Associations of Temperature on Physical Activity in Urban Populations: Implications for Health under Climate Change

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Abstract (English)

Abstract of thesis entitled: Associations of temperature on physical activity in urban populations: Implications for health under climate change

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Background:

Physical activity is an important factor for premature mortality reduction, non-communicable disease prevention, and well-being protection. Temperature has been perceived as a barrier to physical activity, with previous studies focusing on cold temperature effects. However, climate change will alter temperatures globally, as impacts were already found on mortality and morbidity. Improved understanding of predicting factors that may influence physical activity uptake is necessary to guide policy and program development.

Objective:

The study series in this thesis examined the associations of temperature on physical activity in urban adult populations. The relationship was addressed across current published evidence, different climate locations, vegetation greenness levels, extreme temperatures, and health status.

Methodology:

Four studies were conducted in this thesis. A systematic review (**Study 1**) examined bilingual databases for English and Chinese peer-reviewed papers on the temperature-physical activity relationship among adult populations.

An aggregated timeseries study (**Study 2**) in five Chinese cities (Beijing, Shanghai, Chongqing, Shenzhen, and Hong Kong) analysed the associations of temperature on daily smartphone-measured aggregated mean step count using Generalized Additive Models, adjusted for meteorological, air pollution, and time-related variables.

A retrospective repeated measures study (**Study 3**) in four European cities (Barcelona Spain, Stoke-on-Trent UK, Doetinchem Netherlands, and Kaunas Lithuania) assessed the association of apparent temperature, and potential interaction of within-city greenness levels, on smartphone-measured hourly physical activity intensity using linear mixed models, adjusted for meteorological, greenspace, time-related, and demographic variables.

A two-year telephone survey cohort in Hong Kong (**Study 4**) identified the change in self-reported outdoor physical activity and health predictors during extreme temperature events, using multivariable logistic regression models.

<u>Results:</u>

In the four studies, the temperature association on physical activity were found to be as follows:

Study 1 identified an overall inverse U-shaped trend among 79 included papers when summarized by Köppen-Geiger climate classification.

Study 2 found significant decreased associations in high temperatures for cold or temperate climate cities (Beijing, Shanghai, and Chongqing), with maximum physical activity at 16-19.3°C. For cities in warmer climates (Shenzhen and Hong Kong), non-significant associations with high temperatures were found.

Study 3 found significant inverse U-shaped associations between apparent temperature and physical activity at the highest greenness levels in two temperate cities (Stoke-on-Trent and Doetinchem), with maximum physical activity at 14.5-15.2°C. Non-significant interactions were found in a coastal Mediterranean city (Barcelona), while positive associations were found in higher greenness levels for a colder city with woodland spaces (Kaunas).

Study 4 found outdoor physical activity decreased in greater proportion in extreme cold compared to extreme heat in Hong Kong. Decreased physical activity in extreme temperatures was associated with suboptimal seasonal health and cardiovascular-related diseases.

<u>Conclusions:</u>

This study series demonstrates how hot temperatures could reduce physical activity levels in urban adult populations particularly in temperate climates. Climate change will create temperature abnormalities and shift average temperatures in the next decade. As minor reductions in physical activity could consequentially affect health, the findings recommend an integration of physical activity and temperature in climate policies and health guidelines. Adaptations should be made in clinical guidance, recreational facilities, and urban design to enable supportive environments that safely sustain physical activity levels in higher temperatures.

Abstract (Chinese)

論文摘要：溫度與城市人運動量的關係：氣候變化對人類健康的影響

呈交者：何盈恩

學位：哲學博士

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<u>背景</u>

運動有助減低過早死亡、預防非傳染性疾病和增進身心健康。了解環境因素對城市人運動量的影響有助提昇運動參與度。過往文獻發現，溫度是影響個人參與運動的主要障礙之一，但現有文獻大多集中在寒冷溫度的影響上。氣候變化將導致全球溫度改變，且過往文獻已發現這樣的轉變對死亡和患病可產生顯著影響。本論文通過四個研究項目來評估溫度與城市成年人的運動量的關係，文中作者對已發表的證據進行文獻回顧、並考慮不同氣候地區、植被水平、極端溫度和健康狀況對運動量的影響。

<u>研究方法</u>

研究 1 通過搜索英語和中文文獻資料庫，對過往發表的溫度與運動量的學術研究進行系統性文獻回顧，並對現有科學證據進行評估。

研究 2 和 3 使用智能手機運動數據，**研究 2** 運用時間序列方法與廣義相加模型，分析五個中國城市溫度與市民每日匯總平均步數之間的關係。

研究 3 使用線性混合模型，評估分析四個歐洲城市表觀溫度與市民每小時運動強度之間的關係，並考慮植被水平的潛在交互作用。

研究 4 是一項在香港進行的兩輪電話訪問調查。研究通過卡方檢驗和多變量邏輯回歸模型，評估極端溫度下市民自我報告的戶外運動量和健康狀況的變化。

<u>結果</u>

在四項研究中，溫度與運動量的關係如下：

研究 1 將 79 篇相關文章根據不同氣候帶分類後（柯本氣候分類法）進行綜合分析，綜合結果顯示溫度與運動量大致呈倒 U 型曲線關係。

研究 2 發現在寒冷或溫帶氣候城市，在高溫下市民的運動量有明顯的下降，當溫度為 16-19.3°C 時，市民的運動量最高。另一方面，在氣候較溫暖的城市，高溫對市民的運動量沒有顯著關聯。

研究 3 發現溫度與運動量的倒 U 型曲線關聯僅在溫帶氣候城市的最高植被水平下出現，市民的運動量在溫度為 14.5-15.2°C 時達到最高。在沿海地的城市，溫度與植被水平的交互作用對於運動量的影響並不顯著，而在氣候寒冷林地较多的城市，在較高的植被水平下，溫度與市民的運動量呈正相關。

研究 4 發現在香港極端寒冷天氣相比極端高溫天氣，對市民戶外運動減少的影響更大。研究亦發現極端溫度下運動量的減少，與受訪者季節性健康狀況以及是否患有心血管相關疾病有關。

<u>結論</u>

本論文研究分析城市成年人的運動量水平如何因高溫天氣而降低，尤其在溫帶氣候地區。未來十年，氣候變化將會造成溫度異常並使平均溫度升高。由於少量運動量的減少已可能對健康造成不良影響，因此本文建議將運動量和溫度的關係納入氣候政策及健康指南中，並應在臨床指引、休閒設施和城市設計方面做出響應的適應性調整，為大眾創造一個能夠在高溫下安全維持運動水平的環境。

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Being confident of this, that He who began a good work in you
will carry it on to completion until the day of Christ Jesus. Philippians 1:6

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List of Abbreviations

AOR	Adjusted Odds Ratio
AQHI	Air Quality Health Index (used in Hong Kong SAR)
AQI	Air Quality Index (used in mainland China)
AT	Apparent temperature
BMI	Body Mass Index
CI	Confidence interval
COPD	Chronic obstructive pulmonary disease
CWW	Cold Weather Warning (used in Hong Kong SAR)
DALYs	Disability-adjusted life years
df	Degrees of freedom
DOW	Day of week
EHRI	Exertional heat-related illnesses
GPS	Global Positioning System
HKO	Hong Kong Observatory
IPCC	Intergovernmental Panel on Climate Change
LPA	Light physical activity
Max	Maximum
MET	Metabolic Equivalent of Task
Mil	Million
Min	Minimum
MVPA	Moderate-to-vigorous physical activity
NCD(s)	Non-communicable disease(s)
NDVI	Normalized difference vegetation index
OptT	Optimal temperature
OR	Odds Ratio
PA	Physical activity
SD	Standard Deviation
Sig.	Significance
VHWW	Very Hot Weather Warning (used in Hong Kong SAR)
WHO	World Health Organization

Chapter 1 Introduction

1.1 Background

Physical activity (PA) is conducted by people of all ages, places, and abilities. Defined as any bodily movement produced by skeletal muscles that requires energy expenditure (Caspersen, Powell, & Christenson, 1985; World Health Organization, 2018), physical activity occurs in everyday life as a health behaviour inherent to human functioning. It is known as an important protective factor for premature mortality, chronic disease prevention, and well-being.

With trends of urbanization, industrialization, and automation, overall physical activity has decreased worldwide (Hallal et al., 2012). Among adult populations, self-reported estimates have found that 31.1% of adults worldwide are considered physically inactive according to the World Health Organization (WHO) recommendations (Hallal et al., 2012). Insufficient physical activity occurs more frequently among women than men and increases with age (Hallal et al., 2012). Particularly in high-income countries, occupational physical activity has decreased while the leisure physical activity has increased (Hallal et al., 2012). More sedentary office work, use of automobiles, and other sedentary travel modes have contributed to lower overall physical activity in populations.

In order to improve adult physical activity levels, health practitioners and researchers seek to address the multi-faceted factors influencing physical activity (Bauman et al., 2012). Physical activity is often distinguished between urban and rural environments due to differences in lifestyles and infrastructure (Hallal et al., 2012; Van Cauwenberg et al., 2011; Zhu, Chi, & Sun, 2016). Within urban living environments, the natural, built, and social environments influence people's movement and physical activity in everyday life (Bauman et al., 2012). While the social and built environment can be managed by societal changes and policies, aspects of the natural environment are less prone to human regulation. In recent years, governmental and institutional polices have advocated for more enabling factors to promote physical activity, such as the development of outdoor recreational opportunities and indoor sports facilities. Yet, other influences may still affect the uptake of these opportunities.

Temperature and other aspects of weather are elements of the natural environment that are beyond personal control but affect people's physical activity. Not only is there a day-to-day variability in weather, but with climate change, these will be further altered and intensified. Rising atmospheric temperatures and greater precipitation variability will pose multifaceted risks to human health (IPCC, 2014), ranging from impacts on mortality to health behaviours. Increased heat stress from external environmental conditions and internal metabolic heat, generated by physical activity, can increase individuals' risk for heat-related illnesses (Kenny et al., 2010). The prevalence of physical activity at a population level may be affected by extreme temperatures.

It is important to address potential barriers to population level physical activity. Low levels of physical activity would lead to consequent effects on health and well-being (World Health Organization, 2010). By understanding how physical activity is affected by temperatures, precautions at the societal level can be adopted as the impact of climate change increases.

1.2 Thesis Aim and Research Questions

This thesis seeks to examine the associations of temperature on physical activity in urban adult populations. This is addressed through the following research questions, to build evidence for supporting program and policy development:

1. What is the current research evidence regarding the relationship between temperature and physical activity?
2. How does the association of temperature on physical activity vary between cities of different climates?
3. How does the association of temperature on physical activity vary within cities at different greenness levels?
4. What is the effect of extreme temperature events (extreme cold and heat) on physical activity?
5. How does health influence the effects of temperature on physical activity?

1.3 Thesis Organization

This thesis is organized into eight chapters comprising of four empirical studies.

Chapter 1 provides the introduction, research questions and organization of the thesis.

Chapter 2 addresses the background literature and justifications of the thesis topic.

Chapter 3 develops the thesis research questions in more detail.

Chapter 4 (Study 1) examines the current literature on the associations of objectively measured temperature on physical activity in adult populations through a systematic review. This study enables a clearer understanding of the previous work and current gaps in research.

Chapter 5 (Study 2) compares the daily associations between temperature and physical activity in five Chinese cities. Different climate locations in China are assessed at the population level through this multi-location comparative analysis.

Chapter 6 (Study 3) assesses the hourly associations of temperature and surrounding greenness on physical activity in four European cities. In addition to serving as a multi-location comparison, this study further examines the association of temperature within cities, exploring the association of greenness levels on the relationship between temperature and physical activity.

Chapter 7 (Study 4) explores the effect of extreme temperature events on outdoor physical activity in a subtropical city. Health status and chronic disease conditions are examined as predictors of change in physical activity during extreme temperatures.

Chapter 8 provides a joint discussion and policy implications of the four studies.

Chapter 9 concludes the findings of this thesis.

Chapter 2 Background Literature

2.1 Physical activity and health

Physical activity has been found to enhance overall health and well-being across the life span. These benefits extend beyond obesity and weight management to include improved physical functioning, cardiorespiratory fitness, mood, cognition, sleep quality, and perceived quality of life (Physical Activity Guidelines Advisory Committee, 2018). Some benefits may occur with a single session of physical activity, while others are further accumulated through habitual physical activity. For adults, the World Health Organization (WHO) recommends at least 150 minutes of moderate-intensity physical activity, 75 minutes of vigorous-intensity physical activity, or an equivalent combination of moderate and vigorous activity in a week (World Health Organization, 2010). Insufficient physical activity in adults is one of the top four modifiable risk factors for mortality globally, with an estimated 9% attributable fraction of premature mortality (Lee et al., 2012; World Health Organization, 2010). It further contributes to the disease burden of non-communicable diseases (NCDs), accounting for an estimated 21-25%, 27%, and 30% of the breast and colon cancer, type 2 diabetes, and ischaemic heart disease burden, respectively (World Health Organization, 2009).

Non-communicable diseases (NCDs) are diseases that are not transmissible from person to person. These are often chronic conditions, with slow disease progression, but may also produce acute exacerbations, particularly when exposed to climate conditions (Kjellstrom, Butler, Lucas, & Bonita, 2010). NCDs account for a large proportion of morbidity and mortality worldwide, comprising of 62% of global disability-adjusted life years (DALYs) (Kyu et al., 2018), which is the measure of healthy years of life lost to premature death or disabilities. In 2017, NCDs were the cause of death for 73.4% of global mortality or 41.1 million deaths, with the top three causes from cardiovascular diseases, cancers, and chronic respiratory diseases (Roth et al., 2018). Both developed and developing contexts are affected by NCDs, particularly with low- and middle-income countries carrying over 80% of the premature mortality disease burden (World Health Organization, 2013). NCDs are projected to cause 55 million deaths by 2030 according to WHO (World Health Organization, 2013). In order to reduce this disease burden, interventions on physical activity are essential, one of four main modifiable risk factors of NCDs along with tobacco use, unhealthy diet, and harmful use of alcohol (World Health Organization, 2013).

Physical activity is an intervention for NCD prevention, at the primary, secondary, and tertiary prevention levels (Durstine, Gordon, Wang, & Luo, 2013). For primary prevention, physical activity reduces the risks of a wide variety of NCDs. A large body of evidence shows that physical activity reduces the risks of cardio-respiratory diseases, such as coronary heart disease, cardiovascular disease, stroke, and hypertension, although the dose-response relationship is less clear (Shiroma & Lee, 2010; World Health Organization, 2010). Physical activity benefits metabolic-related health such as diabetes and obesity, as well as musculoskeletal and functional health (World Health Organization, 2010). There are benefits in prevention of cancer, particularly breast and colon cancer. Additionally, it reduces the risk of mental health problems such as anxiety, depression, dementia, and Alzheimer's Disease (Bull & Bauman, 2011; Durstine et al., 2013). Among older adults, physical activity is beneficial to the retention of functional ability and helps reduce the risk of falling, particularly by conducting balance training and muscle-strengthening activities (Tak, Kuiper, Chorus, & Hopman-Rock, 2013; Taylor, 2014; World Health Organization, 2010).

In terms of secondary prevention, physical activity improves the survival rates and quality of life of chronic disease patients when it has been incorporated as part of the medical management plan (Durstine et al., 2013). Physical activity interventions have been shown to reduce modifiable risk factors of cardiovascular disease, such as elevated blood pressure, elevated blood cholesterol, blood glucose levels, cigarette smoking, and obesity (Durstine et al., 2013). Treatment programs with physical activity have produced up to 26% reductions in cardiac mortality (Durstine et al., 2013). Aerobic exercise is additionally a foundational aspect for secondary prevention of diabetes mellitus. Physical activity improves body insulin sensitivity and helps maintain a person's blood glucose, lipid, and blood pressure levels, all of which are essential to managing or even improving the disease progression of type 2 diabetes (Durstine et al., 2013). Improved outcomes have been found for people with prostate, colon, and breast cancer, with possible benefits for other varieties of cancer as well (Durstine et al., 2013).

At the tertiary prevention level, physical activity can support the maintenance of functional capacity and quality of life. Conducting regular physical activity can slow down the functional decline among older adults with diseases, disabilities, or functional limitations (Tak et al., 2013). Exercise prescription is recommended as part of cardiac rehabilitation programmes after acute events, heart transplantation, or cardiac surgery (EACPR Committee for Science Guidelines et al., 2010). The prescription varies depending on each individual patient and their careful clinical assessment and functional evaluation (EACPR Committee for Science Guidelines et al., 2010). Physical activity interventions are a cost-effective way to improve prognosis, reduce recurrent hospitalizations, and lessen health care expenditure (EACPR Committee for Science Guidelines et al., 2010). There is also preliminary evidence that physical activity is associated with improved biomarkers related to reduced reoccurrence and longer survival among breast and colorectal cancer patients (Brenner & Chen, 2018; Winzer, Whiteman, Reeves, & Paratz, 2011). Suitable physical activity plans can be established under the direction of health-care providers, according to patients' ability and health status.

Overall, the benefits of physical activity outweigh the risks (Physical Activity Guidelines Advisory Committee, 2018). Injuries are a particular form of NCDs related to adverse events of physical activity. Sudden forceful movements during physical activity can cause acute stress on muscles and joints, leading to strains, tears, and fractures (U.S. Department of Health and Human Services, 1996). Risk of musculoskeletal injuries can increase depending on the type of activity, amount of contact or collision, and the overall volume or sudden change of volume in the physical activity performed (Physical Activity Guidelines Advisory Committee, 2018). However, the risk of these injuries can be reduced by implementing protective equipment and measures, such as padded gear for high contact sports. Caution should be taken to refrain from drastic increases in physical activity and providing sufficient time for adaptation (Physical Activity Guidelines Advisory Committee, 2018).

Despite the growing awareness of the health benefits, low levels of physical activity are reported globally. Among worldwide surveillance data of self-reported physical activity, 31.1% of adults are insufficiently active (Hallal et al., 2012). Consistent patterns have been found across countries, demonstrating decreased physical activity among older persons, women, and those in high-income countries (Hallal et al., 2012). Those with NCDs are even less likely to conduct physical activity (U.S. Department of Health and Human Services, 1996), although physical activity brings benefits for their disease management and maintenance of their health. Without any changes, the global burden of non-communicable diseases will continue to increase in the future. In 2013, the World Health Assembly and World Health Organization developed a Global Action Plan for the prevention and control of non-communicable diseases. It called for a 10% reduction in insufficient physical activity prevalence by 2025 as a fundamental effort to reduce non-communicable diseases worldwide (World Health Organization, 2013). Efforts must be made to increase the physical activity worldwide at the population level.

Health promotion is “the process of enabling people to increase control over, and to improve, their health” (World Health Organization, 1986). The Ottawa Charter for Health Promotion was an international agreement in 1986 that established 5 action areas for health promotion: build healthy public policy, create supportive environments, strengthen community actions, develop personal skills, and re-orient health care services (World Health Organization, 1986). To increase physical activity at the population level, supportive environments and public health policies can be planned and developed. There is a need to understand the various influencing factors of physical activity in order to shape these interventions to be evidence-based and effective.

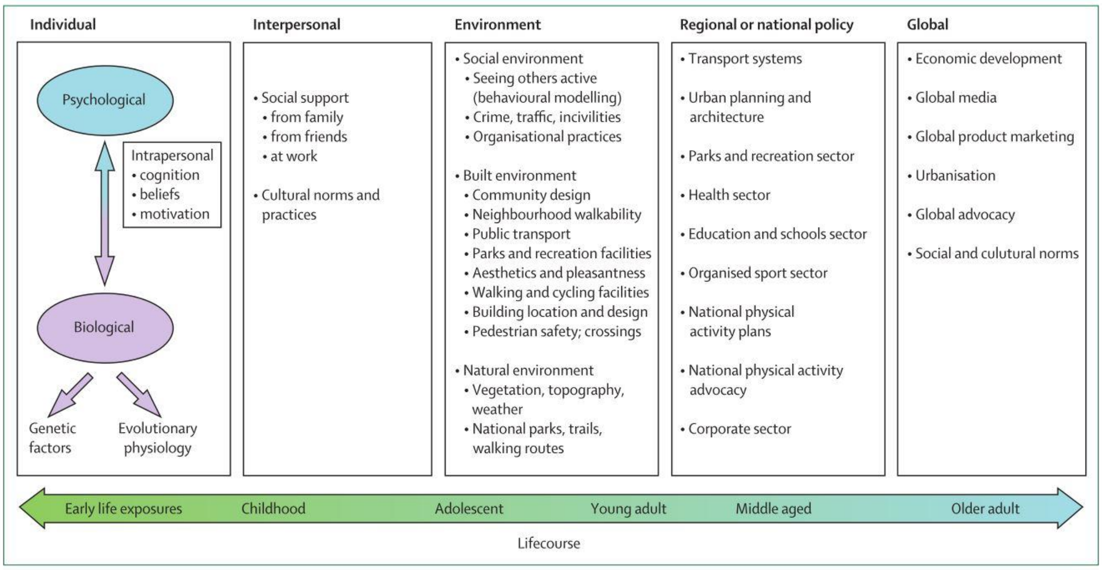
2.2 Temperature as a correlate of physical activity

The factors, or correlates, influencing physical activity differ between adults and children. Adult physical activity is conducted through avenues of active transport, occupation, domestic chores, and leisure activity. Meanwhile the context in which children conduct physical activity are commonly related to family support, active transport, and unstructured or structured recreational play, such as physical education and extra-curricular sessions at school (Bauman et al., 2012; Livingstone, Robson, Wallace, & McKinley, 2003). Correlates affecting physical activity vary even between different age groups from toddlers and preschool children, to high school adolescents. Children of all ages have more complex activity patterns than adults, causing more complications to attain accurate measurements of physical activity (Livingstone et al., 2003). As children’s’ bodies are still growing and developing, the guidelines and benefits of physical activity lack the same emphasis as adults on disease and mortality, as mentioned in Section 2.1. Overall, physical activity research and policies separate the discussion between children and adults (Bauman et al., 2012; Livingstone et al., 2003). In this thesis, only adult physical activity will be addressed to obtain understanding of population-wide physical activity levels for potential population-wide interventions.

Adults may be physically active or inactive depending on determinants and correlates of physical activity at the individual, interpersonal, and environmental level (Bauman et al., 2012; U.S. Department of Health and Human Services, 1996). In the past, research on physical activity and its correlates or determinants, has mostly focused on the individual-level, such as demographic, psychological, and interpersonal factors (Bauman et al., 2012; U.S. Department of Health and Human Services, 1996). Factors such as age, gender, education, self-efficacy, and social support, have been found associated with adult physical activity (Bauman et al., 2012). A person’s health status has been identified as one of the most consistent correlates for physical activity in adults (Bauman et al., 2012). Those with chronic diseases may additionally have different needs, motivations, or barriers to conducting physical activity (Bossen, Veenhof, Dekker, & de Bakker, 2014).

The development of theories such as Theory of Planned Behavior, Health Belief model, Social Cognitive theory, and Transtheoretical model have resulted in physical activity interventions for individuals or small-scale programs (Rhodes & Nasuti, 2011; Sallis et al., 2006). However, these approaches had limited applications to the population scale, as they overemphasized individual behavioral change processes but failed to account for the sociocultural and physical environmental influences on physical activity (U.S. Department of Health and Human Services, 1996). This has led to an increasing adoption of multi-level ecological models, which incorporate the influences of social, cultural, and environmental factors, and the interrelationship between different levels (Figure 2.1) (Bauman et al., 2012; Sallis et al., 2006; Townsend et al., 2003; U.S. Department of Health and Human Services, 1996). Such an approach would link behavioral change to supportive environments that could sustain improvements to physical activity levels at a population-scale (Merrill, Shields, White Jr., & Druce, 2005).

Figure 2.1 An example of an ecological model of physical activity correlates



Source: Bauman et al. (2012)

Looking beyond the individual-level, physical activity researchers began to investigate environmental correlates to physical activity in the 2000s (Rhodes & Nasuti, 2011). Early studies, particularly those in low- and middle-income countries, often used subjective perceptions of the environment rather than objective measures (Bauman et al., 2012). An initial review identified five areas of physical environment correlates for adult physical activity: accessibility to facilities, opportunities for activity, weather, safety, and aesthetic (Humpel, Owen, & Leslie, 2002). A multilevel ecological model by Sallis et al. (2006) mentions different environment categories, encompassing the natural environment, built environment, social cultural environment, and information environment. Yet, research has largely focused on spatial built environmental factors associated with physical activity, such as recreational facilities and locations, neighbourhood design, transportation environment, social environment, and aesthetics (Bauman et al., 2012; World Health Organization, 2011). The concept of weather is much less discussed as an environmental correlate of physical activity, despite its inclusion in ecological models (Bauman et al., 2012; Sallis et al., 2006).

Weather is the state of the air and atmosphere at a particular time and place. As part of the natural environment, weather varies on a day-to-day basis, and is beyond human control. Poor weather has often been described as a 'barrier to physical activity' in qualitative studies, particularly among older adults (Chan & Ryan, 2009; Moran et al., 2014; Tucker & Gilliland, 2007). The qualitative discussion around this barrier has emerged in two aspects, through a dislike of cold, rainy, or windy weather, but also a dislike of hot weather, high humidity, and sun exposure (Moran et al., 2014). Understanding this temporal aspect of physical activity is essential to developing effective interventions and supportive environments for physical activity.

Quantitative research surrounding weather and physical activity have mainly analysed the seasonal variations of physical activity, as identified in two reviews conducted in 2007 and 2009 (Chan & Ryan, 2009; Tucker & Gilliland, 2007) (See Table 2.1). Tucker & Gilliland (2007) found a total of 3 out of 37 studies measured weather attributes quantitatively, while 28 articles focused on seasonal differences, and six studies looked qualitatively at "weather as a barrier". Chan & Ryan (2009) specifically reviewed studies using objective measurements of physical activity and identified 10 of 27 studies measuring weather conditions while the other studies assessed seasonal effect. A main contribution of Chan & Ryan (2009) was confirming that the effect of weather on physical activity extended beyond people's perception, but actually affected physical activity levels, as the trends found in subjective physical activity and qualitative discussions were reflected in objective physical activity studies. In both reviews, the seasonal studies were conducted in colder temperate climates and typically found that cold seasons were a deterrent to physical activity (Chan & Ryan, 2009; Tucker & Gilliland, 2007). The reviews, however, articulated that seasonal variation was “not a set feature of the environment”, as its associations differed due to temperature variations in different regions (Tucker & Gilliland, 2007). Seasonality could only be used as a surrogate to provide insights of how physical activity was affected by specific weather elements, also known as meteorological factors (Chan & Ryan, 2009). There was a need for studies to assess specific meteorological factors for their influence on physical activity: temperature, humidity, precipitation, wind, daylight hours, etc. (Humpel et al., 2002).

Table 2.1 Summary of previous reviews on weather and physical activity studies

Review	Studies identified	PA type	Main findings
Tucker & Gilliland 2007 (Systematic)	**37 total** 28 seasons 6 qualitative 3 weather	Largely subjective PA	Weather is barrier to PA, with cold season and rain as deterrents; hot season as deterrent in 1 study
Chan & Ryan 2009 (Narrative)	**27 total** 17 seasons 10 weather	Objective PA	Objective PA studies confirm subjective PA findings: Cold season (-) Rainfall (-) Temperature (+/-)

Among the early research on the associations of separate meteorological factors on people’s physical activity levels, studies found meteorological factors were significantly associated with physical activity and should be taken into consideration when developing physical activity interventions (Chan, Ryan, & Tudor-Locke, 2006; Togo et al., 2005; Tucker & Gilliland, 2007). While precipitation was found to have the largest correlation with physical activity (Chan & Ryan, 2009), temperature was strongly associated with physical activity on days without precipitation, more so than other meteorological factors (Togo et al., 2005). While precipitation was generally found associated with a reduction in physical activity, a variety of different physical activity measurements and populations limited the ability to summarize the effects of temperature (Chan & Ryan, 2009).

The relationship between temperature and physical activity is important to further understand. As will be discussed in Section 2.3, there are several mechanisms through which temperature has an effect on humans, related to human physiology, thermal comfort, and adverse health outcomes. Additionally, there are several macro-influences that lead to differences in temperature variation, as will be discussed in Section 2.4, including urbanization, adaptations to local climates, and climate change. While cold temperatures in winter seasons seemed to be associated with reduced physical activity in colder temperate climates, a lack of studies was found in consistently warm locations, as researchers may have previously assumed that warm weather would not act as a deterrent to physical activity (Tucker & Gilliland, 2007). Chan & Ryan (2009) recommended that future studies should assess a range of climatic zones, to understand the temperature effect in different locations and develop suitable interventions. As the previous reviews on weather and physical activity were conducted in 2007 and 2009, respectively, an updated understanding is needed for the current literature on the relationship between temperature and physical activity.

2.3 Mechanisms by which temperature affects humans and their physical activity

This section will discuss three main mechanisms by which temperature can affect humans and their physical activity. This includes understandings from a physiological perspective (Section 2.3.1), thermal comfort perspective (2.3.2), and adverse health outcome perspective (2.3.3).

2.3.1 Human physiology and thermoregulation response

The human body maintains a constant core body temperature of 37°C. The body's autonomic thermoregulatory system seeks to attain a balance between metabolic heat production, and heat loss, occurring in two ways: dry heat exchange (conduction, convection, and radiation), and evaporative heat exchange (sweating) (Hajat, O'Connor, & Kosatsky, 2010; Kenny et al., 2010; Kovats & Hajat, 2008). While temperature is the measure of the average heat of the molecules of a substance, heat is the amount of energy contained within a substance (McGregor & Vanos, 2018). Conduction, convection, and radiation enable the exchange of heat through direct contact, movement of air or fluids, or from electromagnetic waves, respectively. The process of evaporation enables the skin to cool as the perspiration is turned from liquid into vapour. The ability to maintain body heat balance is further influenced by environmental conditions such as air temperature, radiant temperature, humidity, air movement (Parsons, 2003), and individual-level factors such as age, clothing, fitness ability, body composition, and hydration levels (Cheung, McLellan, & Tenaglia, 2000).

Heat stress can be caused by both internal metabolic heat production and external heat in the environment. At resting metabolic rate, the body is engaged in minimal heat production, however, this dramatically changes in physical activity (Gonzalez-Alonso et al., 2000). Heat production rises sharply within the first 38 seconds of conducting physical activity, as muscle cells convert chemical energy into mechanical energy (Burton, Stokes, & Hall, 2004; Flouris & Schlader, 2015; Gonzalez-Alonso et al., 2000). Much of the energy is release as heat (~80%), as approximately only ~20% of the converted energy is used for work at maximum conversion efficiency (Burton et al., 2004; Flouris & Schlader, 2015). The rate of heat production doubles during exercise over the first few minutes when assessed at a constant power output (Gonzalez-Alonso et al., 2000). This increase in metabolic heat production remains elevated for the duration of the exercise and elevates the body temperature (Flouris & Schlader, 2015).

When exposed to external environments warmer than the skin temperature (around 36°C), the body can no longer dissipate heat by a natural temperature gradient between the air and skin surface (Kenny et al., 2010). Instead, the warmer surrounding air would add heat to the skin surface through convection (McGregor & Vanos, 2018). High levels of atmospheric moisture may further prevent the sweat from being evaporated, effectively stopping the intended cooling effect (McGregor & Vanos, 2018). Non-evaporated sweat on skin would further increase thermal discomfort in hot conditions (Flouris & Schlader, 2015). In hot and humid environmental conditions, physical activity increases the metabolic heat production of the body but is prevented from dissipating heat, increasing the core body temperature.

The excess heat in body temperature needs to be dissipated by physiological means, whereby autonomic heat loss responses are activated in a healthy body to increase skin blood flow (cutaneous vasodilation) and sweating (Burton et al., 2004; Charkoudian, 2003; Flouris & Schlader, 2015). Blood flow is substantially increased to the skin to convectively transfer heat from the body core to the peripheries (Charkoudian, 2003). Simultaneously, the evaporative cooling process of sweat helps lower the temperature of the skin and the blood in the dilated skin vessels (Charkoudian, 2003). These processes, however, add pressure to the body's systems, particularly when during physical activity. Cardiac output is increased to meet the demands of physical activity and increased skin blood flow. This occurs through both an increase in heart rate and stroke volume (the volume of blood ejected from heart ventricles from contraction of the heart muscle) (Burton et al., 2004). Blood flow to central organs is also reduced (Charkoudian, 2003; Parsons, 2003). Furthermore, the loss of fluids from increased sweating lead to dehydration if not replenished (Parsons, 2003). The cardiovascular system has been found to endure a large demand during passive thermal stress, with or without to the additional strain of physical exertion (Kenney, Craighead, & Alexander, 2014).

Behavioural thermoregulation, as opposed to autonomic thermoregulation, is where the person takes behavioural actions to reduce the heat stress. One main method of behavioural thermoregulation is a voluntary reduction of exercise work rate. Between air temperatures of 30°C and 45°C, the capacity to carry out physical activity declines until it becomes difficult to conduct any physical activity (Kjellstrom, Gabrysch, Lemke, & Dear, 2009; Stamatakis, Nnoaham, Foster, & Scarborough, 2013). The wide temperature range covers the effects of a varying combination of temperature, humidity, windspeed, and solar radiation. Physiological studies have found a linear reduction in work rate and shorter exercise durations in higher air temperatures (Vanos, Warland, Gillespie, & Kenny, 2010). As seen in self-paced exercise studies, participants reduce the rate of metabolic heat production in efforts to minimize the increase of core body temperature (Flouris & Schlader, 2015). Reduction of work rate occurs with an increase in a person's perceived exertion, which is the subjective perception of effort during exercise (Flouris & Schlader, 2015). This sense of perceived exertion is increased in conditions with higher amounts of thermal discomfort and cardiovascular strain (Flouris & Schlader, 2015). A reduction of work rate is necessary even in compulsory work environments, in efforts to prevent the risk of heat-related illnesses (Kjellstrom et al., 2010).

Acclimatization is the physiological adaptative response whereby the human body becomes accustomed to repeated exposures to high temperatures within a short time period such as a season (Arbuthnott, Hajat, Heaviside, & Vardoulakis, 2016). In exercise physiology studies, heat acclimatization is a known method to help prevent heat-related illnesses among athletes – optimally conducted over 10-14 days, with 60-90 minutes of progressive exercise in heat conditions (Nichols, 2014). Acclimatization can occur naturally when populations have been regularly exposed to high temperatures in the summer, such that heat events later in the summer have less of an impact compared with those early in the summer season (Arbuthnott et al., 2016). With this physiological adaptation, proper acclimatization can help to improve heat tolerance in the population, however there are upper limits to which the human body can maintain its core body temperatures in a safe range (Hanna & Tait, 2015).

2.3.2 Thermal comfort

How individual experience heat is often discussed in a related but separate body of research on thermal comfort. Defined as "the state of mind that expresses satisfaction with the thermal environment" (ASHRAE, 2004), thermal comfort is a combination of both a physiological sensory and psychological experience (Parsons, 2003). The concept of thermal comfort arose from the field of architecture and HVAC (heating, ventilation, and air conditioning) engineering, with emphasis on the regulation of indoor environments. Although the basic principles are universal, many different types of thermal comfort models and standards have been developed in efforts to predict what is determined as "thermally comfortable" (de Dear et al., 2013). These models will not be discussed in detail in this thesis.

The subjective perception of thermal sensation can vary between individuals as to what feels uncomfortably cold to uncomfortably hot (Parsons, 2003). In hot and humid environments, field studies have found participants to be comfortable up to temperatures 30°C and above, as people may have adapted to their thermal environments (further discussed in Section 2.4.2), and also potentially adjusted their activity levels (Nicol, 2004). However, most thermal comfort studies have focused on sedentary individuals, with few studies having assessed the thermal comfort during physical activity (Kenny, Warland, Brown, & Gillespie, 2009). Participants conducting physical activity in experimental and natural observational studies reported warmer thermal sensations but were not necessarily at a discomfort, suggesting a broader comfort zone compared to sedentary individuals due to psychological explanations of expectancy and perceived control (Kenny et al., 2009; Lin, Tsai, Liao, & Huang, 2013). However, the natural observational studies also found that park attendance of unshaded high-intensity-activity areas was negatively correlated with temperatures during the hot season in Taiwan, such that there were often less than 10 or even zero in attendance in air temperatures >30°C (Lin et al., 2013). This suggests that people may seek to reduce thermal discomfort by moving to shaded areas (Lin et al., 2013), or by avoiding the park entirely. Overall, the field of thermal comfort aims to harness the built environment to create conditions of comfortable thermal environments for people, whether indoor and outdoor.

2.3.3 Adverse health outcomes of heat

The continual storage of heat, whether from physical activity or hot environmental conditions, would lead to potentially dangerous increases in core body temperature and heat strain (Flouris & Schlader, 2015). When the core body temperature exceeds 38°C, the body becomes sluggish and it becomes difficult to concentrate (Kjellstrom et al., 2010). Heat exposure increases the risk of heat-related disorders such as heat cramps, heat exhaustion, and heatstroke (Kenny et al., 2010; Kovats & Hajat, 2008). Particularly, exertional heat-related illnesses (EHRI) are a spectrum of illnesses occurring during exercise in hot and humid conditions (McGregor & Vanos, 2018; Nichols, 2014). Types of EHRI, ranging from mild to more severe, include heat edema, heat rash, exercise-associated collapse, muscle cramps, heat exhaustion, exercise-associated hyponatremia, exertional rhabdomyolysis, and exertional heatstroke (Nichols, 2014). A heatstroke (exertional or not) is life-threatening, as core body temperatures exceed 40°C and the body experiences central nervous system dysfunction, skeletal muscle injury, and multiple organ damage (Kovats & Hajat, 2008; Nichols, 2014). The amount of damage on the body depends on the duration of time the core body temperature is elevated. Without the ability to cool down the core body temperature, exposures to extreme heat can lead to undesired mortality.

The heat effects on health are aggravated by an ageing population and an increase of non-communicable diseases, as heightened risk of heat-related illnesses has been found among these two populations. Among older persons, the capacity to thermoregulate and dissipate heat is known to decrease with age, for those over 60 years old (Kenny et al., 2010) and as early as 40 years old (Larose et al., 2013). Older adults experience age-related reductions such as lower sensitivity to heat exposure, lower sweating ability, reductions in skin blood flow, and reduced cardiac output (Balmain, Sabapathy, Louis, & Morris, 2018; Kenny et al., 2010). Among people with pre-existing NCDs, such as obesity, hypertension, cardiovascular disease, respiratory disease, and diabetes mellitus, there is also increased vulnerability due to impaired thermoregulatory responses (Kenny et al., 2010). This increases their risk for heat-related illnesses and even death when conducting physical activity in hot weather (Balmain et al., 2018).

2.4 Macro-influences on temperature that change the human experience

This section will discuss three areas that change or are changing the human experience of temperature, including urbanization (Section 2.4.1), adaptations to local climates (2.4.2), and climate change (2.4.3 and 2.4.4). The trends of urbanization and climate change (Mora et al., 2017) will further exacerbate the heat-health impacts mentioned previously in Section 2.3.3, particularly if interventions in the built environment do not take the effect of temperature into account (Vanos et al., 2010).

2.4.1 Urbanization

Urbanization has increased in the past decades such that 55% of the global population lived in urban areas by 2018 (United Nations DESA, 2019). Compared to rural areas, urban areas undergo more development and man-made design. Man-made surfaces of buildings and pavements in these urban environments absorb and retain heat more readily than natural surfaces and vegetation (Vanos et al., 2010). Many urban environments experience an 'urban heat island' (UHI) effect, whereby temperatures are higher than rural areas by several degrees (Galea & Vlahov, 2005). This may lead to an increased risk of thermal discomfort and the health impact of heat. Previous studies have found a higher heat-related mortality risk in urban areas (Gosling, McGregor, & Lowe, 2009).

Vegetation is one of the fundamental methods to reduce the urban heat island effect and regulate temperatures in urban areas (Lindberg & Grimmond, 2011). The experience of heat and thermal comfort may differ widely when outdoors, depending on the shade of nearby trees and buildings, and windspeed within an urban microclimate (Lin et al., 2013; Vanos et al., 2010). Street canyons without trees can produce mean radiant temperatures up to 7.0°C higher than those with trees (Vanos et al., 2010). These localized experiences due to variations in vegetation and buildings can cause varying degrees of thermal discomfort, which can in turn affect outdoor usage and the amount or intensity of human activity (Vanos et al., 2010).

An understanding of localized experiences on the effect of physical activity can support the improvement of urban design. In a study on outdoor thermal environments, seasonal differences not only affected park attendance, but also the utilization of shaded areas within a park (Lin et al., 2013). However, most studies either controlled for physical activity levels through experimental conditions or used direct observation studies and surveys in specific locations of interests, such as parks and plazas (Kenny et al., 2009; Lin et al., 2013). There is a lack of understanding about the effects of thermal conditions on physical activity levels in varying environments and greenness levels throughout a city.

2.4.2 Adaptations to local climates and climate heterogeneity

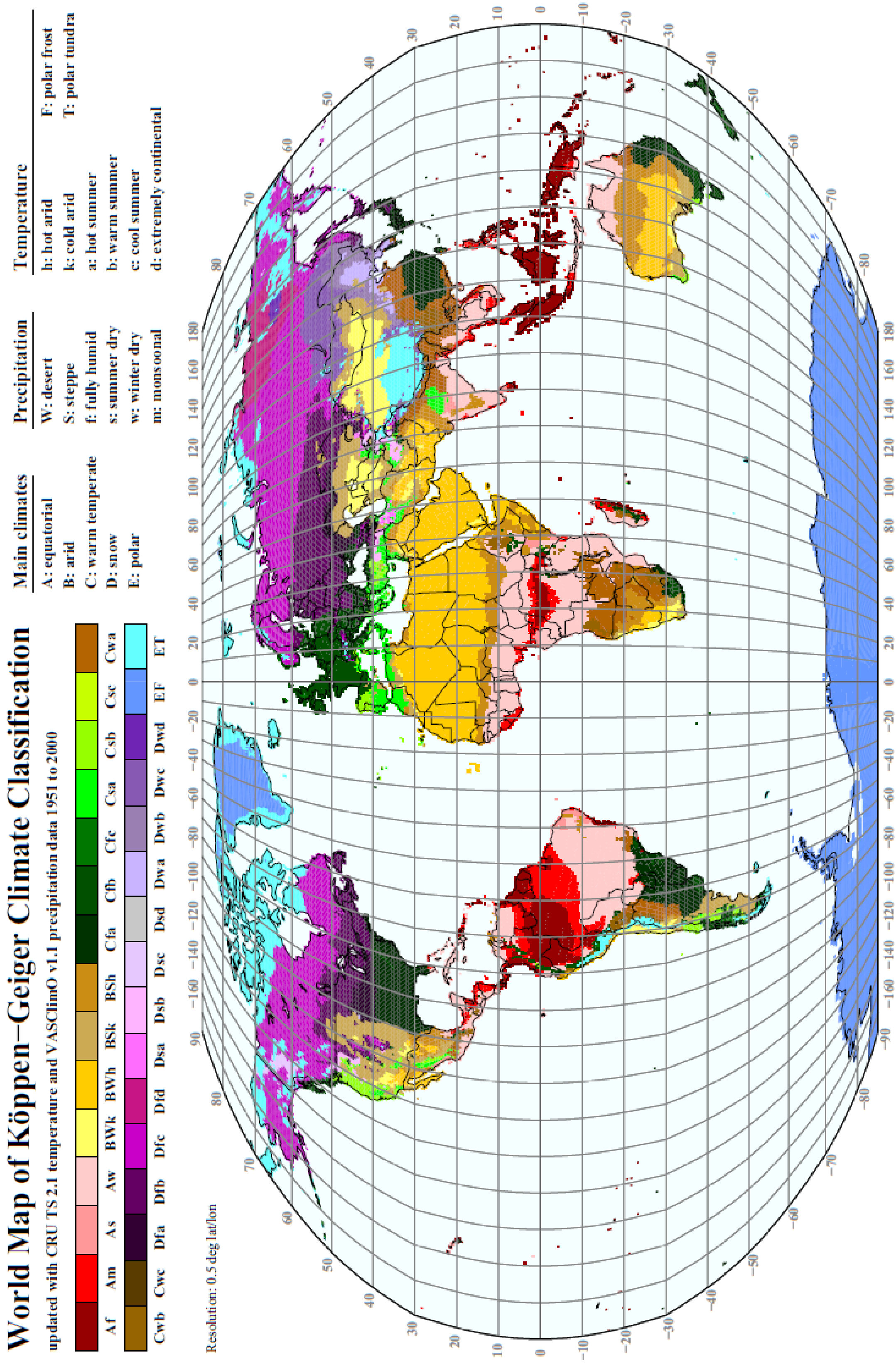
Climate is the long-term weather of a place, often averaged over a 30-year time period (IPCC, 2014). Populations have developed a tolerance to their local climates, with adaptations physiologically, behaviourally, and culturally (Hajat & Kosatky, 2010; McMichael et al., 2008). This adaptation to local climates is reflected in studies on the relationship between temperature and mortality risk, which has been found for both tropical and temperate climates (Gasparrini et al., 2015; McMichael et al., 2008). The temperature-mortality association has found heterogenous effects, whereby U, V, or J-shaped curves are found depending on geographical location (Arbuthnott et al., 2016; Gasparrini et al., 2015; Hajat & Kosatky, 2010; Kovats & Hajat, 2008; McMichael et al., 2008).

In a meta-regression, a country's average temperature and temperature range were identified as factors determining the heterogeneity of temperature-mortality associations (Gasparrini et al., 2015). Studies have shown higher heat thresholds occur in locations with warmer climates and higher summertime temperatures (Arbuthnott et al., 2016; Hajat & Kosatky, 2010; McMichael et al., 2008). For example, in the subtropical city of Hong Kong, mortality increased by 1.8% for every 1°C increase above 28.2°C (Chan, Goggins, Kim, & Griffiths, 2012). When comparing percentile temperatures, however, Gasparrini et al. (2015) found a lower threshold for percentile temperatures in tropical areas compared to temperate regions, with the minimum mortality temperature at the 60th percentile, and 80-90th percentile, respectively. The heterogeneous effects of climate may additionally demonstrate differences in population susceptibility, as an increased temperature-mortality risk was also found associated with older age distribution, higher population density, and decreased GDP among cities (Hajat & Kosatky, 2010).

A climate classification system could be used to assess the heterogeneity of climates globally. The Köppen climate classification was the first quantitative classification of world climates, and still widely used today in teaching and research (Kottek et al., 2006; Peel, Finalayson, & McMahon, 2007). There are three variations, the Köppen-Geiger classification developed by Kottek 2006 (Kottek et al., 2006), the updated version by Peel 2007 (Peel et al., 2007), and the Köppen-Trewartha classification by Belda 2014 (Belda, Holtanová, Halenka, & Kalvová, 2014). The Köppen-Geiger classification by Kottek produced the first digital world map (Belda et al., 2014), enabling accessible identification for any location. It has been used in previous systematic reviews on temperature effects of mortality and morbidity among elderly (Bunker et al., 2016). Furthermore, it has been used to classify studies on human thermal comfort (Mishra & Ramgopal, 2013; Yang & Matazarakis, 2015), and was recently connected with the Sustainable Development Goals (SDGs) (Yang & Matzarakis, 2019).

The Köppen-Geiger climate classification will be applied as a tool to support the understanding of heterogeneity in this thesis. As displayed in Figure 2.2, the classification system (Kottek et al., 2006) was constructed on vegetation zones, with the first letter indicating the zone: A (equatorial/tropical), B (arid), C (warm temperate), D (snow), and F (polar). The second letter indicates the precipitation which can be divided into: W (desert), S (steppe), f (fully humid), s (summer dry), w (winter dry), and m (monsoonal). The third letter indicates the air temperature of the climate area: h (hot arid), k (cold arid), a (hot summer), b (warm summer), c (cool summer), d (extremely continental), F (polar frost), and T (polar tundra). The three letters combine to form a specific climate classification for any location globally. Figure 2.3 displays the classification criteria of each climate using temperature and precipitation.

Figure 2.2 World map of Köppen-Geiger climate classification (1951-2000)



Source: Kottek et al. (2006)

Figure 2.3 Classification criteria for Köppen-Geiger climate classification

Classification criteria for the first two letters

Type	Description	Criterion
A	**Equatorial climates**	$T_{min} \geq +18\ °C$
Af	Equatorial rainforest, fully humid	$P_{min} \geq 60$ mm
Am	Equatorial monsoon	$P_{ann} \geq 25\,(100 - P_{min})$
As	Equatorial savannah with dry summer	$P_{min} < 60$ mm in summer
Aw	Equatorial savannah with dry winter	$P_{min} < 60$ mm in winter
B	**Arid climates**	$P_{ann} < 10\,P_{th}$
BS	Steppe climate	$P_{ann} > 5\,P_{th}$
BW	Desert climate	$P_{ann} \leq 5\,P_{th}$
C	**Warm temperate climates**	$-3\ °C < T_{min} < +18\ °C$
Cs	Warm temperate climate with dry summer	$P_{smin} < P_{wmin}$, $P_{wmax} > 3\,P_{smin}$ and $P_{smin} < 40$ mm
Cw	Warm temperate climate with dry winter	$P_{wmin} < P_{smin}$ and $P_{smax} > 10\,P_{wmin}$
Cf	Warm temperate climate, fully humid	neither Cs nor Cw
D	**Snow climates**	$T_{min} \leq -3\ °C$
Ds	Snow climate with dry summer	$P_{smin} < P_{wmin}$, $P_{wmax} > 3\,P_{smin}$ and $P_{smin} < 40$ mm
Dw	Snow climate with dry winter	$P_{wmin} < P_{smin}$ and $P_{smax} > 10\,P_{wmin}$
Df	Snow climate, fully humid	neither Ds nor Dw
E	**Polar climates**	$T_{max} < +10\ °C$
ET	Tundra climate	$0\ °C \leq T_{max} < +10\ °C$
EF	Frost climate	$T_{max} < 0\ °C$

Classification criteria for the third letter

Type	Description	Criterion
h	Hot steppe / desert	$T_{ann} \geq +18\ °C$
k	Cold steppe /desert	$T_{ann} < +18\ °C$
a	Hot summer	$T_{max} \geq +22\ °C$
b	Warm summer	not (a) and at least 4 $T_{mon} \geq +10\ °C$
c	Cool summer and cold winter	not (b) and $T_{min} > -38\ °C$
d	extremely continental	like (c) but $T_{min} \leq -38\ °C$

For more information, see source paper Kottek et al. (2006)
T = temperature; T_{ann} = annual mean, T_{mon} = month mean, T_{max} = monthly mean of warmest month, T_{min} = monthly mean of coldest month
P = precipitation; P_{ann} = annual accumulated, P_{min} = cumulative of driest month, P_{max} = cumulative of wettest month; P_s/P_w = within the summer/winter half-years, P_{th} = dryness threshold

2.4.3 Climate change and its health impact

Climate change is a change of climate that is attributed directly or indirectly to human activity that alters the composition of the global atmosphere and that is in addition to natural climate variability observed over comparable time periods (United Nations, 1992). Changes in the climate system have been and will continue to affect global temperatures, precipitation variability, mean sea levels, and extreme weather events. Globally, there has been an increase in number of warm days and night, frequency of heat waves, as well as the number of heavy precipitation events (IPCC, 2014). In the 21st century, global surface air temperatures will continue to rise, with more frequent and longer heat waves (IPCC, 2014). At least a 1.5°C increase is projected to occur by 2081 – 2100, compared with 1850 – 1900 levels (IPCC, 2014). More frequent heavier precipitation events are projected in high latitude, wet mid-latitude, and tropical regions, while mid-latitude and dry subtropical regions will likely experience a decrease in precipitation (IPCC, 2014). The impact of extreme weather events, such as flooding, droughts, and cyclones, will also increase in the future, disrupting and damaging ecosystems and human systems (IPCC, 2014).

It is estimated that in 2000, climate change was responsible for 5.5 million disability-adjusted life years (DALYs) (Costello, Grant, & Horton, 2008). The health impacts of climate change can be broken down into direct and indirect impacts, mediated by ecosystems and human institutions (Watts et al., 2018). The direct impacts include the higher risk of mortality and morbidity from high temperatures, exacerbations of chronic diseases from heat exposure, as well as injuries related to extreme weather events and wildfires (IPCC, 2014; Kjellstrom et al., 2010; Smith et al., 2014). The indirect impacts include increased infectious disease risks from vectors and zoonotic hosts, greater food insecurity and its impact on nutrition, increased risk of water-borne diseases, and hygiene and sanitation limitations due to drought or flood conditions (Costello et al., 2008; IPCC, 2014; McMichael, 2013). Mental health problems will also increase from disaster events, climate-related displacement, or livelihood impacts (McMichael, 2013). Particularly in urban areas, climate change will affect people through profound impacts on the city's infrastructure and services, with increasing risks of water scarcity, energy insecurity, and damaged housing (IPCC, 2014).

The direct "health effects of temperature change" is an important indicator in the recent Lancet Countdown on health and climate change (Watts et al., 2018). In hot temperatures, the temperature-mortality risk rises steeply, while the risk is usually more linear for cold temperatures (Gasparrini et al., 2015; McMichael et al., 2008). Hajat & Kosatky (2010) additionally found that locations with higher temperature thresholds was associated with larger heat effects. The exact physiological effects causing heat-related deaths are not yet well established and vary according to different mortality causes (Gasparrini et al., 2015; Hajat & Kosatky, 2010). However, physiologically speaking, extreme heat and cold put pressure on the cardiovascular and respiratory systems, which are often cited as underlying reasons (Hajat & Kosatky, 2010). Similar morbidity impacts were found for heat-related diseases, diabetes, and cerebrovascular, respiratory, and genitourinary diseases, particularly among elderly (Bunker et al., 2016; Song et al., 2017). Increased emergency admissions for respiratory and renal diseases have also been found in higher temperatures, due to dehydration from sweating and inadequate fluid intake (Kjellstrom et al., 2010; Kovats & Hajat, 2008). Overall, higher susceptibility and vulnerability to heat-related outcomes are found among those with frailty, mobility disabilities, dementia, Parkinson's disease, or other illnesses that compromise the body's thermoregulation capacity (Kovats & Hajat, 2008). Higher heat exposure is also associated with reduced work capacity and labour productivity, particularly for outdoor work (IPCC, 2014). Although the impacts of heat and climate change may also affect health behaviours and day-to-day activities of the population, few studies have begun looking at the effects on health behaviors during extreme temperatures, such as help-seeking behavior, information acquisition, and physical activity (Chan, 2019; Stamatakis et al., 2013).

2.4.4 The connection with our climate change response

There are two main responses to climate change: mitigation and adaptation. Mitigation seeks strategies to reduce greenhouse gas emissions in efforts to limit climate change (IPCC, 2014). Adaptation is the process of adjustment to actual or expected climate and its effects. In human systems, adaptation seeks to moderate or avoid harm or utilize beneficial opportunities (IPCC, 2014). Both mitigation and adaptation strategies will help to improve sustainable development, the creation of climate-resilient pathways that support livelihoods, improve socio-economic well-being, and manage the environment (IPCC, 2014). This is also known as the concept of co-benefits, whereby a climate change adaptation or mitigation strategy has additional, positive effects on health or other areas (Spickett, Katscherian, & Brown, 2015).

Adaptation has been argued as the more urgent task for the health sector, as it focuses on identifying the threats to population health, promoting risk reductions, and contributing to the wellbeing of the current population (Ebi, 2011; IPCC, 2014; McMichael, 2013). Adaptation strategies reduce the exposure and vulnerability to climate-related hazards in efforts to prevent adverse health impacts (Huang et al., 2011; IPCC, 2014). Spontaneous or autonomic adaption is when the adaptation occurs reactively to the change in circumstances (Huang et al., 2011). Planned adaptation is where the conscious changes are made to anticipated climate change impacts. Adaptation measures can cover a wide range of sectors and approaches, but their effectiveness depends on local contexts. Both passive heat avoidance and active adaptive management strategies are needed to combat the health effects of excessive heat (Ebi, 2011). Commonly discussed positive adaptations to heat include early heat warning systems, passive cooling of buildings, green infrastructure, and other built environment improvements to reduce heat stress (IPCC, 2014). Maladaptation, on the other hand, increases the vulnerability and harm of climate-related hazards due to poor planning, failure to anticipate consequences, or seeking short-term benefits in face of long-term damage (IPCC, 2014). An increased use of air conditioning can be considered maladaptive and have an adverse side effect of increasing energy demand and greenhouse gas emissions (unless clean energy sources are used).

Both mitigation and adaptation policy measures will have implications on health (Friel et al., 2011), however their recommendations may have contradictory effects between hot temperatures and physical activity. Related to physical activity, a common mitigation strategy has been the promotion of active travel (walking and cycling trips). Active travel would not just mitigate the amount of greenhouse gases emitted from vehicular transport, but also provide co-benefits of reduced air pollution, traffic congestion, road accidents, and increased population-level physical activity (Bull & Bauman, 2011; de Nazelle et al., 2011). In the long run, active travel could help prevent non-communicable diseases, by reducing the risk of cardiovascular diseases, cancer, mental health, and other NCDs (Friel et al., 2011). Despite the benefits, however, the promotion of active travel may also expose the population to adverse weather conditions. During active travel, the exposure to heat (due to physical exertion) and UV radiation would increase, modified by factors such as cloud cover and the presence of tree canopies (de Nazelle et al., 2011). However, no studies on active travel policies have addressed the effect of heat exposures (de Nazelle et al., 2011).

In terms of heat adaptation, health-related messages for heatwave warnings often focus on heat avoidance (Kovats & Hajat, 2008). Common recommendations listed on health or weather-related organizations globally include to “stay indoors in air-conditioned environments”, “avoid or reduce physical activities”, and “avoid going out during the hottest part of the day”, among others (Hajat et al., 2010). Although necessary measures, the increased amount of time indoors and reduced physical activity may also have unintended consequences of adverse health effects (Gronlund et al., 2018). Reduced physical activity could increase people’s susceptibility to heat, through increased risk of cardiovascular disease, social isolation, and poor mental health (Cheng & Berry, 2013). Thus, a negative feedback cycle could develop where increased heat would lead to decreased physical activity, which further increases risk of heat-related health outcomes.

2.5 Measurement of physical activity

The measurement of physical activity can be conceptualized by the frequency, duration, type, and intensity of physical activity (Spinney & Millward, 2011; World Health Organization, 2010). Frequency indicates the number of activity sessions per time period. Duration addresses the length of time per session. The type of physical activity refers to the mode of physical activity which addresses different aspects of physical fitness, such as aerobic, strength, flexibility, and balance. Intensity is the amount of energy or effort, whether measured or estimated, used to perform the physical activity. Intensity is usually measured using Metabolic Equivalent of Task (MET), which quantifies the energy expenditure of activities using the resting metabolic rate (3.5 ml O_2/kg/min) as the basic unit (Jetté, Sidney, & Blümchen, 1990). Physical activity can be categorized from light-intensity activities (such as sitting and standing), to moderate- (such as walking and sweeping the floor), and vigorous-intensity exercises (such as running and carrying heavy loads) (Ainsworth et al., 2011).

Physical activity occurs under the following domains: occupational, transport, household (domestic), and leisure physical activity (Bull & Bauman, 2011). Overall physical activity addresses the total physical activity of an individual regardless of domain. Leisure-time physical activity may include what is typically thought of as physical activity: sports and exercise, which are planned structured and repetitive movements with aims to improve physical fitness (Caspersen et al., 1985). Oftentimes, research on physical activity focus on overall physical activity or one specific domain. Currently the measurement of multiple PA domains is only feasible through subjective surveys.

