URBAN HEAT AND ENERGY DEMAND: APPLICATION OF AN URBAN METEOROLOGICAL NETWORK

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Abstract

The urban heat island (UHI) effect is an inadvertent modification of climate which leads to increased temperatures in urban areas. This in turn increases localised demand for air conditioning and refrigeration which can be a significant drain on energy resources. At a time of increasing economic, political and environmental concerns with respect to energy policy, security, efficiency and climate change, there is a need to focus efforts to understand energy usage in cities for current and future climates. Using data from an Urban Meteorological Network (UMN) along with a critiqued degree days methodology, this thesis analyses the UHI and estimate current and future cooling demand in Birmingham-UK. From the results it was possible to identify that currently the main factor in energy consumption is income, however when isolating income influence through normalization process it is possible to identify the impact of the UHI. A significant finding was that the distribution of the surface UHI appears to be clearly linked to landuse, whereas for canopy UHI, advective processes appear to play an important role. Analysing T_{air} data available from the UMN the cooling demand for summer 2013 and future climate scenarios were calculated and demonstrated the importance of high resolution air temperature measurements in estimating electricity demand within urban areas.

This PhD is dedicated to Ricardo, Jacqueline and Rogério Antunes de Azevedo.

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Publications arising from thesis

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4. Azevedo, Juliana Antunes, Lee Chapman, and Catherine L. Muller. 2015. "Critique and suggested modifications of the degree days methodology to enable long-term electricity consumption assessments: a case study in Birmingham, UK." Meteorological Applications no. 22 (4):789-796. http://dx.doi.org/10.1002/met.1525.

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Contents

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List of Acronyms

BCC : Birmingham City Council

BNG : British National Grid

BPT : Balance Point Temperature

BUCL : Birmingham Urban Climate Laboratory

CDD : Cooling Degree Days

CDH : Cooling Degree Hours

DECC : Department of Energy and Climate Change

DJF : December, January, February

EVI : Enhanced Vegetation Index

GIS : Geographic Information System

IDW : Inverse Distance Weighted

IoT : Internet of Things

IPCC : Intergovernmental Panel on Climate Change

HDD : Heating Degree Days

JJA : June, July, August

JULES : Joint UK Land Environment Simulator

LSOA : Lower Super Output Area

LST : Land Surface Temperature

MIDAS : Met office Integrated Data Archive System

MODIS : MODerate resolution Imaging Spectroradiometer

MORUSES : Met Office Reading Urban Surface Exchange Scheme

MRT : MODIS Reprojection Tool

MSOA : Medium Super Output Area

NDVI : Normalized Difference Vegetation Index

ONS : Office for National Statistics

PET : Physiologically Equivalent Temperature

SVF : Sky View Factor

SOA : Super Output Area

T_{air} : Air Temperature

UHI : Urban Heat Island

$UHI_{boundary}$: Boundary Urban Heat Island

UHI_{canopy} : Canopy Urban Heat Island

$UHI_{surface}$: Surface Urban Heat Island

UK : United Kingdom

UKCP09 : United Kingdom Climate Projections 2009

UKMO : United Kingdom Meteorological Office

UMN : Urban Meteorological Network

UTM : Universal Transverse Mercator

VGI : Volunteered Geographic Information

WRF : Weather Research and Forecasting Model

Chapter 1

Introduction

1.1. Energy demand

Cities are concentrations of population and infrastructure, both of which demand high levels of energy usage. Energy demand in the world is broadly expected to increase in line with population growth (Pérez-Lombard *et al*., 2008; Pasten and Santamarina, 2012; Vassileva *et al*., 2012), leading to a time of increasing economic, political and environmental concerns with respect to energy policy, security and efficiency.

The weather impacts virtually every segment of the energy sector (e.g., infrastructure: McEvoy *et al*., 2012; Vine, 2012; Ward, 2013; demand: Papakostas *et al*., 2010; Golombek *et al*., 2012; Vine, 2012; Savić *et al*., 2014; Zhang *et al*., 2014b; Jovanović *et al*., 2015; generation: Golombek *et al*., 2012; McEvoy *et al*., 2012; Vine, 2012). However, of particular relevance with respect to climate change are the projected increases in air temperature (T_{air}) which could lead to significant changes in energy consumption. The annual relationship between energy demand and T_{air} is well established (Hekkenberg *et al*., 2009), with peaks in energy demand occurring over both summer and winter, explained by the increased use of cooling appliances and space heating, respectively. Hence, it is expected that higher temperatures, caused by climate change, will decrease energy demand over winter but increase demand over summer (Papakostas *et al*., 2010; Golombek *et al*., 2012; Jovanović *et al*., 2015). For example, in California, USA, there is already a demonstrable increase in demand for air conditioning as a result of increasing temperatures, and with more frequent and severe heatwaves there is a possibility that the increased cooling demand in summer may outweigh heating reductions (Vine, 2012).

The International Panel on Climate Change (IPCC) has highlighted some of the major climate events to be observed in the future, which will at some level impact directly on the energy sector, such as the decrease in number of cold days and increase in number of warm days and heatwave events over Europe (Stocker *et al*., 2013).

1.2. The urban heat island

The Urban Heat Island (UHI) is a widely researched phenomenon concerning the difference in temperature between an urban area and the rural surroundings of a conurbation.

A range of factors contribute to the occurrence of the UHI; increased emissions of anthropogenic heat flux, changes to urban geometry and the replacement of vegetation cover by construction material (e.g., asphalt and concrete) - all of which directly change surface albedo, emissivity and evapotranspiration (Oke, 1987), altering the energy balance in urban areas.

Energy balance is determined by solar gains (absorbed and transformed into sensible heat) and heat loss (emitted via longwave radiation). In urban areas the urban geometry relates to the availability of sunlight (solar energy gains) on building facades. The incident solar energy on urban structures (wall, ground and roofs) is absorbed and transformed into sensible heat resulting in surface temperatures several degrees higher than the air temperature. The urban structure emits long wave radiation to the sky after sunset; as the heat absorbed during the day is released, air temperature increases. The heat loss is slower in urban areas due to its different properties (asphalt, concrete, replacement of vegetation cover, and others as mentioned above) compared to rural areas (usually very vegetated), the net balance is positive when compared to the surrounding rural area, resulting in elevated air temperatures after sunset.

The overall result is that cities are generally warmer than their rural surroundings, being common to find urban–rural temperature differences in excess of 5-10 °C under 'ideal' conditions (e.g., clear skies and light winds) for large conurbations as London, UK, and Paris, France (Chandler, 1965; Wilby, 2003; Bohnenstengel *et al*., 2011; Lac *et al.*, 2013), and 1 °C for small conurbations as Ljutomer, Slovenia (Ivajnšič *et al*., 2014).

Studies into the UHI can be largely subdivided into three different types: the surface UHI ($UHI_{surface}$), the canopy UHI (UHI_{canopy}) and the boundary layer UHI ($UHI_{boundary}$) (Oke, 1995; Arnfield, 2003). The urban canopy is the thin layer of the atmosphere between ground level and roof top height and is strongly influenced by urban geometry and microscale energy exchange. The layer is just beneath the urban boundary layer (Oke, 1995) located above roof level and whose characteristics are affected by both mesoscale processes (i.e., prevailing wind) and the microscale processes below (Oke, 1987). T_{air} is the key parameter to measure for UHI_{canopy} and $UHI_{boundary}$ whereas land surface temperature (LST: often derived from satellites) is the parameter reported for $UHI_{surface}$. LST modulates the air temperature of lower layers, impacting on energy exchanges between the surface and air and therefore influences thermal comfort in the canopy layer as well as the internal climate of buildings (Voogt and Oke, 2003).

The UHI_{canopy} is usually measured by station pairs (e.g., Wilby, 2003) or the use of transects (e.g., Smith *et al*., 2011). Techniques for measuring the $UHI_{boundary}$ include the use of tethered balloons, radiosondes or ground based remote sensing techniques (Barlow, 2014). Thermal remote sensing is the traditional way to measure LST (Dousset, 1989; Roth *et al*., 1989; Weng *et al*., 2004; Yuan and Bauer, 2007; Dousset *et al*., 2011a; Keramitsoglou *et al*., 2011; Schwarz *et al*., 2011; Smith *et al*., 2011; Tomlinson *et al*., 2012a). A range of models can also be applied to estimate temperature variations in an urban area, such as the Weather Research and Forecasting model (WRF) (Heaviside *et al*., 2015), Joint UK Land Environment Simulator (JULES) (Bassett *et al*., 2015), and the Met Office Reading Urban Surface Exchange Scheme (MORUSES) (Bohnenstengel *et al*., 2011).

The UHI can impact many aspects of everyday life, such as critical infrastructure, health (Tomlinson *et al*., 2011) and energy consumption (Santamouris *et al*., 2001), with impacts becoming exacerbated under heat wave events. The study of the 2003 heatwave in Paris indicated that, at night-time, a surface temperature increase of ~ 0.5 °C could double the risk of elderly mortality (Dousset *et al*., 2011b). Such events provide an indication of the increased impacts of the UHI in the increasingly warming climate projected to be experienced over the next few decades. Furthermore, the ever-increasing number of people in urban areas will not only further contribute to the exacerbation of the UHI effect, but will also increase the number of people exposed to its potential risks (Smith *et al*., 2011).

The UHI has a direct impact on energy consumption, particularly in the warmer core of the city (Taha *et al.*, 1988; Hassid *et al.*, 2000; Akbari *et al.*, 2001; Kolokotroni *et al.*, 2010). For example, in centrally located buildings in Athens, Greece, where the average UHI can exceed 10 °C, cooling loads can double in summer, whereas winter period heating loads can decrease by 30% (Santamouris *et al*., 2001). By not considering the UHI, energy consumption and peak power could be significantly underestimated (Hassid *et al*., 2000); and under climate change scenarios energy consumption due to the UHI effect could increase even more.

It is very common the use of vegetation and light coloured materials in mitigation and adaptation strategies to decrease urban temperatures.

Urban vegetation (trees and green spaces) influences directly and indirectly the local temperature by evapotranspiration and shadowing, and therefore may contribute to important energy savings (Santamouris, 2001).

Use of high albedo material (light coloured and white coated) reduces the amount of solar radiation absorbed by the buildings envelope (due to its high reflectivity) and keeps their surfaces cooler (Santamouris, 2001). By increasing albedo surface temperature decreases and so does the air temperature as the heat convection intensity from a cooler surface is lower (Syneffa *et al*., 2008).

UHI studies evaluating its temporal variations and magnitude show that the implementation of high albedo strategies decreases the UHI intensity by 1–2 °C on average, indicating that adopting large-scale high albedo measures by using building materials with high solar reflectance can significantly reduce ambient temperatures (Syneffa *et al*., 2008). Such temperatures reductions can have significant impacts on consumption of cooling energy in urban areas (Santamouris, 2001).

1.3. Income

Residential energy demand is not only dependent on climatic factors. There is a close relationship between energy consumption and economic development (i.e., the improvement of living conditions in emerging regions, Lombard-Perez *et al*., 2008). Households in developed countries use more energy than those in emerging economies and it is expected to continue growing due to the proliferation of new appliances and air conditioning (Lombard-Perez *et al*., 2008). Indeed, air conditioning is now common in many developed countries but remains rare in most of the developing world where penetration is limited by both the cost of appliances and energy (Sivak, 2009). However, the proliferation of air conditioning is becoming a major concern in the residential sector of developing countries, as income increases so does the potential to buy air conditioning (Ghisi *et al*., 2007). In general, increasing levels of income will lead to larger numbers of new appliances and not only air conditioning and fans (e.g., television equipment and set-top boxes, personal computing equipment and related peripherals, proliferating charging devices) (Hojjati *et al*., 2012; Vassileva *et al*., 2012).

Allied to increase in income residential energy demand in the world is broadly expected to increase in line with population growth (Lombard-Perez *et al*., 2008; Pasten *et al*., 2012; Vassileva *et al*., 2012), which will bring to an increasing demand for buildings services (Lombard-Perez *et al*., 2008), improved thermal comfort levels (Lombard-Perez *et al*., 2008; Vassileva *et al*., 2012), once again further penetration of air conditioning, advances in electric heat pump technology (Hojjati *et al*., 2012) and other devices.

There are health threats related to the lack of access to affordable energy, by inadequate supply of energy for other basic domestic needs (food storage and cooking, maintenance of personal and domestic hygiene, and artificial lighting) (Ormandy *et al*., 2012). Another issue that relates income and energy access is the fuel poverty issue. Fuel poverty is defined as when a family needs to expend more than 10% of its income to maintain adequate heating, and it is a result of low income, high fuel prices and poor energy efficiency. Some studies have attributed poor health and excess mortality to low standards of energy efficiency (Santamouris *et al*., 2007).

1.4. Research hypothesis

As pointed out the weather impacts on every segment of the energy sector. The UHI impacts on many aspects of everyday life such as energy consumption, and therefore should be carefully analysed and investigated when energy demand in cities is being discussed.

This thesis working hypothesis is that there is already an impact on electricity consumption in Birmingham due to the UHI effect and such impact will increase in face of climate change scenarios.

The working hypothesis of the second Chapter is that there is already an impact on electricity consumption due to the UHI, however there are other variables that reflect on consumption such as vegetation and income, and therefore these need to be analysed as well, in a preliminary investigation, to identify which variable is most relevant.

The working hypothesis of the third Chapter is based on investigating the differences between the surface UHI and canopy UHI in Birmingham. The working hypothesis of the fourth Chapter is based on investigating the most common method to estimate energy demand based on air temperature.

Finally the working hypothesis of the fifth Chapter is that in face of climate change scenarios the impact on electricity consumption in Birmingham will increase even more, and possibly the current impact observed in the city core due to the UHI, will be observed in the entire city, and in the city core will increase even more.

This thesis uses Birmingham the second largest city in the UK, as a case study. It has an estimated population of over 1 million people (BCC, 2014), and is located in the West Midlands county (Figure 1.1.). The reason for choosing Birmingham is related to the fact that it has a high resolution Urban Meteorological Network (UMN). Such networks enable atmospheric parameters to be observed at both high temporal and spatial resolutions (Chapman *et al*., 2014). Variables monitored by UMNs can include wind speed and direction, humidity, T_{air} and others, depending on the network objective (Muller *et al*., 2013a; b). Since this network provides high resolution spatial and temporal data, it is possible to quantify the Birmingham UHI at an unprecedented spatial scale, and investigate the UHI influence on energy consumption.

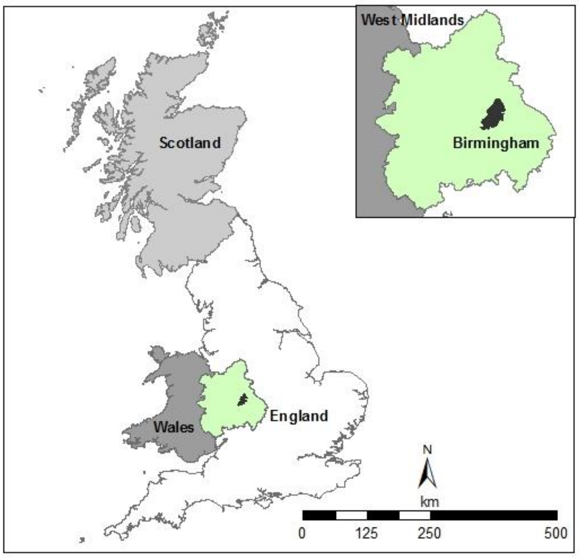

Figure 1.1. Location of Birmingham, UK.

