accessed January 2020 https://www.un.org/sustainabledevelopment/)

Vanderheiden, S. (2008) Atmospheric Justice: A Political Theory of Climate Change (Oxford: Oxford University Press, 2008), 6.

Walmsley, J. D. & Lewis, G.J. (1989) The Pace of Pedestrian Flows in Cities, in Environment and Behavior 21 no. 2.

World Health Organization (1994) Constitution of the World Health Organization. In: WHO basic documents, 40th ed. Geneva, World Health Organization, 1994

III. METHODOLOGY

Introduction

This chapter outlines the array of methods utilised in this dissertation when investigating the systematic relation between microclimatic conditions and people's walking patterns in public space. Comparing pedestrian flows and microclimatic conditions requires a coherent systematic and synthesised assessment of data collected from different sources through a variety of different techniques. Analysing data is not enough: generating meaningful results requires to develop a novel workflow to assess the complex interdependencies, which leads to several scientific challenges:

First, studying these interacting processes requires a strong interdisciplinary approach. In this work, studying the factors that determine urban microclimate and its influence on walking patterns, involves knowledge from climatology, urban design, social sciences, and data science. These complex relationships need to be addressed also through qualitative methods and a theoretical framework.

Second, numerical modelling is an essential tool for the global comprehension of urban dynamics and the underlying processes, which are by nature multi-scalar in space and time. The interactions among the system components cannot be apprehended by human expertise only (Masson et al., 2014).

Third, to highlight these relations, a systemic modelling approach, which is intrinsically interdisciplinary, has to connect models designed for different purposes. The datasets that this workflow is employing, were already existing and not collected for this specific purpose. Generating information with the same granularity requires a broad comprehension of the information embedded in the models themselves and of the exchanges between models.

The following chapter presents the data sources employed and considerations about the sample size. It exposes the methods for the data analysis, the employed tools and it states the limitations of this methodological approach.

1. Data Sources

This section presents the employed datasets. Timeframe, resolution and location are based on the walking trajectories dataset that has been collected in Boston, Massachusetts, and that has been made available by the Senseable City Lab of MIT. This primary data source frames the microclimatic analysis and the focus area, that has used weather data from Boston, Massachusetts as secondary data source.

1.1 Primary Data Source

The primary data source is a dataset collected through an activity-oriented mobile application (AOMA), that has been already used for several studies: it has been collected through a no longer existing free mobile application, formerly downloadable for the iPhone and Android platforms. The application utilised automatically the device's motion co-processor and geo-location to record the time and movements of the portable device (Arcolano e Nuzzo Jones,

2014). The application allowed users to track their movements without any activation running in the background of the phone's operation, automatically keeping track of the user's movement. The device's geolocation service assigned geographic information to those movements (Vanky, 2017). As described in Vanky's work who already employed the dataset for several analyses: "a trip is defined as when a user departs a fifteen-meter geo-fenced area of their current location (the start) until s/he remains in another location for a duration of time, as determined by the application's proprietary stay-detection algorithm." All data is recorded as a geoJSON file.

To avoid identification, the human trajectory data was anonymised by removing a random distance of 0-100 m from the start and end of each trip to further anonymise the users frequently visited locations (Vanky et al., 2016). However, the original GPS locations in those trajectories are very noisy and have location errors because of the obstruction of GPS signals by the high-rise building blocks and street trees in cities. There are obvious mismatches between the human trajectories and the street maps. To reduce the noise of the original GPS locations, the data was normalised using a map-matching algorithm based on the Open Street Map to rectify those mistaken trajectories. In this study, the Hidden Markov Map Matching algorithm (HMM) was used to match the measured longitudes/latitudes in human trace records to roads. The HMM algorithm accounts for the GPS noise and the layout of the road network, and matches the GPS locations to corresponding streets with very good accuracy (Newson and Krumm, 2009).

The processed dataset (Fig. III.1) consist of 246,814 trajectories from 5,432 users in the Boston area, covering a total time period from May 15, 2014, through May 1, 2015. The Boston data collection area was bounded by 41.2284° N, 71.1895° W and 41.3979° N, 70.9852°W, which encompassed 317.06 km² and included the City of Boston, the City of Cambridge, and portions of Somerville, Brookline, Newton and Chelsea. While the data is available for the Boston metropolitan region, the focus on Boston is due to its dense urban structure and to the availability of additional open source data, as described in the following subsection.

As it will be further discussed in section 3 (Limitations), this study does not take a statistical approach. It is rather concerned about discovering useful patterns of information about particular groups or subsets of the population in a non-probabilistic or purposive sample.



Figure III. 1: Visualisation of the walking trajectories' dataset

1.2 Secondary Data Source

To provide insights on the interdependencies between walking patterns and microclimatic conditions, the author employed weather data that corresponds to the location and the time-frame of the primary data source. Therefore, the dataset for the Boston (Massachusetts) weather was collected from the Weather Underground historic data database. These datasets collect the hourly climatic conditions in Boston for the years 2014 and 2015 to cover the period corresponding to the walking trajectories' dataset (May 2014–May 2015). The datasets were downloaded from an API made available by Weather Underground (https://www.wunder-ground.com) through a multiple data log with a one hour timeframe by calculating the mean values and using them for that specific hour.

The author analysed different weather stations: the most complete dataset was available from the KMA BOSTON station located at Logan International Airport, MA (Elev. 16ft 42.36 °N, 71 °W). For a better understanding of the weather data in the city centre, the data was compared to the Wunderground weather stations KMABOS22 and KMABOS35, located respectively Boston – South End KMABOSTO22 Elev 86ft 42.34 °N, 71.07 °W and South Boston KMABOSTO35 Elev 110ft 42.34 °N, 71.06 °W. Those stations are the only ones located in the city centre that have recorded data for the years 2014–2015.

Besides the weather data, the author employed other open access data sources. For the geographical model, the author used the information made available by the city of Boston, planning and developing agency, available at http://www.bostonplans.org/3d-data-maps. The data can be downloaded for free and provides GIS Maps and, since winter 2017, also 3D models divided by neighborhood. Besides this, the city of Boston's open data initiatives gives open access to several georeferenced datasets that were included in this study, to fully depict the urban setting, such as the sidewalk and tree inventory and the Local Access Score (LAS)(www. boston.gov).

For matching the trajectories the author used the freely available OpenStreetMap data (openstreetmap.org), integrated in the GIS model. The datasets made available by the census were employed to gather demographic information (www.census.gov).

2. Methods

This section presents the methods used as well as an explanation of their relevance with regard to the applied processes. As mentioned, identifying the relationship between walking patterns and microclimatic conditions in a complex, varying environment such as urban space requires a set of methods to be combined in a novel workflow this dissertation proposes. Since this dissertation relies on an existing dataset, besides presenting the methods used to filter and get information from it, the following subchapters also illustrate additional qualitative methods that were employed to identify relevant variables fundamental for carrying out the correlational research.

The outlined research design has been developed independently from the employed tools to acquire a relevance independently from software and hardware developments and from computational power. This section presents the set of tools consisting of a combination of data analysis, geographic information systems, and energy and wind modelling tools that allow generating a multilayered model with the targeted spatiotemporal resolution. The tools were chosen after testing their potentials, their performance and their appropriateness, validated by the most recent literature. A priority of this work was using open source and easily accessible tools that are widely used by the scientific community and practitioners.

2.1 Quantitative Methods

During the past decade, a strong body of research has created techniques for analysing mobile phone data as ubiquitous and pervasive sensors networks (Altshuler et al., 2013). These tech-

niques have been used by Alex Pentland's research team at MIT's Human Dynamics Laboratory to detect social relations (Aharony et al., 2011,), evolving behavioural trends (Altshuler et al., 2012a; Pan et al., 2011), mobility patterns (Gonzalez et al., 2008), environmental hazards (Kanaroglou et al., 2005; Puzis et al., 2013), socio-economical properties (Eagle et al. 2010) and various security related features (Altshuler et al., 2011; Altshuler et al., 2012b).

This dissertations' research design uses the presence and dynamic behaviour of people as traced by their portable devices as indicators for comfort conditions. Carrying their portable devices, individuals generate a vast amount of data with a high level of spatial and temporal accuracy that enables an unprecedented possibility of understanding human mobility. Technical limitations that occur when mapping data of individual's positions only provide insufficient information about location and speed. To fill this gap of information, the author filtered the data that was previously matched to the OpenStreetMap ids (osm_id) of the street network.

To rank the frequency and the distribution of the anonymised trajectories, each of them with its unique id, was intersected with the osm_id. This method has the advantage of reducing the noise of the GPS locations, while it places the trajectories on the street segment centreline. By doing so, it restricts the opportunity to have information about which side of the street people are using. On the other hand, merging GPS Data into a geo-referenced platform allows to have clearly defined trajectories and to include other levels of information based on spatial attributes. The author used the formatted dataset to rank the most frequent walking segments and to identify the most frequently reoccurring trajectories.

To reduce the file size and the consequently required computational power, the author clustered the dataset into monthly subsets and looped it with Python to filter the most common trajectories and segments, then pasted the results into a shapefile containing the complete monthly data and the osm_id intersection layer. The frequency of the single segment was used as a value for filtering the segments, saving those that have a frequency higher than 400 on a separate layer. In this way, the most frequented street segments for each month were highlighted.

Besides the frequency of the single segment, the author ranked the most frequent trajectories considering trajectories that are composed by at least four segments; their similarity was defined using a discretionality of 2 segments difference (Fig. III.2). The Python script produced a resulting text file (txt) that was saved into a Comma Separated Value (csv) file and joined to



Figure III.2: Visualisation of the most frequent walking trajectories matched to the osm_id the corresponding shapefile. Here, the author visualised these data using graduated symbols to highlight the different frequency values with different ranges, excluding unique trajectories. The script also updated the time format since the given one was not corresponding to the Eastern Time zone.

In parallel to the walking dataset analysis, the author examined methods to evaluate microclimatic conditions and human thermal comfort. The urban climate research community has already developed several methods to quantify the effects of outdoor environmental conditions on human comfort, so-called biometeorological indices (Johansson et al., 2014: Coccolo et al., 2016). These indices are based on heat budget models of the human body and its environment (Fanger, 1970; ASHRAE, 2013; Coccolo et al., 2016).

Thermal comfort is defined by a subjective evaluation (ASHRAE, 2017) as a function of the four environmental and two personal parameters:

Environmental:

- air temperature;
- air humidity;
- radiant temperature;
- air velocity.

Personal:

- metabolic rate;
- clothing factor.

Out of the large number of comfort indices that were developed during the last century, (Blazejczyk et al., 2012), three are currently used to evaluate outdoor thermal comfort conditions:

PMV - predicted mean vote

One of the most widely used indices is the Predicted Mean Vote Index (PMV) (Fanger, 1986), which predicts the mean thermal response of a large population of people. It is often measured on a seven-point scale (+3 = hot, +2 = warm, +1 = slightly warm, 0 = neutral, 1 = slightly cool, 2 = cool, 3 = cold). In practice, PMV is also commonly interpreted by the Predicted Percentage Dissatisfied Index (PPD), which is defined as the quantitative prediction of the percentage of thermally dissatisfied people at each PMV value. PMV has been included in the International Organization for Standardization ISO standard (ISO, 1994). Originally developed as an indoor thermal comfort index, PMV has also been commonly adopted in outdoor thermal comfort studies in which large groups of people are being surveyed (Cheng et al., 2010; Nikolopoulou, et al., 2001; Thorsson et al., 2004).

PET - Physiological Equivalent Temperature

The Physiological Equivalent Temperature (PET) (Mayer & Höppe, 1987) is another notable example of a steady-state model. PET is a temperature dimension index measured in degrees Celsius (°C), making its interpretation comprehensible to people without a great deal of knowledge about meteorology. PET is based on the Munich Energy-balance Model for Individuals (MEMI) (Höppe, 1984) and is defined as the air temperature at which, in a typical indoor setting, the human energy budget is maintained by the skin temperature, core temperature and sweat rate equal to those under the conditions to be assessed (Höppe, 1999). PET is particularly suitable for outdoor thermal comfort analysis where it translates the evaluation of a complex outdoor climatic environment to a simple indoor scenario on a physiologically equivalent basis that can be easily understood and interpreted. PET has been widely applied in areas with various climatic conditions (Ali-Toudert & Mayer, 2006; Cheng et al., 2010; Matzarakis et al., 1999; Thorsson et al., 2007).

UTCI - Universal thermal climate index

UTCI was developed conceptually as an equivalent temperature for a person with a constant metabolic rate of 2.3 MET walking at 4 km per hour (Bröde et al., 2012). For any combination of air temperature, wind, radiation and humidity, UTCI is defined as the air temperature in the reference condition which would elicit the same dynamic response of the physiological model. It is based on a 187 node model (Fiala et al., 2012: Kampmann et al 2012) of thermal regulation and a dynamic clothing model that imitates human behaviour based on air temperature input (Havenith, et al., 2012).

UTCI was conceptually developed in the COST Action 730 (www.utci.org) as an equivalent temperature allowing for the interpretation of the index values on a familiar scale with unit °C. For any combination of air temperature, wind speed, radiation and humidity, the UTCI values were further categorised into ten categories of thermal stress ranging from "extreme cold stress" to "extreme heat stress" (Bröde et al., 2012), giving significance to the whole range of heat exchange conditions of thermal environments in all climates, seasons and scales (Jendritzky et al., 2007). It assesses the outdoor thermal environment for biometeorological applications by simulating the dynamic physiological response with a model of human thermoregulation coupled with a clothing model (Blazejczyk et al., 2012). The UTCI is defined as follows:

UTCI = 3.21 + 0.872 x T + 0.2459 x MRT - 2.5078 xV - 0.0176 x RH

T is air temperature (C) MRT is mean radiant temperature (C) V is wind speed at 10 m above ground (m/s) RH is relative humidity of air (%)

Calculating the UTCI equivalent temperatures by running the thermoregulation model repeatedly would be too time-consuming for climate simulations and numerical weather forecasts. For this reason, several options to speed up this calculation, polynomial regression equations predicting the UTCI equivalent temperature values are available as an operational procedure which is accessible both as software source code and executable program at the project's website (www.utci.org). The UTCI has been already employed and tested in our past and current research activity and has demonstrated to be the most reliable and accurate metric for evaluating outdoor comfort so far.

However, like other steady-state methods, UTCI cannot effectively account for the dynamic aspects of the course of human thermal adaptation. For example, Höppe (2002) explicitly showed the difference between the dynamic thermal adaptation process of a pedestrian and the steady-state condition using a simple "sunny street segment" simulation case. A similar analysis was conducted by Bruse (2005). As opposed to the various indicators developed to assess steady-state thermal comfort, the methodologies for dynamic assessment show a scattered picture. Although these assessment methods can provide detailed investigations of the dynamic course of human thermal adaptation, they have two major drawbacks when applied in outdoor thermal comfort studies. First, the indicators used, such as skin temperature, require extensive monitoring of human subjects, which is hardly feasible and practical in outdoor cases. Therefore, the current studies are restricted mainly to indoor cases (Foda & Sirén, 2010; Zhang, Huizenga, Arens, & Wang, 2004) or simulation cases in the virtual world (Bruse, 2005; Havenith, 2001; Huizenga, Zhang, & Arens, 2001). Second, these indicators require domain knowledge in biometeorology and physiology and are not informative enough to provide useful implications for planning practice.

In this dissertation, UTCI is used as a biometeorological index to evaluate microclimates and not the dynamic individual response of humans. As such, the author used a computational model to calculate and map spatiotemporal microclimatic conditions expressed as an equivalent temperature. So far, the existing body of research has used several ways to map the spatial distribution of meteorological parameters and obtain continuous data at different spatial scales, including scale model experiments such as wind tunnel tests and remote sensing-based methods or numerical modelling, such as computational fluid dynamic simulation, and geographical mapping. Scale model experiments can generally provide accurate wind field information at the microclimate level. However, in most of the instances, thermal and radiant variables cannot be tested. Remote sensing data can be used to generate continuous spatial distribution of urban climate at the meso- and the local scale but it may not be adequate for the microscale urban climatic studies since those require data in a higher resolution.

Modelling is a ubiquitous word used in simulation research. In terms of simulation, a model is the overall system that simulates the reality being studied. In contrast, the employed simulation strategy aims to replicate in a holistic manner all the relevant variables in the observed setting focusing principally on physical phenomena that generate microclimate, without destroying its natural contextual meaning.

Besides the geometry of the study area, the weather data presented in section 1.2 were employed as the input for the microclimatic model which has been modelled using the source code implemented in Ladybug Tools. The dry bulb temperature (DBT) and relative humidity (RH) hourly values were directly taken from the weather data, while the wind speed at the pedestrian level and the Mean Radiant Temperature (MRT) required additional separate modelling techniques. Perhaps, the only flaw of UTCI is that it was originally conceived to include the wind speed at the meteorological height of 10 meters. As such, it is not directly applicable to the Computational Fluid Dynamics (CFD) at the pedestrian level of 1.1 m.

Research on wind speed modelling around buildings has generated a large body of methods and theories. Their applications are manifold since wind speed affects not only comfort and people's health but also the energy consumption of buildings, particularly in tropical climates. For example, the convective heat flux at the building façade, influencing energy consumption of buildings, depends on the surrounding wind (Defraeye et al., 2011). Wind can also be harnessed for natural ventilation of buildings (Ghiaus and Allard, 2005). CFD simulations have been widely used to simulate wind around and through buildings (Van Hooff and Blocken, 2010; Ramponi and Blocken, 2012). Although guidelines have been established to improve simulation predictions (Franke et al., 2004), large discrepancies remain when simulation predictions are compared to field measurements. Moreover, uncertainties in simulation predictions are usually not quantified (Blocken and Gualtieri, 2012).

The author excluded from the beginning to employ wind tunnel experiments, that require large detailed physical models and accurate measures on the model, the employed method bases on a simplified CFD simulation. Large Eddy Simulation (LES) is an alternative strategy for modelling fluid-flow behaviour in which time-dependent predictions are computed. LES has been found to provide better agreement with wind-tunnel experiments than RANS-based simulations (Tominaga et al., 2008;Vernay et al., 2015). For forces and especially for pressures, wind tunnel studies are at this time the most reliable source of design information for special shapes of buildings (Plate and Kiefer, 2001). In our case, the relevant measure is the wind speed at the pedestrian level, which is influenced by the building geometry and orientation to the wind direction and the roughness of the urban canopy layer. Understanding the urban canopy flow has generated a large body of research since it has particular relevance to the issues related to air pollution (and abatement strategies), energy usage in cities and pedestrian comfort at the neighbourhood scale (Height 100 m to 1 km) (Hamlyn and Britter, 2005).

The employed simulation model was recently developed by Patrick Kastner and Timur Dogan at Cornell University, who created a simplified method to incorporate ventilation analysis into early design stages. Complex urban environments models require computationally extensive Fluid Dynamics (CFD) analysis. The new method is streamlined in order to reduce the time to produce actionable results and can be easily integrated in the proposed workflow, since it is compatible with the employed tools. CFD is a numerical methodology to calculate desired flow variables on a number of grid points within a simulation domain by solving discretised Navier-Stokes equations (NSE). The usual steps of a recurrent CFD analysis for an optimisation process for the built environment consist of:

- Modelling the building geometry with CAD software;
- Meshing the building geometry and topography;
- Simulating the problem with appropriately assigned boundary conditiona;
- Post-processing the variables of interest, likely followed by design alterations and re-
- ferring back to the first step, based on the results obtained. (Kastner and Dogan, 2019).

Besides the air velocity, the mean radiant temperature (MRT) is among the most important variables affecting human thermal comfort in an outdoor urban space (Lindbergh et Thorsson, 2008). MRT is the uniform temperature of an imaginary enclosure in which radiant heat transfer from the human body is equal to those in the actual non-uniform enclosure (ISO 7726; 1998). It is the composite mean temperature of the body's radiant environment. Compared with convection or evaporation, radiative energy exchange accounts for a large share of human heat transfer (Folk, 1974) and is closely correlated with outdoor thermal comfort as well as pedestrian activities (Nikolopoulou and Lykoudis, 2006). For this reason, there is a practical need to model radiative heat transfer between human body and the built environment to assess the human body heat balance, which enables us to calculate UTCI (Huang et al, 2014).

In open outdoor space conditions, the consideration of radiant heat exchange between the human body and its environment in general must take the following long-wave and short wave radiant fluxes into account (Kessling et al. 2013):

- thermal radiation from the ground and other surrounding surfaces
- thermal radiation into the atmosphere
 - direct solar radiation
 - diffuse solar radiation
 - reflected solar radiation

The influence of these radiant fluxes to the MRT of a human being has to be determined for every possible situation as it depends on the person's exposure to surrounding surfaces and the sun (ibidem).

The UTCI model employed in this study calculated an hourly averaged value for each grid point. However, the significance and the objective of this work is to relate microclimate mapping and walking patterns at the same spatiotemporal resolution, therefore the main methodological challenge has been to develop a method to generate outdoor comfort data at the pedestrian level with a resolution that is consistent to the walking data. Since the two datasets were not collected concurrently and with the same spatial resolution, they don not have a common spatiotemporal stamp. Therefore, it was necessary to model comfort conditions with the specific target of creating a dataset with the same granularity in space and time.

To match the walking data and to reduce simulation time, the author calculated the values for the surfaces corresponding to the sidewalks with a linear grid of 5 meters. This step was fundamental to generate consistent adherent data: although the walking trajectories are mapped on the street centreline, people have walked on the sidewalks, encountering the conditions at these locations.

This research design allows to connect the walking trajectories, located precisely on the street centreline with the variations on microclimatic conditions that occur at the street level, influenced by:

- varying radiation levels due to sky conditions, building geometry and material;
- presence of greeneries also according to seasonality;
- dynamic perception influenced by the moving subjects.

Besides the spatial component, it was necessary to develop a metric to generate consistency between the walking dataset and the comfort conditions. The novel metric has been developed to be employed in the applied workflow (Chapter IV) is called STOCA (Spatiotemporal Outdoor Thermal Comfort Availability) and is conceived as a measure for assessing outdoor comfort in a given space throughout a specific time stamp using the UTCI assessment.

The calculation is defined as follows:

$$STOCA = \frac{1}{mp} \sum_{t,st}^{t,end} OTC$$

mp = measurepoints t, st = time, start t, end = time, end

$$OTC = \begin{cases} true \ if \ UTCI \ \in r \\ false \ if \ not \end{cases}$$

r = selected UTCI range

Although a similar metric called OTCA (Outdoor Therma Comfort Autonomy) has been recently developed by Negin Nazarian, Juan A. Acero and Leslie Norford (Nazarian et al., 2019) the metric developed by the author in the past years, presents the following additional advantages related to the methodological framework of this dissertation. First, it needs to correspond to an adaptive spatiotemporal domain. This characteristic allows to evaluate outdoor thermal comfort considering temporal and spatial variables with respect to a maximum comfort availability or to the frequency of comfort conditions in the observed domain.

Unlike previous metrics, the STOCA can refer to varying spatial and temporal domains enabling to identify comfortable conditions within specific seasonal scenarios and comparing proximal spatial domains.Second, it is defined basing on the concept of availability. Unlike the OTCA, which refers to the notion of comfort autonomy with its pre-defined range, the newly developed metric does not refer to annual ranges and schedules and is therefore fully adaptive to the specific case study because it can be overlapped to any other data format. By quantifying comfort availability in a certain time interval, it includes the specificity of seasonal climatic baselines and does not compensate comfort conditions on an annual basis.

With this granularity, thermal stress can be defined as a possible condition since the values that correspond to thermal comfort refer to a set of baseline climatic conditions. This metric allows to map spatiotemporal comfort within a range of microclimatic conditions that occur according to seasonality and that already imply acclimatisation. Acclimatisation is a form of adaptation to climatic conditions. As deeply investigated by Richard DeDear, the concept of adaptation is fundamental in outdoor thermal comfort studies. "The generic term *adaptation* might broadly be interpreted as the gradual diminution of the organism's response to repeated environmental stimulation." In contrast to indoor comfort studies, in fact, "adaptation subsumes all physiological mechanisms of acclimatisation, plus all behavioral and psychological processes which building occupants undergo in order to improve the *fit* of the indoor climate to their personal or collective requirements." Furthermore, "behavioral adjustment represents the most immediate feedback link to the thermal environment. Stated simply, if a person is uncomfort-able or expects to become so, they are to take corrective action" (DeDear et al., 1997).

In urban space, in fact, people move "through diverse and dynamic microclimates, causing them to experience spatial gradients and temporal transients in temperature as well as other climatic parameters including humidity, wind speed, and radiation "(Liu et al., 2020). These inhomogeneities in outdoor thermal environments require frequent adaptation.

Therefore, the STOCA metric defines a baseline condition that depicts spatiotemporal microclimatic conditions, opening up new possibilities for comparative and correlational research, as it will be further described in the following subchapters, allowing to evaluate the following parameters:

- confronting different design scenarios and filling the research gap outlined in Chapter I.2.1;

- variables introduced by individual responses to discomfort or individual preferences that might derive from varying metabolic rate or clothing factors;
- individual psychological and behavioural uncertainties.

In the crowded field of outdoor comfort modelling tools, the author preferred the open access ones, as this workflow was conceived in a cooperative working group and will be shared in the research community.

The urban geometry has been modelled using the commercial NURBS 3D modeller Rhinoceros 5 and 6 versions. All parameters that allow mapping thermal comfort were run using the Grasshopper Ladybug Tools plugin, which connects the Rhino and 3D modelling interfaces to various open source analytical engines. In this case, the open source engines Energy-Plus/OpenStudio were used to model the radiant environment at the pedestrian level (Sadeghipour & Pak, 2013).