Research methods and instruments can be used to measure physical activity of individuals and of populations, including indirect self-reported recall, direct observation, or direct measurement of accelerometers and pedometers (Ainsworth et al., 2011; Chan & Ryan, 2009; Strath et al., 2013). Short-term recall questionnaires such as International Physical Activity Questionnaire (IPAQ) or Global Physical Activity Questionnaires (GPAQ) have had world-wide usage and collect population-wide estimates of physical activity levels in global surveillance projects. Self-reported time logs or diaries record the activities conducted by the participant over a certain period. Self-reported measurement methods are feasible for population-level data collection and can classify physical activity according to domain; however, they are subject to recall bias and over- or under-estimation of actual physical activity levels (Hallal et al., 2012; Prince et al., 2008). While there is higher reliability for vigorous-intensity activities, oftentimes light-to-moderate activities are underreported (Hallal et al., 2012).

Objective measurement methods, on the other hand, do not rely on recall and can provide accurate assessments in free-living conditions (Sasaki, da Silva, Gonçalves Galdino da Costa, & John, 2016). Direct observation methods count the number of persons conducting physical activity at the particular locations of interest, such as recreational facilities, parks, jogging trails, and pedestrian sidewalks for adult populations. However, this only produces aggregated counts of site-specific physical activity and is unable to trace the overall levels of an individual's physical activity. Wearable monitors such as pedometers and accelerometers can track the physical activity of an individual. Pedometers assess step counts, a fundamental unit of human ambulatory activity (Bassett, Toth, LaMunion, & Crouter, 2017). Accelerometers can additionally measure intensity of the movement as well, calculated as accelerometer counts or converted into METs. While ambulatory-related activities, such as sitting, standing, walking, and running, are accurately recognized (Bort-Roig et al., 2014), these wearable monitors cannot identify the type of physical activity conducted, nor capture activities of cycling, aquatic and upper-body activities (Strath et al., 2013). Assessments are furthermore limited by the number of devices and thus few studies have assessed pedometer or accelerometer data at a large population scale, particularly for long assessment periods of the same individuals (Al-Mohannadi et al., 2016; Hino, Lee, & Asami, 2017).

Smartphone accelerometer applications have been increasingly used as convenient instruments in population studies and are validated for their accuracy (Hekler et al., 2015; Presset, Laurenczy, Malatesta, & Barral, 2018). The use of smartphones has been adopted globally, with the number of users rising from 2.5 billion in 2016 to 3.5 billion in 2020 (Newzoo, 2020). Over 154,887 and 103,376 health- and fitness- related applications are currently available on the Apple and Android smartphone application markets, respectively (AppBrain, 2020; pocketgamer.biz, 2020). With the ability to collaborate with mobile application developers, smartphones can provide an accessible way to collect data on participants' physical activity without having to invest in the devices (Aral & Nicolaides, 2017; Vanky et al., 2017). Additionally, smartphones applications can more accurately assess day-to-day or hour-to-hour variations in physical activity compared to self-reported questionnaires or time diaries. A systematic review found that the accuracy of smartphone physical activity measurements ranged from 73-100% regardless of phone placement (n= 10 studies) (Bort-Roig et al., 2014). The accuracy may be limited to a narrow scope of activity, however, as lower activity recognition was found for stair climbing (52-79% accuracy) (Bort-Roig et al., 2014). Harnessing the phone's in-built GPS and accelerometery services, smartphones can provide objective real-time measurements of location-specific physical activity. Smartphones could serve as appropriate instruments for acquiring longitudinal physical activity assessments from population-wide samples in free-living environments.

2.6 The need to understand how temperatures affect physical activity

Physical activity is an important aspect of disease prevention and health promotion. However, an insufficient amount of physical activity means many of these benefits have not been realized in the general population. An increase in physical activity at the population level is necessary to support a reduction in non-communicable diseases worldwide (Section 2.1). Research has focused on many theories and correlates of physical activity in efforts to develop effective interventions (Section 2.2). Focusing on environmental correlates can strengthen the development of supportive environments that encourage physical activity in the community (World Health Organization, 1986, 2013).

The association of temperature on physical activity have been less researched than spatial-related environmental correlates, despite often being cited as a barrier to physical activity in qualitative studies (Section 2.2). However, the effects of temperature are important to understand since heat has physiological effects on the body (Section 2.3.1), which is further exacerbated by engaging in physical activity. Excess heat increases thermal discomfort (Section 2.3.2) and places the body at risk of heat-related illnesses and even mortality (Section 2.3.3). In hotter temperatures, physical activity may be affected due to a physiological reduction of work rate and a lack of personal motivation to engage in physical activity (Sabel et al., 2016). This can result in 'spontaneous adaptations' of lower physical activity at the population level and lead to detrimental health consequences across the population in the future (Townsend et al., 2003). Yet, the understanding of physical activity in hot temperatures has received less attention than cold temperatures.

Particularly with climate change, there is a need to be aware of temperature associations of physical activity in order to develop effective interventions. Climate change will pose increasing challenges to the health sector and public health (Section 2.4.3). Currently, reports on climate change and health rarely address potential consequences on physical activity (IPCC, 2014; Watts et al., 2018). In the field of public health, likewise, physical activity promotion guidelines were scarcely found to address the effect of heat (66th World Health Assembly, 2013; Balmain et al., 2018; World Health Organization, 2016). The nature and extent of the relationship between climate change and physical activity has been under-discussed and under-researched (Stamatakis et al., 2013; Townsend et al., 2003). It is important to ensure climate mitigation and adaptation responses minimize adverse health impacts (Section 2.4.4; (Townsend et al., 2003)). Furthermore, climate adaptations should be "integrated... into existing health promotion and protection activities" (Huang et al., 2011). The more that is understood about the full range of potential climate impacts, the better populations would be able to prepare for the challenge of climate change (Obradovich & Fowler, 2017).

By understanding and quantifying the association of temperature on physical activity, evidence can be built to construct appropriate public health and climate policies, and additionally harness the design of supportive urban environments. However, most studies have focused on the effects of cold temperatures in temperate climates, while warm climates have previously been largely ignored (Tucker & Gilliland, 2007). As found in the research on the relationship between temperature and mortality, climates have heterogenous effects on populations because of cultural and behavioral adaptations, and differences in susceptibility (Section 2.4.2). Studies should be conducted to understand the associations of temperature on physical activity in a variety of climatic zones (Chan & Ryan, 2009). Previously, variations in the study populations and physical activity measurements of studies have restricted the ability to draw conclusive evidence (Section 2.2). Providing consistency in study populations and study methodology could support a more rigorous understanding of the differences between locations.

Urban microclimates may lead to variations in temperatures depending on characteristics of the built environment and vegetation (Section 2.4.1). These variations can affect thermal discomfort and amount of physical activity conducted in a localized area (Vanos et al., 2010). However, rarely have studies assessed the joint associations of spatial and temporal environmental correlates on physical activity. An increased understanding of the temperature effects of varying greenness levels could support the development of suitable urban design policies.

Extreme temperature events may also be an important consideration. Despite the sparse occurrence of these extreme temperatures, the subsequent effect on health may be greater than moderate temperatures, as seen in temperature-mortality studies (Gasparrini et al., 2015; Hajat et al., 2006). Additionally, with climate change, these extreme temperatures will occur more frequently, especially extreme heat (IPCC, 2014). Physical activity studies should seek to understand the effects of extreme temperature events.

Those with NCDs are less likely to be physically active, yet physical activity is beneficial towards the prevention and management of NCD conditions (Section 2.1). Although a person's health status has been identified as a consistent correlate for physical activity in general (Bauman et al., 2012), it is uncertain whether it may also affect the relationship between temperature and physical activity (Robbins, Jones, Birmingham, & Maly, 2013). Particularly, those with chronic diseases may be hindered by temperature differently than those without (Section 2.3.3). An understanding of how health may affect the relationship between temperature and physical activity is necessary to protect those who may be most vulnerable.

Although the focus of this thesis is about the associations of temperature and extreme temperature events on physical activity, humidity and other weather factors may have synergistic effects with temperature and should be taken into consideration when assessing health effects of heat (Hajat et al., 2010). In reality, weather conditions occur simultaneously, and humans respond to the entire weather circumstance (Merrill et al., 2005). Air temperature, radiant temperature, humidity, and air movement all affect the body's ability to maintain heat balance (Parsons, 2003). Higher relative humidity has been shown to require lower temperatures to become lethal (Mora et al., 2017). Heat stress indices have been developed to combine temperature with humidity and other factors to estimate the heat perceived by an individual. These include heat index, apparent temperature, net effective temperature, wet-bulb globe temperature, universal thermal climate index (UTCI), among others (McGregor & Vanos, 2018). Apparent temperature, also known as "feels-like" temperature, measures the "relative discomfort from combined heat and high humidity" (Kenny, Flouris, Yagouti, & Notley, 2019), hence it can be used to estimate the effect on the human body during physical activity.

Chapter 3 Expanding on the thesis research questions

As demonstrated in Chapter 2, there is still much to be understood about the associations of temperature on physical activity in urban adult populations. In order to fill the research gaps mentioned in Section 2.6, this thesis aims to address the following research questions, which was originally stated in Section 1.2 and summarized below in Table 3.1.

Table 3.1 Summary of research questions in this thesis

Research Questions	**Answered through...**
1. What is the current research evidence regarding the relationship between temperature and physical activity?	Chapter 4
2. How does the association of temperature on physical activity vary between cities of different climates?	Chapter 5 and 6
3. How does the association of temperature on physical activity vary within cities at different greenness levels?	Chapter 6
4. What is the effect of extreme temperature events (extreme cold and heat) on physical activity?	Chapter 7
5. How does health influence the effects of temperature on physical activity?	Chapter 7

Research Question 1. What is the current research evidence regarding the relationship between temperature and physical activity?

As previous reviews on weather and physical activity were conducted in 2007 and 2009 (Chan & Ryan, 2009; Tucker & Gilliland, 2007), an assessment should be made to understand the latest research on the relationship between temperature and physical activity. An updated systematic review (Chapter 4) will increase the understanding of the global evidence and the variations found in different countries and climates. This study would further provide insights as to study methodologies, enabling an understanding of the robustness and research gaps from current studies. The hypothesis is that despite variations between locations of different climates, an overall curvilinear relationship will define the association between temperature and physical activity, whereby cold and hot temperatures will lead to decreased physical activity.

Research Question 2. How does the association of temperature on physical activity vary between cities of different climates?

There has been difficulty to conclude the evidence between study locations, due to previous variations in study populations and physical activity measurements (Section 2.2). A comparison between cities in a region can increase the understanding of how the temperature-physical activity relationship may be influenced by climate. Two multi-location comparative studies using objective smartphone physical activity data were conducted in the Asian (Chapter 5) and European regions (Chapter 6). The hypothesis is that, in these two regions, cities with similar climates will have similar outcomes, while outcomes will vary between cities of different climates. Cities in colder climates may not experience decreased associations of physical activity in hot temperatures, while cities in warmer climates will have more apparent associations between hot temperatures and decreased physical activity.

Research Question 3. How does the association of temperature on physical activity vary within cities at different greenness levels?

Studies on the temperature-physical activity relationship have rarely assessed local variations within the city, such as the effects of vegetation. This has limited the understanding of how the temperature-physical activity relationship may be influenced by urban design. An hourly assessment of physical activity and GPS data from smartphones (Chapter 6) would assess the associations of temperature and greenness levels concurrently. Increasing vegetation is expected to cool down the temperatures of the immediate surrounding areas. Exposure to higher greenness levels, a proxy for vegetation, might increase the tolerance of participants to conduct physical activity even in high temperatures. The hypothesis is that higher greenness levels would be less associated with decreased effects of physical activity in hot temperatures.

Research Question 4. What is the effect of extreme temperature events (extreme cold and heat) on physical activity?

As extreme temperatures are less likely to occur than moderate temperatures, studies focusing specifically on these events may produce a clearer understanding of their effect. A prospective cohort telephone survey study in a subtropical city (Chapter 7) would examine the changes in physical activity during two extreme temperature events. The hypothesis is that physical activity would decrease more in extreme heat compared to extreme cold.

Research Question 5. How does health influence the effects of temperature on physical activity?

Those with health conditions such as NCDs acquire greater benefits from physical activity but may be less likely to be active. Different NCDs may also vary in how they are affected by temperatures. Understanding how health may affect the temperature-physical activity relationship would support the development of suitable policies for those who may be more at harm by a reduction in physical activity. The cohort telephone survey from the previous research question (Chapter 7) would identify health conditions related to the temperature-physical activity relationship. The hypothesis is that suboptimal health would be associated with reduced physical activity, particularly those with cardiovascular and respiratory diseases.

Answering these research questions can build the evidence necessary to propose and support suitable interventions and policies. This can strengthen the ability of communities to develop supportive environments that enable sustainable levels of physical activity in urban adult populations, regardless of how climate change may affect temperatures.

Chapter 4 Systematic review on the associations of temperature on physical activity in adult populations – Study (1)

4.1 Introduction

Climate change (temperature, rainfall etc.) impact varies by region. Regional variations also occur in population adaptation of local climates, as seen in the variation of temperature thresholds found in previous temperature-mortality studies. It is important to understand the findings of temperature-physical activity patterns globally. Previous systematic reviews on the relationship between weather and physical activity were conducted in 2007 and 2009 (Chan & Ryan, 2009; Tucker & Gilliland, 2007), when the research field was just emerging. This systematic review aims to update the evidence on the relationship between temperature and physical activity in published literature. A global classification method would be useful to assess the identified studies and develop the understanding of heterogenous effects. This study will use both regional location and the Köppen-Geiger climate classification, as mentioned in Section 2.4.2, to categorize the findings on temperature.

4.2 Methodology

Databases and search strategy

10 English electronic databases were included in this systematic review literature search: CINAHL, PubMed, Scopus, Web of Science, ScienceDirect, Embase, Ovid MEDLINE, PsycINFO, and SportDiscus. Since a previous systematic review by Tucker and Gilliland identified studies between 1980 and 2006, this systematic review focus on papers published on or after 2006 in the 10 electronic databases. Chinese articles were searched from two databases the China Academic Journals Full-text Database and Wanfang. Additionally, reference lists of included studies, and non-indexed journals (such as Nature Climate Change) would be searched and considered for inclusion. Relevant studies from the previous review(s) were also included. An updated search was conducted to include the latest research in all the English and Chinese databases.

Key search terms were:

- weather OR meteorological OR "extreme temperature" OR rain* OR precipitation, AND
- "physical activity" OR exercise OR walking OR sport*
- 气温， 天气， 气象， （降）雨量， 温度， 湿度， 风速，高温， 气候
- 运动，体育， 步行， 步数，体力活动， 户外活动

A full description of the terms and search strategy used for each database is further described in Appendix A1. Although temperature is the meteorological exposure of primary interest, the terms “temperature” and “heat” were not included as stand-alone terms in the English search. A preliminary search with those search terms demonstrated an exponentially increased number of articles. However, many extraneous articles were from the field of physiology but not applicable to the aims of this review. On the other hand, the use of “weather” and “extreme temperature” returned the studies that were applicable to study aims and assessed the associations of temperature. In previous reviews, Tucker and Gilliland (2007) and Chan and Ryan (2009) had also excluded temperature as a search term, but their review findings likewise incorporated studies with temperature results.

Study eligibility criteria

The search adhered to the following inclusion criteria: (1) original empirical peer-reviewed research articles written in English or Chinese language, (2) objective measurement of temperature and other weather conditions as exposure, (3) any type of physical activity (excluding cycling) as a major outcome of the study, and (4) of the adult population. Studies would not be excluded based on study design. Studies on children under 18 were not considered because their contexts were different and usually exclusive to school settings, which is not comparable to the overall adult population. Cycling was excluded from this review since it cannot be captured in the ambulatory movements of accelerometer/ pedometer studies. In addition, cycling studies are often conducted to assess certain facility or company usage whereby many factors, such as membership and bike availability, limit and bias the variability of physical activity assessed. Furthermore, cycling is a specific sub-section of transport physical activity and travel behaviour that has a wealth of its own research (Böcker, Priya Uteng, Liu, & Dijst, 2019). A full description of the inclusion and exclusion criteria can be found on Table 4.1.

Study selection

Following the PRISMA guidelines (Moher et al., 2010), the primary author and an independent reviewer separately screened the title and abstract of all citations. Full texts were retrieved and independently assessed by the reviewers for inclusion. Any disagreements were resolved by discussion and consensus, with the help of a third reviewer if necessary.

Data extraction and analysis

Data extraction was completed for each study determined for inclusion. The extracted data included location, region, Köppen-Geiger climate classification (derived from location), whether multi-location comparisons were conducted, sample size, population type, study dates, seasons assessed, study design, PA domain, whether outdoor PA was assessed, PA data instrument, PA data duration, weather source, study timescale, statistical method, temperature range. The results of each study's main analyses were also extracted, including the PA outcome and each reported meteorological factor with their variable type (binary, categorical, linear, quadratic, graphical), effect direction (see below and in Table 4.2), and effect size. A checklist was kept on the different covariate categories that were controlled for in the main analyses of each study. A list also tracked the types of stratification and/or interactions the studies may have analysed.

The meta-analysis was not conducted due to the heterogenous nature of the studies with different physical activity outcomes. Instead, the strength of evidence was reported for the primary exposure measure of temperature. Adapted from Lachowycz and Jones (2011), this summary measure characterized the association between temperature and physical activity in each study as 1) positive, 2) equivocal (marginally significant or inconsistent results), 3) no evidence, or 4) curvilinear/negative (see Table 4.2). The identified studies were further categorized by regional location and the Köppen-Geiger climate classification in order to analyse the overall results.

Quality assessment criteria

A quality assessment was performed using a methodological quality criterion adapted from Lachowycz and Jones (2011) (see Table 4.2). Each study was scored independently by both the primary author and an independent reviewer. Discrepancies in the scoring were resolved via discussion. In this 10-item scale, items were scored as 1, 0, or N (insufficiently described), and points were summed to obtain a total score out of 10.

Table 4.1 Inclusion and exclusion criteria of the systematic review

Category	**Inclusion**	**Exclusion**
Type of paper	Original empirical research published in peer-reviewed articles, written in English or Chinese language	Non peer-reviewed articles Non original research such as reports, commentaries, and reviews
Exposure	Objectively measured temperature and other weather conditions as exposure	Weather as a barrier but not objectively measured as an exposure Only seasons or air pollution as exposure
Outcome	Any type of physical activity as outcome (cycling excluded)	Health outcomes (injuries, crashes etc.) of exercising in weather conditions Cycling studies (bike usage etc.) Effect of weather conditions on sport events/facilities/sportswear
Population type	Human adult populations	Populations under 18 years old
Methodology	Any type of study design Non-laboratory, free living environments	Studies on exercise physiology, thermoregulation, or performance Methodological or technological assessments

Table 4.2 Methodological quality criterion, adapted from Lachowycz and Jones 2011

Item	Description	Scale
1. Population – Selection bias	Are the individuals selected to participate in the study likely to be representative of the target population?	1: Likely to be representative 0: Unlikely to be representative N: Insufficiently described
2. Population – Inclusion bias	Is there evidence of bias in the percentage of selected individuals who provided data for inclusion in the analysis?	1: No evidence of bias 0: Evidence of bias N: Insufficiently described
3. Outcome measure	Was the outcome objectively measured or self-reported?	1: Objectively measured outcome 0: Self-reported outcome N: Insufficiently described
4. Exposure measure	Was the exposure a valid objective measurement and within a reasonable distance (within the same city) to the outcome location?	1: Exposure objective/nearby 0: Exposure not objective/nearby N: Insufficiently described/not validated
5. Repeated measures	Were the same participants/ locations assessed more than once over time?	1: Repeated measures 0: Not repeated measures N: Insufficiently described
6. Confounding variables	Were key potential confounding variables (demographic and time-related) adjusted for in the analysis?	1: Confounding variable adjusted 0: Confounding variables not adjusted N: Insufficiently described
7. Statistical methodology	Was an appropriate statistical methodology used (i.e. multivariable regression)?	1: Evidence of appropriate methodology 0: No evidence N: Insufficiently described
8. Reporting effect size	Was the measurement of the association reported, including effect size, confidence intervals, and the probability level (p value) for temperature variable?	1: Association/Effect size reported 0: Association/Effect size not reported N: Insufficiently described
9. Simultaneous adjustment	Were multiple meteorological variables (3+) simultaneously assessed as exposures?	1: Simultaneously analyzed 0: Not simultaneously analyzed N: Insufficiently described
10. Level of analysis	Was analysis carried out at individual level or at ecological/aggregated level?	1: Individual level 0: Ecological/aggregated level N: Insufficiently described
Strength of the evidence		
Strength of association between temperature and physical activity	1: Positive relationship, judged as a statistically significant positive relationship (using significance threshold $p \leq 0.05$) after adjustment for confounders, with 'positive' defined as health promoting (e.g. an increase in physical activity). 2: Equivocal relationship, judged as marginally statistically significant or inconsistent results (e.g. different results across sub-groups). 3: No evidence of a relationship, judged as non-statistically significant results. 4: Curvilinear/Negative relationship, judged as a statistically significant negative relationship (using significance threshold $p \leq 0.05$) after adjustment for confounders, where 'negative' is defined as health demoting (e.g. a decrease in physical activity).	

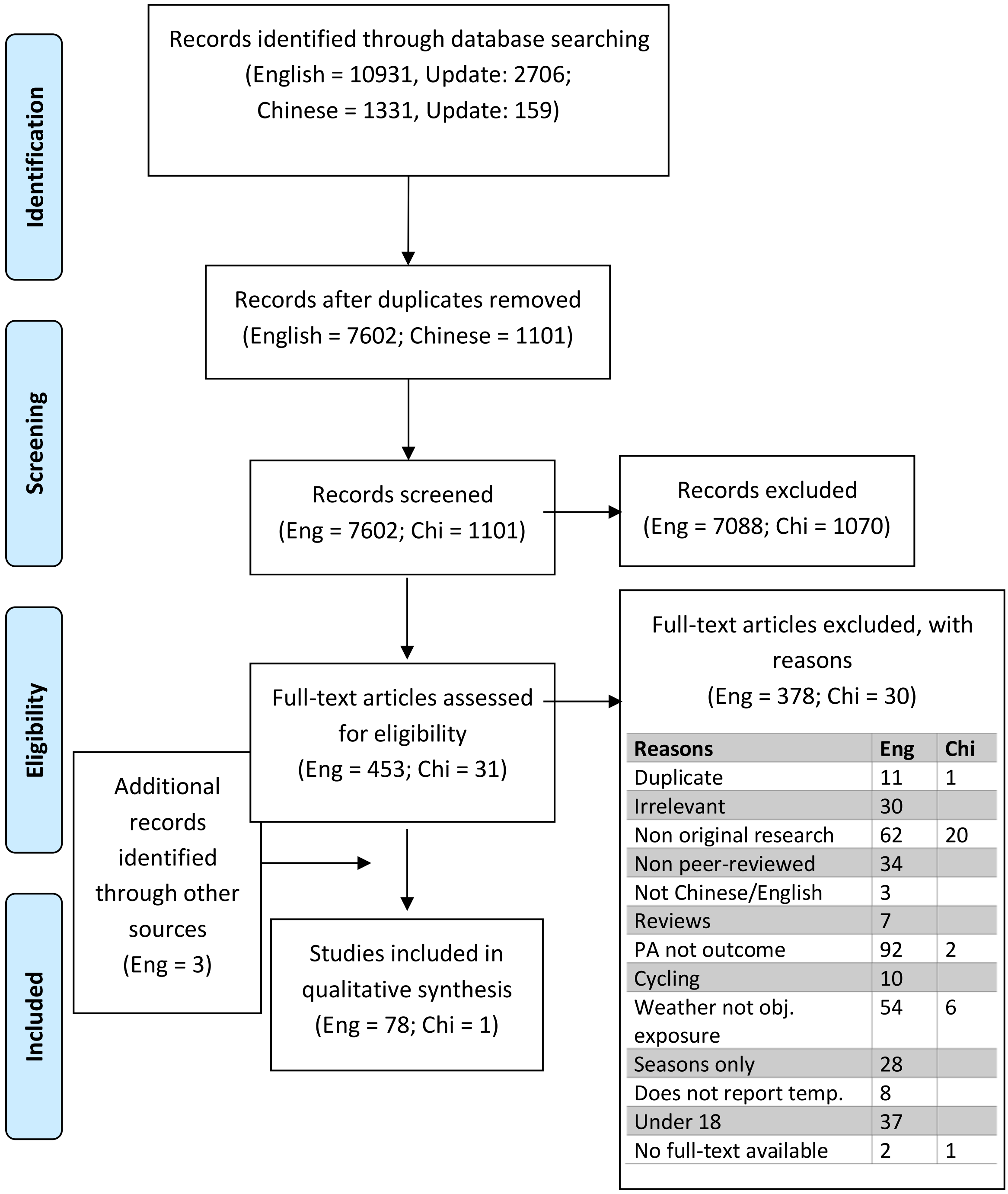
4.3 Results

The PRISMA flow diagram details the study selection process (see Figure 4.1). The systematic search was first performed on May 11, 2018 and identified 10931 references from the 10 English databases and 1331 references from the two Chinese databases. 6135 English references were screened after 4796 duplicates were removed, while 990 Chinese references were screened after 341 duplicates were removed. 367 English references and 29 Chinese references were assessed for full text from the original search. An updated search was conducted on January 2-3, 2020 and identified an additional 2706 references from the English databases and 159 references from the Chinese databases. After duplicates were removed, 1467 English references and 111 Chinese references were screened for exclusion. In the updated search, an additional 86 English and 2 Chinese references were added for assessment of full-text eligibility.

In total, the original and updated search resulted in 453 English and 31 Chinese full-text articles to be assessed for eligibility. In the original search, 62 of 367 English articles and 1 of 29 Chinese articles remained after assessing for full-text eligibility. In the updated search, 16 of 86 English articles and 0 of 2 Chinese articles remained. Three additional records were identified from the reference list of papers and included in this systematic review. Additionally, three related reviews were identified on the topic of temperature and physical activity (Böcker et al., 2019; Chan & Ryan, 2009; Tucker & Gilliland, 2007). Relevant articles from those reviews were already incorporated into this current systematic review.

In total, the search identified 79 articles for final inclusion on the relationship between meteorological conditions and physical activity, one of which was a Chinese-language paper. For each paper, only the main analyses was extracted for record in this review. However, many studies in their main analysis assessed the temperature-physical activity relationship more than once using different temperature exposures, physical activity outcomes, and/or population sub-groups. These analyses were recorded separately as different models under the same paper but considered together as one overall outcome when assessing the strength of evidence. In total, 208 temperature-physical activity models were recorded from the 79 articles.

Figure 4.1 PRISMA flow diagram of the systematic review



Reasons	Eng	Chi
Duplicate	11	1
Irrelevant	30	
Non original research	62	20
Non peer-reviewed	34	
Not Chinese/English	3	
Reviews	7	
PA not outcome	92	2
Cycling	10	
Weather not obj. exposure	54	6
Seasons only	28	
Does not report temp.	8	
Under 18	37	
No full-text available	2	1

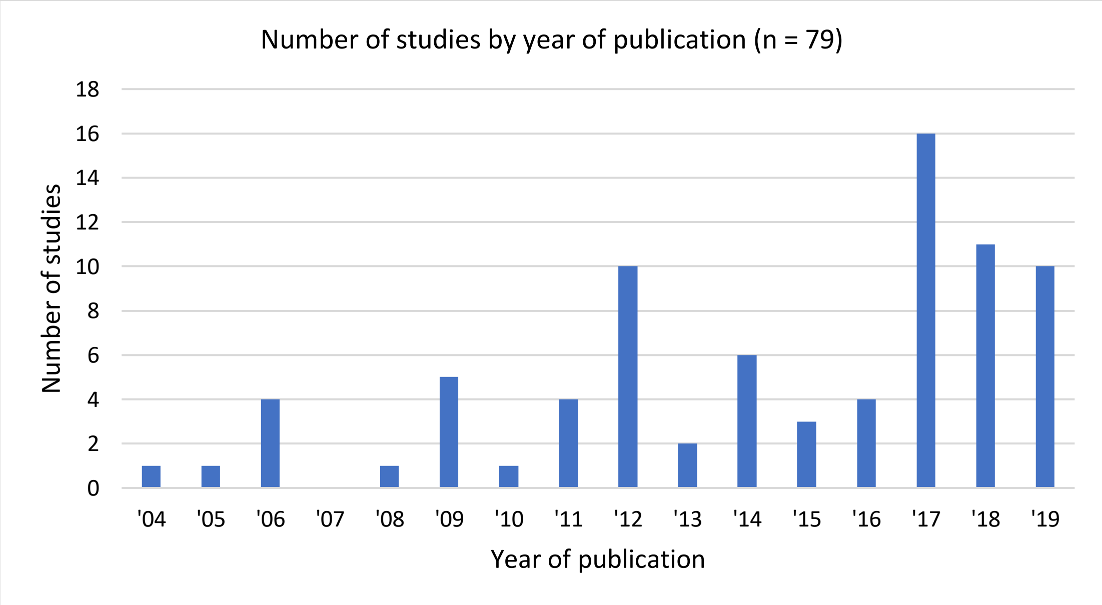
Last updated: Jan 3 2020

4.3.1 Study characteristics

4.3.1.1 Study design and population

An overview of all studies identified in this review and their data extraction results can be found in Appendix A2. There was an initial peak of published studies in 2012, while most studies were published in 2017 or after (see Figure 4.2). Objectively measured physical activity was used in three-fourths of the papers, among which accelerometers (n = 31) were more popular than pedometers (n = 8) and observational counts (n = 20). Most studies were conducted year-round (n = 57) and lasted between 1-5 years (n = 56). The majority of studies assessed associations at the daily level (n = 47), while 15 studies were conducted at the hourly level. Several other studies looked at broader timescales with weekly, monthly, seasonal, or annual temperature. Studies often used fixed effects regressions (n = 39) or multilevel modelling (n = 32), which incorporated the random effect of the individuals.

Figure 4.2 Number of identified studies by year of publication (n = 79)



Studies identified from systematic search conducted on May 2018 (and updated January 2020) in following databases: CINAHL, PubMed, Scopus, Web of Science, ScienceDirect, Embase, Ovid MEDLINE, PsycINFO, SportDiscus, China Academic Journals Full-text Database and Wanfang

Among the identified studies in this review, repeated measures was the most common study design (n = 28), assessing participants with an accelerometer/pedometer usually for 7 consecutive days each. Sometimes these studies also assessed the same participants again in subsequent waves. This enabled a rolling participation with more temperature and participant variation, while maintaining a lower burden on participants. Longitudinal studies (n = 14) tracked smaller numbers of participants with accelerometers/pedometers continuously for at least a month to more than a year. Cross-sectional studies (n = 18) often assessed large sample populations using recall time diaries or subjective surveys, such as the IPAQ or BRFSS. Aggregate-level studies (n = 19) used direct observation methods to count the volume of users at specified locations (sidewalks, trails, parks, beaches etc.), or used aggregated survey data at the county level (An, Li, & Jiang, 2017).

Most papers focused on the general or adult population (n = 47), while there were 23 papers on the elderly and 9 papers on patients. The large majority of elderly and patient studies used objectively measured physical activity. Almost all elderly and patient studies were located in Europe and North America, with two conducted in Japan (Ogawa, Seko, Ito, & Mori, 2019; Togo et al., 2005). Among them, only one study drew comparison between younger and older elderly and found that the seasonal effect of temperature was significant among the younger but not among older elderly above 75 (Cepeda et al., 2018). Patient studies largely addressed patients with COPD (Alahmari et al., 2015; Balish et al., 2017; Boutou et al., 2019; Furlanetto et al., 2017), with a few studies on knee osteoarthritis (Robbins et al., 2013; Timmermans et al., 2016), arthritis (Feinglass et al., 2011), type 2 diabetes (Richardson et al., 2020), and heart failure (Shoemaker, Roper, & Calkins, 2016). Only one comparative study was conducted between patient and non-patient groups, finding an overall higher level of physical activity and stronger temperature-physical activity association among older adults without knee osteoarthritis (Timmermans et al., 2016).

4.3.1.2 Location and climate of studies

The majority of the studies were performed in North America (n = 40) and Europe (n = 24). Other locations include Australia (Badland, Christian, Giles-Corti, & Knuiman, 2011; Provost et al., 2019), Brazil (Martins, Reichert, Bielemann, & Hallal, 2017), Qatar (Al-Mohannadi et al., 2016), Japan (Hino et al., 2017; Ogawa et al., 2019; Togo et al., 2005), Taiwan (Li & Lin, 2012), China (Wang et al., 2017; Zhao, Bian, Zhao, & Zhang, 2018) and Hong Kong, China (Ma et al., 2018). There were also four studies that assessed cross-regional locations (Aral & Nicolaides, 2017; Bosdriesz, Witvliet, Visscher, & Kunst, 2012; de Montigny, Ling, & Zacharias, 2011; Furlanetto et al., 2017). The climatology of location-specific papers, however, were centralized around three types under the Köppen-Geiger classification: Cfa (n = 19), Cfb (n = 19), and Dfb (n =13). Remaining studies were distributed thinly among a wide range of climate types.

Overall, there were a total of 21 studies that assessed multiple locations. Aside from the cross-regional locations, these included assessing multiple EU countries (Böcker et al., 2019; Boutou et al., 2019; Laverty, Thompson, Cetateanu, & Filippidis, 2018; Timmermans et al., 2016), or across the USA (An et al., 2017; Dunn, Shaw, & Trousdale, 2012; Durand, Zhang, & Salvo, 2017; Eisenberg & Okeke, 2009; Ermagun, Lindsey, & Loh, 2018; Obradovich & Fowler, 2017; Vanky et al., 2017), Canada (Balish et al., 2017), UK (Elliott et al., 2019; Farrell, Hollingsworth, Propper, & Shields, 2014; Kokolakakis, Lera-Lopez, & Castellanos, 2014; Sartini et al., 2017), or Netherlands (Fishman, Bocker, & Helbich, 2015). Among them, only 4 of those studies conducted comparisons between locations (Böcker et al., 2019; Ermagun et al., 2018; Furlanetto et al., 2017; Vanky et al., 2017), while others did not differentiate their results by location.

4.3.1.3 Meteorological exposures

Meteorological variables were usually obtained from official weather stations or governmental sources (n= 63 studies), although some studies used non-official sources found on websites (n = 9), presumably due to the lack of data. Sometimes, on-site temperature monitoring was conducted at the study sites of trails (Burchfield, Fitzhugh, & Bassett, 2012; Price, Reed, & Hooker, 2012a; Price et al., 2012b), parks (Zhao et al., 2018), beach (Provost et al., 2019) or farms (Mitchell et al., 2018). However, Burchfield et al. (2012) compared weather information on-site of the trails with the official weather source and concluded that a site-specific weather station was not necessary as it did not affect the associations of meteorological conditions with trail use.

As discussed in the quality assessment section, half of the studies had only one or two meteorological variables in their models. Aside from temperature, the second commonly reported variable was rainfall (n = 50). Windspeed (n= 29), humidity (n = 17), sunshine (n = 13), and other meteorological variables were less commonly reported. In real-life, however, all of these meteorological effects occur simultaneously, contributing to a whole experience of 'weather'. For example, humidity plays a significant role in the tolerance of heat as it inhibits evaporative cooling (Flouris & Schlader, 2015; McGregor & Vanos, 2018). Windspeeds can also affect the perception of temperature on the individual. Rainfall may lower the ambient air temperatures but also independently hinder a population's activity. At the daily or hourly level, the simultaneous adjustment of meteorological variables can enable studies to obtain more precise outcomes.

4.3.1.4 Physical activity domain and type

Physical activity was often assessed as overall physical activity (n = 50/79), without differentiating between types of physical activity conducted. This was the default scenario particularly for current accelerometer and pedometer studies. Separately, there were 18 studies looking specifically at leisure physical activity, 9 studies on transport physical activity, and two studies assessing occupational physical activity. Although most leisure physical activity studies were self-reported surveys, several studies used direct observation methods such as counting hiking participation (Li & Lin, 2012), golf course usage (Scott & Jones, 2006), exercise class attendance (Tu, Stump, Damush, & Clark, 2004), and beach users monitored via drones (Provost et al., 2019). The sole Chinese-language paper found in this review conducted direct observations of recreational activity in public parks, which were then converted into METs using the Compendium of Physical Activities (Zhao et al., 2018). GPS tracking was used independently for two transport studies (Prins & van Lenthe, 2015; Vanky et al., 2017) and as an assistant measurement in prompting travel recall (Clark, Scott, & Yiannakoulias, 2013; Spinney & Millward, 2011). Accelerometers measured the activity intensity of farm workers in California and Florida (Mitchell et al., 2018; Mix et al., 2019).

In the models of temperature-physical activity (208 models extracted from the 79 articles), physical activity was most often assessed using Time (n =72) as continuous variables of the duration participants spent in physical activity at intensities of interest (total PA, low/light/lifestyle PA, walking, and moderate and vigorous PA). These were often measured using objective accelerometers. A less frequent measurement of Time addressed duration in different types of physical activity (transport, leisure, jogging, indoor/outdoor sports), measured using subjective surveys/recall diaries. On the other hand, Average Intensity (n = 33), via raw accelerometer counts or conversion into METs, and Step Count (n = 20) were also common measurements from pedometers or accelerometers. Physical activity was also assessed as direct observation counts (n = 50) of pedestrians, trail users, or various sports participation. Finally, binary measures of physical activity were also used (n = 34), mainly from subjective surveys which assessed whether or not participants engaged in various forms of physical activity, or if their physical activity levels met guidelines. From all of these models, there were a total of 40 models that differentiated and specifically assessed MVPA and 29 models that assessed walking. Physical activity was sometimes assessed using multiple measurements of outcome within the same paper (Badland et al., 2011; Boutou et al., 2019; Eisenberg & Okeke, 2009; Giannouli et al., 2019; Hoppmann et al., 2017; Laverty et al., 2018; Mitchell et al., 2018; Ogawa et al., 2019; Robbins et al., 2013; Sartini et al., 2017; Spinney & Millward, 2011; Suminski et al., 2008; Vanky et al., 2017; Zhao et al., 2018). The direction of the temperature association was often the same (Eisenberg & Okeke, 2009; Giannouli et al., 2019; Mitchell et al., 2018; Ogawa et al., 2019; Robbins et al., 2013; Sartini et al., 2017; Suminski et al., 2008; Vanky et al., 2017; Zhao et al., 2018), although certain activities or more vigorous PA were more easily found significant than other (Badland et al., 2011; Boutou et al., 2019; Hoppmann et al., 2017; Laverty et al., 2018; Spinney & Millward, 2011).

4.3.1.5 Adjustment of confounders, stratification, and interaction

Overall, confounders adjusted in the identified studies could be categorized into demographic, health-related, time-related, environmental-related, and cluster-related variables (Appendix A3). Studies were most likely to control for participant-related demographics (n = 47), although a third of all individual level studies failed to include such confounders. This was followed by time-related (n = 34), health-related (n = 23), and environmental-related variables (n = 22). Around 60% of studies did not control for appropriate confounders of both demographic and time-related variables at the same time. These were determined to be essential, as physical activity levels are known to vary depending on participant differences and seasonal/weekly influences.

Demographic variables commonly included age and gender, with various studies also including education, income, employment, occupation, ethnicity (particularly in USA), ownership of car/bicycle, marital status, and living with children/elderly. Time-related variables commonly included day of study, hour of day, day of week, weekday vs weekend, month or seasonality, and year as appropriate to the datasets. Daily accelerometer wear time (Feinglass et al., 2011; Sartini et al., 2017; Smith, Michl, Katz, & Losina, 2018) and holiday (Böcker et al., 2019; Ermagun et al., 2018) were not often assessed but are important considerations.

Health variables were controlled for mostly in elderly and patient studies. Only seven papers conducted in the general population included health as a confounder, but mainly only addressed Body Mass Index (BMI) as an indicator of obesity (Chan et al., 2006; Hall & Epp, 2013; Ma et al., 2018; Mitchell et al., 2018; Mix et al., 2019; Reich, Fuentes, Herring, & Evenson, 2010; Smith et al., 2018). Elderly and patient studies included other health variables such as self-reported health status (Arnardottir et al., 2017; Feinglass et al., 2011; Hoppmann et al., 2017; Tu et al., 2004; Witham et al., 2014; Wu, Luben, & Jones, 2017a; Wu et al., 2017b), chronic disease (Cepeda et al., 2018; Reich et al., 2010; Sartini et al., 2017; Timmermans et al., 2016; Witham et al., 2014), mobility limitations (Cepeda et al., 2018; Hoppmann et al., 2017; Rapp et al., 2018; Sartini et al., 2017; Smith et al., 2018; Timmermans et al., 2016), mental health scales (Sartini et al., 2017; Smith et al., 2018; Timmermans et al., 2016), lung function (Balish et al., 2017; Boutou et al., 2019), smoking status (Cepeda et al., 2018; Reich et al., 2010; Sartini et al., 2017), alcohol intake (Cepeda et al., 2018; Feinglass et al., 2011), VO2 max (Brandon et al., 2009), time spent in health management (Dunn et al., 2012), blood pressure (Tu et al., 2004), and pain as exercise barrier (Tu et al., 2004).

Studies also considered environmental variables including: urban vs. rural (Farrell et al., 2014; Kokolakakis et al., 2014; Laverty et al., 2018; Reich et al., 2010), population density (Böcker et al., 2019; Chaix et al., 2014; Hankey et al., 2012; Lai & Kontokosta, 2018; Lindsey, Han, Wilson, & Yang, 2006; Saneinejad, Roorda, & Kennedy, 2012; Wang, Lindsey, Hankey, & Hoff, 2014), transport accessibility (Clark et al., 2013; Hankey et al., 2012; Lindsey et al., 2006; Saneinejad et al., 2012), land use (Fishman et al., 2015; Hankey et al., 2012; Lai & Kontokosta, 2018; Lindsey et al., 2006), walkability (Clark et al., 2013; Delclos-Alio et al., 2019), safety (Reich et al., 2010), or prevalence of sport facilities (Farrell et al., 2014; Laverty et al., 2018). The prevalence of green space was adjusted for in several studies (Chaix et al., 2014; Farrell et al., 2014; Fishman et al., 2015; Lindsey et al., 2006). Air pollution was included in 6 papers as Air Quality Index or individual pollutants. It was found to be significantly associated in most studies, although the association varied or was not reported (Alahmari et al., 2015; Brandon et al., 2009; Burchfield et al., 2012; Holmes, Lindsey, & Qiu, 2009; Reich et al., 2010).

Examining the potential contrasting effect between population sub-groups and other variables, 29 papers reported outcomes stratified by selected variables, which can be seen in Table 4.3. Two studies conducted more than one type of stratification concurrently: gender and physical activity intensity (Bosdriesz et al., 2012), trail location and timescale (Zhao et al., 2019). Several papers also found significant interactions between temperature and: weekday/weekend (Al-Mohannadi et al., 2016), income (Balish et al., 2017), sunlight (de Montigny et al., 2011), osteoarthritis (Timmermans et al., 2016), intervention group (Welch, Spring, Phillips, & Siddique, 2018), and walkability (Delclos-Alio et al., 2019). Chaix et al. (2014) on the other hand found no interactions between environmental and weather variables, including neighbourhood education level, presence of green/open spaces, air traffic exposure area and density of destinations.

Table 4.3 Stratification used in analyses of identified studies

Variable	Papers
Sociodemographic	
Gender	Bosderisz 2012, Dunn 2012, Hino 2017, Klenk 2012, Prins 2015, Saneinejad 2012, Aspvik 2018
Age	Cepeda 2018, Hino 2017, Obradovich 2017, Prins 2015, Saneinejad 2012, Witham 2014
Occupation	Bosdreisz 2012, Mix 2019
Income	Eisenberg 2009
Education	Eisenberg 2009
BMI	Obradovich 2017
Dog ownership	Wu 2017a (dog)
Physical activity-related	
PA type	Bosdreisz 2012, Spinney 2011, Provost 2019
Intensity of activity	Zhao 2018 (Harbin)
(In)sufficient active levels	Badland 2011
Fitness levels	Aspvik 2018
Impulsivity	Smith 2018
Environment-related	
Location	Durand 2017, Vanky 2017, Bocker 2019, Zhao 2019 (Seattle), Ermagun 2018
Environment types	Elliott 2019
Time-related	
Weekday/weekend	Alahmari 2015, Lai 2018, Zhao 2019 (Seattle)
Season	Li 2012, Martins 2017, Ogawa 2019, Aspvik 2018

Studies identified from systematic search conducted on May 2018 (and updated January 2020) in following databases: CINAHL, PubMed, Scopus, Web of Science, ScienceDirect, Embase, Ovid MEDLINE, PsycINFO, SportDiscus, China Academic Journals Full-text Database and Wanfang

4.3.2 Quality assessment of studies

Over half of the studies identified in this systematic review received a score of 7 or above (47 studies, 59.5%), whereas 21% of the studies had a score of 6, and 19% of studies were scored below 6. However, no studies achieved a full score of 10 in the methodological quality assessment. Eight of the 79 studies attained the highest score of 9, and were Alahmari et al. (2015), Aspvik et al. (2018), Balish et al. (2017), Burchfield et al. (2012), Cepeda et al. (2018), Mix et al. (2019), Prins and van Lenthe (2015), and Tu et al. (2004). Common fields of poor assessment were lack of control for confounders of time or demographic variables (60% of papers), poor reporting of the associations and effect size (55.7%), and failure to simultaneously adjust for three or more meteorological variables (49.4%). A summary table of the methodological quality in the papers identified in this systematic review can be seen in Table 4.4.

Table 4.4 Overview of the methodological quality among identified studies

Author-Date	1.Selection bias	2.Inclusion bias	3.Outcome	4.Exposure	5.Repeated measures	6.Confounding variables	7.Statistical method	8.Effect size	9.Simultan-eous	10.Analysis Level	Total
Multi-location studies											
An 2017	1	1	0	1	0	0	1	1	1	0	6
Aral 2017	1	1	1	1	1	0	0	0	0	1	6
Balish 2017	1	1	1	1	1	1	1	1	0	1	9
Böcker 2019	1	1	0	1	0	1	1	0	1	1	7
Bosdreisz 2012	1	1	0	0	0	0	1	0	0	1	4
Boutou 2019	1	0	1	1	1	0	1	0	0	1	6
de Montigny 2011	1	1	1	1	1	1	1	0	1	0	8
Dunn 2012	1	1	0	1	0	0	1	1	0	1	6
Durand 2017	1	1	0	1	0	1	1	1	1	1	8
Eisenberg 2009	1	1	0	0	0	1	1	1	0	N	5
Elliott 2019	1	1	0	1	0	1	1	1	1	1	8
Ermagun 2018	1	1	1	1	1	1	1	0	1	0	8
Farrell 2014	1	1	0	N	0	1	1	0	0	0	4
Fishman 2015	1	1	0	1	0	0	1	0	1	1	6
Furlanetto 2017	N	1	1	1	1	0	1	1	0	1	7
Kokolakakis 2014	1	1	0	1	0	0	1	1	0	0	5
Laverty 2018	1	1	0	N	0	0	1	0	1	1	5
Obradovich 2017	1	1	0	1	0	0	1	0	1	1	6
Sartini 2017	1	N	1	1	1	1	1	0	1	1	8
Timmermans 2016	1	0	0	1	0	0	1	1	0	1	5
Vanky 2017	1	1	1	1	1	0	1	0	1	1	8

Table 4.5 (Continued) Overview of the methodological quality among identified studies

Author-Date	1.Selection bias	2.Inclusion bias	3.Outcome	4.Exposure	5.Repeated measures	6.Confounding variables	7.Statistical method	8.Effect size	9.Simultan-eous	10.Analysis Level	Total
Single-location studies											
Alahmari 2015	1	1	1	1	1	0	1	1	1	1	9
Al-Mohannadi 2016	1	1	1	N	1	0	1	1	1	1	8
Arnardottir 2017	1	1	1	N	1	0	0	1	0	1	6
Aspvik 2018	1	1	1	1	1	0	1	1	1	1	9
Aultman-Hall 2009	1	1	1	1	1	1	1	0	1	0	8
Badland 2011	1	N	1	1	1	0	1	0	0	1	6
Brandon 2009	0	0	1	1	1	0	1	0	0	1	5
Burchfield 2012	1	1	1	1	1	1	1	1	1	0	9
Cepeda 2018	1	N	1	1	1	1	1	1	1	1	9
Chaix 2014	0	1	0	1	0	0	1	0	0	1	4
Chan 2006	N	0	1	0	1	1	1	1	1	1	7
Cheadle 2006	1	1	0	1	0	1	1	1	0	1	7
Clark 2014	1	1	0	1	0	0	1	1	1	1	7
Delclos-Alio 2019	0	1	1	1	1	0	1	1	1	1	8
Feinglass 2011	0	N	1	1	1	0	1	1	0	1	6
Giannouli 2019	0	1	1	0	0	0	0	0	0	1	3
Hall 2013	1	1	1	1	1	0	1	0	0	1	7
Hankey 2012	1	1	1	1	N	1	1	0	0	0	6
Hino 2017	1	N	1	1	1	0	0	0	1	0	5
Holmes 2009	1	1	1	1	1	0	1	0	1	0	7
Hoppmann 2017	1	1	1	1	1	1	1	0	0	1	8
Jones 2017	0	N	1	1	1	0	1	0	0	1	5
Klenk 2012	1	N	1	N	1	0	1	0	1	1	6
Lai 2018	1	1	1	0	1	1	1	1	1	0	8
Li 2012	1	1	1	1	1	0	1	0	1	0	7

Table 4.6 (Continued) Overview of the methodological quality among identified studies

Author-Date	1.Selection bias	2.Inclusion bias	3.Outcome	4.Exposure	5.Repeated measures	6.Confounding variables	7.Statistical method	8.Effect size	9.Simultan-eous	10.Analysis Level	Total
Lindsey 2006	1	1	1	0	1	1	1	0	1	0	7
Ma 2018	0	1	1	1	1	1	1	0	1	1	8
Martins 2017	0	1	1	1	1	0	0	0	0	1	5
Merilahti 2016	N	N	1	1	1	0	0	0	0	1	4
Mitchell 2018	0	1	1	1	0	1	1	1	1	1	8
Mix 2019	0	1	1	1	1	1	1	1	1	1	9
Ogawa 2019	0	N	1	1	1	0	1	1	1	1	7
Price 2012a	1	1	1	N	1	1	1	1	0	0	7
Price 2012b (elderly)	1	1	1	1	1	1	1	1	0	0	8
Prins 2015	1	N	1	1	1	1	1	1	1	1	9
Provost 2019	1	1	1	1	1	0	1	0	1	0	7
Rapp 2018	1	1	1	N	1	1	1	1	0	1	8
Reich 2010	N	N	0	1	0	1	1	0	0	1	4
Richardson 2019	0	1	1	1	1	0	1	1	0	1	7
Robbins 2013	1	1	1	1	1	0	1	0	0	1	7
Saneinejad 2012	1	1	0	1	0	1	1	0	1	1	7
Scott 2006	1	1	1	1	1	1	1	0	0	0	7
Shoemaker 2016	1	N	1	0	1	0	0	0	0	1	4
Smith 2018	1	1	1	1	1	1	1	0	0	1	8
Spinney 2011	1	N	0	1	1	0	1	0	1	1	6
Suminski 2008	1	1	1	1	1	0	1	1	1	0	8
Sumukadas 2009	0	1	1	1	1	0	1	1	1	1	8
Togo 2005	0	1	1	1	1	0	0	1	0	0	5
Tu 2004	1	1	1	1	1	0	1	1	1	1	9
Wang 2014	1	1	1	1	1	1	1	0	1	0	8
Wang 2017	0	1	1	1	1	0	1	0	0	1	6

Table 4.7 (Continued) Overview of the methodological quality among identified studies

Author-Date	1.Selection bias	2.Inclusion bias	3.Outcome	4.Exposure	5.Repeated measures	6.Confounding variables	7.Statistical method	8.Effect size	9.Simultan-eous	10.Analysis Level	Total
Welch 2018	1	N	1	1	1	0	1	0	0	1	6
Witham 2014	1	1	1	1	1	0	1	1	0	1	8
Wolff 2011	1	1	1	0	1	1	1	0	1	0	7
Wu 2017a (dog)	1	1	1	1	1	0	1	0	0	1	7
Wu 2017b	1	1	1	1	1	0	1	1	0	1	8
Zhao 2018 (Harbin)	N	1	1	1	1	0	1	0	0	0	5
Zhao 2019 (Seattle)	1	1	1	0	1	0	1	0	1	0	6

Studies identified from systematic search conducted on May 2018 (and updated January 2020) in following databases: CINAHL, PubMed, Scopus, Web of Science, ScienceDirect, Embase, Ovid MEDLINE, PsycINFO, SportDiscus, China Academic Journals Full-text Database and Wanfang

4.3.3 Temperature-physical activity association

Overall, the studies demonstrate inconclusive evidence of the association between temperature and physical activity. While 29 papers found a positive association, 21 papers found a negative or curvilinear association between temperature and physical activity. Additionally, 20 papers had mixed ambiguous results and 9 papers had non-significant results. There were approximately equal proportions of positive and negative associations among those 20 mixed-evidence papers.

Table 4.8 demonstrates the strength of evidence according to the region of the studies, and Table 4.9 according to the climate types. When grouped according to region, most European studies had a positive association with temperature, however mixed associations were found for North America. Other regions had limited number of studies to identify trends.

When grouped according to Köppen-Geiger classification, potential trends of the temperature association was found in various climates. Among the climate types most studied, a positive temperature association with physical activity was commonly found for Cfb and Dfb climate types. However, the studies in Cfa climates suggest a more negative/curvilinear association between temperature and physical activity. As 'a' stands for hot summer temperatures and 'b' stands for warm summer temperatures (Figure 2.2, page 19), these findings suggest that physical activity can increase in warm temperatures, however when the temperatures become too hot, the association turns curvilinear and physical activity begins to decrease.

Table 4.8 Strength of evidence for temperature-physical activity associations, by region

Association	Asia	Australia	Europe	Middle East	North America	South America	Multiple regions	Total
Positive	1	0	13	0	14	0	1	29
Mixed	2	2	6	0	8	1	1	20
Non-significant	1	0	2	0	5	0	1	9
Negative/ curvilinear	3	0	3	1	13	0	1	21
Total	7	2	24	1	40	1	4	79

Studies identified from systematic search conducted on May 2018 (and updated January 2020) in following databases: CINAHL, PubMed, Scopus, Web of Science, ScienceDirect, Embase, Ovid MEDLINE, PsycINFO, SportDiscus, China Academic Journals Full-text Database and Wanfang
Absent region: Africa

Table 4.9 Strength of evidence for temperature-physical activity associations, by Köppen-Geiger climate classification

Köppen-Geiger climates^	BWh	Cfa	Cfb	Cfc	Csa	Csb	Cwa	Dfa	Dfb	Dfc	Dwa
1 Positive	0	5 (7)	11 (7.6)	1 (6)	0	1 (8)	0	1 (8)	7 (6.7)	0	1 (5)
2 Mixed	0	4 (7)	4 (8)	0	1 (6)	1 (6)	0	0	4 (6.3)	1 (4)	0
3 Non-significant	0	2 (7.5)	1 (3)	0	1 (8)	1 (7)	0	2 (6)	0	0	1 (8)
4 Negative/ curvilinear	1 (6)	8 (7.1)	3 (5)	0	1 (8)	0	1 (8)	1 (6)	2 (5.5)	0	0
Total papers	1	19	19	1	3	3	1	4	13	1	2

Studies identified from systematic search conducted on May 2018 (and updated January 2020) in following databases: CINAHL, PubMed, Scopus, Web of Science, ScienceDirect, Embase, Ovid MEDLINE, PsycINFO, SportDiscus, China Academic Journals Full-text Database and Wanfang
^Numbers in parentheses indicate average study quality
Absent climate groups: A (equatorial tropical climates), BS (semi-arid/steppe), Cwb/c (subtropical highland), Csc (cold-summer Mediterranean), Dfd (subarctic), Dwb/c/d (monsoonal continental), Ds (Mediterranean continental), ET (tundra)

In reviewing the non-linear considerations of the 79 studies, a majority of the papers (n= 42) did not assess or mention assessing non-linear trends, while 37 papers assessed for non-linear trends or conducted non-linear analyses. From the seven papers that assessed for non-linear trends, five studies did not find evidence of non-linear associations (Bosdriesz et al., 2012; Boutou et al., 2019; Laverty et al., 2018; Sumukadas et al., 2009; Timmermans et al., 2016), however, most of these studies received a low score on the quality assessment (see Table 4.4). The other two studies found non-linear trends in their unadjusted analyses but strangely did not transfer these findings to their adjusted analyses and used linear temperature terms instead (Alahmari et al., 2015; Zhao et al., 2019). Of the 30 papers that conducted non-linear analyses, there was an even split between studies who assessed temperature as a categorical indicator and continuous variable (n= 15, respectively). Studies using categorical temperature analyses often did not find significant curvilinear associations, while those using a continuous temperature term found significant curvilinear associations. These included methods such as adding quadratic term (n =12), simple correlations (Aral & Nicolaides, 2017; Shoemaker et al., 2016), or GAM models to enable flexibility (Elliott et al., 2019). One study compared linear, quadratic, and binary analysis methods, and found that while the linear analysis was not significant, both the quadratic ($p = 0.025/0.038$) and binary analyses (Normal vs. extreme temperature < 10°C or > 30°C, $p = 0.042$) were significantly associated with temperature (Brandon et al., 2009).

Among studies that found curvilinear associations, there were a wide range of methods to identify the curvilinear relationship. Many studies did not seek to identify or report the optimal temperature at which physical activity peaked, particularly when only a quadratic term was added to the model (Al-Mohannadi et al., 2016; Aral & Nicolaides, 2017; Aultman-Hall, Lane, & Lambert, 2009; Brandon et al., 2009; Farrell et al., 2014). Several studies had pre-set thresholds for estimating the temperature relationship, however these thresholds varied according to study: 75°F/23.89°C (Feinglass et al., 2011), 25°C (Li & Lin, 2012), 30°C (Brandon et al., 2009), 28-29°C (Obradovich & Fowler, 2017), and a heat index of 90°F/32.2°C (Tu et al., 2004). The studies that sought to 'discover' the optimal temperature of peak physical activity were only located in Japan and the USA. Physical activity in Japan was found to peak at 17°C in a simple regression analysis (Togo et al., 2005) and at a range of 19.4-20.7°C mean temperatures (Hino et al., 2017). Two urban trail studies in the USA found peaks at 76°F/24.4°C (Burchfield et al., 2012), and max temperatures 84°F/28.89°C (Wolff & Fitzhugh, 2011). Ermagun et al. (2018) found physical activity to peak between 62.5-100°F/16.9-27.8°C across the USA. Also in the USA, Eisenberg et al. (2009) found that physical activity increased in temperatures less than 60°F/15.6°C but did not find significant associations in higher temperatures. Overall, a wide variety of optimal temperature thresholds were found among the studies.

4.3.3.1 Variation in temperature measurements

The studies assessed various temperature measurement types: average temperature (n = 32), maximum temperature (n = 26), minimum temperature (n= 3), deviation from normal (n=1), some form of index (n = 10), or the temperature type was not specified (n= 14). Temperature indexes used included: WBGT (Al-Mohannadi et al., 2016; Mitchell et al., 2018; Mix et al., 2019), apparent temperature (Delclos-Alio et al., 2019; Suminski et al., 2008), temperature-humidity index (Hino et al., 2017), net effective temperature (Hino et al., 2017), heat/ wind chill index (Holmes et al., 2009; Obradovich & Fowler, 2017; Tu et al., 2004), index of temperature variability (Kokolakakis et al., 2014).