1.5. Aim and objectives

Based on the working hypothesis the overall aim of this thesis is to investigate the impact of the UHI on current and future cooling demand, using high resolution data from an UMN and climate change scenarios.

The thesis is divided into several specific objectives to achieve its overall aim.

- Assess the relationship between income, $UHI_{surface}$, vegetation and residential electricity consumption in Birmingham for 2006, a year that was warmer than average, identifying which currently is the most relevant variable and the present influence of the UHI on residential electricity consumption.

- Using data from a high resolution UMN, quantify and compare the spatial pattern of the daytime and night-time UHI, under a range of stability classes, for both $UHI_{surface}$ and UHI_{canopy}.
- Review and critique existing energy consumption methodologies for producing city scale estimates.
- Using T_{air} data available from an UMN estimate current and future variations of cooling demand at the neighbourhood scale.

1.6. Thesis structure

This Chapter has given an overview of the topics covered in this thesis, and its general aim and objectives. Each Chapter will cover one of the specific objectives (Chapters 2-5). Due to the range of methods used, this thesis does not have traditional Literature Review and Methodology Chapters, but has instead included relevant Literature and Methodology within each of the main Chapters (Chapter 2-5). Chapter 6 concludes the thesis highlighting the contributions made in each chapter and how it fulfils the thesis objectives; it also provides the critique of the thesis. Figure 1.2. provides a framework for this thesis.

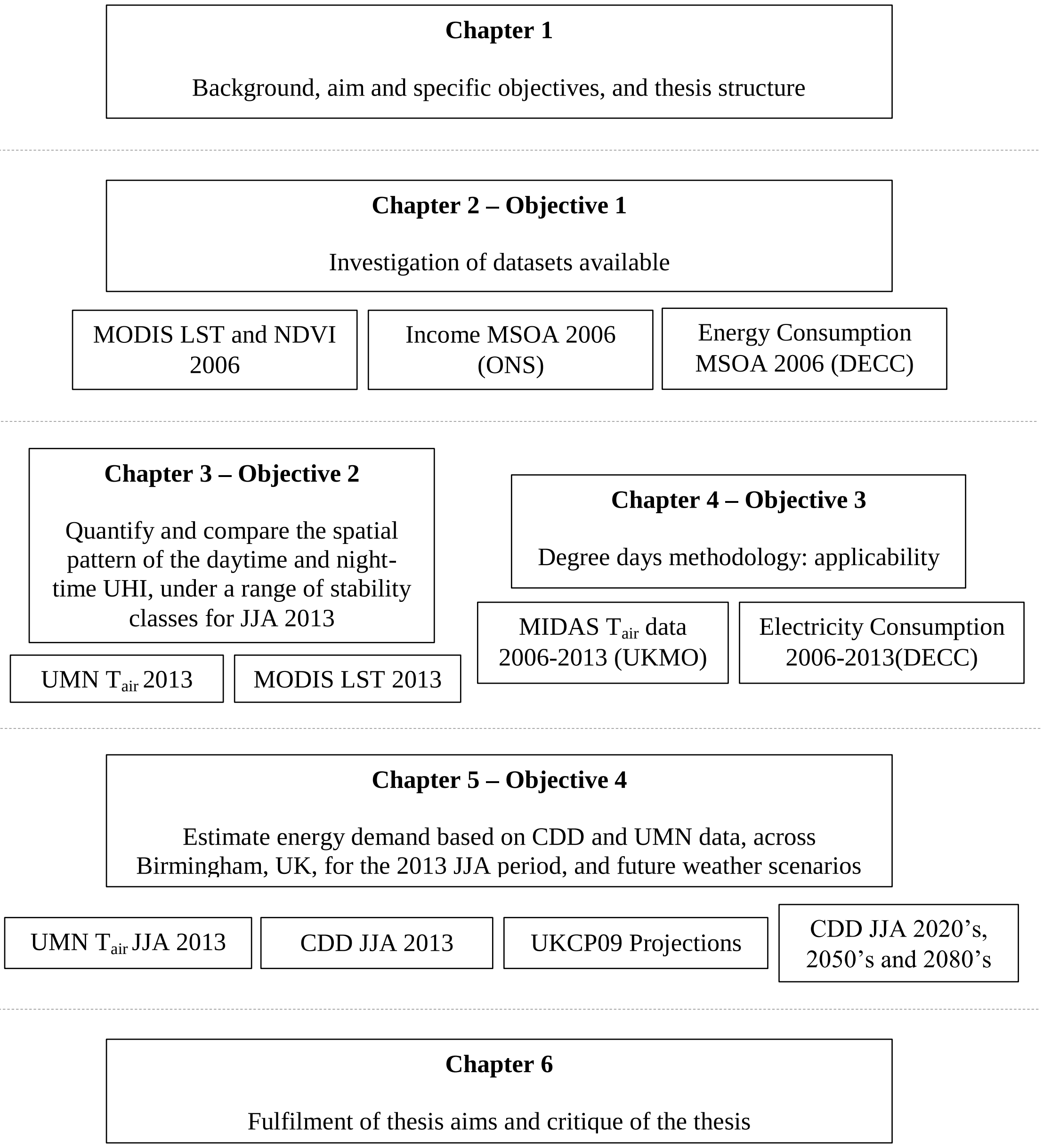

Figure 1.2. Thesis framework divided in Chapters.

Chapter 2

Urban heat and residential electricity consumption: A preliminary study

2.1. Introduction

Energy demand in urban areas is an important facet of energy supply planning. In particular, increasing energy consumption by the residential sector is an issue that could endanger broader economic development since in itself it does not generate wealth and could limit the amount of energy available for other productive sectors (Pereira and Assis, 2013). The electricity consumption by sectors in the UK can be observed in Figure 2.1., which shows that domestic consumption has maintained itself as the larger consuming sector almost throughout the whole period from 1965 to 2013.

Figure 2.1. Total electricity consumption in the UK by sector and year (1965-2013). Others: Public administration, transport, agricultural and commercial sectors (DECC, 2014).

Residential electricity consumption is a complex social and technical issue determined by a combination of physical, demographical and behavioural characteristics of the household inhabitants (Kelly, 2011). Household size, income, building design characteristics and local climatic conditions are all key factors in determining residential energy consumption (Santamouris *et al.*, 2007), as well as, number of occupants, floor area and household efficiency (Kelly, 2011). Generally, small households need less energy due to a reduced transfer area, but they also have lower occupancy, and therefore, fewer appliances when compared with larger households (Pérez-Lombard *et al*., 2008). Similarly, household income is an important factor, with a strong correlation evident between daily electricity consumption and earnings (Ghisi *et al.*, 2007). This pattern is evident spatially, where areas with higher average per capita income consume considerably more energy; a direct result of the relationship between energy consumption and the purchasing power of families (Pereira and Assis, 2013). With increasing levels of income it is expected an increase in ownership of appliances (Hojjati and Wade, 2012; Vassileva *et al*., 2012), as well as for the fact that items, such as air conditioning, are no longer being seen as a luxury item (De Cian *et al*., 2012).

With respect to climatic factors, the UHI is a potentially important localised phenomenon to take into account when assessing consumption in cities. As described in Chapter 1, the UHI is described as the difference in temperature between an urban area and the surrounding rural area of the conurbation; mainly caused by anthropogenic changes to the environment with a range of factors contributing such as urban geometry, density / population of a conurbation, replacement of vegetation cover by construction material (e.g., asphalt and concrete), changing surface's albedo and emissivity thus reducing evapotranspiration and increased emissions of anthropogenic heat (Oke, 1987).

As highlighted in Chapter 1, thermal remote sensing is one of the most popular techniques used for the evaluation of UHI (Dousset, 1989; Roth *et al*., 1989; Weng *et al*., 2004; Yuan and Bauer, 2007; Dousset *et al*., 2011a; Keramitsoglou *et al*., 2011; Schwarz *et al*., 2011; Smith *et al*., 2011; Tomlinson *et al*., 2012a). The main advantage is that remote sensing provides a consistent, repeatable methodology for the end-user, wide spatial coverage and data availability (Tomlinson *et al*., 2011). However, thermal remote sensing observes LST which restricts studies to the $UHI_{surface}$. Although LST plays a major role in urban climatological processes, it can only provide an indication of air temperatures. Furthermore, remote sensing is not ideal to evaluate the UHI in small cities, since the spatial resolution of the sensor can often be coarse (Ivajnšič *et al*., 2014).

Green spaces are a widely adopted strategy to mitigate UHI intensity (Lambert-Habib *et al*., 2013) since they reduce urban temperatures thorough evapotranspiration and shadowing. In modelling experiments carried out for Manchester, UK, it was found that a 5% increase in mature deciduous trees can reduce average hourly surface temperatures by 1 °C during summer (Skelhorn *et al*., 2014). For example, the highest cooling loads in Athens are seen in the western area of the city where there is limited green space (Santamouris *et al*., 2001). In Manchester, it is proposed that if all vegetation was replaced with asphalt, then air temperature would increase by up to 3.2 °C (Skelhorn *et al*., 2014). Similarly, it was found in the USA that for an increase of 25% of tree cover in urban areas can result in a 40% annual residential cooling energy savings in Sacramento and 25% in Phoenix and Lake Charles (Huang *et al*., 1987).

Vegetation abundance is an influential factor in the UHI (Weng *et al.*, 2004) and the Normalized Differenced Vegetation Index (NDVI) is often used to approximate vegetation abundance. The connection between NDVI and LST has been well established in studies, and a negative relationship between NDVI and LST has been shown and proven to be seasonally variable (e.g., Yuan and Bauer, 2007). Other studies have included energy consumption data in the analysis (Akbari *et al*., 2001; Huang *et al*., 1987), but no study has yet investigated all these factors along with income and socioeconomic data at the same temporal and spatial resolution.

This Chapter aims to assess the relationship between income, $UHI_{surface}$, vegetation and residential electricity consumption in Birmingham for 2006, a year that was warmer than average, identifying which currently is the most relevant variable and the present influence of the UHI on residential electricity consumption. It focuses on simple and repeatable steps, based on freely available datasets, so that the methodology can be reproduced for other years and regions in the UK. The results could be used to inform current residential electricity consumption modelling due to the impact of the UHI effect, vegetation and income.

2.2. Methodology, datasets and analysis

2.2.1. Study area

Birmingham is a post-industrial city with distinct range of land use (e.g., the central business district, eastern industrial areas with the majority of residential areas straddling this belt of commerce and industry to the north and south) (Figure 2.2.). Some large parks can be found closer to the higher income neighbourhoods (Figure 2.3.). Altitude varies less than 100 m across the urban area. The Lickey Hills, in the southwest corner of the city (Figure 2.3.), provides the local highpoint and is the only notable topographical feature (297 m), which could exert a noticeable climate influence with respect to surface temperature lapse rates (Minder *et al*., 2010).

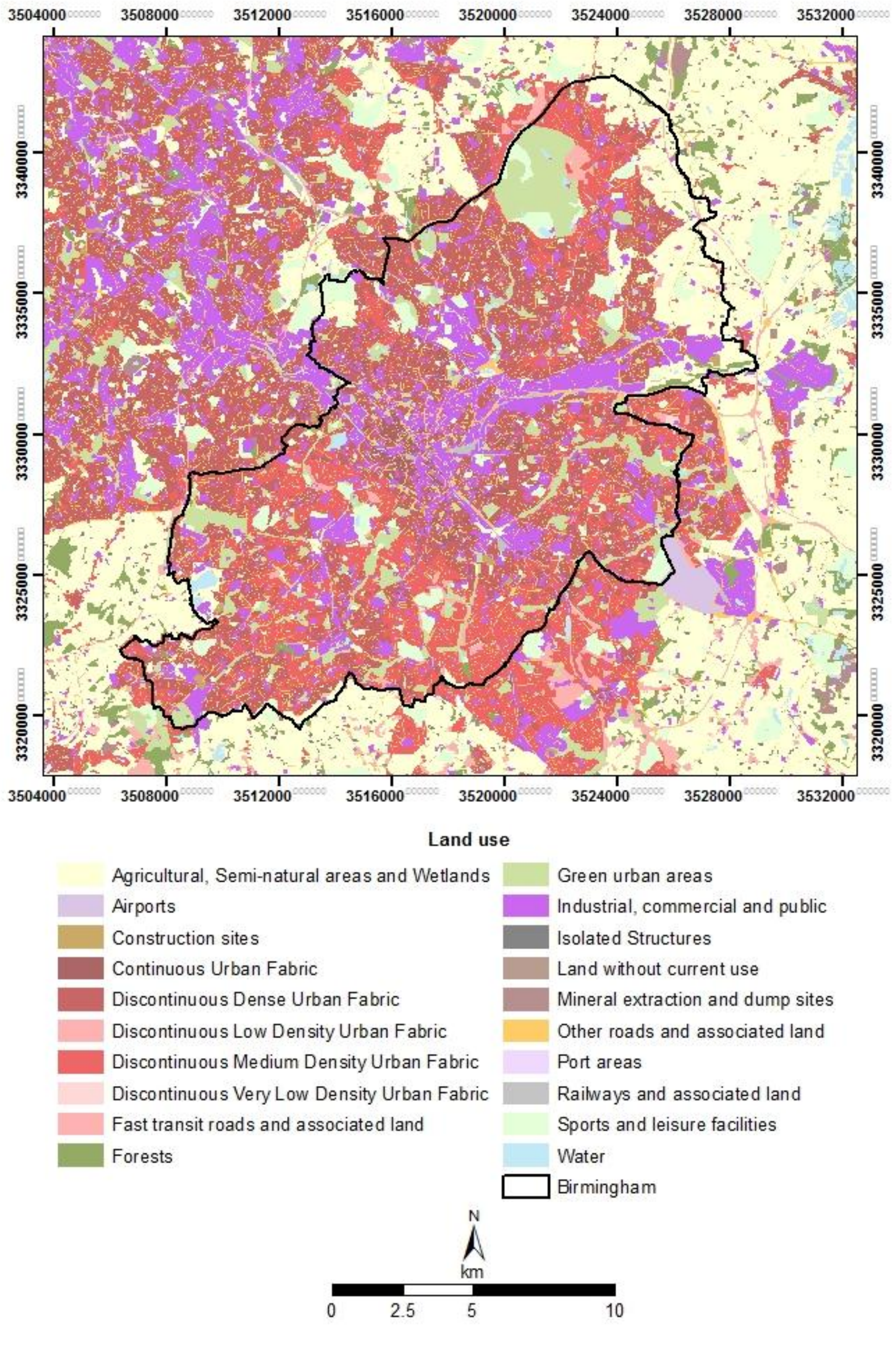

Figure 2.2. Land use classes in Birmingham (EEA, 2010).