Also the wind modelling was performed using the Eddy3D Grasshopper interface to the CFD validated OpenFOAM engine (Kastner & Dogan, 2019). In a first attempt, the author employed the Grasshopper plug-in Butterfly as the wind modelling interface (Mackey et al., 2017). The tool required the accurate setting of parameters and was still under development. Meanwhile, the validation of the Eddy3D tool allowed its use to generate wind simulations with high accuracy and a user friendly interface.

For the data analysis and filtering as well as for the correlational research, the author employed the open source programming language Python (python.org).

ArcMap by ESRI (https://desktop.arcgis.com/en/arcmap/) was employed as a Geographic Information System to visualise the walking trajectories on the map and to manage geographic data. The software was made available by the Leibniz Rechenzentrum of TUM.

2.2 Qualitative Methods

Although this work is largely based on quantitative methods, the author fully recognises the necessity of placing the research process into a qualitative perspective due to its explorative character and its interpretative approach to the subject matter. The formulated hypothesis and the research questions are open-ended and were continuously reshaped to reflect an increased understanding of the problem. Qualitative research depends on an interpretation of the collected data and it achieves this understanding by means of a variety of tactics, employed through a primarily inductive process.

As already stated at the beginning of this chapter, this dissertation draws a holistic methodology that embeds qualitative research to develop a complex picture, "reporting multiple perspectives, identifying the many factors involved in a situation, and generally sketching the larger picture that emerges" (Creswell, 2007).

Due to its intrinsic nature, comfort is not quantitive and linear. Comfort studies have provided metrics to translate qualitative data into quantities; these studies rely on statistical techniques. But since human behaviour in outdoor space is co-shaped by a large variety of parameters that coexist beside thermal comfort, the author sees the strong need of integrating the meth-odological approach with qualitative methods. As outlined by Nikolopoulou and Steemers, "investigating thermal comfort has demonstrated that a quantitative approach is insufficient in

describing comfort conditions outdoors" (Nikolopoulou and Steemers, 2003). In this sense, chapter II provides a theoretical framework that is intended to serve as a fundament for the applied workflow. It contains principles of ethnography, phenomenology and history to frame the technological approach of this work into a wider context.

To understand and trace the human narrative and the dynamic character of walking, the method of direct observation was fundamental to verify quantitative data analysis (Williams, 2015). As pointed out by Sarah Williams, "responsible arguments about civic topics include both qualitative and quantitative data analysis. Perhaps more importantly, it helps to identify the interests of the people as Jane Jacobs advocated in the 60s" (ibidem). Collecting images, making videos and observing the human dynamics of the places can integrate "missing variables in analytical models and help highlight ways to make those models more accurate" (ibidem).

In fact, to get familiar with the urban spaces in Boston, the author conducted direct observations during summer and fall 2017 and 2018. These observations consist of photographs and videos of the areas that are the object of this study. To understand thermal conditions in urban space, video material was collected recording simultaneously a video with an I-Phone and a thermal camera mounted on the bike handlebar. These videos were recorded in the afternoons of October 2 and 4, 2017. In addition to that, direct observations of the focus area were performed on September 3, October 2 and 4, 2017, and on October 10, October 30 and November 14, 2018. The observation usually started at 1:30 pm from the MIT main entrance at 77, Massachusetts Avenue in Cambridge. After crossing the bridge the main attention was targeted to Beacon, Hereford, Commonwealth, Glouchester, Newbury, Exeter and Boylston Street. During these days, the weather conditions presented clear sunny sky and eventually some light breeze.

Furthermore, since the walking data has been collected in the past, synchronised interviews and observations were not possible. Due to the individual nature of comfort, individual behaviour cannot be taken into account. Considering that "behavioral adjustment represents the most immediate feedback link to the thermal environment" (DeDear et al., 1997), direct observation represents the only method to get information about people's responses.

In conclusion, qualitative methods were employed to underpin the complexity of relations that this dissertation addresses. Thermal sensation and the subsequent decision people take can never be completely separated from other human sensations, due to the intrinsic union of senses, defined as synsthesia, that human brains have (Cytowic, 2018).

2.3 Correlational Research

Beyond the described qualitative and quantitative methods, this dissertation presents a methodological approach that can be framed as correlational research.

Correlational research is one of the complex typologies of research designs with specifying options for sequencing quantitative and qualitative components of a research project. It has mainly three specific properties: focus on naturally occurring patterns, the measurement of specific variables and the use of statistics to clarify patterns of relationships (Groat and Wang, 2013). Therefore, sorting and mapping are considered tasks of correlational research.

Studies on the relationship between people and urban space are intrinsically correlational research. Taking inspiration by the afore mentioned studies by Jane Jacobs and William Whyte, also the works of Christoph F. Reinhart (Reinhart et al., 2017), Tarek Rakha (Rakha, 2015), Anthony P. Vanky (Vanky et al., 2017) and Ariane Middel (Middel et al., 2017) present correlational research methodologies to relate people's presence to weather or microclimatic conditions. Particularly the study by Christoph F. Reinhart, Jay Dhariwal and Katy Gero, proposes a novel method to link validated UTCI prediction with the number of people having lunch in the MIT North Court (Reinhart et al., 2017). This study employs Wi-Fi data to record outside dwelling patterns and relate them to UTCI predictions.

Building upon these studies, the proposed methodology adopts a correlational strategy for exploring the relationship among two or more variables of interest that are modelled on the case study presented in chapter IV. The specificity of the present work is that it analyses people flows through dynamic, georeferenced data collected over a year through a large spatial scale, focusing on specific locations and timeframes. With this regard, the novelty is the combination of two different, dynamic, datasets that maintain their granularity and are not aggregated to describe general dependencies, but to depict in depth phenomena at a high spatiotemporal distribution.

Unlike experimental research in which a variable is purposefully manipulated by the researcher, correlational research seeks to document the naturally occurring relationships among variables. This characteristic means that it is particularly appropriate in circumstances when variables either cannot be manipulated for practical reasons or should not be manipulated for ethical reasons. Correlational research can accommodate the study of many variables measured in a variety of instances, therefore the strategy is especially appropriate when the researcher seeks to understand a situation or circumstance broadly (Groat and Wang, 2013). In this sense, this research employs statistical methods such as correlations, quasi poisson and negative binomial regressions to generate information about the occurring interdependencies. For the statistical evaluation the programme R was employed.

3. Limitations

At present, the delineated methodology reveals some limitations, that can be referred mainly to the datasets and the limitations in computational power of the employed tools. Due to the variety of the data sources, integrating them in a coherent way represents a strong challenge with potential imprecisions and approximation. To the best of our knowledge, there are two issues regarding the walking dataset.

First, the temporal resolution is an approximation, because the data recorded the starting and the ending time of each trajectory. This implies a certain temporal imprecision in locating the person at a specific point of the trajectory.

Second, the anonymised dataset is intrinsically not representative of the population, so it does not have a statistical relevance. Already William Whyte's observational studies in New York City (Whyte, 1980) could not provide sufficient information about the observed sample. As such, also the employed primary data source cannot differentiate between the trip intent of a visitor, a resident or a person that is walking by coincidence.

Another limitation of the primary data source is its reliability with regard to the representativeness of the population and the sample size. Since OAMA application users are often young, (Smith & Page, 2015), the users might not be representative of the population. In addition, the anonymisation process cancels any possible attribution to socio-economic, cultural and gender characteristics. Besides the smart phone ownership distribution, research in this field has highlighted that different socioeconomic groups have different walking frequencies and times of the day (Pucher & Renne, 2003), and the influences on recreational physical activity differ between them as well (N.W. Burton, Turrell, & Oldenburg, 2003).

The spatial granularity that this work is aiming at is higher than in other studies. However, it does not allow to upscale the correspondences to the urban system as a whole, since it is related to the specific location and time frame. The applied workflow presented in chapter IV will be representative for itself, because the case is embedded in its context, it does not allow to generalise the results. A replication will be possible reconsidering the quality of the data,

the resolution, location specific climatic factors, and cultural and social circumstances. For this reasons, this dissertation additionally explains causal links, independently from data sources and tools.

Indeed, the depth, complexity, and multifaceted quality of the methodology contribute to its robust capacity as a research design, seeking to understand the complex relations in depth, rather than broadly. In other words, one of the strategy's great advantages is its potential for studying the range and extent of multiple variables. However, its consequent disadvantage is that a general validity may not be revealed, considering, ultimately, the unpredictability of individual human behaviour. The associative analysis aims at providing associations between walking and human thermal comfort generated by microclimatic conditions, opening new opportunities for further investigation based on specifically collected data.

4. Summary and Conclusions

The methodology the author presented in this chapter draws a workflow that combines methods and techniques to document and envision different dimensional arenas. This research design is conceived for putting into evidence the complex relation between people's walking patterns and the microclimatic quality of the built environment.

Unlike previous studies that relate weather and walking frequency and location at an urban scale using aggregated data, this methodology addresses the need of focusing on a high resolution that takes into account biometeorological parameters and, eventually, individual responses. In fact, by creating a common spatiotemporal stamp for different datasets, it sharpens the resolution and increases data density.

Besides defining the workflow to quantify the impact of microclimate on people flows in urban space, the outlined methodology aims at fully including the human component to the kaleidoscope of attributes that converge in urban space, creating a new layer of evidence to the relations between human behaviour and the quality of the physical environment.

References

Aharony, N., Pan, W., Ip, C., Khayal, I. and Pentland, A (2011) Socialfinri: Investigating and shaping social mechanisms in the real world. *Pervasive and Mobile Computing*, 2011.

Ali-Toudert, F., & Mayer, H. (2006) Numerical study on the effects of aspect ratio and orientation of an urban street canyon on outdoor thermal comfort in hot and dry climate. *Building and Environment*, 41, 94–108.

Altshuler, Y., Aharony, N., Elovici, Y., Pentland, A., & Cebrian, M. (2013). Stealing reality: when criminals become data scientists (or vice versa). *Security and Privacy in Social Networks* (pp. 133-151). Springer, New York, NY.

Altshuler, Y., Pan, W., & Pentland, A. S. (2012, a) Trends prediction using social diffusion models. *International Conference on Social Computing, Behavioral-Cultural Modeling, and Prediction* (pp. 97-104). Springer, Berlin, Heidelberg.

Altshuler, Y., Elovici, Y., Cremers, A. B., Aharony, N., & Pentland, A. (Eds.) (2012b) Security and privacy in social networks. *Springer Science & Business Media*.

ArcMap by ESRI (https://desktop.arcgis.com/en/arcmap/)

Arcolano, N., & Nuzzo-Jones, G. (2014). Beyond Steps: How Breeze Puts Context Around Your Movement. Retrieved December 10, 2015, from http://bit.ly/28U2ka8

ASHRAE, ANSI 2017 (2017) Standard 55 specifies conditions for acceptable thermal environments and is intended for use in design, operation, and commissioning of buildings and other occupied spaces.

ASHRAE, ANSI. 2004. Standard 55–2004, *Thermal Environmental Conditions for Human Occupancy*. Atlanta: American Society of Heating, Refrigerating, and Air-conditioning Engineers.

Blazejczyk, K., Epstein, Y., Jendritzky, G., Staiger, H., & Tinz, B. (2012) Comparison of UTCI to selected thermal indices. *International journal of biometeorology*, 56(3), 515-535.

Blocken, B., & Gualtieri, C. (2012). Ten iterative steps for model development and evaluation applied to Computational Fluid Dynamics for Environmental Fluid Mechanics. *Environmental Modelling & Software*, 33, 1-22.

Bröde, P., Fiala, D., Blazejczyk, K., Holmér, I., Jendritzky, G., Kampmann, B., Tinz, B., Havenith, G. (2012) Deriving the operational procedure for the Universal Thermal Climate Index (UTCI). *Int J Biometeorol* 56, 481–94.

Bröde, P., Blazejczyk, K., Fiala, D., Havenith, G., Holmer, I., Jendritzky, G., ... & Kampmann, B. (2013). The Universal Thermal Climate Index UTCI compared to ergonomics standards for assessing the thermal environment. *Industrial health*, 51(1), 16-24.

Bruse, M. (2005). ITCM – A simple dynamic 2-node model of the human thermoregulatory system and its application in a multi-agent system. *Annual Meteorology*, 41, 398–401.

Burton, N.W., Turrell, G. & Oldenburg, B., 2003. Participation in Recreational Physical Activity: Why Do Socioeconomic Groups Differ? *Health Education & Behavior*, 30(2), pp.225–244.

Mackey, C., Galanos, T., Norford, L., Sadeghipour Roudsari, M. (2017) Wind, Sun, Surface Temperature, and Heat Island: The Critical Variables for High Resolution Outdoor Thermal Comfort. *Proceedings of the 15th International conference of Building Performance Simulation Association*. San Francisco, USA, Aug 7-9 2017.

Census https://www.census.gov/data/data-tools.html (Accessed: March 2020)

Cheng, V., Ng, E., Chan, C., & Givoni, B. (2010) Outdoor thermal comfort study in sub-tropical climate: A longitudinal study based in Hong Kong.

Coccolo, S., Kämpf, J., Scartezzini, J. L., Pearlmutter, D. (2016) Outdoor human comfort and thermal stress: a comprehensive review on models and standards, *Urban Clim.* 18 (2016) 33–57.

Creswell, J.W. (2007) Qualitative Inquiry & Research Design: Choosing among Five Approaches (Thousand Oaks, CA: SAGE).

Cytowic, R.E. (2018) Synesthesia, MIT Press, Cambridge, MA.

de Dear, R.. Brager, G., Cooper, D. (1997) Developing an Adaptive Model of Thermal Comfort and Preference. Final Report ASHRAE RP- 884

Defraeye, T., Blocken, B., & Carmeliet, J. (2011). Convective heat transfer coefficients for exterior building surfaces: Existing correlations and CFD modelling. *Energy Conversion and Management*, 52(1), 512–522.

Eagle, N., Macy, M., & Claxton, R. (2010). Network diversity and economic development. *Science*, 328(5981), 1029-1031.

Fanger P.O., (1970) Thermal Comfort. Analysis and Application in Environmental Engineering. Danish Technical Press, Copenhagen.

Fanger, P.O. (1986) Radiation and Discomfort, ASHRAE Journal. February 1986.

Fiala, D., Havenith, G., Bröde, P., Kampmann, B., & Jendritzky, G. (2012). UTCI-Fiala multi-node model of human heat transfer and temperature regulation. *International journal of biometeorology*, 56(3), 429-441.

Franke, J., Hirsch, C., Jensen, A. G., Krüs, H.W., Schatzmann, M., Westbury, P. S., & Wright, N. G. (2004). Recommendations on the use of CFD in predicting pedestrian wind environment. In *Cost action C* (Vol. 14).

Foda, E., & Sirén, K. (2010) A new approach using the Pierce two-node model for different body parts. *International Journal of Biometeorology*.

Folk, G. (1974) Texbook of environmental physiology. Philadelphia: Lea & Febiger.

Ghiaus, C., & Allard, F. (2005). The physics of natural ventilation. *Natural Ventilation in the Urban Environment: Assessment and Design*, 36-80.

Groat, L. N., & Wang, D. (2013) Architectural research methods. John Wiley & Sons.

Hamlyn, D. & Britter, R. (2005) A numerical study of the flow field and exchange processes within a canopy of urban-type roughness. *Atmospheric Environment* 39. 3243–3254

Havenith, G. (2001) Individualized model of human thermoregulation for the simulation of heat stress response. *Journal of Applied Physiology*, 90(5), 1943–1954.

Havenith, G., Fiala, D., Błazejczyk, K., Richards, M., Bröde, P., Holmér, I., Rintamaki, H., Benshabat, Y. & Jendritzky, G. (2012). The UTCI-clothing model. *International journal of biometeorology*, 56(3), 461-470.

Höppe, P. (1984) Die energiebilanz des menschen (Vol. 49) Univ., Meteorolog. Inst..

Höppe, P. (1999) The Physiological Equivalent Temperature – A Universal Index for the Biometeorological Assessment of the Thermal Environment. *International Journal of Biometeorology* 43 (2):71–75.

Huang, J., Cedeño-Laurent, J.G., Spengler, J.D., (2014) CityComfort+: A simulation-based method for predicting mean radiant temperature in dense urban areas. *Building and Environment*. Volume 80, S. 84–95.

ISO 7730:1994 - Moderate thermal environments — Determination of the PMV and PPD indices and specification of the conditions for thermal comfort. (https://www.iso.org/standard/14567.html)

ISO. 1983. Determination of the PMV and PPD Indices and Specification of the Conditions for Thermal Comfort, DIS 7730, Moderate Thermal Environment, 1983.

ISO. 1998. ISO 7726: Ergonomics of the Thermal Environment- instruments for Measuring Physical Quantities. Geneva: International Standard Organization.

Jendritzky, G., Havenith, G., Weihs, P., Batschvarova, E., & DeDear, R. (2008). The universal thermal climate index UTCI goal and state of COST action 730. 18th International Conference on Biometeorology, Tokyo.

Johansson, E., Thorsson, S., Emmanuel, R., & Krüger, E. (2014) Instruments and methods in outdoor thermal comfort studies–The need for standardization. Urban climate, 10, 346-366.

Kanaroglou, P. S., Jerrett, M., Morrison, J., Beckerman, B., Arain, M. A., Gilbert, N. L., & Brook, J. R. (2005). Establishing an air pollution monitoring network for intra-urban population exposure assessment: A location-allocation approach. *Atmospheric Environment*, 39(13), 2399-2409.

Kampmann, B., Broede, P., Jendritzky, G., Fiala, D., & Havenith, G. (2011). The universal thermal climate index UTCI for assessing the outdoor thermal environment., *4th Int. Conf. Human-Environment Syst.* Japan.

Kastner, P., & Dogan, T. (2019) A cylindrical meshing methodology for annual urban computational fluid dynamics simulations. *Journal of Building Performance Simulation*, 13(1), 59-68.

Kessling, W., Engelhardt, M., & Kiehlmann, D. (2013). The human bio-meteorological chart. PLEA 2013 Conference proceedings.

Lin, B., Zhu, Y., Li, X., Qin, Y. (2006) Numerical simulation studies of the different vegetation patterns' effects on outdoor pedestrian thermal comfort. *The forth international symposium on computational wind engineering*, Yokohama.

Lindberg, F., Holmer, B., & Thorsson, S. (2008) SOLWEIG 1.0–Modelling spatial variations of 3D radiant fluxes and mean radiant temperature in complex urban settings. *International journal of biometeorology*, 52(7), 697-713.

Liu, S., Nazarian, N., Niu, J., Hart, M., de Dear, R. (2020) From thermal sensation to thermal affect: A multi-dimensional semantic space to assess outdoor thermal comfort, *Building and Environment*

Mackey, C., Galanos, T., Norford, L., Sadeghipour Roudsari, M. (2017) Wind, Sun, Surface Temperature, and Heat Island: The Critical Variables for High Resolution Outdoor Thermal Comfort. *Proceedings of the 15th International conference of Building Performance Simulation Association*. San Francisco, USA, Aug 7-9 2017.

Masson, V., Marchadier, C., Adolphe, L., Aguejdad, R., Avner, P., Bonhomme, M., ... & Doukari, O. (2014). Adapting cities to climate change: A systemic modelling approach. *Urban Climate*, 10, 407-429.

Matzarakis, A., Mayer, H., & Iziomon, M. G. (1999). Applications of a universal thermal index: physiological equivalent temperature. *International journal of biometeorology*, 43(2), 76-84.

Mayer, H., Höppe, P. (1987) Thermal Comfort of Man in Different Urban Environments. *Theoretical and Applied Climatology* 38 (1): 43–49.

Middel, A., Lukasczyk, J., & Maciejewski, R. (2017). Sky View Factors from synthetic fisheye photos for thermal comfort routing--a case study in phoenix, Arizona. *Urban Planning*, 2(1), 19-31.

Nazarian, N., Acero, J., Norford, L. (2019) Outdoor thermal comfort autonomy: Performance metrics for climate-conscious urban design. *Building and Environment* 155

Newson, P., & Krumm, J. (2009) Hidden Markov map matching through noise and sparseness. *Proceedings of the* 17th ACM SIGSPATIAL international conference on advances in geographic information systems (pp. 336-343). ACM.

Nikolopoulou, M., N. Baker, and K. Steemers (1999) Improvements to the globe thermometer for outdoor use. *Architectural Science Review* 42 (1): 27–34.

Nikolopoulou, M., Baker, N., & Steemers, K. (2001) Thermal comfort in outdoor urban spaces: understanding the human parameter. *Solar energy*, 70(3), 227-235.

Nikolopoulou, M., & Steemers, K. (2003) Thermal comfort and psychological adaptation as a guide for designing urban spaces. *Energy and Buildings*, 35(1), 95-101.

Nikolopoulou, M., & Lykoudis, S. (2006) Thermal comfort in outdoor urban spaces: Analysis across different European countries. *Building and Environment*, 41(11), 1455–1470.

Pan, W., Aharony, N., & Pentland, A. (2011, August). Composite social network for predicting mobile apps installation. *Proceedings of the AAAI Conference on Artificial Intelligence* (Vol. 25, No. 1).

Plate, J., & Kiefer, H. (2001) Wind loads in urban areas. Journal of Wind Engineering and Industrial Aerodynamics 89 1233–1256.

Pucher, J., & Renne, J. L. (2003) Socioeconomics Of Urban Travel: Evidence From The 2001 NHTS. *Transportation Quarterly*, 57(3).

Puzis, R., Altshuler, Y., Elovici, Y., Bekhor, S., Shiftan, Y., & Pentland, A. (2013) Augmented betweenness centrality for environmentally aware traffic monitoring in transportation networks. *Journal of Intelligent Transportation Systems*, 17(1), 91-105.

Python (www.python.org) (Accessed April 2020)

Ramponi, R., & Blocken, B. (2012). CFD simulation of cross-ventilation for a generic isolated building: impact of computational parameters. *Building and Environment*, 53, 34-48.

Rakha, T. (2015) Towards comfortable and walkable cities: spatially resolved outdoor thermal comfort analysis linked to travel survey-based human activity schedules. Massachusetts Institute of Technology

Reinhart, C. F., Dhariwal, J., Gero, K. (2017) Biometeorological indices explain outside dwelling patterns based on Wi-Fi data in support of sustainable urban planning. *Building and Environment* 126 (2017) 422–430.

Sadeghipour, M and Pak, M. (2013). Ladybug: a parametric environmental plugin for grasshopper to help designers create an environmentally-conscious design. *Proceedings of the 13th International IBPSA Conference*. Lyon, France Aug 25–30th.

Shmueli, E., Singh, V. K., Lepri, B., & Pentland, A. (2014) Sensing, understanding, and shaping social behavior. *IEEE Transactions on Computational Social Systems*, 1(1), 22-34.

Smith, A., & Page, D. (2015). The Smartphone Difference. *Pew Research Center*, 53, 1689–1699. http://doi.org/10.1017/CBO9781107415324.004

Tominaga, Y., Mochida, A., Yoshie, R., Kataoka, H., Nozu, T., Yoshikawa, M., & Shirasawa, T. (2008) AIJ guidelines for practical applications of CFD to pedestrian wind environment around buildings. *Journal of wind engineering and industrial aerodynamics*, 96(10-11), 1749-1761.

Thorsson, S., Lindqvist, M., & Lindqvist, S. (2004). Thermal bioclimatic conditions and patterns of behaviour in an urban park in Göteborg, Sweden. *International journal of biometeorology*, 48(3), 149-156.

Thorsson, S.; Lindberg, F.; Eliasson, I.; and Holmer, B. (2007) Different Methods for Estimating the Mean Radiant Temperature in an Outdoor Urban Setting. *International Journal of Climatology* 27, no. 14: 1983–93.

Vanky, A.P., Verma, S. K., Courtney, T. K., Santi, P., Ratti, C. (2017) Effect of weather on pedestrian trip count and duration: City-scale evaluations using mobile phone application data. *Preventive Medicine Reports*, Volume 8, 2017, Pages 30–37, ISSN 2211–3355,.

UTCI https://www.utci.org (Accessed: October 2020)

Vanky, A. P. (2017) To and fro: digital data-driven analyses of pedestrian mobility in urban spaces (Doctoral dissertation, Massachusetts Institute of Technology).

Vernay, D. G., Raphael, B., & Smith, I. F. (2015) A model-based data-interpretation framework for improving wind predictions around buildings. *Journal of Wind Engineering and Industrial Aerodynamics*, 145, 219-228.

Whyte W.H. (1980) The Social Life of Small Urban Spaces. Washington, DC: Conservation Foundation.

Williams, S. (2015) More than data: working with big data for civics. ISJLP, 11, 181.

Wunderground https://www.wunderground.com (Accessed: June 2017)

Van Hooff, T., & Blocken, B. (2010) Coupled urban wind flow and indoor natural ventilation modelling on a high-resolution grid: A case study for the Amsterdam ArenA stadium. *Environmental Modelling & Software*, 25(1), 51-65.

Zhang, H., Huizenga, C., Arens, E., & Wang, D. (2004). Thermal sensation and comfort in transient non-uniform thermal environments. *European journal of applied physiology*, 92(6), 728-733.