Several studies compared the results between absolute temperature and temperature indices. In Qatar, daily temperature and relative humidity were negatively associated with step counts when analysed independently, but a curvilinear relationship was found when assessed as WBGT, with declines at WBGT greater than 28 °C. However, the separate analysis was determined a better fit rather than the combined WBGT index (Al-Mohannadi et al., 2016). When comparing the effect between mean temperature, net effective temperature, and temperature-humidity index, all were found curvilinearly associated with aggregated monthly step counts in Yokohama Japan (Hino et al., 2017), but Hino concluded that Temperature Humidity Index explained the variance in monthly step counts better than the other two (Hino et al., 2017). In the USA, monthly maximum temperatures adjusted for humidity had a curvilinear association that peaked at 28-29°C (Obradovich & Fowler, 2017), but when assessed as monthly mean heat index, the effect plateaued at high temperatures and did not demonstrate a significant decrease. These studies may demonstrate that temperature indices are applicable whether at the daily or monthly level, but whether indices or standalone meteorological variables are more suitable requires further exploration.

Some studies also included a relative temperature indicator. Wang 2014 found that while adjusting for maximum temperatures, outdoor trail users decreased when temperatures deviated from a 30-year normal (Wang et al., 2014). A negative association for trail counts was also found when temperatures were greater than the previous week's average, after adjusting for an independent positive temperature association (Holmes et al., 2009). Lindsey 2006 found a curvilinear association between trail counts and temperature deviation from normal without adjusting for temperature independently, where trail traffic decreased in larger deviations (Lindsey et al., 2006). These findings on temperature deviation support the idea that populations have adapted to the climate 'normal' of their location and that temperature variability due to climate change may have a negative impact on physical activity.

A few studies additionally estimated climate change projections on the effects of physical activity (Obradovich & Fowler, 2017; Scott & Jones, 2006). These studies used temperature projections that were statistically downscaled from global climate models, which is an often-necessary step to produce climate information at the appropriate temporal and spatial scale (Scott & Jones, 2006). Scott et al. (2006) assessed golf course usage in Toronto, Canada and projected that overall, the number of golf rounds would increase by 10.0% - 28.4% by 2080s. With an expanded operating golf season, this would increase the amount of golf rounds played to 31.5% - 72.7%. Obradovich et al. (2017) projected that there would be a net benefit of climate change on monthly recreational PA in the USA, with an increase of 70 physically active person-months per 1000 individuals by 2099. This conclusion largely came from increased physical activity in the warmer winter months throughout the USA, and while reduced physical activity were projected to occur in summer months, only the southernmost areas of the country would experience a net decrease (Obradovich & Fowler, 2017). As these projections were largely located in temperate climates, the projected effect of climate change on physical activity should be further conducted in a variety of climates outside of North America.

4.3.3.2 Large-scale and multi-location studies

Studies with more than 10,000 participants were often subjective national travel or leisure surveys (n=9). Among the few large-scale objectively measured studies, a large cohort in Yokohama Japan (n = 24625) reported curvilinear associations between monthly step count and temperature (Hino et al., 2017). Aral et al. (2017) harnessed the use of accelerometers attached to a global fitness tracking network and demonstrated a curvilinear global association between temperature and running activity of 1.1 million mobile application users. GPS tracking of pedestrian trips and time in pedestrian trips was positively associated with temperature in both Boston and San Francisco (Vanky et al., 2017).

Among multi-location studies, few studies conducted a systematic comparison across several locations. In contrast to the consistent results found in (Vanky et al., 2017), as discussed in the paragraph above, (Böcker et al., 2019) found walking negatively associated with temperature in Utrecht, Netherlands, but not in other cities in Norway and Sweden. COPD patients in Belgium and Brazil increased their daily physical activity by 1 and 6 minutes, respectively for every 1C increase in temperature, suggesting greater temperature effect in a location of smaller climate variation (Brazil) rather than larger climate variation (Belgium) (Furlanetto et al., 2017). (Ermagun et al., 2018) assessed various outdoor urban trails across the entire USA, using American-specific climate zones identified by the U.S. Department of Energy. A significant quadratic relationship between average temperature and urban trail counts was found for all climate regions except for a city with a very cold climate in the USA (eg. Duluth Minnesota) which had a constant positive association (Ermagun et al., 2018). When assessing the optimal temperature in the quadratic relationships, they found an increasing pattern by climate regions: 62.5F/16.94C cold regions (eg. Billings Montana), 75F/23.89C in mixed dry (eg. Albuquerque, New Mexico), mixed humid (eg. Arlington Virginia) and hot dry regions (eg. San Diego California), 83.3F/28.5C in marine regions (eg. Seattle Washington), and 100F/37.78C in hot humid regions (eg. Miami Florida) (Ermagun et al., 2018).

4.3.3.3 Differentiation between indoor and outdoor physical activity

Overall, 29 papers of the 79 papers were able to measure outdoor-specific physical activity, while one study analysed indoor-specific physical activity (Tu et al., 2004). Outdoor studies were mostly aggregated studies conducted in specific outdoor locations (sidewalks, trails, parks, beaches etc.), cross-sectional surveys on leisure visits to outdoor natural environments (Elliott et al., 2019), or leisure physical activity questionnaires that enabled indoor/outdoor classification of activities (Eisenberg & Okeke, 2009; Reich et al., 2010; Spinney & Millward, 2011). A study on indoor exercise attendance among elderly women in Indiana USA found that temperatures of heat index above 90F (32.22C) or wind chill index below 20°F (-6.67°C) was associated with reduced class attendance (Tu et al., 2004).

In comparing indoor and outdoor activities, Eisenberg 2009 found a curvilinear association between monthly temperature and outdoor leisure physical activity that plateaued at temperatures above 60F. The opposite effect was found for indoor exercise, suggesting a potential substitution between indoor and outdoor exercise in low temperatures (Eisenberg & Okeke, 2009). A subjective survey among pregnant women in North Carolina USA also found temperature was positively associated with the PA intensity of weekly occupational, recreational, and outdoor household activity, but negatively associated with indoor household activity (Reich et al., 2010). Spinney 2011 found that participation in outdoor sports and outdoor active leisure was more likely in higher temperatures in Canada (Spinney & Millward, 2011), while no association was found in indoor sports. Yet, time spent in indoor sports was found negatively associated with higher temperatures (Spinney & Millward, 2011). Overall, these studies suggest that favourable temperatures led to a substitution of indoor physical activity for more outdoor physical activity. However, no study was found to demonstrate the trade-off clearly. All of these studies only had a cross-sectional design, limiting their ability to identify within-person substitution. Adverse weather conditions may also affect participants' accessibility to indoor physical activity locations (Spinney & Millward, 2011; Tu et al., 2004).

4.3.4 The humidity effect on physical activity

Humidity is demonstrated to have a significant impact on physical activity, whether measured as dew point temperature, relative humidity, or part of a temperature index. When temperatures are adjusted for humidity (as temperature index, or apparent temperature), higher temperatures could lead to more physical activity, but the increased effect of humidity decreased physical activity (Holmes et al., 2009; Suminski et al., 2008). However, among the studies identified in this review, humidity was only assessed in 56 models in 17 papers (17/79 = 21.5%), with 7 of those assessing humidity as dew point temperature. An additional 12 models from 8 papers incorporated humidity into their temperature index.

Most studies found a negative association of humidity (34 models), while there were some non-significant associations (15 models), and a few positive associations (7 models). Daily or hourly humidity levels were found negatively associated with step counts or time in objectively assessed physical activity of young adults in Qatar (Al-Mohannadi et al., 2016), elderly in Netherlands (Cepeda et al., 2018), Canada (Jones, Brandon, & Gill, 2017), across the UK (Sartini et al., 2017), COPD patients in Brazil and Belgium (Furlanetto et al., 2017), and in trail counts in Vermont (Aultman-Hall et al., 2009), Tennessee (Burchfield et al., 2012), and Seattle (Zhao et al., 2019). However, humidity was positively associated with self-reported travel time in Boston and California (Durand et al., 2017; Vanky et al., 2017). When stratified by climate regions in America, Ermagun et al. 2018 found that colder & drier regions had negative relationships with dew point temperature, while hot-humid regions found a curvilinear association and marine climates were non- significant (Ermagun et al., 2018). The acute effect of humidity on physical activity may vary depending on how humid a location is regularly. The associations of other meteorological variables in the studies are discussed in Appendix A4.

4.4 Discussion

In this systematic review, 79 articles were identified to assess the relationship between temperature and physical activity. Although the number of studies have increased in the last decade, it still remains a relatively new field of research. Many studies measured physical activity objectively and used a repeated measures or longitudinal study design. Over half of the papers were situated in North America, and almost one-third located in Europe. Studies in Asia, Australia, Africa, Middle East, and South America were rare. Only a few studies compared the temperature-physical activity association between different locations. Most studies were also concentrated in only a few climate types (Cfa, Cfb, Dfb) when classified according to Köppen-Geiger classification. However, this classification method provides a valuable synthesis of findings between the different studies. As seen in the quality assessment, the studies commonly failed to adjust for multiple meteorological variables simultaneously and control for key confounders of time and demographic variables. Particularly, relative humidity was only intermittently included in the studies but was found to have a significant impact on physical activity.

The relationship with temperature was overall inconclusive but demonstrated more of a trend when categorized by climate types compared to regional location. Regardless of which region the study was located, more studies in cold or temperate climates with warm summer temperatures (Dfb and Cfb) found positive associations with physical activity, while more studies in temperate climates with hot summer temperatures (Cfa) found curvilinear or negative associations with physical activity. This is aligned with a climate assessment of physical activity in the USA, finding that climates with more “moist tropical” days were less likely to meet physical activity guidelines (Merrill et al., 2005). Due to the variability between study designs, population, timescale, measurement, location and more, it is difficult to ascertain the differences in outcomes as attributable to climate. The four multi-location comparative studies identified in this review were able to depict more clearly the differences between locations. More multi-location comparative studies are required to understand the temperature-physical activity relationship in different locations.

For the studies that used a quadratic relationship for temperature, a significant curvilinear association was commonly found. However, most studies did not seem to assess their data for non-linear trends to inform their temperature analysis. Linear analyses may have been restricting the outcomes, as many studies found non-significant or mixed associations between temperature and physical activity. Furthermore, among the studies that found curvilinear associations, many studies on curvilinear associations did not report the optimal temperature for physical activity or had pre-set the temperature threshold. The few studies that sought to identify the optimal temperature of maximum physical activity found a peak that varied widely between those studies. Future studies can allow flexibility of the temperature association and identify optimal temperatures based on model fit.

The influence of health was rarely accounted for when examining the relationship between temperature and physical activity. Less than a third of the studies identified in this review controlled for any health variables, with most of them focusing on patients and elderly populations. While obesity (BMI) was the most frequently included confounder in the general population, other aspects of health such as general health status and chronic disease conditions were not assessed. Patient studies were generally conducted on COPD patients, with a scarce understanding of other diseases such as cardiovascular disease and type 2 diabetes. However, these chronic diseases should be important considerations in temperature-physical activity studies since they impair thermoregulatory responses and increase the vulnerability in heat (Kenny et al., 2010). While there can be difficulties in assessing health for aggregated studies or direct observation studies, this aspect should be assessed in future studies where possible.

Strengths and limitations

The strengths of this systematic review included a comprehensive search of databases and an updated search for the most recent articles. The search included both Chinese and English articles and was limited to peer-reviewed papers only. The review also conducted a quality assessment of the included studies, which was completed by two independent reviewers. Limitations for this study were the wide inclusion of physical activity types and domains. This was done since this area of study is relatively new, but it may have led to inconclusive results. Different types of physical activity, such as leisure walking, walking for commute, sport activities, winter sports, etc. may be affected by temperature differently. The search strategy brought a wide range of unrelated results because of the generic nature of the exposure and outcome variables: temperature and physical activity. However, the systematic review achieved its specific aim of focusing on the public health angle of the temperature and physical activity relationship.

Future research directions

Using the Köppen-Geiger climate classification, the current systematic review was able to demonstrate potential climatic trends among a variety of studies conducted globally on temperature and physical activity. These findings suggest a non-linear relationship: that physical activity would increase in warm temperatures but decrease when the temperature becomes too hot. However, most studies used linear methods that may have missed out on non-linear findings, particularly of hot temperatures. Previous studies have seldom sought to identify non-linear associations and the temperature thresholds at which the association with physical activity would begin to decline in hot temperatures. Future studies could assess for non-linear trends and enable a more flexible statistical model such as Generalized Additive Models (GAMs). In view of climate change, these studies could focus their discussion on the effects of hot temperatures.

Aside from North America and Europe, studies were sparse in other regions. This review additionally identified that a variety of climate types have not been covered, suggesting that a wider range of locations and climate types should be assessed in future studies. The findings of this review further promote the use of multi-location comparative studies with consistent methodology across locations in order to draw conclusive evidence on the temperature-physical activity relationship. In addition to conducting multi-location comparisons, future studies should adjust for multiple meteorological variables and key confounders and examine the influence of chronic diseases. Finally, studies could further seek to differentiate the effects of indoor-outdoor physical activity.

Chapter 5 Daily associations between temperature and physical activity in five Chinese cities – Study (2)

5.1 Introduction

Research has shown that physical activity can be affected by temperatures. This relationship, however, may vary by regional context and climates. Few studies on the association between temperature and physical activity have been conducted in the Asian region, particularly in China. With a population of 1.4 billion people as of 2019 (National Bureau of Statistics of China, 2019), China currently has the largest population worldwide, indicating many people's physical activity could potentially be affected by temperatures. There is a need to understand the physical activity patterns in China.

In China, the physical activity levels of the population have decreased particularly in more urbanized areas (Yang et al., 2018). A study found that work- and household- physical activity decreased by nearly half between 1991 and 2011, while active leisure and transport physical activity did not see a meaningful change in the same period (Zang & Ng, 2016). The recent Tsinghua-Lancet Commission on healthy cities in China call for integration of health into all policies, including the increased facilitation of physical activity (Yang et al., 2018).

With climate change, temperatures in China are predicted to increase by 2.3°C to 3.3°C from 2000 to 2050 (National Development and Reform Commission, 2007), increasing the occurrence of extremely hot temperatures in the coming decades. Yet there is a lack of understanding about the relationship between temperature and physical activity in China. The systematic review in Chapter 4 incorporated Chinese databases in the search but could only identify three studies done in China. However, these studies had only assessed small samples of the population (Ma et al., 2018; Wang et al., 2017), or observed physical activity ecologically in public parks (Zhao et al., 2018). A more comprehensive understanding about temperature's effect on physical activity is needed at the population level in China. This knowledge would support the development of policies to address these potential impacts and to promote physical activity in the cities, as called for in the Tsinghua-Lancet Commission.

Step counts are an important indicator of physical activity at the population level, as walking is a largely accessible, inexpensive, and a regularly conducted physical activity in everyday life (Hallal et al., 2012). With the advancement of technology, this physical activity indicator can be objectively assessed with accelerometers found in smartphones of the general population. Using smartphones could enable the same objective physical activity measurement and study methodology across locations, facilitating multi-location comparisons as discussed in the systematic review findings of Chapter 4.

This multi-location comparative study examines the associations between temperature and daily step counts in five Chinese cities.

5.2 Methodology

Study setting and design

This is a prospective aggregated timeseries study. Five major Chinese cities were assessed, including Beijing (located in the North), Shanghai (East), Chongqing (Southwest), Shenzhen (South), and Hong Kong (South, Special Administrative Region). These are major cities in China, in terms of the population size, and economic and political significance. The cities are also located in four divergent areas of the country, with varying climates.

Aggregated anonymized data was obtained from the mobile application Wechat's in-app function WeRun (微信运动) for the duration of the study period. Wechat is an app commonly used by smartphone users in China, regardless of age. The in-app function WeRun is a voluntary addition that enables users to compare fitness levels with their community. It reads from the step count data of the phone's health applications (iPhone or Android) or other data sources such as smartwatches as allowed by the user. Both the iPhone and Android phones have been validated against regularly accepted pedometers and accelerometers in field-based research (Amagasa et al., 2019; Hekler et al., 2015). These studies have found comparable estimates in both laboratory and free-living environments, although the phones may be liable to underestimation due to inconstant phone carrying (Amagasa et al., 2019; Hekler et al., 2015).

Ethics approval and funding

Ethics approval was obtained from Survey and Behavioural Research Ethics Committee of The Chinese University of Hong Kong (see Appendix B1). No funding was utilized for this study.

Outcome: Aggregated daily step count

Aggregated mean daily step counts were obtained for each city from anonymized users of the in-app function who were located in the city at night (10 pm). Aggregated mean daily step counts were also obtained for different genders (male; female) and age groups, along with the number of anonymized users included in each aggregate value.

Exposure: Temperature and its variations

Meteorological data was obtained from the China Meteorological Administration, from the following stations for the mainland Chinese cities: Beijing (ID: 54511), Shanghai (ID: 58362), Chongqing (ID: 57516), and Shenzhen (ID: 59493). Data from Hong Kong was obtained from the Hong Kong Observatory. Daily mean temperature was used as the main exposure for this analysis, and also adapted into apparent temperature and percentile temperature of the study period. Apparent temperature was calculated from temperature and relative humidity using the following formulas, where T = temperature and RH = relative humidity (Ballester, Robine, Herrmann, & Rodo, 2011; Sensirion, 2006):

$$H = (log10(RH) - 2)/0.4343 + (17.62 * T_{air})/(243.12 + T_{air})$$

$$T_{dewpt} = 243.12 * H/(17.62 - H)$$

$$T_{apparent} = -2.653 + 0.994(T_{air}) + 0.0153(T_{dewpt})^2$$

Covariates: Precision variables

Other meteorological covariates obtained from the meteorological stations included: relative humidity, rainfall, mean windspeed, atmospheric pressure, and sunshine hours. A square root transformation was done for rainfall and windspeed, in order to reduce the effect of outliers. Extreme weather event information on typhoon days were incorporated as binary indicators from a WMO report on China and the Hong Kong Observatory (China Meteorological Administration, 2018; Hong Kong Observatory, 2018; Meteorological Bureau of Shenzhen Municipality, 2018). The occurrence of super typhoon Mangkhut was included separately due to the severity of the storm, which made landfall in Shenzhen and Hong Kong on Sept 16, 2018. The full list of typhoons can be found in Appendix B2.

Air pollution data was obtained from China National Environmental Monitoring Center network (CNEMC) and Hong Kong Environmental Protection Department. An air quality index was used instead of individual air pollutant variables, to reduce possible collinearity. In China, the Air Quality Index (AQI) is based on the concentration levels of six pollutants (SO2, NO2, PM2.5, PM10, CO, O3) and reported using a scale of 1-300+ (Ministry of Ecology and Environment of the PRC). All hourly AQI values were aggregated to the daily level and further log-transformed to adjust for the right skew. Missing variables were imputed using a simple moving average for consecutively missing data of twelve hours or less. Longer consecutive missing data were left as missing. The imputation was completed with the R package 'imputeTS'. In Hong Kong, the Air Quality Health Index (AQHI) was used, based on the concentration levels of four pollutants (SO2,NO2, O3, and PM2.5/PM10) and reported using a scale of 1-10+ (Environmental Protection Department). Hourly AQHI values were available for twelve general stations located throughout the city, which were averaged together to indicate the daily value for the entire city. The Tap Mun monitoring station was not included, as its rural location is not reflective of the residence of the general population. If the data for a certain station was missing, it was substituted by the data of a similar station. For values '10+', a value of 12 was used in the daily aggregation.

Time-related variables, such as month, day of week (DOW), and public holiday, were included to control the analysis. Mainland China had extra workdays to compensate for extended holiday periods, which were adjusted for in the analysis as well (The State Council PRC, 2018). Special events (e.g. marathon) in Hong Kong were adjusted for in the analysis (Major Sports Events Committee, 2018).

Statistical analysis

The associations of temperature were assessed on aggregated mean daily step count, adjusted by other meteorological conditions, air pollution index, and time-related variables. A stepdown analysis was conducted separately for each city using Generalized Additive Models (GAMs). Meteorological covariates with the highest p-value were removed in each model, until no variables with p-value over 0.1 remained. The AIC was also compared between models to ensure the model quality did not decrease. Air pollution index and time-related variables were kept in the model as control variables. The full model had a formula as follows:

$$E(Daily\ mean\ step\ count) = s(Mean\ temperature, k = 4) + \\ s(Relative\ humidity, k = 4) + s(Precipitation, k = 4) + s(Windspeed, k = 4) + \\ s(Pressure, k = 4) + s(Sunshine, k = 4) + s(AQI\ or\ AQHI, k = 4) + \\ factor(DOW) + factor(Holiday) + factor(Month) + \\ factor\ (Extra\ workdays) + factor\ (Typhoon) + factor\ (Super\ typhoon) + \\ factor\ (Marathon)$$

s() indicates the smoothing function of continuous independent variables in R package "mgcv"
k indicates the basis dimension for the smooth, such that k-1 is the maximum degrees of freedom considered for the variable
factor() indicates the categorical independent variables; variables were excluded if irrelevant to the city

The analysis was further stratified by gender and age groups. Sensitivity analyses assessed the 1) effect of apparent temperature, 2) effect of percentile temperature, 3) removal of air pollution index, and 4) removal of outlier data caused by Typhoon Mangkhut in Shenzhen and Hong Kong. Statistical significance level was set at 0.05. All analyses were conducted using R version 3.5.2 (R Core Team, 2018), using package “mgcv” (gam) (Wood, 2017).

5.3 Results

5.3.1 Descriptive statistics

The study period was from Dec 6, 2017 to Dec 31, 2018. The average amount of anonymized users included during the study period were 11.1 million for Beijing, 9.6 mil for Shanghai, 2.8 mil for Chongqing, 4.9 mil for Shenzhen and 0.4 mil for Hong Kong. The daily number of anonymized users included throughout the study period is further demonstrated in Appendix B3. Compared to census data, the study samples in all five cities had a comparable gender distribution with their respective general populations (see Table 5.1 & Table 5.2). However, the sample populations tended to be significantly younger than the general population.

Table 5.1 Demographic comparison between sample population and city population of five Chinese cities (Unit 10,000 persons)

City	**Sample**				**Population (2018)**			
	Category	**Avg. count**	**SD**	**(%)**	**Category**	**N**	**(%)**	**p-value^**
Beijing								
	Total	1108.92	167.34	100	Total	2154.2	1	
	Gender							
	Male	555.23	81.67	50.07	Male	1095.6	50.86	0.874
	Female	553.7	85.68	49.93	Female	1058.6	49.14	
Shanghai								
	Total	963.52	137.27	100	Total	1462.38	1	
	Gender							
	Male	462.51	63.86	48	Male	724.14	49.52	0.761
	Female	501.01	73.44	52	Female	738.23	50.48	
(Age information available upon reasonable request)								

Table 5.2 (Continued) Demographic comparison between sample population and city population of five Chinese cities (Unit 10,000 persons)

City	Sample				Population (2018)			
	Category	**Avg. count**	**SD**	**(%)**	**Category**	**N**	**(%)**	**p-value ^**
Chongqing								
	Total	285.96	46.14	100	Total	3101.79	1	
	Gender							
	Male	131.39	21.06	45.95	Male	1563.43	50.4	0.373
	Female	154.58	25.09	54.06	Female	1538.36	49.6	
Shenzhen								
	Total	489.78	66.62	100	Total	1302.66	1	
	Gender							
	Male	269.27	37.83	54.98	Male	707.76	54.33	0.896
	Female	220.51	28.88	45.02	Female	594.9	45.67	
Hong Kong								
	Total	42.82	6.7	100	Total	7486.4	1	
	Gender							
	Male	18.65	2.9	43.55	Male	3421.1	45.7	0.666
	Female	24.17	3.81	56.45	Female	4065.3	54.3	
(Age information available upon reasonable request)								

Aggregated anonymized data obtained from in-app function WeRun, Dec 2017- 2018
^Chi-square test was used to measure the overall difference in proportion between the sample and 2018 population data. $p \leq 0.05$ indicates significant difference.
Census data sources: (Beijing Municipal Bureau of Statistics & Survey Office of the National Bureau of Statistics in Beijing, 2019; Census and Statistics Department, 2019; Chongqing Municipal Statistical Bureau & Survey Office of the National Bureau of Statistics in Chongqing, 2019; Shanghai Municipal Statistical Bureau & Survey Office of the National Bureau of Statistics in Shanghai, 2019; Shenzhen Municipal Statistics Bureau, 2019)

Table 5.3 displays the summary findings. The aggregated average step counts for each of the cities averaged 6846 steps for Beijing, 6703 for Shanghai, 7540 for Chongqing, 7209 for Shenzhen and 9040 for Hong Kong. The average step count was higher among males than females. During the study period, daily temperatures averaged from 12.7°C (SD 12.1) in Beijing, to 23.5°C (SD 5.3) in Hong Kong. Meteorological variables were found to be significantly different between the cities.

Table 5.3 Summary findings of five Chinese cities

Variables	Beijing (BJ)	Shanghai (SH)	Chongqing (CQ)	Shenzhen (SZ)	Hong Kong (HK)	p-value^
Observation days	391	391	391	391	391	
Physical activity						
Total avg. daily step count, mean (SD)	6845.95 (478.36)	6702.54 (463.32)	7540.12 (507.61)	7209.39 (402.66)	9039.59 (429.11)	<0.001
Males, mean (SD)	7594.33 (518.17)	7465.32 (500.94)	8079.77 (461.91)	7862.84 (415.23)	9635.18 (430.36)	<0.001
Females, mean (SD)	6095.10 (454.19)	5998.10 (444.26)	7081.42 (561.21)	6412.13 (416.44)	8580.08 (443.35)	<0.001
Meteorological						
Station ID	54511	58362	57516	59493	HKO	
Climate (Köppen-Geiger classification)	Dwa	Cfa	Cfa	Cwa	Cwa	
Temperature, range	-9.2 to 32.5	-1.0 to 32.6	4.5 to 36.5	6.6 to 30.8	9.0 to 31.2	
Temp, mean (SD) °C	12.71 (12.11)	17.03 (9.25)	18.67 (8.39)	23.00 (5.52)	23.50 (5.30)	<0.001
Apparent temp, mean (SD) °C	13.45 (12.61)	17.95 (12.46)	19.62 (11.14)	26.02 (8.69)	26.80 (8.32)	<0.001
Relative humidity, mean (SD)	47.96 (19.19)	73.35 (12.56)	75.23 (11.98)	74.66 (13.98)	76.19 (10.77)	<0.001
Rainfall days, non-zero (%)	58 (14.8)	140 (35.8)	173 (44.2)	122 (31.4)	226 (57.8)	<0.001
Rainfall, mean (SD)	1.40 (7.30)	3.65 (11.32)	3.06 (7.96)	5.04 (15.28)	5.54 (15.97)	<0.001
Windspeed, mean (SD) m/s	2.03 (0.83)	2.56 (0.96)	1.32 (0.43)	1.86 (0.74)	6.59 (2.96)	<0.001
Pressure, mean (SD)	1013.88 (10.62)	1016.76 (9.47)	983.59 (9.20)	1005.72 (6.96)	1013.09 (7.01)	<0.001
Sunshine, mean (SD)	6.79 (3.67)	5.07 (4.22)	3.12 (4.06)	5.27 (3.84)	5.25 (3.86)	<0.001
Precision variables						
AQI, mean (SD)	82.72 (48.67)	64.92 (32.70)	65.12 (31.51)	48.29 (17.04)	\	<0.001
AQHI, mean (SD)	\	\	\	\	3.51 (1.08)	NA
Holiday (%)	25 (6.4)	25 (6.4)	25 (6.4)	25 (6.4)	19 (4.9)	0.863
Extra workdays (%)	7 (1.8)	7 (1.8)	7 (1.8)	7 (1.8)	0 (0.0)	NA
Typhoon (%)	0 (0.0)	5 (1.3)	0 (0.0)	2 (0.5)	9 (2.3)	0.001
Super typhoon (%)	0 (0.0)	0 (0.0)	0 (0.0)	1 (0.3)	1 (0.3)	0.557
Marathon (%)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	1 (0.3)	NA

Aggregated anonymized data on physical activity obtained from in-app function WeRun, Dec 2017-2018

^Chi-square test was used to measure the overall difference in proportion between the cities.

\ indicates the absence of data. p ≤ 0.05 indicates significant difference.

5.3.2 Main model

The final models in Beijing, Chongqing, and Hong Kong underwent a stepdown process, where atmospheric pressure and relative humidity were removed (see Table 5.4). For Shanghai and Shenzhen, no changes were required from the full model.

Table 5.4 Stepdown models of five Chinese cities

	Beijing (BJ)		**Shanghai (SH)**		**Chongqing (CQ)**		**Shenzhen (SZ)**		**Hong Kong (HK)**	
	df	**AIC**	**df**	**AIC**	**df**	**AIC**	**df**	**AIC**	**df**	**AIC**
Full model	34.04	4833.63	38.57	4850.99	39.74	4930.01	38.89	4795.06	32.58	5368.99
Stepdown 1	33.77	4828.11	Process stopped		38.23	4931.55	Process stopped		31.60	5367.05
Stepdown 2	Process stopped				Process stopped				30.64	5365.23
Variables removed	Removed pressure				Removed pressure				Removed pressure, RH	

Aggregated anonymized data on physical activity obtained from in-app function WeRun, Dec 2017-2018
df = degrees of freedom

Three out of five cities had found significant inverse U-shaped associations between temperature and daily step count in high temperatures (see Table 5.5 and Figure 5.1). In low temperatures, Beijing, Shanghai, and Shenzhen had significantly lower physical activity, while no significant association was found in Chongqing and Hong Kong. The optimal temperature of peak step counts varied slightly between cities. In Beijing, the estimate of optimal temperature was at 19.29°C, with a change in -386.04 (95% CI: -626.59, -145.50) steps for a 10°C increase from optimal temperature. In Shanghai, the optimal temperature was 17.92°C, with a change in -432.65 (95% CI: -636.24, -229.05) and in Chongqing, the optimal temperature was 16.05°C, with a -321.69 decrease (95% CI: -526.61, -116.77) in average step count for 10°C increase from optimal temperature. In extremely hot temperatures, the effect on physical activity among recorded temperatures decreased as far as -820 steps at 32.6°C in Shanghai, and -1494 steps at 36.5°C in Chongqing from optimal temperatures.

In Shenzhen, a curvilinear association was found albeit non-significant in higher temperatures. At the highest temperature in the dataset (30.8°C), there was a non-significant decrease of -204.83 step counts (95% CI: -514.46, 104.79) compared to the optimal temperature (24.16°C). However, looking at the trend, it would seem that at 10°C increase from optimal temperature, the average step count would be associated with a significant decrease. On the other hand, a weak non-significant negative linear temperature association was found for Hong Kong.

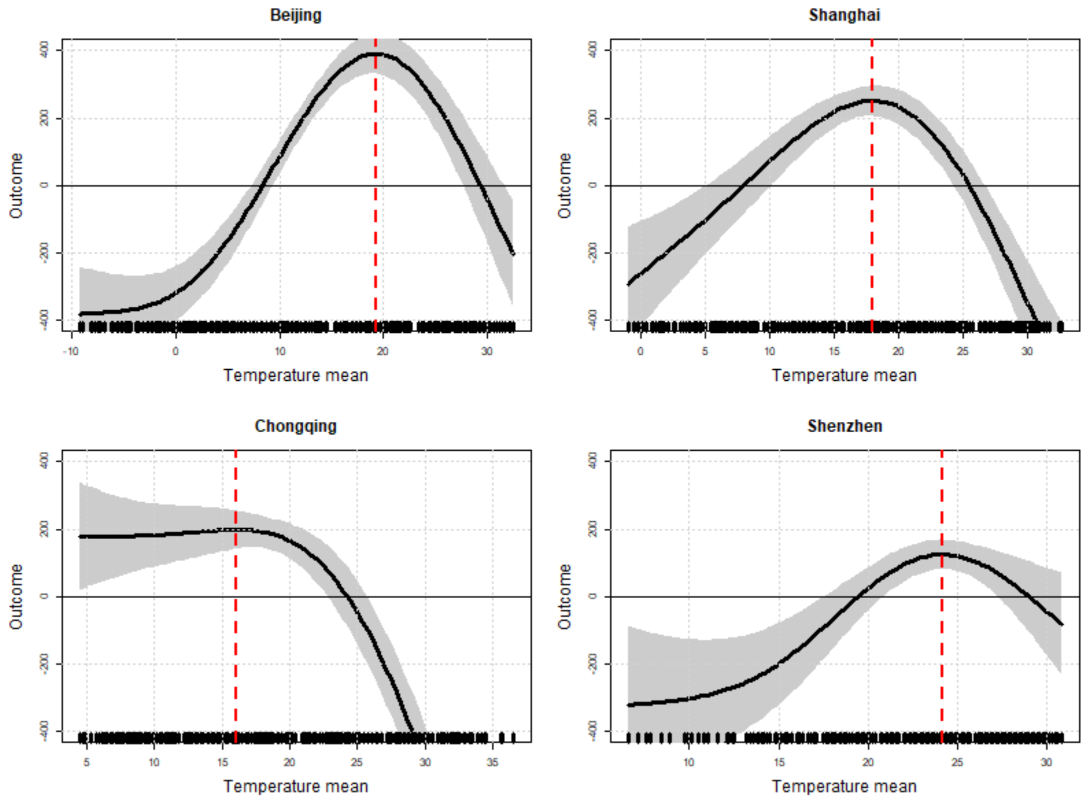
For other meteorological variables, higher relative humidity was negatively associated with Shanghai, Chongqing, and Shenzhen in a non-linear manner (see Appendix B4 and B5). High relative humidity in Beijing found a non-significant association with average step count. Rainfall and windspeeds were negatively associated with all five cities. Sunshine was positively associated, particularly in inland Chongqing. Where atmospheric pressure remained in the model, it was found positively associated in Shenzhen and marginally associated in Shanghai. The air pollution index was significantly associated in all cities except Beijing. Overall, the final model of these cities explained 73% to 88% of the variance (see Figure 5.1 model information). See Appendix B6 for more information on the model fit for each city.

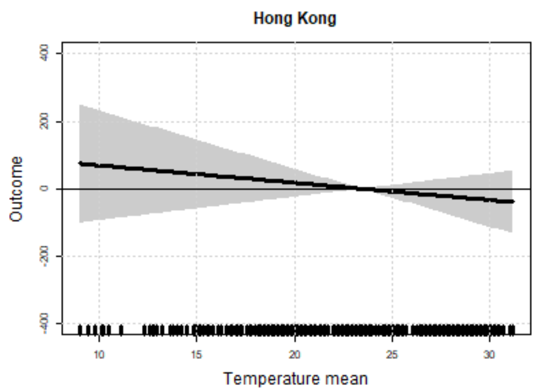
Table 5.5 Mean temperature associations on daily average step count, by city

City	Optimal Temp (OptT)^	OptT - 10C	Change in steps	95% CI	Sig.	OptT + 10C	Change in steps	95% CI	Sig.
BJ	19.29	9.3	-342.81	-452.22, -233.40	*	29.27	-386.04	-626.59, -145.50	*
SH	17.92	7.92	-251.58	-423.02, -80.13	*	27.92	-432.65	-636.24, -229.05	*
CQ	16.05	6.06	-19.09	-293.10, 254.92		26.04	-321.69	-526.61, -116.77	*
SZ	24.16	14.16	-351.73	-614.82, -88.64	*	30.8†	-204.83	-514.46, 104.79	
HK	20	10	-2.96	-331.76, 325.84		30	-105.43	-268.49, 57.64	

Aggregated anonymized data on physical activity obtained from in-app function WeRun, Dec 2017-2018; City abbrev.: BJ = Beijing, SH = Shanghai, CQ = Chongqing, SZ = Shenzhen, HK = Hong Kong
^Where association was not curvilinear, the optimal temperature was pre-set to 20°C; †The upper limit (30.8°C) of temperature data in Shenzhen. Statistical significance set at $p \leq 0.05$.
Models adjusted for relative humidity*, precipitation, windspeed, pressure*, sunshine, AQI/AQHI, month, day of week, public holiday, extra workdays, typhoon, super typhoon, and marathon (*some cities had these variables removed in the stepdown process)

Figure 5.1 Relationships between temperature and daily step count in five Chinese cities





Model information			
City	R^2	N	AIC
Beijing	0.8804	366	4828.11
Shanghai	0.8619	366	4850.99
Chongqing	0.855	366	4931.55
Shenzhen	0.8031	361	4795.05
Hong Kong	0.7327	391	5365.23

Aggregated anonymized data on physical activity obtained from in-app function WeRun, Dec 2017-2018
Black markings along the x-axis indicate the actual existing temperature data of each city; vertical red dotted lines indicate the identified optimal temperature.
Models adjusted for relative humidity*, precipitation, windspeed, pressure*, sunshine, AQI/AQHI, month, day of week, public holiday, extra workdays, typhoon, super typhoon, and marathon (*some cities had these variables removed in the stepdown process)

5.3.3 Stratification analyses

When stratified by gender, a lower optimal temperature was found among females than males in all four cities with curvilinear associations (Beijing, Shanghai, Chongqing, and Shenzhen) (see Table 5.6). A slightly larger effect was found in Beijing among females at 10°C above optimal temperature. Alternately, in Shenzhen a slightly larger effect was found among females at 10°C colder temperatures from optimal. In Hong Kong, the associations among both males and females remained non-significant.

Table 5.6 Stratification results of the temperature-physical activity associations in five Chinese cities

City	Stratifi-cation	OptT^	OptT – 10C	Change in steps	95% CI	Sig.	OptT + 10C	Change in steps	95% CI	Sig.
BJ	Male	19.95	9.97	-344.91	-453.18, -236.64	*	29.94	-353.35	-614.02, -92.67	*
	Female	18.67	8.69	-339.23	-456.42, -222.04	*	28.66	-405.38	-641.13, -169.62	*
SH	Male	18.59	8.59	-249.56	-422.60, -76.53	*	28.59	-427.44	-656.20, -198.69	*
	Female	17.31	7.32	-250.58	-427.51, -73.66	*	27.31	-418.71	-609.06, -228.36	*
CQ	Male	17.97	7.98	16.08	-200.40, 232.55		27.96	-336.22	-551.57, -120.88	*
	Female	15.56	5.57	-76.56	-383.25, 230.13		25.55	-376.71	-588.95, -164.46	*
SZ†	Male	24.31	14.32	-291.75	-536.94, -46.57	*	29.31†	-124.7	-346.63, 97.22	
	Female	23.49	13.49	-338.11	-629.86, -46.36	*	28.49†	-132.57	-334.20, 69.06	
HK	Male	20	10.01	-4.51	-312.73, 303.70		30	-128.86	-281.80, 24.08	
	Female	20	10.01	-3.39	-358.39, 351.61		30	-96.71	-272.87, 79.45	
(Age information available upon reasonable request)										

Aggregated anonymized data on physical activity obtained from in-app function WeRun, Dec 2017-2018
City abbreviations: BJ = Beijing, SH = Shanghai, CQ = Chongqing, SZ = Shenzhen, HK = Hong Kong
^Where association was not curvilinear, the optimal temperature was pre-set to 20°C. Statistical significance set at $p \leq 0.05$.
†An interval of 5°C above optimal temperature was used for Shenzhen, as wider intervals would hit the upper limit (30.8°C) and prevent comparisons between groups.

5.3.4 Sensitivity analyses

Several sensitivity analyses were conducted on the 1) effect of apparent temperature and 2) effect of percentile temperature, 3) removal of air pollution index, and 4) removal of outlier data caused by Typhoon Mangkhut in Shenzhen and Hong Kong on Sept 16, 2018. The results were largely consistent with the primary findings (see Table 5.7).

For apparent temperature models, the AIC was higher than the original model in all cities aside from Hong Kong. A slightly higher optimal apparent temperature was found in Beijing, Shanghai, and Shenzhen. A slightly lower optimal apparent temperature was found in Chongqing, although the effect at +10°C was no longer significant. In Hong Kong, the effect at +10°C from 20°C was significantly decreased by -83.74 (95% CI: -150.39, -17.10).

Optimal percentile temperature were found at the 48th percentile in Chongqing, 54th percentile in Shanghai, 58th percentile in Shenzhen, and 68th percentile in Beijing. Similar to the main model, no optimal percentile temperature was found for Hong Kong. The model AIC improved when using percentile temperature for all cities except Chongqing. See Appendix B7 for the plots using percentile temperature.

Without the pollution index, the results remained consistent in Beijing, Shanghai, and Shenzhen, although the model AIC had a substantial increase from each city's original model. In Chongqing, the optimal temperature increased from 16°C to 19.3°C. Additionally, a curvilinear association was found in Hong Kong, with optimal temperatures at 21.9°C and a marginally significant decrease of -347.98 (95% CI: -697.80, 1.84) for a 10°C increase from optimal temperature.

The results remained consistent when removing the typhoon outlier for Shenzhen and Hong Kong, while the model AIC improved from the original. When the two cities were hit by Typhoon Mangkhut on Sept 16, 2018, the aggregated daily step counts on that date dropped significantly to 3992 and 4682, respectively compared to average step counts.

Table 5.7 Sensitivity analyses of the temperature-physical activity associations in five Chinese cities

City	Model	OptT^	OptT - 10C	Change in steps	95% CI	Sig.	OptT + 10C	Change in steps	95% CI	Sig.	df	AIC
BJ	Original (Mean Temp)	19.29	9.30	-342.81	-452.22, -233.40	*	29.27	-386.04	-626.59, -145.50	*	33.77	4828.11
	Apparent Temperature	22.11	12.12	-250.24	-362.74, -137.73	*	32.10	-344.71	-610.28, -79.15	*	33.33	4836.08
	Percentile Temp^	68th	10th	-767.05	-965.41, -568.69	*	90th	-353.75	-581.84, -125.66	*	34.81	4814.30
	Without pollution index	18.76	8.77	-310.48	-419.70, -201.27	*	28.74	-377.00	-613.14, -140.87	*	31.90	5161.61
SH	Original (Mean Temp)	17.92	7.92	-251.58	-423.02, -80.13	*	27.92	-432.65	-636.24, -229.05	*	38.57	4850.99
	Apparent Temperature	18.55	8.55	-145.16	-297.77, 7.44		28.56	-187.3	-362.51, -12.09	*	36.62	4878.3
	Percentile Temp^	54th	10th	-356.87	-571.74, -142.01	*	90th	-513.99	-744.07, -283.92	*	37.53	4845.4
	Without pollution index	17.9	7.9	-237.85	-408.19, -67.51	*	27.89	-402.16	-597.86, -206.47	*	35.04	5193.56
CQ	Original (Mean Temp)	16.05	6.06	-19.09	-293.10, 254.92		26.04	-321.69	-526.61, -116.77	*	38.23	4931.55
	Apparent Temperature	15.31	5.30	1.76	-253.60, 257.11		25.31	-138.26	-319.75, 43.23		35.76	4984.71
	Percentile Temp^	48th	10th	-51.33	-284.18, 181.51		90th	-812.00	-1079.99, -544.02	*	38.26	4949.13
	Without pollution index	19.32	9.32	-126.11	-398.63, 146.40		29.31	-500.98	-808.02, -193.95	*	36.40	5273.90
SZ	Original (Mean Temp)	24.16	14.16	-351.73	-614.82, -88.64	*	30.8	-204.83	-514.46, 104.79		38.89	4795.06
	Apparent Temperature	27	17.02	-95.95	-274.75, 82.85		36.99	-126.51	-367.75, 114.73		36.19	4832.15
	Percentile Temp^	58th	10th	-279.65	-509.85, -49.45	*	90th	-171.82	-390.31, 46.68		37.97	4794.83
	Without Pollution index	23.82	13.82	-310.13	-577.82, -42.45	*	30.8	-213.35	-511.84, 85.15		36.07	5137.36
	Without Typhoon	24.15	14.16	-352.58	-613.61, -91.55	*	30.8	-204.58	-513.15, 103.99		37.93	4781.08
HK	Original (Mean Temp)	20	10	-2.96	-331.76, 325.84		30	-105.43	-268.49, 57.64		30.64	5365.23
	Apparent Temperature	20	9.99	-9.45	-272.98, 254.09		29.99	-83.74	-150.39, -17.10	*	30.65	5365.01
	Percentile Temp^	50th	10th	-10.38	-221.33, 200.56		90th	-173.07	-382.91, 36.78		30.67	5363.27
	Without Pollution index	21.89	11.89	-128.83	-522.98, 265.33		31.20	-347.98	-697.80, 1.84		34.74	5373.68
	Without Typhoon	20	10.01	-3.65	-328.92, 321.62		30	-104.22	-261.12, 52.68		29.87	5350.36

Aggregated anonymized data on physical activity obtained from in-app function WeRun, Dec 2017- 2018

City abbreviations: BJ = Beijing, SH = Shanghai, CQ = Chongqing, SZ = Shenzhen, HK = Hong Kong

^Where association was not curvilinear, the optimal temperature was pre-set to 20°C or 50th percentile. Percentile temperatures were set to 10th and 90th percentiles for analysis. Statistical significance set at p ≤ 0.05.

5.4 Discussion

Curvilinear associations of temperature on city-wide aggregated step counts in four of five Chinese cities (Beijing, Shanghai, Chongqing, and Shenzhen) were found. Step counts peaked at optimal temperatures ranging from 16.0°C in Chongqing, 17.9°C in Shanghai, 19.3°C in Beijing, to 24.2°C in Shenzhen. In warm temperatures, an average decrease of 322 to 433 steps was found for those cities at 10°C increase from optimal temperature, while temperatures in Shenzhen did not extend high enough to find a significant association. In Hong Kong, a non-significant association was found between temperature and step count, however, a marginally significant curvilinear association was found with optimal temperatures at 21.9°C when the city-specific air pollution index (AQHI) was taken out of the model, and a significant negative association was found in high apparent temperatures. Optimal percentile temperatures ranged between 48th percentile in Chongqing to 68th percentile in Beijing. Other results remained largely consistent in the sensitivity analyses.

Only a few temperature-physical activity studies had previously been conducted in China or in the Asian region. Two studies, located in Cfa and Dfb climates in Japan, had similarly found curvilinear associations between temperature and step counts (Hino et al., 2017; Togo et al., 2005), although a separate study among elderly had only found positive associations (Ogawa et al., 2019). In studies located in Dwa cold climates in China, northernmost Harbin found a positive temperature association during the spring months with the intensity of activity and number of active persons in the public park (Zhao et al., 2018). Meanwhile, a previous study in Beijing found no association between hourly temperature and physical activity when assessed linearly among 40 Chinese participants of an accelerometer study (Wang et al., 2017). In Hong Kong, a study on Pokémon Go users found a negative association between temperature and daily distance travelled in the summer (Ma et al., 2018). With a large proportion of young participants, this was similar to the negative association among those in the stratified results for Hong Kong.

In previous multi-location studies, a trail study across the USA found increasing optimal temperatures with warmer American-centric climate regions (Ermagun et al., 2018). In this study, locations with similar climates found similar effects, however warmer locations did not necessarily have the higher thresholds. Chongqing and Shanghai (climate Cfa) had similar optimal temperature peaks and clear decreased physical activity associations in warm temperatures. Warmer Shenzhen and Hong Kong (climate Cwa) found similar optimal temperature peaks ranging in the early 20s°C, particularly in the Hong Kong model without air pollution. As both cities had lower extreme temperatures (maximum temp: 30.8°C and

31.2°C, respectively) compared to the other cities, non-significant associations were found in warm temperatures, although the trend hinted at significant associations in more extreme temperatures. Surprisingly, Beijing (climate Dwa) had a relatively high optimal temperature (19.3°C) and the highest percentile optimal temperature at 68th percentile, despite having an overall colder climate.

Overall, these findings are consistent with Gasparrini et al. (2015), which found that both average temperature and temperature range accounted for the heterogeneity between locations in the temperature-mortality relationship. As indicated by Beijing's climate classification Dwa, the 'a' demonstrates hot summer temperatures in an overall cold snow climate zone 'D' (see Figure 2.2, page 19). This produces a wider temperature range than other cities, as found in Table 5.3. With half of annual temperatures below 12°C in Beijing, the population may seek to take advantage of the warmer temperatures and other connected weather conditions (increased daylight hours, absence of icy surfaces etc.) to conduct more active leisure activities (Aspvik et al., 2018), leading to the findings of a greater increase of physical activity in warmer temperatures and higher optimal temperature than other cities.

This study found that optimal temperatures for physical activity ranged between 48th to 68th percentile. These results seem to correspond to a temperature-mortality study in China, which found minimum mortality thresholds near the 75th percentile in the pooled analysis of 66 Chinese communities (Ma et al., 2015). It would be expected that optimal temperatures for physical activity are at a lower percentile than mortality thresholds. Similar to this study, the mortality analysis found that northern regions had greater heat effects, while the southern regions had less heat effects (Ma et al., 2015). Additionally, mortality in the eastern region, which included Shanghai, was distinctly affected by both cold and heat (Ma et al., 2015). The mortality analysis, however, found greater cold effects in the southern regions (Ma et al., 2015), which was not necessarily captured in this physical activity analysis. The inter-city variations in physical activity patterns, as seen by the range of optimal percentile temperatures, seem to demonstrate population adaptation to local climates (Ma et al., 2015) and may have also been influenced by variations in infrastructural or spatial patterns of the urban environment, such as the city density and urban sprawl (LV et al., 2017). As found in a study in Beijing, the built environment can significantly affect people's allocation of time and pursuit of activities (Wang, Chai, & Li, 2011).

In the stratification analysis, lower optimal temperatures were found among females in almost all cities. Among previous studies that stratified by gender, only one of those studies found overall lower step counts among females compared to males (Hino et al., 2017), while other studies did not find clear differences between males and females (Aspvik et al., 2018; Bosdriesz et al., 2012; Klenk et al., 2012; Saneinejad et al., 2012). When stratified by age, this study also found that older age groups had lower optimal temperatures and larger decreases of step count in warmer temperatures compared with younger age groups. The findings on older age groups are consistent with several previous studies that stratified by age and found stronger temperature effects among those over 65, particularly over 80 (Hino et al., 2017; Obradovich & Fowler, 2017; Witham et al., 2014). These are also aligned with the physiological understanding of a lower heat tolerance among older adults, even as early as 40 years old, due to a decreased capacity to thermoregulate (Balmain et al., 2018; Kenny et al., 2010; Larose et al., 2013).

Strengths and limitations

This was the first multi-location comparative study on temperature and physical activity located in Asia. This study demonstrated a decrease of daily physical activity in high temperatures using aggregated objectively measured step counts from a large, anonymized sample size. The data collection method ensured that anonymized users were located in the respective cities in order to be included in the analysis. A non-linear statistical analysis allowed for flexible associations between temperature and physical activity, as well as all other meteorological variables. The analysis comprised over a year's duration, covered all seasons, and controlled for time-related variables and holidays and special events (typhoons and marathons) where feasible.

However, this study's data collection was limited by those who voluntarily downloaded the mobile application, and may have skewed towards the health-conscious, able-bodied (no mobility problems), younger, and more active subset of the population. This can be seen by the relatively high average daily step count of each city and the skewed age distribution compared to the general population. The accelerometer data could only collect information on ambulatory activities when the phone was located with the person and was unable to account for any cycling or aquatic activities. As this study could not control for whether the anonymized users kept their phones on them, the aggregation from a large data sample could be an underestimation of actual physical activity levels. Finally, the aggregated data could not control for individual participants and would have included any visitors or temporary stay individuals who used the in-app function and were located in the city during any evenings of the study period.

Future research directions

Future studies should assess the temperature-physical activity relationship in more climate types and geographical locations of China and other regions. An increased understanding is needed on the role of urban planning and spatial patterns in affecting the relationship between temperature and physical activity. Extreme temperature events could be assessed in warmer subtropical climate locations like Shenzhen and Hong Kong, to elucidate the effect of extreme temperatures. Furthermore, the singular effect of the super typhoon in these two cities also hints at the large impact that extreme weather events can have on population activity. With climate change and an increased frequency of typhoons, storms, and other climate-related hazards, there may be increased days where population activity is lowered by such extreme events. Studies could further examine and project the impact of physical activity in extreme weather events.

Implications on public health policy

This study demonstrates that optimal temperatures for physical activity between a range of 16°C to 24°C in the major cities in China. The impact of temperature seemed to be greater in climates with wider temperature ranges. In extremely hot temperatures, the physical activity of a city population decrease as far as 800 to 1500 steps compared to the optimal temperature. This overall reduction of physical activity at the population level occurred despite any substitutions of indoor physical activity that may have occurred among the urban population. A growing awareness of decreased physical activity in cold and heat would help formulate adaptations to the promotion of physical activity in China. Healthcare providers could suggest suitable adaptations to patients to help maintain their physical activity regardless of temperature. Possible interventions could include indoor exercise routines, indoor mall-walking, and subsidises on exercise-related fees, especially for those who cannot afford private memberships. Physicians should particularly be alerted to the added impact of temperatures on older patients.

In China, communities have limited access to indoor recreational facilities, as many sporting venues not commonly available for public use (Gao & Cao, 2018). This was particularly highlighted in a Beijing study, where increased leisure activities was associated with parks but not sporting venues (Liu, Zhang, Jin, & Liu, 2020). The study suggested that the entry fees caused sporting venues to be “popular amongst sports enthusiasts, ...[but] not...

attractive for the general public” (Liu et al., 2020). Instead, people tended to go to free public spaces for exercise or leisure activities (Liu et al., 2020). However, solely increasing the availability of public spaces may have limited impact on physical activity promotion, as this study found that physical activity decreased in non-optimal temperatures. Cities in China should increase the access and affordability of recreational facilities, opening it up to the public.

Chapter 6 Hourly temperature, surrounding greenness, and physical activity in four European cities – Study (3)

6.1 Introduction

Although many temperature-physical activity studies have been conducted in the European region, rarely have these studies compared across different locations. In the systematic review in Chapter 4, only one study was found to compare transport physical activity between Northern European countries (Böcker et al., 2019). Additionally, among the European studies, many studies were either subjective surveys of the general population, or objective assessments of elderly or patient-specific populations. There is a lack of objectively measured physical activity studies in the general population of European countries.

As discussed in Section 2.3.2, human experience of ambient temperature is affected by the surrounding built environment. Greenspace and vegetation has been known to contribute to urban temperature regulation with a cooling effect extending 200m to 500m (Ca, Asaeda, & Abu, 1998; Hamada & Ohta, 2010). Urban greenery could affect apparent temperatures through processes such as evapotranspiration (which transforms sensible heat into latent heat by evaporating liquid water into water vapour), shading from tree cover, and regulation of air movements and heat exchange (Bowler, Buyung-Ali, Knight, & Pullin, 2010). A meta-analysis on urban greenery found that parks reduced urban air temperatures by 1°C on average, with larger parks and trees possibly having a greater effect (Bowler et al., 2010). In London, a recent study found that heat-related mortality was modified by urban vegetation levels, whereby neighbourhoods with the highest tree cover and vegetation had lower odds of heat-related mortality (Murage et al., 2020). The cooling effect of greenspaces may further promote the physical activity conducted in those spaces.

Only four studies previously assessed the effect of greenspace while analyzing the relationship between temperature and physical activity, as identified in the systematic review (Section 4.3.1.5). The studies found mixed associations between greenspace and physical activity (Farrell et al., 2014; Fishman et al., 2015; Lindsey et al., 2006). Weekly temperatures and residential neighbourhood greenspace were found to be positively associated with self-reported weekly physical activity in Paris, but no interactions were found (Chaix et al., 2014). These findings indicate possible interactions between surrounding greenness and temperature on physical activity, however, all these studies were assessed over broad timescales, of daily, weekly, or monthly effects. Such broad timescales are limited in their control of temporal concurrence of both meteorological conditions and greenspace use. An hourly analysis that includes continuous monitoring of the weather, location, and physical activity level during people's daily life can be used to capture the large variation in people's physical activity locations and increase the sensitivity to weather changes within a day (Burchfield et al., 2012; Prins & van Lenthe, 2015). Smartphones, with their GPS and accelerometery services, enable this concurrent objective measurement of time- and location-specific physical activity, which may help better explain linkages between temperature, surrounding greenness, and physical activity.

This multi-location comparative study assesses the synergetic effects of temperature and surrounding greenness on hourly physical activity in four European cities, using objective personal measures in a subsample of participants from the Positive Health Effects on the Natural Outdoor Environment in Typical Populations of Different Regions in Europe (PHENOTYPE) Project (Nieuwenhuijsen et al., 2014).

6.2 Methodology

Study setting and design

Secondary data were obtained from a smartphone-based monitoring study, recruited from a random sample of participants residing in four cities: Barcelona (Spain), Stoke-on-Trent (United Kingdom), Doetinchem (The Netherlands), and Kaunas (Lithuania) in the PHENOTYPE project (Nieuwenhuijsen et al., 2014; Smith et al., 2017; Triguero-Mas et al., 2017). All study participants of the PHENOTYPE project questionnaire (N=3946) were invited to participate in this smartphone study, with the aim of recruiting around 100 participants per city. The study inclusion criterion was to be able to walk 300 m on level ground. In total, the subsample smartphone study recruited 431 participants: 109 in Barcelona (10.4% of invited participants from that city), 49 (4.7%) in Stoke-on-Trent, 111 (12.9%) in Doetinchem, and 112 (11.2%) in Kaunas. In Stoke-on-Trent, participation was further boosted through randomised mail invitations and opportunistic sampling (n = 50) (Triguero-Mas et al., 2017).

Each participant was instructed to wear a smartphone installed with the CalFit mobile application for seven consecutive days during the May – December 2013 study period. During this time, the smartphone was to be removed only during charging, sleeping or when performing activities that could damage the smartphone (i.e. aquatic activities). The Calfit application, which has been validated against the Actigraph accelerometer (Donaire-Gonzalez et al., 2013), used accelerometer motion sensor and global positioning system

(GPS) receivers to collect data on participant physical activity and geographical location. More details of the study protocol can be found at (Nieuwenhuijsen et al., 2014; Triguero-Mas et al., 2017).

Ethics approval and funding

Ethical approval was obtained from each city's corresponding authority: Clinical Research Ethics Committee of the Municipal Health Care (CEIC PS-MAR), Spain (2012/4978/I); Staffordshire University Faculty of Health Science ethics committee, United Kingdom; Medical Ethical Committee of the University Medical Centre Utrecht, Netherlands; Lithuanian Bioethics Committee, Lithuania (2012-04-30 Nr.6B-12-147). The PHENOTYPE project was funded from the European Commission's Seventh Framework Programme (FP7/2007-2013) under grant agreement no. 282996.

Outcome: Physical activity

Physical activity was estimated using Metabolic Equivalent of Task (MET), which is a measurement quantifying the energy expenditure of activities using the resting metabolic rate (3.5 ml O_2/kg/min) as the basic unit (Jetté et al., 1990). The Calfit raw accelerometer data was summarized into 1-minute intervals and transformed into METs using an adapted equation from (Freedson, Melanson, & Sirard, 1998) (see original paper Donaire-Gonzalez et al. (2013) for more information). These METs at the minute level were then averaged to produce Average hourly MET. Non-wear time of smartphone data was removed from the dataset, defined as episodes of 40 or more consecutive minutes with the accelerometer's vertical axis below 0.3g (Donaire-Gonzalez et al., 2013; Triguero-Mas et al., 2017). A valid hour was defined as having both physical activity counts and surrounding greenness counts for over 30 minutes within the hour. Only waking hours (6:00 to 23:59) were included in the analysis. A valid user was defined as having at least four days with a minimum of 10 valid hours per day during the waking hours.