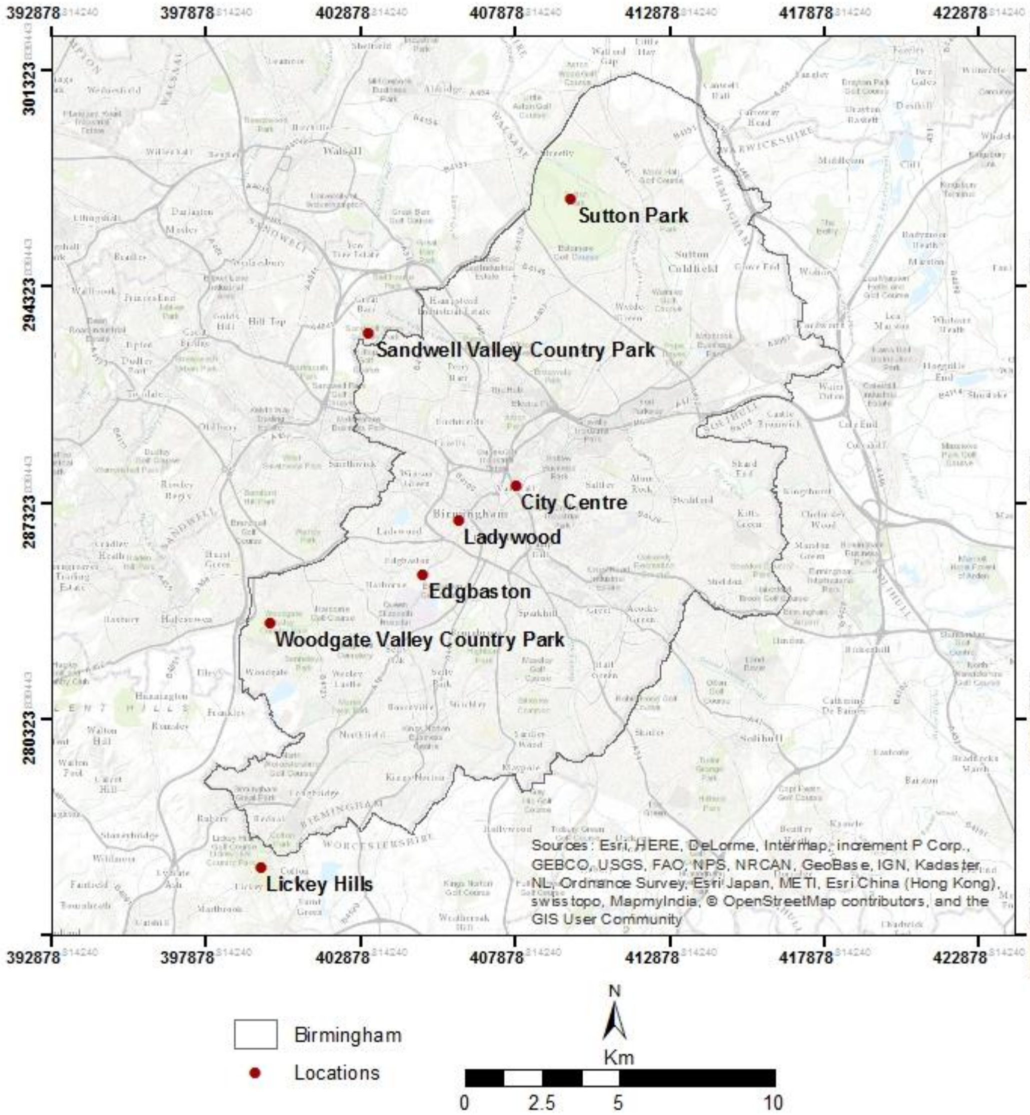

Figure 2.3. Birmingham locations mentioned in the text.

A number of studies have previously investigated the Birmingham UHI. Using night-time MODIS imagery for the summer of 2003-2009, it was identified that in periods of high atmospheric stability, the intensity of $UHI_{surface}$ in Birmingham can reach up to 5 °C (Tomlinson *et al.*, 2012a). The cooling effect of green areas in Birmingham was also evident in this study, with notable cold spots in Sutton Park, Woodgate Valley and the Lickey Hills (Figure 2.3.). A significant LST gradient was observed extending northwards from the city centre to Sutton Park (~ distance of 10 km) where temperatures can be 7-8 °C cooler than the urban core under heatwave conditions (Tomlinson *et al*., 2013). A further study investigated both the UHI_{canopy} (via station pairs) and MODIS $UHI_{surface}$ of Birmingham in relation to Lamb Weather Types and identified that the strongest mean and maximum UHI_{canopy} and $UHI_{surface}$ were during 'ideal' anticyclonic conditions, reaching 7 °C and 4 °C, respectively (Zhang *et al*., 2014a). Modelling approaches have also been used in the city with JULES showing a UHI_{canopy} of 4 °C under stable conditions (Bassett *et al*., 2015) whereas the higher resolution WRF model, complete with an urban canopy scheme, highlighted a maximum intensity of 5.6 °C (Heaviside *et al*., 2015).

Using the baseline of 1961-1990 (Table 2.1), the year of 2006 was in general dry and warm. January was the driest January since 1997; February and March had mean temperature below average; from the last week of March temperatures and sunshine were above average; June was dry and had temperatures 1-2 ºC above average, followed by an exceptionally warm July (warmest July since 1914 using areal series), sunshine was also above average. August, September, October and November were as well exceptionally warm and with sunshine above average, which characterized the year of 2006 by having the warmest summer since the heat wave of 2003 and the warmest autumn (using 1914 areal series) with the sunniest November in history, followed by a December with above average temperatures, rainfall and sunshine, which confirmed 2006 as the warmest year on record for most of the UK using 1914 areal series.

Table 2.1. 2006 Summary - Regional values compared with 1961 to 1990 averages * (UKMO, 2006)

(Act=Actual, Anom=Anomaly)

Region	Max temp		Min temp		Mean temp		Sunshine		Rainfall		Days rain ≥1 mm		Days air frost	
	Act	Anom	Act	Anom	Act	Anom	Act	Anom	Act	Anom	Act	Anom	Act	Anom
	°C	°C	°C	°C	°C	°C	hours	%	mm	%	days	days	days	days
UK	13.38	1.53	6.11	1.3	9.73	1.41	1495.6	112	1179.2	107	155.3	1.3	47.8	-13
England	14.42	1.62	6.81	1.45	10.61	1.54	1626	113	846.7	102	132.3	0.6	43.4	-11.7
Midlands	14.42	1.71	6.68	1.54	10.55	1.63	1579.9	114	795.7	103	132.1	1.4	45	-13.2

*Regional values use the latest available data from the UK climate network observing stations

2.2.2. Electricity consumption and income data

Ordinary residential electricity consumption data and income model based estimates are available from the UK Department of Energy and Climate Change (DECC) and the UK Office for National Statistics (ONS), respectively. Both datasets are aggregated into Super Output Areas (SOAs), a standard unit used in the UK to report areal statistics (although any areal statistic unit is viable to reproduce the work elsewhere). SOAs do not have consistent physical size, but are instead based on established ranges of population and households for Census purposes (Table 2.2 – ONS, 2011a). Income data are not available for the Lower Level (LSOA), hence Middle Level (MSOA) is the universal unit considered for this study. In 2006 there were 131 MSOAs in Birmingham, in 2011 this number increased to 132, due to number of people and households increasing over the established ranges.

Table 2.2. Ranges of lower and middle Super Output Areas (ONS, 2011a)

Geography	Minimum population	Maximum population	Minimum number of households	Maximum number of households
LSOA	1,000	3,000	400	1,200
MSOA	5,000	15,000	2,000	6,000

The fact that SOAs do not have a consistent physical size can raise questions regarding the stability of the estimates. Indeed, the spatial aggregation processing of geographical units has been extensively reviewed, and a number of different techniques are available to overcome bias (Jacobs-Crisioni *et al.*, 2014). For example, Bayes adjustment (Assunção *et al.*, 2005) is a possible means to overcome the problems related to the demographic data, however the approach would not be applicable to the other data used in this study. Furthermore, the stability of the unit areas from one Census to the next is a known problem when using Census units (Fotheringham and Wong, 1991). Despite these concerns, such units continue to be used in scientific studies and remain effective for spatial risk assessments being applicable to both the scale and preliminary focus of the research (Tomlinson *et al*., 2011; Pereira and Assis, 2013).

Three types of electricity data are available from DECC (DECC, 2013) recorded as total consumed over a year; Economy 7, Ordinary electricity consumption and Total electricity consumption (Figure 2.4.). Economy 7 is a cheaper tariff (NB: this tariff is unique to the UK, other countries might or might not have similar alternatives), which offers the opportunity for users to concentrate their usage during a 7 hour period at night (for example, the charging of night storage heaters) 22% of domestic electricity consumption is consumed under this tariff, where as ordinary consumption is the reminder of other tariffs and refers to 78% of domestic consumption. Total electricity consumption is simply the combination of the two. This Chapter considers only ordinary energy consumption data as Economy 7 has a tendency to be used independently of weather as it lacks the ‘controllability’ of other tariffs – i.e., a ‘set point’ where users turn on heating and cooling systems.

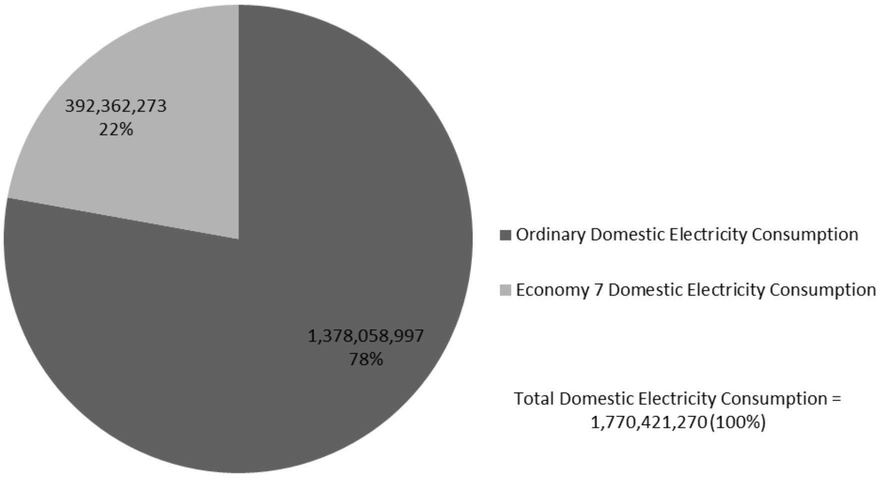

Figure 2.4. 2006 Domestic electricity consumption in Birmingham, divided by Economy 7 (22%) and Ordinary (78%) (remaining tariffs), Total consumption is the added up total of both (DECC, 2006).

For the analysis, MSOA consumption data for 2006 were used normalized by the number of households. Firstly, a simple normalization through division was performed indicating the average consumption (the total ordinary consumption by MSOA) by household (number of households by MSOA). Secondly, MSOA consumption by household was normalized by the household income.

With respect to income data, the ONS income estimate model has a 95% confidence level and estimates households average weekly income. Model based income estimates per MSOA for 2007/2008 were used (the closest to 2006 - other releases are 2001/2002, 2004/2005, and 2011/2012) (ONS, 2011b).

2.2.3. LST data

Satellite data, from 2006, were aggregated to produce an annual summary. LSTs were analysed for both daytime and night-time for cloudless conditions to evaluate general UHI pattern for the year. Absolute temperatures values were used and considered to be more appropriate than residual temperatures for the analyses in this Chapter.

LST data were acquired from MODIS, which is deployed on board both the Terra and Aqua satellites. Birmingham overpass times for Terra are ~ 10:30 and ~ 22:30 whereas Aqua is between ~ 13:30 and ~ 01:30. During the British summer, sunset is between 20:00 and 22:00, with the maximum UHI being present ~ 3–5 h after sunset (Oke, 1987), making Aqua the ideal choice for analysis. Likewise, with respect to daytime observations, the Aqua satellite overpass at 13:30 should also provide a good reference since solar irradiance at the time is high (although it is accepted that this is not the time of maximum LST). MODIS was selected over other platforms for its temporal resolution, which greatly increases image availability for the analyses. Landsat TM offers a higher spatial resolution (Landsat 7 thermal band is collected at 60 m but resampled to 30 m) (USGS, 2010), but the 16 days temporal resolution is prohibitive.

The freely available product MYD11A1 (V5)-MODIS/Aqua Land Surface Temperature and Emissivity Daily L3 1km Grid SIN (USGS, 2013) was used. This product uses split window algorithms to correct for atmospheric effects for water vapour (gaseous absorption) and aerosols effects (aerosol scattering) (LPDAAC, 2015a; detailed algorithm can be found in Vermote *et al*., 1997) and surface emissivity (Tomlinson *et al*., 2012a). Such data have been used in previous studies in Birmingham

(Tomlinson *et al*., 2012a). However, care needs to be taken during interpretation due to the split window technique that works well over homogeneous surfaces, but is not applicable to spatially variable urban surfaces.

The MODIS Reprojection Tool (MRT) (LPDAAC, 2014) was used to convert images to GeoTIFF format at UTM (Universal Transverse Mercator), and subsequently converted to British National Grid (BNG) in ArcGIS (MODIS products are released in Sinusoidal Projection). For the night-time analysis, 45 cloud free images were available and for daytime, 27 images were retained (Tables 2.3 and 2.4). In both cases the largest amount of images available were during summer and autumn, where for night-time there was 8 winter images, 8 spring images, 17 summer images and 12 autumn images; and for daytime there was 1 winter image, 3 spring images,16 summer images and 7 autumn images. This is because of the more stable weather conditions on those seasons with decreasing cloud clover. Data averaging and quality control was then conducted in ArcGIS, where the final 100% cloud free images were selected, before being converted from Kelvin to Celsius, and clipped to the study area. The result was one averaged image for daytime LST (Figure 2.5.a) and one for night-time LST (Figure 2.5.b).