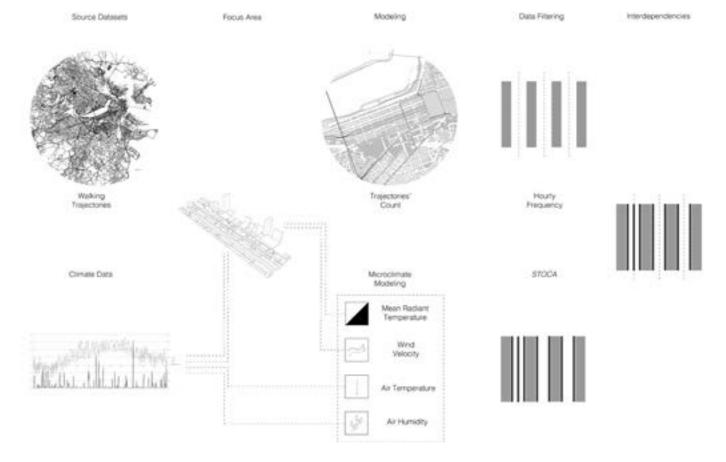


Figure IV.1: Graphical representation of the proposed workflow

IV. APPLIED WORKFLOW

Introduction

In chapter II, the dynamic relations between the domains that are subject to this dissertation — climate, health and public space — have been described and contextualised by providing a qualitative framework. This chapter presents the methodology developed in chapter III and employs quantitative methods at the case of a specific area in Boston. In this way, the research design can be tested and verified. In the application, the author modelled microclimatic conditions in an area in Boston, selected according to the data analysis performed on the primary data source. The workflow includes a spatiotemporal comfort evaluation and puts it in relation to the trajectories' frequency. To achieve this target, the STOCA index has been developed to link OTC to human movement patterns. The novelty of this workflow is the spatiotemporal resolution and the definition of metrics that allow to relate microclimatic conditions to the walking trajectories. The principal expected output is the significance of the interdependencies between microclimatic conditions and people flows, tackling the research questions with quantifiable results (Fig. IV.1).

1. Preliminary Data Analysis

This subchapter illustrates the preliminary analyses of the primary and secondary data sources. This step is fundamental to assess relationships, to detect general patterns, create distributions, and detect limitations. Tactics that are both exploratory and preparatory for defining the workflow and that test the data's reliability and validity.

An important aspect of this workflow that needs to be specified is its unique resolution which is not providing annual averaged values, as already done in the cited existing correlational research. It rather focuses on specific days and hours, which requires an accurate preliminary data filtering.

The data analysis is the pivotal strategy to define the scale of the observation and, subsequently, to develop a workflow that is targeted to provide knowledge at that resolution.

1. 1 Quantitative Data Analysis

In a first phase, the author carried out a quantitative analysis of the walking trajectories to characterise the walking data: distribution, distance and duration, time of the day. These analyses resulted in indicating walking trajectories' distribution, length and frequency of walked street segments, according to the method presented in III.2.1.

The first outcome was understanding the distribution of the number of trajectories per month. Due to computational power's limitations, the author divided the dataset into months for filtering. The database has an unequal distribution of the number of trajectories per month. The available data differs from month to month, with no evident reason: for example, in September 2014, 33,114 trajectories were recorded; in February 2015, 19,302 trajectories. This difference is not only related to weather conditions since hot months such as May, June, July

and August have less records than February (Fig. IV.2).

The author grouped the trajectories according to their length in meters (considering stepping intervals of 200 m) and plotted their normalised frequencies (counts). Grouping the trajectories into weekdays and weekends allowed to highlight potential specific patterns assuming different behaviours during working and leisure routines. The resulting graphs show very similar patterns: the subdivision in weekdays and weekends does not show substantial differences (Fig. IV.3 and IV.4). Moreover, the author analysed the most frequent street segments (osm_ids) throughout all the trajectories in the database, showing the total counts of the first 100 most frequent street segments, ordered by their rank. The different ordinate's axis scale is due to the fact that the total number of trajectories in February is approximately double of the one for the trajectories in September (Fig. IV.5 and IV.6).

The author plotted the duration and the trip density for the months from July to March (the months with a consistent amount of data) in relation to weather conditions. Comparing rainy and non rainy days, the graphs show a certain continuity in terms of duration whereas the number of trips/hour is clearly higher during non rainy days.

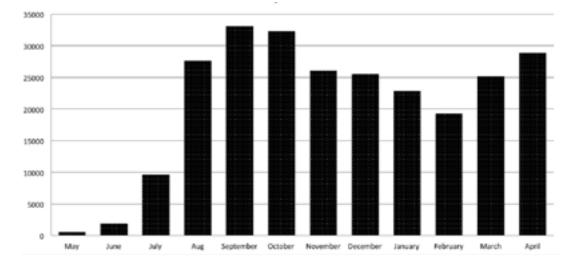
In a further step that employed more powerful computational tools, the author analysed the trajectories's distribution in terms of duration and distance. The distributions show a certain analogy: most of the people walk for short distances that correspond to short durations in time, underpinning the concept introduced in the 1980s by Yacov Zahavi of travel time budget, according to which travellers make a constant amount of time available for moving from one place to the other in their daily routine (Marchetti, 1994). The graphs show that 50% of pedestrian trips fall between 368 m and 948 m, with a median of 510 m (mean of 789 m); a large portion of trips fall in the range of 4 to 17 min and both of them present a log-normal distribution. More specifically, the 2nd and 3rd quartiles of pedestrian trips falls between 3.9 and 12.4 min with a median of 7 min. (Bongiorno et al., 2019) (Fig. IV.7 and IV.8).

Figure IV.9 demonstrates the temporal regularity of the trip data: trip frequencies peak in the morning, at lunch and again in the afternoon, suggesting a typical working day pattern. As extensively demonstrated by Pushkarev, the degree to which daily travel is concentrated in the peaks is significant for walking analysis (Pushkarev, 1975). The graph clearly shows a peak between 5 and 6 pm and two lower peaks between 8 and 9 am and 12 and 1 pm, suggesting that the sample shows mainly walking to reach work and going back home, with some significant activity during lunchtime.

In terms of spatial analysis, the author ranked the osm_ids of the entire database to detect the most reoccurring segments. The script's results were matched to the osm_id and mapped to identify the areas with the most dense recorded walking activity. The segment count shows a quite strong relation to the major axes, despite the Back Bay and downtown area where most of the street segments have high frequencies. This pattern clearly shows that these two areas are the most frequented (Fig. IV.10).

The trajectories analysis shows reoccurring segments throughout the year. The Back Bay area, in particular, Boylston Street and the adjacent streets, belong to the most occurring trajectories. Also the airport is among the areas with highest frequencies. In additional studies, we filtered the reoccurring trajectories, that were filtered according to the starting and ending point within a diameter of 30 m, and their starting and ending time. This step was fundamental to detect the areas with the most consistent and continuous data, which led to framing the walking pattern analysis to the focus area presented in section 2 (Fig. II.11).

In parallel to the primary dataset analysis, the author filtered the weather data to obtain information about the general climatic characteristics over the year and to determine the representative days for each season. In this case the author compared the data of the three weather underground stations located next to central Boston: KMABOS, KMABOS35, KMABOS22. The comparison shows evident lacks in the data collection and patching for the stations KMABOS35 and KMABOS22. Due to this reason, the author employed only the data col-



0.07

0.06

0.05

0.04

0.02

0.01

0.00

8000

6000

4000

2000

0.10

0.08

0.06

0.04

0.00

Density

20 S ó

2000

20

10

40

Duration [min]

4000

Septe

Trajecto

6000

with [m]

60

ŵ.

Pedestrians

40

50

100

8000

10000

September

Weekdays

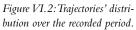


Figure VI.3: Frequency of trajectory lengths for February

Figure IV.4: Frequency of trajectory lengths for September

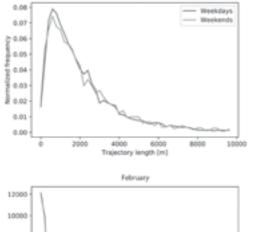
Figure VI.5 Segment count for February

Figure VI.6: Segment count for September

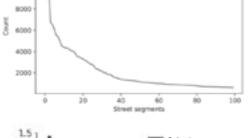
Figure VI.7: Distribution of trajectories - distance

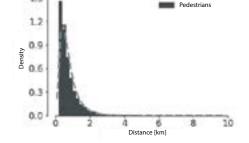
Figure VI.8: Distribution of trajectories - duration

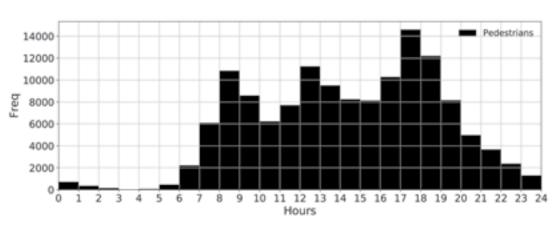
Figure IV.9: Distribution of trip departure times



February







77

lected in the KMABOS station, putting it into a TMY (Typical Meteorological Year) format to prepare the input for the model. The dataset contains hourly measured meteorological quantities of the dry bulb temperature, relative air humidity, wind speed and radiation.

In a first step, the author selected typical days to facilitate the simulation process. The author selected 39 typical days to identify the most representative days for each season in terms of air temperature (Fig. IV.12), relative humidity, wind speed and direction, presence of snow and precipitation (Fig. IV.13) that are considered typical in relation to the season's averages. This classification was used as a fundamental clustering of mesoclimatic conditions throughout the year to reduce the number of simulations and the subsequent required time and computation-al power (s. Appendix).

Figure VI. 10: Visualisation of the most reoccurring segments



Figure IV.11 : Visualisation of the most reoccurring segments in the Boston Back Bay and Downtown Areas.

Figure VI.12: Boston, hourly air temperature

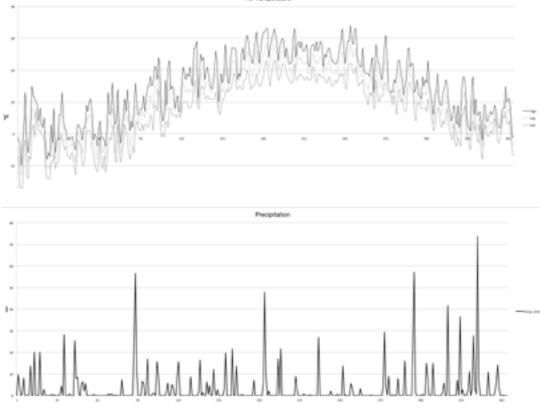


Figure VI.13: Boston, hourly precipitation

During the model setup, it became clear that this clustering was not sufficient to depict microclimatic variations. For this reason, basing on the filtered data, the author selected seasonal representative weeks that were used in the interdependency study.

1.2 Qualitative Data Analysis

The collected data has been visualised to generate a multifaceted array of sources. The purposes of collecting and analysing qualitative data was twofold: generating direct experience of people's behaviour as well as collecting additional information about the city, the buildings and urban life, besides what the quantitative data offered. In particular, experiencing urban life directly allowed to see people's behaviour, the density at different times of the day, in relation to different streets and corresponding to different purposes of visits (i.e. shopping, outdoor activity, working etc.).Furthermore, the collected photographic and video material allowed to verify the information of the digital model and to integrate it with all the necessary information, also to verify the quality of data. More specifically, the qualitative data analysis provided useful information about:

- The architecture, building typologies and functions;
- Facade material of buildings and streetscape;
- The distance between trees, their position and type;
- Sidewalks' size and conditions.

The gathered information was fundamental to fulfil the targets of the outlined research design. The level of resolution requires detailed information about the built environment, besides what digital data is providing so far

The aim of the qualitative analysis was also to observe the human dynamics of places and to verify to what extent human behaviour is related to OTC. Since the comfort metric is inadequate to describe the thermal individual sensation, observing — also a small sample — suggests tendencies. As outlined by Liu et al, 2020, "the descriptor *warm* can represent either comfortably warm or uncomfortably hot depending on different contexts and users." The mentioned concept of *alliesthesia*, proposed by Parkinson and de Dear (2015), can be regarded as the hidden face of the individual perception. Parkinson & de Dear (2015) differentiated two types of thermal *alliesthesia*: temporal and spatial (Parkinson et al., 2016). This diverging

individual perception is the reason to differentiate between the terms thermal comfort and microclimate, the latter describes a condition, besides individual perceptions.

2. Focus area

The focus area has been chosen according to a preliminary data analysis presented in chapter II. The dataset that collects walking trajectories from May 2014 to April 2015 in the Greater Boston area shows a higher density in the Boston Back Bay area.

As the largest city in Massachusetts, the city of Boston has a total population of about 692,000, according to the recent census data (American Census Estimates 2019 data, https://www.census.gov/quickfacts/bostoncitymassachusetts). Boston is located in the northeast of the United States, with the land area of 125 km², with spatially varied street canyon types ranging from skyscrapers in the downtown area and the low-lying residential area in the periphery. Due to its relatively compact layout, Boston is considered as one of the most walkable cities in the United States.

The Back Bay area in Boston is characterised by an orthogonal west-east oriented grid and by low and mid-rise buildings, built mainly in the second half of the 19th century (Fig. IV.14). Originally the buildings were purely residential, today the buildings host also offices and shops, especially in Newbury Street and Boylston Street.

The focus area includes Commonwealth Avenue, Newbury Street and Boylston Street – three important streets that have the same orientation, but present different widths, aspect ratios and characters. It is confined by the Boston Public Garden from the east and by Massachusetts Avenue from the south (Fig. IV.15-20).

Boylston Street mainly has a commercial character, it is composed by mid-rise buildings and host public buildings such as the Public Library. Being tangent to Copley Square, it also incorporates the access to the subway stations of the T line. In this sense, it has the highest traffic related to public transport and to office commuters. Its width of 35 m determines higher aspect ratios (0,62) compared to the two other streets. Newbury Street is widely known for its shops hosted in the Victorian houses. Its width is around 30 m but due to its low-rise buildings it has an average aspect ratio of 0,5. Being mainly a commercial street, it attracts people for shopping and leisure and features large sidewalks with small trees.

The segment of Commonwealth Avenue included in the focus area has a residential character with low rise Victorian houses. It is the widest of the three with 73 m and incorporates a linear park in its central part, Boston's nine-block long Commonwealth Avenue Mall, that links the Boston Common and Public Garden to the city's great park system, The Emerald Necklace. Initially designed in 1856 with additional sections of the boulevard added over the following several decades, the mall is the central green axis of the Back Bay neighborhood. Its scale and definition of space make it one of the great physical features of Boston as well as one of the world's finest examples of the tree-lined avenue; a cathedral-like canopy of double rows of trees. The initial nine-block portion of the mall has been constructed between the late 1860s and 1881, connecting Back Bay Fens to the Public Garden and Boston Common. In addition to American elms (*Ulmus americana*), sweetgum (*Liquidambar styraciflua*), green ash (*Fraxinus pennsylvanica*), maple (*Acer rubrum*), linden (*Tilia Americana*), zelkova (*Zelkova serrata*), and Japanese pagoda (*Sophora japonica*), trees were planted in organised rows to define the for-

Figure IV.14: Section and map of the focus area

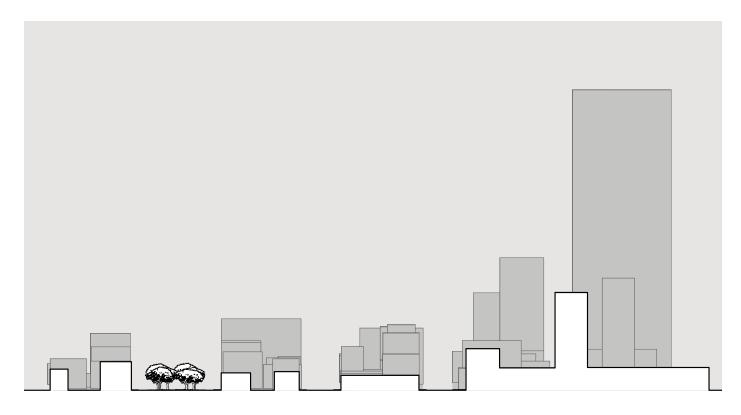




Figure IV.15 (left): Commonwealth Avenue, view of the linear Park.

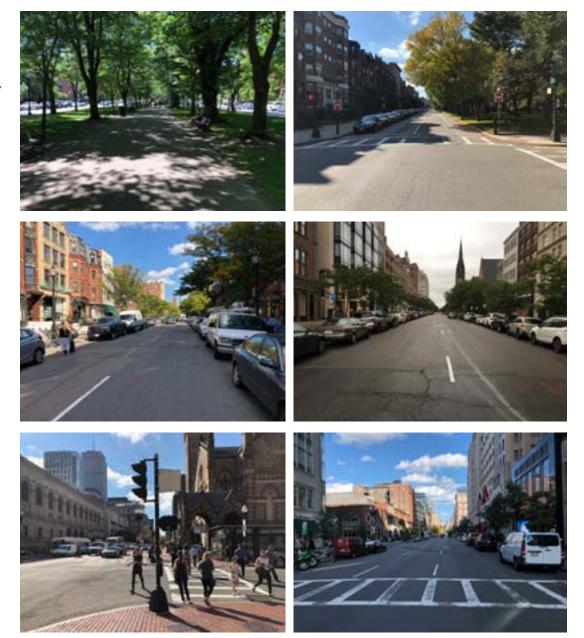
Figure IV.16 (right): Commonwealth Avenue, view of the South sidewalk Park. Source: Author

Figure IV.17 (l): Newbury Street, view to the East.

Figure IV.18 (r): Newbury Street, view to the West. Source: Author

Figure IV.19 (l): Boylston Street, view to the West.

Figure IV.20 (r): Boylston Street, view to the East. Source: Author



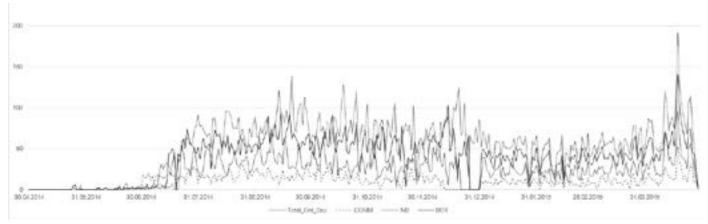
mal avenue. (https://www.boston.gov/parks/commonwealth-avenue-mall). Due to its peculiar character, it has the lowest aspect ratio of 0,25.

Since the complex interactions that occur in urban space, generating attractive environments cannot be easily quantified and enumerated. The focus area has been chosen because it offers a variety of functions, morphological characteristics and presence of greenery; this uniqueness attracts a diverse group of people in for walking.

3. Walking Trajectories' Analysis

As already outlined in section 1 of this chapter, the walking dataset has the highest density of trajectories in the Back Bay area. In particular, Boylston Street and the adjacent streets have the highest number of reoccurring trajectories. Over the year, 26,638 trajectories cross the area. Commonwealth Avenue is walked by 3906 trajectories, Newbury Street by 8,450 trajectories, Boylston Street by 14,282 (Fig. IV.21).

Also when considering only the repeated trajectories, this area has the highest density of walking trajectories. Despite the anonymisation it was possible to identify repeated trajectories, those that occur frequently and within the same path. In a first step, we considered analysing only the repeated trajectories (6600 in total). Indeed, this reduced dataset is too limited to generate consistent information to be related to the comfort conditions.



Besides the total quantity of walked trajectories, the number of trajectories per hour and street is limited compared to the total number of 246,814. In the selected area, the day with the highest number of trajectories is Saturday, April 18, assumably in preparation of the Boston Marathon that took place on April 20, with 192 (Boston Budget, 2015).

Based on the trajectories analysis, the commuting times from 8 to 9 am, from noon to 1 pm and from 5 to 6 pm were taken specifically into account. The preliminary data analysis had demonstrated that during these time intervals, the trajectories' frequency is higher.

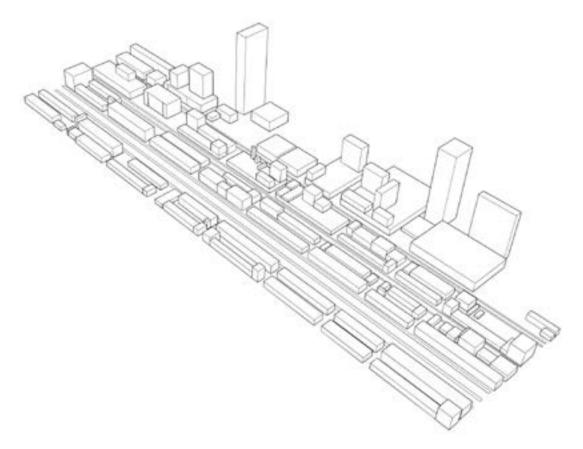
The analysis has been limited to four periods of two weeks that include both weekdays and weekends. These periods were identified according to the climate analysis presented in section 1, to cluster the analysis into different seasonal scenarios. Although, the preliminary data analysis has shown an equal distribution of trajectories between weekends and weekdays. A relevant aspect is the fact, that trajectories usually intersect more than one of the analysed streets, since people move from one street to the others, therefore, within the analysed hour, people could potentially walk on both streets. This reduced dataset has been generated with the aim of constituting a format that is adherent to the OTC simulations' results presented in the following section, to set the basis for calculating the interdependencies.

4. Microclimate Modeling

The representation of the microclimatic conditions of the focus area are a fundamental component of this work. Since the walking data has been collected in the past, the corresponding microclimatic conditions needed to be modelled with computational tools using the recorded weather data. This section presents the employed workflow that generates a dataset of microclimatic conditions in a high spatiotemporal resolution. As mentioned in chapter I.2.1, this work integrates past research in the field of outdoor thermal comfort studies, employing the widely used and validated UTCI metric.

UTCI is "the isothermal air temperature of the reference condition that would elicit in the same dynamic response (strain) of the physiological model" as the actual environment (Jendritzky et al., 2012). Calculating the UTCI requires four variables: air temperature, mean radiant temperature, air humidity and wind speed. The UTCI model includes clothing using correlations derived from observations of human adaptive behaviour in the outdoors. All other personal factors such as age, height and weight are averaged over the population (Mackey et al., 2017). In this case, the UTCI results were fed into the STOCA metric to quantify spatiotemporal microclimate patterns. The factor gives a measure of comfort availability on a given day at a specific time that makes different locations comparable. One of the most relevant choices was to choose a resolution that combines a high granularity with acceptable computing time. Combining existing computational tools with the novel spatiotemporal index that is consistent to the walking trajectories dataset allowed to analyse interdependencies and to formulate conclusions.

Figure IV.21: Trajectories' count per each street



4.1. Model and Resolution

The focus area was modelled using the commercial NURBS 3D modeller Rhinoceros 6. The geometric model was rebuilt upon the open source available 3D Models provided by the Boston Planning and Development Agency (http://www.bostonplans.org/3d-data-maps/3d-smart-model/3d-data-download). After several simulation tests, the model's geometry has been slightly simplified because the high detailing of the original was too complex for the available computational power for running the simulations (Fig. IV.22). The author modelled the 24 blocks within the area of interest, including the blocks surrounding the area of interest for the purposes of CFD modelling.

The weather data used for carrying out the simulations was fed into an EnergyPlus weather format (epw) file using the Elements Software, was collected from the KMABOS station and is composed by hourly values (EnergyPlus). The author chose the timeframe from May 1, 2014 to April 30, 2015 to correspond to the activity-oriented mobile application (AOMA) data. Elements is a free, open-source, cross-platform software tool for creating and editing custom weather files for building energy modelling (bigladdersoftware). The author employed a combination of methods to model each parameter of the outdoor comfort analysis with a specific engine, merging them through a RHINO/Grasshopper interface.

Wind Speed

The author ran four directions CFD simulations to map the variations of airflow patterns within the site. Due to the prevailing wind directions occurring in the selected area, the author reduced the simulations to the four prevailing directions (N_E_S_W 0, 90, 180, 270). The resulting data provides a high resolution of wind direction patterns. The simulations were carried out with the Eddy3D software, a Grasshopper interface for the OpenFOAM Computational Fluid Dynamics (CFD), RANS based simulation engine. This tool was developed by Patrick Kastner and Timur Dogan at Cornell University (Kastner and Dogan, 2018). the author performed 1000 iterations using a boundary wind tunnel with a diameter of 2600 m x 1500 m height, following a best practice (Tominaga et al., 2008) that suggests the size of the simulation domain to be $z = 6H_{\rm max}$, $l = 20H_{\rm max}$ and w given by a blocking ratio of $\leq 3\%$, where z, l, and w are the dimensions of the domain and $H_{\rm max}$ is the height of the tallest building in the building agglomeration to be simulated (Fig. IV.23). The advantage of the simulation

tion technique the author applied is to reduce the complexity of running a yearly simulation; instead, this novel approach uses wind reduction factors. In this case, the author calculated the wind factors for an area of $2000 \text{ m} \times 5000 \text{ m} \times 1000 \text{ m}$ height, with 1.250.000 points (Fig. IV.24). The wind factors were calculated at a height of 1.5 m and were fused into the UTCI model.

Mean radiant temperature

To model the mean radiant temperature, the author calculated the surface temperature of the buildings and the ground and the sky heat transfer. These calculations were performed using the EnergyPlus engine. The author used a solar distribution setting of FullExteriorWithRe-flections to ensure that a correct portion of solar energy was calculated for each urban surface on a 1 hour time step. Each building was divided into zones with a 3 m floor height. For the external walls, the author used a 30 cm brick without insulation. In order to compute a mean radiant temperature (MRT) for the outdoor comfort model, a base long wave MRT was computed using the surface temperatures of the previous step and following formula (Thorsson, 2007):

$$MRT = \left[\sum_{i=1}^{N} F_i T_i^{4}\right]^{1/4}$$

where F is the fraction of the spherical view occupied by a given indoor surface, T is the temperature of the surface. View factors (F) to each of the EnergyPlus surfaces were calculated using the ray-tracing capabilities of the Rhino 3D modelling engine. The long-wave temperature of the sky was estimated using the horizontal infrared radiation contained within the TMY data along with the following formula (Blazejczyk, 1992).

$$T_{sky} = \frac{L_a}{(\varepsilon_{person}\sigma)^{1/4}}$$

where L_{α} is the downwelling long wave radiation from the sky in W/m, e is the emissivity of the human (assumed to be 0.95), and s is the Stefan-Boltzmann constant (5.667×10-8). To account for shortwave solar radiation that falls on people, the SolarCal model was used to produce an effective radiant field (ERF) and corresponding MRT delta that was added to the base longwave MRT (Arens et al., 2015). Published in the ASHRAE-55 standard for thermal comfort (2016), the SolarCal model offers advantages over other models to estimate shortwave radiation falling on people. Notably, it allows for inputs of seated vs. standing among other variables. The formula to calculate the ERF with SolarCal is as follows:

 $ERF_{solar} = (0.5 f_{eff}f_{svv} (I_{diff} + I_{TH} R_{floor}) + A_p f_{bes} I_{dir} / A_D) (\alpha SW / \alpha LW)$

where f_{eff} is the fractional of the body that can radiate heat (0.725 for a standing person), f_{svv} is the sky view factor (computed here through ray-tracing) and f_{bes} is a 1/0 value indicating whether direct sun is on the person (computed by tracing the sun vector). I_{diff} is the diffuse sky radiation, I_{TH} is the global horizontal radiation, and I_{dir} is the direct radiation. A_p and A_D are geometry coefficients of the human body, which are computed based on sun altitude and azimuth. Finally, R_{floor} is the reflectivity of the ground (assumed to be 0.25) and the a values refer to the absorptivity and reflectivity of the person's clothing. This ERF is converted into a MRT delta using the following equation:

$$ERF = f_{eff} h_r (MRT - T_{LW})$$

Where h_r is the radiation heat transfer coefficient (W/m²K) and T_{LW} is the base longwave MRT temperature (°C)(Mackey et al., 2017).