Exposure: Apparent temperature

Meteorological records were obtained for year 2013 from the respective nearest local meteorological stations: Zona Universitària in Barcelona (41.379 °N, 2.105 °E), Keele University in Stoke-on-Trent (52.999 °N, 2.268 °W), Hupsel in Doetinchem (52.067 °N, 6.500 °E), and Kaunas station in Kaunas (54.883 °N, 23.835 °E). Apparent temperature was calculated from temperature and relative humidity (Ballester et al., 2011; Sensirion, 2006). Apparent temperature was both kept as a continuous variable and categorized into five-degree width intervals (reference: 5 to 10°C) in order to facilitate the assessment of its relationship with physical activity.

Exposure: Surrounding greenness

Contact with surrounding greenness was measured through hourly average Normalized Difference Vegetation Index (NDVI). NDVI captures the level of vegetation or greenness on a scale with minimum/maximum values of -1 and +1. Cloud-free Landsat 8 satellite images (resolution 30mx30m) during the study period were used to create NDVI maps for each city area. The maps were then used to assign NDVI values for every GPS point location obtained from Calfit smartphone data of the participants, which were then summarized per hour to obtain the total average hourly NDVI. The variable was further categorized into city-specific NDVI quartiles.

Covariates: precision variables

For the other meteorological covariates obtained from the meteorological records, rainfall was transformed into a binary variable (zero; non-zero rainfall), while windspeed remained as a continuous variable. Daily dawn and dusk times were obtained for each city from the ‘suncalc’ R package (Thieurmel & Elmarhraoui, 2019), and these times were rounded to the nearest hour to create a binary variable of sky darkness (no; yes).

Residential surrounding greenness was measured as mean residential NDVI within 300m circular buffer, which is commonly used in international studies to assess the natural greenness participants would have been exposed to near their home (Kruize et al., 2020).

To control for time trend and seasonality, month (reference: September), day of week (ref: Monday), hour of day (ref: 1 pm of each time zone), and public holiday were included in the analyses. The following sociodemographic variables were linked from the PHENOTYPE project survey data of each participant and also included as potential precision variables: gender (ref: male), age (ref: 26-45; 18-25; 46-65; 66-75), education level (ref: university degree or higher; secondary school/ education (up to 18 years); no education or primary school only), chronic disease status (ref: no; yes), and dog ownership (ref: no; yes), employment (ref: employed; unemployed or retired), having children under age 12 (no; yes), meeting physical activity guidelines (no; yes as estimated in the survey questionnaire), and perceived income (enough; comfortable; not enough).

Statistical analysis

A linear mixed model was conducted separately for each city, to assess the interaction effects of apparent temperature and surrounding greenness on physical activity (hourly average MET), controlling for other meteorological, time-related, and demographic variables. A random effect of participant in the intercept was included to consider within-participant correlation. As the outcome variable average MET per hour was highly right-skewed, it was log transformed to be properly modelled. A preliminary model was used to assess the shape of the association between apparent temperature and physical activity, using a categorical temperature variable. Then, assuming a parabolic relationship between apparent temperature and physical activity, the main model was fitted using an interaction term between the quadratic apparent temperature term and surrounding greenness. Such an interaction term allowed the optimal temperature of maximum MET, to vary across the different greenness levels. If the quadratic effect was not significant, a linear interaction effect was used in the model. The temperature-greenness interaction was examined for its significance and between-city variation using ANOVA. Statistical significance level was set at 0.05. All analyses were conducted using R version 3.5.2 (R Core Team, 2018), including the "lme4" package.

Because the outcome was log transformed, model results were interpreted in terms of the median or, equivalently, the geometric mean of the average MET per hour. Specifically, a *c* unit increase in the covariate of interest is associated to a percentage change in the median of the outcome $\Delta M\% = 100(e^{\beta c} - 1)\%$, where β is the coefficient of interest in the model (Barrera-Gómez & Basagaña, 2015). For binary variables, *c = 1*, whereas for continuous variables *c* was set at the interquartile difference. To characterize the relationships under the model with quadratic temperature and interaction effects, two measures were computed. The optimal temperature for the quadratic effect was derived as $T_o = -(\beta_1 + \gamma_1) / (2(\beta_2 + \gamma_2))$, where β_1 and β_2 are the coefficients for the linear and quadratic terms for temperature, respectively, and γ_1 and γ_2 are the coefficients for the corresponding interaction terms with greenness variable. As a measure of the effect adjusted by precision variables included in the model, the percentage change (%) in the MET median associated with a departure of +/- T degrees from the optimal temperature was ΔM% derived as

$= 100(e^{(\beta 2 + \gamma 2)T\string^2} - 1)\%$. In the case of non-significant quadratic effect of temperature, $\beta_2 = 0$ for ΔM%, marking the percentage change in MET median associated with T degrees increase in apparent temperature. 95% confidence intervals were computed using 100,000

Monte Carlo simulations in the case of T_o. In the case of no interactions (i.e. assuming that T_o is independent of greenness), $\gamma_1 = \gamma_2 = 0$ in previous formulas for T_o and $\Delta M\%$.

Sensitivity analyses

Sensitivity analyses were conducted to assess the following effects on the main model: (1) the potential lagged effect (up to 3 days) of daily temperature, (2) the removal of month from the main model, (3) the effect of distance from the weather stations, and (4) the effect of transportation options. Additional sensitivity models assessed (5) the effect of percentile apparent temperature, (6) the effect of a separate greenspace indicator: contact with greenspace, and (7) the effect of employment on the physical activity patterns, via stratification. More information can be found in Appendix C3.

6.3 Results

6.3.1 Descriptive statistics

The PHENOTYPE smartphone data had recorded an overall of 31,788 valid hourly observations between May and December 2013 from 352 participants who were included in the final analysis (Barcelona: n = 95, 87.2% of participants; Stoke-on-Trent: n = 79, 79.8%; Doetinchem: n = 94, 84.7%; Kaunas: n = 84, 75.0%). A comparison was conducted between the included and excluded participants of the final analysis (Appendix C1). Excluded participants were more likely to have lower education in Barcelona ($p = 0.002$), to meet active guidelines in Stoke-on-Trent ($p = 0.037$), and to self-report poorer health ($p = 0.006$) and have chronic disease ($p = 0.002$) in Doetinchem. No statistically significant differences were found in Kaunas between excluded and included participant characteristics.

Table 6.1 displays the summary statistics of this study, while Table 6.2 shows the participant demographics of those included in the final analysis. Average MET per hour was practically invariant across the four cities (mean: Barcelona 2.04; Stoke-on-Trent 1.97; Doetinchem 1.98; and Kaunas 2.02). Age, education, and dog ownership were significantly different across the four cities. Dog ownership is often used as a proxy for dog walking and is known to be associated with increased walking time and greenspace or park visits (Zijlema et al., 2019).

Apparent temperature had similar distributions for Stoke-on-Trent (mean 10.0°C, SD 6.3), Doetinchem (12.4°C, SD 7.2) and Kaunas (12.4°C, SD 7.5), while Barcelona had a higher and narrower range of temperatures (23.2°C, SD 4.0). Rainfall was less prevalent in Barcelona (2.8% of the study period) compared with the other three cities (10.3-15.8%), while windspeeds averaged 2.3 m/s to 3.1 m/s across the four cities. Sky darkness was more prevalent in in Stoke-on-Trent (26.5% of hours) and Doetinchem (23.7%) compared with Barcelona (17.9%) and Kaunas (18.7%).

For all cities, the correlation between apparent temperature and surrounding greenness was low ($r \leq 0.1$). The median of hourly average NDVI was the highest in Doetinchem (0.5; IQR 0.4, 0.6), followed by Kaunas (0.5; IQR 0.4, 0.5), Stoke-on-Trent (0.4; IQR 0.3, 0.5) and lowest in Barcelona (0.2; IQR 0.2, 0.3) (see Figure 6.1). Average residential NDVI was lowest in Barcelona (mean = 0.2) compared with the other cities (ranging from 0.5 to 0.6).

Table 6.1 Summary findings of four European cities

Variables	Barcelona, Spain	Stoke-on-Trent, United Kingdom	Doetinchem, Netherlands	Kaunas, Lithuania	p-value^
Observations (Total = 31788)	8978	6769	8894	7147	
Physical Activity					
Average hourly MET, mean (SD)	2.04 (0.80)	1.97 (0.80)	1.98 (0.91)	2.02 (0.74)	<0.001
Meteorological					
Station name (elevation m)	Zona Universitària (79 m)	Keele University (179 m)	Hupsel (30 m)	Kaunas (77 m)	
Climate (Köppen-Geiger classification)	Csa	Cfb	Cfb	Dfb	
Apparent temperature, range	8.46 to 34.45	-3.98 to 30.68	-4.91 to 33.72	-3.13 to 33.60	
Apparent temperature, mean (SD) °C	23.23 (4.00)	10.03 (6.27)	12.42 (7.16)	12.43 (7.46)	<0.001
Rainfall cases, non-zero (%)	253 (2.80)	842 (12.40)	1407 (15.80)	733 (10.30)	<0.001
Non-zero rainfall, mean (SD) mm	1.13 (2.73)	0.88 (1.25)	0.80 (1.28)	1.42 (2.35)	<0.001
Windspeed, mean (SD) m/s	2.29 (1.12)	3.00 (1.52)	3.13 (1.82)	3.04 (1.64)	<0.001
Sky darkness, hours (%)	1608 (17.90)	1791 (26.50)	2108 (23.70)	1338 (18.70)	<0.001
Surrounding Greenness					
NDVI Quartiles, city-specific					<0.001
Quartile 1 Lowest	-0.06 to 0.15	0.05 to 0.32	0.01 to 0.38	0.03 to 0.37	
Quartile 2	0.15 to 0.20	0.32 to 0.41	0.38 to 0.47	0.37 to 0.45	
Quartile 3	0.20 to 0.26	0.41 to 0.49	0.47 to 0.56	0.45 to 0.51	
Quartile 4 Highest	0.26 to 0.81	0.49 to 0.79	0.56 to 0.83	0.51 to 0.77	
Residential NDVI within 300m, mean (SD)	0.21 (0.09)	0.49 (0.09)	0.56 (0.10)	0.54 (0.07)	<0.001
Time-Related (selected)					
Public Holiday (%)	401 (4.5)	101 (1.5)	0 (0.0)	50 (0.7)	<0.001
Month (%)					<0.001
May	0 (0.0)	0 (0.0)	0 (0.0)	205 (2.9)	
June	2068 (23.0)	0 (0.0)	0 (0.0)	524 (7.3)	
July	1685 (18.8)	356 (5.3)	645 (7.3)	419 (5.9)	
Aug	162 (1.8)	1290 (19.1)	762 (8.6)	1182 (16.5)	
Sept (ref)	2707 (30.2)	1533 (22.6)	3031 (34.1)	1567 (21.9)	
Oct	2356 (26.2)	1006 (14.9)	2629 (29.6)	2532 (35.4)	
Nov	0 (0.0)	1352 (20.0)	1125 (12.6)	665 (9.3)	
Dec	0 (0.0)	1232 (18.2)	702 (7.9)	53 (0.7)	

Data on physical activity and surrounding greenness obtained from the PHENOTYPE project, May-Dec 2013

^Chi-square test was used to measure the overall difference in proportion between the cities. $p \leq 0.05$ indicates significant difference.

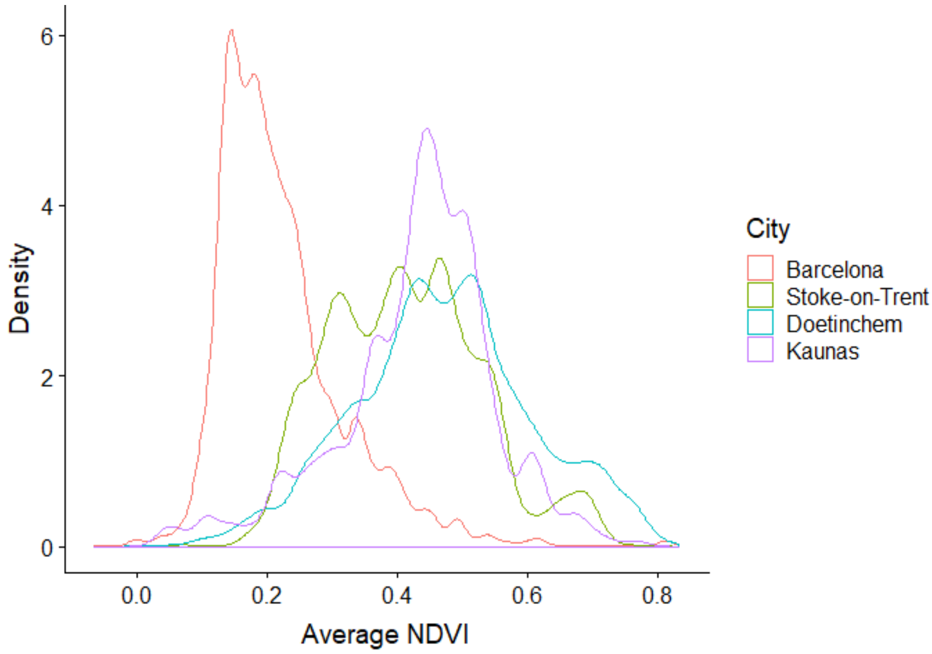
Table 6.2 Participant demographics of four European cities

Variables	Category	Barcelona, SP	Stoke-on-Trent, UK	Doetin-chem, NL	Kaunas, LI	p-value ^
N of Participants		95	79	94	84	
Gender	Female (%)	48 (50.5)	45 (57.0)	53 (56.4)	43 (51.2)	0.751
Age (%)						<0.001
	18-25	16 (16.8)	8 (10.1)	0 (0.0)	12 (14.3)	
	26-45 (ref)	40 (42.1)	34 (43.0)	18 (19.1)	13 (15.5)	
	46-65	33 (34.7)	27 (34.2)	55 (58.5)	50 (59.5)	
	66-75	6 (6.3)	10 (12.7)	21 (22.3)	9 (10.7)	
Education (%)						<0.001
	High (ref)	55 (57.9)	37 (46.8)	45 (47.9)	65 (77.4)	
	Medium	31 (32.6)	41 (51.9)	49 (52.1)	18 (21.4)	
	Low	9 (9.5)	1 (1.3)	0 (0.0)	1 (1.2)	
Dog ownership	Yes (%)	22 (23.2)	28 (35.4)	21 (22.3)	52 (61.9)	<0.001
Chronic disease	Yes (%)	24 (25.3)	21 (26.6)	36 (38.3)	32 (38.1)	0.103
Employment	Unemployed/ retired (%)	30 (31.6)	25 (31.6)	38 (40.4)	26 (31.0)	0.471
Children	With children <12 yrs (%)	25 (26.3)	18 (22.8)	16 (17.0)	10 (11.9)	0.079
Born in country	Yes (%)	80 (84.2)	75 (94.9)	89 (94.7)	74 (88.1)	0.036
BMI (mean (SD))		25.03 (4.62)	26.35 (5.58)	25.92 (4.38)	25.83 (4.81)	0.361
General Health (%)						<0.001
	Excellent/ very good	37 (38.9)	35 (44.3)	76 (80.9)	14 (16.7)	
	Good	40 (42.1)	28 (35.4)	15 (16.0)	37 (44.0)	
	Bad to very bad	18 (18.9)	16 (20.3)	3 (3.2)	33 (39.3)	
Meet PA guidelines	Yes (%)	41 (43.2)	19 (24.1)	34 (36.2)	54 (64.3)	<0.001
Mobility problems	Yes (%)	3 (3.2)	11 (13.9)	28 (29.8)	50 (59.5)	<0.001
Perceived income (%)						<0.001
	Comfortable	29 (31.9)	42 (58.3)	46 (48.9)	19 (26.8)	
	Enough	49 (53.8)	26 (36.1)	27 (28.7)	48 (67.6)	
	Not enough	13 (14.3)	4 (5.6)	21 (22.3)	4 (5.6)	
Own a car	Yes (%)	56 (58.9)	58 (73.4)	84 (89.4)	57 (67.9)	<0.001
Own a motorcycle	Yes (%)	15 (15.8)	5 (6.3)	11 (11.7)	3 (3.6)	0.028
Own a bicycle	Yes (%)	49 (51.6)	33 (41.8)	92 (97.9)	43 (51.2)	<0.001
Near public transport	Yes (%)	92 (96.8)	73 (92.4)	83 (88.3)	63 (75.0)	<0.001

Data obtained from the PHENOTYPE project, May-Dec 2013

^Chi-square test was used to measure the overall difference in proportion between the cities. $p \leq 0.05$ indicates significant difference.

Figure 6.1 Distribution of surrounding greenness (average NDVI), by city



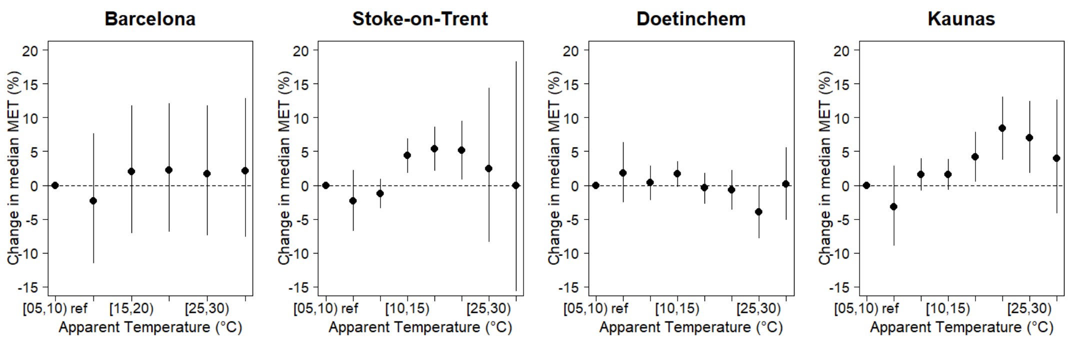
Data obtained from the PHENOTYPE project, May-Dec 2013

6.3.2 Preliminary model

The preliminary models of each city showed a potential curvilinear or negative relationship between categorical apparent temperature and physical activity for Stoke-on-Trent, Doetinchem, and Kaunas (see Figure 6.2A). For Barcelona and Doetinchem, higher surrounding greenness was significantly associated with higher METs. In Stoke-on-Trent and Kaunas, higher surrounding greenness was significantly associated with lower METs (see Figure 6.2B).

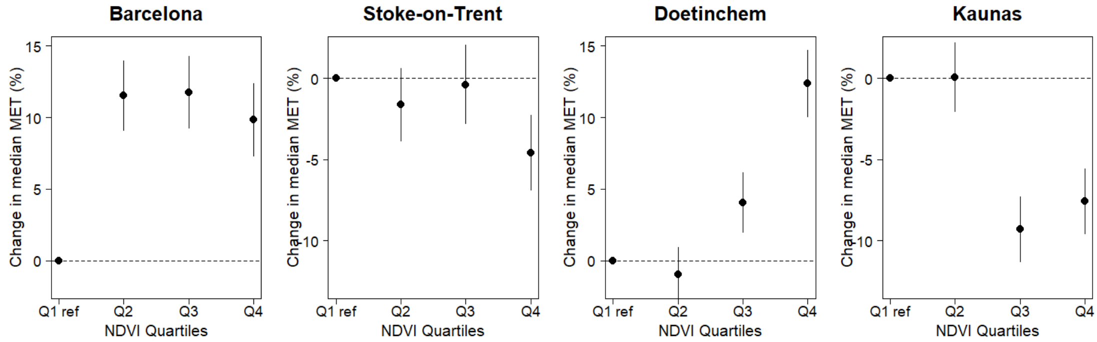
Figure 6.2 Apparent temperature and NDVI patterns in preliminary models of four European cities

Figure 6.2A Apparent temperature patterns in preliminary models



Data on physical activity and surrounding greenness obtained from the PHENOTYPE project, May-Dec 2013 ; The first two categories after [05,10)ref are [-5,0) and [0,5) for Stoke-on-Trent, Doetinchem and Kaunas.

Figure 6.2B NDVI patterns in preliminary models



Data on physical activity and surrounding greenness obtained from the PHENOTYPE project, May-Dec 2013

6.3.3 Main model

Surrounding greenness levels significantly interacted with apparent temperature in three out of four cities: Stoke-on-Trent ($p = 0.023$), Doetinchem ($p < 0.001$), Kaunas ($p < 0.001$). The same interaction in Barcelona was not found to significantly improve the city's model. While physical activity was found independent of temperature at the lowest NDVI level, the relationship was significant at higher NDVI levels (see Table 6.3 and Figure 6.3). Regarding between-cities comparison using ANOVA, the hypothesis of equal pattern of the joint effect of apparent temperature and NDVI on MET was rejected.

In Stoke-on-Trent (n = 6769) and Doetinchem (n=8894), the quadratic association of apparent temperature was significant, with downward parabolic effects for the highest NDVI Quartile 4. For Stoke-on-Trent, the estimate of optimal temperature at NDVI Quartile 4 was 15.2°C (95%CI: 11.3°C, 25.3°C), with a -4.1% change in median MET (95% CI: -7.0%, -1.1%) at +-10°C departure from optimal temperature. For Doetinchem, the optimal temperature at NDVI Quartile 4 was 14.5°C (95%CI: 11.3°C, 17.5°C) and associated with a -3.9% change in median MET (95% CI: -5.8%, -2.1%) for +-10°C departure from optimal temperature. A significant upward parabolic association was also found for Quartile 3 in Doetinchem, with a 2.2% change in median MET (95% CI: 0.3%, 4.2%) for +-10°C departure from optimal temperature of 13.7°C (95%CI: 3.1°C, 21.7°C). Other NDVI Quartiles did not find significant quadratic associations.

In Kaunas (n = 7147), a significant linear association of temperature was found instead of a quadratic association: a 10°C increase in temperature was found associated with 4.3% (95% CI: 1.4%, 7.3%), 3.1% (95% CI: 0.2%, 6.0%), and 4.6% (95% CI: 1.7%, 7.7%) increase in median MET for Quartiles 2, 3, and 4, respectively. In Barcelona (n = 8978), a 10°C increase in temperature was weakly found associated with 4.0% linear increase in median MET in

NDVI Quartile 2 (95% CI: 0.1%, 8.1%). However, the interaction model for Barcelona was not a significant improvement over the non-interaction model.

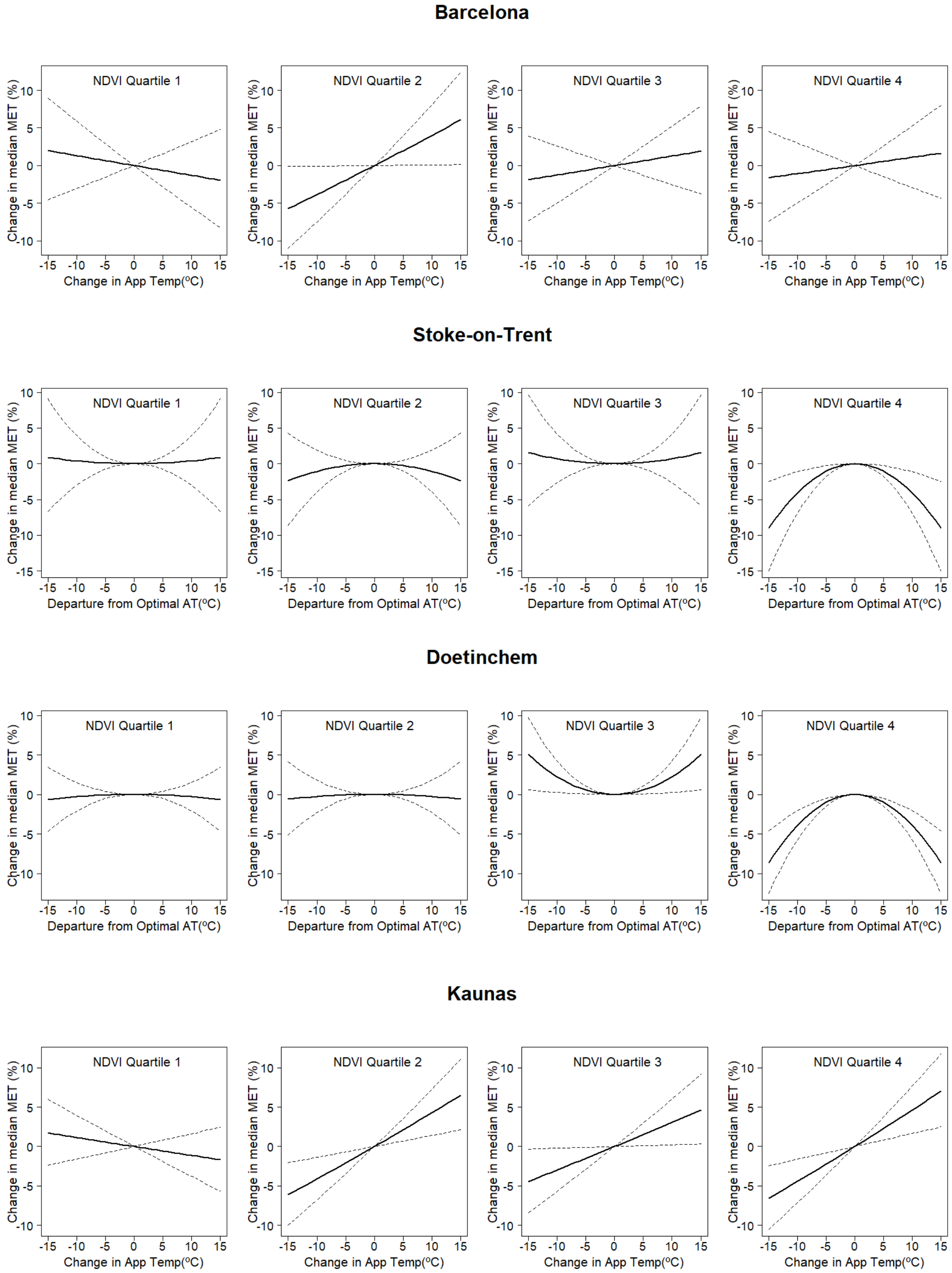
Among the meteorological covariates, rainfall (-2.8%, 95% CI: -4.9%, -0.7%) and a 2.3 m/s increase of windspeed (-1.4%, 95% CI: -2.4%, -0.3%) was negatively associated with average MET in Kaunas (see Appendix C2). Sky darkness was negatively associated with average MET in Stoke-on-Trent (-4.7%, 95% CI: -7.1%, -2.3%). The model also adjusted for residential NDVI of 300 m buffer, month, day of week, hour of day, public holiday, gender, age, education, chronic disease, dog ownership, and participant ID as random effect. Other demographic variables, such as having children under age 12, employment, meeting physical activity guidelines, and perceived income were considered as potential precision variables but not found to improve the model.

Table 6.3 Joint associations of apparent temperature and NDVI on median MET, by city

City	NDVI Quartile	Optimal temp. (C°)	95% CI	Change in median MET for +/- 10°C (%)	95% CI of Change	Sig.
Barcelona						
	Q1			-1.30	-5.57, 3.16	
	Q2			4.00	0.08, 8.08	*
	Q3			1.27	-2.53, 5.21	
	Q4			1.10	-2.91, 5.27	
Stoke-on-Trent						
	Q1	13.55	-47.67, 68.43	0.40	-3.02, 3.93	
	Q2	19.29	-64.45, 93.41	-1.07	-3.94, 1.89	
	Q3	-29.18	-224.01, 240.16	0.69	-2.67, 4.16	
	Q4	15.22	11.26, 25.29	-4.08	-6.96, -1.12	*
Doetinchem						
	Q1	-51.49	-326.34, 330.06	-0.30	-2.1, 1.53	
	Q2	-0.99	-71.54, 98.60	-0.27	-2.32, 1.82	
	Q3	13.74	3.09, 21.73	2.21	0.25, 4.21	*
	Q4	14.49	11.31, 17.46	-3.94	-5.77, -2.08	*
Kaunas						
	Q1			-1.13	-3.8, 1.62	
	Q2			4.29	1.4, 7.26	*
	Q3			3.07	0.21, 6.02	*
	Q4			4.63	1.65, 7.69	*

Data on physical activity and surrounding greenness obtained from the PHENOTYPE project, May-Dec 2013
Barcelona and Kaunas are reporting a linear effect in temperature; Stoke-on-Trent and Doetinchem are reporting quadratic effects and a +-10°C departure from optimal temperature.
Models adjusted for rainfall, windspeed, sky darkness, residential NDVI of 300 m buffer, month, day of week, hour of day, public holiday, gender, age, education, chronic disease, dog ownership, and participant ID (random effect); * $p \leq 0.05$

Figure 6.3 Joint associations of apparent temperature and NDVI on median MET, by city



Data on physical activity and surrounding greenness obtained from the PHENOTYPE project, May-Dec 2013

6.3.4 Sensitivity analyses

Several sensitivity analyses were conducted using different temperature indicators and other adjustments (see Appendix C3). When adjusting for daily or lag temperatures, transportation options, or removing the month covariate, the interaction results remained largely consistent in all cities except in Barcelona, where the linear association became non-significant. Distance from the weather station did not affect the interaction results, despite being statistically significant itself. Physical activity was found to peak at 66.2nd percentile temperature for Doetinchem, whereas percentile temperature no longer had a significant quadratic association in Stoke-on-Trent. When assessing 100% contact with greenspace per hour, Stoke-on-Trent and Doetinchem found significant downward parabolic associations compared with the absence of any contact with greenspace (0%). The interaction effect was found among non-employed participants in Kaunas, while the other cities were influenced by employed participants when stratified by employment. Overall, the sensitivity results were largely consistent with the primary findings.

6.4 Discussion

Significant interaction effects were found between apparent temperature and surrounding greenness on their effects on hourly physical activity among residents of three out of four European cities. The pattern of such interaction was significantly different between the cities. For Stoke-on-Trent and Doetinchem, downward parabolic associations of apparent temperature were found for the highest level of surrounding greenness, which peaked at optimal apparent temperatures: 15.2°C and 14.5°C, respectively. A 10°C increase from optimal temperatures was associated with approximately 4% decrease in median hourly MET in both cities. For Kaunas, positive linear associations were found at all higher levels of surrounding greenness, with a 3-4.6% change in median MET was found for every 10°C increase in temperature. However, the interaction in Barcelona was not found significantly better than the non-interaction model and was less robust in the sensitivity analyses.

Previous studies assessed the temperature-physical activity relationship among elderly populations and found positive associations in the UK (Alahmari et al., 2015; Sartini et al., 2017; Wu et al., 2017b) and Netherlands (Prins & van Lenthe, 2015), while a non-significant association was also found in Barcelona (Delclos-Alio et al., 2019). No previous studies were found on the general population or from Lithuania or Eastern Europe. In this study, Stoke-on-Trent and Doetinchem found curvilinear associations, both of which have a temperate climate with warm summer temperatures (climate Cfb). The lower intensity of physical activity in high temperatures (as measured by METs) supports the physiological concept of voluntary reduction in exercise work rate, in order to reduce heat stress (Flouris & Schlader, 2015; Tucker & Gilliland, 2007). Meanwhile, positive associations and non-significant associations were found in Kaunas and Barcelona, which had a continental climate (Dfb) and Mediterranean climate (Csa), respectively (Kottek et al., 2006; Peel et al., 2007). These climatic differences may have influenced the study findings.

Interaction effects between temperature and surrounding greenness on physical activity has not been discussed in previous literature. Overall, higher levels of surrounding greenness had significant temperature-physical activity associations, particularly at the highest level for Stoke-on-Trent and Doetinchem. The sensitivity analysis also consistently found temperature-physical activity associations for 100% contact with greenspace in Stoke-on-Trent, Doetinchem and Kaunas. This is similar to previous studies on residential greenspace and self-reported physical activity that have found significant effects in the highest levels of greenness only (Astell-Burt, Feng, & Kolt, 2014; Lachowycz & Jones, 2014; Mytton, Townsend, Rutter, & Foster, 2012). These studies suggested that more frequent sessions of walking and moderate-to-vigorous physical activity may occur among those who live in the greenest areas, although it was unclear whether those sessions took place within greenspaces (Astell-Burt et al., 2014; Lachowycz & Jones, 2014).

Physical activity was independent of temperature at the lowest greenness level in this study, suggesting that the findings may have been confounded by indoor and outdoor locations. Previous studies found opposing relationships between indoor and outdoor comparisons for sports and household activity (Eisenberg & Okeke, 2009; Reich et al., 2010; Spinney & Millward, 2011). Physical activity conducted in higher surrounding greenness may have more likely been outdoor locations. For Barcelona, however, the temperature-physical activity associations were found at the second level of surrounding greenness but overall the model was not significant compared to a model without interaction. Barcelona was the only coastal city in this analysis and had a much lower distribution of surrounding greenness compared to the other three cities (Figure 6.1). It is likely that a large quantity of coastal areas or blue spaces was available for participants to engage with while conducting physical activity (Gascon et al., 2017). These coastal spaces would not be associated with greenness, explaining why the findings for Barcelona were different from other cities in this analysis.

Despite an initial similarity with other cities of a curvilinear pattern in the preliminary model, Kaunas found a positive linear temperature association in the interaction model instead of quadratic effects. This suggests the influence of variations in outdoor spaces and physical activity culture between these cities. As the only city located in Eastern Europe, a larger proportion of civic spaces and woodland/forests was found for Kaunas compared to the other cities (Smith et al., 2017). Civic spaces may provide large outdoor areas without much greenness, thus resulting in Kaunas' temperature associations in lower greenness levels. More tree cover may reduce people's exposure to temperatures compared to open-air settings (Ziter, Pedersen, Kucharik, & Turner, 2019) and subsequently reduce temperature's effect on physical activity, leading to a positive association in the main model. Physical activity in Kaunas may also differ culturally compared with the other cities. A recent study conducted in Kaunas found non-employed to be more likely to engage in self-reported physical activity compared to employed individuals (Dedele, Miskinyte, Andrusaityte, & Nemaniute-Guziene, 2019). The sensitivity analysis in this study similarly found non-employed participants to be more influential in the temperature-physical activity associations, as opposed to the employed participants in other cities.

Strengths and limitations

This is the first multi-location comparative study to examine the synergetic effect of apparent temperature and surrounding greenness on objectively measured physical activity at the hourly level. A strength of this study was the common methodology between different geographical locations. Four different cities with different cultures, climates, and greenspace characteristics were studied and all applied similar sampling protocols and exposure assessment methods, which enabled us to draw conclusions on the variation between cities. Objective GPS and physical activity data were concurrently collected through the smartphone app, which reduced the effects of recall and self-report bias, and any timing mismatch between the participant's physical activity levels and surrounding greenness level. A broad range of participant characteristics were considered in the analyses because the smartphone data was linked to additional survey data. The analyses were controlled for time-related variables commonly used in other climate-health analyses.

However, the design of this study limited the possibility to determine whether the participants were located indoors or outdoors, which is highly relevant to their exposures of both meteorological conditions and surrounding greenness. The accelerometer physical activity data could not account for cycling or aquatic activities. Additionally, the analysis was unable to differentiate between different domains of physical activity (leisure, transport, occupational etc.) which may affect patterns of greenspace usage. Personal exposure to temperature and other meteorological conditions could not be detected, since meteorological data was only available from one meteorological station per city, which was sometimes located as far as 27 km away from the city center (Doetinchem). The measures of NDVI could not differentiate between vegetation types, such as trees, grass, green roofs etc (Nieuwenhuijsen, 2015), nor determine its accessibility. The study was also unable to account for blue or coastal spaces. Study participants were also not limited to city boundaries during their study period. However, the sensitivity analysis of the distance to weather station demonstrated that results remained robust even after its inclusion.

Future research directions

Future studies should further characterize the usage of locations associated with different greenness levels and examine the temperature-physical activity association for indoor and outdoor spaces. Information about activities conducted in each location may also be helpful. For example, park settings are venues that not only facilitate moderate-to vigorous physical activity, but also sedentary activities such as scenery viewing and picnics (Bedimo-Rung, Mowen, & Cohen, 2005). On the other hand, certain indoor facilities (gyms, shopping malls etc.) may promote physical activity. Future studies can also examine the effect of temperature on physical activity at more extreme temperatures.

Implications on public health policy

This study demonstrates that physical activity was associated with both temperature and surrounding greenness in four European cities. While the impact varied between cities, temperate climates (climate Cfb) particularly found a decreasing physical activity association in high greenness levels for apparent temperatures below or above ~15°C. The results may have been confounded by indoor and outdoor locations, since this study could not control for participant locations. However, the more prominent temperature association in higher greenness areas suggest that the design of greenspaces should consider the effects on temperature. NDVI is limited in its ability to differentiate between types of greenness, yet, tree canopies and grass of the same greenness may differently influence how temperature is experienced within a microclimate, as trees provide not only evapotranspirative cooling but also shading (Brown, Vanos, Kenny, & Lenzholzer, 2015). Increasing shaded areas within greenspaces can reduce the heat felt during warm summers, while providing a mixture of tree patches and open areas can enable warmth from solar radiation in cold climates (Brown et al., 2015). Increased cooperation between public health and urban design practitioners is needed (Coutts, 2016, p. 236), such that cities make urban planning decisions to support physical activity in low and high temperatures.

Chapter 7 Outdoor physical activity during extreme temperature events in the subtropical city of Hong Kong – Study (4)

7.1 Introduction

With climate change, extreme heat days are becoming increasingly common, and while the number of cold days is projected to decrease, there will still be cold extremes that occur (Cattiaux et al., 2010; IPCC, 2014; Kretschmer et al., 2017). Both extreme cold and heat have implications for public health. An increased risk in mortality has been found in hot and cold temperatures, with U, V, or J-shaped curves for the temperature and mortality relationship (Arbuthnott et al., 2016; Gasparrini et al., 2015; Kovats & Hajat, 2008; McMichael et al., 2008). Cold spells are a significant health problem (Barnett, Hajat, Gasparrini, & Rocklov, 2012), while many mortality and morbidity studies have often focused on the effects of extreme heatwave events (Gasparrini et al., 2015). However, not much has been studied about the effects of extreme temperatures on physical activity.

Assessing extreme temperature events could help to illuminate the effects on physical activity. In a study conducted among elderly in Canada, temperatures showed constant physical activity levels until a temperature threshold of 30°C, whereby there was a rapid decrease (Brandon et al., 2009). This result was further captured when comparing extreme temperatures <10°C or > 30°C with normal temperatures between 10°C and 30°C (Brandon et al., 2009). In Chapter 5 (Study 2), both Shenzhen and Hong Kong hinted at decreased physical activity in higher temperatures but were unable to strongly see the potential effects in hot temperatures. A narrower range of temperatures in subtropical climates may have affected the associations seen between temperature and physical activity when analysed as a continuous variable.

Extreme cold and heat heighten the additional stress to cardiovascular and respiratory systems (Beker, Cervellera, De Vito, & Musso, 2018; Hajat et al., 2010). Those with NCDs are more vulnerable to heat and have a greater risk of temperature-related mortality and morbidity (Barnett et al., 2012; Kovats & Hajat, 2008). A few physical activity studies have assessed temperature effects among patients with chronic NCDs, mostly related to COPD and arthritis (Alahmari et al., 2015; Feinglass et al., 2011; Robbins et al., 2013). However, studies conducted in the general population have rarely adjusted for self-reported health status and NCDs (Kenny et al., 2010; Wagner, Keusch, Yan, & Clarke, 2016). More must be understood about how health conditions influence physical activity during extreme temperatures in the general population.

Furthermore, studies on temperature and physical activity have not previously included the effects of temperature-related awareness and attitudes, and the influence of protective behaviours. These have been assessed in extreme temperature warning system studies and serve as pathways to reduce the risk of adverse health outcomes in extreme temperatures (Ban et al., 2019; Kalkstein & Sheridan, 2007; Liu et al., 2013; Nitschke et al., 2013; Sheridan, 2007). As such, these may also influence whether physical activity is conducted in extreme temperatures.

This study aims to explore the change of outdoor physical activity during extreme cold and heat events in a subtropical city and identify health-related predictors, while controlling for sociodemographic characteristics, temperature-related awareness and attitude, and protective behaviours.

7.2 Methodology

Study setting and design

Hong Kong is a sub-tropical Chinese city which experiences average monthly mean temperatures ranging between 16-29°C (Hong Kong Observatory, 2015). During periods of extreme temperatures, the local meteorological authority Hong Kong Observatory issues warnings to alert the public and relevant government departments to take preventive measures (Chau, Chan, & Woo, 2009). The Cold Weather Warning (CWW) is hoisted when the temperatures drop below 12°C or when the Weather Stress Index is below the 2.5th percentile (Li & Chan, 2000). The Very Hot Weather Warning (VHWW), on the other hand, is hoisted when the measurements cross 30.5°C on the Hong Kong Heat Index, a calculation based on a combination of natural wet bulb temperature, globe temperature and dry bulb temperature (Lee et al., 2016).

Secondary data was obtained from a two-year telephone survey cohort conducted a week after the hoisting of a Cold Weather Warning in 2016 and followed-up a week after the hoisting of a Very Hot Weather Warning in 2017. The telephone survey used a Random Digit Dialing method to randomize the households sampled from each of Hong Kong's 18 districts. Selection of the eligible participant within each household was further randomized using the 'last birthday method', whereby the eligible household member with the most recent birthday was asked to participate in the survey. The target population of this study was all Cantonese-speaking non-institutionalized Hong Kong residents over age 15, as

94.6% of the Hong Kong population regularly speak or are able to speak Cantonese (Census and Statistics Department, 2017a). The study excluded i) overseas visitors holding tourist visas to Hong Kong or two-way permit holders from mainland China; and ii) those unable to be interviewed due to medical reasons. To collect adequate representation of the working population, calls were made from 6:30pm to 10:00 pm on weekdays, and during the daytime on weekends.

At the end of the 2016 survey, participants were asked to provide their phone number if they were willing to participate in the follow-up survey of the study. The recorded number was used to contact the same participant in the 2017 follow-up survey. At least five attempts were made to reach the participant before they were considered “lost-to-follow-up”. This use of landline telephone surveys is common in Hong Kong, with a penetration rate of 94.92% in 2016 and shown to be more representative of population statistics than cell phone surveys (Chiu & Jiang, 2017). All interviews were administered by trained interviewers and participants gave a verbal consent prior to the start of each survey.

Ethics approval and funding

Ethics approval for this study was obtained from Survey and Behavioural Research Ethics Committee of The Chinese University of Hong Kong (See Appendix D1). This study was co-funded with the Chinese University of Hong Kong (CUHK) Focused Innovations Scheme – Scheme A: Biomedical Sciences (Phase 2), and the CUHK Climate Change and Health research project fund.

Survey instrument

A similar survey instrument was used over the two-year study, with the main differences related to the seasonal time point of the survey (See Appendix D2 and D3). The survey measures were based on previous studies that examined self-reported health outcomes in the subtropical urban population (Chan et al., 2015a; Chan et al., 2015b). The main outcome of physical activity was assessed through the following question: “Since {date Cold Weather Warning/Very Hot Weather Warning was hoisted} till today, have you increased, decreased, or remained the same in the amount of outdoor physical activity?”. The survey questionnaire also collected information on sociodemographic characteristics, health conditions, temperature-related awareness and attitudes, and protective behaviours (see Table 7.1). A pilot study (n = 53) was administered to test the reliability of the survey in December 2015.

Table 7.1 Included variables from the telephone survey instrument

Sociodemo-graphic	Health-related	Temperature-related awareness and attitude	Protective behaviours
Gender	General self-rated health	Awareness of CWW/ VHWW	Avoid prolonged exposure to cold winds/ avoid staying out in the sun
Age	Seasonal self-rated health	Knowledge of today's min/max temperature	
Education	Seeking medical treatment	Agree cold/hot weather impacts health	Use heating devices/AC
District	Long-term medications	Agree the health impacts of cold/hot weather can be avoided	Sum measure of other protective behaviours*
Income	*Chronic NCDs*	Agree I have adequate knowledge to handle the health impact of cold/hot weather	
Occupation	Cancer		
Marital status	Cardiovascular disease		
Living alone	Chronic pain (arthritis)		
Housing	Diabetes		
Home ownership	Hypercholesterolemia Hypertension Respiratory disease		
	Multimorbidity		

Variables included from telephone survey cohort conducted in Hong Kong, 2016-2017
*The sum measure combined the responses of the following protective behaviours: wearing suitable clothes, using sunscreen, drinking more (warm) water, paying attention to weather information, maintaining indoor ventilation, paying attention to elderly, and to young children. It was used as a proxy to assess if compliance with overall heat or cold-related protective behaviours is associated with participants' outdoor physical activity. All protective behaviours were taken from the recommended guidelines by Hong Kong Observatory (Hong Kong Observatory). Two additional protective behaviours to "rest and avoid overexertion when working or conducting activities outdoors" and to "get to cooler places when feeling unwell" were bivariately associated with decreased outdoor physical activity but removed from further analysis due to the conceptual similarity with the outcome of interest.

Statistical analysis

The study periods were defined as the time from the issuing of a Cold Weather Warning/Very Hot Weather Warning, which prompted the survey administration one week later, until the end of the survey administration period, completed in the following week. T-tests were used to test the significance of differences in meteorological variables between the study periods and the preceding days in the study period month. Both separate and grouped physical activity responses were reported. Grouped physical activity responses refer to a comparison across both the extreme temperatures (cold and heat).

Multivariable forward stepwise logistic regression models were conducted to identify health-related predictors of changing outdoor PA in the two extreme temperature events, while controlling for sociodemographic characteristics, temperature-related awareness and attitude, and protective behaviours. Chi-squared test and T-tests were first used to screen bivariate associations of variables with the physical activity responses. Variables which had initial screening chi-square results of $p < .25$ were included in the multivariable forward stepwise logistic regression model adjusted for age, gender, and education. Where variables were interviewed in both surveys (such as age), the 2017 variable was chosen for the grouped analyses. All statistical tests were conducted with IBM SPSS Statistics for Windows, Version 20.0. (IBM Corp, Released 2011). Statistical significance was set at $p \leqslant 0.05$.

7.3 Results

7.3.1 Descriptive statistics

The final study periods were January 21 – February 4, 2016 for the 2016 extreme cold, and July 28 – August 13, 2017 for the 2017 extreme heat. In the 2016 extreme cold survey, 3,500 telephone numbers were dialled and 1,598 of those calls reached an eligible respondent. Among the eligible respondents, 1,125 verbally consented to participate in the survey, and a total of 1,017 successfully completed the interview (response rate 1,017/1,598 = 63.6%).

Of the 1017 participants in the 2016 survey, 436 participants were successfully followed-up during the 2017 extreme heat (response rate = 42.87%). One participant was excluded from further analysis due to missing data on the main outcome of interest. Compared to the initial sample, the follow-up sample had a slightly different age distribution, as there was more lost-to-follow-up among working adults aged 25-44. Other demographic factors remained comparable between the initial and follow-up samples. The final study sample (n=435) was representative of the general population in gender, district regions, marital status, and household income, but tended to be older and more well-educated (see Table 7.2). To account for these differences, the multivariable analyses were adjusted for gender, age, and education.

During the 2016 study period, the Cold Weather Warning (CWW) was hoisted for a cumulative amount of 243 hours and 35 minutes, or 10.15 days over the 15-day study period. It included the coldest day since 1957, which had the 6th lowest ever recorded minimum temperature of 3.1°C during the afternoon of January 24, 2016 (Hong Kong Observatory, 2016). In the 2017 study period, the Very Hot Weather Warning (VHWW) was hoisted for a cumulative amount of 226 hours and 45 minutes, or 9.45 days over the 17-study period. The 2017 study period saw one of the highest daily mean temperatures for

July on record, 31.8°C on July 30, 2017 (Hong Kong Observatory, 2017). When using the T-test to compare the meteorological variables and air pollutants of the study periods with preceding days in the study months, mean pressure, maximum, mean, minimum, and dewpoint temperatures, and selected air pollutants were found significantly different for both the 2016 extreme cold and 2017 extreme heat study periods (see Table 7.3).

Table 7.2 Demographic comparison between the telephone survey cohort and Hong Kong general population

Demographics		Initial 2016 Survey		Follow-up 2017 survey		Population 2016 Census		Follow-up vs. Census p-value^	
		n	%	n	%	%	Derived n		
Gender		N= 1017		N = 435					
	Male	437	43	200	46	47.6	207.06	0.498	
	Female	580	57	235	54	52.4	227.94		
Age		N= 1017		N = 435					
	15-24	126	12.4	65	14.9	12.6	54.81	<0.001	**
	25-44	315	31	101	23.2	31.8	138.33		
	45-64	384	37.8	168	38.6	36.8	160.08		
	≥65	192	18.9	101	23.2	18.8	81.78		
Region		N= 1015		N = 435					
	Kowloon	315	31	140	32.2	30.8	133.98	0.818	
	Hong Kong Island	182	17.9	70	16.1	16.6	72.21		
	New Territories	518	51	225	51.7	52.6	228.81		
Marital Status		N = 1012		N = 435					
	Single	330	32.6	147	33.8	30.1	130.935	0.223	
	Married	602	59.5	243	55.9	58.3	253.605		
	Separated/ divorced	80	7.9	45	10.3	11.6	50.46		
Household Income (HKD)		N = 945		N = 407					
	$40,000+	317	33.5	132	32.4	30.8	125.356	0.069	
	$20,000-$39,999	333	35.2	129	31.7	27.9	113.553		
	< $20,000	295	31.2	146	35.9	41.3	168.091		
Education		N=1015		N = 434					
	Post-secondary	377	37.1	154	35.5	33.2	144.088	<0.001	**
	Secondary	501	49.4	222	51.2	46.2	200.508		
	Primary or below	137	13.5	58	13.4	20.6	89.404		

Data obtained from telephone survey cohort conducted in Hong Kong, 2016-2017
^Chi-square test was used to measure the overall difference in demographic proportions between this study and the 2016 Hong Kong Population Census (Census and Statistics Department, 2017a). Census numbers excluded foreign domestic helpers and those under age 15. District region census numbers were calculated from (Census and Statistics Department, 2017b).
* p-value ≤ 0.05 ** p-value ≤ 0.01

Table 7.3 Comparison of meteorological variables and air pollutants between 2016 and 2017 study periods and prior months, T-test

	2016 Prior Days in Jan (N=20)	**2016 Extreme Cold (N=15)**	**T-test**		**2017 Prior Days in Jul (N=27)**	**2017 Extreme Heat (N= 17)**	**T-test**	
Meteorological	*Mean (S.D.)*	*Mean (S.D.)*	*p-value*		*Mean (S.D.)*	*Mean (S.D.)*	*p-value*	
Mean Pressure	1018.78 (3.22)	1023.25 (5.19)	.004	**	1007.9 (2.02)	1004.01 (3.74)	.001	**
Max Temp	19.54 (2.12)	14.75 (3.54)	<.0005	**	31.04 (1.82)	32.37 (1.53)	.017	*
Mean Temp	17.82 (1.77)	12.73 (3.75)	<.0005	**	28.37 (1.22)	29.94 (1.02)	<.0005	**
Min Temp	16.38 (1.93)	10.91 (4.16)	<.0005	**	26.57 (1.07)	27.93 (1.26)	<.0005	**
Dewpoint Temp	15.1 (2.35)	9.19 (6.49)	.004	**	25.46 (0.35)	25.85 (0.54)	.005	**
Rel. Humidity	84.4 (7.69)	80.53 (15.68)	.390		84.74 (5.71)	79.06 (4.62)	.001	**
Cloud cover	74.1 (21.2)	85.53 (21.59)	.127		80.11 (9.23)	73.88 (13.04)	.071	
Rainfall	8.52 (14.55)	7.2 (13.17)	.784		21.11 (42.37)	8.55 (16.25)	.250	
Sunshine Hrs	2.64 (3.23)	1.59 (3.38)	.356		4.84 (3.53)	6.29 (3.76)	.203	
Wind Speed	26.82 (10.84)	30.92 (13.17)	.320		21.5 (6.15)	22.82 (9.36)	.576	
Wind Direction (South=0)	131.50 (18.14)	144.00 (18.44)	.053		72.59 (40.44)	65.88 (28.08)	.553	
Air pollutants								
Mean CO	99.52 (10.39)	85.07 (21.51)	.027	*	47.24 (3.25)	56.12 (12.1)	.009	**
Mean NO_2	50.14 (11.21)	48.01 (14.23)	.623		25.18 (4.62)	36.05 (12.8)	.003	**
Mean NO_X	81.41 (26.65)	95.22 (39.19)	.223		49.96 (12.87)	60.51 (14.73)	.016	*
Mean O_3	37.07 (15.46)	24.99 (15.26)	.028	*	21.71 (3.9)	38.57 (24.61)	.012	*
Mean SO_2	7.49 (2.13)	7.38 (2.4)	.887		5.34 (1.21)	8.37 (2.9)	.001	**
Mean RSP^	39.89 (18.35)	30.07 (14.67)	.098		12.89 (2.22)	26.78 (16.39)	.003	**
Mean FSP^	29.07 (12.91)	20.52 (9.27)	.037	*	7.1 (1.51)	16.44 (12.68)	.008	**

Data obtained from Hong Kong Observatory and Environmental Protection Department, 2016-2017; ^ RSP = Respirable Suspended Particulates; FSP = Fine Suspended Particulates
* p-value ≤ 0.05 ** p-value ≤ 0.01

Overall, a large proportion of respondents reported a decrease in outdoor physical activity during the 2016 extreme cold (41.6%) and the 2017 extreme heat (35.2%) (see Table 7.4). There was a significantly greater proportion of respondents reporting a decreased effect in the 2016 extreme cold compared to the 2017 extreme heat (p = 0.029, McNemar's test). Increased outdoor physical activity, which was reported among 10.3% of participants across either extreme temperature, was significantly greater in extreme heat than extreme cold (p≤0.001, McNemar's test). When grouped together, 36.3% of the participants reported to maintain their original level of outdoor physical activity during both the extreme temperature periods, while 20.7% reported decreased outdoor physical activity in both.

In terms of health-related predictors, most participants self-reported having normal to very good health, while 4.8% reported having bad health (see Table 7.5). A large majority of participants reported an unchanged health status during the winter season (69.9%) and summer season (77.0%). During the extreme temperature events, 15.4% of participants sought medical treatment. A total of 148 participants (34.0%) reported to take long-term medications, while 141 participants (32.6%) reported to have chronic diseases. Of those, 55 participants reported having two or more chronic diseases. The top five chronic diseases reported were hypertension (15.4%), diabetes (8.0%), cardiovascular disease (5.1%), hypercholesterolemia (4.1%), and chronic pain (2.5%) such as arthritis.

Table 7.4 Comparison of changes in outdoor physical activity across 2016 extreme cold and 2017 extreme heat (N = 435)

	2016 extreme cold			
2017 extreme heat	Increase	No Change	Decrease	Total
Increase	5 (1.1%)	25 (5.7%)	10 (2.3%)	40 (9.2%)
No change	3 (0.7%)	158 (36.3%)	81 (18.6%)	242 (55.6%)
Decrease	2 (0.5%)	61 (14.0%)	90 (20.7%)	153 (35.2%)
Total	10 (2.3%)	244 (56.1%)	181 (41.6%)	435 (100%)

Data obtained from telephone survey cohort conducted in Hong Kong, 2016-2017

Table 7.5 Responses on self-rated health status from the telephone survey cohort

	General health		**Seasonal health**	**Winter (2016)**	**Summer (2017)**
Very good	74 (17.0%)		Better	33 (7.6%)	47 (10.8%)
Good	141 (32.4%)		Same	304 (69.9%)	335 (77.0%)
Normal	199 (45.7%)		Worse	93 (22.5%)	53 (12.2%)
Bad	21 (4.8%)				

Data obtained from telephone survey cohort conducted in Hong Kong, 2016-2017

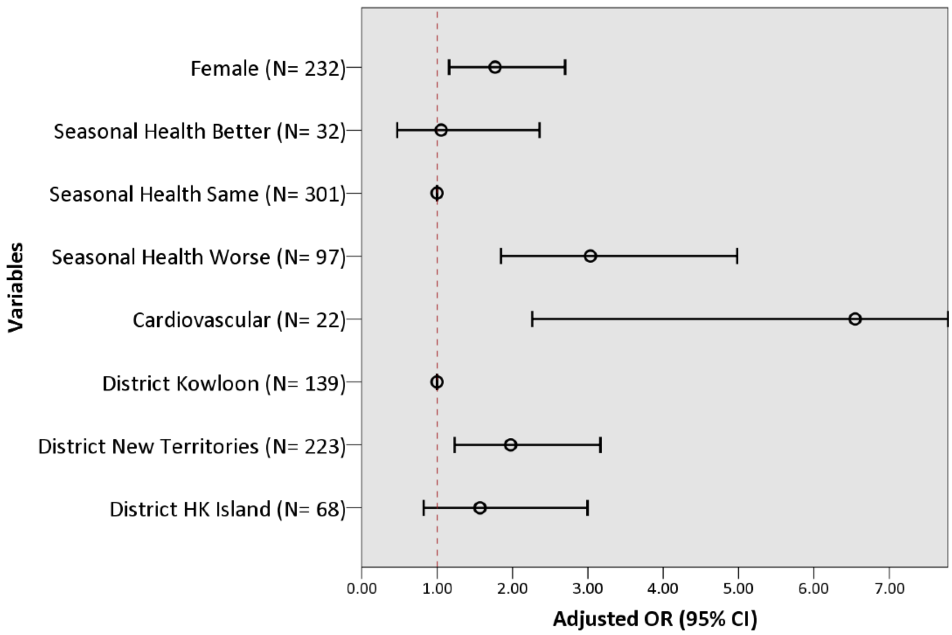
7.3.2 Multivariable logistic regression models

During the 2016 extreme cold, decreased outdoor physical activity was associated with being female (AOR = 1.77, 95% CI: 1.16-2.70), living in the more suburban region of New Territories (AOR = 1.98, 95% CI: 1.23-3.17), self-reporting worsened health in the winter (AOR = 3.03, 95% CI: 1.85-4.98), and those with cardiovascular disease (AOR = 6.55, 95% CI: 2.26-18.94) (see Figure 7.1).

During the 2017 extreme heat, decreased outdoor physical activity was associated with being female (AOR = 2.20, 95% CI: 1.41-3.44), self-reporting worsened health in the summer (AOR = 2.41, 95% CI: 1.21-4.77), awareness of VHWW (AOR = 2.47, 95% CI: 1.16-5.26), and agreeing that heat impacts health (AOR = 1.19, 95% CI: 1.02-1.40), while inversely associated with hypertension (AOR = 0.38, 95% CI: 0.18-0.82). Using AC remained in the final model but was slightly above the threshold of statistical significance (AOR = 2.74, 95% CI: 0.98-7.69) (see Figure 7.2).