Table 2.3. Forty five available night-time MODIS images for LST, Maximum, Minimum and Mean Pixel Temperature Value for Birmingham

Date	Julian Date	Maximum Pixel Value (ºC)	Minimum Pixel Value (ºC)	Mean Pixel Value (ºC)
21 January 2006	21	3.61	0.85	2.53
22 January 2006	22	-0.69	-2.97	-2.0
26 January 2006	26	1.05	-1.67	-0.11
10 February 2006	41	-2.01	-4.77	-2.96
19 February 2006	50	0.31	-2.27	-0.95
1 March 2006	60	-2.11	-5.07	-3.34
4 March 2006	63	-3.59	-5.83	-4.44
5 April 2006	95	-1.23	-3.67	-2.41

10 April 2006	100	-0.11	-2.89	-0.94
26 April 2006	116	6.93	4.31	5.90
10 May 2006	130	9.25	7.23	8.39
11 May 2006	131	8.75	4.47	7.55
12 May 2006	132	9.99	7.05	8.71
2 June 2006	153	9.57	6.61	8.76
3 June 2006	154	10.61	6.57	9.24
5 June 2006	156	11.61	7.77	10.51
9 June 2006	160	14.43	8.93	11.90
10 June 2006	161	14.79	10.33	13.35
13 June 2006	164	11.97	5.67	10.20
16 June 2006	167	12.65	4.85	10.91
10 July 2006	191	13.11	10.05	12.25
12 July 2006	193	13.31	6.51	11.16
14 July 2006	195	12.49	6.69	10.63
17 July 2006	198	15.29	10.49	13.11
18 July 2006	199	18.15	11.11	15.63
19 July 2006	200	18.35	12.57	16.73
24 July 2006	205	14.63	9.83	12.71
28 July 2006	209	16.65	12.19	15.20
25 August 2006	237	9.65	6.01	8.34
30 August 2006	242	10.51	8.57	9.80
8 September 2006	251	9.65	4.99	7.90
9 September 2006	252	11.23	5.03	9.17
10 September 2006	253	10.29	6.79	8.69
11 September 2006	254	15.07	10.19	13.75
19 September 2006	262	11.47	9.41	10.93
30 September 2006	273	11.23	8.17	10.03
4 October 2006	277	9.67	6.03	8.35
12 October 2006	285	8.75	5.83	7.56
1 November 2006	305	3.95	0.79	2.36
9 November 2006	313	4.63	0.11	3.15
18 November 2006	322	3.23	0.51	2.59
29 November 2006	333	4.95	2.11	3.48
4 December 2006	338	5.03	2.21	3.79
12 December 2006	346	3.95	0.41	1.94
17 December 2006	351	2.29	-0.39	1.10

Table 2.4. Twenty seven available MODIS daytime images for LST, Maximum, Minimum and Mean Pixel Temperature Value for Birmingham

Date	Julian Date	Maximum Pixel Value (ºC)	Minimum Pixel Value (ºC)	Mean Pixel Value (ºC)
9 February 2006	40	7.17	4.23	6.06
5 May 2006	125	33.67	23.37	29.29
10 May 2006	130	31.71	22.15	28.36
11 May 2006	131	31.69	22.53	27.78
3 June 2006	154	32.43	22.49	28.07
5 June 2006	156	27.15	14.03	22.91
9 June 2006	160	39.79	27.57	35.06
10 June 2006	161	37.11	28.49	33.35
12 July 2006	193	34.87	26.69	31.59
13 July 2006	194	40.79	28.55	36.17
14 July 2006	195	32.25	25.47	29.28
15 July 2006	196	39.87	29.25	36.17
17 July 2006	198	44.19	33.93	40.45
18 July 2006	199	46.57	36.99	42.75
19 July 2006	200	42.43	35.31	39.85
24 July 2006	205	41.29	29.81	37.27
25 July 2006	206	35.67	30.77	33.67
28 July 2006	209	39.95	31.25	36.42
3 August 2006	215	35.23	26.87	32.29
5 August 2006	217	24.41	23.93	24.10
8 September 2006	251	29.51	21.93	26.74
21 September 2006	264	29.33	24.47	27.54
29 October 2006	302	17.57	8.41	14.79
1 November 2006	305	11.25	8.49	9.95
2 November 2006	306	11.73	8.09	10.13
4 November 2006	308	13.41	10.67	12.24
6 November 2006	310	13.73	10.31	12.62

2.2.4. NDVI dataset

The NDVI data were also obtained from Aqua MODIS products, MYD13Q1 (V5) – MODIS/Aqua Vegetation Indices 16-Day L3 Global 250m Grid SIN (LPDAAC, 2015b), available in Sinusoidal Projection, every 16 days at 250 m resolution. The product is the difference between pigment absorption features in bands 1 (red reflectance) and 2 (near infrared). It is atmosphere-corrected and quality controlled, based on a 16 day composite (LPDAAC, 2015b). Two vegetation indices are available for each product NDVI and EVI (Enhanced Vegetation Index). EVI was not used in this study since it is more applicable to monitor changes in canopy structure and leaf area, whereas NDVI is used to verify vegetation density and is the index most frequently used by urban climate studies (Weng *et al.*, 2004; Yuan and Bauer, 2007). NDVI ranges from -1 to 1, being positive values increasing amount of vegetation in a pixel (Yuan and Bauer, 2007), while 0 and negative values indicate rock, asphalt, clouds, snow, ice and water.

As per the LST product, the NDVI product was downloaded and converted in MRT to GeoTIFF format at UTM, and subsequently to BNG in ArcGIS. All NDVI images available for 2006 were used, resulting in 23 images for the study period (one every 16 days – Table 2.5). ArcGIS was then used to apply a scale factor (as indicated in reference material – LPDAAC, 2015b) to adjust the range from -1 to 1. Finally, the 23 images were averaged into a single image for the year and clipped to the Birmingham area (Figure 2.5.c).

Table 2.5. Twenty three available MODIS images for NDVI

Date	Julian Date
9 January 2006	9
25 January 2006	25
10 February 2006	41
26 February 2006	57
14 March 2006	73
30 March 2006	89
15 April 2006	105
1 May 2006	121
17 May 2006	137
2 June 2006	153
18 June 2006	169
4 July 2006	185
20 July 2006	201
5 August 2006	217
21 August 2006	233
6 September 2006	249
22 September 2006	265
8 October 2006	281
24 October 2006	297
9 November 2006	313
25 November 2006	329
11 December 2006	345
27 December 2006	361

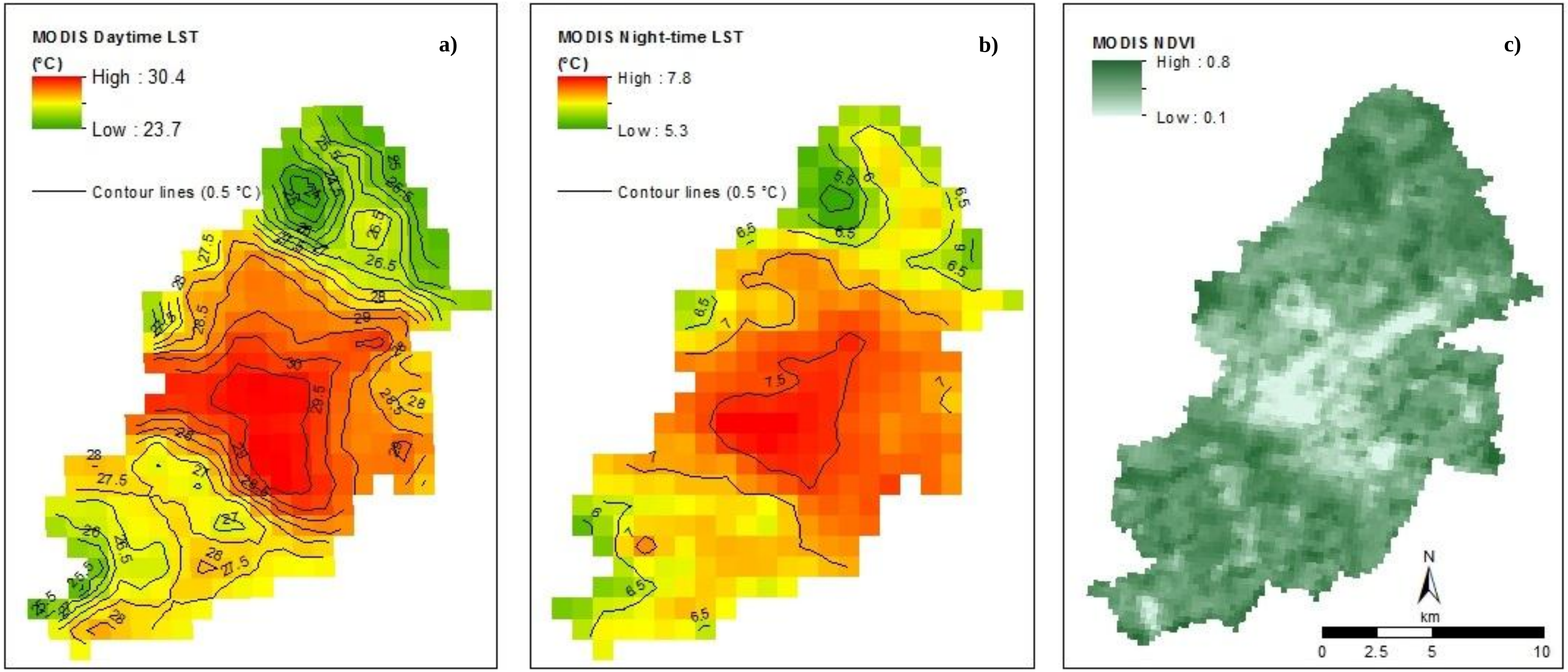

Figure 2.5. a) Averaged daytime LST, **b)** Averaged night-time LST and **c)** Averaged NDVI for Birmingham in 2006.

2.2.5. Data aggregation and analysis

As income and residential electricity consumption data are available by MSOA, for analysis purposes, there was a need to average and aggregate LST and NDVI into MSOAs (Figure 2.6.). The processed LST and NDVI raster images were simply summed and then averaged by the number of images used before being converted into a point dataset. All points located within each MSOA were then averaged, resulting in a unique LST or NDVI value by MSOA. Correlations between the variables were then calculated by using Spearman Rank correlation coefficients (Table 2.6). Due to the fact that income does not have a normal distribution, parametric statistics would not be appropriate and therefore non-parametric statistics was applied. This was carried to analyse the impact of LST, NDVI and income (independent variables) on electricity consumption (dependent variable). Spearman correlation was also carried between the MSOA consumption by household normalized by the income data and the aggregated LST and NDVI by MSOAs (Table 2.7). This was carried to analyse the impact of LST and NDVI (independent variables) on income normalized electricity consumption (dependent variable). *P-values* lower than 0.01 were found for all correlations; considering a standard $\alpha = 0.05$ cut off, all analyses are significant at a 95% confidence interval. Scatter plot diagrams with intercept, slope and R^2 are shown in Figure 2.7.

Table 2.6. Spearman Rank Correlation between datasets

	Income	MODIS night-time LST	MODIS daytime LST	MODIS NDVI
Ordinary Electricity/ Household	0.58	-0.39	-0.40	0.36

Table 2.7. Spearman Rank Correlation between datasets and normalized electricity consumption

	MODIS night-time LST	MODIS daytime LST	MODIS NDVI
Ordinary Electricity/Household - Normalized by Income	0.45	0.55	-0.50

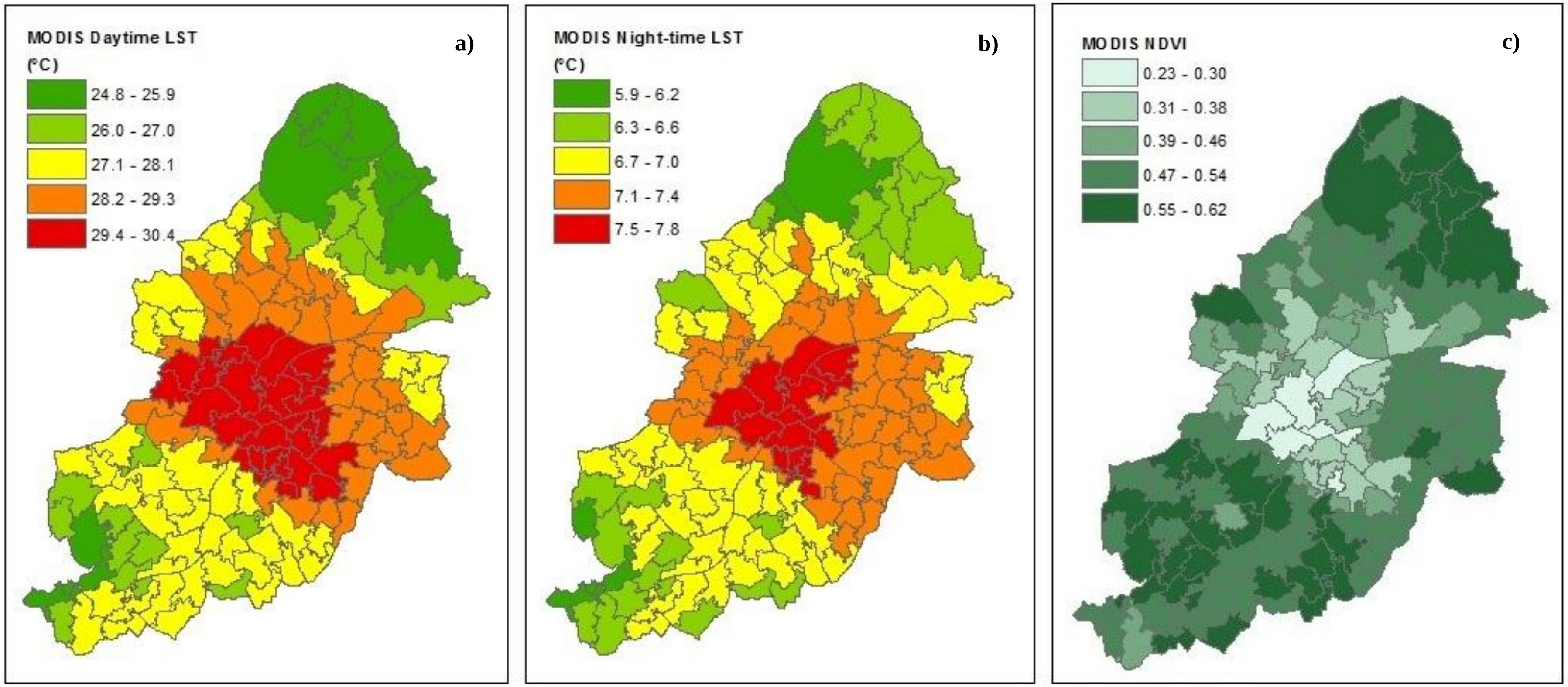

Figure 2.6 part 1. Aggregated data to MSOA for **a)** 2006 average day UHI, **b)** 2006 average night UHI, **c)** 2006 average NDVI.