Figure IV.23: Proposed cylindrical simulation domain

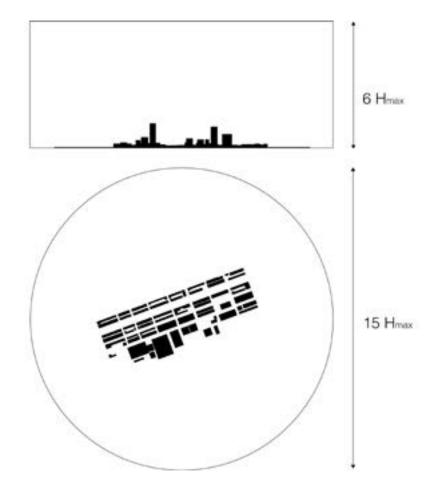
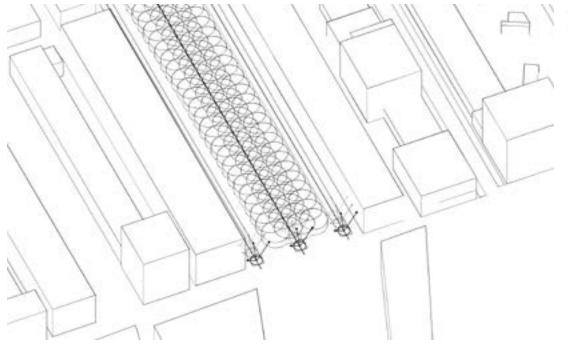


Figure IV.24: Top view visualisation of the wind speed simulation



Figure IV.25: Three dimensional representation of the view factors



To reduce the simulation time and optimise the efforts to the scope of this work, the view factors (F) were chosen on the sidewalks' centrelines, with an interval of 5 m (Fig. IV.25).

Tree modeling

To model the linear park in Commonwealth Avenue, the author employed the newly developed tool PANDO. PANDO is a numerical process-based simulation tool that enables the user to model individual trees and canopies as a Rhino Grasshopper interface. This plugin simulates radiation fluxes in three different wavebands of photosynthetic (PAR), near infrared (NIR) and thermal (Chokhachian & Hiller, 2020). The PANDO tool uses the MAESPA simulation engine and it imports files directly from the 3D Rhinoceros model. The tree geometries were generated according to the existing park array, using a 10 x 10 m grid to model the four lines of American elms, with a trunk diameter of 0.5 m, a height of 5 m, and a crown height of 8 m.

The author simulated the annual perceived temperatures with the Universal Thermal Climate Index (UTCI) for a shaded person under the tree (Blazejczyk et al., 1992). The Mean Radiant Temperature (MRT) modelling integrates exposure to shortwave and longwave radiation in a three-dimensional environment assuming that the radiant heat transfer from the human body is equal to the radiant heat transfer in the actual non-uniform enclosure (Thorsson, et al., 2007). To calculate MRT, the process is divided into shortwave fluxes (direct, diffuse and reflected solar radiation) and long-wave radiation (urban surfaces, trees and sky) using the afore mentioned weather data. To be accurately represented, direct and diffused shortwave solar radiation is simulated using radiance raytracing with Daysim's hourly irradiation method. For the longwave fluxes, the surface temperatures are estimated based on air temperature, wind velocity, net all wave radiation and Bowen ratio (Oke, 2002). The sky temperature is calculated based on the method developed by Martin and Berdahl (Martin & Berdahl, 1984), taking into account the emissivity model introduced by Duffie, Beckman and Worek (Duffie at al., 2013).

The author used PANDO to model the leaf surface temperature and the shading effect according to a seasonal phenology model. The average leaf temperature of the tree canopy is extracted from the PANDO model for every hour. Having radiant fluxes from the adjacent surfaces based on the view factors from the body position, the MRT component is calculated for each hour of the year based on the Stefan-Boltzman law (Matzarakis et al., 2010, Chokhachian & Hiller, 2020). Combining the annual hourly MRT values with local wind speed, air temperature and humidity gathered from the epw file, the perceived temperatures expressed with the UTCI were calculated for a point aligned to the park's central path, assuming no variations along the path.

To obtain a full yearly dataset, the author calculated UTCI values (for all 8760 hours composing a year) for the view factors points in a 5 m interval, for each sidewalk of each street. This choice allowed to reduce the simulation efforts and generates only the relevant data, corresponding to the areas where people actually walk. Each sidewalk is composed by 294 points, considering a total length of approximately 1500 m for each hour of the year. The outcome of the simulated data is contingent and represents outdoor thermal comfort conditions with a high resolution.

During the simulation phase we encountered several limitations: in general, these workflows require that each component is simulated separately, which implies that results are visible only in the following calculation step. This means that the process is very time consuming and requires many iterations.

4.2. Spatiotemporal Thermal Comfort Maps

In order to get a spatiotemporal mapping of comfort conditions, the hourly results calculated for each sidewalk were fused into the STOCA factor. As mentioned in chapter III, the factor is defined as the number of data-points in a given spatial domain over a prescribed period that are within a defined comfort range. The factor allows to analyse comfort potential according to the overall climatic conditions and seasonal variations.

In this case, the author calculated the factor for each hour, dividing the domain by the number of data-points (294). The result is a value between 0 and 1 that describes the spatial comfort availability. In fact, the availability in cold winters differs substantially from hot summers. In this sense the factor gives the opportunity to depict very specific conditions and compare them in a high resolution, such as different sides of a street canyon or different streets within a neighborhood.

To select seasonal representative periods, the author used the secondary dataset presented in chapter III to analyse Boston's climatic conditions. In particular, the hourly climate data corresponding to the walking trajectories' dataset were clustered into four two-weeks long representative periods corresponding to the four seasons.

Due to its coastal location and its exposure to the winds of the Atlantic ocean, Boston's weather is highly variable also within short periods of time. The maximum variation between the highest and lowest temperature is 55 Kelvin, which corresponds to hot summers and cold winters, while spring days have high variation with cold and warm days, fall has rather warm and sunny days.

The selected periods consist of 14 days, two weeks including weekends, since the weekends often have more trajectories than weekdays as the preliminary data analysis in section 1 shows. For the winter period, the days from February 9 to 22 were considered, for the spring period April 13 to 26, for the summer period September 1 to 14, for the autumn period November 3-16. The winter and summer periods include respectively the lowest and highest air temperature. The clustering aims at creating seasonal representative scenarios. With more powerful computational tools and with the use of automated techniques, the entire year could be simulated to create a complete interdependencies study.

To calculate the STOCA factor, the author chose different comfort ranges to match different seasonal scenarios.

Besides the "no thermal stress category" (from 9 to 26 °C ET) which is valid for all seasons, for the winter scenario, the author included the "light cold stress" category (0 to 9 °C ET), in summer, the "light heat stress" (26 to 32 °C ET), according to the definitions provided by the UTCI scale (Fig. IV. 26). This decision was made because in summer and winter the "no thermal stress" conditions are rarely reached, which would have lead to many null cases. The STOCA factor includes sun exposure allowing to draw clear distinctions between sides



Figure IV.26: UTCI Universal Thermal Climate Index scale [Equivalent Temperature] 88

of the street with different orientations and between one street and the other. In this sense, it allows to characterise comfort in a defined spatial domain referring to the maximum available comfort within given climatic conditions. The factor is expressed in a value between 0 and 1 and is calculated for each hour in a 14 days time interval representing each season. It was calculated separately for each sidewalk of the three streets, as shown in fig. IV.27.

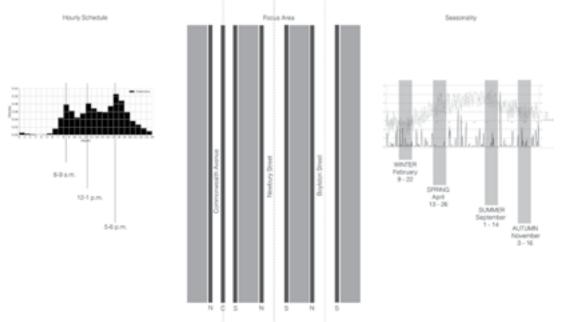


Figure IV.27:Seasonal and daily schedule employed for the analysis

The spatiotemporal comfort maps represent the hourly comfort availability in the selected spatial domain expressed as STOCA factor. Fig. IV 28 shows an exemplary plot: the y-axis maps the 24 hours values (from 12 am to 12 am), the x-axis the 14 days' period. Each pixel corresponds to a factor value (between 0 and 1) for the entire sidewalk length.

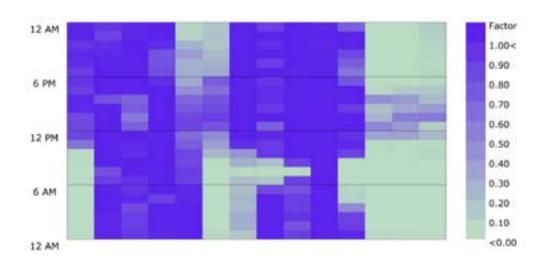


Figure IV:28:Exemplary spatiotemporal comfort map

The maps (Figures IV. 29–33) represent the comfort availability, calculated using the STOCA factor, for each of the selected periods and for each sidewalk. The juxtaposition highlights similarities and differences between streets, between the different sides of the street and between the seasons.

In the winter season (Fig. IV.29) a very similar pattern between the street sides can be observed that is reflected also when comparing the different streets. Only the central sidewalk in the park has a radically different pattern. The factor was generated considering, in addition to the "no thermal stress" UTCI classification, the "light cold stress" category (0 to 9 °C ET). Nevertheless, the winter has a high number of hours without any comfort availability throughout all the streets. As represented in the Δ maps, the difference between the sides of the streets has a rather minor impact, while the south sidewalk in Commonwealth Avenue has a higher availability than the park.

In Spring (Fig. IV.30) a similar trend ca be observed. In this case, the factor was generated considering only the "no thermal stress" UTCI classification (9 to 26 °C ET). Compared to the winter, the comfort availability on all streets and sidewalks is very high. The exception is, as already seen in winter, the central sidewalk of Commonwealth Avenue, that still provides comfortable conditions occasionally during daytime. The Δ map, in fact, highlights the strongest difference in Commonwealth Avenue.

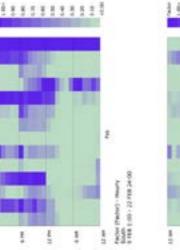
During the summer period, the effect of the linear park becomes evident. The factor for the summer season was generated considering, in a first step, only the "no thermal stress" UTCI classification (Fig. IV.31). The centre sidewalk of Commonwealth Avenue has by far the highest comfort availability, while all other segments have similar patterns, with a lower availability in Commonwealth Avenue on the north and south sidewalks. In the central sidewalk, we see four days without any comfort availability that correspond to the hottest days of the year and two nights at the end of the selected period with light cold stress.

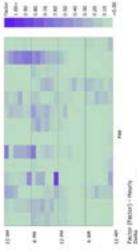
In a second step, the "moderate heat stress" category has been added (26 to 32 °C ET) to carry out the correlations to avoid too many null values. In this case (Fig. IV.32) the comfort availability is highest throughout the area, with a conspicuous effect of the linear park: out of the 336 hours that compose the period, the central sidewalk has only 18 hours with light cold stress during the night hours, while the other guarantee full comfortable conditions. Similar to spring, autumn (Fig. IV.33) was evaluated considering only the "no thermal stress" UTCI classification (9 to 26 °C ET) and presents a similar pattern. The discomfort occurrence can be caused both by moderate heath stress as well as by light cold stress, a specific characteristics of Boston's varying weather conditions. Also int his case we recognise the reoccurring patterns with a lower comfort availability in the central Commonwealth Avenue.

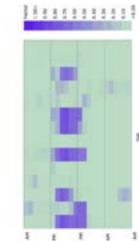
Summarising, the two more evident tendencies are visible in Commonwealth Avenue and Boylston Street: comparing the trends for each street separately, we notice a high fluctuation on comfort conditions in Commonwealth Avenue, comparing the south and central sidewalk, while in Boylston Street we see the lowest differences between one side and the other. This effects can be assigned to the aspect ratio of the streets: Commonwealth has the lowest (0,25) exposing the central path to the highest extent, while Boylston has the highest (0,62), reducing the exposure to the maximum. The higher aspect ratio that corresponds to the lowest SVF reduces the differences between the sides because it reduces solar access. However, the presence of the wide central strip in Commonwealth Avenue that hosts the park increases comfort in summer when the foliage guarantees shading and evaporative cooling, but reduces it in winter and spring when the higher exposure generates discomfort. The influence of the linear park is particularly interesting because it creates a high difference in comfort availability within a few meters in the dense urban tissue, requiring additional space.

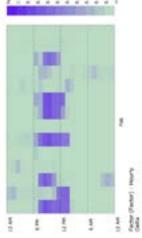
Figure IV.29: Spatiotemporal comfort map - Winter



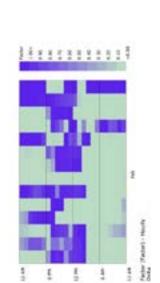


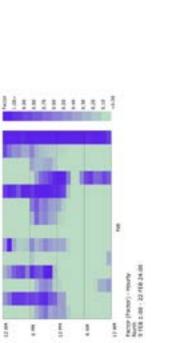




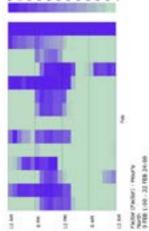












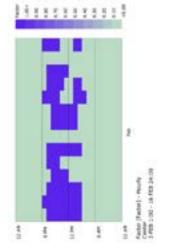
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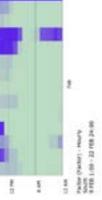
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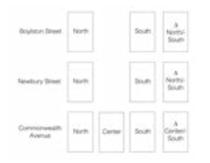
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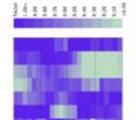
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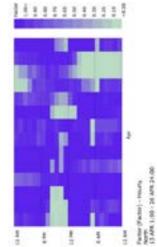
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Figure IV.30: Spatiotemporal comfort map - Spring





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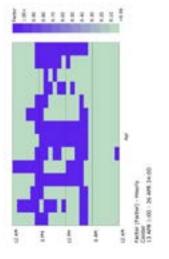


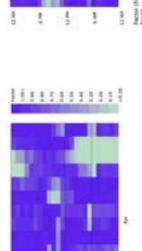
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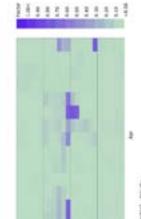
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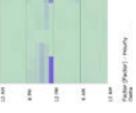
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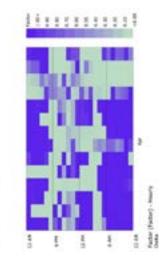
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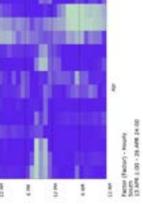
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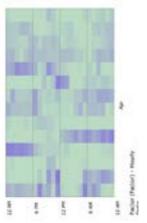








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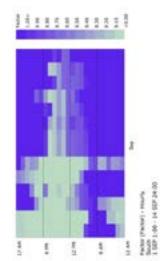
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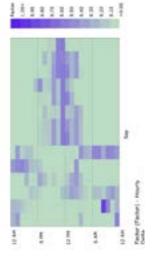
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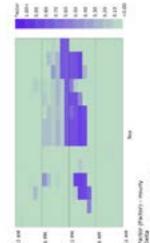
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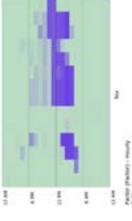
Figure IV.31: Spatiotemporal comfort map - Summer, 9 to 26° C domain





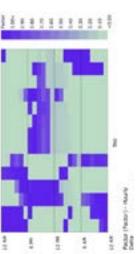


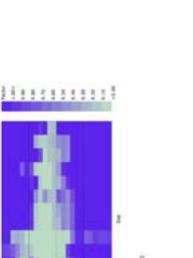






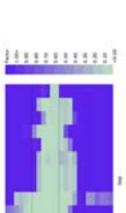


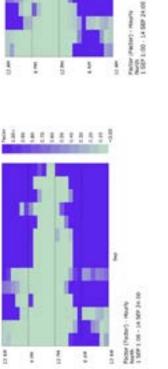


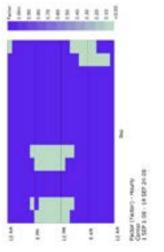


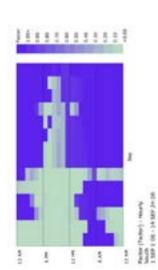
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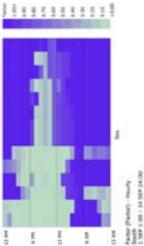


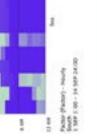


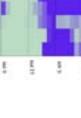
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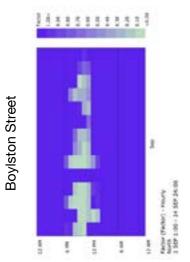
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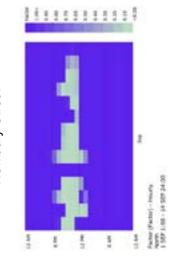
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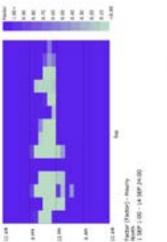
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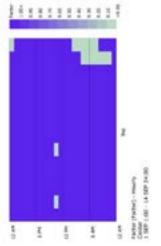
Figure IV.32: Spatiotemporal comfort map - Summer, extended comfort range

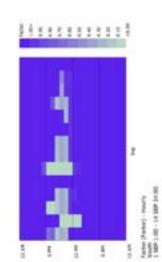












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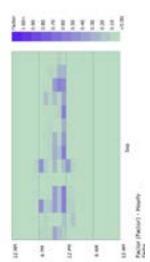
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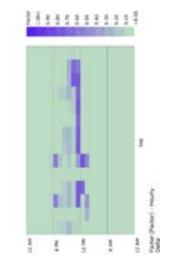
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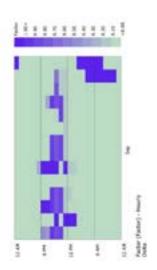
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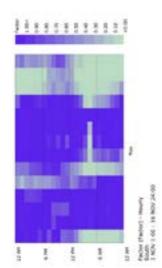


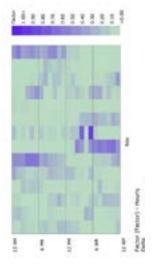
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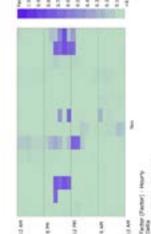
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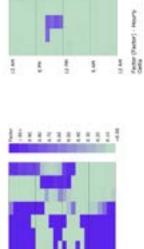
Figure IV.33 Spatiotemporal comfort map - Autumn

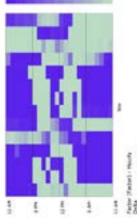








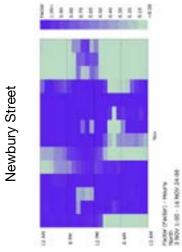


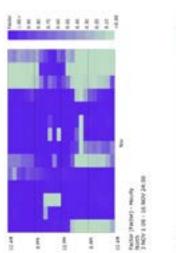


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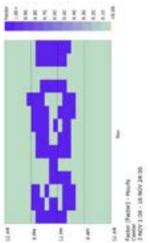
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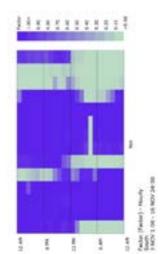
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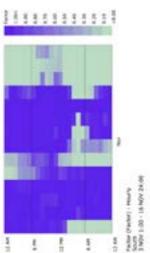




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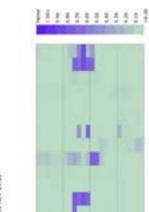






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5. Interdependences

The main aim of this research is to give evidence to the interdependencies between microclimatic conditions and human individual mobility. To detect the relation between the microclimatic variations and people pedestrian flows, the author employed the statistical analyses that are presented in the following subsection.

These analyses rely on the trajectories' count and the STOCA factor values and are targeted at detecting patterns, both in terms of temporal and spatial variations. In the interdependency analysis, the author considered the trajectories' count for the daily peaks: 8–9 am, 12–1 pm and 5–6 pm as explained in section 2 of this chapter.

5.1. Correlations

In a first step, the total trajectories where plotted against the corresponding averaged UTCI value for each street segment. These values refer to the four seasonal scenarios during the selected time frames. The graph (Fig. IV.34) shows the relation between UTCI values and number of trajectories. The UTCI ranges were defined by the International Society of Biometeorology Commission for individuals "walking lightly" (UTCI, 2012) The interval 18–26 C is indicated as the "thermal comfort zone" according to the Commission for Thermal Physiology of the International Union of Physiological Sciences (Bröde et al., 2012). The relation between number of trajectories and UTCI ranges is clear, showing a strong relation between the comfort zone and people's presence.

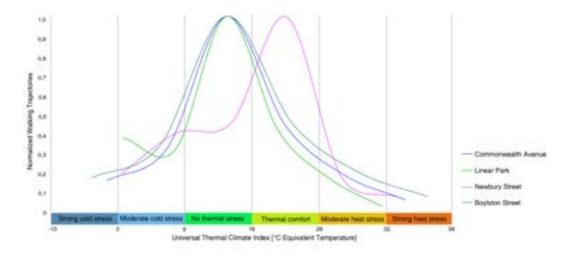
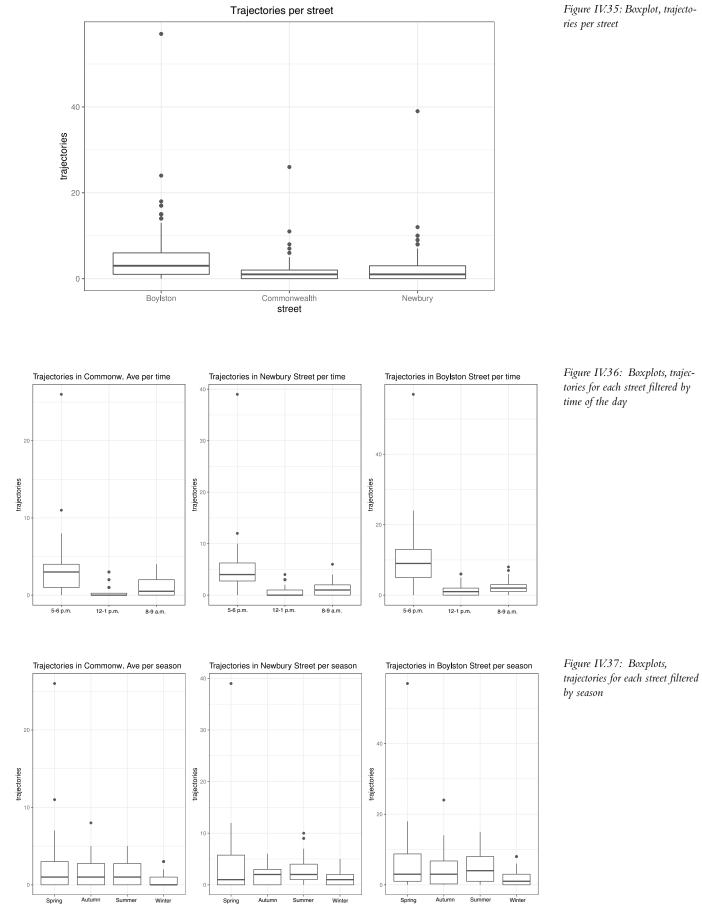


Figure IV.34: Relation between UTCI and number of trajectories over the year

However, basing on this clear relation obtained by aggregated data, the author investigated the interdependencies of the unaggregated data, analysing each street segment separately and keeping the spatiotemporal distribution of UTCI values, as defined in the STOCA metric.

Therefore, the author plotted box-plots with the number of the total trajectories for each street (Fig. IV.35). In addition, the author included the time of the day (Fig. IV.36), considering peak times and the seasonality (Fig. IV.37).

Boylston Street is always walked by a higher number of trajectories, while Commonwealth Avenue and Newbury Street, besides the differences in terms of absolute values, have a similar median value. In all cases, the frequency of walking trajectories is higher in the evening and lowest at noon. Looking at the different seasons, Commonwealth Avenue has almost no walking activity in winter, while it is rather consistent in the other season. The same trend applies to Boylston Street, while Newbury Street shows more trajectories in summer and autumn than in spring and winter.