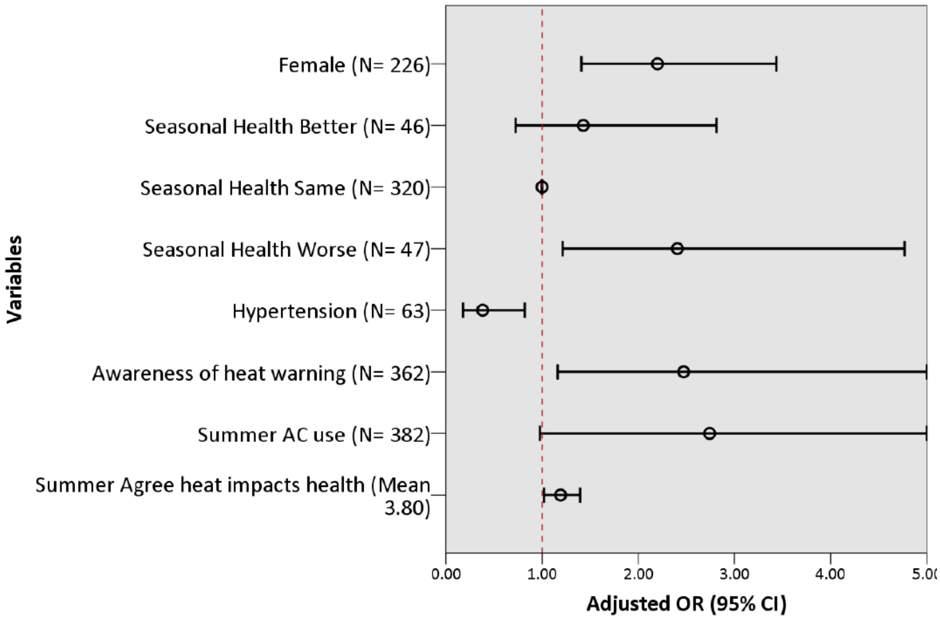
Increased outdoor physical activity during either extreme temperature event was inversely associated with older age compared with those under 25 (aged 25-44 AOR = 0.35, 95% CI: 0.13-0.96; aged 45-64 AOR = 0.12, 95% CI: 0.04-0.36; aged 65 and above AOR = 0.08, 95% CI: 0.02-0.34), those in public housing (AOR = 0.29, 95% CI: 0.10-0.81), avoiding exposure to cold winds (AOR = 0.35, 95% CI: 0.15-0.83), but was positively associated with conducting protective behaviours during the extreme heat (AOR = 1.39, 95% CI: 1.04-1.87) (see Figure 7.3)

Figure 7.1 Multivariable logistic regression results for decreased outdoor PA, 2016 extreme cold (N = 178 reported decrease)



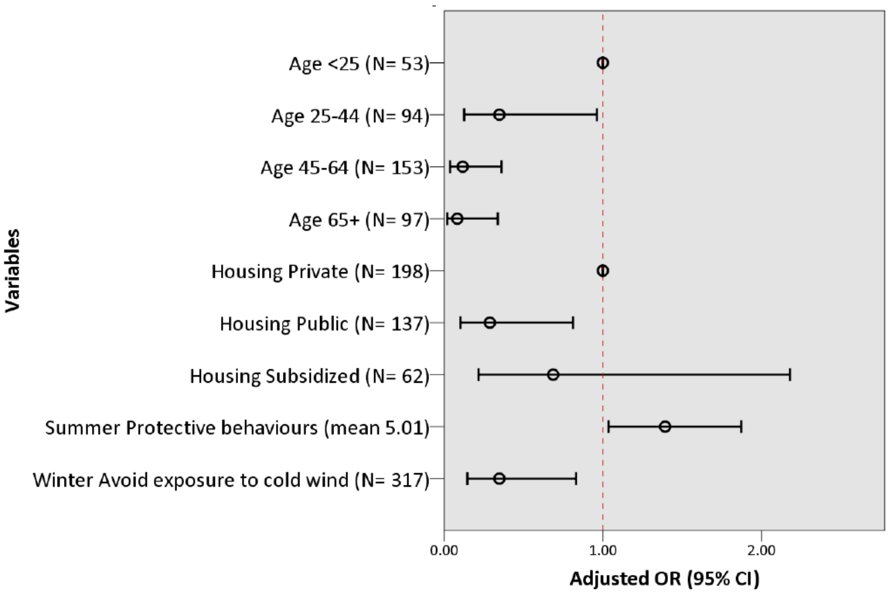
Data obtained from telephone survey cohort conducted in Hong Kong, 2016-2017
Final model: N= 430, Predicted 66.3%, Nagelkerke R^2 0.155; Not included in final model: General health, Hypertension, Respiratory disease, Seek medical care, Know today's minimum temperature, Agree cold impacts health, Avoid exposure to cold winds, Use heating devices, and Sum of protective behaviours

Figure 7.2 Multivariable logistic regression results for decreased outdoor PA, 2017 extreme heat (N = 147 reported decrease)



Data obtained from telephone survey cohort conducted in Hong Kong, 2016-2017
Final model: N= 413, Predicted 67.3%, Nagelkerke R^2 0.165; Not included in final model: Marital status, Occupation, Live alone, Home ownership, Diabetes, Hypercholesteremia, Arthritis pain, Multimorbidity, Long-term medication, Seek medical care, Agree I have adequate knowledge to handle the health impact of heat, Avoid staying out in the sun, and Sum of protective behaviours

Figure 7.3 Multivariable logistic regression results for increased outdoor PA in either extreme temperature event (N = 31 reported increase)



Data obtained from telephone survey cohort conducted in Hong Kong, 2016-2017
Final model: N= 397, Predicted 92.7%, Nagelkerke R2 0.194; Not included in final model: Marital status, Income, Occupation, Home ownership, Seasonal winter health, Cardiovascular disease, Hypertension, Long-term medication, Multimorbidity, Agree cold impacts health, and Agree health impacts of cold can be avoided. Education was excluded from the model since there were zero cases of increased physical activity among those with primary education or below.)

7.4 Discussion

In subtropical Hong Kong, over a third of the participants reported a decrease in outdoor physical activity in either extreme cold (41.6%) or extreme heat (35.2%), while 10.3% reported an increase in physical activity. Decreased physical activity in extreme cold was associated with predictors of being female, suboptimal health in winter, cardiovascular disease, and living in a colder district. Decreased physical activity in extreme heat was associated with predictors of being female, suboptimal health in summer, heat warning awareness, and an attitude that heat impacts health, while hypertension was inversely associated. Increased physical activity in either temperature event was associated with age under 25, living in private housing, those who do not avoid exposure to cold winds, but who conduct protective behaviours during extreme heat.

Extreme cold led to a slightly greater proportion of reported decreased outdoor physical activity compared with extreme heat. This study's findings demonstrate that even in a sub-tropical climate like Hong Kong (Cwa), extreme cold has a large effect on physical activity behaviour. Previous research in sub-tropical settings also identified cold temperature effects on mortality, particularly finding the cold temperature effect to be larger in warmer cities (Analitis et al., 2008; Goggins, Chan, Yang, & Chong, 2013). The prevalence of increasing outdoor physical activity was greater in extreme heat rather than extreme cold. This indicates that there may be less barriers to conducting outdoor physical activity in extreme heat, or a better adaptation towards heat in a sub-tropical setting.

The findings of this study demonstrate the importance of considering cardiovascular conditions in temperature-physical activity studies. Seeking medical treatment, use of long-term medications, and other chronic disease conditions, such as respiratory diseases, were not found associated with changes in outdoor physical activity. Among the chronic NCDs assessed, only cardiovascular disease was associated with a 6.5 times likelihood of decreasing physical activity in extreme cold. This was aligned with previous research showing that up to 70% of excess winter deaths were cardiovascular-related (Mercer, 2003). Cold temperatures have been associated with an increased risk of cardiovascular mortality and cardiovascular markers, such as blood pressure, blood viscosity, serum LDL-C, and platelet count (Atsumi et al., 2013; Hong et al., 2012; Keatinge et al., 1984; Mercer, Osterud, & Tveita, 1999). As cardiac symptoms are exacerbated in cold temperatures, those with cardiovascular disease could instinctively decrease their outdoor physical activity levels in efforts to avoid the cold. However, previous studies have also found that winter outdoor physical activity was associated with lower winter mortality (The Eurowinter

Group, 1997), and regular exercise was necessary to reduce the effect of cold on physiological changes for ischaemic heart disease patients (Lloyd, 1991). Extreme cold could inhibit the physical activity essential to the disease management of cardiovascular patients and accelerate their deterioration and adverse outcomes in the long run.

In terms of chronic diseases in extreme heat, this study found that those with hypertension were less likely to decrease outdoor physical activity in extreme heat. Conversely, a previous small-scale study found that temperatures above 25°C in Germany were associated with reduced physical activity among 15 hypertensive patients (Jehn et al., 2014). The effects of hypertension on exercise in hot conditions are still unclear in physiological studies (Fonseca et al., 2015; Kenny et al., 2010). Studies in the general population have found that high ambient temperatures and summer season were associated with lower blood pressure and better hypertension control (Modesti et al., 2013; Stotz et al., 2014; Su et al., 2014; van den Hurk, de Kort, Deinum, & Atsma, 2015). Among those with hypertension, lower skin blood flow and less core-to skin heat transfer was found during exercise-induced heat stress (Kenny et al., 2010). Meanwhile, another study identified greater heat dissipation and body cooling among hypertensive persons during exercise recovery in heat (Fonseca et al., 2015). The use of anti-hypertensive medications may further alter the thermoregulatory response to heat. Despite the uncertainty, hypertensive patients are at an increased risk of heat-related complications during exercise (Zaleski, Taylor, Pescatello, & Armstrong, 2018). Further studies should be conducted to assess the physical activity levels of hypertensive patients in extreme heat, and the subsequent risk of heat-related illnesses.

Strengths and limitations

The strengths of this study included a repeated measures study design which followed the same participants in both extreme hot and cold temperature events. The short study periods and the one-week lag between the onset of the temperature events and data collection periods helped to reduce any potential recall bias of participants self-reported outdoor physical activity. However, this study was limited in the design of the survey questions. The survey was unable to measure the frequency and intensity of physical activity to quantify the amount of change in extreme temperatures. Baseline physical activity levels were not measured, which may have influenced the study findings. Although the study focus was on outdoor physical activity, it is not understood whether the respondents had subsequently substituted outdoor physical activity for indoor physical activity. Under the weather warnings, the results of this study were unable to tease out the effect of air pollution compared with meteorological variables. Finally, the study experienced a loss to follow-up, leading to a smaller final sample size. This may have implications on the generalizability of the study findings and should be interpreted with caution.

Future research directions

Future studies should aim at those with underlying chronic diseases, particularly of the cardiovascular nature and examine the consequent health outcomes of reduced physical activity in extreme temperatures. Future studies should also use objective physical activity measurements or more validated questionnaires when assessing the effect of extreme temperature events. Analyses including measurements of physical activity frequency or intensity, baseline physical activity levels, and substitution effect of indoor physical activity may further enhance the understanding between outdoor physical activity and extreme temperatures.

Implications on public health policy

This study demonstrates outdoor physical activity decreased in extreme temperatures in over a third of the participants in a subtropical urban population. A greater proportion of participants were affected in extreme cold rather than extreme heat. Suboptimal seasonal health was associated with decreased physical activity in extreme temperatures. Importantly, those with cardiovascular disease were more likely to decrease physical activity in extreme cold, while those with hypertension were less likely to decrease physical activity in extreme heat. Healthcare providers should pay attention to patients' physical activity levels in extreme temperatures, particularly those with cardiovascular disease or hypertension. Specific efforts should be made to enquire about patients' physical activity habits to ensure their exercise programmes (Pelliccia et al., 2020) can be feasibly sustained in extreme temperatures. In order to reduce risk of extreme heat or cold exposures, recommendations could be made to diversify physical activity options or schedules, whether it is conducting more indoor activity or finding appropriate times of the day to conduct outdoor activities. Government entities and public sport facilities could also encourage the general population to conduct physical activity in the extreme cold, while opening up more accessible indoor opportunities in extreme heat.

Chapter 8 Discussion

8.1 Synthesis of key findings

Physical activity among adults is essential to health promotion, disease prevention, and reduction of premature mortality (Section 2.1). However, efforts must be made globally to increase physical activity at the population level, to support a reduction in non-communicable diseases (Section 2.1). An understanding of factors facilitating or hindering physical activity can strengthen the development of effective interventions and supportive environments to encourage physical activity in urban populations (Section 2.2). Temperature has often been cited as a barrier to physical activity, yet its effects on physical activity have been less understood than other environmental correlates (Section 2.2). It is important to understand temperature effects on physical activity, as heat affects the body physiologically, leading to thermal discomfort, and an increased risk of heat-related illnesses and mortality (Section 2.3). Additionally, climate change will alter temperatures levels globally and pose a challenge to public health and the health sector (Section 2.4). More must be understood about such that policies in health promotion, climate mitigation and adaptation are able to minimize adverse health impacts and sustain physical activity levels (Section 2.6).

The main objective of this thesis was to examine the associations of temperature on physical activity in urban adult populations. This was addressed through five research questions, summarized again in Table 8.1 along with their hypotheses. The thesis sought to answer the research questions through four empirical studies (Chapters 4 - 7).

Table 8.1 Summary of research questions and hypotheses in this thesis from Chapter 3

Research Questions	**Answered through...**
1. What is the current research evidence regarding the relationship between temperature and physical activity? *Hypothesis: Despite variations in climate, an overall curvilinear relationship will define the association between temperature and physical activity, whereby cold and hot temperatures will lead to decreased physical activity.*	Chapter 4
2. How does the association of temperature on physical activity vary between cities of different climates? *Hypothesis: Cities with similar climates will have similar outcomes, while outcomes will vary between cities of different climates. Cities in colder climates may not experience decreased associations of physical activity in hot temperatures, while cities in warmer climates will have more apparent associations between hot temperatures and decreased physical activity.*	Chapter 5 and 6
3. How does the association of temperature on physical activity vary within cities at different greenness levels? *Hypothesis: Higher greenness levels would be less associated with decreased effects of physical activity in hot temperatures.*	Chapter 6
4. What is the effect of extreme temperature events (extreme cold and heat) on physical activity? *Hypothesis: Physical activity would decrease more in extreme heat compared to extreme cold.*	Chapter 7
5. How does health influence the effects of temperature on physical activity? *Hypothesis: Suboptimal health would be associated with reduced physical activity, particularly those with cardiovascular and respiratory diseases.*	Chapter 7

In response to Research Question 1, Chapter 4 reviewed the latest evidence on the association between temperature and physical activity through a systematic review. 79 articles were identified to assess the relationship between temperature and physical activity, which initially demonstrated an inconclusive association affected by a wide variability in locations, study designs, and physical activity measurements. When categorized by the Köppen-Geiger climate classification, positive temperature-physical activity associations were found in more studies located in cold or temperate climates with warm summer temperatures (Cfb and Dfb), while negative or curvilinear associations were found in more studies located in temperate climates with hot summer temperatures (Cfa). These trends support the hypothesis, demonstrating an overall curvilinear relationship in the association between temperature and physical activity, despite variations between locations of different climates. However, the studies were concentrated in only three climates types, with evidence still lacking in a variety of climate types. The systematic review also found a lack of multi-location comparative studies that would examine the temperature-physical activity association across different locations using a consistent methodology. A majority of studies did not assess non-linear associations that might enable the identification of possible temperature thresholds for decreasing physical activity in warmer temperatures. Studies were also sparsely located in regions outside of North America and Europe. The influence of health and chronic diseases on the temperature-physical activity was rarely examined in the general population. Common areas of poor methodological quality included the absence of adjusting for multiple meteorological variables and insufficient control for key confounders. These gaps were addressed in subsequent studies of this thesis, as the multi-location comparative studies in Chapter 5 and 6 were conducted in a variety of climate types in the Asian and European regions. The studies also used non-linear methods to identify the temperature thresholds, while adjusting for other meteorological variables and key confounders. The study in Chapter 7 addressed possible health influences related to the temperature effects on physical activity.

In response to Research Question 2, two multi-location comparative studies were conducted on the relationship between temperature and physical activity in the Asian and European regions. Chapter 5 investigated the daily association between temperature and city-wide step counts in five Chinese cities using aggregated data from a mobile application. Significant curvilinear associations in temperatures were found in three out of five cities, with an average decrease of 322-432 steps for a 10°C increase from optimal temperature. Optimal temperatures for physical activity varied for Beijing (climate Dwa, optimal temperature: 19.3°C), Shanghai (Cfa, 17.9°C), and Chongqing (Cfa, 16.0°C). In Shenzhen and Hong Kong (Cwa), warm temperatures had non-significant associations with physical activity, however, the trends suggest decreased step counts in more extreme temperatures. Lower optimal temperatures were found for females and older age groups, and older age groups additionally had larger decreases of step count compared to younger age groups.

Chapter 6 examined the interaction effects of hourly apparent temperature and physical activity in four European cities, moderated by surrounding greenness. Curvilinear associations were found for Stoke-on-Trent and Doetinchem (both Cfb) at only the highest level of surrounding greenness, peaking at 15.2°C and 14.5°C, respectively. A positive relationship was found for Kaunas (Dfb) at all higher levels of surrounding greenness. Barcelona (Csa), on the other hand, did not find a significant interaction between temperature and surrounding greenness as a coastal city. In the significant relationships of these cities, an average 4% change in median MET was found for 10°C increase from optimal temperature.

The findings of the two multi-location studies partially supported the hypothesis of Research Question 2, as similar climates were found to have similar outcomes, while outcomes varied between cities of different climates. The positive linear findings in Kaunas (Dfb) were aligned with the hypothesis that cities in colder climates may not experience decreased associations of physical activity in hot temperatures, however, contrary to expectations, the majority of other cities in colder or temperate climates (Dwa, Cfa, Cfb), particularly those with hot summers (Cfa, Dwa) found decreased associations of physical activity in hot temperatures. The findings in cities of warmer subtropical or Mediterranean climates (Cwa, Csa) also contradicted the hypothesis, since instead of finding more apparent associations in hot temperatures compared with other cities, they found non-significant associations in hot temperatures. The Cwa (Hong Kong, Shenzhen) and Csa (Barcelona) climates had higher average temperatures and a narrower temperature range compared to other studied climates, while the climates of Dwa (Beijing), Dfb (Kaunas), and Cfb (Stoke-on-Trent, Doetinchem) had wide temperature ranges. This supports the results from Gasparrini et al. (2015), whereby meta-predictors of average temperature, temperature range and country indicators modify the temperature-mortality association between countries.

In response to Research Question 3, the smartphone-based monitoring study in Chapter 6 found significant interaction effects between temperature and greenness levels. In all four European cities assessed, temperature was significantly associated with physical activity in higher levels of surrounding greenness, particularly at the highest level. While positive linear relationships were found for Kaunas (Dfb) in high greenness levels and non-significant interactions for Barcelona (Csa), curvilinear associations were found for Stoke-on-Trent and Doetinchem (both Cfb) only at the highest level of surrounding greenness. This was contrary to the hypothesis, as higher greenness levels were not found to be less associated with decreased effects of physical activity in hot temperatures, rather the decreased effects were only found in the highest greenness level. The lack of association in the lower levels of greenness suggest that the study findings could have been confounded by undifferentiated indoor and outdoor locations in the analysis. As identified in the systematic review (Chapter 4), previous studies that compared indoor and outdoor physical activity found opposing relationships (Eisenberg & Okeke, 2009; Reich et al., 2010; Spinney

& Millward, 2011). Differences in the spatial composition of the cities may have also affected the results, such as the coastal areas of Barcelona and woodlands of Kaunas (Smith et al., 2017).

In response to Research Question 4, Chapter 7 explored the impact of extreme temperature events on outdoor physical activity and its predictors through a telephone survey cohort in Hong Kong (Cwa). When previously assessing temperature as a continuous variable in Chapter 5, a non-significant association was found in Hong Kong between temperature and physical activity. However, the temperatures of that study rarely passed the threshold at which the heat warning was activated (above 30.5°C of the Hong Kong Heat Index) (Lee et al., 2016). However, in extreme temperatures events, over 53% of participants reported a decrease in outdoor physical activity, with a slightly greater proportion occurring in extreme cold. This was contrary to the hypothesis that had expected physical activity to decrease more in extreme heat compared to extreme cold. Meanwhile, 10.3% of participants reported an increase of physical activity, with a greater proportion from extreme heat. The study findings were in agreement with temperature-mortality studies in other subtropical locations (Analitis et al., 2008; Goggins et al., 2013), demonstrating that those in hotter climates are more capable of managing in extreme heat (Kenny et al., 2019). Decreased physical activity in extreme heat was associated with heat warning awareness and increased understanding that heat impacts health, supporting the effectiveness of the heat warning system.

In response to Research Question 5, suboptimal self-reported seasonal health was associated with decreased outdoor physical activity in extreme temperatures in the population-based telephone survey cohort of Chapter 7. Those with cardiovascular disease were found associated with decreased physical activity in extreme cold, while those with hypertension, a related risk factor, were less likely to decrease their physical activity in extreme heat. These findings of suboptimal seasonal health and cardiovascular diseases only partially supported the hypothesis since general health status and respiratory diseases were not found associated with physical activity. As identified by the systematic review (Chapter 4), health was not commonly assessed in previous temperature-physical activity studies in the general population, with only rare instances of controlling for obesity. Previous studies conducted among patients have mostly focused on COPD and joint-related arthritis. Cardiovascular diseases have seldomly been addressed, despite the knowledge that cardiac output and cardiovascular strain are elevated by physical activity and changes in core body temperature (Burton et al., 2004). The findings of Chapter 7 and the documented risks on thermoregulatory ability, and temperature-related hospital admissions and mortality (Kenny et al., 2010; Stewart, Keates, Redfern, & McMurray, 2017) highlight the importance of assessing cardiovascular-related conditions in the research on temperature and physical activity. Particularly, an understanding of physical activity in heat among those with hypertension is necessary to develop appropriate guidelines to alleviate any potential risks of heat-related illnesses or health complications.

8.2 Summary and joint interpretation

8.2.1 Evidence of temperature-physical activity association, according to understanding of climate

In summary, the evidence from this thesis demonstrated that people's physical activity can be affected by temperatures. The findings of Chapter 4, 5, and 6 identified curvilinear associations between temperature and physical activity in colder or temperate climates when using the Köppen-Geiger climate classification. The curvilinear association was furthermore found more apparent in areas of highest greenness levels within the cities of these climates (Chapter 6). While associations in these time-series analyses of colder or temperate climates found clear decreases of physical activity in high temperatures, warmer subtropical or Mediterranean climates did not find associations in high temperatures. However, when looking at extreme temperature events specifically, the findings in Chapter 7 found participants in a subtropical climate were still likely to report a decrease in outdoor physical activity in extreme heat and cold.

Table 8.2 demonstrates how the study findings of Chapter 5 and 6 adds to the global evidence from the systematic review of Chapter 4. Among the climate types that have been commonly assessed by previous studies (as identified in Chapter 4), the findings from Chapter 5 and 6 in climates Cfa (Shanghai and Chongqing) and Dfb (Kaunas) were consistent with the trends identified in these climates. On the other hand, the hourly curvilinear findings from Cfb (Stoke-on-Trent and Doetinchem) were contrary to the positive associations commonly found in that climate classification. The findings of cities in other climate types (Csa Barcelona; Cwa Shenzhen and Hong Kong; Dwa Beijing) added to the overall global evidence, but further evidence is required to determine the trends of temperature-physical activity associations in these climate types.

Table 8.2 Updated strength of evidence for temperature and physical activity associations, by Köppen-Geiger climate classification from Table 4.6 and thesis findings

Köppen-Geiger climates^	BWh	Cfa	Cfb	Cfc	Csa	Csb	Cwa	Dfa	Dfb	Dfc	Dwa
1 Positive	0	5 (7)	11 (7.6)	1 (6)	0	1 (8)	0	1 (8)	7 (6.7) *+1*	0	1 (5)
2 Mixed	0	4 (7)	4 (8)	0	1 (6)	1 (6)	0 *+2*	0	4 (6.3)	1 (4)	0
3 Non-significant	0	2 (7.5)	1 (3)	0	1 (8) *+1*	1 (7)	0	2 (6)	0	0	1 (8)
4 Negative/ curvilinear	1 (6)	8 (7.1) *+2*	3 (5) *+2*	0	1 (8)	0	1 (8)	1 (6)	2 (5.5)	0	0 *+1*
Total papers	1	19	19	1	3	3	1	4	13	1	2

Studies identified from systematic search conducted on May 2018 (and updated January 2020) in following databases: CINAHL, PubMed, Scopus, Web of Science, ScienceDirect, Embase, Ovid MEDLINE, PsycINFO, SportDiscus, China Academic Journals Full-text Database and Wanfang
^Numbers in parentheses indicate average study quality
Absent climate groups: A (equatorial tropical climates), BS (semi-arid/steppe), Cwb/c (subtropical highland), Csc (cold-summer Mediterranean), Dfd (subarctic), Dwb/c/d (monsoonal continental), Ds (Mediterranean continental), ET (tundra)

The difference between the results of Cfb climate locations in this thesis and previous studies could be explained by the restriction of linear analyses and a potential distinction between daily and hourly physical activity. Previous analyses had often only assessed linear temperature associations, which may have masked potential non-linear findings. Additionally, most of the previous studies in Cfb were conducted on daily physical activity, meanwhile Chapter 6 of this thesis assessed hourly physical activity. A similar study on hourly travel behaviour had also previously found negative or curvilinear relationships of temperature with walking or outdoor leisure activities in Utrecht, Netherlands (Cfb) and Oslo Norway (Dfb) (Böcker et al., 2019). This could indicate possible variations in the temperature-physical activity association between the daily and hourly levels.

The context of physical activity likely varies between the hourly and daily levels. When comparing between daily and hourly associations, a study conducted in outdoor trails of Seattle (Csb) also found varied findings, with consistent positive associations at the daily level, but both non-significant and slightly positive associations at the hourly level (Zhao et al., 2019). In Chapter 5, the daily temperature-physical activity models explained a large proportion of day-to-day physical activity variation at the population level, albeit supported by the study design and aggregated data. However, as demonstrated in Chapter 6, more variables and context may additionally affect the temperature-physical activity relationship at the hourly level, such that information on time utilization (Pratt et al., 2004) and physical activity domains would help strengthen future analyses. Methods such as distinguishing between participant locations, or the indoor-outdoor exposure would further support an understanding of temperature and physical activity at the hourly level. Future studies should seek to identify the characteristics and influencing factors of both hourly and daily temperature-physical activity associations.

8.2.2 Generalizability of findings

This thesis found that both physical activity levels (Chapter 5) and physical activity intensity (Chapter 6) are affected by high temperatures, with optimal temperatures ranging from 14.5-19.3°C. These findings are likely generalizable to the physical activity of other adult populations in similar climate types, since the thesis results supported the research hypothesis that similar climates have similar outcomes. As for other climate types, it can be hypothesized based on the trends of this thesis' findings that physical activity in cooler climates may also find strong curvilinear associations with temperature, as the population has not adapted to high temperatures. On the other hand, warmer climates may demonstrate a weaker association with temperatures as populations adaptations have enabled them to continue their activities in high temperatures. However, a negative effect of physical activity could likely still become apparent in extreme heat.

The scale of the cities assessed in this thesis differed greatly. While the Asian cities in Chapter 5 had urban populations ranging between 7.5 million in Hong Kong to 31 million in Chongqing, the European cities assessed in Chapter 6 had urban populations of 56,247 in Doetinchem, up to a maximum of 1.6 million in Barcelona (Smith et al., 2017). Whether the temperature-greenness interactions found on physical activity in the European cities are generalizable to large megacities remains to be seen. The availability of high greenness locations in the smaller-scale European cities may be limited in these large megacities of other regions. Additionally, as demonstrated by the non-significant findings of temperature-greenness interactions in the coastal city of Barcelona, other terrains and geographical factors may be influencing the temperature-physical activity association. An understanding is needed of how vegetation may affect physical activity differently in varying terrains and larger, more populated cities. Particular attention should be paid to cities of rapid urbanization or cities with low levels of greenspace (Zhao et al., 2013).

This thesis focused on overall physical activity as measured by overall daily step counts (Chapter 5), hourly intensity of movement (Chapter 6), and self-reported levels (Chapter 7). These findings demonstrate that people's overall physical activity are associated with temperatures, regardless of indoor or outdoor location. However, different domains of physical activity (transport, leisure, occupational etc) and different physical activity types (Provost et al., 2019) may exhibit different patterns with temperature. Similar to previous studies identified in the systematic review (Chapter 4), future studies could continue to examine distinctive trends of specific activities located at venues, such as swimming pools, indoor gyms, recreational facilities, hiking trails, beaches etc. A widescale understanding of the temperature-physical activity associations in these venues could support targeted policies for physical activity promotion. Additionally, whether compensation or substitution of indoor physical activity occurs in high temperatures remains to be thoroughly investigated, as limited discussion has taken place in previous studies (see Section 4.3.3.3).

8.2.3 Synthesis of findings in Hong Kong, China

The same Hong Kong urban context was examined in two separate studies through Chapter 5 and 7. While Chapter 5 found non-significant associations of daily step count with high and low temperatures, Chapter 7 found over 53% of participants self-reported a decrease of outdoor physical activity when looking specifically at extreme temperature events. Both these two epidemiological approaches are commonly used to assess the heat effects in temperature-mortality studies: continuous temperature time-series analysis or an episodic analysis (Gasparrini et al., 2015; Gosling et al., 2009). While the time-series approach provides a more comprehensive view of the temperature effects, this is at expense of capturing the specific effects of a heat event (Hajat et al., 2006). Meanwhile, episodic analyses are useful for capturing insights of the short-term response of the population (Gosling et al., 2009). This could help justify why decreased physical activity was found in the extreme temperature event analysis (Chapter 7), but not significant in the continuous time series analysis (Chapter 5).

Furthermore, the temperature effects were likely to be found more apparent in Chapter 7 compared to Chapter 5 due to the following variations: an older age distribution, a distinction between qualitative and quantitative physical activity measurement, and the comparison between outdoor vs. overall physical activity. While a large proportion of the Hong Kong sample in the time series analysis tended to be of working age, the population of the telephone survey was generally older (45 and above). The age stratification analysis of Chapter 5 complements the findings of Chapter 7, demonstrating curvilinear temperature effects among the older population. The difference between qualitative and quantitative measurement has not been investigated specifically related to temperature studies, however previous studies have demonstrated that self-reported physical activity are often an over- or under-estimation of objective physical activity levels (Prince 2008).

Additionally, Chapter 7 only captured the effect on outdoor physical activity, which may be more connected to temperatures than the overall physical activity of Chapter 5. Future studies should assess whether the reported decrease of outdoor physical activity is compensated by an increase of indoor physical activity.

8.2.4 *Vulnerable sub-populations: the influence of health and sociodemographic factors*

This thesis found that suboptimal seasonal health and cardiovascular disease were associated with decreased physical activity among general populations in extreme temperatures. These findings highlight evidence not discussed in previous literature, as most studies in the general population did not control for or consider the effects of health in their analyses, as summarized in the systematic review of Chapter 4. Additionally, previous studies on patients largely only considered respiratory diseases (such as COPD) or joint-related arthritis as risk factors. However, Chapter 7 found that those with suboptimal health or cardiovascular disease were up to 6.5 times more likely to report a decrease in physical activity in extreme temperatures. Physical activity recommendations should consider the vulnerabilities of those in worsened health conditions during extreme temperatures and these health factors should be controlled for in future temperature-physical activity studies. Particularly, this finding in cardiovascular disease is important for shaping future research, as there is a demonstrated need to further understand the vulnerability and risks of physical activity posed towards people with cardiovascular-related conditions in extreme temperatures.

Sociodemographic groups including females and older persons were also found associated with greater decreases of physical activity in high temperatures (Chapter 5 and 7). Although there is no evidence of higher risk of heat-related illnesses among females, males and females may experience different responses to temperatures due to differences in muscle mass, body size, aerobic fitness and/or sweating rates (Yanovich, Ketko, & Charkoudian, 2020). On average, females were more inactive than men (see Table 5.3, page 66), a finding which has also been supported in previous literature (Hallal et al., 2012). Females may also be more prone to dislike and avoid the sweaty feeling of doing activity in hot weather. On the other hand, older persons are physiologically demonstrated to have a decreased capacity to thermoregulate, with a lower ability to increase cardiac output and sweating (Kenney et al., 2014). This leads to an overall lower tolerance of heat starting as early as 40 years old (Larose et al., 2013). Future research could seek to understand the barriers and develop protective measures to support these sub-populations to safely conduct physical activity in hot temperatures.

8.2.5 Strengths and limitations

The strengths of this thesis included a comparison of the temperature-physical activity relationship across different communities and urban contexts. This provided added insight across various urban communities that have conducted previous studies on the climate effects on health and are known to be affected by climate. The focus on adult populations enabled greater understanding of the factors affecting adult physical activity levels, which can in turn can support the development of effective health promotion efforts and improve their health and productivity. As adults represent a large proportion of a population, especially the working population, improving their health would also benefit the socio-economic development of communities. Additionally, the data collections of the different studies occurred within a 6-year timeframe, whereby the global climate and time period were comparable. Population-wide physical activity levels may be affected by worldwide or city-wide events, such as the global pandemic of Covid-19 (Tison et al., 2020), the launch of Pokémon Go in summer of 2016 (Khamzina et al., 2020), or different events of social and political unrest (Hughes, 2011; Shek, 2020). The data collections in this thesis, however, were completed in the absence of such large-scale events.

With regards to the strengths found among individual studies, the systematic review was comprehensively conducted in both the English and Chinese languages via searching twelve databases (Chapter 4). Two multi-location comparative studies (Chapter 5 and 6) with consistent data collection methodologies enabled comparisons across different cities. The studies included several climate locations that were seldom assessed in previous studies (Csa, Cwa, and Dwa). Physical activity was objectively measured using accelerometer data, which removed recall and self-report bias. The use of accelerometers within smartphone applications furthermore enabled the large-scale data collection and access to GPS data for verification of surroundings. The studies included the simultaneous adjustment of other meteorological variables and key time-related precision variables. The studies that incorporated survey data in this thesis (Chapter 6 and 7) were able to consider a broad range of participant characteristics in the analyses from collected data. This thesis further provided an assessment of chronic diseases in the general population, rarely conducted in previous studies.

However, this thesis also encountered several limitations. Physical activity, particularly at the hourly level, may be dependent on the utilization of time and constrained by different activities throughout the day (Pratt et al., 2004). Due to data limitations, the studies were only able to assess overall physical activity and could not differentiate between different domains of physical activity (transport, leisure, occupational etc), although this information may have been beneficial to the analyses. The studies collected data on individual or aggregated physical activity patterns but did not obtain information about the usage of recreational facilities, parks, or other locations of particular interest. This limited the ability to evaluate existing facility usage and associate the thesis findings with current programmes and policies. The thesis findings also are insufficient to develop indexes or indicators as to inform tool developments for physical activity promotion. Recommendations could not be made for specific physical activity types, as only overall physical activity was assessed.

With regards to the limitations found among individual studies, the use of accelerometers in Chapter 5 and 6 restricted the physical activity to non-aquatic ambulatory activities. Other physical activities could not be measured, such as swimming and winter sports, which may have different temperature patterns. Additionally, the opt-in design of smartphone apps may have produced a sampling bias towards more fitness-driven individuals. While Chapter 5 used longitudinal city-wide aggregated data that could not follow individuals, Chapter 6 assessed individuals repeatedly over four to seven days but did not follow them for long periods. The analyses could not differentiate between indoor and outdoor locations of participants, aside from Chapter 7 which focused on outdoor physical activity. The indoor-outdoor differentiation may be a confounder particularly if assessing within city variations at the hourly level.

Although temperature and other meteorological conditions may also vary throughout the city, personalized exposure could not be detected since meteorological data was available from only one meteorological station in most study cities. Study participants in Chapter 5 and 6 were furthermore not necessarily limited to city boundaries during the study periods. The study of Chapter 7 used a subjective survey with a non-validated question to assess outdoor physical activity. The study design prevented a statistical analysis on the association between the extreme temperature events and physical activity, which could only be inferred. The survey furthermore experienced a loss to follow-up, leading to a smaller final sample size. Overall, the focus of the studies were only on the able-bodied population. Those with mobility limitations or other disabilities were not assessed, despite the fact that their vulnerability to temperatures may be greater.

8.3 Implications

8.3.1 On health

As found in this thesis, low and high temperatures were associated with decreasing physical activity, particularly in cities of cold or temperate climates. A decrease of 380 daily steps, or 4% change in hourly median MET was found for a 10°C increase from optimal temperatures. Reduced physical activity due to high or extreme temperatures may lead to consequent effects in health and wellbeing (Sabel et al., 2016; Spickett, Brown, & Katscherian, 2008). In the general population, pooled analyses of the dose-response between physical activity and physical health have demonstrated that only 8.25 MET hours (or 150 minutes) of MVPA is required to attain 70% of the maximum benefit between physical activity and reduced all-cause mortality risk (Physical Activity Guidelines Advisory Committee, 2018). A meta-analysis found that walking alone was associated with reduced all-cause mortality by 11% risk for a dose of 11.25 MET-hours per week compared with no walking, while adjusted for other self-reported physical activity (Kelly et al., 2014).

Among chronic disease patients of breast cancer, ischemic heart disease, type two diabetes, and COPD, a meta-analysis found that all-cause mortality was reduced by 22%, 12%, 4% and 30% (very low certainty), respectively, for an increase of 10 MET-hours per week (Geidl et al., 2020b). Risk reductions are also found for NCDs and their risk factors, such as cancer mortality (Li et al., 2016), metabolic syndrome (Zhang et al., 2017), dementia (Xu et al., 2017), type 2 diabetes mellitus (Smith, Crippa, Woodcock, & Brage, 2016a). A meta-analysis found that leisure time physical activity and active commuting was associated with reductions for myocardial infarction, CVD, heart failure, stroke, type 2 diabetes, and colon and breast cancer (Raza, Krachler, Forsberg, & Sommar, 2020).

In terms of mental and social health, the research has been less developed on the dose-response effects of physical activity, with no studies found for the dose-response of social health. Cohort studies among women found positive associations between self-reported physical activity and mental health or quality-of-life scores (Heesch, van Uffelen, van Gellecum, & Brown, 2012; Wolin et al., 2007). Among cross-sectional studies, self-reported mental health, general well-being, positive mood, and lower levels of depression and anxiety was positively associated with physical activity (Abu-Omar, Rutten, & Lehtinen, 2004; Stephens, 1988), with an optimal level of 5000-16000 steps daily (Bernard et al.,

2018) or 150-450 minutes of physical activity weekly, even among older adults (Kim et al., 2012; Mummery, Schofield, & Caperchione, 2004). Lower psychological distress was associated with a minimal level of at least 20 min/week for any physical activity, with greater benefits for activities at higher volume or intensity (Hamer, Stamatakis, & Steptoe, 2009). Although evidence on mental health dose-response relationships may not be robust, the findings suggest that mental health benefits may also occur with minor increases in physical activity.

For these physical activity and mortality risk dose-response meta-analysis studies, the greatest reduction of mortality risk occurred when shifting from inactive to minimally active (Geidl et al., 2020b; Kelly et al., 2014; Physical Activity Guidelines Advisory Committee, 2018). No minimum dose of physical activity was required to experience its health benefits (Geidl et al., 2020b; Physical Activity Guidelines Advisory Committee, 2018; Zhang et al., 2017). This prompts the understanding that even minor changes in physical activity on a weekly basis can have consequential health effects. In Japan, official physical activity guidelines have recently adopted a low-dose physical activity recommendation of adding 10 minutes of MVPA, or approximately 1000 steps per day to their current lifestyle (Miyachi, Tripette, Kawakami, & Murakami, 2015). In Germany, physical activity recommendations for adults with NCDs have focused on patient-centred planning based on individual functionality and ability, emphasizing “Every step counts” for health benefits (Geidl et al., 2020a; Geidl et al., 2020b). An increase in the number of days above optimal temperature could produce physical activity reductions at the population level that lead to clinically significant detriments on human health.

8.3.2 On global trends

The world will experience increasing trends of urbanization, ageing, non-communicable diseases, and climate change. The global population living in urban areas is expected to continue rising from 55% in 2018 to 68% in 2050 (United Nations DESA, 2019). Although Europe has a high rate of urbanization (74%), in general, the urban populations in Europe are relatively “small” with many major cities having 3 million people or fewer (United Nations DESA, 2019; Wikipedia, 2020). Contrarily, other more-recently developed or developing regions, such as Asia, Africa and Latin America have seen and will continue to see the growth of many megacities, which are cities with 10 million or more in population (United Nations DESA, 2019). The creation of active environments in urban areas will play a substantial role on physical activity in those populations (World Health Organization, 2018).

Attention on temperature impacts is recommended for the policies of active-promoting transport systems, green infrastructure, and urban design.

Although this study does not consider the age extremes of young children, it develops the understanding of temperature-physical activity relationships among adults, a large proportion of the population. This thesis furthermore found that the elderly reduced more physical activity in high temperatures than younger populations (Chapter 5). In many countries, the proportion of older people over the age of 60 will increase from 1 in 8 in 2017 to 1 in 5 by 2050 (World Health Organization, 2020). By then the global population of older people would also be twice the size, an increase from 1 billion to 2.1 billion people (World Health Organization, 2020). The World Health Assembly has recently endorsed the proposal for the Decade of Healthy Ageing 2020-2030. A focus on Healthy Ageing emphasizes "the development and maintenance of functional ability that enables well-being in older age" (World Health Organization, 2020). As physical activity is an essential component to maintaining intrinsic physical and mental capacity into old age (World Health Organization, 2020), specific efforts should be made to ensure the elderly can sustainably and safely conduct physical activity in extreme temperatures without additional health risks. Climate controlled elderly-friendly facilities and sheltered accessible transport options may promote their engagement. Physical activity recommendations for older adults may also need to emphasize guidelines for exercising in the heat and cold.

In terms of the implications on non-communicable diseases (NCDs), a reduction of physical activity could contribute to increased risk of NCDs at the population level. NCDs are a huge burden to health systems and expenditure, despite being largely preventable. NCDs resulted in over 71% of worldwide mortality in 2016 and comprised of 57% of premature mortality from those under 70 (Bennett et al., 2018). In most countries, there is a higher risk of premature mortality from NCDs than other conditions of communicable, maternal, perinatal, and nutritional (Bennett et al., 2018). Future projections demonstrate an increasing burden if current trends continue, particularly in low- and middle-income countries (Kassa & Grace, 2019). Global targets have been set to reduce NCDs by 2030, aiming for a 25% relative reduction of the four major types of NCDs (World Health Organization, 2013). As physical activity plays a major role as one of the modifiable risk factors, the reduction of physical activity due to high and low temperatures, as found in Chapters 5 and 6, would likely frustrate this progress. Habitual physical activity levels need to be increased or maintained for the population to prevent and manage chronic diseases (World Health Organization, 2013). Additionally, as found in Chapter 7, suboptimal health and cardiovascular disease were found to affect the decrease of physical activity in extreme temperatures. This could lead to a possible downward cycle of deconditioning of health, particularly among those with existing NCDs (Durstine et al., 2013). NCD patients may experience confounded effects as physical activity places further strain on the body's cardiovascular and respiratory systems during periods of high heat, yet it is required for the management of their disease. An awareness among healthcare providers and increased clinical guidance may be important to influence the maintenance of physical activity without harming health. More could be explored about the decision-making interlinkages between physical activity and heat among those with NCDs.

Climate change will bring about rising temperatures in most regions of the world. For example, the year this thesis was written, 2020 was the hottest summer on record for Hong Kong. By 2100, global temperatures are likely to have increased over 1.5°C (IPCC, 2014). This thesis demonstrates that the direct health impacts of climate change could extend beyond mortality and morbidity to influence even human activity at the daily level. There would be increasing days where physical activity at the population-level could be lowered by high temperature, precipitation, and extreme weather events. However, the reduction of cold winter temperatures may support increased physical activity, as fewer cold extremes is also expected (IPCC, 2014). Previous climate change projections approximated a net increase of physical activity in temperate climates (Obradovich & Fowler, 2017; Scott & Jones, 2006). At the same time, warmer winters may also reduce the abundance of natural snow and stifle the engagement in winter sports (Steiger et al., 2017). More must be studied on the uptake of alternative activities when people's preferred choice may be limited. Accurate climate projections are needed to support the estimation of how physical activity will be affected by temperatures in the future and its net effect in a variety of climates. Nearing the completion of this thesis, a growing recognition has been found on the potential impacts of climate change on physical activity (Evans, 2019; Wallace, Wiedenman, & McDermott, 2019).

8.3.3 On policy & practice

The findings of this thesis suggest the importance of addressing physical activity levels in hot temperatures. Particularly as the effects of climate change become more evident, preventative measures should be taken to ensure a resilient health-promoting adaptation to temperature abnormalities and shifts from climate change. Interventions should be developed in both the public health sector and the general community to support and sustain the physical activity of local urban populations, with overall aims to reduce the subsequent risk of consequential health effects. A summary of the recommended interventions for policy and practice can be found in Table 8.3.

Table 8.3 Summary of recommended interventions in policy & practice from this thesis

Sector	Recommended interventions
Public health sector	*Physical activity guidelines & research:* • Integrate temperature and heat into physical activity guidelines for the general population and specifically targeting at-risk groups • Promote ways to safely stay active even in heat • Review physical activity recommendations for at-risk groups (elderly, chronic disease patients, mobility etc.) • Control for temperature in longitudinal and intervention research *Surveillance and monitoring:* • Year-round surveillance on physical activity through surveys and recreational facility records, ideally at daily/weekly timescale • Monitor for related injury patterns as potential indicator of unprotected physical activity in heat *Health workforce:* • Receive training in knowledge on the effects of climate change on health, including physical activity, and risk communication • Provide education of heat-related risks to patients and suggestions on safely maintaining physical activity in heat • Address temperature-related barriers to physical activity for patients prescribed with exercise • Be attentive to physical activity and well-being of at-risk groups in heat
Physical activity sector	• Develop indoor climate-controlled or sheltered semi-outdoor facilities for sustainable usage regardless of weather conditions • Provide a variety of sport and recreational options for local communities throughout the year • Utilize equipment and sportswear technologies to support physical activity in heat • Ensure facilities are accessible to at-risk populations

Built environment sector	• Monitor local temperatures throughout the city, specifically along transport routes, public transportation stations/stops, and greenspaces, to identify problematic locations where heat concentrates for future re-design and renewal
	• Use bioclimatic approach to urban design, including cooling strategies such as:
	    o Increasing green infrastructure, particularly tree cover
	    o Constructing ventilated and shaded pathways
	    o Using non-heat-retaining materials
	    o Using mist spraying systems for immediate cooling effect

Climate and meteorological sector	*Climate policies* • Take heat impacts into consideration while developing active travel policies for climate mitigation • Take physical activity promotion into consideration when developing climate adaptation strategies *Heat warning systems* • Incorporate recommendations of physical activity variations instead of only recommending physical activity avoidance
Global Policy Agendas	Aligned with Sustainable Development Goals, New Urban Agenda, and Paris Agreement (21st Conference of the Parties of the UNFCCC)

8.3.3.1 Public health sector

This thesis emphasizes the need to begin an integration of temperature and heat issues in the public health sector, particularly in physical activity promotion. As discussed in Section 2.6, mainstream discussions of physical activity largely do not address the impacts of heat and climate change (66th World Health Assembly, 2013; Balmain et al., 2018; World Health Organization, 2016). The discussion on heat and physical activity has been developing for selected populations such as athletic, occupational, military, and educational settings (Hong Kong Education Bureau, 2020; Hosokawa et al., 2019; Peiser & Reilly, 2004). However, this concern for heat in physical activity is not as prevalent in general populations, who contrarily are usually not as young and fit as those assessed for athletic or military purposes (Yao, Troyanos, D'Hemecourt, & Roberts, 2017). Particularly with the trends of ageing and NCDs mentioned in Section 8.3.2, the proportion of at-risk groups in the general population would increase in the coming decades, causing additional heat vulnerability that would require added support.

Physical activity guidelines & research

Physical activity guidelines for the general population should address the risk of heat, with further attention on at-risk populations. Guideline reports should seek heat-related evidence on physical activity and incorporate it into the development of their recommendations with alternate options for sustaining physical activity. Physical activity recommendations should be reviewed periodically for at-risk populations including, but not limited to, the elderly, chronic disease patients, those with mobility problems, and those on long-term medications. In terms of research, longitudinal studies on physical activity interventions should control for the effects of temperatures in their analyses.

Currently, information on heat and physical activity seem to not be found in formal physical activity guideline reports but make appearances in related promotional materials and press releases of extreme temperature events. The recent 2018 Global Action Plan on Physical Activity 2018-2030 by WHO had no mention of ‘temperature’ or ‘heat’ throughout its report to promote physical activity, whereas ‘air quality’ and pollution is mentioned ten times (World Health Organization, 2018). The American 2018 Physical Activity Guidelines Advisory Committee Scientific Report never mentioned the word ‘temperature’ in its literature review and only referred to “making sensible choices, such as avoiding extreme heat or cold” in its 779-page report, in addressing the reduction of adverse events such as heat-related illnesses (Physical Activity Guidelines Advisory Committee, 2018). However, the public edition of the American guidelines improves by briefly addressing methods to reduce risk of heat stress during physical activity, as seen in Figure 8.1. Similarly, a few well-established government, health, and physical activity organizations websites have produced short articles on how individuals can minimize the heat risk to safely conduct physical activity (American Heart Association, 2015; Health Canada, 2020; Mayo Clinic, 2017; Sports Medicine Australia, 2008; Yabsley, 2017). More organizations should follow suit to communicate the risk to their constituents and provide alternative options.

Figure 8.1 Example of heat-related physical activity guidelines as found in Physical Activity Guidelines for Americans, 2nd edition

Make Sensible Choices About When and How to Be Active

A person's choices can obviously influence the risk of adverse events. By making sensible choices, injuries and adverse events can be prevented. For example, wearing reflective clothing and lights when doing outdoor activities (walking, running, or bicycling) in the early morning or evening can help increase visibility. Consider weather conditions such as extremes of heat and cold, and apply sunscreen as appropriate. For example, during very hot and humid weather, people lessen the chances of dehydration and heat stress by:

- Exercising in the cool of early morning as opposed to mid-day heat;
- Switching to indoor activities (playing basketball in the gym rather than on the playground);
- Changing the type of activity (swimming rather than playing soccer);
- Lowering the intensity of activity (walking rather than running); and
- Paying close attention to resting, seeking shade, drinking enough fluids, and finding other ways to minimize effects of heat.

Source: U.S. Department of Health and Human Services (2018)

Physical activity surveillance and monitoring

The physical activity guidelines often assume that the population is continuing to conduct physical activity under hot circumstances. But what if, as found in this thesis, populations may be at risk of doing less physical activity? At the city, regional, or national levels, there should be an increased awareness and monitoring on the effects of heat on physical activity. An integration of heat concerns is necessary within health promotion and surveillance. City-wide or nation-wide continuous surveillance should be conducted for population-level physical activity. This could be completed using standardised, culturally relevant, self-reported surveys for an understanding of population-wide levels, or monitoring the usage of public facilities such as parks, country parks, recreational venues etc. In order to track the effects of temperature variation, the procedures would ideally collect data throughout the whole year and assess physical activity at fine timescales of the daily or weekly level. Additionally, related injury patterns can be identified and monitored as indicators of unprotected physical activity in heat.

Health workforce

Within the health sector, physicians play a key role in promoting physical activity and alerting patients of heat impacts (Parker, Wellbery, & Mueller, 2019; Sallis, 2009). Education and training should be given to the health workforce on the effects of heat and climate change on health, including the effects on physical activity (Crowley, Health, & Public Policy Committee of the American College of, 2016). Additional training could be provided on effective risk communication strategies. In prescribing exercise to patients (Sallis, 2009), physicians can intimately understand the barriers to physical activity a patient may face. Doctor recommendations should inform patients to risks of physical activity in extreme temperatures and explore options with them on how to maintain target physical activity levels while combating these risks. Additional education could be given on symptoms of heat-related illnesses, hydration, and cooling methods (Parker et al., 2019). Health practitioners could also extend concern particularly to the physical activity and well-being of at-risk populations in heat, such as the elderly, chronic disease patients, those with mobility problems, and on medications. In light of climate change, it may be critical to reassess expert recommendations of physical activity participation, particularly for those at high-risk of heat-related illnesses (Wallace et al., 2019).

8.3.3.2 Other sectors

Much of physical activity promotion is located beyond the health sector in the community (Bull & Bauman, 2011). Thus, the implementation of physical activity promotion in heat will require a “whole-of-government” approach (Bull & Bauman, 2011). How can different stakeholders promote the continued levels of physical activity in extreme temperatures? Multisectoral and multidisciplinary responses are needed for climate change public health adaptation (Huang et al., 2011). The following sections recommend possible adaptations in different sectors, however, these adaptations for physical activity will vary between different locations and climates, as determined by their relationship between temperature and physical activity, as well as identified barriers of physical activity in heat.

Physical activity sector

At the community level, public community facilities, private recreational venues, and the sports industry may experience adjustments to changing temperatures, whether these adjustments occur passively or actively. The sports industry has begun to address the effects of high temperatures and relative humidity on more professional level athletic events such as marathons, competitions, and international events like the summer Olympic games (Ely & Ely, 2020; Peiser & Reilly, 2004; Roberts, 2010). Climate change will affect these events, including the location selection for international games (Peiser & Reilly, 2004; Smith et al., 2016b) and management of sports grounds (Dingle & Stewart, 2018; Mallen & Dingle, 2017; McDonald, Stewart, & Dingle, 2014). In a study identified in the systematic review of Chapter 4, Scott discussed the increased costs of managing Canadian golf courses due to warmer temperatures, water scarcity, and increased occurrence of pests and grass diseases (Scott & Jones, 2006). Publicly funded government- and community-owned leisure facilities should develop a progressive lens on infrastructure provisions. The development could focus on indoor climate-controlled or sheltered semi-outdoor facilities instead of outdoor unshaded tennis and basketball courts to increase usage throughout the year. Indoor swimming pools have been found to have higher use throughout the year compared to outdoor pools (Howat, Crilley, & Murray, 2005). The private sector could also be encouraged to expand their services in climate-friendly options. Additionally, sports equipment and clothing could harness new technologies to support physical activity in the heat. Accessibility of these indoor facilities and equipment should be ensured so that those most vulnerable to extreme temperatures can participate.

Built environment sector

At the city level, urban planning policies can be modified to ensure support for physical activity in extreme temperatures. Increased awareness and monitoring of immediate temperatures throughout the urban environment would help identify and adapt the 'hot-spot' locations where physical activity is conducted, whether for active travel commuters, running enthusiasts, or playgrounds and parks etc. Transport planners should be attentive to how temperature experiences may vary between different travel routes and modes of transport such as walking, cycling, and waiting for the bus. The design of green spaces should also consider the temperature effects on human usage or physical activity. An increase in bioclimatic approach to urban design is essential, as it addresses the design of buildings and landscapes based on local climate, with health and comfort in mind (Watson, 2013). Measures can be taken to alleviate the experiences of high temperatures, through the provision of cooling strategies such as vegetation, shading, proper materials, and cooling equipment. Green infrastructure, particularly tree canopies, can lower air temperatures by 1°C at the pedestrian level when comprising 33% of the urban area (Ng, Chen, Wang, & Yuan, 2012). Trees have been found more effective than grass to reduce daytime radiant temperature and have the largest impact in open areas (Lindberg, Thorsson, Rayner, & Lau, 2016; Ng et al., 2012). The use of ventilated and shaded pathways, and materials designed to decrease albedo and overheating of surfaces, could further reduce heat exposure. Small-scale mist spraying systems can be implemented to harness evaporative cooling and reduce thermal stress with minimal energy consumption (Ulpiani, 2019). These policies could ensure the built environment is conducive to physical activity and active travel even in warm or hot temperatures.

Climate policies and meteorological services

Physical activity promotion should be integrated into heat-related work and climate policies. As mentioned in Section 2.4.4, previous mitigation policies on active travel have not considered the heat impacts (de Nazelle et al., 2011). Increasing awareness on the heat effects in the designs of these mitigation policies could encourage the adoption of heat-reducing urban designs. Climate adaptation strategies could also pay attention to how they may influence and reduce physical activity. Heat warnings systems in governmental meteorology services could provide more physical activity-related suggestions instead of only recommending an avoidance of physical activity. For example, heat warning recommendations could include conducting exercise in cooler parts of the day or choosing indoor or climate-controlled options where possible (refer back to Figure 8.1 for examples). This would help promote sustained physical activity levels even as temperatures increase with climate change.

8.3.3.3 Linkage with global policy agendas

At the global level, inter-governmental agendas have been adopted by countries, to tackle global challenges together in partnership. Three agendas relevant to this thesis include the Sustainable Development Goals (SDGs), the New Urban Agenda, and the Paris Agreement under the United Nations Framework Convention on Climate Change, all of which were adopted in 2015 or 2016. The SDGs sets out 17 ambitious goals to address by 2030, striving for a balance of economic growth, social inclusion, and environmental protection (United Nations General Assembly, 2015). This thesis simultaneously highlights the interconnections of three of those goals: SDG 3 to ensure healthy lives and promote well-being for all at all ages; SDG 11 to make cities and human settlements inclusive, safe, resilient, and sustainable; and SDG 13 to take urgent action to combat climate change and its impacts.

The New Urban Agenda aims for sustainable and inclusive urbanization, setting out a policy framework for implementation over 20 years (United Nations General Assembly, 2017). It envisions cities where all inhabit "healthy, accessible... and sustainable cities... to foster prosperity and quality of life for all", with specific relevant commitments on the "creation and maintenance of well-connected and well-distributed networks of... accessible green and quality public spaces, to improve the resilience of cities to disasters and climate change, including... heat waves, improving... physical and mental health... and promoting attractive and liveable cities" (Article 67), as well as "access.. to safe, age- and gender-responsive... accessible and sustainable urban mobility, [prioritizing] non-motorized options such as walking and cycling" (Article 114) (United Nations General Assembly, 2017).

The Paris Agreement is a binding agreement among countries to pledge action against climate change, aiming to hold global average temperatures below a 2°C increase (Conference of the Parties UNFCCC, 2016). The Agreement also promotes the formulation and implementation of adaptation policies nationally, "emphasizing the enduring benefits of ambitious and early action, including major reductions in the cost of future mitigation and adaptation efforts" (Conference of the Parties UNFCCC, 2016).

The findings of this thesis are aligned with these three global policy agendas and reenergize the ambition to fulfil them. Among these three global agendas, however, no global indicators or targets have been found to address physical activity specifically. The development of global indicators on physical activity could be a potential step for consideration in future global policy agendas.

8.4 Future research directions

The impact of temperatures on physical activity have still yet to be assessed in multiple climates. Multi-comparative studies conducted in a variety of climates could support the argument of heterogeneity using Köppen-Geiger climate classification, particularly if the studies include more locations of each climate type. This thesis did not assess the African and South American regions. The variation in climate change impacts and prevalence of low- and middle-income countries of the regions may affect their temperature-physical activity responses and moreover necessitate local adaptation solutions to this phenomenon. Due to data limitations, the studies in this thesis nor the studies identified in the systematic review do not provide a rigorous comparability across regions. As discussed earlier, differences between regions in terms of urbanization and size of the cities limits the comparability across regions. As there may be an influence of the urban context and cultural, physiological, or behavioural adaptations between different regions, a coherent understanding across regional variability would be useful to inform global surveillance methods.

Future research should tie the temperature-physical activity association with subsequent effects on health outcomes. This would develop the understanding of whether there are clinical outcomes from this physical activity reduction. It would be useful for future research on temperature-physical activity to stratify by habitual active levels (Badland et al., 2011). However, self-reported habitual levels may not be the most effective, as these were initially controlled for but later removed as it was not found to improve the model in Chapter 6. Accurate assessments of habitual active levels would expand the understanding on health benefits, as those at minimally active levels could benefit the greatest reductions on mortality from increased physical activity (Geidl et al., 2020b). Studies could be conducted to compare the effects in the general population with those with chronic diseases, particularly of the cardiovascular nature.

A finer measurement of the temperature exposure variable could be used. As shown in previous studies, there are within-city differences and even differences between indoor and outdoor temperatures (Kenny et al., 2019). Finer measurements of spatial and temporal variability may be able to assess urban heat island and microclimate effects on physical activity. Additionally, analyses can be conducted on the association of extreme temperature events, such as heat waves and cold spells. Studies could project the potential changes of physical activity due to climate change (Obradovich & Fowler, 2017). Health

Impact Assessments (HIA) can also include the effects of heat in active travel policies, which was not done previously (Mueller et al., 2015).