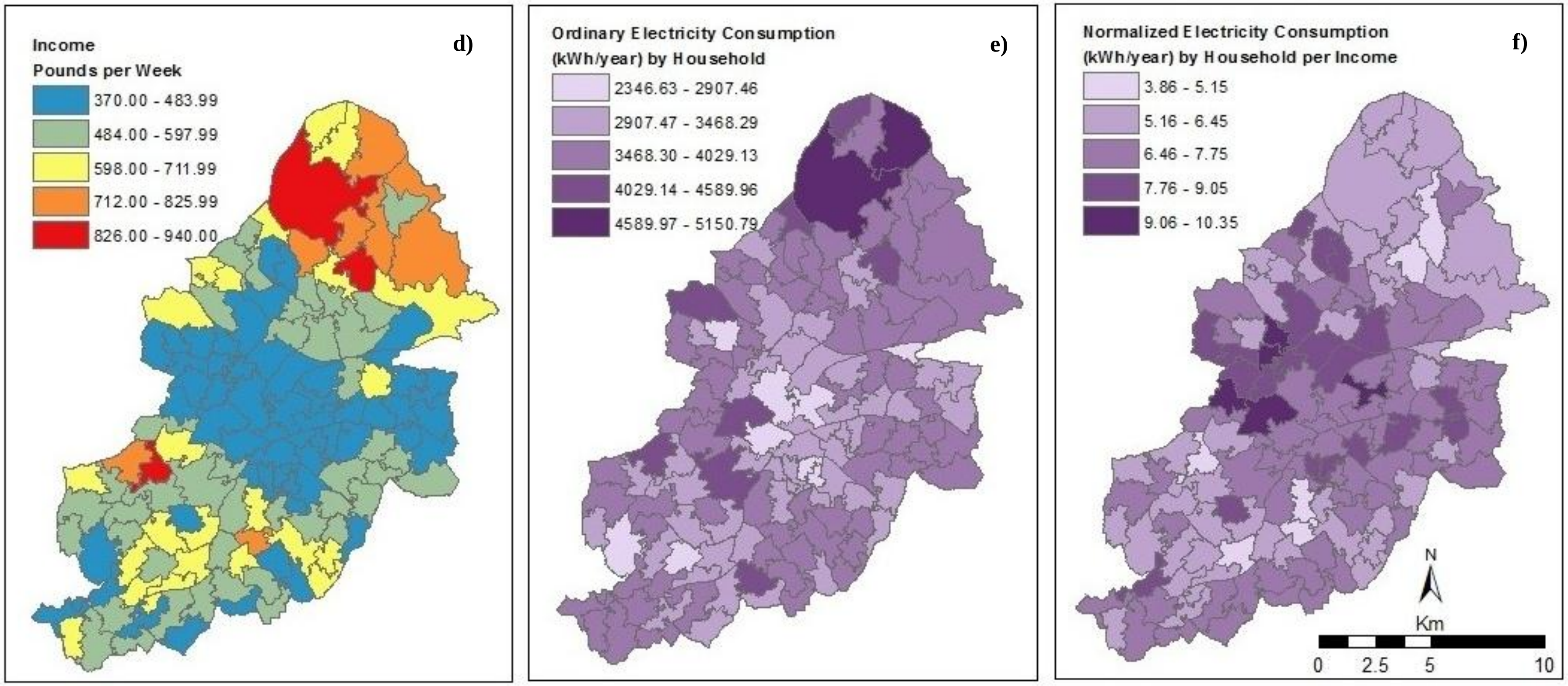

Figure 2.6 part 2. Aggregated data to MSOA for **d)** 2007/2008 Income, **e)** Ordinary Residential Electricity Consumption and **f)** Income Normalized Ordinary Residential Electricity Consumption.

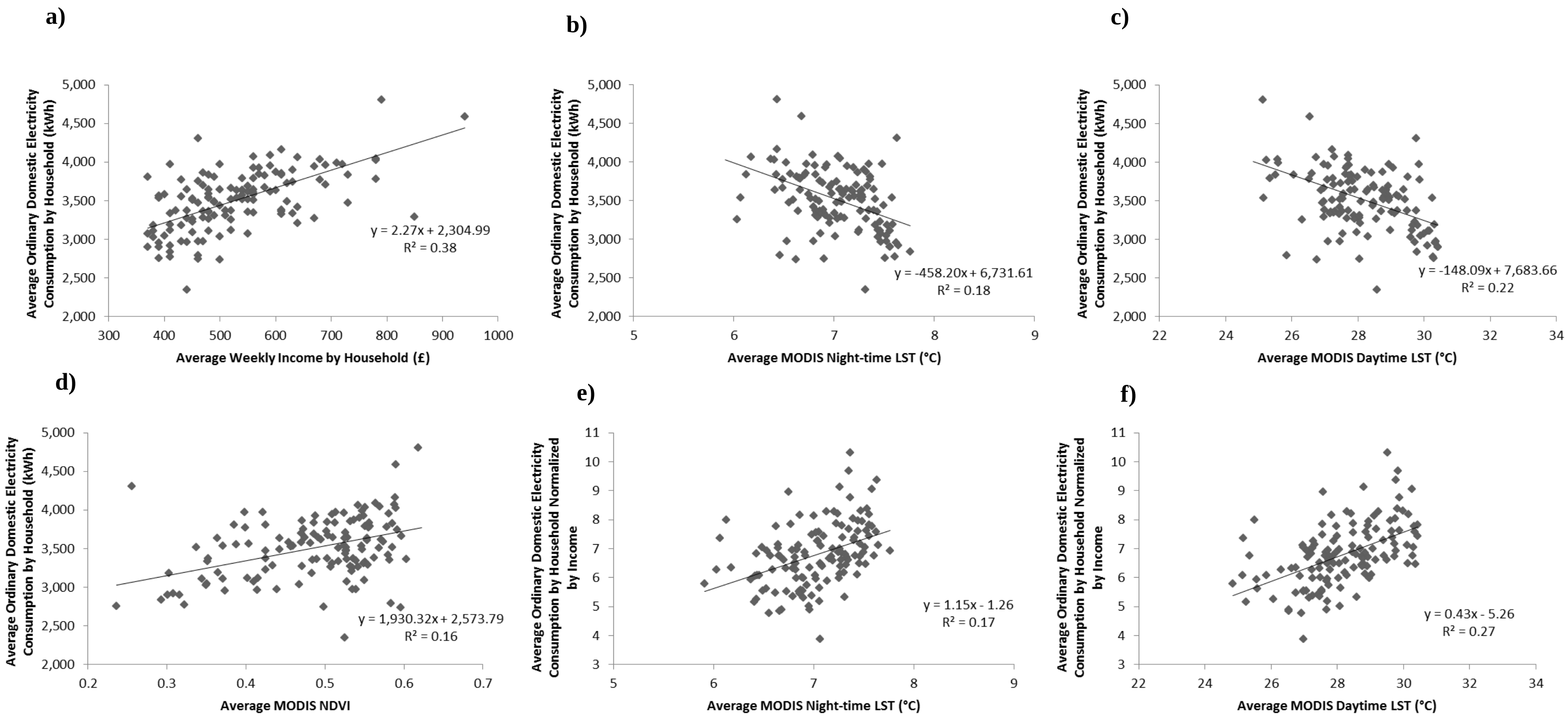

Figure 2.7 part 1. Scatter plot diagrams with slope, intercept and R^2 **a)** Consumption by Income, **b)** Consumption by Night-time LST, **c)** Consumption by Daytime LST, **d)** Consumption by NDVI, **e)** Income Normalized Consumption by Night-time LST and **f)** Income Normalized Consumption by Daytime LST.

g)

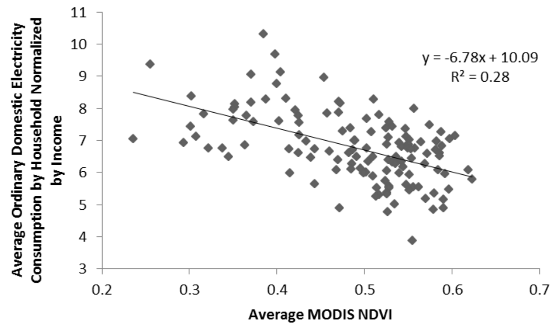

Figure 2.7 part 2. Scatter plot diagrams with slope, intercept and R^2 **g)** Income Normalized Consumption by NDVI.

2.3. Discussion

2.3.1. Data quality

All MODIS products used in these analyses were obtained for free online (USGS, 2013) and are available since 2002 with worldwide coverage. The advantage of using the MODIS Aqua dataset is that is well-suited to non-specialists due to the fact that it is atmospheric corrected with NDVI already calculated. Add to this, the fact that is free and available either twice a day for the LST, or in a 16 days composite for NDVI, it allows the user to determine the temporal scale of the study being carried, for yearly period, seasonally, monthly or daily. Census data are usually available in most countries and free, which provides demographic investigation data and areal units. Other variables, sophisticated datasets, and areal units can be used for the analyses, depending on the scope and aim of the study and availability.

Although the UK electricity data have good spatial resolution, data are only available as an annual summary per MSOA and therefore do not allow seasonal interpretation. Indeed, this can be seen as a problem, since the correlation between climate and electricity consumption has different patterns during summer and winter, and so does the UHI pattern and vegetation. However, for preliminary investigation focusing on freely available datasets at the same spatial and temporal resolution to provide results for spatial risk assessment it can still be used, and it is simple and repeatable.

2.3.2. Analysis Part 1

The year of 2006 was chosen for investigation due to the data availability and to the fact that it was an anomalous year, with warm summer and autumn, and therefore it is expected that there would be an increase in the electricity consumption. Indeed when looking at total residential electricity consumption from 2005-2013 (Figure 2.8.), 2006 was the year with highest consumption. Since temperature is expected to increase in future climate scenarios, due to climate change, 2006 works as a temporal analogue of how consumption may look in the future.

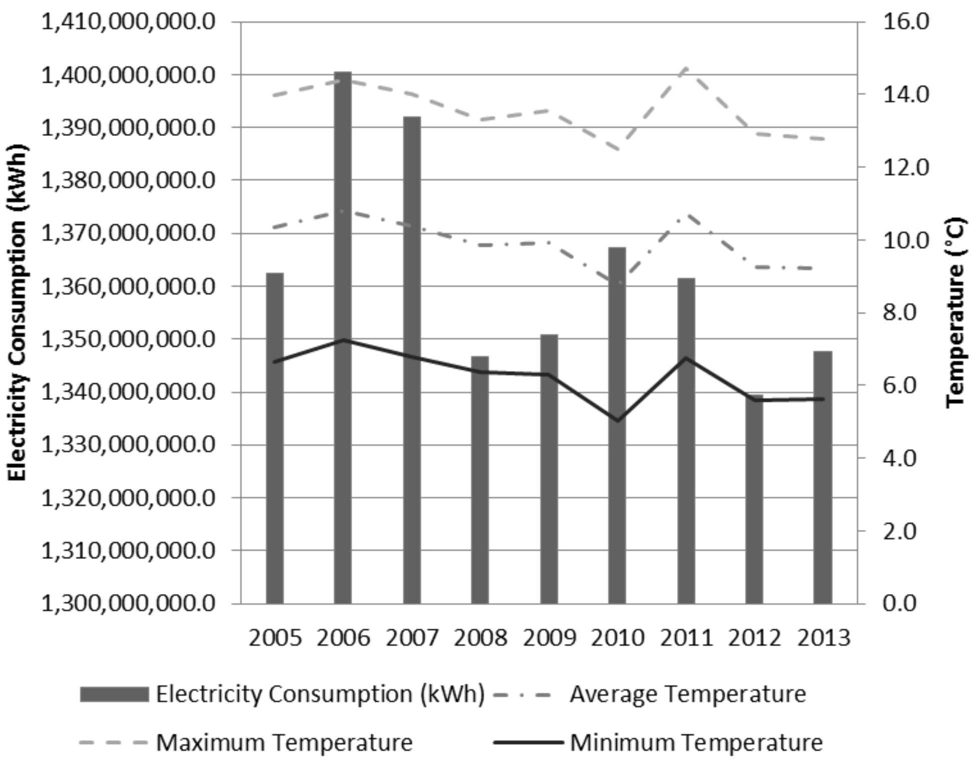

Figure 2.8. Variations in total ordinary electricity consumption (kWh) with respect to yearly average temperatures (ºC) in Birmingham from 2005-2013.

As per Tomlinson *et al*. (2011), a clear UHI is evident in the averaged LST data with temperatures peaking in the city centre and significantly lower LST in the urban green space (Figures 2.5.a and 2.5.b). The range of LST evident during the day is higher than during the night, a consequence of differential solar heating of surfaces with different thermal properties during the daytime. After sunset surfaces start releasing energy absorbed during the day, cooling down. In the second case, air temperature is usually higher than LST.

The averaged NDVI distribution for Birmingham (Figure 2.5.c) was also as expected ranging from 0.2 in the city centre to 0.7 in the larger urban green spaces. As demonstrated in previous studies (Weng *et al*., 2004; Yuan and Bauer, 2007).

It is hypothesised in this chapter that there is already an impact on electricity consumption due to the UHI, however other variables have also been investigated as they are known to have impact in electricity consumption as well. In this first part of the analysis the strongest relationship found with electricity consumption was with income ($r = 0.58$), highlighting that although low income groups have a greater need for heating (less well insulated housing stock) and air conditioning (increased exposure to UHI), the main driver for consumption is purchasing power (Table 2.6 and 2.8). It is primarily for this reason why correlations with LST are negative (daytime $r = -0.40$; night-time $r = -0.39$) meaning that there is an inverse correlation between LST and electricity consumption (high consumption, low LST). It was hypothesised that higher temperatures due to the UHI effect in the city would result in increases electricity consumption by the use of air conditioners and fans, however that was not identified in the first part of the analysis (Table 2.6).

Table 2.8. Average electricity consumption by household income, England 2005 to 2011 (kWh)

	<£15,000	£15,000 - £19,999	£20,000 - £29,999	£30,000 - £39,999	£40,000 - £49,999	£50,000 - £59,999	£60,000 - £69,999	£70,000 - £99,999	£100,000 - £149,999	£150,000 and over	Unknown	Total
2005	3,900	4,200	4,400	4,700	4,900	5,100	5,200	5,500	6,200	6,700	5,000	4,600
2006	3,800	4,000	4,200	4,600	4,800	5,000	5,200	5,400	6,100	6,800	4,900	4,500
2007	3,700	4,000	4,200	4,500	4,800	4,900	5,100	5,400	6,100	6,700	4,900	4,500
2008	3,500	3,800	4,000	4,300	4,600	4,700	4,900	5,200	5,900	6,600	4,700	4,300
2009	3,500	3,700	3,900	4,300	4,500	4,700	4,900	5,200	5,900	6,600	4,700	4,200
2010	3,500	3,700	3,900	4,300	4,500	4,700	4,900	5,200	6,000	6,700	4,700	4,200
2011	3,400	3,700	3,800	4,200	4,500	4,700	4,900	5,200	5,900	6,700	4,600	4,200

2.3.3. Analysis Part 2

As a second part of the analysis, electricity consumption data were normalized by income to isolate income influence (the main factor in energy consumption according to the literature and first part of the analysis). Applying normalization in the electricity consumption data a positive correlation between LST and consumption was observed. The correlation with the income normalized consumption was higher for daytime UHI (daytime r = 0.55; night-time r = 0.45). The positive correlation expected in the hypothesis was achieved when isolating the impact of income, and therefore the higher the LST, the higher the consumption. A negative correlation with NDVI was observed (r = -0.50), this is also expected from the hypothesis, as areas with less vegetation, have higher LST and therefore more consumption. In this second part of the analysis, all correlations marginally improved, but are still limited, and the correlation between income and electricity consumption remains the strongest.