To verify which comfort availability each street offers, the author plotted the STOCA factors for every street. In this context, it is worth re-mentioning the fact that the trajectories are matched to the osm_id centreline. This precludes to recognise which side of the street people were walking along. Since the STOCA factor was calculated for each side separately, the author included this differentiation in the next analysis.

Boylston Street (Fig. IV.38) guarantees full comfort availability in summer, both on its north and south sidewalk. While observing similar trends in the other seasons, the south sidewalk has always a slightly higher availability. The winter has the lowest availability with median values between 0.10 and 0.20 followed by the autumn (0.80 – 0.87) and spring (0.90).

Newbury Street (Fig. IV.39) also shows a similar tendency, with a median full availability in summer, high values in spring and autumn and low (0.10–0.20) in winter. Also in this case, the availability is higher on the north sidewalk.

Commonwealth Avenue (Fig. IV.40), where we considered also the central sidewalk in the linear park, has almost full availability on all the three paths in spring and summer. While the northern and southern sidewalks have similar trends, the park has a more extreme trend: it has very low values both in autumn and in winter, while it has full availability in summer and spring. This can be related to the presence of leaf coverage with its beneficial effects on thermal comfort. The northern sidewalk has higher availability in winter (0.28), due to the longer exposure to the sun, compared to the southern sidewalk (0.08).

Since these box-plots are only descriptive of relation between the walking frequency and the comfort levels for each street, the author calculated bivariate correlations between the number of trajectories and the comfort availability for each of the streets.

In a first step, the correlation did not include subsetting, presenting the following results:

In Boylston Street, a positive linear correlation for both sidewalks can be observed, with a slightly higher coefficient in the northern one (Fig. IV.41). Same for Newbury Street (Fig. IV.42), where both sidewalks have almost the same coefficients. Also in Commonwealth Avenue, linear correlations for all sidewalks can be observed, with a higher significance in the central one (Fig. IV.43). Summarising, all sidewalks present a positive linear correlation without significant differences between the street sides, except for Commonwealth Avenue on the south sidewalk, where the significance (R value) is lowest.

R is the Pearson correlation coefficient that measures the linear correlation between two variables divided by the product of their standard deviations. p indicates the statistical significance. The p-value is a number between 0 and 1 representing the probability that this data would have arisen if the null hypothesis were true. A low p-value (such as 0.01) is taken as evidence that the null hypothesis can be 'rejected'. Statisticians say that a p-value of 0.01 is 'highly significant' or say that 'the data is significant at the 0.01 level'

To generate more accurate results, the author included seasonality and time of the day as subsetting to the regression model.

The influence of seasonality is significant in Boylston Street on both sides, with a R = 0,36, p = 0,02 in winter on the south side (Fig. IV.44) and R = 0,31, p = 0,044 in summer on the north (Fig. IV.45). In Newbury Street (Fig. IV.46) the correlation is positive and significant R = 0,34, p = 0,028 in winter on the south and in Commonwealth Avenue in summer on the north sidewalk R = 0,37, p = 0,016 (Fig. IV.47)

The influence of the time of the day is slightly under the threshold for both sidewalks of Boylston Street (North: R = 0,26, p = 0,052 South: R = 0,23, p = 0,087) (Fig. IV.48) and Newbury Street (Fig. IV.49) in the evening hour (5-6 pm). Commonwealth Avenue has the only significant value for the centre sidewalk in the evening (R = 0,29, p = 0,032) (Fig. IV.50).

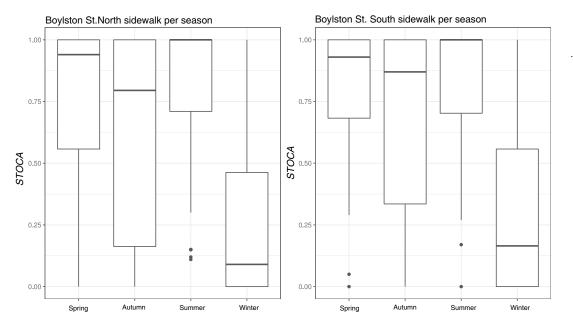


Figure IV.38: Boxplots, Boylston Street: STOCA factor filtered for each season.

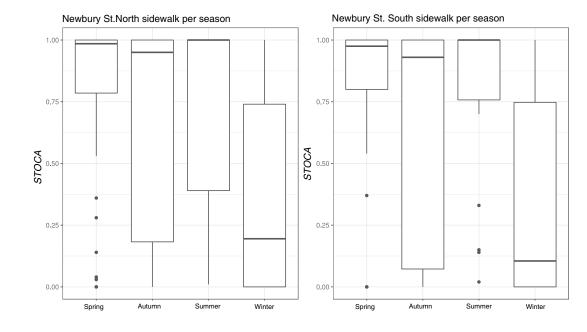
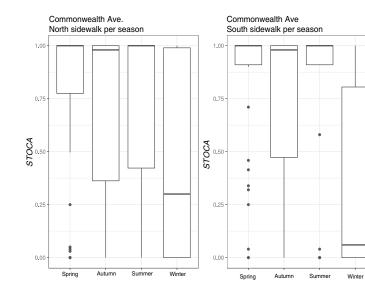


Figure IV.39: Boxplots, Newbury Street: STOCA factor filtered for each season.



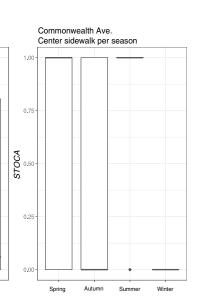


Figure IV.40: Boxplots, Commonwealth Avenue: STOCA factor filtered for each season.

Figure IV.41: Correlation between STOCA factor and trajectories in Boylston Street.

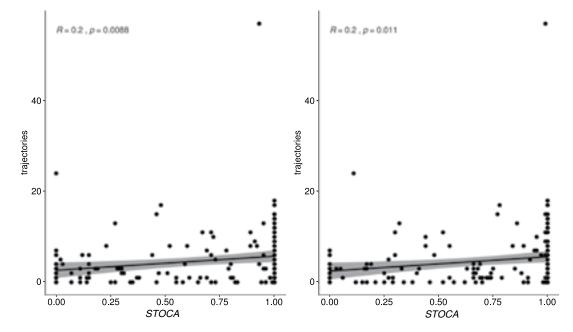


Figure IV.42: Correlation between STOCA factor and trajectories in Newbury Street.

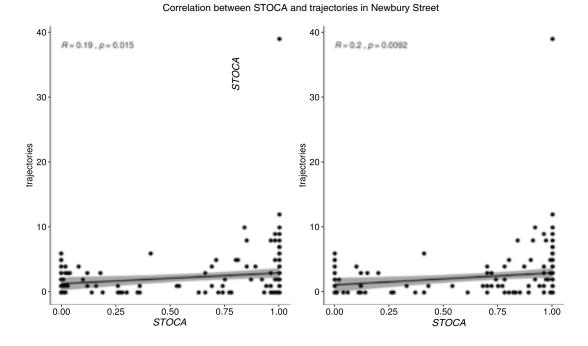
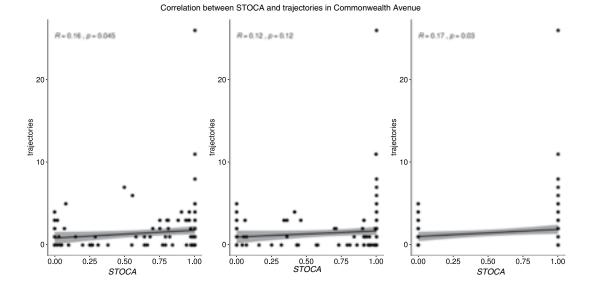
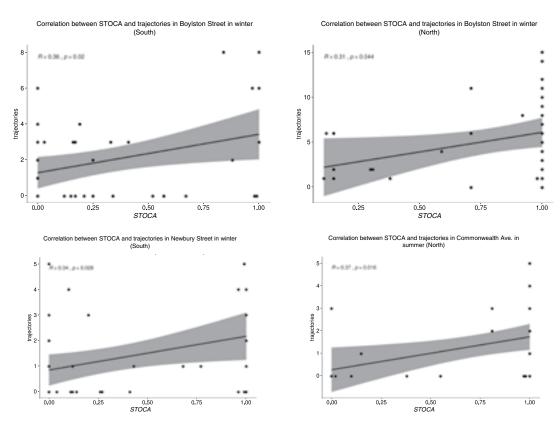
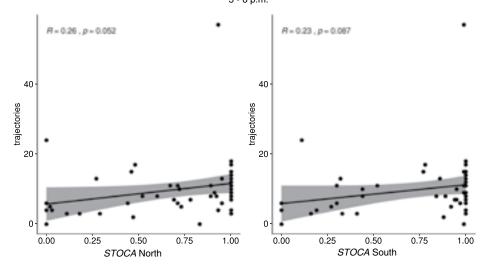


Figure IV.43: Correlation between STOCA factor and trajectories in Commonwealth Avenue





Correlation between STOCA (N. and S.) and trajectories in Boylston Street 5 - 6 p.m.



Correlation between STOCA (N. and S.) and trajectories in Newbury Street 5 - 6 p.m.

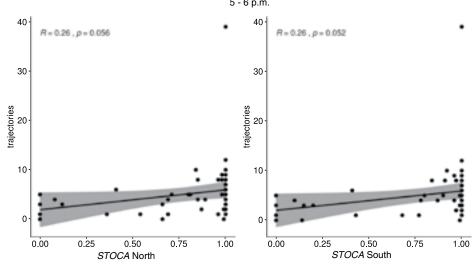


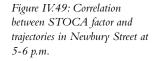
Figure IV.44: (l) Correlation between STOCA factor and trajectories in Boylston Street in winter for the south sidewalk.

Figure IV.45: (r) Correlation between STOCA factor and trajectories in Boylston Street in winter for the north sidewalk

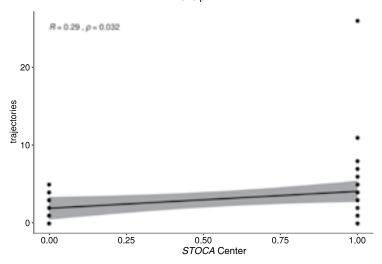
Figure IV.46: (l) Correlation between STOCA factor and trajectories in Newbury Street in winter for the north sidewalk

Figure IV.47: (r) Correlation between STOCA factor and trajectories in Commonwealth Avenue in summer for the north sidewalk

Figure IV.48: Correlation between STOCA factor and trajectories in Boylston Street at 5-6 p.m.



Correlation between STOCA and trajectories in Commonwealth Ave. 5 -6 p.m.



5.2. Multivariate Analysis

The presented correlations show a significant dependency from seasonality, particularly between summer and winter. Seasonality is highly related with comfort, which leads to unsurprising results. Since counted data is employed, multivariate models that fit this scale were necessary. A Poisson model would be used as a common choice, but its assumption of equality of the expected value and the variance are only met in the rarest of cases. For this reason, the author modelled a multivariate quasi poisson and a negative binomial distribution: first, without considering seasonality, later including it.

These models describe the correlation of trajectories' number and comfort availability, supported by the coexistence of more variables, such as the hour of the day, the season and the Local Access Score (Reardon et al., 2016).

The Local Access Score (LAS) is a metric developed by the regional planning agency for Greater Boston together with the Metropolitan Area Planning Council (MAPC) to provide "a relative measure of how important any particular road segment would be for providing a connection for residents from their homes to public schools, shops and restaurants, parks, and transit stations" (Reardon et al., 2016). These trip destinations were selected because of their strong potential for walking and biking, combined with interest from municipal partners in encouraging active transportation in these arenas. The scores were created with a four-step travel demand model, using census blocks as analysis zones for a very high degree of spatial resolution. Scores are available for each trip purpose by two modes—cycling and walking. MAPC also compiled these eight basic scores into two composite scores, bike utility and walk utility, then finally combined these two composite scores into an overall measure of active transportation utility. The resulting total of eleven metrics are available for every street segment across the state of Massachusetts and have been published in a web map where the results can be viewed or downloaded. Although a travel demand modelling software package was used to create the LAS, the scores do not attempt to model real human behaviour, either current or projected. Model inputs were based on two major assumptions 1) all existing roadways constitute complete streets that are comfortable for cyclists and pedestrians and 2) this idealised infrastructure would encourage people to walk or bike to local destinations, distance permitting.

The author included the walking utility score as a variable to differentiate the streets according to their relevance in terms of accessibility for daily routines. As already shown by the box-plots, Boylston Street has a much higher density of walking trajectories due to different reasons, but probably due to its higher accessibility to public transportation nodes. The LAS supports this assumption, assigning to it a very high score, in particular compared to Newbury Street and Boylston Street. The score, in fact, bases on the question which road segments people would walk or bike to have the most direct route to nearby schools, shops, restaurants, parks, and transit stations.

Both models, the multivariate quasi poisson regression and a negative binomial distribution, were run for each street separately and for the entire area (Appendix). In addition, since a linear regression has not been used, the y axis is just a function of the amount of trajectories. However the interpretation is similar: if the curve increases, it corresponds to an increasing number of trajectories. The difference is that it is not linear as in the correlation model, but exponential.

Due to the higher number of trajectories, the evening case (time_evening) and the spring season was taken as the reference (Intercept).

In Boylston Street, the sidewalk exposure has no significant influence on the trajectories. In summer a negative influence can be observed, compensated by summer mornings, where the influence is positive (Table IV.1-2).

In Newbury Street, the south sidewalk has a positive influence, the northern has a negative (only according to the NB model) influence on trajectories. Including seasonality and time, shows a positive influence in summer mornings.

In Commonwealth Avenue, only the central sidewalk has a significant influence on trajectories in addition to the times of the day. The central sidewalk in the linear park attracts walkers. Adding seasonality and the time of the day variables, an increased influence in winter mornings in both models can be seen (Table IV.3).

Finally, the interactions between all variables against each other adding the LAS variable were modelled. It reveals that the influence is significant and negative for the north sidewalks, at noon in autumns and positive at noon in summer (29–32). Particularly significant and positive, however, is the LAS score, which highly affects the number of trajectories. Also the central sidewalk in the linear park with a high STOCA factor (Cfactor2) has a less negative influence compared to (Cfactor1), central sidewalk with STOCA factor = 0), meaning that its influence is significant within the limited amount of trajectories that are walked there over the year.

6. Discussion

The results of the multivariate analysis identify the sensitivity to microclimatic conditions. The models depict tendencies that arise from a complexity of relations that cannot be considered without including multiple layers. It is difficult to formulate statements about the causality because the dataset lacks of important socio-demographical variables that influence the path choices. However, also the notion of comfort is an approximation and is depending, besides the environmental parameters, on contextual factors such as age, gender, previous experience and adaptation and metabolic rate (Parkinson et al., 2012).

Within the outlined system boundaries, the correlations show positive values and are significant, more in summer and the mid seasons, less in winter.

The differences in comfort availability between the side of the street are relevant only in relation to seasonality. Here it is worth underlining that the side choice depends also on individual factors such as individual physiological response, clothing factor, activity and travel purposes. The author calculated which side has the higher availability at a given time, but availability changes over time due to exposure.

The linear park has the strongest correlation in summer afternoons, the effect of vegetation on comfort availability is evident in summer and spring. In this context, it is important to underline that the linear park has a particular relevance because it is located in a dense environment bringing a high influence to comfort navigation for its location close to other functions,

Table IV.1: Quasi Poisson regression, Boylston Street

Coefficients					
	Estimate St. Dev.	Error	t value	Pr(> t)	
(Intercept)	2,7916	0,198	5 14,061	< 2E-16	***
North	-0,0864	0,366	-0,236	8,1398E-01	
South	0,0395	0,352	0,112	9,1097E-01	
Time_noon	-1,8762	0,282	-6,646	4,91E-10	***
Time_morning	-2,4011	0,356	-6,743	2,94E-10	***
Season_Autumn	-0,5197	0,170	-3,046	2,73E-03	**
Season_Summer	-0,3648	0,169	-2,158	0,03250	*
Season_Winter	-1,3922	0,243	-5,724	5,28E-08	***
noon x autumn	-1,6134	0,823	-1,958	5,199E-02	
morning x autumn	1,4186	0,4374	3,244	1,45E-03	**
noon x summer	0,2558	0,425	2 0,602	5,483E-01	
morning x summer	1,0197	0,453	5 2,248	2,597E-02	*
noon x winter	-0,5337	0,768	-0,694	4,8851E-01	
morning x winter	1,4564	0,527	3 2,762	6,44E-03	**
Significance codes	0 = "***"	0,001 = '**'	0,01 = '*'	0,05 ='.'	0,1 =' '
Deviance Residuals	Min	1Q	Median	3Q	Max
	-3,1938	-0,9393	-0,4572	0,8630	

8,0413

5,8582

Table IV.2: Negative Binomial regression, Boylston Street

Coefficients

	Estimate St. Dev.	Error	z value	Pr(> z)	
(Intercept)	2,88408	0,20608	13,995	< 2E-16	***
North	0,01932	0,34664	0,056	9,55553E-01	
South	-0,16232	0,33829	-0,48	6,31348E-01	
Time_noon	-1,88556	0,24471	-7,705	1,3E-14	***
Time_morning	-2,42131	0,28325	-8,548	< 2E-16	***
Season_Autumn	-0,5348	0,19529	-2,738	6,173E-03	**
Season_Summer	-0,38305	0,19669	-1,947	5,1485E-02	
Season_Winter	-1,41186	0,23205	-6,084	1,17E-09	***
noon x autumn	-1,60909	0,587	-2,741	6,121E-03	**
morning x autumn	1,41443	0,36529	3,872	1,08E-04	***
noon x summer	0,26968	0,36534	3,872	4,60421E-01	
morning x summer	1,06156	0,37519	2,829	4,664E-03	**
noon x winter	-0,57628	0,55607	-1,036	3,00046E-01	
morning x winter	1,41521	0,41498	3,41	6,49E-04	***
Significance codes	0 = '***'	0,001 = '**'	0,01 = '*'	0,05 ='.'	0,1 =' '
coucs					
Deviance Residuals	Min	1Q	Median	3Q	Max
	-2,5443	-0,8397	-0,3366	0,5609	3,5285

Table IV.3: Quasi Poisson regression, Commonwealth Avenue

Coefficients					
	Estimate St. Dev.	Error	t value	Pr(> t)	
(Intercept)	1,38496	0,33694	4,11	6,42E-05	***
North	-0,01654	0,37583	-0,044	9,64956E-01	
South	-0,0704	0,34005	-0,207	8,36265E-01	
Center	0,54237	0,26373	2,057	4,1432E-02	*
Time_noon	-1,92078	0,45789	-4,195	4,61E-05	***
Time_morning	-2,78951	0,60908	-4,58	9,58E-06	***
Season_Autumn	-0,42082	0,26628	-1,58	1,16093E-01	
Season_Summer	-0,99594	0,27958	-3,562	4,91E-04	***
Season_Winter	-1,08742	0,40546	-2,682	8,125E-03	**
noon x autumn	-1,99078	1,41784	-1,404	1,62317E-01	
morning x autumn	2,14379	0,70295	3,05	2,7E-03	**
noon x summer	0,35697	0,72998	0,489	6,25537E-01	
morning x summer	2,16878	0,73021	2,97	3,458E-03	**
noon x winter	0,63576	0,82333	0,772	4,41199E-01	
morning x winter	1,93855	0,84022	2,307	2,2384E-02	*
Significance codes	0 = "***"	0,001 = '**'	0,01 = '*'	0,05 ='.'	0,1 ='
Deviance Residuals	Min	1Q	Median	3Q	Max
	-3,5494	-1,0275	-0,4087	0,5135	

representing an alternative route to every day routines. Moreover, a variety of factors such as a safe walking route, less interference with cars, seating opportunities and the presence of trees, converge in the linear park and reciprocally enhance its attractiveness. Summarising, a full influence of comfort availability is observed in summer, where the STOCA factor was calculated considering also moderate heat stress conditions. In spring and autumn, the comfort availability has been limited to the "no thermal stress category" whereas in winter the moderate cold stress has been added. These considerations were done according to Boston's climate that has extreme summer and winter conditions.

The multilevel regression analysis that includes the local access score intends to neutralise the uneven distribution of trajectories over the three streets. In this sense, it contributes to make the streets more comparable, limiting the differences in terms of accessibility, presence of amenities and public functions. The author intends this as an attempt to limit the observation to comfort availability. These results show a weak influence of the functional setup of the streets, if we limit the observation to thermal comfort and observe the entire area excluding the pedestrian counts. With regard to the analyses' results, a clear relation to MRT can be noticed which corresponds to direct sun exposure. Comfort availability is more significant in summer, during exposure to high radiation, when heat stress can inhibit walking.

In other words, morphological characteristics are significant because they influence the exposure to radiation: streets with a lower aspect ratio have higher exposure that can determine heat stress in summer, streets with a higher aspect ratio have a lower exposure, maintaining more stable conditions throughout longer periods.

To further validate these results, a deeper investigation with a larger sample combined to direct observation could be beneficial. The fact that the data has been collected in the past and that simultaneous measurements and interviews could not be performed is an inherent limitation of the dataset. It is worth to question the limitations of the data driven approach, since it limits the observation to specific groups of people and cannot be considered necessarily as a representative sample. In this sense, the direct observations that were carried out on the focus area support the understanding of these results.

Concluding, limiting the application to a relatively small focus area is considered an opportunity in methodological terms: analysing a smaller sample but keeping the dynamic component of walking in relation to varying microclimatic sequences points out a strategy that can be applied also with common computational power, open source data and tools as well as in reasonable time.

The applied workflow was used as a case to verify the methodology, test the hypothesis and answer the research questions. It has put into evidence in the underlying mechanism that relates flows and microclimatic conditions supported by metrics and quantities that were specifically combined and confirms that the employed metrics are capable of representing interdependencies and thus could be employed to support design and development of comfortable public space.

The results show a significant influence of microclimate on people flows and suggest that the proposed methodology can be used to provide meaningful insights to encourage policy-making, urban planning and design interventions to increase comfort availability in dense urban environments.

References

Arens, E., Hoyt, T., Zhou, X., Huang, L., Zhang, H., Schiavon, S. (2015) Modeling the Comfort Effects of Short-Wave Solar Radiation Indoors. *Building and Environment*, 88 : 3–9.

bigladdersoftware https://bigladdersoftware.com/projects/elements/ (Accessed September 9th 2018)

Blazejczyk, K., Epstein, Y., Jendritzky, G., Staiger, H., & Tinz, B. (2012). Comparison of UTCI to selected thermal indices. *International journal of biometeorology*, 56(3), 515-535.

Boston Budget, (2015) https://bostononbudget.com/cheap-weekend-fun-in-boston-for-april-18-20-2015/ (Accessed, April 2020)

Boston Plans, http://www.bostonplans.org/3d-data-maps/3d-smart-model/3d-data-download (Accessed September 2018)

Bröde P, Fiala D, Blazejczyk K, Holmér I, Jendritzky G, Kampmann B, Tinz B, Havenith G (2012) Deriving the operational procedure for the Universal Thermal Climate Index (UTCI). *International journal of biometeorology* 56, 481–94.

Census https://www.census.gov/quickfacts/bostoncitymassachusetts, Accessed, June 2018

Chokhachian, A. & Hiller, M. (2020) PANDO: Parametric Tool for Simulating Soil-Plant Atmosphere of Tree Canopies in Grasshopper. SIMAUD 2020 Conference Proceedings, Vienna.

Duffie, J.A., Beckman, W.A., Worek, W. (2013) *Solar engineering of thermal processes*. Vol. 3. Wiley Online Library. EnergyPlus https://energyplus.net/weather (Accessed September 2018)

Jendritzky, G., de Dear, R., & Havenith, G. (2012) UTCI—why another thermal index?. International journal of biometeorology, 56(3), 421-428.

Reardon, T., Wallace, E., Brown, C. (2016) Active Transportation Network Utility Scores Technical Report http://localac-cess.mapc.org (accessed September 2018).

Mackey, C., Galanos, T., Norford, L., & Roudsari, M. S. (2017) Wind, sun, surface temperature, and heat island: critical variables for high-resolution outdoor thermal comfort. *Proceedings of the 15th international conference of building performance simulation association*. San Francisco, USA.

Martin, M. & Berdahl, P. (1984) Characteristics of infrared sky radiation in the United States. Solar Energy, 33(3): p. 321-336.

Matzarakis, A., Rutz, F., Mayer, H. (2010) Modelling radiation fluxes in simple and complex environments: basics of the RayMan model. *International journal of biometeorology*. 54(2): p. 131-139.

Oke, T.R. (2002) Boundary layer climates. Routledge.

Thorsson, S., Lindberg, F., Eliasson, I., Holmer, B. (2007). Different Methods for Estimating the Mean Radiant Temperature in an Outdoor Urban Setting. *International Journal of Climatology* 27, no. 14: 1983–93.

Parkinson, T., de Dear, R., Candido, C. (2012) Perception of Transient Thermal Environments: pleasure and alliesthesia. *Proceedings of 7th Windsor Conference*, Windsor, UK, 2012

Pushkarev, B. (1975.) Urban Space for Pedestrians.

Tominaga, Y., Mochida, A., Yoshie, R., Kataoka, H., Nozu, T., Yoshikawa, M., & Shirasawa, T. (2008) AIJ guidelines for practical applications of CFD to pedestrian wind environment around buildings. *Journal of wind engineering and industrial aerodynamics*, 96(10-11), 1749-1761.

UTCI Assessment Scale, (2012). http://www.utci.org/utci_doku.php. (Accessed October 2020)

V. CONCLUSIONS

This final chapter summarises the dissertation's results and confronts them with its ultimate intention to provide indications which will be able to contribute to the reconfiguration of the physical built environment. The variety of methods used included digital data from individ-uals to assess the influence of microclimatic conditions on people's flows in urban space. The novel methodology, that has been developed in the context of this dissertation with the aim to generate knowledge about the nexus between the built environment and individual pedestrian mobility, has been applied, tested and critically evaluated.