Future studies should seek to conduct indoor-outdoor comparisons of physical activity, particularly focusing on within-person differences. The challenges may be significant to get detailed data. Even with the GPS data available in Chapter 6, it was near-impossible to distinguish indoor and outdoor physical activity. GPS locations alone can be difficult to pinpoint whether the user is indoors or outdoors. For example, GPS data may be located at a building, but the building may be open-air, or the person may be located at the roof top or outskirts of the building instead of within. Particularly in dense and tall building environments, the GPS accuracy may also be limited. An interactive mobile application that requests participant input of their location details could be a solution that provides the needed level of information (indoor/outdoor) in an easy and accurate manner that would assist data processing. Descriptions about the activities conducted in each location may also be helpful, as certain locations facilitate physical activity (ie. indoor gyms). Another method, albeit high-technology method requiring intensive data, may be smart cameras or sensors that can detect the immediate surroundings of the participant. For studies on temperature and physical activity, this type of sensor may be conveniently combined with personal heat exposure monitoring (Kuras et al., 2017).

Future studies should also explore the reasons for doing less physical activity in extreme temperatures. What are the barriers? Is it physiological, psychological, or environmental? Are these barriers localized to specific urban environments? This would help the development of policy solutions to sustain physical activity. Furthermore, the assessment of different physical activity types, such as swimming and winter sports, could reveal specific temperature patterns. This would be beneficial to develop tools for the government and private sector to optimize resources and facilitate the uptake of different physical activities throughout the year.

Lastly, future studies could address the temperature effects on physical activity in people of different active levels, ages, and physical abilities, such as professional athletes, sport enthusiasts, young children, and those with disabilities. Studies should be conducted to enable a greater understanding of how public health policies and interventions such as temperature warning systems, promotional initiatives for physical activity, and health risk education, may affect physical activity behaviour and influence outcomes in extreme temperatures. Longitudinal cohort studies and natural experiments imitating randomized controlled trials could be conducted to investigate the effects of such community interventions and city planning on the influence of temperature on physical activity. This would enable cities in rapidly developing contexts to be able to build systems and develop program policies that protect and facilitate well-being in increasing temperatures.

Chapter 9 Conclusions

This thesis examines the associations of temperature on physical activity in urban adult populations. A systematic review, two multi-location studies, and a telephone survey cohort were conducted to develop the understanding on the association between temperatures and physical activity, in different climates, greenness levels, extreme temperatures, and health status. Overall, temperature was found to be associated with physical activity in multiple climate types. Curvilinear associations demonstrating decreased physical activity in hot temperatures were more evident in cold or temperate climates and at highest greenness levels. The effect of hot temperatures was not as apparent in warmer climates, supported by the larger decrease of outdoor physical activity during extreme cold in the telephone survey. Suboptimal health and cardiovascular diseases were associated with decreased physical activity in extreme temperatures.

With the rising trends of urbanization, ageing populations, non-communicable diseases, and climate change, these findings are significant as even minor reductions in physical activity levels could increase the risk of consequential health effects like mortality and NCDs. An integration between physical activity and temperature concerns is needed in physical activity guidelines and promotion, as well as climate mitigation and adaptation policies. Increased awareness of the heat impacts on physical activity among healthcare providers, public recreational facilities, sports industry, and urban planners and designers can assist the development of supportive environments to sustain physical activity in the increasing temperatures of climate change. As highlighted by the aims of SDGs and other global agendas, cities are currently far from flourishing as accessible, safe, and sustainable urban environments that promote the health and well-being of all. The findings of this thesis provide population-based insights toward climate-sensitive urban policies for public health adaptation under climate change.

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Appendixes

A1. Search strategy of each database in the systematic review

Database	Search terms	Articles found	
English		**May-18**	**Jan-20**
PubMed	((weather[Title/Abstract] OR meteorological[Title/Abstract] OR "extreme temperature"[Title/Abstract] OR rain*[Title/Abstract] OR precipitation[Title/Abstract])) AND ("physical activity"[Title/Abstract] OR exercise[Title/Abstract] OR walking[Title/Abstract] OR sport*[Title/Abstract])	573	219
Scopus	TITLE-ABS-KEY (((weather OR meteorological OR "extreme temperature" OR rain* OR precipitation)) AND ("physical activity" OR exercise OR walking OR sport*)) AND PUBYEAR > 2005 AND (LIMIT-TO (LANGUAGE , "English") OR LIMIT-TO (LANGUAGE , "Chinese"))	3292	801
Science Direct	((weather OR meteorological OR "extreme temperature" OR rain* OR precipitation)) AND ("physical activity" OR exercise OR walking OR sport*) Year: 2006-2018	351	138
Web of Science – Web of Science Core Collection	1. TS = ((weather OR meteorological OR "extreme temperature" OR rain* OR precipitation)) OR TI= ((weather OR meteorological OR "extreme temperature" OR rain* OR precipitation)) Indexes=SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, BKCI-S, BKCI-SSH, ESCI Timespan=All years 2. TS = ("physical activity" OR exercise OR walking OR sport*) OR TI = ("physical activity" OR exercise OR walking OR sport*) Indexes=SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, BKCI-S, BKCI-SSH, ESCI Timespan=All years 3. (#2 AND #1) AND LANGUAGE: (English OR Chinese) Indexes=SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, BKCI-S, BKCI-SSH, ESCI Timespan=2006-2018	3323	842
OVID (Embase 1910 to Present, Global Health 1973 to 2018 Week 17, Ovid MEDLINE(R) 1946 to Present with Daily Update, PsycINFO 1806 to April Week 5 2018)	1. (weather or meteorological or "extreme temperature" or rain* or precipitation).tw. 2. ("physical activity" or exercise or walking or sport*).tw. 3. 1 and 2 4. limit 3 to yr="2006 -Current"	2502	524

Appendix A1. (Continued) Search strategy of each database in the systematic review

Database	Search terms	Articles found	
English		**May-18**	**Jan-20**
CINAHL	1. "physical activity" OR (MH "Physical Activity") OR (MH "Exercise") OR (MH "Sports") OR (MH "Walking") 2. (MH "Temperature") OR (MH "Heat") OR (MH "Weather") OR (MH "Humidity") OR (MH "Meteorological Factors") OR (MH "Rain") 3. S1 AND S2 Limiters - Published Date: 20060101-20181231	482	110
SportDiscus	1. TI(weather OR meteorological OR "extreme temperature" OR rain* OR precipitation) OR SU(weather OR meteorological OR "extreme temperature" OR rain* OR precipitation) OR AB(weather OR meteorological OR "extreme temperature" OR rain* OR precipitation) 2. TI("physical activity" OR exercise OR walking OR sport*) OR SU("physical activity" OR exercise OR walking OR sport*) OR AB("physical activity" OR exercise OR walking OR sport*) 3. S1 AND S2 4. S1 AND S2 Limiters - Published Date: 20060101-20181231 5. Non-magazine	408	72
	Total	10931	2706
Chinese			
中國期刊全文數據庫 China Journal Net (CJN)	(TI=气温 OR TI=天气 OR TI=气象 OR TI=雨量 OR TI=温度 OR TI=湿度 OR TI=风速 OR TI=高温 OR TI=气候) AND (TI=运动 OR TI=体育 OR TI=步行 OR TI=步数 OR TI=体力活动 OR TI=户外活动)	566	64
萬方數據 WanFang Data	(题名:(气温) + 题名:(天气) + 题名:(气象) + 题名:(雨量) + 题名:(温度) + 题名:(湿度) + 题名:(风速) + 题名:(高温) + 题名:(气候)) * (题名:(运动) + 题名:(体育) + 题名:(步行) + 题名:(步数) + 题名:(体力活动) + 题名:(户外活动))	765	95
	Total	1,331	159

Original search: May 11, 2018; Search last updated: January 2-3, 2020

A2. List of identified studies in the systematic review

Studies identified from systematic search conducted on May 2018 (and updated January 2020) in following databases: CINAHL, PubMed, Scopus, Web of Science, ScienceDirect, Embase, Ovid MEDLINE, PsycINFO, SportDiscus, China Academic Journals Full-text Database and Wanfang

Abbreviations and explanations:

Region: North Am = North America; South Am = South America

Comparison = whether study reported results for different cities to allow for multi-city comparison

Pop. type: A = Adults/general population; E = Elderly; P = Patients

PA domain: O = overall; L = leisure; T = transport; Occ = Occupational; (Y) = if have outdoor specific physical activity

PA duration: amount of time physical activity was assessed; pp = per participant

Weather source: OR = Official records (official meteorological stations, government public records); On-site obs = on-site observations; Website = unofficial websites (Weather Underground etc.)

QA = Quality Assessment total score ; S of E = Strength of Evidence (for temperature variable only)

Multi-location studies

Author-Date	Location; Region	Köppen	Comp-arison	Sample size, n	Pop. type	Study dates	Season	Study design	PA domain	PA instrument	PA duration	Weather source	Time-scale	Stats method	Temp. range	QA	S of E
An 2017	across the USA; North Am	#N/A	N	NA, aggregated	A	2004 - 2013	All	Aggregated/ecological	L	Survey: BRFSS	"previous month"	OR	Daily	Fixed - geographically weighted reg	65.31F (SD 8.65)	6	4
Aral 2017	Global; Multiple regions	#N/A	N	1.1 million	A	not reported	All	Longitudinal	L	Accelerometer: global fitness tracking network	5 years	OR	Daily	Bivariate	mean 59.46F (SD 15.25)	6	4
Balish 2017	across Canada; North Am	#N/A	N	189 (4157	P	1 year	All	Repeated measures (waves)	O	Pedometer: Yamax Digi-Walker	7 days pp, 4 waves	OR	Daily	Multilevel – hier. linear	not reported	9	1

Appendix A2. (Continued) List of identified studies in the systematic review – Multi-location studies

Author-Date	Location; Region	Köppen	Comp-arison	Sample size, n	Pop. type	Study dates	Season	Study design	PA domain	PA instrument	PA duration	Weather source	Time-scale	Stats method	Temp. range	QA	S of E
				obs. days)													
Böcker 2019	3 Euro countries (Norway, Sweden, Netherlands); Europe	Cfb / Dfb	Y	4413+2087+6454+1981	A	2010-2014 (1-3 years per city)	All	Cross-sectional	T (Y)	Recall: National Travel Survey	1 day pp	OR	Hourly	Fixed - SEM	6.5C to 10.9C depending on city	7	2
Bosdreisz 2012	38 low and middle income countries; Multiple regions	#N/A	N	177035	A	2002-2005	All	Cross-sectional	O	Survey: IPAQ-S	"previous 7 days"	Website	Year	Multilevel - log	10th to 90th percentile = 8.57 - 27.00C	4	2
Boutou 2019	5 Euro centers in 4 countries (UK, Belgium, Greece, Netherlands); Europe	#N/A	N	157	P	not reported	All	Repeated measures (waves)	O	Accelerometer: Actigraph GT3X, Dynaport MiniMod	2 weeks pp, then 2 waves of 1 week pp	OR	Daily	Fixed - GLM	between 12.9C to 20.7C between centers	6	2
de Montigny 2012	9 cities (from Canary Islands, Scotland, Bulgaria, Poland,	#N/A	N	NA, aggregated (6255 obs.)	A	19 Nov 2007 - 25 May 2008	Winter, spring, summer	Aggregated/ecological	O (Y)	Obs. counts: web-based cameras	6 mths	OR	Daily	Fixed - quasi-Poisson	approx -7 to 27C	8	1

Appendix A2. (Continued) List of identified studies in the systematic review – Multi-location studies

Author-Date	Location; Region	Köppen	Comp-arison	Sample size, n	Pop. type	Study dates	Season	Study design	PA domain	PA instrument	PA duration	Weather source	Time-scale	Stats method	Temp. range	QA	S of E
	Finland, Switzerland, US); Multiple regions																
Dunn 2012	across the USA; North Am	#N/A	N	793 (2447 obs.)	E	Sept-Oct of 2001, 2003, 2005, 2007	Fall	Repeated cross-sectional	O	Survey: Consumption and Activities Mail Survey	"previous week"	OR	Season Fall avg	Multilevel - log	Mean 64.15F, (SD 5.02)	6	2
Durand 2017	California, USA; North Am	#N/A	N	65,905	A	Feb 2012-Jan 2013	All	Cross-sectional	T (Y)	Recall: California Household Travel Survey (1 day travel diary)	1 day pp	OR	Hourly	Fixed - gamma regression	mean 62.14F IQR: 3.72, 69.46	8	2
Eisenberg 2009	48 contiguous states of US; North Am	#N/A	N	522,939	A	1993 - 2000	All	Cross-sectional	L (Y)	Survey: BRFSS	"previous month"	OR	Month	Fixed - linear	Mean 66.1F (SD 18.1F)	5	4
Elliott 2019	across UK; Europe	Cfb	N	47,613	A	2009 - 2013	All	Cross-sectional	L (Y)	Survey: visit activity and visit duration	leisure visits in the "previous week"	OR	Hourly	Fixed - GAM	avg 14C (SD 6)	8	2

Appendix A2. (Continued) List of identified studies in the systematic review – Multi-location studies

Author-Date	Location; Region	Köppen	Comp-arison	Sample size, n	Pop. type	Study dates	Season	Study design	PA domain	PA instrument	PA duration	Weather source	Time-scale	Stats method	Temp. range	QA	S of E
Ermagun 2018	across the USA; North Am	#N/A	Y	NA, aggregated	A	2014 - 2016	All	Aggregated/ecological	O (Y)	Obs. counts: infrared trail counter	2 years	OR	Daily	Fixed - negative binomial	Avg 60.49 (SD 17.49, min 13 max 94)	8	4
Farrell 2014	England, UK; Europe	Cfb	N	1,002,216	A	2005 - 2011 (5 waves)	All	Cross-sectional	L	Survey: Active People Survey	"previous 4 weeks"	Not reported	Month	Fixed - linear probability	Mean 14.137, (SD 5.816)	4	4
Fishman 2015	Netherlands; Europe	Cfb	N	74465 (239,929 trips)	A	2010-2012	All	Cross-sectional	T (Y)	Recall: Dutch National Travel Survey (travel diary)	1 day pp	OR	Daily	Fixed - Tobit regression	max air temp: -9 to 35.9	6	4
Furlanetto 2017	Londrina, Brazil and Leuven, Belgium; Multiple regions	#N/A	Y	19 + 18	P	2013	Winter, summer	Repeated measures (waves)	O	Accelerometer: SenseWear Armband	7 days pp, 2 waves	OR	Daily	Mixed	Brazil 23.1-31.18; Belgium 5.3 - 23.7 max temp	7	3
Kokolakakis 2014	England, UK; Europe	Cfb	N	NA, aggregat	A	Oct 2010	All	Cross-sectional	L	Survey: Active	"previous 4 weeks"	OR	Month	Fixed - GLM	NA (used a	5	4

Appendix A2. (Continued) List of identified studies in the systematic review – Multi-location studies

Author-Date	Location; Region	Köppen	Comp-arison	Sample size, n	Pop. type	Study dates	Season	Study design	PA domain	PA instrument	PA duration	Weather source	Time-scale	Stats method	Temp. range	QA	S of E
				ed (325 Local Authoriti es)		- Oct 2011				People Survey					variabilit y differenc e index)		
Laverty 2018	28 EU countries; Europe	#N/A	N	24577	A	Nov - Dec 2013	Winter	Cross-sectional	O	Survey: IPAQ	"previous 7 days"	Website	Year	Mixed - log	annual temp range: 2.3C to 21C	5	2
Obradovich 2017	across the USA; North Am	#N/A	N	1.9 million	A	2002-2012	All	Cross-sectional	L	Survey: BRFSS	"previous month"	OR	Month	Fixed - linear prob., least squares	monthly mean max temp -5 to 40C	6	2
Sartini 2017	England, UK; Europe	Cfb	N	1361 men	E	2010-2012	All	Repeated measures	O	Accelerome ter: Actigraph GT3X	7 days pp	OR	Daily	Multilevel - linear	max temp range - 3.5 to 29.5C	8	1
Timmerma ns 2016	6 Euro countries; Europe	#N/A	N	2439	P	Dec 2010-2011	All	Cross-sectional	L (Y)	Survey: LASA PA questionnai re: freq. and dura. of activities in past 2 weeks	"previous 2 weeks"	OR	Week (bi-week)	Fixed - linear	SP mean 14.4 (SD 5.4), NL mean 7.6 (SD 4.6)	5	1

Appendix A2. (Continued) List of identified studies in the systematic review – Multi-location studies

Author-Date	Location; Region	Köppen	Comp-arison	Sample size, n	Pop. type	Study dates	Season	Study design	PA domain	PA instrument	PA duration	Weather source	Time-scale	Stats method	Temp. range	QA	S of E
Vanky 2017	Boston and San Francisco, USA; North Am	Cfa / Csb	Y	5432 + 8256	A	May 2014 - May 2015	All	Longitudinal	T (Y)	GPS tracking: GPS data on mobile app	50 weeks pp	Website	Hourly	Multilevel – hier. log-linear	temp range: < 0 to > 40	8	1

Studies identified from systematic search conducted on May 2018 (and updated January 2020) in following databases: CINAHL, PubMed, Scopus, Web of Science, ScienceDirect, Embase, Ovid MEDLINE, PsycINFO, SportDiscus, China Academic Journals Full-text Database and Wanfang

Abbreviations and explanations:

Region: North Am = North America; South Am = South America

Comparison = whether study reported results for different cities to allow for multi-city comparison

Pop. type: A = Adults/general population; E = Elderly; P = Patients

PA domain: O = overall; L = leisure; T = transport; Occ = Occupational; (Y) = if have outdoor specific physical activity

PA duration: amount of time physical activity was assessed; pp = per participant

Weather source: OR = Official records (official meteorological stations, government public records); On-site obs = on-site observations; Website = unofficial websites (Weather Underground etc.)

QA = Quality Assessment total score ; S of E = Strength of Evidence (for temperature variable only)

Appendix A2. (Continued) List of identified studies in the systematic review –Single-location studies

Single location studies

Author-Date	Location; Region	Köppen	Sample size, n	Pop. type	Study dates	Season	Study design	PA domain	PA instrument	PA duration	Weather source	Timescale	Stats. method	Temp. range	QA	S of E
Alahmari 2015	London, UK; Europe	Cfb	73	P	Apr 2011 - Mar 2013	All	Longitudinal	O	Pedometer: Yamax Digi-Walker SW-200	Avg 267 days pp	OR	Daily	Multilevel - GEE	Approx -3 to 25C	9	1
Al-Mohannadi 2016	Doha, Qatar; Middle East	BWh	2088 (894,987 obs. days)	A	Jan 2013 - Dec 2014	All	Longitudinal	O	Pedometer: Omron HJ-720ITC USA	Avg 428.6 day pp	Website	Daily	Mixed - backward linear	15C - 40C	8	4
Arnardottir 2017	Iceland; Europe	Cfc	138	E	Apr 2009 - Jun 2010	Winter, summer	Repeated measures	O	Accelerometer: Actigraph GT3X	7 days pp	Website	Daily	Fixed - ANCOVA	winter 2.6 C (SD 2.6), summer 8.5 (SD 2.4)	6	1
Aspvik 2018	Trondheim, Norway; Europe	Cfb	1219 (110,888 obs. hours)	E	Aug 2012 - Jun 2013	All	Repeated measures	O	Accelerometer: Actigraph	7 days pp	OR	Hourly	Fixed	colder month: -2.4C, warmer month 6.8C	9	1
Aultman-Hall 2009	Montpelier, Vermont, USA; North Am	Dfb	NA, aggregated	A	Nov 2006 - Nov 2007	All	Aggregated/ecological	O (Y)	Obs. counts: automated pedestrian counts in downtown	1 year	OR	Hourly	Fixed - linear	air temp = -26.7C - 32.8C; mean 7.47 SD 11.5	8	4
Badland 2011	Perth, Australia; Australia	Csa	1754	A	Sept 2003 - Mar 2005	All	Repeated measures	O	Pedometer / Survey: Yamax Digiwalker; NPAQ	7 days pp; "typical week"	OR	Daily	Fixed - linear	mean 24C, SD 6	6	2

Appendix A2. (Continued) List of identified studies in the systematic review –Single-location studies

Author-Date	Location; Region	Köppen	Sample size, n	Pop. type	Study dates	Season	Study design	PA domain	PA instrument	PA duration	Weather source	Timescale	Stats. method	Temp. range	QA	S of E
Brandon 2009	London, Canada; North Am	Dfb	48	E	30 May - 9 Aug 2006	Summer	Repeated measures	O	Accelerometer: Actigraph GT1M; log book	7 days pp	OR	Hourly	Fixed - linear	10C to 30C	5	2
Burchfield 2012	Knoxville, Tennessee, USA; North Am	Cfa	NA, aggregated	A	Aug 2005 - Apr 2006	All	Aggregated/ecological	O (Y)	Obs. counts: infrared trail counter	1 year	OR	Hourly	Fixed - poisson	monthly avg 40.2 - 80.8F	9	4
Cepeda 2018	Rotterdam, Netherlands; Europe	Cfb	48 (1166 obs.)	E	Jul '11 - Jun '14; Jul '14 - May '16	All	Repeated measures	O	Accelerometer: GENEActiv	7 days pp	OR	Daily	Mixed - linear	Temp -9.8 to 27	9	2
Chaix 2014	Paris, France; Europe	Cfb	7105	A	2007-2008	All	Cross-sectional	L	Survey: IPAQ	"previous 7 days"	OR	Week	Multilevel - spatial reg	not reported	4	1
Chan 2006	Charlottetown, PEI, Canada; North Am	Dfb	203	A	Mar-Jul 2002; Dec 2002-Apr 2003	All	Longitudinal	O	Pedometer: Yamax Digi-Walker SW-200	Avg 63.7 days pp	OR	Daily	Mixed - linear	mean temp per month: -9.9 to 17.7C	7	1
Cheadle 2006	King County, Washington, US; North Am	Csb	2035	E	1987-2003	All	Cross-sectional	L	Survey: BRFSS	"previous month"	OR	Month	Fixed - log	45F in Dec to 76F in Aug	7	3

Appendix A2. (Continued) List of identified studies in the systematic review –Single-location studies

Author-Date	Location; Region	Köppen	Sample size, n	Pop. type	Study dates	Season	Study design	PA domain	PA instrument	PA duration	Weather source	Timescale	Stats. method	Temp. range	QA	S of E
Clark 2014	Halifax, Nova Scotia; North Am	Dfb	1855	A	Apr 2007-May 2008	All	Cross-sectional	T (Y)	Recall: GPS prompted recall diary	1 day pp	OR	Daily	Multilevel - binary logit	mean 7.3C, SD 9.43	7	1
Delclos-Alio 2019	Barcelona, Spain; Europe	Csa	227	E	2017-2018	All	Repeated measures	T	Accelerometer: Actigraph GT3X & GPS device	7 days pp	OR	Daily	Multilevel - linear	8.9C January, to 23.6C August, min -5 max 35	8	3
Feinglass 2011	Chicago, IL, USA; North Am	Dfa	241 (4823 obs. days)	P	May of 2006-2009 (up to 6 waves)	All	Repeated measures (waves)	O	Accelerometer: Actigraph GT1M	7 days pp, up to 6 waves	OR	Daily	Mixed - linear	11.3% days <20F, 7.7% days >75F	6	4
Giannouli 2019	Cologne, Germany; Europe	Cfb	154	E	2014; 2016	All	Repeated measures	O	Accelerometer: Smartphone Galaxy S3	7 days pp	Not reported	Week	Bivariate - correlation	range 10.6 - 29.5 °C, Mean(SD)= 21.5 °C (3.7 °C)	3	3
Hall 2013	Saskatchewan, Canada; North Am	Dfb	208	A	2005-2007	All	Repeated measures	O	Accelerometer: tri-axial accelerometer	7 days pp	OR	Week	Multilevel – hier. linear	from -17.39 to 25.51C	7	1
Hankey 2012	Minneapolis, USA; North Am	Dfa	NA, aggregated (436 obs.)	A	2007-2010	Fall	Aggregated/ecological	O (Y)	Obs. counts: pedestrian and cyclist counts at 259 locations	3 years	OR	Daily	Fixed - type 2 negative binomial	daily high temp: mean 23, SD 3.6	6	3

Appendix A2. (Continued) List of identified studies in the systematic review –Single-location studies

Author-Date	Location; Region	Köppen	Sample size, n	Pop. type	Study dates	Season	Study design	PA domain	PA instrument	PA duration	Weather source	Timescale	Stats. method	Temp. range	QA	S of E
Hino 2017	Yokohama, Japan; Asia	Cfa	24,625	A	Apr 2015 - Mar 2016	All	Longitudinal	O	Pedometer: Omron HJ-326F Japan	1 year	OR	Month	Fixed - two-piece linear	6.2 - 26.8C	5	4
Holmes 2009	Indianapolis, IN, USA; North Am	Cfa	NA, aggregated	A	May 2004 - Aug 2006	All	Aggregated/ecological	O (Y)	Obs. counts: pedestrian and cyclist counts at 30 locations	2 years	OR	Daily	Fixed	temp mean 55.8F, SD 22; min-max -8.61 to 93.6	7	1
Hoppmann 2017	Vancouver, Canada ; North Am	Cfb	126 (1178 obs. days)	E	May-Sept 2011	Summer	Repeated measures	O	Accelerometer: Actigraph GT3x	up to 10 days pp	OR	Daily	Multilevel – hier. linear	16.16C, SD 2.04	8	2
Jones 2017	London, Ontario, Canada; North Am	Dfb	50	E	Feb-Apr 2007	Winter, spring	Repeated measures	O	Accelerometer: ActiGraph GT1M	7 days pp	OR	Hourly	Mixed - backward linear	range -20 to 24C	5	1
Klenk 2012	Ulm, Germany; Europe	Cfb	1324 (7525 obs.)	E	Mar 2009 - Apr 2010	All	Repeated measures	O	Accelerometer: activPAL	5 days pp	OR	Daily	Multilevel - linear	not reported	6	1
Lai 2018	New York, USA; North Am	Cfa	NA, aggregated	A	2010-2015	Spring, fall	Aggregated/ecological	O (Y)	Obs. counts: pedestrian count	6 years	Website	Hourly	Fixed - ordinary least squares	not reported	8	3

Appendix A2. (Continued) List of identified studies in the systematic review –Single-location studies

Author-Date	Location; Region	Köppen	Sample size, n	Pop. type	Study dates	Season	Study design	PA domain	PA instrument	PA duration	Weather source	Timescale	Stats. method	Temp. range	QA	S of E
Li 2012	Mount Guanyin, New Taipei City, Taiwan; Asia	Cfa	NA, aggregated	A	2005-2010	All	Aggregated/ecological	L (Y)	Obs. counts: hiking participation	5 years	OR	Month	Fixed - stepwise	avg temp: 21.93 (SD 4.99)	7	2
Lindsey 2006	Indianapolis, IN, USA; North Am	Cfa	NA, aggregated (30 locations on 5 trails)	A	2001-2005	All	Aggregated/ecological	O (Y)	Obs. counts: infrared trail counter	4 years	OR	Daily	Fixed - stepwise	NA (temperature deviation)	7	4
Ma 2018	Hong Kong, China; Asia	Cwa	210	A	Aug 2016	Summer	Longitudinal	L	Accelerometer: iPhone Health data, and survey	35 days pp	OR	Daily	Multilevel	not reported	8	4
Martins 2017	Pelotas, Brazil; South Am	Cfa	16 (176 obs.)	A	Oct 2012 - Sept 2013	All	Longitudinal	O	Accelerometer: Actigraph GT3X	1 year pp	OR	Month	Bivariate - Spearman's	avg temp 10.2 to 21.2	5	2
Merilahti 2016	Oulu, Finland; Europe	Dfc	2	E	2006-2008	All	Longitudinal	O	Accelerometer: Actigraphy - online activity monitor (IST WristCare)	Avg 988 days pp	OR	Daily	Bivariate - Spearman's	not reported	4	2
Mitchell 2018	Davis, California,	Csa	575	A	2014; 2015	Summer	Cross-sectional	Occ	Accelerometer: from Actical Philips Respi-	1 work-shift pp	On-site obs.	Daily	Fixed - linear	not reported	8	4

Appendix A2. (Continued) List of identified studies in the systematic review –Single-location studies

Author-Date	Location; Region	Köppen	Sample size, n	Pop. type	Study dates	Season	Study design	PA domain	PA instrument	PA duration	Weather source	Timescale	Stats. method	Temp. range	QA	S of E
	USA; North Am								ronics; Murrysville, PA							
Mix 2019	Apopka, Florida, USA; North Am	Cfa	244	A	2015 - 2017	Summer	Repeated measures	Occ	Accelerometer: Actigraph GT3X+	3 days pp	OR	Daily	Mixed - GLM	WBGT 28.3C (SD 1.5)	9	2
Ogawa 2019	Chitose City, Hokkaido, Japan; Asia	Dfb	35	E	Sept 2015; Feb 2016	Spring, fall	Longitudinal	O	Accelerometer: Kenz Lifecorder GS (Suzuken Co., Japan)	1 month pp, 2 waves	OR	Daily	Fixed - linear	by seasons: -4.1C (SD 3.9), and 17.0C (SD 2.4)	7	2
Price 2012a	Spartanburg County, South Carolina, USA; North Am	Cfa	NA, aggregated (4,468 obs.)	A	2006-2009	All	Aggregated/ecological	O (Y)	Obs. counts: System for Observing Play and Recreation in Communities (SOPARC)	3 years	On-site obs.	Daily	Fixed - log	<60F, 61-80F, >81F	7	4
Price 2012b (elderly)	Spartanburg County, South Carolina, USA; North Am	Cfa	NA, aggregated (1053 obs.)	E	2006-2009	All	Aggregated/ecological	O (Y)	Obs. counts: System for Observing Play and Recreation in Communities (SOPARC)	3 years	On-site obs.	Daily	Fixed - log	<60F, 61-80F, >81F	8	4

Appendix A2. (Continued) List of identified studies in the systematic review –Single-location studies

Author-Date	Location; Region	Köppen	Sample size, n	Pop. type	Study dates	Season	Study design	PA domain	PA instrument	PA duration	Weather source	Timescale	Stats. method	Temp. range	QA	S of E
Prins 2015	Rotterdam, Netherlands; Europe	Cfb	43 (3,248 obs.)	E	Feb - Apr 2013	Spring	Repeated measures	T (Y)	Obs. counts: GPS logger	7 days pp	OR	Hourly	Multilevel - linear	mean 5.9, SD 5	9	1
Provost 2019	New South Wales, Australia; Australia	Cfa	NA, aggregated	A	2017	Winter, spring, summer	Aggregated/ecological	L (Y)	Obs. counts: beach users	1 year	On-site obs.	Daily	Fixed - GLM	not reported	7	2
Rapp 2018	Ulm, Germany; Europe	Cfb	1289	E	2009-2010	All	Repeated measures	O	Accelerometer: activPAL	7 days pp	Not reported	Daily	Multilevel - linear	Mean 12.2 (SD 9.7)	8	1
Reich 2010	Durham county, North Carolina, USA; North Am	Cfa	921	A	2005	not reported	Cross-sectional	O	Survey: MVPA in the past week	"previous week"	OR	Week	Multilevel - Bayesian	mean 59.46 (SD 15.25)	4	1
Richardson 2019	Birmingham, Alabama, USA; North Am	Cfa	46	P	2017	Summer	Repeated measures	O	Pedometer: Yamax Digi-Walker SW-200	7 days pp	OR	Daily	Mixed - linear	mean: 78.9 +/- 3.2 (range 69.3, 90.0)	7	3
Robbins 2013	southwestern Ontario, Canada; North Am	Dfb	38	P	Oct 2008 - Feb 2010	All	Repeated measures	O	Accelerometer: Actigraph GT1M	7 days pp	OR	Daily	Fixed - forward linear	temp range: -6.5 to 27.6	7	1

Appendix A2. (Continued) List of identified studies in the systematic review –Single-location studies

Author-Date	Location; Region	Köppen	Sample size, n	Pop. type	Study dates	Season	Study design	PA domain	PA instrument	PA duration	Weather source	Timescale	Stats. method	Temp. range	QA	S of E
Saneinejad 2012	Toronto, Canada; North Am	Dfb	25065 trips	A	Sept-Dec 2001; May-Jun 2002	Spring, fall	Cross-sectional	T (Y)	Recall: Transportation Tomorrow Survey (trip diary survey)	1 day pp	OR	Hourly	Fixed - backward multinomial logit	below 0 to above 35C	7	1
Scott 2006	Greater Toronto Area, Canada; North Am	Dfb	NA, aggregated	A	2002; 2003	Spring, summer	Aggregated/ecological	L (Y)	Obs. counts: golf course participation (one course)	2 years	OR	Daily	Fixed - stepwise	not reported	7	1
Shoemaker 2016	Grand Rapids, Michigan, USA; North Am	Dfb	16	P	Dec 2013 - 2016	All	Longitudinal	O	Accelerometer: single-axis accelerometer	1 year pp	Website	Week	Bivariate - wilcoxon signed rank	avg weekly temp: -14 to 24C	4	4
Smith 2018	Milton, MA, USA; North Am	Cfa	292	A	Jul 2014-Jun 2015	All	Longitudinal	O	Accelerometer: Fitbit flex activity monitor	6 months pp	OR	Week	Fixed	27F to 56F	8	1
Spinney 2011	Halifax, Canada; North Am	Dfb	1971 households	A	Apr 2007-May 2008	All	Cross-sectional	L (Y)	Recall: time diary survey & GPS data logger	2 days pp	OR	Daily	Fixed - linear	max temp range -14.8 to 31.9C	6	2
Suminski 2008	Columbus, Ohio, USA; North Am	Cfa	NA, aggregated	A	Apr - Aug	Spring, summer	Aggregated/ecological	L (Y)	Obs. counts: in-person observations	< 6 mths	OR	Hourly	Fixed - linear	temp mean: 17.3 SD 7.3;	8	1

Appendix A2. (Continued) List of identified studies in the systematic review –Single-location studies

Author-Date	Location; Region	Köppen	Sample size, n	Pop. type	Study dates	Season	Study design	PA domain	PA instrument	PA duration	Weather source	Timescale	Stats. method	Temp. range	QA	S of E
									in 12 census tracts, schools and track					highest around 27C		
Sumukadas 2009	Dundee, UK; Europe	Cfb	127	E	Oct 2003 - Mar 2006	All	Repeated measures	O	Accelerometer: RT3 tri-axial accelerometer	7 days pp	OR	Daily	Multilevel - stepwise linear	temp range: -0.1-26.4C	8	1
Togo 2005	Nakanojo, Japan; Asia	Cfa	41	E	Jul 2001 - Sept 2002	All	Longitudinal	O	Pedometer: uni-axial electronic PA monitor (Suzuken, Japan)	450 days pp	OR	Daily	Bivariate - linear, quad, exp reg	mean ambient temp: around -2C to 29C	5	4
Tu 2004	Indianapolis, IN, USA; North Am	Cfa	110 women (21538 obs.)	E	1999 - 2001	All	Longitudinal	L	Obs. counts: exercise class attendance at local community center close to clinic	up to 2 years	OR	Daily	Fixed - log	not reported	9	4
Wang 2014	Minneapolis, USA; North Am	Dfa	NA, aggregated	A	Jun 2010 - Sept 2011	All	Aggregated/ecological	O (Y)	Obs. counts: infrared trail counter	1.3 years	OR	Daily	Fixed - maximum likelihood estimation	Max temp mean = 14.06C	8	1
Wang 2017	Beijing, China; Asia	Dwa	34	A	Jan - Nov 2015	All	Repeated measures (waves)	O	Accelerometer: Actigraph GT3x	7 days pp, 6 waves	OR	Hourly	Mixed	hourly avg temp range < 0 to 34C	6	3

Appendix A2. (Continued) List of identified studies in the systematic review –Single-location studies

Author-Date	Location; Region	Köppen	Sample size, n	Pop. type	Study dates	Season	Study design	PA domain	PA instrument	PA duration	Weather source	Timescale	Stats. method	Temp. range	QA	S of E
Welch 2018	Chicago, IL, USA; North Am	Dfa	204	A	2005-2008	All	Repeated measures (waves)	O	Accelerometer: Actigraph 7164	5 weeks pp	OR	Daily	Mixed - linear	avg season winter 27F (11.2 SD), summer 75F (5.9 SD)	6	3
Witham 2014	Tayside, Scotland; Europe	Cfb	574 (3282 obs. days)	E	2009-2011	All	Repeated measures	O	Accelerometer: RT3 tri-axial accelerometer	7 days pp	OR	Daily	Multilevel - linear	range max temp -2.3 to 22, min temp -8.9 to 12.2	8	1
Wolff 2011	Tennessee, USA; North Am	Cfa	NA, aggregated (611 obs.)	A	Jul 2007 - Aug 2009	All	Aggregated/ecological	O (Y)	Obs. counts: infrared trail counter	2 years	Website	Daily	Fixed - stepwise	monthly temp in Jan: 46.6F (SD 10.8), Aug: 91.0F (SD 5.84)	7	4
Wu 2017a (dog)	Norfolk, UK; Europe	Cfb	3123	E	Sept 2006; Dec 2011	All	Repeated measures	O	Accelerometer: Actigraph GT1M	7 days pp	OR	Daily	Multilevel - autoregressive time-series	avg summer max 22C, winter night-time min 1C	7	1
Wu 2017b	Norfolk, UK; Europe	Cfb	4207 (27446 obs. days)	E	Sept 2006; Dec 2011	All	Repeated measures	O	Accelerometer: Actigraph GT1M	7 days pp	OR	Daily	Multilevel	avg summer max 22C, winter night time min 1C	8	1
Zhao 2018 (Harbin)	Harbin, China; Asia	Dwa	NA, aggregated (2284 obs.)	A	Apr - May	Spring	Aggregated/ecological	L (Y)	Obs. counts: observation and coding using Compendium	< 6 mths	On-site obs.	Daily	Bivariate - ANOVA	not reported	5	1

Appendix A2. (Continued) List of identified studies in the systematic review –Single-location studies

Author-Date	**Location; Region**	**Köppen**	**Sample size, n**	**Pop. type**	**Study dates**	**Season**	**Study design**	**PA domain**	**PA instrument**	**PA duration**	**Weather source**	**Timescale**	**Stats. method**	**Temp. range**	**QA**	**S of E**
									of Physical Activities							
Zhao 2019 (Seattle)	Seattle, USA; North Am	Csb	NA, aggregated	A	2014	All	Aggregated/ecological	T (Y)	Obs. counts: automated counters	1 year	Website	Hourly, Daily	Fixed - autoregressive	daily: mean 11.87 (SD 5.88, min -4.6, max 25.4)	6	2

Studies identified from systematic search conducted on May 2018 (and updated January 2020) in following databases: CINAHL, PubMed, Scopus, Web of Science, ScienceDirect, Embase, Ovid MEDLINE, PsycINFO, SportDiscus, China Academic Journals Full-text Database and Wanfang

Abbreviations and explanations:

Region: North Am = North America; South Am = South America

Comparison = whether study reported results for different cities to allow for multi-city comparison

Pop. type: A = Adults/general population; E = Elderly; P = Patients

PA domain: O = overall; L = leisure; T = transport; Occ = Occupational; (Y) = if have outdoor specific physical activity

PA duration: amount of time physical activity was assessed; pp = per participant

Weather source: OR = Official records (official meteorological stations, government public records); On-site obs = on-site observations; Website = unofficial websites (Weather Underground etc.)

QA = Quality Assessment total score ; S of E = Strength of Evidence (for temperature variable only)

A3. Covariate categories included in identified studies (systematic review)

Author-Date	Demo-graphic	Health	Time-related	Environ-mental	Air pollution	Cluster	Other variables
Multi-location studies							
An 2017	Yes	N	N	Yes	N	N	
Aral 2017	N	N	N	N	N	N	
Balish 2017	Yes	Yes	Yes	N	N	N	
Böcker 2019	Yes	N	Yes	Yes	N	N	
Bosdreisz 2012	Yes	N	N	N	N	Yes	
Boutou 2019	Yes	Yes	N	N	N	Yes	
de Montigny 2012	N	N	Yes	N	N	Yes	
Dunn 2012	Yes	Yes	N	N	N	N	
Durand 2017	Yes	N	Yes	N	N	N	
Eisenberg 2009	Yes	N	Yes	N	N	Yes	
Elliott 2019	Yes	N	Yes (week-day/end)	N	N	N	PA in the previous week
Ermagun 2018	N	N	Yes (daily time lag)	N	N	N	
Farrell 2014	Yes	N	Yes	Yes	N	N	
Fishman 2015	Yes	N	N	Yes	N	N	transport resources
Furlanetto 2017	N	N	Yes	N	N	Yes	
Kokolakakis 2014	Yes	N	N	Yes	N	N	
Laverty 2018	Yes	N	N	Yes	N	N	
Obradovich 2017	N	N	N	N	N	Yes	
Sartini 2017	Yes	Yes	Yes	N	N	N	
Timmermans 2016	Yes	Yes	N	N	N	Yes	PA pattern; psychological (mastery, anxie-ty, depression)
Vanky 2017	N	N	N	N	N	N	
Sub-total	**15**	**5**	**10**	**6**	**0**	**7**	
Single location studies							
Alahmari 2015	N	N	Yes	N	Yes	N	
Al-Mohannadi 2016	Yes	N	N	N	N	N	
Arnardottir 2017	Yes	Yes	N	N	N	N	
Aspvik 2018	N	N	N	N	N	N	
Aultman-Hall 2009	N	N	N	N	N	N	
Badland 2011	Yes	N	N	N	N	N	
Brandon 2009	Yes	Yes	Yes	N	Yes	N	
Burchfield 2012	N	N	Yes	N	Yes	N	
Cepeda 2018	Yes	Yes	Yes	N	N	N	

Appendix A3. (Continued) Covariate categories included in identified studies

Author-Date	Demo-graphic	Health	Time-related	Environ-mental	Air pollution	Cluster	Other variables
Chaix 2014	Yes	N	N	Yes	N	N	
Chan 2006	Yes	Yes	Yes	N	N	N	
Cheadle 2006	Yes	N	Yes	N	N	N	
Clark 2014	Yes	N	Yes (week-day/end)	Yes	N	N	
Delclos-Alio 2019	Yes	N	N	Yes	N	N	
Feinglass 2011	Yes	Yes	Yes (week-day/end)	N	N	N	
Giannouli 2019	N	N	N	N	N	N	
Hall 2013	Yes	Yes	N	N	N	N	psychological (long-term planning)
Hankey 2012	Yes	N	Yes	Yes	N	N	
Hino 2017	N	N	N	N	N	N	
Holmes 2009	N	N	N	N	Yes	Yes	
Hoppmann 2017	Yes	Yes	Yes	N	N	N	Intention for PA
Jones 2017	N	N	Yes	N	N	N	
Klenk 2012	N	N	N	N	N	N	
Lai 2018	Yes	N	(controlle d for)	Yes	N	N	
Li 2012	N	N	N	N	N	N	
Lindsey 2006	Yes	N	Yes	Yes	N	N	
Ma 2018	Yes	Yes	N	Yes	N	N	
Martins 2017	N	N	N	N	N	N	
Merilahti 2016	N	N	N	N	N	N	
Mitchell 2018	Yes	Yes	N	N	N	N	Work- related (shift length, years worked, employer etc)
Mix 2019	Yes	Yes	Yes	N	N	N	
Ogawa 2019	N	N	N	N	N	N	
Price 2012a	Yes	N	Yes	N	N	N	
Price 2012b (elderly)	Yes	N	Yes	N	N	N	
Prins 2015	Yes	N	Yes	N	N	N	
Provost 2019	N	N	N	Yes (water-related)	N	Yes	water-related indicators (Sea-state, surf rating, water temp.)
Rapp 2018	Yes	Yes	Yes (week-day/end)	N	N	N	social network scale
Reich 2010	Yes	Yes	N	Yes	Yes	N	
Richardson 2019	N	N	N	N	N	Yes	intervention

Appendix A3. (Continued) Covariate categories included in identified studies

Author-Date	**Demo-graphic**	**Health**	**Time-related**	**Environ-mental**	**Air pollution**	**Cluster**	**Other variables**
Robbins 2013	Yes	Yes	N	N	N	N	
Saneinejad 2012	Yes	N	Yes (time of day)	Yes	N	N	
Scott 2006	N	N	Yes (week-day/end)	N	N	N	
Shoemaker 2016	N	N	N	N	N	N	
Smith 2018	Yes	Yes	Yes	N	N	N	impulsivity (delay discounting)
Spinney 2011	N	N	N	N	N	N	
Suminski 2008	N	N	N	N	N	N	
Sumukadas 2009	N	N	N	N	N	N	
Togo 2005	N	N	N	N	N	N	
Tu 2004	Yes	Yes	N	N	N	N	
Wang 2014	Yes	N	Yes (week-day/end)	Yes	N	N	
Wang 2017	N	N	Yes	N	Yes	N	
Welch 2018	N	N	N	N	N	Yes	
Witham 2014	Yes	Yes	N	N	N	N	psychological (perceived behavioural control, people to turn to)
Wolff 2011	N	N	Yes	N	N	N	
Wu 2017a (dog)	Yes	Yes	N	N	N	N	
Wu 2017b	Yes	Yes	N	N	N	N	
Zhao 2018 (Harbin)	N	N	N	N	N	N	
Zhao 2019 (Seattle)	N	N	N	N	N	N	
Sub-total	32	18	24	11	6	4	
Total	47	23	34	17	6	11	

Studies identified from systematic search conducted on May 2018 (and updated January 2020) in following databases: CINAHL, PubMed, Scopus, Web of Science, ScienceDirect, Embase, Ovid MEDLINE, PsycINFO, SportDiscus, China Academic Journals Full-text Database and Wanfang
Abbreviation: PA = physical activity

A4. Associations of other meteorological variables in identified studies (systematic review)

A4.1 Rainfall

124 models from 50 papers included an association with rainfall. Rainfall was usually assessed using a linear variable (n = 68 models), factor/categorical variable (39 models), or binary variable (13 models). The association between rainfall and physical activity was found to be negative in 69 models in 37 papers, although the relationship may not necessarily be linear. At the daily level, the relationship between rainfall and physical activity found a negative linear association from 25 out of 35 models. Studies that used categorical analyses to differentiate between light rain and heavy rain, however, generally found that rain had a non-linear effect that was greater with heavier rain (Feinglass 2011, Holmes 2009, Wu 2017a, Wu 2017b, Zhao 2019, Boutou 2019). This non-linear association is further confirmed by several papers looked at the rainfall association non-linearly and found L shaped associations, whether using pedometer step counts (Chan 2006), pedestrians on urban trails (Ermagun 2018), or running activity tracked from mobile applications (Aral 2017). However, the categorization of light vs heavy rain differed by location and a consistent measurement has not been determined yet. A study assessing accelerometer counts among arthritis patients in Chicago differentiated between <1 inch and more than 1 inch (Feinglass 2011). While a multi-city study in Europe on COPD patients assessed the association by <1.7 hours/day, 1.7-2.6 hours/day, and >2.6 hours/day (Boutou 2019). A UK elderly accelerometer study distinguished between 0mm, 0.2-0.6mm, 0.6-2.6 mm and >2.8mm (Wu 2017a; Wu 2017b). Meanwhile, trail count studies in Indiana assessed rainfall in terms of trace rain (non-measurable amount) versus measurable amount of rain (Holmes 2009), whereas in Seattle, this was further broken down into 0 mm vs. light rain (0-10mm), moderate rain (10-25mm), and heavy rain (> 25mm) (Zhao 2019). These categorizations were largely based on the proportions of rainfall occurring in each study dataset, demonstrating that the hinderance of rain is relative to amount of rainfall regularly received.

Daily precipitation unexpectedly had a strong negative effect for self-reported indoor sports in Canada in addition to affecting outdoor leisure activities (Spinney 2011), which suggests that rainfall may hinder participants' accessibility to locations of physical activity. The association may be affected by the built environment, as the negative effect of daily rainfall was larger for those residing in high walkability areas compared to low walkability areas in Barcelona (Delclos-Alio 2019).

At the hourly level, the results for rainfall were highly variable and contextual. Rainfall negatively affected pedestrian volumes (Aultman-hall 2009), trail counts (Burchfield 2012), and GPS tracking in Dutch older adults (Prins 2015). However, positive associations were also identified between physical activity and hourly rainfall. Aspvik et al. 2018 found seasonal difference in rainfall's effect on elderly accelerometer counts in Norway, whereby negatively associated in warmer months but positively associated in colder months, particularly among males of higher cardiorespiratory fitness (Aspvik 2018). Similarly, Vanky 2017 found a positive association in the number of hourly pedestrian trips in Boston, while the effect was negative in San Francisco (Vanky 2017). In the spring and autumn seasons, a positive association between rainfall and walking was found in Toronto Canada, perhaps due to a shift from cycling to walking in rainy conditions (Saneinejad 2012).

Hourly rainfall was non-significant when comparing the choice between car and walking trip modes (Bocker 2019). Durand 2017 only found negative association for walking duration to school, not other destinations. Lai 2018 did not find association between hourly rainfall and pedestrian volume in densely populated Manhattan NYC during weekdays, although not enough information was available to assess the effect during weekends. Zhao 2019 conducted analyses for trail counts at both the daily and hourly levels, and found that while daily associations were consistently negative, hourly associations had some variations of non-significant and negative associations. This supports the interpretation that hourly transport activity is more affected by other factors than rainfall. For leisure physical activity, a UK survey assessing visits to natural environments found a lack of association between rainfall and intensity of physical activity, probably since those who were willing to visit on rainy days may have been prepared for the inclement weather (Elliott 2019; 0-0.5mm, >0.5 mm).

At the annual and monthly levels, annual precipitation was not found associated with the physical activity among 28 EU countries (Laverty 2018), suggesting people in different timescales have gotten accustomed to the "normal" weather conditions in their local area. Monthly rainfall was non-significantly or marginally significant with UK self-reported sports participation (Kokolakakis 2014), where the amount of rainy days was relatively low (mean 4.8 days, SD 0.14). Meanwhile, in a nation-wide survey in the USA, rainfall demonstrated an effect on monthly physical activity when more than 10 days of the month had rainfall (Obradovich 2017). A negative association was found when assessed for average rainfall in past month (Eisenberg 2009, Farrell 2014), but not when assessing total monthly precipitation (Cheadle 2006) or average seasonal precipitation (Dunn 2012), possibly due to collinearity with the seasonal effect.

Overall, we found a negative effect of rainfall on physical activity, particularly at the daily level. Although this effect may be non-linear, standardized proportions of the effect have yet to be determined. Assessing rainfall at the hourly level is highly contextual and likely affected by other variables rather than rainfall. Larger timescales such as monthly or annual rainfall seems to have a negligent effect unless there are over 10 days of rainfall in the month (Obradovich 2017).

A4.2 Windspeed

81 models from 29 papers included an association with windspeed, which were almost all assessed linearly. There was a mixed association, with 18 models suggesting a negative association, 10 models with a positive association and 52 models found a non-significant association. Windspeeds were negatively associated with objective accelerometer studies in hot dry Qatar (Al-Mohannadi 2016), humid Hong Kong (Ma 2018), and cooler Canada (Chan 2006). In the USA, objective trail traffic was found negatively associated with windspeeds when cycling could not be separated from the analysis (Wang 2014, Wolff 2011), whereas pedestrian-specific studies only found negative associations on weekdays but not weekends (Zhao 2019), or only in very cold climate regions (Ermagun 2018).

Among vulnerable populations, windspeed was only sometimes negatively associated: with daily walking duration among German elderly (Klenk 2012), marginally negatively associated with COPD patients in the UK (Alahmari 2015), and only negatively associated among older-elderly in Netherlands, whereas younger elderly were not associated (Cepeda 2018). However, the association was not found significant among Japanese elderly step counts (Ogawa 2019) and functionally impaired older persons in UK (Sumukadas 2009), or when self-reported walking or leisure activities was assessed (Fishman 2015, Sanneinejad 2012, Clark 2014, Bocker 2019, Spinney 2011). At the hourly level, walking duration was positively associated with windspeed among older adults in Netherlands (Prins 2015). While pedestrian trip duration in Boston was negatively associated, the number of trips taken found a positive association with windspeed in Boston and San Francisco (Vanky 2017). Windspeed was also found positively associated with self-reported hourly walking duration to personal, work, transit, shopping, and food destinations in California (Durand 2017).

In location-specific studies, the results demonstrate that the effect of windspeed may be affected by the activity conducted. Windspeed was negatively associated with leisure visit, particularly for parks and inland water areas, but not for woodlands (sheltered from wind) or coastal visits (different activities which may be encouraged by windier conditions) (Elliott 2019). Similarly, Provost 2019 found a negative association with surfing, but did not affect other beach activities in Australia (Provost 2019). Seasonally, a study on Norwegian elderly found negative association of windspeed in colder months (Nov – Mar) but positive association in warmer months (Apr – Oct) (Aspvik 2018). Similarly, a study on hiking participation in Taiwan found negative associations in winter and positive associations in summer (Li 2012). Future studies could analyse an interaction between windspeed and temperature in order to understand the associations further. As windspeed is a very contextual variable, the association with physical activity may be highly dependent on the built environment and geographical topography, contributing to the variability found among the results.

A4.3 Day length

Day length is also termed as sunlight hours, daylight hours, or an inverse term of sky darkness, indicating the length of time per day where the sun is in the sky, usually between sunrise and sunset, or between dawn and dusk. Only 40 models from 13 papers included an assessment of day length, but these studies consistently found a positive association between day length and physical activity (17/40 models= 42.5%). Such studies were usually located in higher latitude countries such as UK, USA, Canada, and other European countries, although one was located in Qatar (Al-Mohannadi 2016). In addition, most studies focused on outdoor locations or older persons. In Halifax Canada, positive associations were found for outdoor sports, while the association was non-significant for indoor sports or outdoor active leisure (activities such as walking, skiing, etc) (Spinney 2011). Outdoor location studies included urban trails and active transport (Fishman 2015, Hankey 2012, Ermagun 2018, Bocker 2019) and visits to natural environments (Elliott 2019). The positive association was also found for studies of older persons (Prins 2015, Wu 2017b), some with mobility impairments (Sumukadas 2009) or arthritis (Feinglass 2011). Bocker 2019 used the inverse variable of sky darkness and found a negative association with active travel at the hourly level. In a comparative study between two cities in Brazil and Belgium, both locations separately found positive associations with daylight (Furlanetto 2017). However, a study on COPD patients from a combined analysis of five European cities (Athens Greece, Edinburgh UK, Leuven Belgium, London UK, and Groningen Netherlands) did not find significant association when day length was assessed as a factor variable (Boutou 2019).

Although most of the studies included day length if they were in high latitude locations (ie with high variability of day light variation), the extent to which day length only affects high latitude locations and not lower latitudes is uncertain. Particularly, as Ermagun 2018 demonstrated an effect in lower latitudes: having found positive associations in Mixed humid and Hot humid climate regions located at lower latitudes, but no association in the colder regions of higher latitudes. Al-Mohannadi 2016 found a positive association of day length with step count among young adults in Qatar. These interesting findings suggests that day length may have an effect on lower latitude locations, even if there is less variability in the variable itself, although it has not been included in other lower latitude studies previously. Depending on the study nature/timescale (hourly/daily etc), day length may be a confounding variable in locations even of lower latitudes, thus should be considered in future analyses.

A4.4 Other weather variables

Various other weather variables were included in 28 studies of this systematic review, including: sunshine, cloudiness, snow, visibility, wind direction, atmospheric pressure, thunder, fog, or storms. The association between sunshine and physical activity was largely positive from the 29 models in 13 papers, although several models adjusted for sunshine but did not report its outcome. Cloudy associations were assessed in 17 models from 8 papers and found a mix of positive, negative, and non-significant associations, possibly depending on whether the cloud cover was light or heavy (Li 2012, Vanky 2017).

Snow (33 models in 10 papers) was usually found non-significant, while some studies found a negative association (de Montigny 2012, Vanky 2017, Zhao 2019), even for indoor exercise attendance (Tu 2004), and others were positively associated (Holmes 2009, Chan 2006). Chan 2006 found a distinction between snowfall and accumulated snow on the ground, which were associated with increased PA and decreased PA, respectively. These findings highlight that the relationship between snow and physical activity may be multi-faceted, affected not only by activity type, but also whether the snow accumulates on the ground.

Visibility was assessed in 8 models in 2 papers and was non-significant or negatively associated with physical activity (Al-Mohannadi 2016, Cepeda 2018). Wind direction was assessed in 5 models in 1 paper and found positively associated for sunbathing and swimming when the wind blew onshore from sea towards the beach (Provost 2019). This association was not found for other activities such as surfing, fishing, and walking along the beach (Provost 2019). Atmospheric pressure was assessed in 4 models in 3 papers and mostly found positive (Al- Mohannadi 2016, Tu 2004), but was negatively associated in one model assessing outdoor activities (Suminski 2008). The associations with thunderstorm/fog were non-significantly or positively associated, in 5 models in 2 papers (Al-Mohannadi 2016, Vanky 2017). Stormy days was negatively associated with hiking participation in Taiwan (Li 2012).

B1. Ethics approval for Study 2 (Chapter 5)

THE CHINESE UNIVERSITY OF HONG KONG

MEMO

To	:	HO, Ying-en Janice The Jockey Club School of Public Health and Primary Care (PhD student, Year 2)
From	:	Secretary Survey and Behavioural Research Ethics Committee (SBREC)
Tel.	:	3943 4209
Date	:	13 August 2018

<u>Survey and Behavioural Research Ethics</u>

I write to inform you that the Survey and Behavioural Research Ethics Committee has granted approval in principle for you to conduct the surveys or observation of human behaviour by non-clinical means as declared in the application for the following research:

Project Title	:	Analysis of daily weather effect on physical activity levels in multiple Chinese cities
Source of Funding	:	Nil
Reference, if any	:	Nil

Kindly be reminded that you should also obtain approval from other research ethics committees within the University (e.g., Clinical Research Ethics Committee, Animal Experimentation Ethics Committee) if any parts of your research do not fall under the scope of our Committee. Thank you for your attention.