In the first part of the analysis a strong positive correlation between income and NDVI (r = 0.61) was observed which is explained by increased real estate values surrounding parks and green space (Lambert-Habib *et al.*, 2013). It is evident that wealthier families and individuals usually live in more vegetated areas (e.g., Sutton Coldfield in Birmingham); whereas lower income groups live in flats in cheaper areas (Santamouris *et al.*, 2007), often close to the city centre (e.g., Ladywood in Birmingham). In Birmingham, it is not uncommon to find low-income groups living in areas where the UHI reaches its maximum, which when factored with the poor housing stock found in such areas (i.e., less efficient construction/insulation), has implications for not only energy consumption but the general wellbeing and health of the population in these areas (Tomlinson *et al*., 2012a). The same was found for Athens (Santamouris *et al*., 2007), however such statement should be analysed individually depending on the city studied, due to differences in culture, urban form and development of cities across the world. Income is an indirect factor of household size, meaning higher income, larger houses, and higher electricity consumption, being another factor that explains why the highest correlations were found with income, however such analyses are beyond the scope of this study.

The resolution and aggregation level of the variables may have influenced in the results found here. There is a clear need for other variables and data with higher spatial and temporal resolution to be taken into account in future and more detailed research. However, despite these limitations, it is evident that income is the most influential factor in electricity consumption. The UHI appears to play a role, but these results are presently tempered and even with the presence of a strong UHI, high temperatures are still not an issue in Birmingham, therefore there is actually no significant need for cooling appliances at the moment.

2.4. Conclusions

Despite electricity consumption data not being available at the desired temporal scale, it was possible to assess residential electricity consumption distribution and its correlation with income, NDVI and LST for yearly aggregated data, at a preliminary stage. Large differences are evident in the distribution of urban heat and vegetation across Birmingham, but the results show that the dominant factor that influences residential electricity consumption at these scales is not climate but income. Whether this is true at other scales is difficult to assess given the present spatial and temporal limitations of the available data. From this Chapter, it would be reasonable to conclude that electricity consumption due to increasing temperatures does not appear to be a current or urgent issue in temperate countries, however considering climate change scenarios, an increasing frequency of heatwaves and energy security concerns, overlooking behavioural changes of the millions of people who live in mid-latitude cities would be an oversight. In face of climate change scenarios in Birmingham, temperatures will increase, exacerbating the UHI effect and impacts on electricity consumption. Furthermore, the increasing number of people in urban areas will not only contribute to the exacerbation of the UHI effect but will also increase the number of people exposed to its potential risks (Smith *et al*., 2011), therefore, overlooking increasingly important climate drivers would be foolhardy.

2.5. Chapter Summary

This Chapter has encountered a major limitation related to the energy consumption data available by MSOA. Although it is a major advance to have the data aggregated at an intra-urban level, freely available to anyone, divided by both domestic and industrial consumers, the major problem relies on the fact that it is aggregated by year, and energy consumption fluctuates with temperature and meteorological seasons. Therefore, it would be more or less impossible to identify large climate impact, unless there are extreme circumstances such as a heatwave.

Still on the energy data, the gas consumption data are weather corrected before being released, meaning the data are already isolated from climate impacts. Considering that consumption for space heating is possibly more important than consumption for cooling in the UK due to its mild weather, it is a big limitation to not be able to analyse such impact.

Remote sensing data provide good spatial scale for a city with the size of Birmingham. They also provide more or less a good temporal scale, but in certain seasons the availability can be compromised by cloudiness. However, the key limitation still relies on the fact that it is representative of LST and not T_{air}. The two parameters, although related, are clearly different and hence there is a need to better understand the relationship between the two in Birmingham before any more detailed analyses are possible and this is explored next in this thesis.

Chapter 3

Quantifying the daytime and night-time Urban Heat Island: A comparison of satellite derived land surface temperature and high resolution air temperature observations

3.1. Introduction

Traditional ways in which UHI_{canopy} are measured include station pairs (e.g., Wilby, 2003) or the use of transects (e.g., Smith *et al*., 2011). Given the paucity of traditional T_{air} observations, and their limited spatial resolution (Smith *et al*., 2011; Muller *et al*., 2013b), there has been an ongoing challenge to quantify the intensity and spatial extent of the UHI_{canopy}. A compromise is nearly always needed, whether it be temporal (i.e., the transect approach) or spatial (i.e., the station pair approach).

It is for these reasons that numerical modelling techniques have proven to be so popular in urban climatology (Grimmond *et al*., 2010). As mentioned in Chapter 1, a range of models can be applied to estimate temperature variations in an urban area, such as WRF, JULES, and MORUSES. WRF is a mesoscale numerical weather prediction model, with incorporated urban schemes and used operationally for forecasting and research. JULES and MORUSES are land surface models that effectively provide information of land conditions (e.g., surface energy balance), which is subsequently passed on to atmospheric models, such as the Met Office Unified Model. Although modelling has brought tremendous advances in our understanding of urban atmospheric processes, models need observation data for initialisation and verification meaning that a wider number of urban measurements, other than data from one or two weather stations, would help to evaluate models' output.

To this end, there has been a recent increase in interest in the deployment of high resolution UMNs (Muller *et al*., 2013a), driven by advances in technology, communications and the ever-increasing miniaturisation of low cost electronics (Muller *et al*., 2013b). Such networks enable atmospheric processes to be observed at both high temporal and spatial resolutions, which is especially important when considering the heterogeneous nature of urban areas (Chapman *et al*., 2014). Variables monitored by UMNs can include wind speed and direction, humidity, T_{air} and others. These data can be incorporated into microclimate models that can be further integrated into planning tools and other industrial applications to inform policy and decision-making. Despite the advantages, the logistics of operating high resolution networks means that the number of fully working UMNs across the world is limited (Muller *et al*., 2013b).

However, new approaches (e.g., crowdsourcing Muller *et al*., 2015) may help to improve this over time.

There are numerous studies in the literature that have quantified the $UHI_{surface}$ using remote sensing techniques (Dousset, 1989; Roth *et al*., 1989; Weng *et al*., 2004; Yuan and Bauer, 2007; Dousset *et al*., 2011a; Dousset, *et al*., 2011b; Keramitsoglou *et al*., 2011; Schwarz *et al*., 2011; Smith *et al*., 2011; Tomlinson *et al*., 2012a). The key advantages are that regardless of the scale of study, remote sensing provides a consistent, repeatable and relatively cheap methodology for the end-user (Tomlinson *et al*., 2011). Although the initial cost of remote sensing platforms remains high, the data availability and temporal and spatial coverage available of LST measurements and other co-located variables (e.g., cloud, vegetation, surface emissivity) are important for $UHI_{surface}$ measurements and spatial risk mapping (Dousset *et al*., 2011a; Dousset *et al*., 2011b; Tomlinson *et al*., 2011).

Despite the advantages, there are complexities in the retrieval of urban LST including satellite viewing geometry, atmospheric attenuation of IR radiation, urban surface emissivity and sub-pixel variations of land cover and heat balance. As a result, thermal remote sensing studies in urban areas had been slow on developing results beyond qualitative descriptions of thermal patterns and simple correlations between LST and T_{air} (Voogt and Oke, 2003). However, over the last decade, satellite derived LST were progressively integrated into climate models (De Ridder *et al*., 2012; Wouters *et al*., 2013) and used to retrieve T_{air} (Keramitsoglou *et al*., 2012). To this end, the increasing availability of UMNs, of unprecedented resolution, have an important role to play. High resolution T_{air} datasets are not only providing new information on UHI_{canopy} but also provide an opportunity to further evaluate the relationship between T_{air} and

LST using datasets of comparable spatial resolution. Furthermore, given the paucity of UMNs, this relationship is potentially useful allowing LST to be used in a wider range of applications that presently depend on T_{air} measurements (e.g., seasonal estimation of energy use, and electricity transformer ageing, Tomlinson *et al*., 2013). To begin to meet this need, this Chapter uses a high resolution UMN (the Birmingham Urban Climate Laboratory: BUCL), to quantify and compare the spatial pattern of the daytime and night-time UHI in Birmingham, under a range of stability classes, for both $UHI_{surface}$ and UHI_{canopy}.

3.2. Methodology and datasets

3.2.1. Birmingham Urban Climate Laboratory (BUCL)

Figure 3.1. shows BUCL: a near real time, high-resolution urban meteorological network of automatic weather stations and low-cost non-standard Wi-Fi air temperature sensors (Aginova Sentinel Micro) (Chapman *et al*., 2014). Data availability peaked in summer 2013, when the network consisted of: 82 low-cost, Wi-Fi air temperature sensors with bespoke radiation shields located in schools and on lampposts, 3 m from the ground (see Chapman *et al*., 2014 and Young *et al*., 2014 for more details); and 25 automatic weather stations (Vaisala WXT520) measuring temperature, precipitation, relative humidity, wind speed and direction, pressure, and solar radiation. Both temperature sensors and weather stations provide minute data. The weather stations provide accuracies of: air temperature ±0.3 °C (20 °C) (Scientific, 2006), whereas the

low cost sensors provide good accuracy in laboratory testing with mean errors of < ±0.22 °C (between -25 and 30 °C), subsequent field tests presented an accuracy (in the bespoke shield) of root-mean square error of 0.13 °C over a range of meteorological conditions relative to a traceable operational UK Met Office platinum resistance thermometer (Young *et al*., 2014). To ensure and improve data quality, a metadata protocol for UMNs was proposed and followed during implementation, maintenance and data acquisition. Juliana Antunes Azevedo attended as well the installation and maintenance visits, from November 2012 to April 2013 to learn the installation process and to certify that metadata protocol was being followed; after the visitations the metadata was uploaded into the database, and later there would be constant follow up checking the database to guarantee that data was being received with no faults, to make sure that data would be available and trustworthy for this research to be carried. Furthermore, strict calibration procedures were rigorously followed (for detailed information see Muller *et al*., 2013a), and this process was also learned by Juliana Antunes Azevedo. The network ensures that Birmingham is one of the most densely-instrumented urban areas for meteorological studies and offers high quality data at an unprecedented resolution for a city of its size.

Finally, Coleshill (~ 4.5 km east of the outer edge of Birmingham), is the station in the national network frequently used as the rural reference site for UHI studies in Birmingham (Tomlinson *et al*., 2012a; Zhang *et al*., 2014a) and is considered an “agricultural, semi-natural and wetland” area in land use classifications (EEA, 2010) (Figure 2.2. – Chapter 2).

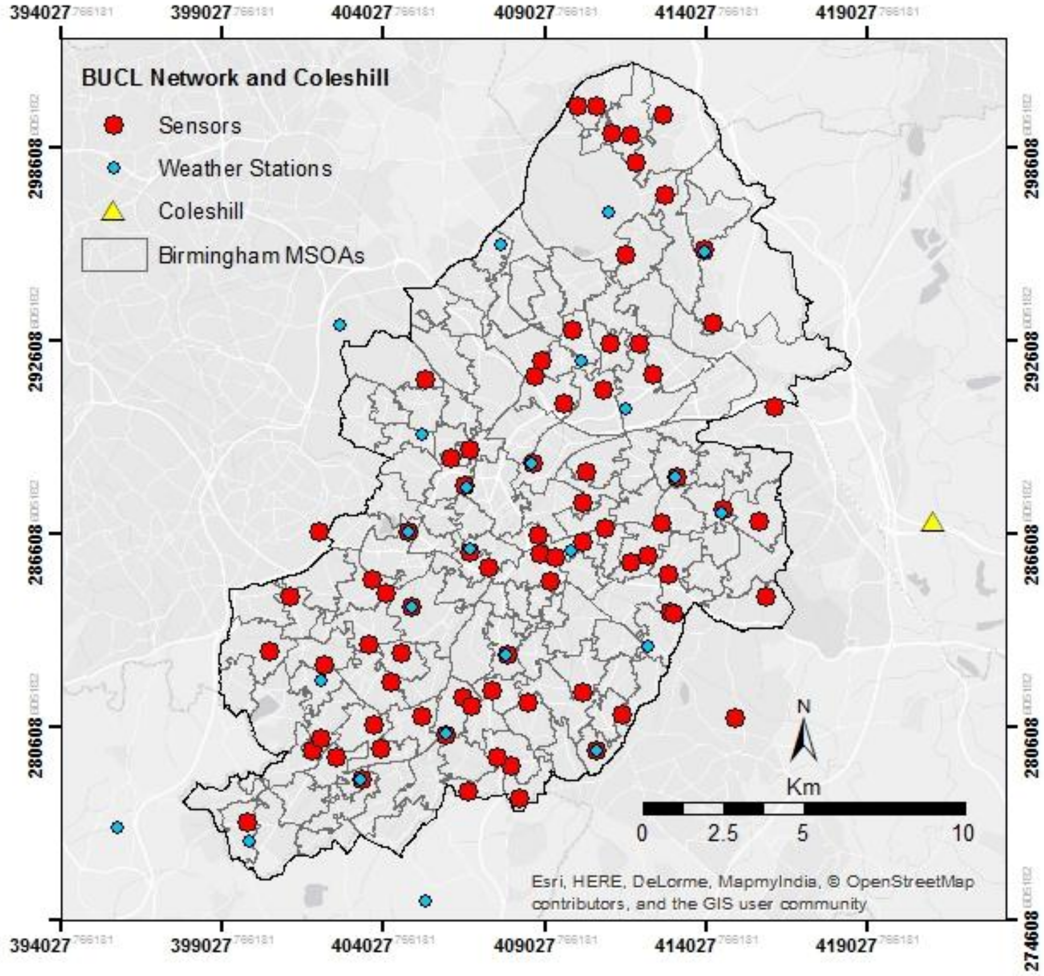

Figure 3.1. BUCL network, Coleshill location and Birmingham MSOAs.

The meteorological statistics for 2013 were near average (Table 3.1). However it had a late start to winter and exceptionally cold spring (with late snowfalls). March was the second coldest March for the UK on record, after 1962. The annual rainfall was drier than average but not exceptionally. May, October and December were the only months to record above average rainfall for the UK.

The year 2013 had the warmest summer in the UK since 2006, with a prolonged heat wave from 3 to 22 July, when high pressure was established across the UK. It was a drier than average (ending a period of 6 consecutive wet summers 2007-2012), also having the sunniest summer since 2006, being the sunniest July since 2006 and the third sunniest July in the series from 1929 (Table 3.2).