In the symbiotic relation between the built city and people flows in public space, the interdependencies of urban microclimatic conditions and the recorded data of individual pedestrian mobility highlight this reciprocity. In this sense, the relation between digital information and its physical manifestation is strongly linked to the microclimatic conditions obtained by simulations of the urban microclimate in selected areas. This framework allows to analyse the interplay between climate, urban morphology and people presence from a human perspective by utilising collected data over a long period of time. With the final aim to provide knowledge in the congested arena of pedestrian research, this dissertation contributes with a novel methodological approach to fill the research gaps presented in the introduction and provides indications for spatial reconfiguration in planning and design practice.

In this sense, the findings of this research need to be seen through the lens of its interdisciplinary, novel approach.

1. Discussion of the Findings

The influence of climate on urban practices and on the use of public space has already generated a wide body of research. However, the pressure that climate change is putting on urban environments intensifies the urgency to provide precise actions underpinned by evidence. The city is the space where the challenges related to climate change collide and confront; the reconfiguration of public space is crucial for promoting a tangible improvement in terms of social justice and public health. The ongoing pandemic has exacerbated our attention to public space: the paradox of living in a city where the use of public space is inhibited, long-standing routines are disrupted, new, improvised urban practices and ad-hoc solutions proliferate. Empty streets and plazas remind us of John Cage's provocative composition 4'33", that uses silence to demonstrate the value of sound. Similarly, we realise the value of public space through its emptiness. Moreover, the idea to mitigate climate with artefacts and technologies has become obsolete: as Eva Horv points out, "Yet, with the insight at the earth of the idea of Anthropocene — the fact that man has started to alter and disrupt climate not only on a local but on a planetary scale — a separation of climate and culture, nature and technology, environment and humanity is becoming untenable" (Horv, 2016).

In this context, data science is undoubtedly generating new isights to provide evidence about dynamic phenomena. However, we have to be aware of its limitations, particularly when it comes to clustering and disclosing mechanisms that try to quantify the unquantifiable. The thread is, as Bruno Latour has outlined, that we still feel compelled to cleanly separate "social needs and natural reality, meanings and mechanisms, signs and things" (Latour, 1993).

The results of this work require to be contextualised within the proposed structure. The methodology introduced and described in chapter III attempts to generate a workflow to relate microclimatic variations and human walking patterns in urban space. The methodology builds upon the dynamic relations between the interacting domains relevant in this dissertation as discussed in chapter II to find an application in a case study as presented in chapter IV.

The defined methodology is a result of interdisciplinary thinking and mixed methods that were combined to approach the main research questions of this dissertation. As such, its theoretical framework and its application are testing and validating the methodology, attempting to include variables to depict the synesthetic capture; in other words, without isolating the thermal experience from other layers of psychophysical involvement.

Considering walking as a sensual and physical bodily experience in which the thermal exchange with the environment is perceived sequentially and, typically, in a state of distraction, understanding single elements of its complex nature does not necessarily correspond to the sum of its parts.

The literature has already demonstrated that "psychological adaptation is very important for the thermal evaluation of outdoor spaces, and there is strong influence between the different parameters" (Nikolopoulou & Steemers, 2003). Nevertheless, "the physical environment and psychological adaptation is argued to be complementary rather than contradictory" leading to the conclusion that desirable spaces facilitate people's presence and therefore social interactions (ibidem).

Building upon this line of research, this dissertation proposes answers to the question about the reliability of data in order to provide information about sensory well-being, shaped by subjective, physical and mental states.

The case study's results are clearly pointing to a significant impact of microclimate on people flows, considering that this study focuses on one specific area as a part of a complex system. The impact has variations according to seasonality: a higher sensitivity in hot conditions, when microclimate causes stress conditions on humans. For this reason, the presence of the linear park in Commonwealth Avenue acquires a fundamental significance in summer, when the difference in comfort availability is strong, while in winter, when conditions are similar throughout the urban environment, the influence of microclimatic conditions on walking patterns is weak. Also, the impact of microclimate on peoples' walking patterns is strong when they have the choice: while function and daily routines determine peoples' obligation to certain routes, green spaces as such as the linear park are free choices and here thermal comfort plays a crucial role. People walk there because there is a strong thermal diversity. Summarising, comfort navigation occurs when the thermal experience is significantly different and when people are free to choose their paths.

Trying to characterise the intrinsic microclimatic character of each place, the author coined the term *microclimatic genius loci*, to describe the very unique conditions that occur when navigating through the city, that are shaped by urban morphology, materiality and vegetation.

In this sense, the proximity of vegetation is a crucial aspect; in fact, the presence of green spaces in dense urban environments is fundamental, but its effects on people's walking patterns are relevant if it provides an improvement of microclimatic conditions on their paths and with a perceivable intensity. The linear park in Commonwealth Avenue is an outstanding example to show how to combine paths for motorised mobility with large green spaces. It does not surprise that this example comes from the pre-car era, where distances between buildings, the street sections and the urban fabric were not designed to accommodate individual motorised mass transport. The use of voids, the interstitial spaces that often coincide with public space, is therefore one of the major challenges in future urban design practice.

Another important contribution of this dissertation is related to data reliability in the context of massive use of digital tools and data collection. Relying exclusively on data based methods

to formulate conclusions is critical, particularly when it comes to describing dynamic phenomena of living organisms. As such, formulating conclusions about urban dynamics is lacking a more diversified view.

The novel approach this work has taken is the empirical, bottom-up approach that uses collected dynamic data and not simulated, hypothetical data. The walking trajectories' dataset collects movement in space and time and needed to be matched to climatic data that is, in-trinsically, dynamic in space and time as well. Finding the methodological array to match two dynamic datasets, is one of the major contributions of this work.

Besides the dataset limitations, the results present limitations that are intrinsic to the nature of data based approaches and to anonymised data. The discussion around data collection and its legal implications is vast. Alex Pentland has dedicated an extensive body of work to the (mis) use of data in detecting social phenomena in urban science (Pentland, 2014). The thread is represented by positivistic ideas that underpin urban science ignoring human bias or framing. Anderson (2008) argues that "the data deluge makes the scientific method obsolete" because "correlation supersedes causation, and science can advance even without coherent models, unified theories, or really any mechanistic explanation at all". This means that data can abrogate theory and can be manipulated to detect a specific phenomenon. Furthermore, data-driven science can maintain a scientific method though generating hypotheses "born from the data rather than born from the theory" (Kelling et al., 2009 p. 613). "It uses guided knowledge discovery techniques to mine the data to identify potential hypotheses, before a traditional deductive approach is employed to test their validity" (Kitchin, 2016).

In the arena of urban science, there is no objective, super partes view of the complexity that regulates urban life and its dynamics. As Ribes and Jackson argue, "on the one hand, the data used do not exist independently of the ideas, instruments, practices, contexts, knowledge and systems used to generate and process them" (Ribes & Jackson, 2013). In other words, "data are never raw, but always already cooked" (Bowker, 2005).

In fact, databases and data analyses are "similarly not neutral, technical means of assembling and making sense of data but rather are socio-technical in nature, shaped by philosophical ideas and technical means" (Kitchin, 2016). As Kitchin, Lauriault and McArdle point out, "urban science needs to openly acknowledge its contingencies, shortcomings and inherent politics and to recognise that it does not reflect the world as it actually is, but rather actively frames and produces the world" (Kitchin et al., 2015). In other words, also the data anonymisation represent a fundamental limitation to its significance, because it is a form of manipulation that limits its relevance.

Another aspect that needs to be taken into account, is the validity of the results: those are location specific and do not allow to formulate general assumptions that are always valid. This is not to say that the fundamental approach of analytics, modelling and simulation is radically altered, rather that the data driven approach, indeed, needs a critical reflection to avoid generalisation and to generate relevant knowledge. However, the relations this dissertation explores can help influencing the design of urban public space.

This dissertation has shown that thermal comfort and attractiveness of public space coexist. Like a *pareidolia* — the hidden face, the incorrect perception of a stimulus as a pattern known to the observer — the findings show that we can never detach activity from attractivity.

Revisiting the research questions initially proposed in this dissertation, the following outcomes can be summarised:

1.) Can a systematic relation between microclimatic conditions and people's spatiotemporal walking patterns in public space be confirmed, when employing data collected from mobile phone applications?

The interdependencies presented in chapter IV.4 and the resulting outcomes clearly identify a systemic relation in space and time. The developed methodology that is targeted to putting into evidence the interdependencies between two dynamic datasets has been tested and confirmed. Therefore, this dissertation complements the existing body of research employing digital data and tools to highlight the nexus between pedestrian movement and microclimatic conditions in urban systems.

2.) Which are the relevant metrics to evaluate these relations and how can they be used to express results?

The employed UTCI metric to evaluate outdoor thermal comfort has already been tested in the last two decades in the vast research body on this topic. The novelty that the methodology introduced in this dissertation presents is the definition of a spatiotemporal outdoor comfort availability factor (STOCA) composed by spatial UTCI values. Constructing the factor allows to identify microclimatic characteristics of a specific location over a given timeframe including seasonal thresholds, to highlight variations between different spatial domains and to compare them to the spatiotemporal analysis of the walking trajectories. In this sense, the UTCI metric is used with an integrated and adapted scale to local conditions. This metric generates useful results and allows to confirm UTCI as an effective metric to reflect human thermal experience. The tools this dissertation employs to model microclimate basing on mesoclimate data (air temperature and humidity, solar radiation, and wind speed) have been tested and provide a consistent dataset in a reasonable computing time and with limited computational power. Moreover, the developed workflow generates microclimatic information at the human scale in a high granularity which allows to predict the effects of design strategies for increasing outdoor thermal comfort. Since both datasets were not averaged or aggregated, the results base on the dynamic nature of the original data.

3.) Under which spatial and thermal conditions does human thermal comfort influence people flows in public space?

The results presented in chapter IV clearly confirm a dependency between outdoor thermal comfort ranges and people's walking intensity over the year. The multivariate regression analysis emphasises that the extent varies according to seasonality and daily routines. When the difference in terms of thermal comfort is significant and people have the option to choose, comfort navigation is evident, whereas daily routines are not affected by thermal diversity rather than by weather conditions.

4.) Can the results generated by applying the proposed data-based methodology be employed to formulate indications for facilitating walking in cities?

The variety of microclimatic conditions depends on the differences of the streetscapes of the focus area: even if the streets have the same orientation and are located in proximity, the variations are visible and depend from aspect ratio, street section, presence of vegetation. The results that this dissertation presents can be used to inform indications targeted to redesign public urban space for walking. Walking remains a complex topic because it includes behavioural, mental, physical and social components that requires further research based on dynamic environmental data acquisition at the human scale, that integrates environmental information with human physiological e psychological response. In the context of climate change, the use of public urban space goes beyond the topic of thermal comfort becoming a matter of public health.

5.) Can these findings be instrumental for design, urban planning and governance of public spaces?

The core component of this dissertation is formulating strategies for the application to practice, that will be outlined more extensively in the conclusive section. Towards this objective, it provides a solid methodology, supported by tools and validated by results that brings evidence to invisible, dynamic phenomena. As evidence-based facts, these results can be seen as a convincing tactic for public and private bodies, administrations, designers and policy makers. First strategies have been recently proposed in Paris with the concept of the 15-minute-city, in Barcelona with the *superblock* and in Berlin with the newly introduced pedestrian law (Fußgängergesetz), to implement measures that facilitate walking in dense urban environments (Jacobs, 2021).

Concluding, the hypothesis formulated in this dissertation has been confirmed.

Particularly in dense urban environments, microclimatic conditions determine people's walking trajectories. Large urban georeferenced datasets collected by mobile phone applications provide evidence to pedestrian comfort navigation.

2. Application to Practice

Across the world, many cities will most likely experience a decline in the quality of their thermal environment due to increasingly extreme weather conditions as an effect of climate change. According to Bastin et al. (2019) "the climate conditions of over 77% of world's major cities will change to such a great extent that they will resemble more closely the conditions of another major city." In their study, they demonstrate the spatial climatic shift that will occur in 2050 basing on climate change forecasts, highlighting the extent "of this climate change threat and associated risks for human health." Moreover, they reveal that "22% of the world's cities are likely to exist in a climatic regime that does not currently exist on the planet today" (ibidem).

Only in the United States, 162 million people — nearly one in two — will be exposed to such transformations. Climate change will create an additional pressure on urban systems, accelerating their uncontrolled growth, testing their capacity to provide basic services and amplifying existing inequities (Lustgarten, 2020).

Since, in parallel, the urban population is continuously growing, the increasing heat the cities already experience is a central topic for public health. In this sense, it is mandatory to incorporate health as an outcome in planning studies. As outlined by Boarnet and Takahashi (2005), "planners often focus on problems that touch on human health, but planning research typically stops short of measuring health as an outcome. Instead, planners have assumed that the health implications of their work will be addressed by other fields." Linking urban design to public health is becoming crucial for the spatial reconfiguration of the practices of daily life.

Together with public health, urban design is fundamentally shaping social inclusion. Walking inherently reduces social inequalities and segregation and promotes cohesion in the context of a fragile sense of the public common. When people walk, they are in constant energy exchange with the environment. By comparison, motorised mobility represents an insulation that reduces the exchange to environmental conditions. Insulation derives from the latin word *insula* (island) and means to detach, isolate. In this sense, insulating creates isolation. The urban design of the last century has promoted the individual experience of driving: vehicles are capsules that block the exchange to the environment and, by that, generate a distorted experience of the public realm and, supported by functional separation, create social segregation. In the 1960s, while Jane Jacobs was professing a more inclusive use of public space, Buckminster Fuller developed the *Dome over Manhattan* project (1960): a gigantic indoor environment that can be conditioned to guarantee continuous, comfortable conditions. As Lisa Heschong years later noted: "This climatic envelope would enable the entire city to be air conditioned, indoors and outdoors. Indeed, (outdoors) would be a thing of the past" (Heschong, 1979).

In contrast, today the city is the space where the challenges of climate change collide and request interventions that disrupt the idea of isolation and insulation; instead, it requires an enhancement of environmental conditions to facilitate social cohesion and dismantle inequalities. Away from imagining the city as a thermally homogeneous space, the thermal quality of public space attracts and enriches the urban experience for those that are exposed. Besides the notion of thermal comfort, dynamic environments can enhance public health making thermal places desirable (ibidem).

This dissertation employed presumably one of the largest available datasets with 240,000 walking trajectories traced by thousands of participating subjects, providing evidence that can inform policy-makers and support the formulation of strategies on how to reshape public space. Embedded in an era of increasing collection of personal data, it used a bottom up-approach, where people are indicators in a resolution that would have been impossible with conventional approaches such as surveys and observations. As such, it generates new quantified climatic knowledge and an evidence based understanding of the built environment in a multilayered, transscalar way that avails spatial interventions for promoting a tangible improvement of the city. Having demonstrated a positive correlation between desirable microclimates and people flows, the implementation of actual measures requires a choral effort to promote an impact on space. In this sense, Boston represents a consonant case due to the open access that the municipality gives to the vast data, generating multiple opportunities for the community. Environmental data acquisition and availability becomes fundamental for guiding the design of public space and decision-making processes.

Quantifying the benefits of walking is still difficult despite the technologies and data sources that are at stake. The more convincing metric is time and therefore proximity. In recent years, the concept of the "15-min city" has gained increasing interest and stimulated several applications. Particularly Paris' mayor Anne Hidalgo has promoted and implemented this concept (O'Sullivan, 2020). Another equal access planning topic in the agenda of researchers and policy-makers is the first/last mile access to the public transit network (Boarnet et al., 2017).

Both concepts draft a spatiotemporal domain where people access all their principal needs without using individual motorised mobility. The impacts are manifold: on mobility, functional mix, safety, social cohesion and diversity. These concepts that imply walking are generating a continuous exposure to environmental conditions, acquiring an additional relevance. The microclimatic genius loci shapes the desirability of a specific place and becomes fundamental for avoiding suffering and facilitating walking. Therefore, comfort availability needs to be combined with the proximity of heat stress release spots: the proximity of parks, vegetation or cold spots becomes more important than its size. In fact, comfort navigation is particularly evident for heat stress conditions which will occur more frequently and ubiquitously in the near future. Providing stress release with local interventions in public space will redefine its attractiveness and rephrase its use. Concluding this dissertation tackles three main topics when addressing indications for transformation:

Density

The advantages of a dense, compact city are widely recognised: dense urban agglomerations facilitate social inclusion, guarantee basic services and generate the aspired functional mix. Character, materials, uses, proportions, flair and density of the quarters, as conceived in European cities in the second half of the 19th century, correspond to what has recently been rediscovered as quality of life and sustainability. This spatial domain can be considered the baseline for the development of future cities, particularly because through their morphological characteristics they inherently accommodate pedestrian mobility and generate a variety of microclimates.

Mobility

The car-friendly post-war urban environments testify the fact that urban planning shapes our lives. Prioritising pedestrian and non motorised networks generates more inclusive societies and facilitates access to daily routines, with tremendous impacts on human health and environmental quality. Transforming mobility patterns generates more space for gathering outdoors that will surely lead to greater resilience and bring us closer to the promises of the "15-minute city". In fact, the car-oriented city did not generate a density where public space and private mobility harmoniously coexist. In the digital era, the unprecedented opportunity of having information about millions of people allows to shape mobility flows with focused strategies. The symbiotic relationship between density and mobility underpins the importance of proximity and access: replacing individual motorised mobility will generate a reconfiguration of public space with unprecedented impacts on the use of surfaces.

Public space

With regard to our social responsibilities as architects and urban designers and our responsibility for human beings that are in our space, the negotiation of public space is paramount. In our cities, where open space is increasingly reduced and monetised for the purposes of speculation, the agency of defending public space as a common good with equal access becomes crucial. Reorganising the city by reducing private vehicles' traffic represents a fundamental act to generate more space for vegetation. Particularly in dense urban environments, the repercussions on mobility, safety, health and to the wider challenges of social inclusion and cohesion would be enormous. In opposition to common assumptions, our cities are facing worldwide tree loss at a massive and unprecedented rate. The opportunity of replacing road networks with linear parks creates the possibility for walking routes with a significant thermal diversity to the surrounding neighborhood. Parking space can be replaced by pocket parks, that function as cold spots for heat stress release and eventually integrate food production also in dense urban space. As outlined, proximity of green spaces is fundamental for thermal stress release, therefore the necessity is to integrate multiple pocket parks in the dense urban environment rather than creating mono-functional periphery parks.

Climate and humans coexist with their reciprocal influences. With this dynamic relation, microclimatic manipulation is crucial for shaping inclusive and healthy urban space, connecting the bodily experience to design substance.

References

Anderson, C. (2008) The end of theory: the data deluge makes the scientific method obsolete. *Wired*, 23 June 2008. See http://www.wired.com/science/discoveries/magazine/16-07/pb_theory (Accessed October 2019).

Bastin, J. F., Clark, E., Elliott, T., Hart, S., van den Hoogen, J., Hordijk, I., ... & Mo, L. (2019) Understanding climate change from a global analysis of city analogues. *PloS one*, 14(7), e0217592.

Boarnet, M. G., & Takahashi, L. M. (2005). Bridging the gap between urban health and urban planning. *Handbook of Urban Health* (pp. 379-402). Springer, Boston, MA.

Boarnet, M. G., Giuliano, G., Hou, Y., & Shin, E. J. (2017) First/last mile transit access as an equity planning issue. *Transportation Research Part A: Policy and Practice*, 103, 296–310.

Bowker, G. (2005) Memory practices in the sciences. Cambridge, MA: MIT Press.

Heschong, L. (1979) Thermal Delight in Architecture, Cambridge, Massachusetts, p. 20.

Horv, Eva (2016) Air Conditioning: Taming the Climate as a Dream of Civilization. *Climates: Architecture and the Planetary Imaginary*

Jacobs, S. (2021) Berlin beschließt bundesweit erstes Fußgängergesetz. *Tagesspiegel*, Berlin 2021 (https://www. tagesspiegel.de/berlin/laengere-gruenphase-mehr-sitzbaenke-berlin-beschliesst-bundesweit-erstes-fussgaengerge-setz/26859710.html, Accessed February 2021)

Kelling, S., Hochachka, W., Fink, D., Riedewald, M., Caruana, R., Ballard, G., Hooker, G. (2009) Data-intensive science: a new paradigm for biodiversity studies. *BioScience* 59, 613–620.

Kitchin, R. (2016) The ethics of smart cities and urban science. Phil. Trans. R. Soc. A 374: 20160115.

Kitchin, R., Lauriault, T.P., McArdle, G., (2015) Knowing and governing cities through urban indicators, city benchmarking & real-time dashboards. *Reg. Stud. Reg. Sci.* 2, 1–28.

Latour, B. (1993) We have never been modern, trans. Catherine Porter (Cambridge, MA, Harvard University Press.

Lustgarten, A. (2020) How Climate Migration will reshape America. Millions will be displaced. Where will they go? *The New Your Times*, NYC.

Nikolopoulou, M., & Steemers, K. (2003) Thermal comfort and psychological adaptation as a guide for designing urban spaces. *Energy and Buildings*, 35(1), 95-101.

O'Sullivan, F. (2020) It's Time for a '15-Minute City' in Paris Mayor: https://www.citylab.com/environment/2020/02/paris-election-anne-hidalgo-city-planning-walks-stores-parks/606325/ (Accessed: February 2020)

Pentland, A. (2014) Social physics: how good ideas spread-the lessons from a new science. New York, NY: Penguin.

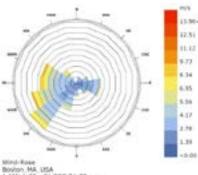
Ribes, D. & Jackson, S.J., (2013) Data bite man: the work of sustaining long-term study. '*Raw data' is an oxymoron* (ed. L Gitelman), pp. 147–166. Cambridge, MA: MIT Press.

APPENDIX

1. Python script for data filtering: total counts of the first 100 most frequent street segments. import os, csv, operator

```
files = os.listdir(base_dir)
file = files[0]
print (file)
# Store all the data in a list of dicts with 1 dict per month
annual\_rank = \{\}
annual_data = []
street_names = {}
for file in files:
   if file.endswith('.csv'):
       dict = \{\}
       with open(file, 'r') as f:
          reader = csv.reader(f, delimiter=';')
          for row in reader:
              if 'osm_id' not in row:
                 dict[row[1]] = row[2]
                 annual_rank[row[1]] = 0
street_names[row[1]] = row[3]
       annual\_data.append(dict)
       #print (dict)
#print (annual_data)
\#\,\mathrm{Add} all the prequencies of the months together
for dict in annual_data:
for k in dict.keys():
       annual_rank[k] += int(dict[k])
sort\_annual\_rank = reversed(sorted(annual\_rank.items(), key=operator.itemgetter(1)))
topranks = []
for k in sort_annual_rank:
topranks.append(k)
topranks = topranks[:200]
out_file = 'annual_rank.txt'
f_out = os.path.join(base_dir, out_file)
f2 = open(f_out,'w')
f2.close()
f3 = open(f_out,a')
for k in topranks:
id = k[0]
```

2. Windrose (Boston KMA-BOS 35 weather data)



frequency = k[1]street_name = street_names[k[0]]

f3.write(line) f3.close()

print ('%s %s: %d' %(id, street_name, frequency)) line = '%s;%s;%d; \n' %(id, street_name, frequency)

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DAY	80	27	43	46	47	59	105	106	107	123	139	140	146	151	157	188	195	196	225	241	242	249	251	269	273	283	289	332	346
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ű	0	24.13 Fc	0.76 Fc	9.91 Fc	0 Sr	0	0	0	1.52 Rain	0	6.86 Rain	0	0	23.11 Rain	2.29 Rair	0.51 Rair	0.76 Rain	2	0	0	0	0	5.08	0	62.48 Fog , Rain	0	2	5.33 R	0
Precip. (mm)																													
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	23	36	6	33	32	14	19	16	21	14	16	22	26	22	11	17	13	12	13	12	14	15	12	16	21	16	19	16	12
Wind (km/h)	40	52	26	53	50	24	40	37	35	27	26	42	37	50	32	37	34	32	27	26	27	52	34	32	52	47	35	29	26
Wind	16	0	1	0	4	16	16	16	11	16	e	11	16	2	4	16	S	11	16	16	16	16	10	16	1	16	16	9	16
	16	1	10	5	15	16	16	16	16	16	13	16	16	12	15	16	16	16	16	16	16	16	14	16	6	16	16	14	16
(km)	16	9	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16
Visibility (km)	1020	666	1005	992	600	.035	.018	1025	011	.016	.006	.006	1019	1016	1011	1013	1003	1002	1012	1019	1015	1019	012	029	.003	600	010	.020	013
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	41	77	61	50	31	27	16	24	50	45	83	36	44	69	46	61	51	73	45	66	37	48	41	51	78	32	8	67	42
	49	85	17	71	44	43	28	46	70	61	92	65	59	85	73	77	72	87	62	59	28	69	63	64	89	53	57	80	60
Humidity (%)	56	92	92	92	56	58	39	67	89	76	100	93	73	100	100	93	93	100	78	78	78	90	84	11	100	74	74	83	77
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3. Typical days selection according to climate data analysis

4. Quasi Poisson regression for Commonwealth Avenue

	Estimate St. Dev.	Error	t value	Pr(> t)	
(Intercept)	0,0875	0,2673	3021	0,00293	**
North	-0,181	0,3985	-0,454	-0,65019	
South	0,1792	0,3658	0,49	0,65019	
Center	0,5666	0,239	2,371	0,01892	*
Time_noon	-2,0637	0,3515	-5,871	2,38E-08	***
Time_morning	-1,204	0,2415	-4,985	1,58E-06	***
Significance codes	0 =:***	0,001 = '**'	0,01 = '*'	0,05 ='.'	0,1 =' '
Deviance Residuals	Min	1Q	Median	3Q	Max
	-2,8086	-1,0860	-0,7539	0,5103	7,3454