Alice Hung

c.c. Panel Secretary concerned

B2. Typhoons affecting the five Chinese cities in 2018

Typhoon name	City affected	Dates
Tropical storm Ewiniar	Hong Kong	2018-06-07 to 08
Tropical storm Son-Tinh	Hong Kong	2018-07-17 to 18
Severe tropical storm AMPIL	Shanghai	2018-07-22
Typhoon JONGDARI	Shanghai	2018-08-03
Severe tropical storm YAGI	Shanghai	2018-08-12
Tropical storm Bebinca	Hong Kong	2018-08-14
Severe tropical storm RUMBIA	Shanghai	2018-08-16 to 17
Tropical storm Barijat	Hong Kong	2018-09-12
Super typhoon MANGKHUT	Hong Kong, Shenzhen	2018-09-15 to 17 *
Typhoon Yutu	Hong Kong	2018-11-01

Typhoons with a yellow warning signal or above, or Typhoon signal no.3 or above, were included for mainland cities and Hong Kong, respectively
* Super typhoon MANGKHUT made landfall in Shenzhen and Hong Kong on 2018-09-16, and led to Typhoon Signal no. 10 for Hong Kong Observatory, which indicates severity of winds

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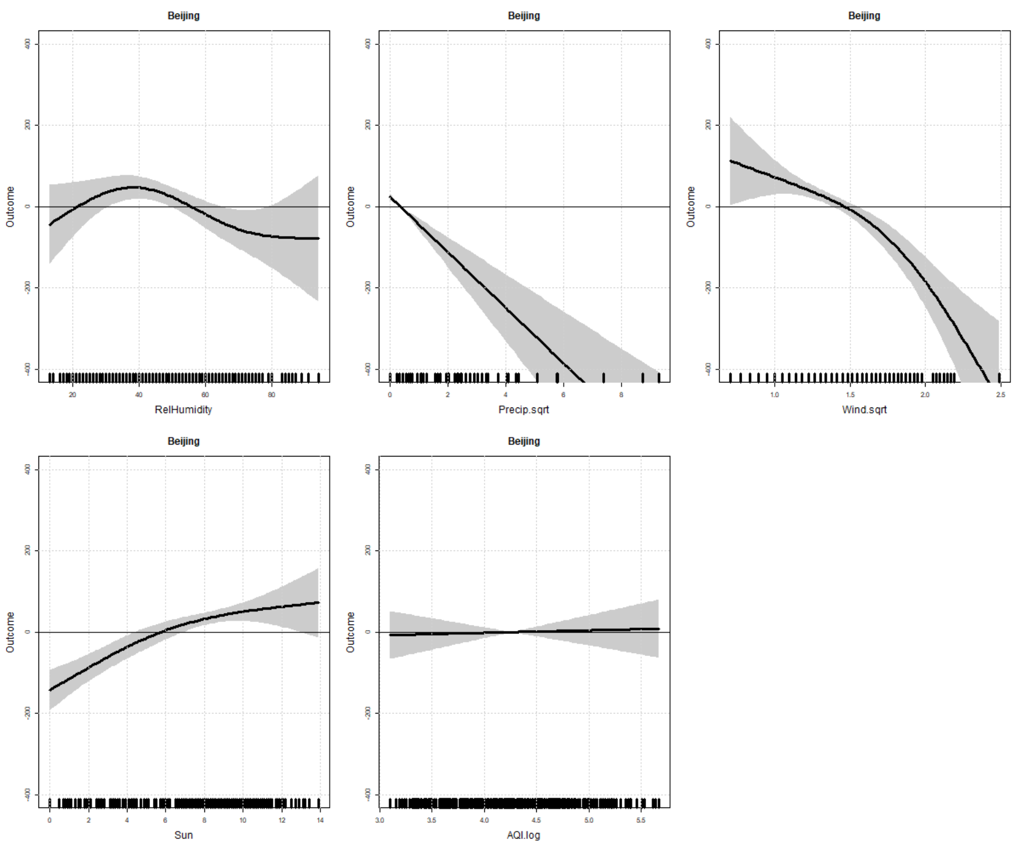
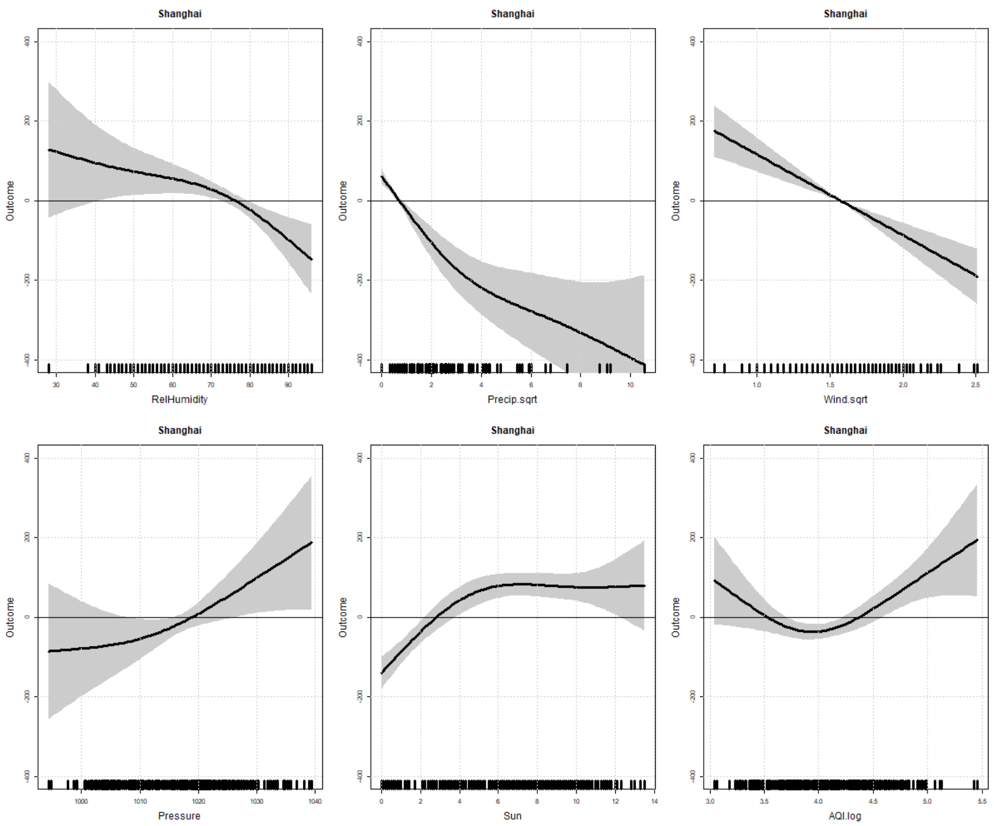
B3. Change in number of anonymized users during the study period

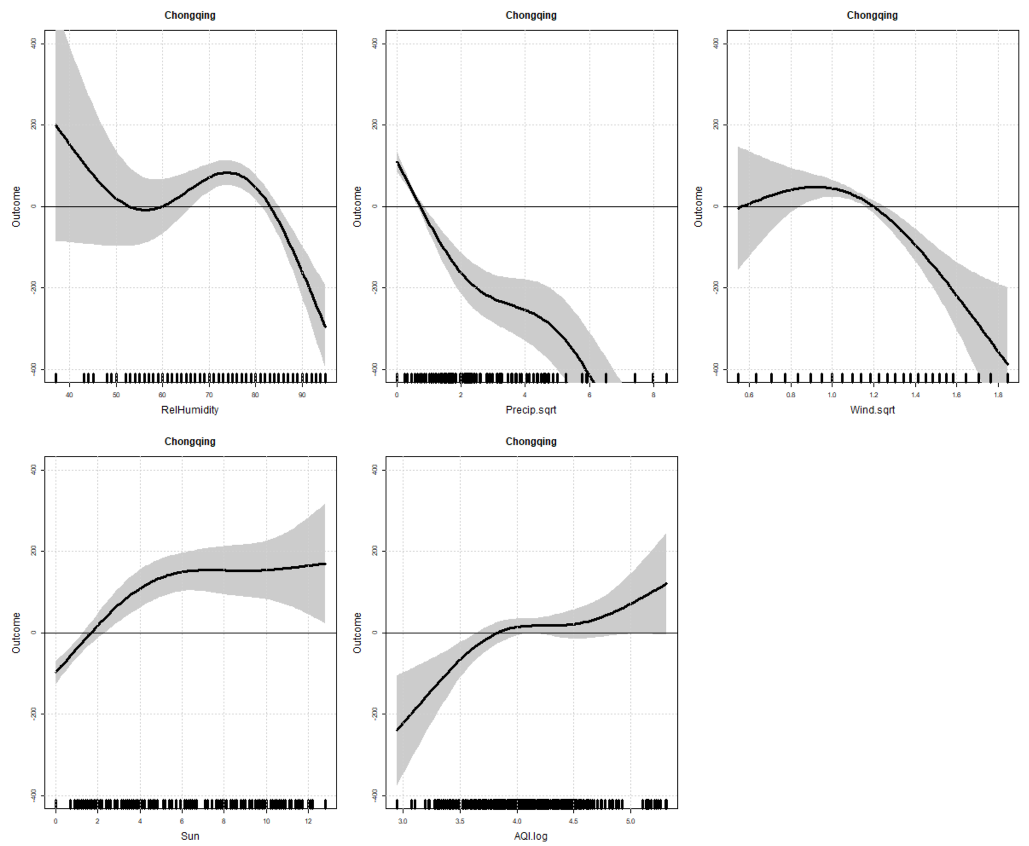
Aggregated anonymized data obtained from in app function WeRun, Dec 2017- 2018

B4. Relationships of other meteorological variables in main model

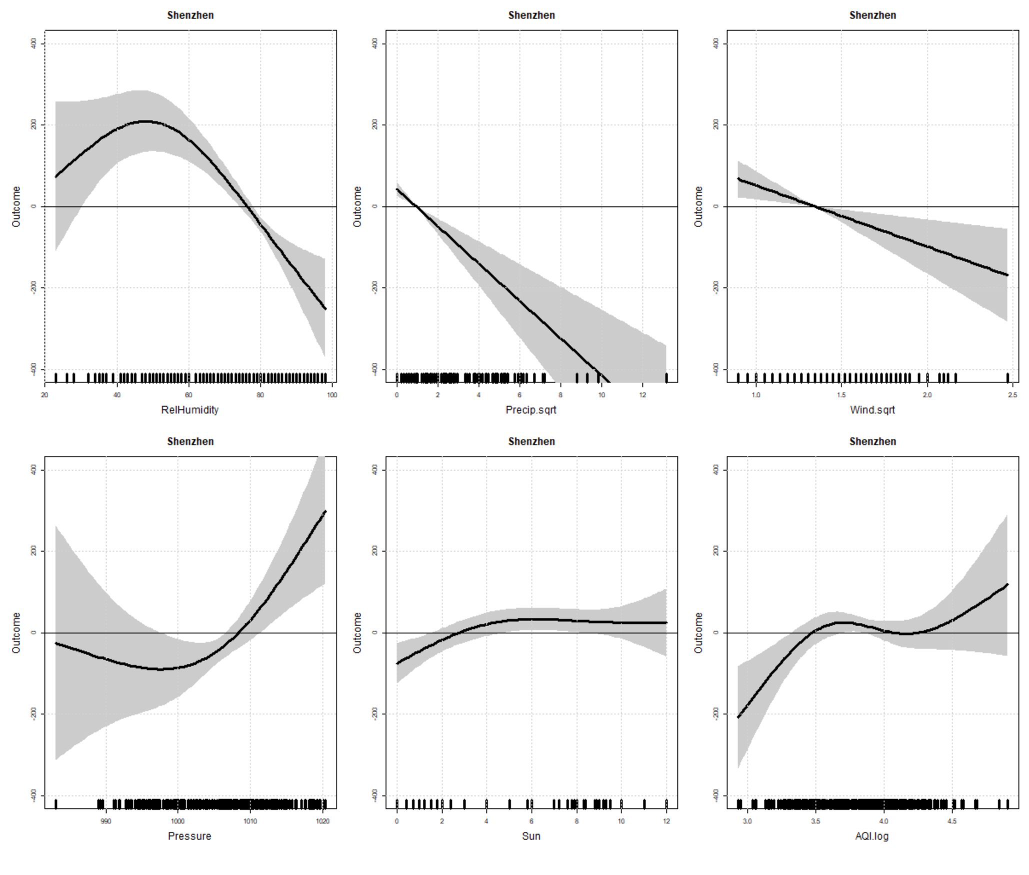
BJ	
SH	

Appendix B4. (Continued) Relationships of other meteorological variables in main model

CQ

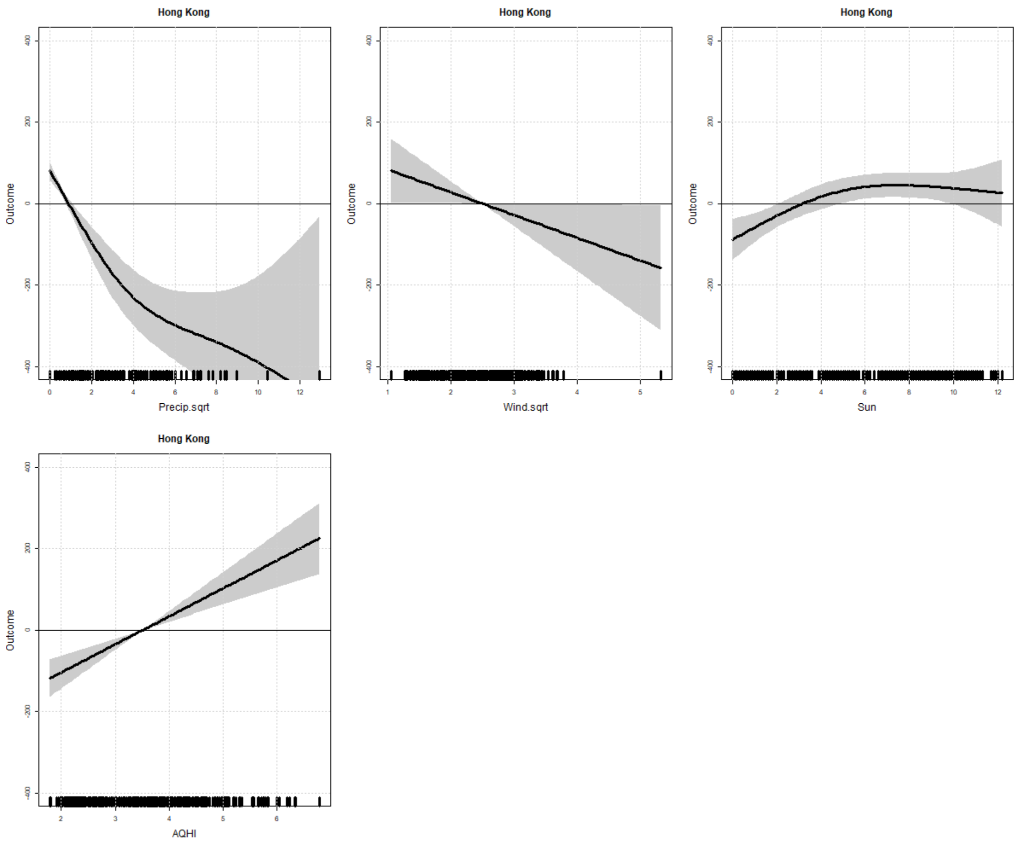


SZ



Appendix B4. (Continued) Relationships of other meteorological variables in main model

HK



Aggregated anonymized data on physical activity obtained from in-app function WeRun, Dec 2017-2018; City abbreviations: BJ = Beijing, SH = Shanghai, CQ = Chongqing, SZ = Shenzhen, HK = Hong Kong

B5. Full table of main model, for five Chinese cities

	Beijing				**Shanghai**				**Chongqing**				**Shenzhen**				**Hong Kong**			
N	366				366				366				361				391			
Adjusted R^2	0.88				0.862				0.855				0.803				0.733			
	edf	Ref.df	F	p-value	edf	Ref.df	F	p-value	edf	Ref.df	F	p-value	edf	Ref.df	F	p-value	edf	Ref.df	F	p-value
s(Tmean)	2.98	3	63.88	<0.001	2.95	3	44.67	<0.001	2.92	2.99	47.27	<0.001	2.89	2.99	11.54	<0.001	1	1	0.72	0.396
s(RelHumidity)	2.58	2.88	4.49	0.016	1.96	2.38	5.07	0.005	2.87	2.98	13.65	<0.001	2.6	2.89	13.28	<0.001	\	\	\	\
s(Precip.sqrt)	1	1	36.45	<0.001	2.14	2.51	19.95	<0.001	2.77	2.96	35.36	<0.001	1	1	26.33	<0.001	1.96	2.3	24.89	<0.001
s(Wind.sqrt)	2.28	2.68	13.8	<0.001	1	1	30.02	<0.001	2.36	2.75	10.82	<0.001	1	1	8.83	0.003	1	1	4.25	0.04
s(Sun)	1.82	2.21	14.77	<0.001	2.52	2.83	17.99	<0.001	2.37	2.71	19.99	<0.001	2.09	2.47	4.32	0.015	1.96	2.35	5.41	0.003
s(AQI.log)	1	1.01	0.06	0.811	2.52	2.85	7.29	<0.001	2.51	2.84	5.41	<0.001	2.7	2.94	4.38	0.012	1	1	26.82	<0.001
s(Pressure)	\	\	\	\	1.62	2.01	2.79	0.061	\	\	\	\	2.19	2.6	4.75	0.006	\	\	\	\
	Est.	SE	t value	p-value	Est.	SE	t value	p-value	Est.	SE	t value	p-value	Est.	SE	t value	p-value	Est.	SE	t value	p-value
(Intercept)	6704.41	59.87	111.98	<0.001	6514.98	56.33	115.66	<0.001	7309.43	71.48	102.25	<0.001	7176.03	57.9	123.93	<0.001	8967.41	66.06	135.74	<0.001
factor(DOW)2	-24.93	33.29	-0.75	0.454	3.68	34.4	0.11	0.915	-7.7	38.67	-0.2	0.842	-36.18	35.45	-1.02	0.308	-53.35	42.3	-1.26	0.208
factor(DOW)3	42.19	33.97	1.24	0.215	17.06	34.8	0.49	0.624	30.38	39.1	0.78	0.438	-23.73	36.08	-0.66	0.511	-54.2	42.83	-1.27	0.207
factor(DOW)4	29.17	33.39	0.87	0.383	-43.7	34.27	-1.28	0.203	16.54	38.43	0.43	0.667	-25.46	35.5	-0.72	0.474	-17.92	42.9	-0.42	0.676
factor(DOW)5	92.66	33.31	2.78	0.006	68.23	34.75	1.96	0.05	113.08	38.4	2.95	0.003	74.22	35.61	2.08	0.038	135.16	42.73	3.16	0.002
factor(DOW)6	-268.02	33.79	-7.93	<0.001	-143.85	35.14	-4.09	<0.001	-214.04	38.78	-5.52	<0.001	24.9	36.37	0.68	0.494	318.23	43	7.4	<0.001
factor(DOW)7	-479.44	33.42	-14.35	<0.001	-400.06	34.5	-11.6	<0.001	-351.66	38.59	-9.11	<0.001	-191.52	35.69	-5.37	<0.001	-200.69	43.04	-4.66	<0.001
factor(Holiday)1	-426.21	38.22	-11.15	<0.001	-407.06	39.9	-10.2	<0.001	-350.68	44.45	-7.89	<0.001	-248.23	39.93	-6.22	<0.001	-173.92	54.17	-3.21	0.001
factor(Month)2	-29.58	47.4	-0.62	0.533	-61.67	48.63	-1.27	0.206	98.56	55.6	1.77	0.077	-152.53	49.67	-3.07	0.002	179.53	59.6	3.01	0.003
factor(Month)3	503.66	57.66	8.74	<0.001	543.83	55.11	9.87	<0.001	553.5	78.47	7.05	<0.001	278.65	55.83	4.99	<0.001	122.13	62.28	1.96	0.051
factor(Month)4	480.03	75.79	6.33	<0.001	539.38	68.64	7.86	<0.001	548.65	93.72	5.85	<0.001	269.93	60.97	4.43	<0.001	199.96	70.61	2.83	0.005

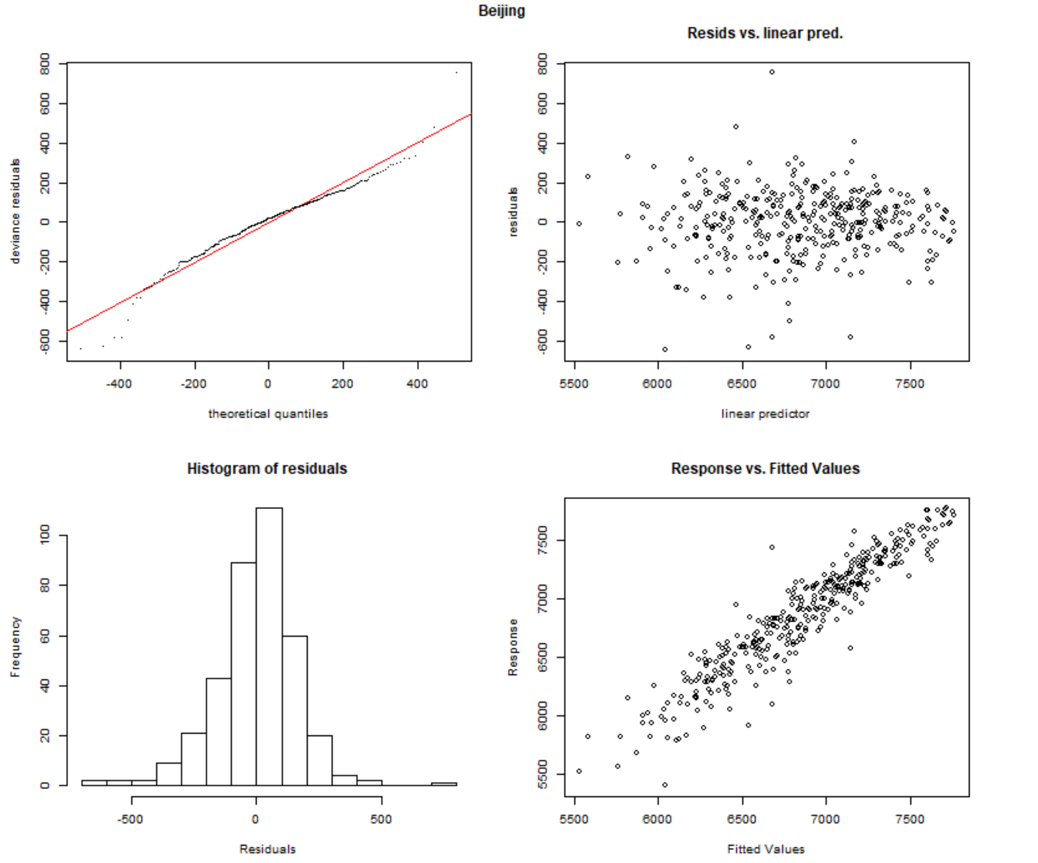
Appendix B5. (Continued) Full table of main model, for five Chinese cities

	Beijing				**Shanghai**				**Chongqing**				**Shenzhen**				**Hong Kong**			
	Est.	SE	t value	p-value	Est.	SE	t value	p-value	Est.	SE	t value	p-value	Est.	SE	t value	p-value	Est.	SE	t value	p-value
factor(Month)5	356.92	88.31	4.04	<0.001	471.22	76.84	6.13	<0.001	416.14	103.21	4.03	<0.001	179.33	84.94	2.11	0.036	40.21	90.66	0.44	0.658
factor(Month)6	325.92	100.29	3.25	0.001	455.35	83.95	5.42	<0.001	452.37	110	4.11	<0.001	4.09	93.03	0.04	0.965	-40.22	96.42	-0.42	0.677
factor(Month)7	147.51	114.58	1.29	0.199	313.55	96.57	3.25	0.001	305.83	120.03	2.55	0.011	13.55	96.81	0.14	0.889	107.49	99.71	1.08	0.282
factor(Month)8	-36.97	115.7	-0.32	0.75	242.71	101.03	2.4	0.017	-17.54	118.84	-0.15	0.883	-92.05	102.64	-0.9	0.37	45.14	97.08	0.46	0.642
factor(Month)9	159.1	93.42	1.7	0.089	401.81	86.63	4.64	<0.001	301.37	103.71	2.91	0.004	90.95	82.08	1.11	0.269	-137.88	89.13	-1.55	0.123
factor(Month)10	345.35	73.13	4.72	<0.001	269.35	75.72	3.56	<0.001	412.94	82.11	5.03	<0.001	88.42	71.26	1.24	0.216	26.04	78.91	0.33	0.742
factor(Month)11	426.24	57.33	7.43	<0.001	227.96	63.53	3.59	<0.001	403.67	64.8	6.23	<0.001	137.75	62.89	2.19	0.029	52.22	70.69	0.74	0.461
factor(Month)12	262.32	40.3	6.51	<0.001	160.9	47.92	3.36	0.001	311.71	47.49	6.56	<0.001	142.45	48.51	2.94	0.004	188.86	51.92	3.64	<0.001
factor(ExtraWorkChina)1	302.84	69.34	4.37	<0.001	225.07	71.22	3.16	0.002	283.17	79.17	3.58	<0.001	-4.4	73.41	-0.06	0.952	\	\	\	\
factor(Typhoon)1	\	\	\	\	-53.84	100.73	-0.53	0.593	\	\	\	\	-258.4	138.34	-1.87	0.063	-173.77	80.81	-2.15	0.032
factor(Super typhoon)1	\	\	\	\	\	\	\	\	\	\	\	\	-2271.54	257.67	-8.82	<0.001	-3120.13	335.03	-9.31	<0.001
factor(Marathon)1	\	\	\	\	\	\	\	\	\	\	\	\	\	\	\	\	447.48	228.65	1.96	0.051

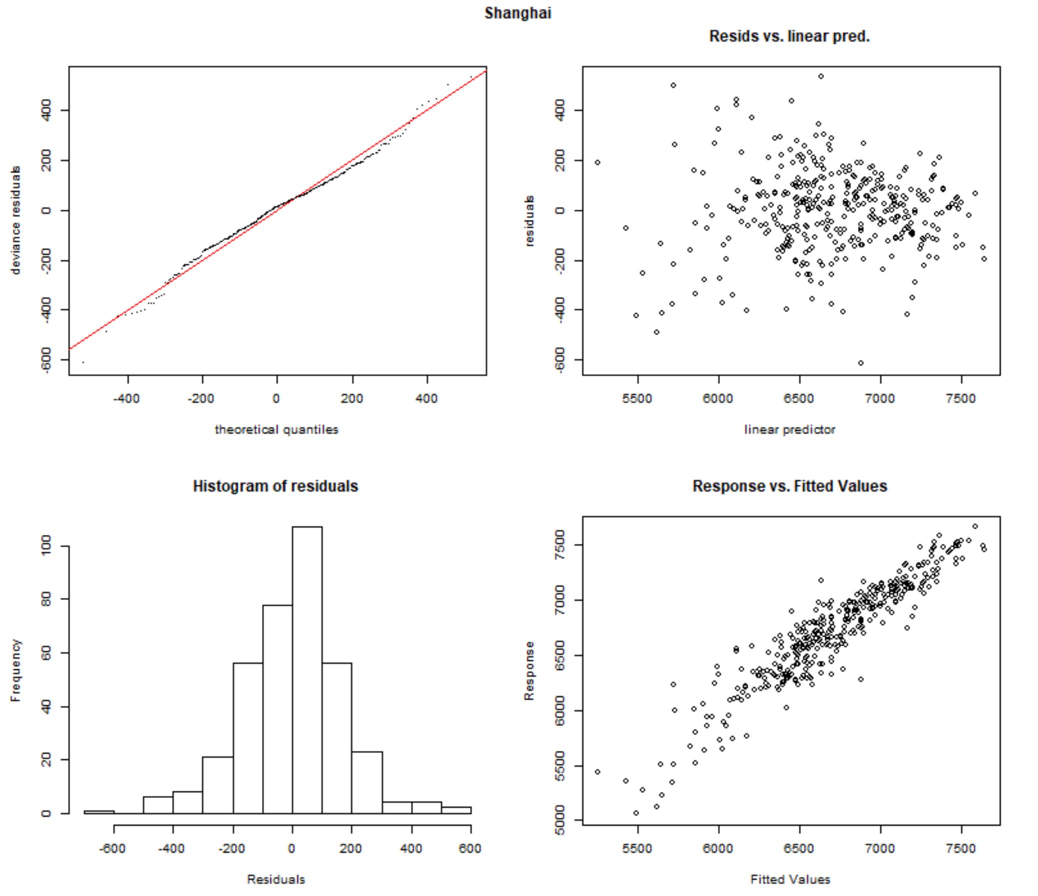
Aggregated anonymized data on physical activity obtained from in-app function WeRun, Dec 2017- 2018
\ indicates the absence of data for that category.

B6. Residual plots for model evaluation of main models

BJ

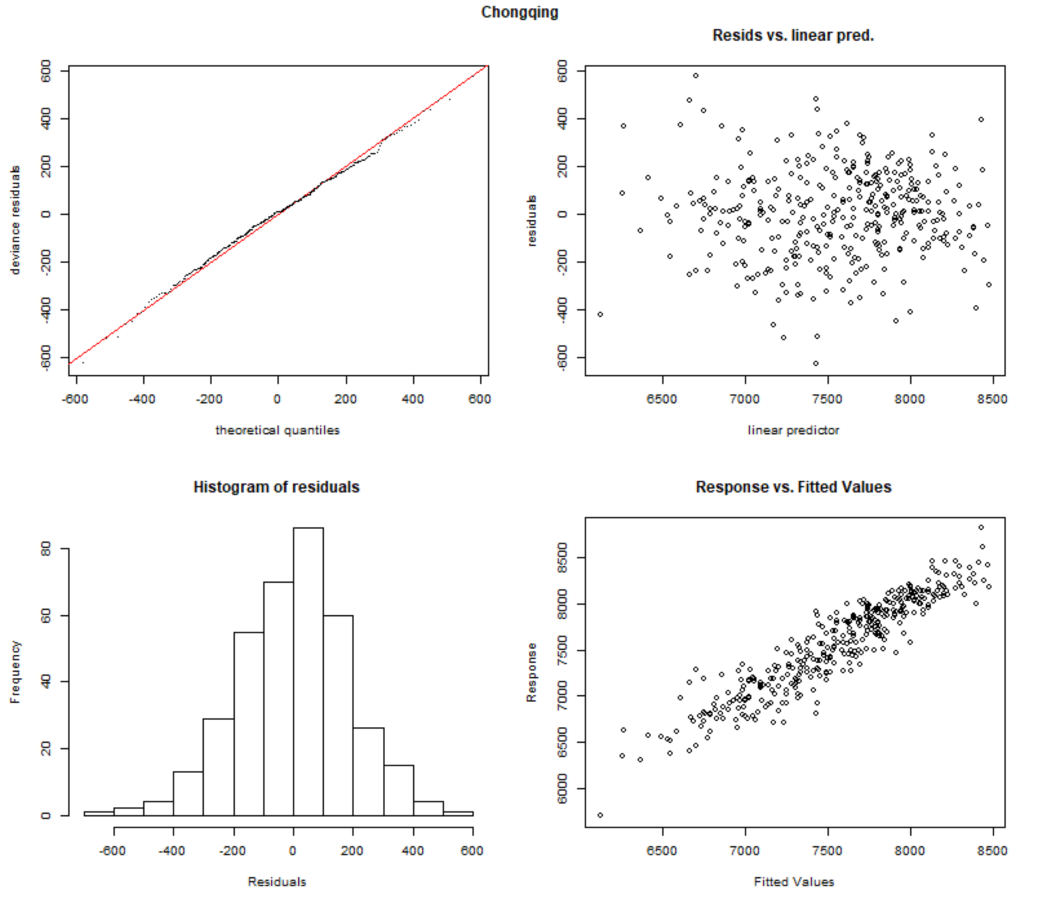


SH

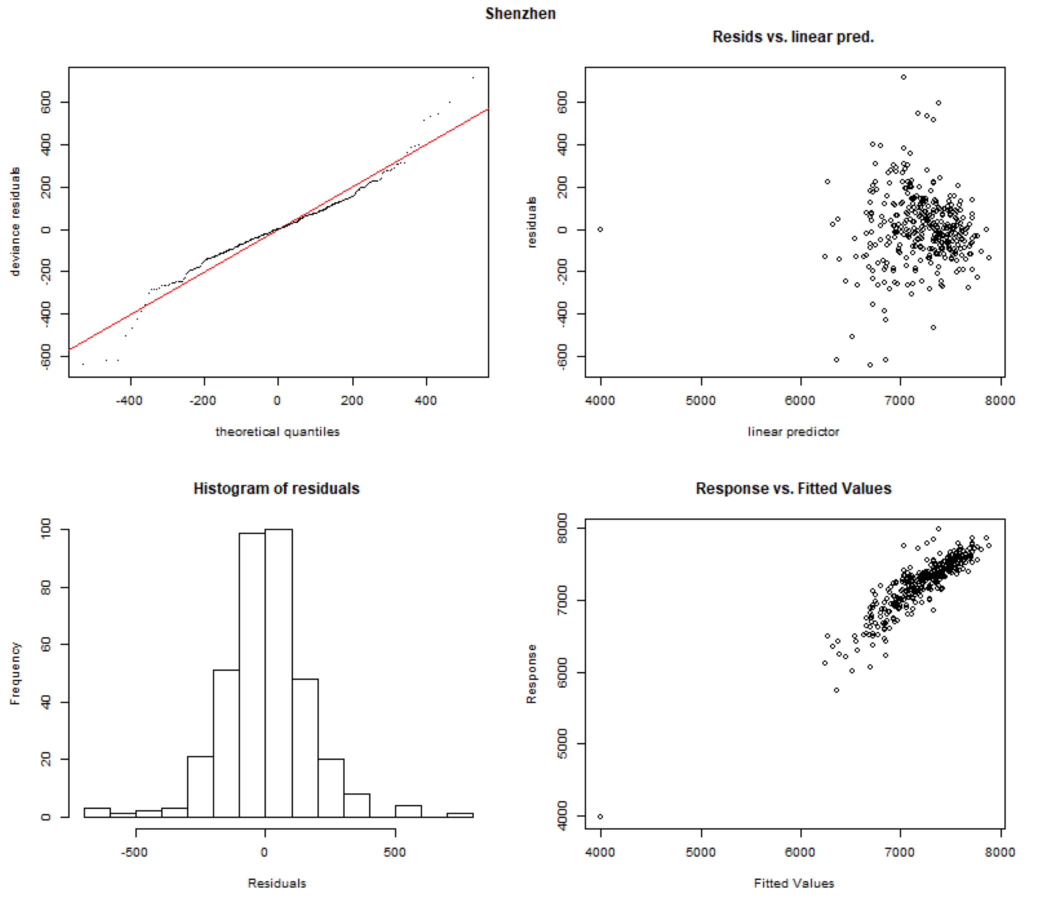


Appendix B6. (Continued) Residual plots for model evaluation of main models

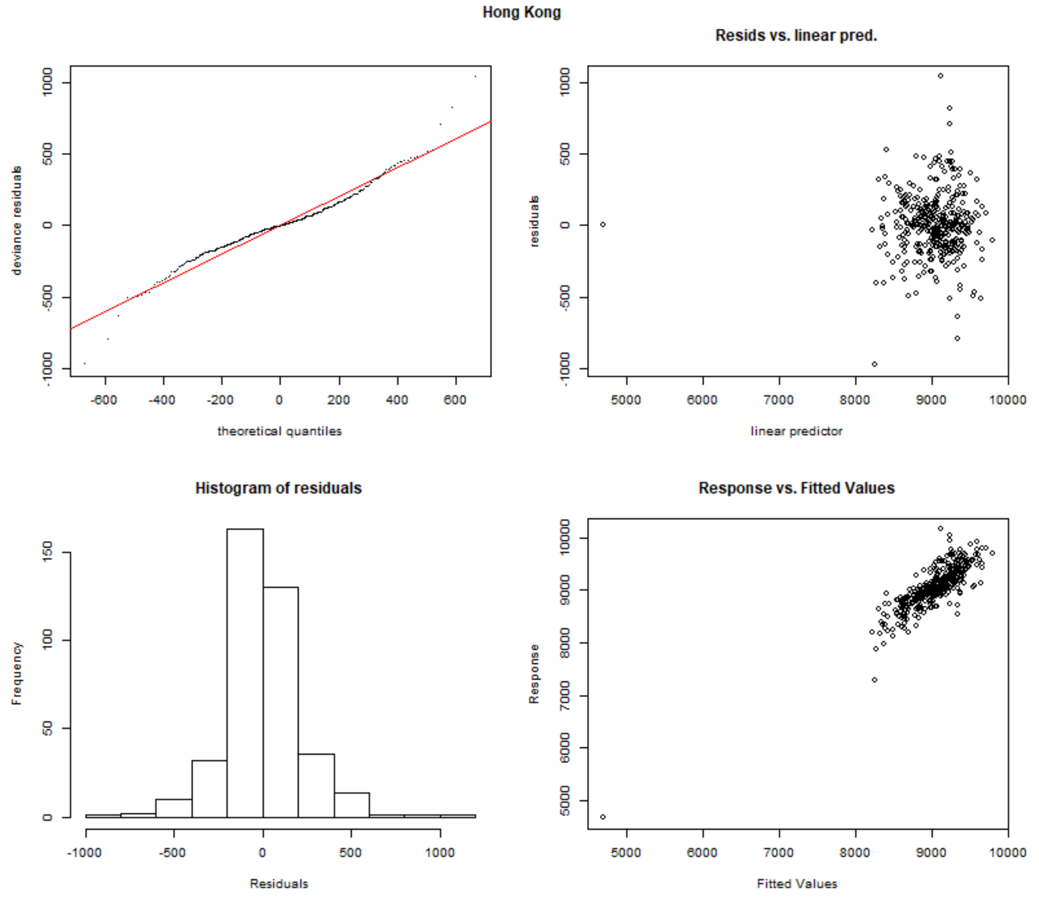
CQ



SZ

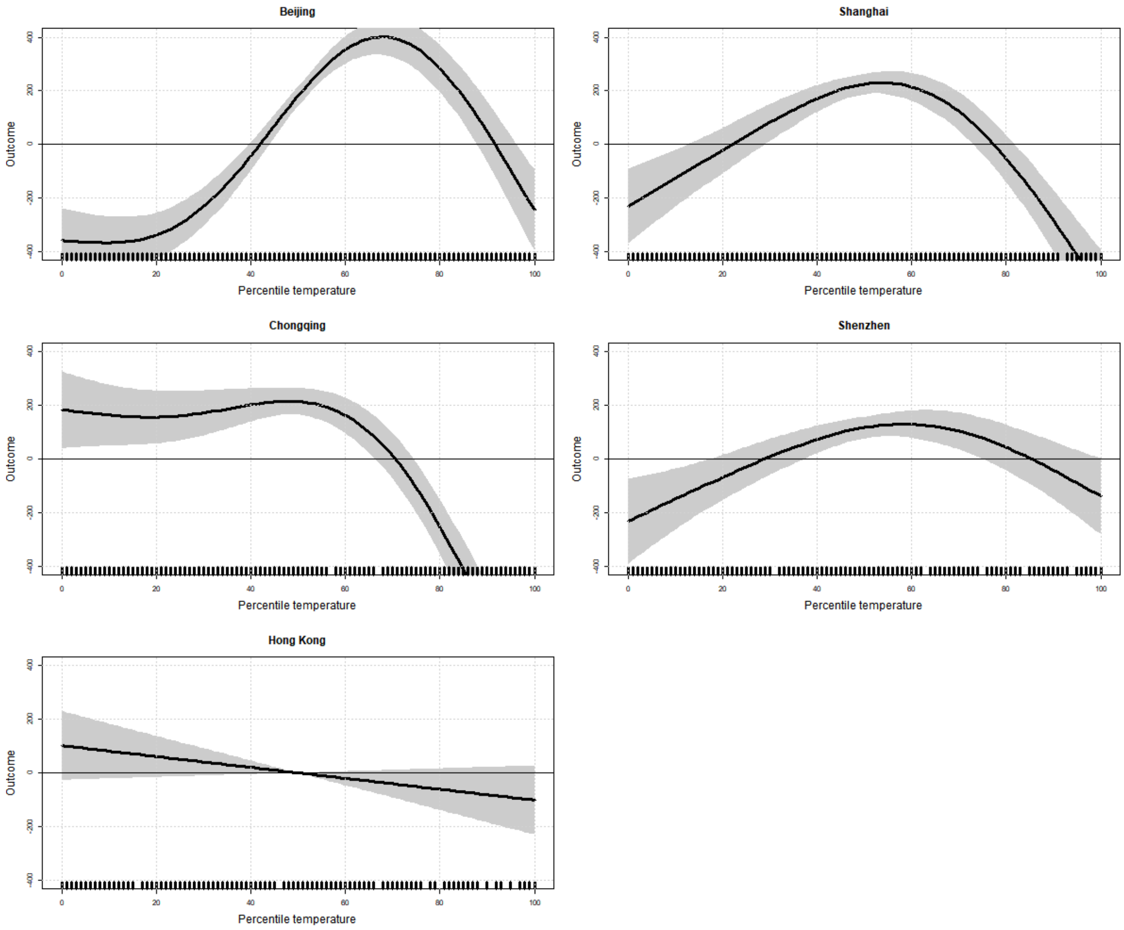


Appendix B6. (Continued) Residual plots for model evaluation of main models

HK	

Aggregated anonymized data on physical activity obtained from in-app function WeRun, Dec 2017-2018; City abbreviations: BJ = Beijing, SH = Shanghai, CQ = Chongqing, SZ = Shenzhen, HK = Hong Kong

B7. Association between percentile temperatures and daily step counts in five Chinese cities



Aggregated anonymized data on physical activity obtained from in-app function WeRun, Dec 2017-2018; Black markings along the x-axis indicate the actual existing percentile temperature data of each city.

C1. Comparison of included and excluded participants in final analysis

	Barcelona			Stoke-on-Trent			Doetinchem			Kaunas		
	Included	Excluded	p-value	Included	Excluded	p-value	Included	Excluded	p-value	Included	Excluded	p-value
Observations	12131	1221		9109	2048		11866	1370		9799	2823	
METavg (mean (SD))	2.04 (0.84)	2.16 (1.34)	<0.001*	1.92 (0.80)	1.94 (0.75)	0.22	1.93 (0.87)	1.94 (0.79)	0.644	2.01 (0.74)	1.95 (0.65)	<0.001*
n	95	14		79	20		94	17		84	28	
Gender = female (%)	48 (50.5)	3 (21.4)	0.08	45 (57.0)	9 (52.9)	0.973	53 (56.4)	9 (52.9)	1	43 (51.2)	15 (68.2)	0.236
Age (%)			0.15			0.345			0.867			0.152
18-25	16 (16.8)	6 (42.9)		8 (10.1)	3 (18.8)		NA	NA		12 (14.3)	3 (14.3)	
26-45	40 (42.1)	4 (28.6)		34 (43.0)	6 (37.5)		18 (19.1)	4 (23.5)		13 (15.5)	4 (19.0)	
46-65	33 (34.7)	3 (21.4)		27 (34.2)	7 (43.8)		55 (58.5)	10 (58.8)		50 (59.5)	8 (38.1)	
66-75	6 (6.3)	1 (7.1)		10 (12.7)	0 (0.0)		21 (22.3)	3 (17.6)		9 (10.7)	6 (28.6)	
Education (%)			0.002*			0.492			0.904			0.318
Low	9 (9.5)	6 (42.9)		1 (1.3)	0 (0.0)		NA	NA		1 (1.2)	0 (0.0)	
Medium	31 (32.6)	5 (35.7)		41 (51.9)	6 (37.5)		49 (52.1)	8 (47.1)		18 (21.4)	8 (36.4)	
High	55 (57.9)	3 (21.4)		37 (46.8)	10 (62.5)		45 (47.9)	9 (52.9)		65 (77.4)	14 (63.6)	
Dog ownership, yes (%)	22 (23.2)	3 (21.4)	1	28 (35.4)	4 (23.5)	0.508	21 (22.3)	6 (35.3)	0.402	52 (61.9)	9 (40.9)	0.126
Chronic disease, yes (%)	24 (25.3)	4 (28.6)	1	21 (26.6)	4 (23.5)	1	36 (38.3)	14 (82.4)	0.002*	32 (38.1)	8 (36.4)	1
Employment = unemployed/retired (%)	30 (31.6)	5 (35.7)	0.998	25 (31.6)	7 (41.2)	0.636	38 (40.4)	6 (35.3)	0.898	26 (31.0)	6 (27.3)	0.941
With children < 12 yrs (%)	25 (26.3)	0 (0.0)	0.065	18 (23.1)	4 (23.5)	1	16 (17.0)	4 (23.5)	0.764	10 (11.9)	2 (9.1)	1

Appendix C1. (Continued) Comparison of included and excluded participants in final analysis

	Barcelona			**Stoke-on-Trent**			**Doetinchem**			**Kaunas**		
	Included	Excluded	p-value	Included	Excluded	p-value	Included	Excluded	p-value	Included	Excluded	p-value
Born in country, yes (%)	80 (84.2)	10 (71.4)	0.424	75 (94.9)	14 (82.4)	0.195	89 (94.7)	17 (100.0)	0.736	74 (88.1)	18 (81.8)	0.674
BMI (mean (SD))	25.03 (4.62)	25.67 (5.47)	0.637	26.35 (5.58)	25.78 (4.31)	0.727	25.92 (4.38)	26.66 (5.95)	0.565	25.83 (4.81)	27.98 (6.13)	0.088
General Health (%)			0.19			0.345			0.006*			0.394
Excellent/ very good	37 (38.9)	9 (64.3)		35 (44.3)	5 (29.4)		76 (80.9)	10 (58.8)		14 (16.7)	2 (9.1)	
Good	40 (42.1)	3 (21.4)		28 (35.4)	6 (35.3)		15 (16.0)	3 (17.6)		37 (44.0)	8 (36.4)	
Bad to very bad	18 (18.9)	2 (14.3)		16 (20.3)	6 (35.3)		3 (3.2)	4 (23.5)		33 (39.3)	12 (54.5)	
Meet PA guidelines, yes (%)	41 (43.2)	6 (42.9)	1	19 (24.1)	9 (52.9)	0.037*	34 (36.2)	4 (23.5)	0.464	54 (64.3)	10 (45.5)	0.173
Mobility problems, yes (%)	3 (3.2)	0 (0.0)	1	11 (13.9)	3 (17.6)	0.987	28 (29.8)	9 (52.9)	0.113	50 (59.5)	13 (59.1)	1
Perceived income (%)			0.786			0.481			0.64			0.469
Cannot make ends meet	13 (14.3)	3 (21.4)		4 (5.6)	0 (0.0)		21 (22.3)	5 (33.3)		4 (5.6)	0 (0.0)	
Enough to get along	49 (53.8)	7 (50.0)		26 (36.1)	5 (29.4)		27 (28.7)	4 (26.7)		48 (67.6)	13 (65.0)	
Comfortable	29 (31.9)	4 (28.6)		42 (58.3)	12 (70.6)		46 (48.9)	6 (40.0)		19 (26.8)	7 (35.0)	
Own a car, yes (%)	56 (58.9)	6 (42.9)	0.398	58 (73.4)	13 (76.5)	1	84 (89.4)	14 (82.4)	0.677	57 (67.9)	17 (77.3)	0.551
Own a motorcycle, yes (%)	15 (15.8)	1 (7.1)	0.653	5 (6.3)	0 (0.0)	0.643	11 (11.7)	0 (0.0)	0.296	3 (3.6)	2 (9.1)	0.602
Own a bicycle, yes (%)	49 (51.6)	6 (42.9)	0.747	33 (41.8)	6 (35.3)	0.825	92 (97.9)	15 (88.2)	0.21	43 (51.2)	11 (50.0)	1
Near public transport, yes (%)	92 (96.8)	14 (100.0)	1	73 (92.4)	16 (94.1)	1	83 (88.3)	15 (88.2)	1	63 (75.0)	20 (90.9)	0.186

Data obtained from the PHENOTYPE project, May-Dec 2013
Chi-squared test was used to measure the difference in proportion between included and excluded participants.
* p ≤ 0.05

C2. Full table of main model, for four European cities

	Barcelona, Spain				Stoke-on-Trent, United Kingdom				Doetinchem, Netherlands				Kaunas, Lithuania			
N (Observations)	95 $_{id}$ (8978)				79 $_{id}$ (6769)				94 $_{id}$ (8894)				84 $_{id}$ (7147)			
Marginal R^2/ Conditional R^2	0.105 / 0.162				0.130 / 0.200				0.167 / 0.225				0.126 / 0.193			
Variables	**Effect**	**95% CI**	**p-value**	**Sig**	**Effect**	**95% CI**	**p-value**	**Sig**	**Effect**	**95% CI**	**p-value**	**Sig**	**Effect**	**95% CI**	**p-value**	**Sig**
Original Log(MET) of interaction terms																
Apparent temperature	- 0.00131	-0.00573, 0.00311	0.561		- 0.00108	-0.00941, 0.00726	0.8		-0.0031	-0.00884, 0.00265	0.291		- 0.00114	-0.00388, 0.00161	0.417	
Apparent temperature²	\	\	\	\	0.00004	-0.00031, 0.00039	0.822		- 0.00003	-0.00021, 0.00015	0.746		\	\	\	\
NDVI (ref: Q1 lowest)																
NDVI Q2	- 0.01449	-0.13022, 0.10125	0.806		- 0.04989	-0.10434, 0.00455	0.072		- 0.04731	-0.09451, - 0.00011	0.049	*	- 0.0693	-0.11081, - 0.02778	0.001	**
NDVI Q3	0.05003	-0.06520, 0.16526	0.395		- 0.05999	-0.11722, - 0.00276	0.04	*	0.02524	-0.02629, 0.07677	0.337		- 0.1533	-0.19720, - 0.10940	<0.001	**
NDVI Q4	0.03784	-0.08258, 0.15827	0.538		- 0.12215	-0.17896, - 0.06533	<0.001	**	0.00835	-0.04556, 0.06225	0.762		- 0.15562	-0.19961, - 0.11164	<0.001	**
Apptemp * NDVI Q2	0.00524	0.00040, 0.01007	0.034	*	0.00522	-0.00474, 0.01518	0.304		0.00304	-0.00412, 0.01021	0.405		0.00533	0.00257, 0.00809	<0.001	**
Apptemp * NDVI Q3	0.00257	-0.00231, 0.00744	0.302		0.00509	-0.00546, 0.01564	0.344		- 0.00291	-0.01030, 0.00448	0.44		0.00416	0.00134, 0.00699	0.004	**
Apptemp * NDVI Q4	0.0024	-0.00270, 0.00750	0.357		0.01377	0.00332, 0.02422	0.01	*	0.01476	0.00724, 0.02228	<0.001	**	0.00566	0.00284, 0.00848	<0.001	**
Apptemp² * NDVI Q2	\	\	\	\	- 0.00015	-0.00057, 0.00028	0.499		0.0000	-0.00025, 0.00026	0.981		\	\	\	\
Apptemp² * NDVI Q3	\	\	\	\	0.00003	-0.00044, 0.00050	0.903		0.00025	0.00000, 0.00050	0.048	*	\	\	\	\
Apptemp² * NDVI Q4	\	\	\	\	- 0.00046	-0.00089, - 0.00002	0.041	*	- 0.00037	-0.00062, - 0.00013	0.003	**	\	\	\	\

Appendix C2. (Continued) Full table of main model, for four European cities

	Barcelona, Spain				**Stoke-on-Trent, United Kingdom**				**Doetinchem, Netherlands**				**Kaunas, Lithuania**			
Variables	**Effect**	**95% CI**	**p-value**	**Sig**	**Effect**	**95% CI**	**p-value**	**Sig**	**Effect**	**95% CI**	**p-value**	**Sig**	**Effect**	**95% CI**	**p-value**	**Sig**
Change in median MET of covariates^																
Rainfall	1.88	-1.84, 5.74	0.327		0.52	-1.42, 2.49	0.603		-0.86	-2.48, 0.78	0.302		-2.83	-4.87, -0.74	0.008	**
Windspeed	0.31	-0.86, 1.50	0.605		0.1	-0.60, 0.81	0.772		-0.08	-0.81, 0.66	0.836		-1.35	-2.42, -0.28	0.014	*
Sky darkness	-1.1	-4.08, 1.97	0.479		-4.72	-7.08, -2.29	<0.001	**	-2.21	-4.50, 0.14	0.066		-2.57	-5.10, 0.02	0.052	
Residential NDVI within 300m	-0.43	-1.52, 0.66	0.437		-0.61	-3.18, 2.03	0.648		-0.79	-3.23, 1.71	0.533		-1.11	-3.56, 1.40	0.382	
Gender, female (ref: male)	-4.06	-7.19, -0.83	0.014	*	-1.52	-5.36, 2.48	0.451		0.69	-2.59, 4.07	0.685		-1.06	-4.88, 2.92	0.596	
Age group (ref: 26-45)																
18-25	-1.18	-5.98, 3.86	0.639		5.47	-1.53, 12.97	0.129		\	\	\	\	3.42	-3.77, 11.15	0.361	
46-65	1.13	-3.31, 5.77	0.624		-1.1	-5.71, 3.74	0.651		-5.39	-9.24, -1.39	0.009	**	5.15	-0.53, 11.16	0.077	
66-75	-4.9	-11.63, 2.34	0.179		-5.02	-10.92, 1.26	0.115		-5.23	-9.83, -0.39	0.035	*	-0.42	-8.02, 7.81	0.917	
Education (ref: High)																
Medium	-2.29	-6.00, 1.57	0.242		-0.91	-4.56, 2.88	0.632		-1.04	-4.19, 2.21	0.527		0.89	-3.63, 5.62	0.704	
Low	3.84	-2.57, 10.68	0.246		9.91	-7.00, 29.89	0.267		\	\	\	\	5.8	-10.47, 25.04	0.508	
Chronic disease (ref: no)	-2.07	-6.29, 2.33	0.35		-4.73	-9.19, -0.04	0.048	*	-6.49	-9.59, -3.29	<0.001	**	-2.32	-6.30, 1.83	0.269	
Dog ownership (ref: no)	2.14	-2.02, 6.47	0.318		1.71	-2.35, 5.94	0.415		5.63	1.61, 9.80	0.006	**	2.33	-1.71, 6.52	0.263	
Public Holiday	-7.57	-10.44, -4.61	<0.001	**	-0.72	-6.32, 5.21	0.807		\	\	\	\	1.13	-6.69, 9.61	0.784	
Month (ref: Sept)																
May	\	\	\	\	\	\	\	\	\	\	\	\	-0.08	-7.56, 8.01	0.984	
June	6.3	1.90, 10.89	0.005	**	\	\	\	\	\	\	\	\	-5.36	-11.77, 1.53	0.124	
July	0.48	-3.92, 5.09	0.832		-7.21	-12.89, -1.16	0.02	*	5.55	-1.08, 12.63	0.103		-0.78	-6.85, 5.69	0.809	
Aug	2.31	-4.67, 9.80	0.526		-1.81	-6.27, 2.87	0.443		0.9	-3.03, 4.99	0.658		-2.17	-6.59, 2.46	0.352	
Oct	1.61	-1.96, 5.31	0.381		-3.56	-8.25, 1.37	0.154		-4.25	-7.24, -1.16	0.007	**	2.59	-1.35, 6.69	0.201	

Appendix C2. (Continued) Full table of main model, for four European cities

	Barcelona, Spain				Stoke-on-Trent, United Kingdom				Doetinchem, Netherlands				Kaunas, Lithuania			
Variables	**Effect**	**95% CI**	**p-value**	**Sig**	**Effect**	**95% CI**	**p-value**	**Sig**	**Effect**	**95% CI**	**p-value**	**Sig**	**Effect**	**95% CI**	**p-value**	**Sig**
Nov	\	\	\	\	-1.75	-7.11, 3.92	0.538		-3.99	-8.13, 0.34	0.071		3.28	-4.05, 11.17	0.391	
Dec	\	\	\	\	0.99	-4.57, 6.87	0.734		-1.14	-6.21, 4.21	0.67		9.8	-7.79, 30.74	0.294	
Day of week (ref: Monday)																
Tuesday	0.64	-1.55, 2.88	0.568		1.81	-0.61, 4.28	0.144		-1.04	-3.09, 1.05	0.325		-0.68	-2.93, 1.63	0.563	
Wednesday	1.87	-0.31, 4.10	0.093		2.68	0.27, 5.15	0.029	*	1.08	-0.96, 3.16	0.303		-0.32	-2.64, 2.06	0.791	
Thursday	0.24	-1.94, 2.47	0.83		2.8	0.36, 5.31	0.024	*	1.42	-0.63, 3.51	0.176		-0.4	-2.70, 1.95	0.735	
Friday	2.19	-0.03, 4.46	0.053		3.69	1.28, 6.15	0.002	**	1.93	-0.15, 4.05	0.069		0.64	-1.69, 3.03	0.591	
Saturday	-2.79	-4.96, -0.57	0.014	*	3.85	1.39, 6.37	0.002	**	1.7	-0.37, 3.83	0.109		1.77	-0.62, 4.22	0.149	
Sunday	-2.85	-5.05, -0.60	0.013	*	-2.55	-4.85, -0.19	0.034	*	-1.56	-3.61, 0.53	0.142		-4.19	-6.46, -1.87	<0.001	**
Hour of day (ref: Hour 13)																
Hour 6	-26.15	-29.69, -22.43	<0.001	**	-17.76	-21.61, -13.73	<0.001	**	-24.27	-27.51, -20.89	<0.001	**	-18.33	-22.09, -14.40	<0.001	**
Hour 7	-14.2	-17.70, -10.55	<0.001	**	-12.53	-16.11, -8.78	<0.001	**	-15.93	-18.94, -12.80	<0.001	**	-7.72	-11.33, -3.96	<0.001	**
Hour 8	-2.18	-5.74, 1.52	0.245		-2.44	-6.01, 1.27	0.195		-1.19	-4.40, 2.13	0.479		-3.38	-6.81, 0.18	0.062	
Hour 9	-2.19	-5.52, 1.26	0.21		-0.1	-3.49, 3.42	0.957		-2.51	-5.45, 0.53	0.105		-5.06	-8.24, -1.76	0.003	**
Hour 10	-4.34	-7.47, -1.11	0.009	**	2.39	-0.98, 5.86	0.167		-3.2	-6.03, -0.28	0.032	*	-3.68	-6.83, -0.42	0.027	*
Hour 11	-2.35	-5.45, 0.85	0.149		0.49	-2.71, 3.80	0.766		1.26	-1.66, 4.28	0.401		-0.38	-3.60, 2.96	0.823	
Hour 12	-2.23	-5.32, 0.96	0.168		0.35	-2.84, 3.65	0.83		1.52	-1.42, 4.54	0.314		0.64	-2.60, 3.97	0.704	
Hour 14	-6.66	-9.64, -3.57	<0.001	**	-0.88	-4.01, 2.35	0.588		2.06	-0.88, 5.08	0.171		-0.4	-3.61, 2.92	0.812	
Hour 15	-9.02	-11.97, -5.97	<0.001	**	1.08	-2.14, 4.40	0.516		-2.01	-4.84, 0.90	0.174		-4.01	-7.09, -0.82	0.014	*
Hour 16	-9.55	-12.49, -6.51	<0.001	**	-0.18	-3.42, 3.16	0.913		-4.58	-7.35, -1.73	0.002	**	-4.39	-7.49, -1.19	0.008	**
Hour 17	-4.13	-7.28, -0.87	0.013	*	-2	-5.31, 1.42	0.248		-3.81	-6.65, -0.88	0.011	*	-3.96	-7.11, -0.70	0.018	*
Hour 18	-2.08	-5.39, 1.35	0.231		-3.07	-6.43, 0.40	0.083		-9.43	-12.19, -6.58	<0.001	**	-6.18	-9.34, -2.91	<0.001	**
Hour 19	0.12	-3.36, 3.72	0.946		-8.39	-11.71, -4.94	<0.001	**	-9.77	-12.68, -6.76	<0.001	**	-8.43	-11.71, -5.03	<0.001	**
Hour 20	-1.83	-5.54, 2.02	0.347		-11.59	-15.08, -7.95	<0.001	**	-13.58	-16.59, -10.46	<0.001	**	-12.91	-16.30, -9.38	<0.001	**

Appendix C2. (Continued) Full table of main model, for four European cities

	Barcelona, Spain				Stoke-on-Trent, United Kingdom				Doetinchem, Netherlands				Kaunas, Lithuania			
Variables	**Effect**	**95% CI**	**p-value**	**Sig**	**Effect**	**95% CI**	**p-value**	**Sig**	**Effect**	**95% CI**	**p-value**	**Sig**	**Effect**	**95% CI**	**p-value**	**Sig**
Hour 21	-10.45	-14.05, -6.70	<0.001	**	-14.9	-18.57, -11.07	<0.001	**	-17.06	-20.24, -13.76	<0.001	**	-17.57	-21.04, -13.94	<0.001	**
Hour 22	-16.89	-20.89, -12.69	<0.001	**	-15.64	-19.58, -11.50	<0.001	**	-18.71	-22.07, -15.21	<0.001	**	-20.82	-24.45, -17.02	<0.001	**
Hour 23	-19.16	-23.17, -14.95	<0.001	**	-16.76	-20.86, -12.45	<0.001	**	-22.39	-25.79, -18.82	<0.001	**	-22.67	-26.47, -18.68	<0.001	**

Data on physical activity and surrounding greenness obtained from the PHENOTYPE project, May-Dec 2013

^Effects (and 95% CI) show the adjusted percentage change in the median (or, equivalently the geometric mean) of the hourly average MET associate to each covariate.