Table 3.1. 2013 - Regional values compared with 1961 to 1990 averages (UKMO, 2013)

(Act=Actual, Anom=Anomaly)

Region	Max temp		Min temp		Mean temp		Sunshine		Rainfall		Days rain ≥1 mm		Days air frost	
	Act	Anom	Act	Anom	Act	Anom	Act	Anom	Act	Anom	Act	Anom	Act	Anom
	°C	°C	°C	°C	°C	°C	hours	%	mm	%	days	days	days	days
UK	12.4	0.5	5.2	0.4	8.8	0.5	1421.1	106	1091	99	150.2	-3.9	66.2	5.3
England	13.2	0.4	5.7	0.3	9.5	0.4	1539.1	107	813.9	98	128.1	-3.6	60.9	5.8
Midlands	13.2	0.5	5.5	0.3	9.3	0.4	1512.7	110	758.7	98	125.1	-5.6	66.6	8.4

Table 3.2. Summer (JJA) 2013 - Regional values compared with 1961 to 1990 averages (UKMO, 2013)

(Act=Actual, Anom=Anomaly)

Region	Max temp		Min temp		Mean temp		Sunshine		Rainfall		Days rain ≥1 mm		Days air frost	
	Act	Anom	Act	Anom	Act	Anom	Act	Anom	Act	Anom	Act	Anom	Act	Anom
	°C	°C	°C	°C	°C	°C	hours	%	mm	%	days	days	days	days
UK	19.7	1.7	10.7	1.1	15.2	1.4	577.7	115	186.8	79	28.5	-4.8	0.1	-0.1
England	21.1	1.7	11.3	1	16.2	1.3	642.4	118	149.7	78	23.2	-5	0	-0.1
Midlands	21.2	1.8	11.2	1	16.2	1.4	626.5	119	156.5	84	23	-5.3	0	-0.1

3.2.2. T_{air} data acquisition and processing

T_{air} data for June, July and August (JJA) 2013 were obtained from BUCL (Warren *et al.*, 2016) and Coleshill weather station. Twice daily meteorological averages were calculated for each sensor and weather station for daytime (06:00–17:59) and night-time (18:00–05:59 following day). Then, using ArcGIS, the data were interpolated by the kriging before being averaged and trimmed to the study area, resulting in a daytime (representative of data averaged from 06:00 to 17:59) and night-time (18:00–05:59 the following day) interpolation for each day of the study period. Average temperature values were used due to the rapidly changing nature of the UK climate. Although skies were clear during the time of the satellite passes used in this study, the proceeding weather conditions will potentially have a large impact. The use of averaging helps to overcome this limitation. During British summer time sunrise and sunset can be quite variable, therefore 18:00-05:59 was chosen for the night period, because of the large time variation of sunset during summer (from 18:00 to 22:00) and to maintain a consistency of 12 hours of 'night' and 12 hours of 'day', although it is considered early for the start of the night period.

Kriging is a common spatial interpolation method applied to T_{air} (Chapman and Thornes, 2003; Ustrnul and Czekierda, 2005). Spatial interpolation methods are divided in deterministic and stochastic. Deterministic methods are conceptual and use physical models to explain spatial phenomena, whereas stochastic methods apply probability theory and the concept of randomness (Ustrnul and Czekierda, 2005). Kriging is a stochastic method. Examples of deterministic methods are Inverse Distance Weighted (IDW), Natural Neighbour and Spline.

Spatial interpolation methods must be chosen carefully as a bad choice of methodology can result in errors and maps that inaccurate (Ustrnul and Czekierda, 2005); for instance, kriging is usually not appropriate for area with complex topography and highly varying densities and elevation distribution of climate (e.g., British Columbia, Canada influence of lapse rates), in these cases usually IDW is used and performs better (Stahl *et al.*, 2006).

There are several kigring methods which can be applied such as ordinary kriging, cokriging, universal kriging and residual kriging; and several geographical parameters (elevation, latitude, longitude, and distance to the coast) are usually used as predictor variables. For this study ordinary kriging with Gaussian semivariogram, and default parameters. With any interpolation method, there is the possibility of bias, however, the larger the sample, the smaller the possible bias, therefore larger samples of data provide better results (Stahl *et al.*, 2006); therefore, BUCL provides an improvement on estimations carried by having a wider sample of data.

It is possible that some stations might give anomalous readings, data from the network is carefully quality controlled by the technician enabling a reliable dataset for subsequent analysis (Chapman *et al.*, 2014). A total of 82 sensors and 25 weather stations were used, which were functioning and reliable during the study period (including the sites outside the Birmingham urban area). The UHI_{canopy} intensity (T_{urban}-T_{rural}: in this case the difference between the interpolated T_{air} for the urban area and T_{air} in Coleshill) was then calculated. Finally, the daytime and night-time datasets were averaged according to Pasquill-Gifford stability classes (Table 3.3).

Table 3.3. Pasquill-Gifford Class Names

Class	Definition	Period of the day
A	Extremely Unstable	Day
B	Moderately Unstable	Day
C	Slightly Unstable	Day
D	Neutral	Day/Night
E	Slightly Stable	Night
F	Moderately Stable	Night
G	Extremely stable	Night

3.2.3. Pasquill-Gifford stability classes

Coleshill is the closest station in the national network (Met Office MIDAS WH hourly: UKMO, 2013) to Birmingham City Centre in which cloud observations are frequently made, crucial to enabling subsequent datasets to be classified into Pasquill-Gifford stability classes (Pasquill and Smith, 1983). Daytime classes are calculated based on wind speed and levels of insolation (determined by cloud cover and solar elevation - Table 3.5), whereas night-time classes are calculated based on wind speed and cloud cover Table 3.4. Meteorological data used to assign stability classes is from the rural reference site at Coleshill and, whilst it is assumed to be representative of regional conditions, there is a need to acknowledge atmospheric stability in the urban area could be different to that calculated.

Table 3.4. Pasquill-Gifford Stability Classes Parameters

Surface wind speed ($m \cdot s^{-1}$)	Night		Day with insolation		
	Cloud Cover		Insolation*		
	≥4/8 Oktas	<4/8 Oktas	Strong	Moderate	Slight
<2	G	G	A	A-B	B
2-3	E	F	A-B	B	C
3-5	D	E	B	B-C	C
5-6	D	D	C	C-D	D
>6	D	D	C	D	D

* Refer to Table 3.5. for the understanding of how insolation categories are determined for Pasquill-Gifford Stability Classes.

Table 3.5. Insolation Categories for Pasquill-Gifford Day Stability Classes

Sky cover	Solar elevation		
	Angle > 60°	35° > Angle < 60°	15° > Angle < 35°
≤4/8 or any amount of high thin clouds	Strong	Moderate	Slight
>4/8 middle clouds (700 foot - 16000 foot base)	Moderate	Slight	Slight
>4/8 low clouds (less than 7000 foot base)	Slight	Slight	Slight

3.2.4. LST data acquisition and processing

As Chapter 2, MYD11A1 (V5)-MODIS/Aqua Land Surface Temperature and Emissivity Daily L3 1km Grid SIN (USGS, 2013) product was used. Data were obtained for JJA 2013 and were reprojected using MRT (LPDAAC, 2014) to convert images to GeoTIFF format at UTM, and subsequently converted to BNG in ArcGIS. Quality control of the images was achieved in ArcGIS selecting only images that were 100% cloud free (i.e., whenever the image had a pixel with no value, the image was rejected), before converting LST from Kelvin to degree Celsius and trimming the images to the study area. Cloudiness is a recurrent problem in the UK, which significantly reduces data availability, which can sometimes be overcome by masking cloud on partially clear images. However, due to the spatial resolution of MODIS (1 km) and following an inspection of the nature of rejected images, the scientific gain of this additional processing was considered to be of limited value in this study, given the small increase in data such a step would provide.

The $UHI_{surface}$ intensity (T_{urban}-T_{rural}: i.e., the pixel containing the Coleshill rural reference site) was then calculated. From each daytime and night-time image, the pixel LST converted to degree Celsius was extracted at the location of the sensor sites and weather stations (Figure 3.1.) for later comparison analyses between pixel extracted LST and sensor/weather station T_{air}. Finally, the images were averaged resulting in one daytime (at ~ 13:30) and one night-time (at ~ 01:30) image for each Pasquill-Gifford stability class.

3.3. Results

3.3.1. Stability classification

Table 3.6 summarises the total number of images for daytime and night-time with respect to atmospheric stability. The difficulties in obtaining cloud free imagery in the study area becomes apparent with only 11 images for daytime and 13 images for night-time available for analysis during the study period. The image availability tends to increase with atmospheric stability for the night pass, whereas for daytime conditions the majority of imagery was available for the moderately unstable classes.

Table 3.6. Pasquill-Gifford Classification Results

LST = 11 daytime images	T_{air} = 87 days analysed	Pasquill-Gifford class	Description
0	12	A and A-B	Extremely Unstable
8	22	B and B-C	Moderately Unstable
2	50	C and C-D	Slightly Unstable
1	3	D	Neutral
LST = 13 night-time images	**T_{air} = 86 days analysed**	**Pasquill-Gifford class**	**Description**
0	23	D	Neutral
0	19	E	Slightly Stable
3	13	F	Moderately Stable
10	31	G	Extremely stable

The T_{air} data were also classified using the same approach. By using this more extensive dataset, it can be seen that despite the settled climate experienced by the UK during the summer of 2013 (characterized by a mild heat wave and warmest temperatures since 2006), the most frequent stability classes encountered during the study period for the daytime were slightly unstable and moderately unstable. However, as per the LST data, more stable conditions were present during the night.

3.3.2. Daytime $UHI_{surface}$

The averaged LST images for each stability class with sufficient LST imagery available are shown in Figure 3.2., accompanied with an average image representing the overall averaged dataset for the period, independently of stability class. A clear

$UHI_{surface}$ is evident across all stability classes, with LST in the city centre being several degrees warmer than Coleshill. The maximum difference recorded during this study was 9 °C (class B) and is comparable in magnitude to the 10 °C recorded in a study in Manchester, a similar sized conurbation in the north of the UK (Smith *et al*., 2011). The clear spatial pattern found in all stability classes has peak LST in the land use classes for industrial, commercial and continuous urban fabric.

Significant cold spots are evident in city parks. LSTs recorded in Sutton Park to the north of the city are 9 °C lower than the city centre (~ distance of 10 km) in class B, and 7-8 °C lower than the city centre in classes C and D, respectively. In class B, Sutton Park was 1 °C lower than Coleshill (~ distance of 15 km), and similar in classes C and D. In the southwest and northeast corners of the city, lower temperatures were also found and correspond to semi-rural areas with agricultural, semi-natural and wetland land use. These differences are particularly noticeable in the southwest border where the slightly increased altitude has a discernable effect especially in Class B. Indeed, it is under these moderately unstable conditions that the maximum daytime $UHI_{surface}$ is present. This finding is not unique to this study, with a maximum daytime temperature difference of 8.9 °C also occurring during partially cloudy periods in London, UK (Kolokotroni and Giridharan, 2008).

Overall, the results show a strong daytime $UHI_{surface}$, with peak temperatures corresponding to high urban density and lower temperatures in green areas across all stability classes. This outcome is to be expected due to the fact that LST maximum occurs in hours of maximum solar irradiance. Differences in the spatial pattern across the stability classes are attributed to wind speed and cloud cover (as used for the stability class classification).

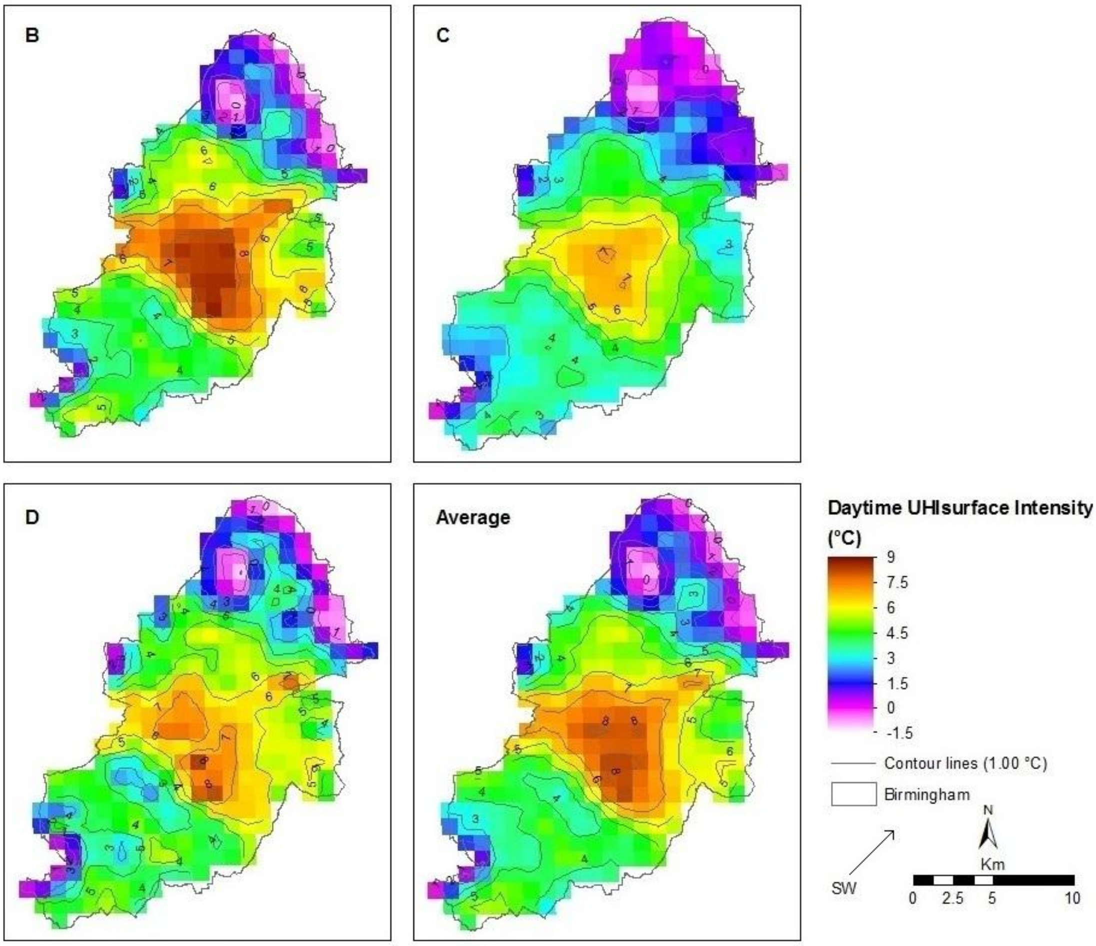

Figure 3.2. Daytime $UHI_{surface}$ intensity, for Pasquill-Gifford Stability Classes B, C and D, and Average for June, July, August 2013 and prevailing wind direction for the period. Based on MODIS Aqua LST product.

3.3.3. Daytime UHI_{canopy}

As with the $UHI_{surface}$ during the day, the UHI_{canopy} is also more evident under unstable conditions (Figure 3.3.). However, it is identified that with the exception of the city centre core in classes A (~ 0.3 °C) and D (~ 1.8 °C), T_{air} during the day is lower than the rural reference site (and up to ~ −1.8 °C lower in green areas and southwest, north and northeast semi-rural areas). Furthermore, in contrast to the $UHI_{surface}$, the intensity of the UHI_{canopy} spatial pattern is much smaller (between 1.7 °C and −1.8 °C), a result in line with other studies (e.g., Roth *et al*., 1989).