5. Negative Binomial regression for Commonwealth Avenue

Coefficients							
	Estimate St. Dev.	Error	z value		Pr(> z)		
(Intercept)	0,789478	0,246701		3,2		0,00137	**
North	-0,006507	0,351449		-0,019		0,98523	
South	0,065365	0,347312		0,188		0,85072	
Center	0,0481082	0,226881		2,12		0,03397	*
Time_noon	-2,004657	0,278099		-7,208		5,66E-13	***
Time_morning	-1153707	0,219497		-5,256		1,47E-07	***
Significance codes	0 = "****	0,001 = "**"	0,01 = ***		0,05 ='.'		0,1 =' '
Deviance Residuals	Min	1Q	Median		3Q		Max
	-1,9975	-0,9443		-0,6895		0,3240	3.2510

6. Quasi Poisson regression for Newbury Street

Estimate St. Dev. Error t value Pr(>t) (Intercept) 2,057 0,2722 7,563 2,91E-12 " North -1,1457 0,5333 -2,148 3,319E-02 " South 1,1383 0,5497 2,071 3,998E-02 " Time_noon -2,1746 0,0302 -7,186 2,39E-03 " Season_autumn -0,6064 0,2085 -2,908 4,15E-03 " Season_summer -0,3358 0,1834 -1,831 6,889E-02 . Season_winter -1,0859 0,2579 -4,211 4,23E-05 . Significance 0=***** 0,01 = *** 0,01 = *** 0,01 = ** 0,01 = ** . Peviance Min 1Q Median 3Q Max . -2,9126 -1,1554 -0,308 0,5058 7,5669								
North -1,1457 0,5333 -2,148 3,319E-02 * South 1,1383 0,5497 2,071 3,998E-02 * Time_noon -2,1746 0,3026 -7,186 2,39E-09 ** Time_morning -1,274 0,1924 -6,623 5,08E-10 ** Season_autumn -0,6064 0,2085 -2,908 4,15E-03 ** Season_summer -0,3358 0,1834 -1,831 6,889E-02 . Season_winter -1,0859 0,2579 -4,211 4,23E-05 *** Significance codes 0 = **** 0,001 = *** 0,01 = *** 0,05 =*.' 0,1 = *	r	mate St. Dev.	Error	t value		Pr(> t)		
South 1,1383 0,5497 2,071 3,998E-02 Time_noon -2,1746 0,3026 -7,186 2,39E-09 Time_morning -1,274 0,1924 -6,623 5,08E-10 Season_autumn -0,6064 0,2085 -2,908 4,15E-03 Season_summer -0,3358 0,1834 -1,831 6,889E-02 Season_winter -1,0859 0,2579 -4,211 4,23E-05 Significance codes 0 =**** 0,001 = *** 0,01 = *** 0,05 =*.' 0,1 = '		2,0587	7 0,27	2	7,563	2,91E-12	***	
Time_noon -2,1746 0,3026 -7,186 2,39E-09 *** Time_morning -1,274 0,1924 -6,623 5,08E-10 *** Season_autumn -0,6064 0,2085 -2,908 4,15E-03 ** Season_summer -0,3358 0,1834 -1,831 6,889E-02 . Season_winter -1,0859 0,2579 -4,211 4,23E-05 *** Significance codes 0 = **** 0,001 = *** 0,01 = *** 0,05 =*.' 0,1 = ' Deviance Residuals Min 1Q Median 3Q Max		-1,1457	7 0,533	3	-2,148	3,319E-02	*	
Time_morning -1,274 0,1924 -6,623 5,08E-10 *** Season_autumn -0,6064 0,2085 -2,908 4,15E-03 ** Season_summer -0,3358 0,1834 -1,831 6,889E-02 . Season_winter -1,0859 0,2579 -4,211 4,23E-05 *** Significance codes 0 = **** 0,001 = **** 0,01 = *** 0,05 =*.* 0,1 = ** Deviance Residuals Min 1Q Median 3Q Max		1,1383	3 0,54	7	2,071	3,998E-02	*	
Season_autumn -0,6064 0,2085 -2,908 4,15E-03 ** Season_summer -0,3358 0,1834 -1,831 6,889E-02 . Season_winter -1,0859 0,2579 -4,211 4,23E-05 ** Significance codes 0 = **** 0,001 = *** 0,01 = *** 0,05 =*.' 0,1 = ' Deviance Residuals Min 1Q Median 3Q Max		-2,1746	6 0,30	6	-7,186	2,39E-09	***	
Season_summer -0,3358 0,1834 -1,831 6,889E-02 . Season_winter -1,0859 0,2579 -4,211 4,23E-05 *** Significance codes 0 = '***' 0,001 = '**' 0,01 = '*' 0,05 = '.' 0,1 = ' Deviance Residuals Min 1Q Median 3Q Max		-1,274	4 0,19	4	-6,623	5,08E-10	***	
Season_winter -1,0859 0,2579 -4,211 4,23E-05 *** Significance codes 0 = **** 0,001 = *** 0,01 = *** 0,05 = *.* 0,1 = * Deviance Residuals Min 1Q Median 3Q Max		-0,6064	4 0,20	5	-2,908	4,15E-03	**	
Significance codes 0 = """ 0,001 = "" 0,01 = "" 0,05 = "." 0,1 = " Deviance Min 1Q Median 3Q Max		-0,3358	8 0,18	4	-1,831	6,889E-02		
codes openance Min 1Q Median 3Q Max Residuals No No No No No		-1,0859	9 0,25	9	-4,211	4,23E-05	***	
Residuals	1 = '*	***1	0,001 = "**"	0,01 = '*'		0,05 ='.'	0,1 =' '	
-2,9126 -1,1554 -0,3808 0,6508 7,9569			1Q	Median		3Q	Max	
		-2,9126	6 -1,15	4	-0,3808	0,6508		7,9569

7. Negative Binomial regression for Newbury Street

Coefficients								
	Estimate St. Dev.	Error		z value		Pr(> z)		
(Intercept)	2,0044	L .	0,2579		7,772	7,72E-1	5 ***	
North	-1,2079)	0,4323		-2,794	5,21E-0	3 **	
South	1,137	,	0,4606		2,47	1,352E-0	2 *	
Time_noon	-2,1647	,	0,2405		-9,001	<2E-1	6 ***	
Time_morning	-1,203	,	0,1702		-7,073	1,52E-1	2 ***	
Season_autumn	-0,4552	2	0,2023		-2250	2,443E-0	2 *	
Season_summer	-0,2452	2	0,1866		-1,314	1,8878E-0	1	
Season_winter	-0,9882	2	0,2395		-4,126	3,7E-0	5 ***	
Significance codes	0 ='***'	0,001 = '**'		0,01 = '*'		0,05 ='.'	0,1 =' '	
Deviance Residuals	Min	1Q		Median		3Q	Max	
	-2,362	,	-0,9683		-0,3051	0,422	6	3,8323

Coefficients							
ocentricients	Estimate St. Dev.	Error	t value	Pr(> t)			8. Quasi Poisson regression for
(Intercept)	2,823	0,1988	14,2	< 2E-16	***		Boylston Street
North	-0,3927	0,3659	-1,073	2,8483E-01			
South	0,1912	0,3566	0,536	5,9258E-01			
Time_noon	-2,0785	0,205	-10,141	< 2E-16	***		
Time_morning	-1,4834	0,1585	-9,357	< 2E-16	***		
Season_autumn	-0,4277	0,157	-2,724	7,16E-03	**		
Season_summer	0,1778	0,1503	-1,183	2,3852E-01			
Season_winter	-1,2981	0,2209	-5,876	2,37E-08	***		
.							
Significance codes	0 = "***"	0,001 = '**'	0,01 = '*'	0,05 ='.'	0,1 =' '		
Deviance Residuals	Min	1Q	Median	3Q	Max		
	-3,0315	-1,1430	-0,3207	0,7174		8,5651	
							9. Negative Binomial regression
Coefficients							for Boylston Street
0	Estimate St. Dev.	Error	z value	Pr(> z)			jor Doyision Siree
(Intercept)	2,92099			58 < 2E	-16 ***		
North	-0,39376						
South	0,01603						
Time_noon	-2,12755				-16 ***		
Time_morning	-1,46429	9 0,1398	3 -10,47	72 < 2E-	-16 ***		
Season_autumn	-0,41368	8 0,1631	2 -2,53	36 1,12E	-02 *		
Season_summer	-0,07383						
Season_winter	-1,28852	2 0,2013	1 -6,40	01 1,55E	-08 ***		
Significance	o (***)	0.004 (#1	0.01 (*)	0.05 (1			
Significance codes	0 = ****'	0,001 = '**'	0,01 = '*'	0,05 ='.'	0,1 =' '		
Deviance Residuals	Min	1Q	Median	3Q	Max		
Residuais	-2,566	7 -1,019	8 -0,308	34 0,50	121	3,5356	
	2,000		0,000	0,00		0,0000	
Coefficients							10. Quasi Poisson regression for
	Estimate St. Dev.	Error	t value	Pr(> t)			all street segments
(Intercept)	Estimate St. Dev. 2,085408	Error 0,159045	t value 13,112	Pr(> t) < 2E-16	; ***		all street segments
(Intercept) North							all street segments
	2,085408	0,159045 0,220787	13,112	< 2E-16	!.		all street segments
North South C_factor 1	2,085408 -0,419261	0,159045 0,220787	13,112 -1,899	< 2E-16 5,816E-02 1,5467E-01 6,83E-05			all street segments
North South C_factor 1 C_factor 2	2,085408 -0,419261 0,309812	0,159045 0,220787 0,217347	13,112 -1,899 1,425	< 2E-16 5,816E-02 1,5467E-01 6,83E-05 3,76E-06	· ·		all street segments
North South C_factor 1 C_factor 2 Time_noon	2,085408 -0,419261 0,309812 -0,718472 -0,615911 -2,057313	0,159045 0,220787 0,217347 0,17889 0,131683 0,14362	13,112 -1,899 1,425 -4,016 -4,677 -14,325	< 2E-16 5,816E-02 1,5467E-01 6,83E-05 3,76E-06 < 2E-16	: . ; *** ; ***		all street segments
North South C_factor 1 C_factor 2 Time_noon Time_morning	2,085408 -0,419261 0,309812 -0,718472 -0,615911 -2,057313 -1,377269	0,159045 0,220787 0,217347 0,17889 0,131683 0,14362 0,106258	13,112 -1,899 1,425 -4,016 -4,677 -14,325 -12,962	< 2E-16 5,816E-02 1,5467E-01 6,83E-05 3,76E-06 < 2E-16 < 2E-16	; *** ; ***		all street segments
North South C_factor 1 C_factor 2 Time_noon Time_morning LAS_max	2,085408 -0,419261 0,309812 -0,718472 -0,615911 -2,057313 -1,377269 0,017736	0,159045 0,220787 0,217347 0,17889 0,131683 0,14362 0,106258 0,002653	13,112 -1,899 1,425 -4,016 -4,677 -14,325 -12,962 6,684	< 2E-16 5,816E-02 1,5467E-01 6,83E-05 3,76E-06 < 2E-16 < 2E-16 6,3E-11			all street segments
North South C_factor 1 C_factor 2 Time_noon Time_morning LAS_max Season_autumn	2,085408 -0,419261 0,309812 -0,718472 -0,615911 -2,057313 -1,377269 0,017736 -0,468805	0,159045 0,220787 0,217347 0,17889 0,131683 0,14362 0,106258 0,002653 0,108765	13,112 -1,899 1,425 -4,016 -4,677 -14,325 -12,962 6,684 -4,31	< 2E-16 5,816E-02 1,5467E-01 6,83E-05 3,76E-06 < 2E-16 6,3E-11 1,97E-05			all street segments
North South C_factor 1 C_factor 2 Time_noon Time_morning LAS_max Season_autumn Season_summer	2,085408 -0,419261 0,309812 -0,718472 -0,615911 -2,057313 -1,377269 0,017736 -0,468805 -0,286805	0,159045 0,220787 0,217347 0,17889 0,131683 0,14362 0,106258 0,002653 0,108765 0,102368	13,112 -1,899 1,425 -4,016 -4,677 -14,325 -12,962 6,684 -4,31 -2,802	< 2E-16 5,816E-02 1,5467E-01 6,83E-05 3,76E-06 < 2E-16 6,3E-11 1,97E-05 5,28E-03	· · · · · · · · · · · · · · · · · · ·		all street segments
North South C_factor 1 C_factor 2 Time_noon Time_morning LAS_max Season_autumn	2,085408 -0,419261 0,309812 -0,718472 -0,615911 -2,057313 -1,377269 0,017736 -0,468805	0,159045 0,220787 0,217347 0,17889 0,131683 0,14362 0,106258 0,002653 0,108765 0,102368	13,112 -1,899 1,425 -4,016 -4,677 -14,325 -12,962 6,684 -4,31	< 2E-16 5,816E-02 1,5467E-01 6,83E-05 3,76E-06 < 2E-16 6,3E-11 1,97E-05	· · · · · · · · · · · · · · · · · · ·		all street segments
North South C_factor 1 C_factor 2 Time_noon Time_morning LAS_max Season_autumn Season_summer	2,085408 -0,419261 0,309812 -0,718472 -0,615911 -2,057313 -1,377269 0,017736 -0,468805 -0,286805	0,159045 0,220787 0,217347 0,17889 0,131683 0,14362 0,106258 0,002653 0,108765 0,102368 0,148116	13,112 -1,899 1,425 -4,016 -4,677 -14,325 -12,962 6,684 -4,31 -2,802 -8,022	< 2E-16 5,816E-02 1,5467E-01 6,83E-05 3,76E-06 < 2E-16 6,3E-11 1,97E-05 5,28E-03 7,66E-15	· · · · · · · · · · · · · · · · · · ·		all street segments
North South C_factor 1 C_factor 2 Time_noon Time_morning LAS_max Season_autumn Season_summer Season_winter	2,085408 -0,419261 0,309812 -0,718472 -0,615911 -2,057313 -1,377269 0,017736 -0,468805 -0,286805 -1,188136	0,159045 0,220787 0,217347 0,17889 0,131683 0,14362 0,106258 0,002653 0,108765 0,102368	13,112 -1,899 1,425 -4,016 -4,677 -14,325 -12,962 6,684 -4,31 -2,802	< 2E-16 5,816E-02 1,5467E-01 6,83E-05 3,76E-06 < 2E-16 6,3E-11 1,97E-05 5,28E-03	· · · · · · · · · · · · · · · · · · ·		all street segments
North South C_factor 1 C_factor 2 Time_noon Time_morning LAS_max Season_autumn Season_summer Season_winter Significance codes	2,085408 -0,419261 0,309812 -0,718472 -0,615911 -2,057313 -1,377269 0,017736 -0,46805 -0,286805 -0,286805 -1,188136	0,159045 0,220787 0,217347 0,17889 0,131683 0,14362 0,106258 0,002653 0,102368 0,102368 0,148116 0,001 = ****	13,112 -1,899 1,425 -4,016 -4,677 -14,325 -12,962 6,684 -4,31 -2,802 -8,022 0,01 = ***	< 2E-16 5,816E-02 1,5467E-01 6,83E-05 3,76E-06 < 2E-16 6,3E-11 1,97E-05 5,28E-03 7,66E-15 0,05 ='.'			all street segments
North South C_factor 1 C_factor 2 Time_noon Time_morning LAS_max Season_autumn Season_autumn Season_summer Season_winter	2,085408 -0,419261 0,309812 -0,718472 -0,615911 -2,057313 -1,377269 0,017736 -0,468805 -0,286805 -1,188136	0,159045 0,220787 0,217347 0,17889 0,131683 0,14362 0,106258 0,002653 0,108765 0,102368 0,148116	13,112 -1,899 1,425 -4,016 -4,677 -14,325 -12,962 6,684 -4,31 -2,802 -8,022	< 2E-16 5,816E-02 1,5467E-01 6,83E-05 3,76E-06 < 2E-16 6,3E-11 1,97E-05 5,28E-03 7,66E-15	· · · · · · · · · · · · · · · · · · ·		all street segments
North South C_factor 1 C_factor 2 Time_noon Time_morning LAS_max Season_autumn Season_summer Season_winter Significance codes	2,085408 -0,419261 0,309812 -0,718472 -0,615911 -2,057313 -1,377269 0,017736 -0,46805 -0,286805 -0,286805 -1,188136	0,159045 0,220787 0,217347 0,17889 0,131683 0,14362 0,106258 0,002653 0,102368 0,102368 0,148116 0,001 = ****	13,112 -1,899 1,425 -4,016 -4,677 -14,325 -12,962 6,684 -4,31 -2,802 -8,022 0,01 = ***	< 2E-16 5,816E-02 1,5467E-01 6,83E-05 3,76E-06 < 2E-16 6,3E-11 1,97E-05 5,28E-03 7,66E-15 0,05 ='.'		8,4235	all street segments
North South C_factor 1 C_factor 2 Time_noon Time_morning LAS_max Season_autumn Season_summer Season_winter Significance codes Deviance Residuals	2,085408 -0,419261 0,309812 -0,718472 -0,615911 -2,057313 -1,377269 0,017736 -0,468805 -0,286805 -1,188136 0 =*****	0,159045 0,220787 0,217347 0,17889 0,131683 0,14362 0,106258 0,002653 0,108765 0,102368 0,148116 0,001 = ****	13,112 -1,899 1,425 -4,016 -4,677 -14,325 -12,962 6,684 -4,31 -2,802 -8,022 0,01 = *** Median	< 2E-16 5,816E-02 1,5467E-01 6,83E-05 3,76E-06 < 2E-16 6,3E-11 1,97E-05 5,28E-03 7,66E-15 0,05 ='.' 3Q		8,4235	
North South C_factor 1 C_factor 2 Time_noon Time_morning LAS_max Season_autumn Season_summer Season_winter Significance codes	2,085408 -0,419261 0,309812 -0,718472 -0,615911 -2,057313 -1,377269 0,017736 -0,468805 -0,286805 -1,188136 0 =***** Min -3,1743	0,159045 0,220787 0,217347 0,17889 0,131683 0,106258 0,002653 0,108765 0,102368 0,148116 0,001 = **** 1Q -1,1416	13,112 -1,899 1,425 -4,016 -4,677 -14,325 -12,962 6,684 -4,31 -2,802 -8,022 0,01 = *** Median -0,4285	< 2E-16 5,816E-02 1,5467E-01 6,83E-05 3,76E-06 < 2E-16 6,3E-11 1,97E-05 5,28E-03 7,66E-15 0,05 ='.' 3Q 0,5368		8,4235	11. Negative Binomial regres-
North South C_factor 1 C_factor 2 Time_noon Time_morning LAS_max Season_autumn Season_summer Season_winter Significance codes Deviance Residuals	2,085408 -0,419261 0,309812 -0,718472 -0,615911 -2,057313 -1,377269 0,017736 -0,468805 -0,286805 -1,188136 0 =***** Min -3,1743 Estimate St. Dev.	0,159045 0,220787 0,217347 0,17889 0,131683 0,106258 0,002653 0,108765 0,102368 0,148116 0,001 = **** 1Q -1,1416 Error	13,112 -1,899 1,425 -4,016 -4,677 -14,325 -12,962 6,684 -4,31 -2,802 0,01 = *** Median -0,4285 z value	< 2E-16 5,816E-02 1,5467E-01 6,83E-05 3,76E-06 < 2E-16 6,3E-11 1,97E-05 5,28E-03 7,66E-15 0,05 ='.' 3Q 0,5369 Pr(> z)		8,4235	
North South C_factor 1 C_factor 2 Time_noon Time_morning LAS_max Season_autumn Season_summer Season_winter Significance codes Deviance Residuals Coefficients (Intercept)	2,085408 -0,419261 0,309812 -0,718472 -0,615911 -2,057313 -1,377269 0,017736 -0,468805 -0,286805 -1,188136 0 =***** Min -3,1743 Estimate St. Dev. 2,10114	0,159045 0,220787 0,217347 0,17889 0,131683 0,106258 0,002653 0,102368 0,148116 0,001 = **** 1Q -1,1416 Error 0,16032	13,112 -1,899 1,425 -4,016 -4,677 -14,325 -12,962 6,684 -4,31 -2,802 -8,022 0,01 = *** Median -0,4285 z value 13,106	< 2E-16 5,816E-02 1,5467E-01 6,83E-05 3,76E-06 < 2E-16 6,3E-11 1,97E-05 5,28E-03 7,66E-15 0,05 ='.' 3Q 0,5369 Pr(> z) < 2E-16		8,4235	11. Negative Binomial regres-
North South C_factor 1 C_factor 2 Time_noon Time_morning LAS_max Season_autumn Season_summer Season_winter Significance codes Deviance Residuals Coefficients (Intercept) North	2,085408 -0,419261 0,309812 -0,718472 -0,615911 -2,057313 -1,377269 0,017736 -0,468805 -0,286805 -1,188136 0 =***** Min -3,1743 Estimate St. Dev. 2,10114 -0,43156	0,159045 0,220787 0,217347 0,17889 0,131683 0,106258 0,10258 0,102368 0,148116 0,001 = **** 1Q -1,1416 Error 0,16032 0,19814	13,112 -1,899 1,425 -4,016 -4,677 -14,325 -12,962 6,684 -4,31 -2,802 0,01 = *** 0,01 = *** Median -0,4285 z value 13,106 -2,178	< 2E-16 5,816E-02 1,5467E-01 6,83E-05 3,76E-06 < 2E-16 6,3E-11 1,97E-05 5,28E-03 7,66E-15 0,05 ='.' 3Q 0,5369 Pr(> z) < 2E-16 2,9406E-02	0,1 =' ' Max	8,4235	11. Negative Binomial regres-
North South C_factor 1 C_factor 2 Time_noon Time_morning LAS_max Season_autumn Season_summer Season_winter Significance codes Deviance Residuals Coefficients (Intercept) North South	2,085408 -0,419261 0,309812 -0,718472 -0,615911 -2,057313 -1,377269 0,017736 -0,468805 -0,286805 -1,188136 0 =***** Min -3,1743 Estimate St. Dev. 2,10114 -0,43156 0,22303	0,159045 0,220787 0,217347 0,17889 0,131683 0,14362 0,106258 0,002653 0,102568 0,102368 0,102368 0,148116 0,001 = **** 1Q -1,1416 Error 0,16032 0,19814 0,20219	13,112 -1,899 1,425 -4,016 -4,677 -14,325 -12,962 6,684 -4,31 -2,802 -8,022 0,01 = *** Median z value 13,106 -2,178 1,103	< 2E-16 5,816E-02 1,5467E-01 6,83E-05 3,76E-06 < 2E-16 6,3E-11 1,97E-05 5,28E-03 7,66E-15 0,05 ='.' 3Q 0,53669 Pr(> z) < 2E-16 2,9406E-02 2,69995E-01	0,1 =' ' Max	8,4235	11. Negative Binomial regres-
North South C_factor 1 C_factor 2 Time_noon Time_morning LAS_max Season_autumn Season_autumn Season_winter Season_winter Season_winter Coefficients Coefficients (Intercept) North South C_factor 1	2,085408 -0,419261 0,309812 -0,718472 -0,615911 -2,057313 -1,377269 0,017736 -0,468805 -0,286805 -1,188136 0 =***** Min -3,1743 Estimate St. Dev. 2,10114 -0,43156 0,22303 -0,70364	0,159045 0,220787 0,217347 0,17889 0,131683 0,106258 0,002653 0,108765 0,102368 0,148116 0,001 = **** 1Q -1,1416 Error 0,16032 0,19814 0,20219 0,14955	13,112 -1,899 1,425 -4,016 -4,677 -14,325 -12,962 6,684 -4,31 -2,802 0,01 = *** 0,01 = *** Median -0,4285 z value 13,106 -2,178 1,103 -4,702	< 2E-16 5,816E-02 1,5467E-01 6,83E-05 3,76E-06 < 2E-16 6,3E-11 1,97E-05 5,28E-03 7,66E-15 0,05 ='.' 3Q 0,53669 Pr(> z) < 2E-16 2,9406E-02 2,69995E-01 2,58E-06	0,1 =' ' Max	8,4235	11. Negative Binomial regres-
North South C_factor 1 C_factor 2 Time_noon Time_morning LAS_max Season_autumn Season_summer Season_winter Significance codes Deviance Residuals Coefficients (Intercept) North South	2,085408 -0,419261 0,309812 -0,718472 -0,615911 -2,057313 -1,377269 0,017736 -0,468805 -0,286805 -1,188136 0 =***** Min -3,1743 Estimate St. Dev. 2,10114 -0,43156 0,22303 -0,70364 -0,61418	0,159045 0,220787 0,217347 0,17889 0,131683 0,14362 0,106258 0,002653 0,102568 0,102368 0,102368 0,148116 0,001 = **** 1Q -1,1416 Error 0,16032 0,19814 0,20219 0,14985 0,12408	13,112 -1,899 1,425 -4,016 -4,677 -14,325 -12,962 6,684 -4,31 -2,802 -8,022 0,01 = *** Median z value 13,106 -2,178 1,103 -4,702 -4,95	< 2E-16 5,816E-02 1,5467E-01 6,83E-05 3,76E-06 < 2E-16 6,3E-11 1,97E-05 5,28E-03 7,66E-15 0,05 ='.' 3Q 0,5369 Pr(> z) < 2E-16 2,9406E-02 2,69995E-01 2,58E-06 7,42E-07	0,1 =' ' Max	8,4235	11. Negative Binomial regres-
North South C_factor 1 C_factor 2 Time_noon Time_morning LAS_max Season_autumn Season_autumn Season_winter Season_winter Season_winter Coefficients Coefficients (Intercept) North South C_factor 1 C_factor 2	2,085408 -0,419261 0,309812 -0,718472 -0,615911 -2,057313 -1,377269 0,017736 -0,468805 -0,286805 -1,188136 0 =***** Min -3,1743 Estimate St. Dev. 2,10114 -0,43156 0,22303 -0,70364 -0,61418 -2,0625	0,159045 0,220787 0,217347 0,17889 0,131683 0,14362 0,106258 0,002653 0,102368 0,102368 0,148116 0,001 = **** 1Q -1,1416 Error 0,16032 0,19814 0,20219 0,14985 0,12408 0,2151	13,112 -1,899 1,425 -4,016 -4,677 -14,325 -12,962 6,684 -4,31 -2,802 -8,022 0,01 = *** Median -0,4285 z value 13,106 -2,178 1,103 -4,702 -4,95 -16,974	< 2E-16 5,816E-02 1,5467E-01 6,83E-05 3,76E-06 < 2E-16 6,3E-11 1,97E-05 5,28E-03 7,66E-15 0,05 ='.' 3Q 0,5369 Pr(> z) < 2E-16 2,9406E-02 2,69995E-01 2,58E-06 7,42E-07 < 2E-16	0,1 =' ' Max	8,4235	11. Negative Binomial regres-
North South C_factor 1 C_factor 2 Time_noon Time_morning LAS_max Season_autumn Season_autumn Season_winter Season_winter Season_winter Coefficients Coefficients (Intercept) North South C_factor 1 C_factor 2 Time_noon	2,085408 -0,419261 0,309812 -0,718472 -0,615911 -2,057313 -1,377269 0,017736 -0,468805 -0,286805 -1,188136 0 =***** Min -3,1743 Estimate St. Dev. 2,10114 -0,43156 0,22303 -0,70364 -0,61418	0,159045 0,220787 0,217347 0,17889 0,131683 0,14362 0,106258 0,002653 0,102368 0,102368 0,148116 0,001 = **** 1Q -1,1416 Error 0,16032 0,19814 0,20219 0,14965 0,12408 0,2151 0,09808	13,112 -1,899 1,425 -4,016 -4,677 -14,325 -12,962 6,684 -4,31 -2,802 -8,022 0,01 = *** Median z value 13,106 -2,178 1,103 -4,702 -4,95	< 2E-16 5,816E-02 1,5467E-01 6,83E-05 3,76E-06 < 2E-16 6,3E-11 1,97E-05 5,28E-03 7,66E-15 0,05 ='.' 3Q 0,5369 Pr(> z) < 2E-16 2,9406E-02 2,69995E-01 2,58E-06 7,42E-07	0,1 =' ' Max	8,4235	11. Negative Binomial regres-
North South C_factor 1 C_factor 2 Time_noon Time_morning LAS_max Season_autumn Season_summer Season_winter Season_winter Season_winter Coefficients (Intercept) North South C_factor 1 C_factor 2 Time_noon Time_morning	2,085408 -0,419261 0,309812 -0,718472 -0,615911 -2,057313 -1,377269 0,017736 -0,468805 -0,286805 -1,188136 0 =***** Min -3,1743 Estimate St. Dev. 2,10114 -0,43156 0,22303 -0,70364 -0,61418 -2,0625 -1,31238	0,159045 0,220787 0,217347 0,17889 0,131683 0,14362 0,106258 0,002653 0,102368 0,102368 0,102368 0,148116 0,001 = **** 1Q -1,1416 Error 0,16032 0,19814 0,20219 0,14965 0,12408 0,2151 0,09808 0,00275	13,112 -1,899 1,425 -4,016 -4,677 -14,325 -12,962 6,684 -4,31 -2,802 -8,022 0,01 = *** Median -0,4285 z value 13,106 -2,178 1,103 -4,702 -4,95 -16,974 -13,380	< 2E-16 5,816E-02 1,5467E-01 6,83E-05 3,76E-06 < 2E-16 6,3E-11 1,97E-05 5,28E-03 7,66E-15 0,05 ='.' 3Q 0,53669 Pr(> z) < 2E-16 2,9406E-02 2,69995E-01 2,58E-06 7,42E-07 < 2E-16 < 2,2E-16 < 2,2E-16	0,1 =' ' Max	8,4235	11. Negative Binomial regres-
North South C_factor 1 C_factor 2 Time_noon Time_morning LAS_max Season_autumn Season_winter Season_winter Season_winter Season_winter Coefficients (Intercept) North South C_factor 1 C_factor 2 Time_noon Time_morning LAS_max	2,085408 -0,419261 0,309812 -0,718472 -0,615911 -2,057313 -1,377269 0,017736 -0,468805 -0,286805 -1,188136 0 =***** Min -3,1743 Estimate St. Dev. 2,10114 -0,43156 0,22303 -0,70364 -0,61418 -2,0625 -1,31238 0,01686	0,159045 0,220787 0,217347 0,17889 0,131683 0,14362 0,106258 0,002653 0,102368 0,102368 0,102368 0,148116 0,001 = **** 1Q -1,1416 Error 0,16032 0,19814 0,20219 0,14965 0,12408 0,2151 0,09808 0,00275	13,112 -1,899 1,425 -4,016 -4,677 -14,325 -12,962 6,684 -4,31 -2,802 -8,022 0,01 = *** Median -0,4285 z value 13,106 -2,178 1,103 -4,702 -4,95 -16,974 -13,380 6,13	< 2E-16 5,816E-02 1,5467E-01 6,83E-05 3,76E-06 < 2E-16 6,3E-11 1,97E-05 5,28E-03 7,66E-15 0,05 ='.' 3Q 0,5369 Pr(> z) < 2E-16 2,9406E-02 2,69995E-01 2,58E-06 7,42E-07 < 2E-16 8,78E-10	0,1 =' ' Max	8,4235	11. Negative Binomial regres-
North South C_factor 1 C_factor 2 Time_noon Time_morning LAS_max Season_autumn Season_winter Season_winter Season_winter Season_winter Coefficients (Intercept) North South C_factor 1 C_factor 2 Time_noon Time_morning LAS_max Season_autumn	2,085408 -0,419261 0,309812 -0,718472 -0,615911 -2,057313 -1,377269 0,017736 -0,468805 -0,286805 -1,188136 0 =***** Min -3,1743 Estimate St. Dev. 2,10114 -0,43156 0,22303 -0,70364 -0,61418 -2,0625 -1,31238 0,01686 -0,39695	0,15945 0,220787 0,217347 0,17889 0,131683 0,14362 0,106258 0,002653 0,102368 0,102368 0,148116 0,001 = **** 1Q -1,1416 Error 0,16032 0,19814 0,20219 0,14965 0,12408 0,02151 0,09808 0,0275 0,11507 0,10966	13,112 -1,899 1,425 -4,016 -4,677 -14,325 -12,962 6,684 -4,31 -2,802 -8,022 0,01 = *** Median -0,4285 z value 13,106 -2,178 1,103 -4,702 -4,95 -16,974 -13,380 6,13 -3,45	< 2E-16 5,816E-02 1,5467E-01 6,83E-05 3,76E-06 < 2E-16 6,3E-11 1,97E-05 5,28E-03 7,66E-15 0,05 ='.' 3Q 0,5369 Pr(> z) < 2E-16 2,9406E-02 2,69995E-01 2,58E-06 7,42E-07 < 2E-16 8,78E-10 5,61E-04		8,4235	11. Negative Binomial regres-
North South C_factor 1 C_factor 2 Time_noon Time_morning LAS_max Season_autumn Season_winter Season_winter Season_winter Season_winter Coefficients (Intercept) North South C_factor 1 C_factor 2 Time_noon Time_morning LAS_max Season_autumn Season_autumn	2,085408 -0,419261 0,309812 -0,718472 -0,615911 -2,057313 -1,377269 0,017736 -0,468805 -0,286805 -1,188136 0 =***** Min -3,1743 Estimate St. Dev. 2,10114 -0,43156 0,22303 -0,70364 -0,61418 -2,0625 -1,31238 0,01686 -0,39695 -0,19168	0,15945 0,220787 0,217347 0,17889 0,131683 0,14362 0,106258 0,002653 0,102368 0,102368 0,148116 0,001 = **** 1Q -1,1416 Error 0,16032 0,19814 0,20219 0,14965 0,12408 0,02151 0,09808 0,0275 0,11507 0,10966	13,112 -1,899 1,425 -4,016 -4,677 -14,325 -12,962 6,684 -4,31 -2,802 -8,022 0,01 = *** Median -0,4285 z value 13,106 -2,178 1,103 -4,702 -4,95 -16,974 -13,380 6,13 -3,45 -1,748	< 2E-16 5,816E-02 1,5467E-01 6,83E-05 3,76E-06 < 2E-16 6,3E-11 1,97E-05 5,28E-03 7,66E-15 0,05 ='.' 3Q 0,5369 Pr(> z) < 2E-16 2,9406E-02 2,69995E-01 2,58E-06 7,42E-07 < 2E-16 8,78E-10 5,61E-04 8,0466E-02		8,4235	11. Negative Binomial regres-
North South C_factor 1 C_factor 2 Time_noon Time_morning LAS_max Season_autumn Season_winter Season_winter Season_winter Season_winter Coefficients (Intercept) North South C_factor 1 C_factor 2 Time_noon Time_morning LAS_max Season_autumn Season_autumn	2,085408 -0,419261 0,309812 -0,718472 -0,615911 -2,057313 -1,377269 0,017736 -0,468805 -0,286805 -1,188136 0 =***** Min -3,1743 Estimate St. Dev. 2,10114 -0,43156 0,22303 -0,70364 -0,61418 -2,0625 -1,31238 0,01686 -0,39695 -0,19168	0,15945 0,220787 0,217347 0,17889 0,131683 0,14362 0,106258 0,002653 0,102368 0,102368 0,148116 0,001 = **** 1Q -1,1416 Error 0,16032 0,19814 0,20219 0,14965 0,12408 0,02151 0,09808 0,0275 0,11507 0,10966	13,112 -1,899 1,425 -4,016 -4,677 -14,325 -12,962 6,684 -4,31 -2,802 -8,022 0,01 = *** Median -0,4285 z value 13,106 -2,178 1,103 -4,702 -4,95 -16,974 -13,380 6,13 -3,45 -1,748	< 2E-16 5,816E-02 1,5467E-01 6,83E-05 3,76E-06 < 2E-16 6,3E-11 1,97E-05 5,28E-03 7,66E-15 0,05 ='.' 3Q 0,5369 Pr(> z) < 2E-16 2,9406E-02 2,69995E-01 2,58E-06 7,42E-07 < 2E-16 8,78E-10 5,61E-04 8,0466E-02		8,4235	11. Negative Binomial regres-