In the case of numerical covariates (i.e. windspeed, residential NDVI), effects are for an increase equivalent to the interquartile range.

IQR of Windspeed: Barcelona 1.65 m/s, Stoke-on-Trent 1.54 m/s, Doetinchem 2 m/s, Kaunas 2.3 m/s

IQR of Residential NDVI: Barcelona 0.06, Stoke-on-Trent 0.12, Doetinchem 0.14, Kaunas 0.10

\ indicates the absence of data for that category.

* p ≤ 0.05, ** p ≤ 0.01

C3. Sensitivity analyses and results

Sensitivity analyses were conducted on the following effects: (1) the potential lagged effect (up to 3 days) of daily temperature, (2) the removal of month from the main model, (3) the effect of distance from the weather stations, and (4) the effect of transportation options. Additional sensitivity models assessed (5) the effect of percentile apparent temperature, (6) the effect of a separate greenspace indicator: contact with greenspace, and (7) the effect of employment on the physical activity patterns, via stratification.

Additional variable details:

(1) Variables of same-day apparent temperature, one day lag of daily apparent temperature, and average three-day lag of daily apparent temperature were created by averaging 24-hour apparent temperature records. These were included in the model as categorical, linear, or quadratic terms.

(3) Distance from weather stations (km) was calculated using the Haversine formula for the distance between each participant's GPS location and the respective weather station at the minute level, which was then averaged per hour.

(4) Transportation options from the survey data indicated access to (a) car, (b) bicycle, and (c) public transport stop within 15 minutes' walk of their home.

(5) Percentiles of apparent temperature were computed from the temperature values of the entire 2013.

(6) Contact with greenspace was measured through hourly time spent in greenspace. Land use maps were obtained from Urban Atlas (2012) for urban areas, with a minimum mapping unit of 2500m^2. Top10NL was used for Doetinchem, and Corine Land Cover was used for all the other areas not covered by Urban Atlas (Smith et al., 2017). Natural environments were extracted from the Urban Atlas using the following categories (and codes): Green Urban Areas (14100), Agricultural & Semi Natural Areas (20000) and Forests (30000). For every GPS point location, exposure to greenspace was included if a greenspace intersected the participant's 50m circular buffer. This was resampled to binary values at the minute level and further aggregated to indicate how long a participant had exposure to a greenspace within the hour (out of 100%). Hourly contact with greenspace was further transformed into a three-factor variable according to the bivariate relationship identified with average MET. The analysis of contact with greenspace was controlled for residential

presence of greenspace, calculated as the count of greenspaces within 1000m of residence which approximates to a 10-minute walking distance (Smith et al., 2017).

(7) The effect of employment was assessed via stratification (employed; unemployed or retired), as hourly patterns likely differ between employed and non-employed participants, and surrounding greenness may not be a relevant factor for work-related physical activity (Kruize et al., 2019).

Summary findings of Contact with greenspace

Variables	**Barcelona, SP**	**Stoke-on-Trent, UK**	**Doetinchem, NL**	**Kaunas, LI**	**p-value ^**
Observations	8978	6769	8894	7147	
Surrounding Greenness					
Contact with greenspace, % of hour					<0.001
0%, n (%)	7268 (81.0)	4177 (61.7)	3427 (38.5)	4202 (58.8)	
1-99%, n (%)	1301 (14.5)	1322 (19.5)	2608 (29.3)	1871 (26.2)	
100%, n (%)	409 (4.6)	1270 (18.8)	2859 (32.1)	1074 (15.0)	
Residential presence of greenspace within 1000m, mean (SD)	7.05 (6.44)	8.76 (3.46)	17.24 (6.00)	5.86 (2.77)	<0.001

Data obtained from the PHENOTYPE project, May-Dec 2013
^Chi-square test was used to measure the overall difference in proportion between the cities. p ≤ 0.05 indicates significant difference.

Sensitivity results:

When adjusting for (1) the potential lag effect of daily temperatures in the main models, the interaction results remained consistent in Stoke-on-Trent but the associations in NDVI Quartile 3 for Doetinchem and Kaunas became marginally non-significant (see Table C3.1). The association was non-significant in the interaction model for Barcelona. The four cities had varying significant associations of daily same-day or lag temperatures. While Kaunas only found significant associations of average 1-3 day lag temperatures, the other cities found significant associations of linear same-day temperature. Stoke-on-Trent and Doetinchem also found significant associations for one-day lag, and Stoke-on-Trent for categorical 1-3 day lag.

When (2) removing month from the model, the interaction effects were non-significant for Barcelona, while the effects changed between quartiles in Kaunas (see Table C3.2). The associations remained consistent in Stoke-on-Trent and Doetinchem. The (3) inclusion of distance from weather station found a statistically significant association between the variable and physical activity but did not affect the interaction results in the model. When

(4) transportation options (car, bicycle, or public transport) were included, the interaction models remained largely consistent. However, in Barcelona, the interaction effect was non-significant when adding the effect of car access. In Doetinchem, having access to a bicycle was significantly associated with increased hourly physical activity.

When (5) apparent temperature was substituted for percentile apparent temperature in the interaction model, quadratic effects remained significant in Doetinchem only, with optimal apparent temperature at the 66th percentile for the highest NDVI quartile (see Table C3.3). Quadratic effects in Stoke-on-Trent became non-significant, however, when assessed linearly, positive associations were found for the upper two NDVI quartiles. For the other cities, the effects of percentile temperature were consistent with the original findings of the interaction model.

When (6) using Contact with greenspace as the surrounding greenness indicator, Stoke-on-Trent and Doetinchem found significant downward parabolic effects at 100% contact with greenspace within the hour (see Table C3.4). A significant upward parabolic effect was also found at 1-99% contact with greenspace for Doetinchem. For Kaunas, positive linear effects were found for 0% and 100% contact with greenspace, while no significant interaction effect was found for Barcelona.

When assessing (7) the effect of employment on the physical activity patterns via stratification, the interaction effects were found largely influenced by employed participants in Barcelona, Stoke-on-Trent and Doetinchem (see Table C3.5). However, the interaction effects for Kaunas were largely found among the non-employed participants.

C3.1 Sensitivity analysis 1: Same-day and lag daily temperatures for four European cities

		Barcelona			**Stoke-on-Trent**					**Doetinchem**					**Kaunas**		
Model/ Variable	**NDVI Q**	**10°C change (%)**	**95% CI of Change**	**Sig***	**Optimal AT^**	**95% CI**	**10°C change (%)**	**95% CI of Change**	**Sig***	**Optimal AT^**	**95% CI**	**10°C change (%)**	**95% CI of Change**	**Sig***	**10°C change (%)**	**95% CI of Change**	**Sig***
Original Interaction model (for comparison)																	
Interaction	Q1	-1.3	-5.57, 3.16		13.55	-47.67, 68.43	0.4	-3.02, 3.93		-51.49	-326.34, 330.06	-0.3	-2.10, 1.53		-1.13	-3.80, 1.62	
	Q2	4	0.08, 8.08	*	19.29	-64.45, 93.41	-1.07	-3.94, 1.89		-0.99	-71.54, 98.60	-0.27	-2.32, 1.82		4.29	1.40, 7.26	*
	Q3	1.27	-2.53, 5.21		-29.18	-224.01, 240.16	0.69	-2.67, 4.16		13.74	3.09, 21.73	2.21	0.25, 4.21	*	3.07	0.21, 6.02	*
	Q4	1.1	-2.91, 5.27		15.22	11.26, 25.29	-4.08	-6.96, - 1.12	*	14.49	11.31, 17.46	-3.94	-5.77, -2.08	*	4.63	1.65, 7.69	*
Same-day daily AT (linear)																	
Interaction	Q1	-5.73	-11.30, 0.20		48.5	-174.84, 201.56	0.58	-2.84, 4.13		16.43	-100.14, 120.92	-0.36	-2.16, 1.47		-0.13	-4.56, 4.51	
	Q2	-0.89	-6.53, 5.09		-1.53	-108.48, 127.98	-0.87	-3.75, 2.10		52	-220.26, 248.79	-0.44	-2.48, 1.65		5.35	0.60, 10.33	*
	Q3	-3.41	-8.84, 2.33		1	-90.65, 106.03	0.77	-2.59, 4.24		4.31	-40.81, 13.74	2.18	0.22, 4.18	*	4.11	-0.55, 8.99	
	Q4	-3.39	-8.84, 2.38		10.46	-1.74, 17.80	-3.81	-6.70, - 0.82	*	19.35	15.26, 25.93	-4	-5.82, -2.14	*	5.68	0.89, 10.70	*
Daily AT (linear)		2.89	0.24, 5.61	*			6.33	0.91, 12.05	*			-4.92	-7.96, -1.78	**	-1.44	-6.47, 3.86	
Same-day daily AT (quadratic)																	
Interaction	Q1	-5.77	-11.35, 0.15		-10.6	-137.88, 161.00	-0.96	-4.89, 3.14		14.89	-44.40, 73.76	-1.12	-3.19, 1.00		-0.34	-4.79, 4.33	
	Q2	-0.84	-6.48, 5.14		6.1	-56.65, 63.85	-2.07	-5.34, 1.30		28.09	-117.88, 160.12	-1.18	-3.46, 1.16		5.16	0.40, 10.16	*
	Q3	-3.31	-8.74, 2.45		24.27	-83.65, 106.83	-0.62	-4.41, 3.31		-0.68	-140.72, 136.85	1.42	-0.80, 3.69		3.96	-0.70, 8.85	
	Q4	-3.39	-8.83, 2.38		10.71	2.95, 15.85	-4.95	-8.19, - 1.60	*	18.54	15.09, 24.00	-4.71	-6.78, - 2.59	*	5.55	0.75, 10.57	*
Daily AT (quadratic)		2.28	-2.81, 7.66				3.23	-1.13, 7.80				1.94	-0.83, 4.81		0.81	-1.29, 2.95	

Appendix C3.1 (Continued) Sensitivity analysis 1: Same-day and lag daily temperatures for four European cities

		Barcelona			**Stoke-on-Trent**					**Doetinchem**					**Kaunas**		
Model/ Variable	**NDVI Q**	**10°C change (%)**	**95% CI of Change**	**Sig***	**Optimal AT^**	**95% CI**	**10°C change (%)**	**95% CI of Change**	**Sig***	**Optimal AT^**	**95% CI**	**10°C change (%)**	**95% CI of Change**	**Sig***	**10°C change (%)**	**95% CI of Change**	**Sig***
Same-day daily AT (categorical)																	
Interaction	Q1	-2.41	-7.17, 2.61		9.36	-47.27, 68.06	-1.12	-4.82, 2.71		4.21	-88.20, 93.07	-1.34	-3.32, 0.69		-0.68	-4.33, 3.11	
	Q2	2.73	-2.03, 7.73		14.71	-19.90, 52.70	-2.27	-5.40, 0.97		16.64	-37.75, 71.65	-1.25	-3.45, 0.99		4.72	0.84, 8.74	*
	Q3	0.01	-4.55, 4.79		49.48	-201.27, 220.30	-0.7	-4.32, 3.06		7.59	-67.97, 83.72	1.15	-1.01, 3.36		3.42	-0.36, 7.35	
	Q4	-0.1	-4.74, 4.76		14.18	10.34, 20.51	-5.2	-8.30, - 1.98	*	15.59	12.61, 18.96	-5.09	-7.11, - 3.02	*	5.06	1.15, 9.12	*
Daily AT (categorical, ref: -5,0C or earliest)	[0,5)	\	\	\			-3.13	-7.99, 1.99				-1.87	-6.51, 3.00		3.09	-6.18, 13.28	
	[05,10)	\	\	\			-5.83	-11.51, 0.21				-4.82	-10.65, 1.38		2.22	-5.95, 11.09	
	[10,15)	\	\	\			-2.41	-9.31, 5.02				-6.72	-13.19, 0.24		2.4	-4.91, 10.28	
	[15,20)	1.36	-4.19, 7.23				-1.86	-9.51, 6.44				-7.29	-14.28, 0.26		3.59	-2.78, 10.37	
	[20,25)	2.17	-4.17, 8.93				0.6	-10.30, 12.83				-6.51	-14.26, 1.94		4.26	-1.60, 10.46	
	[25,30)	3.62	-4.09, 11.95				\	\	\			-0.28	-11.04, 11.77		\	\	\
	[30,35]	-0.64	-16.63, 18.41				\	\	\			\	\	\	\	\	\

Appendix C3.1 (Continued) Sensitivity analysis 1: Same-day and lag daily temperatures for four European cities

		Barcelona			Stoke-on-Trent					Doetinchem					Kaunas		
Model/ Variable	**NDVI Q**	**10°C change (%)**	**95% CI of Change**	**Sig***	**Optimal AT^**	**95% CI**	**10°C change (%)**	**95% CI of Change**	**Sig***	**Optimal AT^**	**95% CI**	**10°C change (%)**	**95% CI of Change**	**Sig***	**10°C change (%)**	**95% CI of Change**	**Sig***
Daily AT Lag 1 (linear)																	
Interaction	Q1	-2.06	-6.44, 2.52		17.42	-50.67, 73.97	0.43	-2.99, 3.96		-48.54	-246.17, 266.80	-0.24	-2.04, 1.59		-2.23	-5.15, 0.78	
	Q2	3.04	-1.11, 7.36		18.13	-58.49, 87.45	-1.04	-3.92, 1.92		16.8	-61.29, 90.62	-0.22	-2.27, 1.87		3.18	0.06, 6.39	*
	Q3	0.37	-3.63, 4.53		-27.73	-211.63, 225.81	0.67	-2.68, 4.15		11.84	-2.18, 18.20	2.31	0.34, 4.32	*	1.95	-1.16, 5.16	
	Q4	0.34	-3.79, 4.66		14.86	10.71, 24.43	-4.07	-6.95, - 1.10	*	15.55	12.43, 19.08	-3.91	-5.73, - 2.05	*	3.56	0.37, 6.85	*
Lag 1 AT (linear)		1.01	-0.55, 2.59				1.28	-1.76, 4.43				-2.06	-3.93, - 0.16	*	2.8	-0.43, 6.13	
Daily AT Lag 1 (categorical)																	
Interaction	Q1	-1.46	-5.83, 3.11		10.71	-46.42, 67.98	0.66	-2.81, 4.25		-21.36	-241.70, 264.50	-0.48	-2.33, 1.40		-1.8	-4.73, 1.21	
	Q2	3.74	-0.36, 8.01		21.31	-76.18, 104.34	-0.9	-3.79, 2.08		11.58	-60.35, 85.80	-0.33	-2.41, 1.80		3.57	0.44, 6.79	*
	Q3	0.98	-2.99, 5.13		-37.51	-241.91, 257.87	0.61	-2.76, 4.11		12.21	-8.12, 24.18	1.94	-0.07, 3.99		2.38	-0.74, 5.60	
	Q4	0.9	-3.25, 5.23		15.92	11.44, 29.79	-3.83	-6.74, - 0.83	*	15.13	12.10, 18.36	-4.12	-5.98, - 2.23	*	3.92	0.71, 7.23	*
Lag 1 AT (categorical, ref: -5,0C or earliest)	[0,5)	\	\	\			6.35	1.41, 11.54	*			-2.65	-7.17, 2.09		-2.11	-9.17, 5.50	
	[05,10)	\	\	\			6.68	1.33, 12.31	*			-0.31	-5.86, 5.56		-3.42	-9.91, 3.54	
	[10,15)	\	\	\			5.96	-0.01, 12.29				-2.97	-8.69, 3.10		-0.93	-7.11, 5.66	
	[15,20)	1.37	-3.85, 6.87				5.3	-1.15, 12.17				-3.11	-9.07, 3.24		-0.47	-5.99, 5.37	
	[20,25)	1.17	-4.01, 6.63				1.73	-7.61, 12.01				-2.36	-8.86, 4.60		2	-3.33, 7.63	
	[25,30)	3.19	-3.11, 9.90				\	\	\			-6.6	-15.64, 3.42		\	\	\
	[30,35]	-6.8	-20.44, 9.17				\	\	\			\	\	\	\	\	\

Appendix C3.1 (Continued) Sensitivity analysis 1: Same-day and lag daily temperatures for four European cities

		Barcelona			Stoke-on-Trent					Doetinchem					Kaunas		
Model/ Variable	**NDVI Q**	**10°C change (%)**	**95% CI of Change**	**Sig***	**Optimal AT^**	**95% CI**	**10°C change (%)**	**95% CI of Change**	**Sig***	**Optimal AT^**	**95% CI**	**10°C change (%)**	**95% CI of Change**	**Sig***	**10°C change (%)**	**95% CI of Change**	**Sig***
Daily AT Lag 1-3 average (linear)																	
Interaction	Q1	-1.78	-6.08, 2.71		13.59	-47.78, 68.44	0.4	-3.02, 3.93		-50.34	-319.23, 332.39	-0.3	-2.10, 1.53		-2.18	-4.91, 0.63	
	Q2	3.37	-0.62, 7.53		19.52	-64.07, 94.57	-1.04	-3.92, 1.93		-0.5	-71.20, 97.77	-0.27	-2.31, 1.82		3.28	0.34, 6.30	*
	Q3	0.71	-3.15, 4.72		-26.97	-219.93, 240.47	0.73	-2.63, 4.21		13.69	2.87, 21.72	2.21	0.25, 4.22	*	1.98	-0.94, 4.99	
	Q4	0.63	-3.42, 4.84		15.26	11.23, 25.62	-4.04	-6.92, - 1.07	*	14.53	11.32, 17.53	-3.94	-5.77, - 2.08	*	3.62	0.60, 6.74	*
Lag 1-3 AT (linear)		1.14	-0.49, 2.79				-1.07	-4.88, 2.90				-0.13	-1.85, 1.62		4.6	1.61, 7.67	**
Daily AT Lag 1-3 average (categorical)																	
Interaction	Q1	-1.65	-5.97, 2.87		17.04	-47.61, 69.30	0.28	-3.17, 3.85		-79.24	-322.23, 363.87	-0.22	-2.03, 1.63		-1.52	-4.23, 1.27	
	Q2	3.55	-0.45, 7.70		20.22	-67.94, 91.92	-0.78	-3.68, 2.22		-12.46	-77.90, 104.26	-0.18	-2.25, 1.93		4.09	1.16, 7.10	*
	Q3	0.79	-3.07, 4.81		-61.01	-229.50, 247.72	0.38	-2.99, 3.86		13.74	2.03, 22.27	2.16	0.18, 4.18	*	2.7	-0.20, 5.70	
	Q4	0.59	-3.47, 4.82		15.05	11.11, 24.42	-4.16	-7.05, - 1.18	*	14.45	11.24, 17.42	-3.97	-5.80, - 2.11	*	4.23	1.22, 7.32	*
Lag 1-3 AT (categorical, ref: -5,0C or earliest)	[0,5)	\	\	\			15.85	6.20, 26.37	**			-7.26	-14.28, 0.33		-12.27	-18.55, -5.50	**
	[05,10)	\	\	\			15.4	5.64, 26.06	**			-3.99	-12.30, 5.10		-11.94	-18.05, -5.37	**
	[10,15)	ref	\	\			16.43	6.13, 27.74	**			-3.89	-12.41, 5.45		-9.52	-15.44, -3.19	**
	[15,20)	-3.66	-8.29, 1.21				15.82	5.27, 27.42	**			-2.32	-11.22, 7.48		-8.82	-14.29, -3.00	**
	[20,25)	-3.49	-8.31, 1.58				\	\	\			-5.72	-14.51, 3.97		-7.32	-12.79, -1.52	*
	[25,30)	-0.95	-6.88, 5.35				\	\	\			\	\	\	\	\	\

Data on physical activity and surrounding greenness obtained from the PHENOTYPE project, May-Dec 2013

^Barcelona and Kaunas are reporting a linear effect in temperature; Stoke-on-Trent and Doetinchem are reporting a quadratic effects and departure from optimal temperature. Models adjusted for precipitation, windspeed, sky darkness, residential NDVI of 300 m buffer, month, day of week, hour of day, public holiday, gender, age, education, chronic disease, dog ownership, and participant ID (random effect)

\ indicates the absence of data for that category; * p ≤ 0.05, ** p ≤ 0.01

C3.2 Sensitivity analysis 2-4: Month, distance from weather station, and transportation options for four European cities

		Barcelona			Stoke-on-Trent					Doetinchem					Kaunas		
Model/ Variable	**NDVI Q**	**10°C change (%)**	**95% CI of Change**	**Sig***	**Optimal AT^**	**95% CI**	**10°C change (%)**	**95% CI of Change**	**Sig***	**Optimal AT^**	**95% CI**	**10°C change (%)**	**95% CI of Change**	**Sig***	**10°C change (%)**	**95% CI of Change**	**Sig***
Original Interaction model (for comparison)																	
Interaction	Q1	-1.3	-5.57, 3.16		13.55	-47.67, 68.43	0.4	-3.02, 3.93		-51.49	-326.34, 330.06	-0.3	-2.10, 1.53		-1.13	-3.80, 1.62	
	Q2	4	0.08, 8.08	*	19.29	-64.45, 93.41	-1.07	-3.94, 1.89		-0.99	-71.54, 98.60	-0.27	-2.32, 1.82		4.29	1.40, 7.26	*
	Q3	1.27	-2.53, 5.21		-29.18	-224.01, 240.16	0.69	-2.67, 4.16		13.74	3.09, 21.73	2.21	0.25, 4.21	*	3.07	0.21, 6.02	*
	Q4	1.1	-2.91, 5.27		15.22	11.26, 25.29	-4.08	-6.96, -1.12	*	14.49	11.31, 17.46	-3.94	-5.77, -2.08	*	4.63	1.65, 7.69	*
No month																	
Interaction	Q1	-2.16	-6.32, 2.18		13.42	-39.34, 60.55	0.82	-2.58, 4.33		-98.24	-267.87, 296.02	-0.15	-1.91, 1.65		-2.5	-4.86, -0.07	*
	Q2	3.09	-0.67, 6.99		19.26	-59.18, 87.51	-0.69	-3.55, 2.25		49.16	-56.26, 81.71	0.01	-2.01, 2.06		2.87	0.32, 5.48	*
	Q3	0.48	-3.19, 4.29		-10.56	-177.66, 188.46	1.22	-2.11, 4.67		12.1	0.61, 17.67	2.32	0.39, 4.28	*	1.63	-0.87, 4.18	
	Q4	0.37	-3.54, 4.44		15.56	10.63, 31.47	-3.39	-6.22, -0.47	*	15.51	12.67, 18.83	-3.83	-5.63, -1.99	*	3.36	0.69, 6.09	*
Distance from weather station																	
Interaction	Q1	-0.86	-5.14, 3.62		20.74	-55.10, 76.13	0.47	-2.94, 4.00		364.76	-277.81, 315.32	0.05	-1.75, 1.88		-0.7	-3.39, 2.07	
	Q2	4.15	0.23, 8.22	*	18.24	-59.72, 85.82	-0.86	-3.73, 2.10		-1.71	-64.81, 92.27	-0.19	-2.23, 1.89		4.69	1.79, 7.68	*
	Q3	1.27	-2.52, 5.21		-20.42	-181.47, 201.51	0.74	-2.61, 4.21		13.1	-1.44, 22.24	2.03	0.08, 4.03	*	3.31	0.44, 6.26	*
	Q4	0.69	-3.30, 4.84		15.2	11.38, 24.63	-4.18	-7.05, -1.23	*	14.71	11.47, 17.85	-3.81	-5.64, -1.96	*	4.26	1.29, 7.31	*
Distance from weather station		0.34	0.19, 0.49	**			0.64	0.43, 0.84	**			0.39	0.28, 0.51	**	0.28	0.13, 0.43	**
Access to Car																	
Interaction	Q1	-1.48	-5.74, 2.97		13.01	-46.87, 68.53	0.37	-3.05, 3.90		-49.91	-317.77, 331.95	-0.31	-2.10, 1.52		-1.12	-3.80, 1.63	
	Q2	3.79	-0.13, 7.86		18.95	-62.14, 90.67	-1.06	-3.94, 1.90		-4.96	-69.23, 98.68	-0.21	-2.26, 1.88		4.29	1.40, 7.26	*
	Q3	1.06	-2.73, 5.00		-32.2	-232.15, 244.73	0.66	-2.70, 4.13		13.83	3.56, 21.69	2.23	0.27, 4.24	*	3.07	0.21, 6.01	*
	Q4	0.9	-3.11, 5.07		15.1	11.05, 25.13	-4.04	-6.91, -1.07	*	14.47	11.27, 17.44	-3.93	-5.75, -2.07	*	4.64	1.66, 7.70	*
Car		-3.27	-6.68, 0.27				-3.46	-7.76, 1.05				3.87	-1.62, 9.65		-0.63	-4.97, 3.91	

Appendix C3.2 (Continued) Sensitivity analysis 2-4: Month, distance from weather station, and transportation options for four European cities

		Barcelona			Stoke-on-Trent					Doetinchem					Kaunas		
Model/ Variable	**NDVI Q**	**10°C change (%)**	**95% CI of Change**	**Sig***	**Optimal AT^**	**95% CI**	**10°C change (%)**	**95% CI of Change**	**Sig***	**Optimal AT^**	**95% CI**	**10°C change (%)**	**95% CI of Change**	**Sig***	**10°C change (%)**	**95% CI of Change**	**Sig***
Access to Bicycle																	
Interaction	Q1	-1.25	-5.52, 3.20		14.84	-47.37, 69.28	0.36	-3.05, 3.90		-41.67	-302.57, 329.58	-0.36	-2.15, 1.47		-1.12	-3.80, 1.62	
	Q2	3.94	0.03, 8.01	*	18.59	-59.89, 88.79	-1.08	-3.95, 1.88		-1.6	-72.91, 99.98	-0.29	-2.33, 1.80		4.28	1.40, 7.25	*
	Q3	1.26	-2.54, 5.20		-41.51	-226.05, 245.06	0.52	-2.83, 3.99		14.01	3.57, 22.43	2.19	0.23, 4.19	*	3.07	0.21, 6.01	*
	Q4	1.08	-2.93, 5.25		15.15	11.27, 24.77	-4.14	-7.02, -1.18	*	14.38	11.13, 17.34	-3.92	-5.74, -2.06	*	4.67	1.69, 7.73	*
Bike		2.64	-0.77, 6.16				-3.4	-7.18, 0.54				13.24	0.82, 27.19	*	-1.25	-5.02, 2.67	
Access to Public transport																	
Interaction	Q1	-1.31	-5.57, 3.15		13.55	-47.73, 68.53	0.4	-3.02, 3.93		-56.56	-326.79, 329.60	-0.28	-2.07, 1.55		-1.13	-3.80, 1.62	
	Q2	4	0.08, 8.07	*	19.26	-63.57, 93.92	-1.07	-3.95, 1.89		-1.83	-69.84, 96.54	-0.24	-2.29, 1.85		4.29	1.40, 7.26	*
	Q3	1.26	-2.54, 5.20		-29.37	-223.57, 239.88	0.69	-2.67, 4.16		13.75	3.11, 21.70	2.21	0.25, 4.21	*	3.08	0.21, 6.02	*
	Q4	1.09	-2.91, 5.27		15.22	11.26, 25.28	-4.08	-6.96, -1.12	*	14.49	11.32, 17.46	-3.94	-5.77, -2.08	*	4.63	1.65, 7.69	*
Public transport		0.71	-8.31, 10.61				0.28	-6.67, 7.76				4.66	-0.72, 10.33		-0.06	-4.32, 4.39	

Data on physical activity and surrounding greenness obtained from the PHENOTYPE project, May-Dec 2013

^Barcelona and Kaunas are reporting a linear effect in temperature; Stoke-on-Trent and Doetinchem are reporting a quadratic effects and departure from optimal temperature. Models adjusted for precipitation, windspeed, sky darkness, residential NDVI of 300 m buffer, month, day of week, hour of day, public holiday, gender, age, education, chronic disease, dog ownership, and participant ID (random effect); * p ≤ 0.05, ** p ≤ 0.01

C3.3 Sensitivity analysis 5: Percentile apparent temperature for four European cities

City	NDVI Quartile	Optimal Percentile AT^	95% CI	+/- 10 percentile change	95% CI of Change	Sig.*
Barcelona	Q1			-0.62	-1.93, 0.72	
	Q2			1.27	0.06, 2.49	*
	Q3			0.2	-0.94, 1.35	
	Q4			0.26	-0.96, 1.49	
Stoke-on-Trent	Q1	72.52	-147.99, 255.28	0.01	-0.25, 0.26	
	Q2	15.84	-287.75, 385.77	0.07	-0.18, 0.33	
	Q3	19.72	-272.49, 315.79	0.19	-0.08, 0.45	
	Q4	91.07	-173.02, 355.80	-0.18	-0.44, 0.08	
Doetinchem	Q1	-36.27	-674.81, 798.07	-0.06	-0.28, 0.16	
	Q2	33.76	-146.03, 261.88	-0.03	-0.27, 0.21	
	Q3	69.45	-108.40, 233.01	0.08	-0.16, 0.32	
	Q4	66.2	58.43, 77.12	-0.48	-0.74, -0.22	*
Kaunas	Q1			-0.16	-1.32, 1.03	
	Q2			1.86	0.67, 3.06	*
	Q3			1.47	0.29, 2.67	*
	Q4			2.04	0.84, 3.26	*

Data on physical activity and surrounding greenness obtained from the PHENOTYPE project, May-Dec 2013
^Barcelona and Kaunas are reporting a linear effect in temperature; Stoke-on-Trent and Doetinchem are reporting a quadratic effects and departure from optimal temperature. Linear effects in Stoke-on-Trent were significant: Q3 1.31 (95% CI 0.45, 2.18), Q4 1.10 (95% CI 0.24, 1.97). Models adjusted for precipitation, windspeed, sky darkness, residential NDVI of 300 m buffer, month, day of week, hour of day, public holiday, gender, age, education, chronic disease, dog ownership, and participant ID (random effect); * $p \leq 0.05$

C3.4 Sensitivity analysis 6: Contact with greenspace for four European cities

City	Contact with Greenspace (% of 100%)	Optimal AT^	95% CI	+/- 10 C from optimal temp	95% CI of Change	Sig.*
Barcelona	0%			1.98	-0.73, 4.77	
	1-99%			-0.06	-4.23, 4.30	
	100%			-1.16	-8.47, 6.74	
Stoke-on-Trent	0%	-0.24	-107.38, 118.42	0.79	-1.13, 2.73	
	1-99%	26.58	-126.78, 160.13	-1.38	-4.50, 1.84	
	100%	14.34	11.31, 20.28	-5.39	-8.56, -2.11	*
Doetinchem	0%	0.69	-119.50, 127.59	-0.91	-2.48, 0.68	
	1-99%	10.86	-6.25, 16.42	1.97	0.25, 3.72	*
	100%	11.29	-13.08, 19.48	-1.58	-3.08, -0.06	*
Kaunas	0%			2.39	0.29, 4.53	*
	1-99%			-0.03	-2.29, 2.29	
	100%			8.43	5.03, 11.95	*

Data on physical activity and surrounding greenness obtained from the PHENOTYPE project, May-Dec 2013

^Barcelona and Kaunas are reporting a linear effect in temperature; Stoke-on-Trent and Doetinchem are reporting a quadratic effects and departure from optimal temperature. Models adjusted for precipitation, windspeed, sky darkness, residential NDVI of 300 m buffer, gender, age group, education, chronic disease, dog ownership, public holiday, month, day of week, hour of day, and random effect of participant ID; * p ≤ 0.05

C3.5 Sensitivity analysis 7: Stratification by employment for four European cities

City	Stratification	Obs.	NDVI Q	Optimal AT^	95% CI	10°C change (%)	95% CI of Change	Sig. *
Barcelona	Employed	1075	Q1			-2.7	-8.46, 3.42	
		1803	Q2			5.96	1.33, 10.80	*
		1517	Q3			3.47	-1.32, 8.48	
		1385	Q4			3.97	-1.01, 9.21	
	Non-employed	1063	Q1			2.35	-4.05, 9.18	
		507	Q2			-0.39	-8.14, 8.01	
		768	Q3			-2.88	-8.81, 3.45	
		860	Q4			-5.08	-11.63, 1.94	
Stoke-on-Trent	Employed	1249	Q1	-0.65	-48.36, 70.62	-0.49	-5.18, 4.42	
		1183	Q2	1.5	-80.65, 96.82	1.23	-2.61, 5.23	
		938	Q3	6.4	-12.44, 11	6.23	0.43, 12.37	*
		1165	Q4	13.62	11.41, 17.22	-8.94	-13.08, -4.60	*
	Non-employed	435	Q1	7.95	-35.79, 49.62	3.09	-1.97, 8.40	
		517	Q2	16.29	-13.23, 54.32	-3.69	-7.99, 0.81	
		678	Q3	23.47	-83.82, 104.65	-0.62	-4.71, 3.64	
		604	Q4	10.5	-66.57, 90.65	0.38	-3.65, 4.58	
Doetinchem	Employed	1183	Q1	-18.36	-227.55, 244.4	-0.54	-2.70, 1.66	
		1214	Q2	35.88	-128.10, 157.29	0.67	-2.16, 3.58	
		1271	Q3	11.07	-26.25, 41.81	1.88	-0.55, 4.37	
		1551	Q4	14.61	10.73, 17.76	-4.16	-6.21, -2.07	*
	Non-employed	988	Q1	-312.87	-220.21, 244.26	-0.08	-3.61, 3.57	
		1062	Q2	16.07	-50.86, 82.53	-0.98	-3.98, 2.11	
		952	Q3	17.54	-16.80, 56.69	2.27	-0.97, 5.61	
		673	Q4	6.75	-38.69, 45.92	3.88	-0.98, 8.97	
Kaunas	Employed	1436	Q1			-6.99	-12.22, -1.45	*
		1144	Q2			-5.3	-10.68, 0.41	
		1197	Q3			-2.94	-8.38, 2.81	
		1286	Q4			-2.04	-7.53, 3.78	
	Non-employed	351	Q1			-0.7	-5.62, 4.48	
		631	Q2			17.2	11.78, 22.87	*
		530	Q3			6.77	1.97, 11.79	*
		572	Q4			8.28	3.04, 13.79	*

Data on physical activity and surrounding greenness obtained from the PHENOTYPE project, May-Dec 2013

^Barcelona and Kaunas are reporting a linear effect in temperature; Stoke-on-Trent and Doetinchem are reporting a quadratic effects and departure from optimal temperature. Models adjusted for precipitation, windspeed, sky darkness, residential NDVI of 300 m buffer, month, day of week, hour of day, public holiday, gender, age, education, chronic disease, dog ownership, and participant ID (random effect); * $p \leq 0.05$

D1. Ethics approval for Study 4 (Chapter 7)

D1.1 Ethics approval for 2016 telephone survey

THE CHINESE UNIVERSITY OF HONG KONG

MEMO

To	:	Prof. CHAN, Ying Yang, Emily The Jockey Club School of Public Health and Primary Care
From	:	Secretary Survey and Behavioural Research Ethics Committee (SBREC)
Tel.	:	3943 9263
Date	:	13 January 2016

<u>Survey and Behavioural Research Ethics</u>

I write to inform you that the Survey and Behavioural Research Ethics Committee has granted approval in principle for you to conduct the surveys or observation of human behaviour by non-clinical means as declared in the application for the following research:

Project Title	:	Does socioeconomic factors have an effect on cold-related health outcomes in sub-tropical city? - The case of Hong Kong
Source of Funding	:	Nil
Reference, if any	:	Nil

Kindly be reminded that you should also obtain approval from other research ethics committees within the University (e.g., Clinical Research Ethics Committee, Animal Research Ethics Committee) if any parts of your research do not fall under the scope of our Committee. Thank you for your attention.

Maisie

Maisie Chow

c.c. Panel Secretary concerned

D1.2 Ethics approval for 2017 telephone survey

THE CHINESE UNIVERSITY OF HONG KONG

MEMO

To : Prof. CHAN, Ying Yang Emily
Collaborating Centre for Oxford University and CUHK for Disaster and Medical Humanitarian Response
The Jockey Club School of Public Health and Primary Care

From : Secretary
Survey and Behavioural Research Ethics Committee (SBREC)

Tel. : 3943 4209

Date : 17 August 2017

Survey and Behavioural Research Ethics

I write to inform you that the Survey and Behavioural Research Ethics Committee has granted approval in principle for you to conduct the surveys or observation of human behaviour by non-clinical means as declared in the application for the following research:

Project Title : Heat, extreme environmental conditions and health survey

Source of Funding : Nil

Reference, if any : Nil

Kindly be reminded that you should also obtain approval from other research ethics committees within the University (e.g., Clinical Research Ethics Committee, Animal Research Ethics Committee) if any parts of your research do not fall under the scope of our Committee. Thank you for your attention.

Alice Hung

c.c. Panel Secretary concerned

D2. 2016 Survey questionnaire (Chinese, selected questions)

寒冷天氣與健康調查問卷 2015 v3.3 　　　**問卷號碼 ☐☐☐☐**

訪問日期: ☐☐年☐☐月☐☐日 　**開始時間:☐☐: ☐☐** 　**被訪者電話:☐☐☐☐ - ☐☐☐☐**

訪問員姓名: ________________ 　覆核結果: ___________

先生 / 女士，你好!
我係 MOV 嘅訪問員，我地依家受香港中文大學公共衛生及基層醫療學院嘅委託，進行緊一項問卷調查，目的想了解民眾對寒冷天氣的認知及其健康影響。請問你屋企依家有幾多位 15 歲或以上嘅人係度呢？____位當中，邊一位係最近過左生日嘅呢？可以請他/ 她聽電話嗎?

你好！我係 MOV 嘅訪問員，我地依家受香港中文大學公共衛生及基層醫療學院嘅委託，進行緊一項問卷調查，目的係想了解寒冷天氣對民眾嘅健康影響以及市民對該議題嘅認知、態度與行為。所收集到的資料可以幫助制定更有效嘅公共衛生政策及醫療服務。**而閣下提供嘅資料會絕對保密**，並且只會作醫學研究用途。（如有任何疑問，可致電 2252-8850 聯絡劉思達先生。）請你放心作答，多謝你的幫忙!

0a) 你願唔願意參加呢項研究?（不必讀出此題，如果被訪問者沒有拒絕參加此次調查，視為"願意"）
1. ☐ 願意 　　2. ☐ 唔願意(訪問結束，謝謝!)

0b) 你願唔願意我地將訪問過程錄音?
1. ☐ 願意 (開始錄音訪問) 　　2. ☐ 唔願意 (繼續訪問, 但不要錄音!)

部分 I：健康狀況及影響

1) 你有無香港居民身份證?
1. ☐有 - 係香港永久居民 →有， 繼續訪問
2. ☐有 - 係香港非永久性居民 （外傭、持工作或讀書簽證）→ 有， 繼續訪問
3. ☐無 →訪問結束，謝謝!

2) 受訪者性別：（如已經聽出對方性別，不需问） 1. ☐男 　2. ☐女

4) 你嘅年齡係？（唔要讀出選項，記錄實際年齡___歲。如果不願意答，嘗試讀出選項）

1.	☐ 15-19	2.	☐ 20-24	3.	☐ 25-29	4.	☐ 30-34
5.	☐ 35-39	6.	☐ 40-44	7.	☐ 45-49	8.	☐ 50-54
9.	☐ 55-59	10.	☐ 60-64	11.	☐ 65-69	12.	☐ ≥70
999.	☐ 拒答(終止訪問)						

5) 你覺得你平時嘅健康狀況係？（請讀出選項）
1. ☐極好 　2. ☐非常好 　3. ☐好 　4. ☐一般 　5. ☐差

6) 一般來講，你覺得你冬季嘅健康狀況比其他季節？（請讀出選項）
1. ☐差好多 　2. ☐較差 　3. ☐差不多 　4. ☐較好 　5. ☐好好多

7) 你有無被診斷為有長期病患（需要至少 6 個月嘅治療）？如有，你有邊類型嘅長期疾病?（不讀出選項，可多選）

1.	☐無長期病患	2.	☐心血管病（包括心臟病）	3.	☐糖尿病	4.	☐高血壓
5.	☐中風	6.	☐腎病	7.	☐肝病	8.	☐精神病
9.	☐呼吸道疾病	10.	☐痛症(關節炎等)	11.	☐癌症	12.	☐眼病
13.	☐腦科	14.	☐婦科	15.	☐腸胃疾病	16.	☐甲狀腺疾病
17.	☐其他______	18.	☐膽固醇高	19.	☐血糖高		
888.	☐唔知道	999.	☐拒答				

8) 由上禮拜四（2016 年 1 月 21 日）到今日，你有無因為寒冷天氣引起以下症狀 （請讀出問題，可多選）

	1	2	888	999
a. 感冒相關				
1. 發燒	☐無	☐有	☐唔知道	☐拒答
2. 流鼻涕	☐無	☐有	☐唔知道	☐拒答
b. 呼吸系統症狀				
3. 氣喘	☐無	☐有	☐唔知道	☐拒答
4. 持續咳嗽	☐無	☐有	☐唔知道	☐拒答
5. 喘鳴（呼吸有聲）	☐無	☐有	☐唔知道	☐拒答
6. 痰多	☐無	☐有	☐唔知道	☐拒答
c. 心血管系統症狀				
7. 胸口痛	☐無	☐有	☐唔知道	☐拒答
8. 心跳不規律	☐無	☐有	☐唔知道	☐拒答
d. 肌肉骨骼疼痛				
9. 頭部及頸部	☐無	☐有	☐唔知道	☐拒答
10. 肩部	☐無	☐有	☐唔知道	☐拒答
11. 手肘及前臂	☐無	☐有	☐唔知道	☐拒答
12. 手腕及手掌	☐無	☐有	☐唔知道	☐拒答
13. 手指	☐無	☐有	☐唔知道	☐拒答
14. 腰部	☐無	☐有	☐唔知道	☐拒答
15. 膝蓋，大腿及小腿	☐無	☐有	☐唔知道	☐拒答
16. 腳腕及腳	☐無	☐有	☐唔知道	☐拒答
e. 消化系統症狀				
17. 腸胃痛	☐無	☐有	☐唔知道	☐拒答
18. 肚痾 （24 小時排便 3 次以上）	☐無	☐有	☐唔知道	☐拒答
19. 嘔吐	☐無	☐有	☐唔知道	☐拒答
f. 其他				
20. 皮膚敏感	☐無	☐有	☐唔知道	☐拒答
21. 濕疹（位移性皮肌炎）	☐無	☐有	☐唔知道	☐拒答
22. 意外受傷	☐無	☐有	☐唔知道	☐拒答

9) 你有無因為頭先你講到嘅任何症狀而需要睇醫生或接受治療？如有，睇過幾次

1. ☐無 →to 14) 2. ☐有，____次 →to 10) 999. ☐拒答 →to 14)

10) 你主要係接受邊種類型治療方法呢? （讀出選項，單選）

1.	☐去急症室	2.	☐睇公立醫生(衛生署同醫管局個 D)	3.	☐睇西醫私家醫生	4.	☐睇中醫
5.	☐自己買西藥食	6.	☐自己買中藥食	7.	其他_______	888.	☐唔知道
999.	☐拒答						

18) 由上禮拜四（2016 年 1 月 21 日）到今日，你以下的情況會係增加/好左或減少/差左? (请讀出問題)

	增加	減少	無影響	唔知道	拒答
a. 外出做運動	1	2	3	888	999
b. 社交活動	1	2	3	888	999
	好左	差左	無影響	唔知道	拒答
c. 胃口	1	2	3	888	999
d. 心情	1	2	3	888	999
e. 睡眠質素	1	2	3	888	999

部分 III：對寒冷天氣與健康的態度

以下問題請你比一個分數，總共 6 分，其中 1 分代表**完全唔同意**，6 分代表分**完全同意**	完全唔同意	---				完全同意	唔知道	拒答
23) 你同唔同意寒冷天氣對你嘅健康有好大影響	1	2	3	4	5	6	888	999
24) 你同唔同意寒冷天氣對健康的影響可以避免	1	2	3	4	5	6	888	999
25) 你同唔同意你有足夠嘅知識去應對寒冷天氣所帶來的健康影響	1	2	3	4	5	6	888	999

部分 IV：寒冷天氣警告

26) 你之前有無聽過"寒冷天氣警告"呢樣嘢呢?

1. ☐無聽過 →to 29)　2. ☐聽過 →to 27)　999. ☐拒答 →to 29)

27) 你知唔知天文台前幾日發佈過"寒冷天氣警告"?

1. ☐唔知　2. ☐知　999. ☐拒答

31) 你知唔知今日市區嘅最低氣溫係?

1. ☐唔知　2. ☐知, ______度(°C)　999. ☐拒答

Appendix D2. (Continued) 2016 Survey questionnaire (Chinese, selected questions)

	32) 你覺得以下邊 D 行為會對應對寒冷天氣有幫助？(讀出問題，可多選)				33) 由上禮拜四（2016 年 1 月 21 日）到依家，你有無做過呢 D 行為呢？			
	唔會	會	唔知道	拒答	無	有	唔知道	拒答
a. 著多 D 衫	1	2	888	999	1	2	888	999
b. 避免長時間置身在寒風中	1	2	888	999	1	2	888	999
c. 使用取暖設備	1	2	888	999	1	2	888	999
d. 保持室內空氣流通	1	2	888	999	1	2	888	999
e. 飲多 D 熱水	1	2	888	999	1	2	888	999
f. 關注獨居長者及長期病患者	1	2	888	999	1	2	888	999
g. 關注小朋友	1	2	888	999	1	2	888	999
h. 關注天氣信息	1	2	888	999	1	2	888	999

部分 V：個人資料

40) 你嘅教育程度係?

1. ☐無接受過正式教育 2. ☐小學 3. ☐初中 4. ☐高中
5. ☐預科 6. ☐文憑 7. ☐高級文憑 8. ☐副學士
9. ☐學士 10. ☐碩士或以上 11. ☐其他(請註明): ________________
888. ☐唔知道 999. ☐拒答

41) 你每月嘅家庭總收入係幾多（港幣）？

1. ☐<$2000 2. ☐$2000-3999 3. ☐$4000-5999 4. ☐$6000-7999
5. ☐$8000-9999 6. ☐$10000-14999 7. ☐$15000-19999 8. ☐$20000-24999
9. ☐$25000-29999 10. ☐$30000-39999 11. ☐>$40000 888. ☐唔知道
999. ☐拒答

42) 你依家係唔係接受緊“綜合社會保障援助”（綜援）？

1. ☐唔係 2. ☐係 999. ☐拒答

43) 你嘅職業係?

1. ☐經理及行政級人員 2. ☐專業人員 3. ☐輔助專業人員
4. ☐文員 5. ☐服務工作及商店銷售人員 6. ☐工藝及有關人員
7. ☐機台及機器操作員及裝配員 8. ☐非技術工人 9. ☐漁農業熟練工人
10. ☐家庭主婦 11. ☐學生 12. ☐失業
13. ☐退休 14. ☐其他(請註明): __________ 888. ☐唔知道
999. ☐拒答

44) 你嘅婚姻狀況係?

1. ☐未婚 2. ☐同居 3. ☐已婚 4. ☐分居 / 離婚
5. ☐喪偶 6. ☐其他(請註明): ________ 999. ☐拒答

45) 你居住係香港邊一區?

1.	☐中西區	2.	☐灣仔	3.	☐東區	4.	☐南區
5.	☐油尖旺	6.	☐深水埗	7.	☐九龍城	8.	☐黃大仙
9.	☐觀塘	10.	☐葵青	11.	☐荃灣	12.	☐屯門
13.	☐元朗	14.	☐北區	15.	☐大埔	16.	☐沙田
17.	☐西貢 (需回答 45a)	18.	☐離島	888.	☐唔知道	999.	☐拒答

45a) (如住在西貢區，請追問) 你係唔係住喺將軍澳? (1. ☐唔係 2. ☐係)

部分 VI 家居情況

46) 你嘅住屋屬於邊種類型?

1.	☐公屋（公營租住房屋）	2.	☐資助自置居所房屋	3.	☐私人大廈/樓宇
4.	☐私人村屋 / 別墅	5.	☐非住宅用房屋	6.	☐臨時房屋
7.	☐其他(請註明): _________	888.	☐唔知道	999.	☐拒答

47) 你住宅租住權屬於邊種類型?

1. ☐自置 (有產權) 2. ☐全租 3. ☐合租/二房東/三房客 4. ☐其他______
888. ☐唔知道 999. ☐拒答

49) 計埋你本人在內，你屋企有幾多人（包括傭人）同你一齊住（一週內至少住四晚）

1. ☐______人 999. ☐拒答

56) 下次天文台再次發佈寒冷天氣警告嗰陣，香港中文大學可能會再打俾你問下你嘅意見，你介唔介意留低你個手提電話方便可以直接聯絡到你呢?

1. ☐ 唔介意 – 記錄電話 ☐☐☐☐ - ☐☐☐☐ 2. ☐ ☐ 唔願意留低手提電話

== 問卷完畢。謝謝! ==

結束時間: ☐☐:☐☐

D3. 2017 Survey questionnaire (Chinese, selected questions)

酷熱天氣與健康調查問卷 2017 v3.0 **問卷號碼 □□□□**

訪問日期: □□年□□月□□日 開始時間:□□: □□ 被訪者電話:□□□□ - □□□□

訪問員姓名: ________________ 覆核結果: __________

先生 / 女士，你好！
我係 MOV 嘅訪問員，我地依家受香港中文大學公共衛生及基層醫療學院嘅委託，進行緊一項跟進電話訪問。你地屋企一位家庭成員（根據資料請讀出受訪家庭成員的性別和年齡）接受了我們一個關於寒冷天氣嘅認知和健康嘅訪問。我們宜家想進行一個跟進訪問，請問可唔可以請呢位家庭成員聽電話？

你好！我係 MOV 嘅訪問員，我地依家受香港中文大學公共衛生及基層醫療學院嘅委託，進行緊一項跟進問卷調查。你收到電話是因為之前曾經接受了我們一個關於寒冷天氣的認知和健康的訪問。首先非常感謝你的參與，而今日我們想進行一項跟進調查，了解炎熱天氣對公眾生活的影響。所收集到的資料可以幫助制定更有效嘅公共衛生政策及醫療服務。而閣下提供嘅資料會絕對保密，只會作醫學研究用途，並不會向第三方作任何用途的資料披露。（如有任何疑問，可致電 2252-8469 聯絡林靖宇博士。）請你放心作答，多謝你的幫忙！

0a) 你願唔願意參加呢項研究?(不必讀出此題, 如果被訪者沒有拒絕參加此次調查, 視為"意")
1. ☐ 願意 2. ☐ 唔願意(訪問結束，謝謝!)

0b) 你願唔願意我地將訪問過程錄音?
1. ☐ 願意 (開始錄音訪問) 2. ☐ 唔願意 (繼續訪問, 但不要錄音!)

1) 受訪者性別：（如已經聽出對方性別，不需问） 1. ☐男 2. ☐女

2) 你嘅年齡係？（唔要讀出選項，記錄實際年齡___歲。如果不願意答，嘗試讀出選項）

1. ☐ 15-19	2. ☐ 20-24	3. ☐ 25-29	4. ☐ 30-34
5. ☐ 35-39	6. ☐ 40-44	7. ☐ 45-49	8. ☐ 50-54
9. ☐ 55-59	10. ☐ 60-64	11. ☐ 65-69	12. ☐ ≥70
999. ☐ 拒答			

3) 你居住係香港邊一區?

1. ☐中西區	2. ☐灣仔	3. ☐東區	4. ☐南區
5. ☐油尖旺	6. ☐深水埗	7. ☐九龍城	8. ☐黃大仙
9. ☐觀塘	10. ☐葵青	11. ☐荃灣	12. ☐屯門
13. ☐元朗	14. ☐北區	15. ☐大埔	16. ☐沙田
17. ☐西貢 (需回答 3a)	18. ☐離島	889. ☐唔知道	999. ☐拒答

3a) (如住在西貢區，請追問) 你係唔係住喺將軍澳?（1. ☐唔係 2. ☐係）

4) 你有無被診斷為有長期病患（需要至少 6 個月嘅治療）？如有，你有邊類型嘅長期疾病?（不讀出選項，可多選）

1.	☐無長期病患	2.	☐心血管病（包括心臟病）	3.	☐糖尿病	4.	☐高血壓
5.	☐中風	6.	☐腎病	7.	☐肝病	8.	☐精神病
9.	☐呼吸道疾病	10.	☐痛症(關節炎等)	11.	☐癌症	12.	☐眼病
13.	☐腦科	14.	☐婦科	15.	☐腸胃疾病	16.	☐甲狀腺疾病
17.	☐其他 ________	18.	☐膽固醇高	19.	☐血糖高		
889.	☐唔知道	999.	☐拒答				

5) 你有無需要長期食藥（包括長期病藥、保健藥、減肥藥）？

1. 無 → 回答 6)　　2. 有→回答 5a)　　999. 拒答 → 回答 6)

5a)喺咩藥？(可選多於一個答案)

1. ☐西藥　2. ☐中藥　3. ☐保健藥（如維他命）　4. ☐美容相關的藥（如減肥藥）　5. ☐其他藥物

888. ☐唔知道　999. ☐拒答

7) 一般來講，你覺得你夏季嘅健康狀況比其他季節？（請讀出選項）

1. 差好多　2. 較差　3. 差不多　4. 較好　5. 好好多

9) 由 2017 年 7 月 28 日(上兩個禮拜五)到今日，你有無以下症狀（請讀出問題，可多選）

	1	2	888	999
a. 流感相關				
23. 發燒	無	有	唔知道	拒答
24. 喉嚨痛	無	有	唔知道	拒答
25. 流鼻水	無	有	唔知道	拒答
26. 肌肉酸痛	無	有	唔知道	拒答
b. 呼吸系統症狀				
27. 氣喘	無	有	唔知道	拒答
28. 持續咳嗽	無	有	唔知道	拒答
29. 喘鳴（呼吸有聲)	無	有	唔知道	拒答
30. 痰多	無	有	唔知道	拒答
c. 心血管系統症狀				
31. 胸口痛	無	有	唔知道	拒答
32. 心跳不規律	無	有	唔知道	拒答
d. 消化系統症狀				
33. 腸胃痛	無	有	唔知道	拒答
34. 肚痾 （24 小時排便 3 次以上）	無	有	唔知道	拒答
35. 嘔吐	無	有	唔知道	拒答
36. 惡心	無	有	唔知道	拒答
e. 手足口病症狀				
37. 口腔潰瘍	無	有	唔知道	拒答
38. 皮疹	無	有	唔知道	拒答

Appendix D3. (Continued) 2017 Survey questionnaire (Chinese, selected questions)

12) 你有無因為頭先你講到嘅任何症狀而需要睇醫生或接受治療？如有，睇過幾次

1. 無 → 回答 12f)　　2. 有→ 回答 12a)-12f)　　999. 拒答 → 回答 12f

16) 由 2017 年 7 月 28 日(上兩個禮拜五)到今日，你以下的情況會係增加/好左或減少/差左？(请讀出問題)

		增加	減少	無影響	唔知道	拒答
f.	外出做運動	1	2	3	888	999
g.	社交活動	1	2	3	888	999
		好左	差左	無影響	唔知道	拒答
h.	胃口	1	2	3	888	999
i.	心情	1	2	3	888	999
j.	睡眠質素	1	2	3	888	999

18) 以下問題請你比一個分數，總共 6 分，其中 1 分代表**<u>完全唔同意</u>**，6 分代表分**<u>完全同意</u>**	完全唔同意---完全同意						唔知道	拒答
a) 你同唔同意酷熱天氣對你嘅健康有好大影響	1	2	3	4	5	6	888	999
b) 你同唔同意酷熱天氣對健康的影響可以避免	1	2	3	4	5	6	888	999
c) 你同唔同意你有足夠嘅知識去應對酷熱天氣所帶來的健康影響	1	2	3	4	5	6	888	999

19) 你有冇留意到天文台喺過去兩星期發出過酷熱天氣警告?

1. 冇→回答 Q20　2. 有→回答 Q19a　888.唔知道→回答 Q20　999.拒答→回答 Q20

23) 你知唔知今日市區嘅最高氣溫係?

1. ☐唔知　　2. ☐知→回答 23a)　　999. ☐拒答

23a) 如知，______度(℃)

	26) 一般而言，當天文台酷熱天氣警告生效時，你認為以下措施有冇效?				**27) 由 2017 年 7 月 28 日(上兩個禮拜五)到今日，你有冇做以下措施?**				
	無	有	唔知道	拒答	無	有	不適用	唔知道	拒答
a) 喺戶外工作或活動時，多加休息和不要過度勞累	1	2	888	999	1	2	3	888	999
b) 於感覺不適時，盡快到陰涼嘅地方休息	1	2	888	999	1	2	3	888	999
c) 使用冷氣	1	2	888	999	1	2	3	888	999
d) 喺冇冷氣的室內時，盡量打開窗戶以保持空氣流通	1	2	888	999	1	2	3	888	999
e) 避免長時間在陽光下曝曬，以免受太陽紫外線曬傷及中暑	1	2	888	999	1	2	3	888	999
f) 穿上鬆身衣服及配戴適當嘅帽和能阻隔紫外線的太陽眼鏡	1	2	888	999	1	2	3	888	999
g) 喺戶外遊玩時，應重複搽防曬系數 15 或以上的太陽油	1	2	888	999	1	2	3	888	999
h) 飲多 D 水	1	2	888	999	1	2	3	888	999
i) 關注獨居長者或慢性病患者	1	2	888	999	1	2	3	888	999
j) 關注小朋友	1	2	888	999	1	2	3	888	999
k) 關注天氣資訊	1	2	888	999	1	2	3	888	999

44) 下次天文台再次發佈天氣警告嗰陣，香港中文大學可能會再打俾你問下你嘅意見，你介唔介意留低你個手提電話方便可以直接聯絡到你呢？（如之前已經比過手提電話號碼則不用問）

1. 唔介意 – 記錄電話 □□□□ - □□□□
2. 唔願意留低手提電話

== 問卷完畢。謝謝! ==

結束時間: □□:□□

Personal Biography & List of publications

Personal Biography

Janice Ying-en Ho, BSc (U.Michigan), PhD Candidate (CUHK), is a PhD candidate in Public Health at the Chinese University of Hong Kong. Previously, she has worked for the Collaborating Centre for Oxford University and CUHK for Disaster & Medical Humanitarian Response (CCOUC), World Resources Institute, and World Green Organisation. She obtained her Bachelor's degree from the University of Michigan with a double major in Environmental Science and Psychology. Her research interests include the health impacts of climate change and vulnerable populations.

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- Teaching Assistant Award (2017/18), The Chinese University of Hong Kong JC School of Public Health and Primary Care (Awarded Nov 20, 2018)
- Travel Scholarship Award, Inaugural Planetary Health GeoHealth Annual Meeting; 29-30 April 2017; Boston, USA.
- Young Investigator Travel Award, 48th Asia-Pacific Consortium for Public Health (APAPCH) conference; 15-19 Sept 2016; Tokyo, Japan.

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- Croucher Summer Course 2017- Research Methodology for Disaster and Medical Humanitarian Response, hosted by Collaborating Centre for Oxford University and CUHK for Disaster and Medical Humanitarian Response; 3 – 7 July, 2017; Hong Kong, China
- Climate Change and Health Research Methods Course hosted by Umea University; 30 May – June 10, 2016; Umea, Sweden