Deviance Residuals

Min

1Q

-2,5116

Median

-1,0288

3Q

-0,3744

Max

3,7111

0,4230

Composite Utility Walk Utility Score Score	8,89 8,31	9,25 15,71	6,63 5,74	8,67 8,83	13,50 8,57	6.04 7.41	17,1	2,29 5,85	7,62 8,48								
Sco																	
re Crossing Street name	Artington Street	25,59 Berkeley Street	30,68 Clarendon Street	34,37 Darmouth Street	28,30 Exeter	46,79 Fairtield	44,08 Gloucester	45,61 Hereford	48,20 Massachusetts Ave	805							
Composite Utility Walk Utility Score Crossing Street Score		23,91 21	28,27 31	32,48 3.	26,58 21	47,03 41	45,50 4.	46,63 41	45,59 41	37,9525							
Comp	0706	3068	5208	7330	9096	1776	3732	5261	7721								
Ĕ	71.070706	35 -71.073068	57 -71.075206	65 -71.077330	19 -71.079509	81 -71.081776	51 -71.083732	45 -71.085261	91 -71.087721								
Boylston Street Long	42.361870	42.351235	42.350657	42.350.085	42.349519	42.34889	42.348351	42.347945	42.347291								
		0,51	6,77	5,63	4,75	0,62	2,45	2,33	0,30	2,92							
Composite Utility Walk Utility Score Score		0.39	7,01	6,15	5,45	0,49	2,22	225	0.25								
Ĕ	-71.071082	-71.073470	-71.075649	-71.077716	-71.079890	-71.082181	-71.084134	-71.085645	-71.088113								
Long	42.352676	42.352.052	42.351458	42.350882	42.350300	42.349690	42.349166	42.348748	42.348092								
Newbury Street		8	50	P	9	2	z	8	4	E							
Walk Utility Score		3,22	5,73	62'6	10,76	23,17	5 24,34	24,89	2,14	13,01							
Composite Utility Score		2,4	4	2,5	8,40	21,4	22,3	23	2,0								
Lat	-71.071496	-71.073845	-71.0760.08	-71.078134	-71.080303	-71.082578	-71.084536	-71.086039	-71.088526								
Long	42.353489	42.352865	42.352281	42.351693	42.351137	42.350511	42.3499.65	42.349547	42.3489.05								
Let	-71.071593	-71.073917	-71.076083	-71.078220	-71.080389	-71.082672	-71.084603	-71.086144									
Long	42.353659	0,44 42.353036	0,87 42.352436	1,18 42.351879	1,11 42.351300	1,23 42.350679	1,30 42.350147	1,41 42.3497.39									
Walk Utility Score									0,01	0,94							
Composite Utility Walk Utility Score Long Score		0.34	0,67	0,92	-	1,23	1,39	1,58	0,01			BOYLSTON		37,9525			
Lat	-71.071661	-71.074026	-71.076158	-71.078306	-71.080462	-71.082752	-71.084700	-71.086216	-71.088718			NEWBURY		2,92			
Long	42.353846	2 42.353214	3 42.352.606	4 42.352.053	42.351479	6 42.350863	42.350308	8 42.349913	9 42.349274				s	13,005			
Commonwealth Ave		64		4	4)	ç	~	**			LOCAL ACCESS SCORE	COMMONWEALTH	z	0,94375			
	Intersection	Intersection	Intersection	Intersection	Intersection	Intersection	Intersection	Intersection	Intersection								

13. Quasi Poisson regression for Commonwealth Avenue with all variables

Coefficients					
	Estimate St. Dev.	Error	t value	Pr(> t)	
(Intercept)	1,38496	0,33694	4,11	6,42E-05	
North	-0,01654	0,37583	-0,044	9,64956E-01	
South	-0,0704	0,34005	-0,207	8,36265E-01	
Center	0,54237	0,26373	2,057	4,1432E-02	
Time_noon	-1,92078	0,45789	-4,195	4,61E-05	
Time_morning	-2,78951	0,60908	-4,58	9,58E-06	
Season_Autumn	-0,42082	0,26628	-1,58	1,16093E-01	
Season_Summer	-0,99594	0,27958	-3,562	4,91E-04	
Season_Winter	-1,08742	0,40546	-2,682	8,125E-03	
noon x autumn	-1,99078	1,41784	-1,404	1,62317E-01	
morning x autumn	2,14379	0,70295	3,05	2,7E-03	
noon x summer	0,35697	0,72998	0,489	6,25537E-01	
morning x summer	2,16878	0,73021	2,97	3,458E-03	
noon x winter	0,63576	0,82333	0,772	4,41199E-01	
morning x winter	1,93855	0,84022	2,307	2,2384E-02	•
Significance codes	0 ='****'	0,001 = ****	0,01 = ***	0,05 ='.'	0,1 =' '
Deviance Residuals	Min	1Q	Median	3Q	Max
	-3,5494	-1,0275	-0,4087	0,5135	5,8582

14. Negative Binomial regression for Commonwealth Avenue with all variables

Coefficients					
	Estimate St. Dev.	Error	z value	Pr(> z)	
(Intercept)	1,3199	0,3473	3,801	1,44E-04	***
North	0,1286	0,3689	0,349	7,27367E-01	
South	-0,1582	0,3397	-0,466	6,41531E-01	
Center	0,5519	0,2681	2,059	3,9518E-02	*
Time_noon	-1,8933	0,4166	-4,545	5,5E+06	***
Time_morning	-2,7952	0,511	-5,47	4,49E-08	***
Season_Autumn	-0,4068	0,3043	-1,337	1,81268E-01	
Season_Summer	-1,0071	0,305	-3,302	9,61E-04	***
Season_Winter	-1,0548	0,3966	-2,659	7,828E-03	**
noon x autumn	-2,0267	1,126	-1,8	7,1878E-02	
morning x autumn	2,1778	0,6161	3,535	4,08E-04	***
noon x summer	0,4264	0,642	0,664	5,0656E-01	
morning x summer	2,1994	0,6343	3,468	5,25E-04	***
noon x winter	0,5704	0,7062	0,808	4,19219E-01	
morning x winter	1,9719	0,7101	2,777	5,49E-03	**
Significance codes	0 = ****	0,001 = "**"	0,01 = '*'	0,05 ='.'	0,1 =' '
Deviance Residuals	Min	1Q	Median	3Q	Max
	-2,6274	-0,9396	-0,4032	0,4617	2,8220

Newbury Street QP

Coefficients					
	Estimate St. Dev.	Error	t value	Pr(> t)	
(Intercept)	1,9828	0,22679	7,401	8,16E-12	***
North	-0,6049	0,5681	-1,065	2,887E-01	
South	0,8698	0,571	1,523	1,2975E-01	
Time_noon	-2,1497	0,3793	-5,667	6,96E-08	***
Time_morning	-2,6354	0,4653	-5,664	7,07E-08	***
Season_Autumn	-1,0063	0,2376	-4,236	2,91E+05	***
Season_Summer	-0,5611	0,2013	-2,787	6E-03	**
Season_Winter	-1,2741	0,2737	-4,655	6,93E-06	***
noon x autumn	-0,3322	0,7926	-0,419	6,7574E-01	
morning x autumn	2,4272	0,5577	4,352	2,45E-05	***
noon x summer	0,6135	0,5143	1,193	2,3472E-01	
morning x summer	1,2542	0,5831	2,151	3,306E-02	*
noon x winter	-0,4671	1,0791	-0,433	6,6572E-01	
morning x winter	2,0994	0,6207	3,303	9,1E-04	***
Significance codes	0 = '***'	0,001 = '**'	0,01 = '*'	0,05 ='.'	0,1 =' '
Deviance Residuals	Min	1Q	Median	3Q	Max
	-3,0862	-1,0518	-0,4560	0,5441	7,1673

Coefficients					
	Estimate St. Dev.	Error	z value	Pr(> z)	
(Intercept)	2,0107	0,2575	7,808	5,79E-15	***
North	-0,6491	0,4868	-1,333	1,8238E-01	
South	0,8855	0,4971	1,781	7,483E-02	
Time_noon	-2,1577	0,33	-6,539	6,19E-11	***
Time_morning	-2,6404	0,382	-6,912	4,79E-12	***
Season_Autumn	-1,0065	0,2411	-4,174	2,99E-05	***
Season_Summer	-0,5721	0,2224	-2,573	1,01E-02	*
Season_Winter	-1,2907	0,265	-4,871	1,11E-06	***
noon x autumn	-0,3349	0,6342	-0,528	5,9743E-01	
morning x autumn	2,4257	0,4917	5,124	2,99E-07	***
noon x summer	0,6024	0,4527	1,311	1,8327E-01	
morning x summer	1,2707	0,4917	2,584	9,76E-03	**
noon x winter	-0,4475	0,8403	-0,533	5,9435E-01	
morning x winter	2,0889	0,5171	4,04	5,35E-05	***
Significance codes	0 ='***'	0,001 = "**"	0,01 = '*'	0,05 ='.'	0,1 =' '
Deviance Residuals	Min	1Q	Median	3Q	Max
	-2,3119	-0,8333	-0,3165	0,4544	:

16. Negative Binomial regression for Newbury Street with all variables

17. Quasi Poisson regression for Boylston Street with all variables

Coefficients	Estimate St. Dev.	Error	t value	Pr(> t)	
<i>.</i>					
(Intercept)	2,7916	0,1985	14,061	< 2E-16	***
North	-0,0864	0,3666	-0,236	8,1398E-01	
South	0,0395	0,3526	0,112	9,1097E-01	
Time_noon	-1,8762	0,2823	-6,646	4,91E-10	***
Time_morning	-2,4011	0,3561	-6,743	2,94E-10	***
Season_Autumn	-0,5197	0,1706	-3,046	2,73E-03	**
Season_Summer	-0,3648	0,1691	-2,158	0,03250	*
Season_Winter	-1,3922	0,2432	-5,724	5,28E-08	***
noon x autumn	-1,6134	0,8239	-1,958	5,199E-02	
morning x autumn	1,4186	0,4374	3,244	1,45E-03	**
noon x summer	0,2558	0,4252	0,602	5,483E-01	
morning x summer	1,0197	0,4535	2,248	2,597E-02	*
noon x winter	-0,5337	0,7686	-0,694	4,8851E-01	
morning x winter	1,4564	0,5273	2,762	6,44E-03	**
Significance codes	0 = '***'	0,001 = '**'	0,01 = '*'	0,05 ='.'	0,1 =' '
Deviance Residuals	Min	1Q	Median	3Q	Max
	-3,1938	-0,9393	-0,4572	0,8630	8,04

18. Negative Binomial regression for Boylston Street with all variables

Coefficients					
	Estimate St. Dev.	Error	z value	Pr(> z)	
(Intercept)	2,88408	0,20608	13,995	< 2E-16	***
North	0,01932	0,34664	0,056	9,55553E-01	
South	-0,16232	0,33829	-0,48	6,31348E-01	
Time_noon	-1,88556	0,24471	-7,705	1,3E-14	***
Time_morning	-2,42131	0,28325	-8,548	< 2E-16	***
Season_Autumn	-0,5348	0,19529	-2,738	6,173E-03	••
Season_Summer	-0,38305	0,19669	-1,947	5,1485E-02	
Season_Winter	-1,41186	0,23205	-6,084	1,17E-09	***
noon x autumn	-1,60909	0,587	-2,741	6,121E-03	**
morning x autumn	1,41443	0,36529	3,872	1,08E-04	***
noon x summer	0,26968	0,36534	3,872	4,60421E-01	
morning x summer	1,06156	0,37519	2,829	4,664E-03	**
noon x winter	-0,57628	0,55607	-1,036	3,00046E-01	
morning x winter	1,41521	0,41498	3,41	6,49E-04	***
Significance	0 =*****	0,001 = '**'	0,01 = '*'	0,05 ='.'	0,1 =' '
codes					
Deviance Residuals	Min	1Q	Median	3Q	Max
	-2,5443	-0,8397	-0,3366	0,5609	

Coefficients					
	Estimate St. Dev.	Error	t value	Pr(> t)	
(Intercept)	2,253903	0,168927	13,342	< 2E-16	***
North	-0,77378	0,353947	-2,186	2,928E-02	•
South	-0,376026	0,302833	-2,186	2,1495E-01	
C_factor 1	-0,723804	0,164356	-4,404	1,31E-05	***
C_factor 2	-0,595447	0,120512	-4,941	1,07E-06	***
Time_noon	-1,906594	0,192469	-9,906	< 2E-16	***
Time_morning	-2,587173	0,24679	-10,483	< 2E-16	***
Season_autumn	-0,717299	0,111567	-6,008	3,68E-09	***
Season_summer	-0,539920	0,111567	-4,839	1,75E-06	***
Season_winter	-1,386119	0,160658	-8,628	< 2E-16	***
LAS_max	0,018756	0,002436	7,699	7,75E-10	***
North x South	1,072508	0,414333	2,589	9,93E-03	**
noon x autumn	-1,214186	0,507556	-2,392	1,713E-02	•
morning x autumn	1,829985	0,295319	6,197	1,23E-09	***
noon x summer	0,488716	0,284317	1,719	8,627E-02	
morning x summer	1,285563	0,0307264	4,184	2,4E-05	***
noon x winter	-0,192094	0,465063	-0,413	6,7975E-01	
morning x winter	1,628155	0,348267	4,675	3,81E-06	***
Significance codes	0 ='***'	0,001 = "**"	0,01 = '*'	0,05 ='.'	0,1 =
Deviance Residuals	Min	1Q	Median	3Q	Max
	-3,5223	-1,0629	-0,4429	6292	

7,4623

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19. Quasi Poisson regression	
for all street segments with all	
variables	

20. Negative Binomial regression for all street segments with all variables

Coefficients					
	Estimate St. Dev.	Error	z value	Pr(> z)	
(Intercept)	2,23405	0,17236	12,962	< 2E-16	***
North	-0,55752	0,33849	-1,647	9,954E-02	
South	-0,32946	0,28468	-1,157	2,4714E-01	
C_factor 1	-0,72658	0,14249	-5,099	3,41E-07	***
C_factor 2	-0,59793	0,22655	-5,13	2,89E-07	***
Time_noon	-1,92013	0,17858	-10,752	< 2E-16	***
Time_morning	-2,59202	0,21021	-12,331	< 2E-16	***
Season_autumn	-0,72185	0,1389	-5,197	2,03E-07	***
Season_summer	-0,58506	0,13438	-4,354	1,34E-05	***
Season_winter	-1,26869	0,16291	-8,401	< 2E-16	***
LAS_max	0,01821	0,00245	7,17	7,49E-13	***
North x South	0,83279	0,40618	2,05	4,4304E-02	*
noon x autumn	-1,20281	0,39996	-3,007	2,64E-03	**
morning x autumn	1,87524	0,26332	7,121	1,07E-12	***
noon x summer	0,5413	0,26067	2,077	3,784E-02	*
morning x summer	1,35403	0,27131	4,991	6,02E-07	***
noon x winter	-0,20638	0,3733	-0,553	5,8037E-01	
morning x winter	1,65928	0,29802	5,568	2,58E-08	***
Significance codes	0 ="****	0,001 = '**'	0,01 = '*'	0,05 ='.'	0,1 =' '
Deviance Residuals	Min	1Q	Median	3Q	Max
	-2,8006	-0,9489	-0,3881	0,4753	3,4