The spatial distribution of T_{air} during the period shows some similarities with LST with the highest temperatures in the city centre and cooler temperatures in urban parks (Sutton Park and southwest corner). However, there is a marked difference with respect to the spatial distribution of urban heat on the T_{air} dataset with the thermal core extending to the east of the city. In contrast, the thermal core extends to the west for the LST dataset. Whilst this pattern could be explained by land use for LST (Figure 2.2., Chapter 2), as the T_{air} pattern extending to east becomes more evident as the atmosphere becomes more stable (A to D), it is hypothesised that advection may play a more significant role in the spatial pattern of UHI_{canopy}. In WRF model simulations for August 2003, temperature variations in Birmingham were attributed to the influence of a particular wind direction in which areas downwind became warmer (up to 2.5 °C) than those upwind (Heaviside *et al*., 2015). Hence, this temperature pattern can be explained by the prevailing wind for the region which is south-westerly (UKMO, 2015). Similar results regarding advection have also been found for other cities. In London, the peak UHI intensity was found to be located northeast of the city centre, possibly explained by the prevailing south-westerly winds (Chandler, 1965) and in Hungary, the spatial UHI pattern in both Szeged and Debrecen, was determined by the prevailing wind direction (Unger *et al*., 2010a). Rural weather stations in the Netherlands were also found to be approximately 1 °C warmer when the wind passed across nearby towns (Brandsma *et al*., 2003). Overall, it appears advection plays an important role in investigating the pattern of UHI_{canopy} in the city, but this is beyond the scope of the present study.

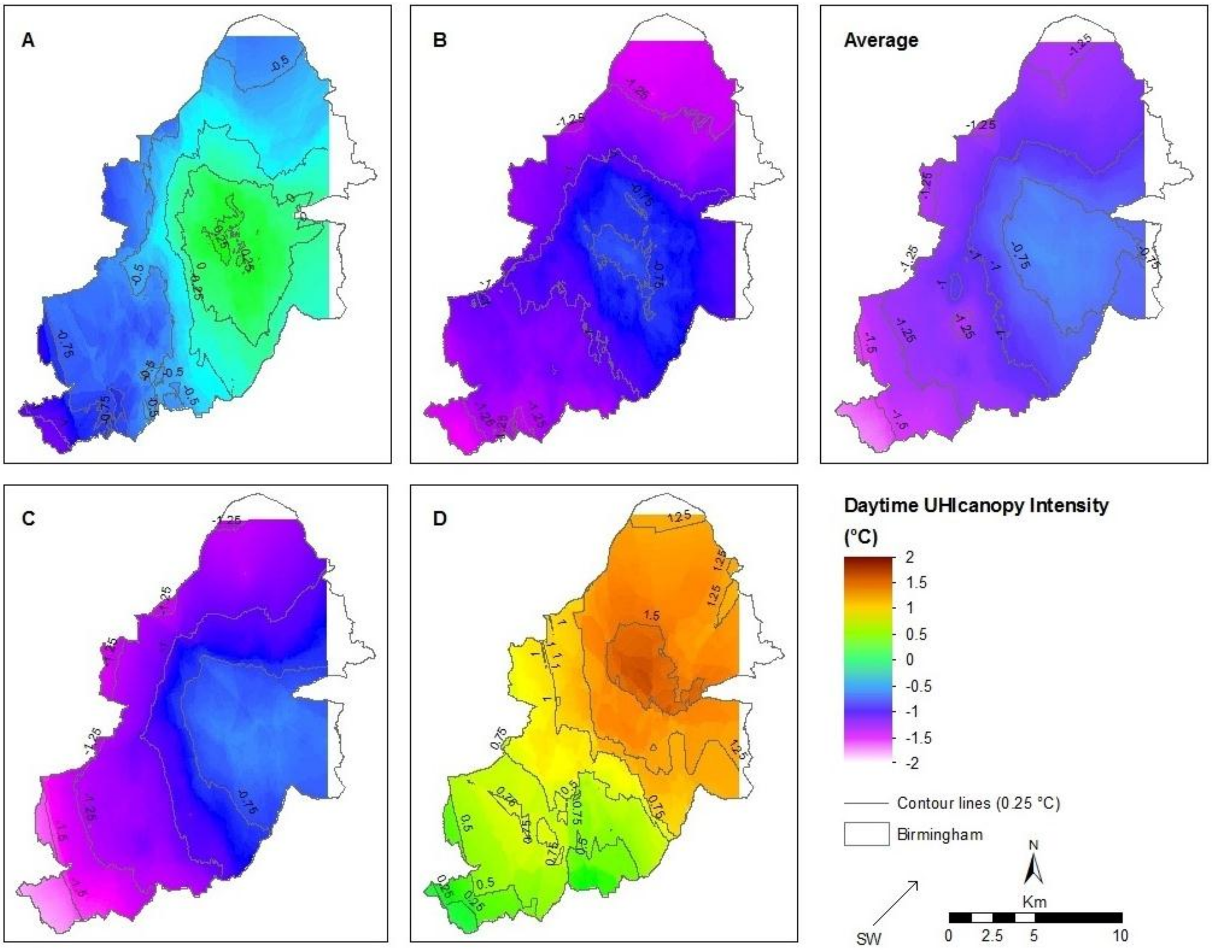

Figure 3.3. Daytime UHI_{canopy} intensity, for Pasquill-Gifford Stability Classes A, B, C and D, and Average for June, July, August 2013 and prevailing wind direction for the period. Based on the BUCL dataset.

3.3.4. Night-time $UHI_{surface}$

Previous work in Birmingham identified an increase in the $UHI_{surface}$ intensity with respect to atmospheric stability (Tomlinson *et al*., 2012a). That study used a larger dataset (2003–2009) than that used in this Chapter (i.e., summer 2013), yet the spatial pattern remains broadly comparable. The range for class F is from −1 to 2.5 °C, and class G from −1.6 to 3.0 °C; whereas for this study the ranges for class F are −0.25 to 2.75 °C, and class G from −1 to 3 °C (Figure 3.4.). During a heatwave event (class G), which occurred on 18th of July 2006, the $UHI_{surface}$ peaked >4.5 °C. Unfortunately, given the smaller time period of this study, insufficient data are available in this analysis to assess the decline in $UHI_{surface}$ intensity for classes E and D.

Overall, the spatial pattern of the $UHI_{surface}$ at night-time is very similar to daytime. LST in the city centre is higher (~ 3 °C) than Coleshill and in parks and southwest and northeast borders it is lower (up to −1 °C). As expected, UHI intensity during night-time is lower (−1 °C to 3 °C) than daytime during the times of maximum solar irradiance (−1 °C to 8.7 °C).

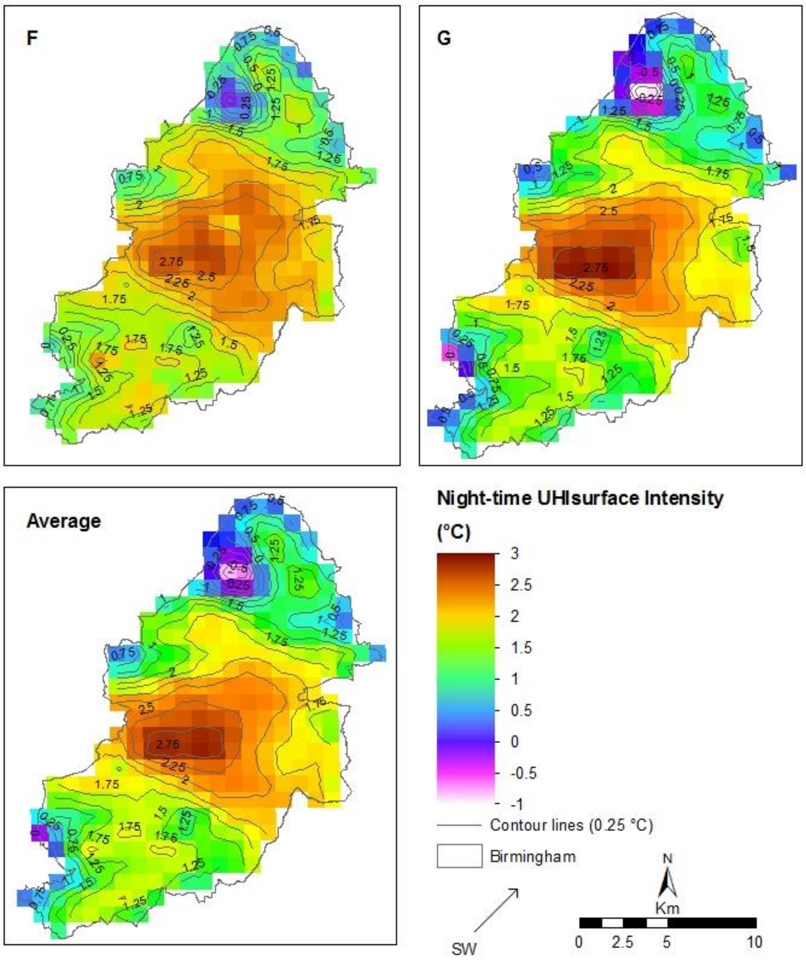

Figure 3.4. Night-time $UHI_{surface}$ intensity, for Pasquill-Gifford Stability Classes F and G, and Average for June, July, August 2013 and prevailing wind direction for the period. Based on MODIS Aqua LST product.

3.3.5. Night-time UHI_{canopy}

As with night $UHI_{surface}$, UHI_{canopy} is most evident under stable conditions, with the greatest intensity and a particularly well developed urban core in class G (Tomlinson *et al*., 2012a). The spatial distribution of T_{air} during night-time (Figure 3.5.) is also very similar to that highlighted during the daytime, with the core of urban heat becoming less defined and spreading eastwards across the city, again highlighting the potential role of advection in the structure of the UHI_{canopy}. For example, an investigation of the London UHI using MORUSES examined the factors shaping the spatial and temporal structure of the London's atmospheric boundary layer. It was found that whilst land use is the dominant factor, even weak advection is sufficient to increase nocturnal temperatures downwind of built up areas (Bohnenstengel *et al.*, 2011).

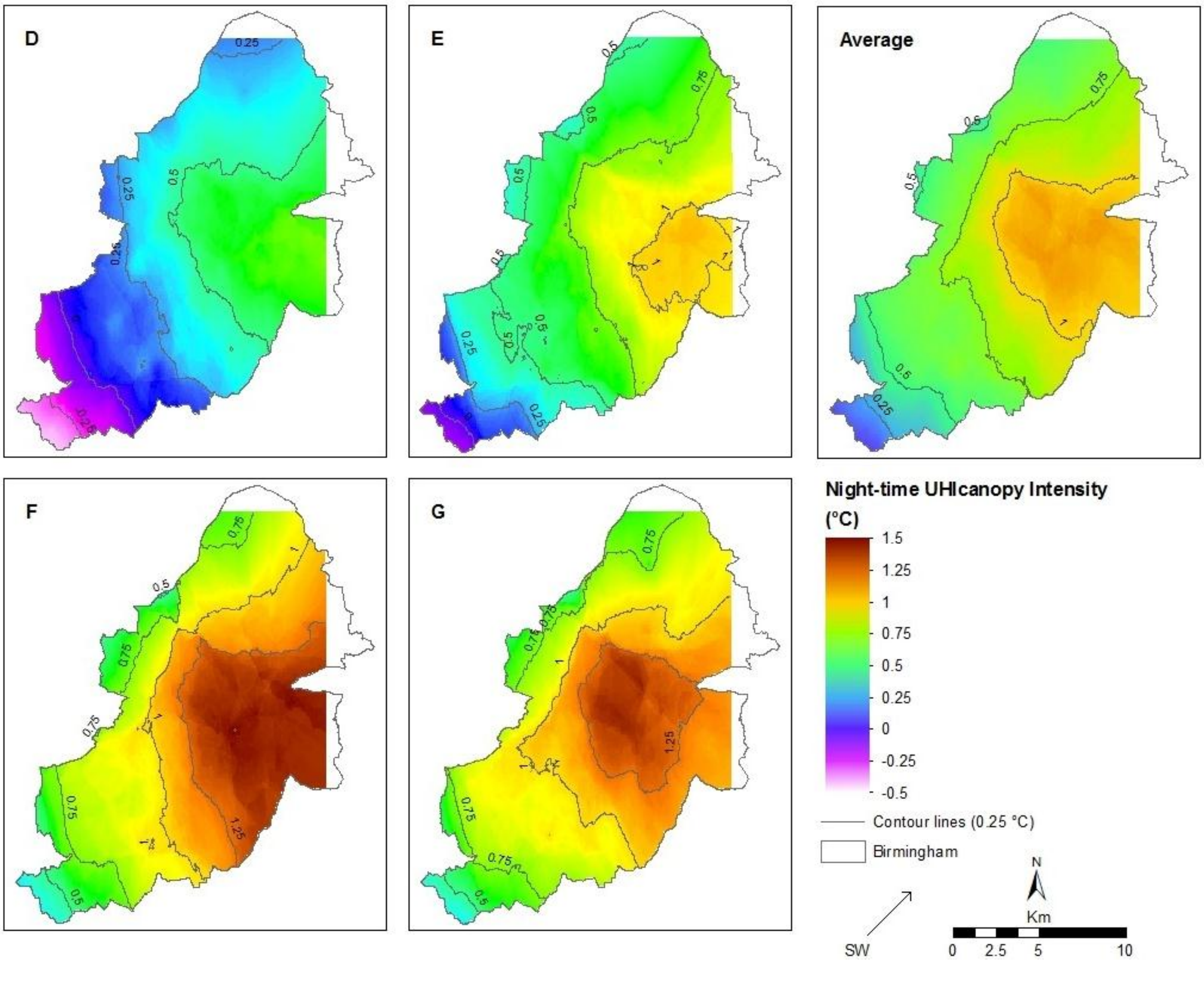

Figure 3.5. Night-time UHI_{canopy} intensity, for Pasquill-Gifford Stability Classes D, E, F and G, and Average for June, July, August 2013 and prevailing wind direction for the period. Based on the BUCL dataset.

3.4. Comparisons between Land Surface and Air Temperatures

Using the datasets presented in this Chapter, direct temperature differences (LST-T_{air}) and R^2 (coefficient of determination) were calculated between LST and T_{air} for each sensor site and weather station (neighbourhood scale) and later combined to investigate the relationship at the city scale. Note that T_{air} and LST are intrinsically different measurements (Dousset *et al*., 2011b). T_{air} represents the ambient temperature at 2 m above the surface and LST represents the surface radiant temperature averaged over a 1 km horizontal surface (including different levels within the canopy layer). The time lag between maximum LST and T_{air} depends mainly upon the physical characteristics of the surface and the convection. Although a strong correlation between the datasets is not expected, general patterns are helpful to retrieve T_{air} from LST (De Ridder *et al*., 2012).

3.4.1. Daytime

Figure 3.6.a shows large differences between LST and T_{air} data collected at the time of the satellite overpass. These differences vary with land use (Table 3.7) and range from around 3 °C in suburban areas, to over 13 °C directly adjacent to the thermal core, further highlighting the significance of the different processes contributing to $UHI_{surface}$ and UHI_{canopy} in these areas. For comparison, an intensive study of Los Angeles, USA, using 44 meteorological stations and seven AVHRR images during three

days in August 1984, indicates a 5.4 °C difference between radiant surface and air temperatures in the afternoon (standard deviation of 2.3 °C) (Dousset, 1989).

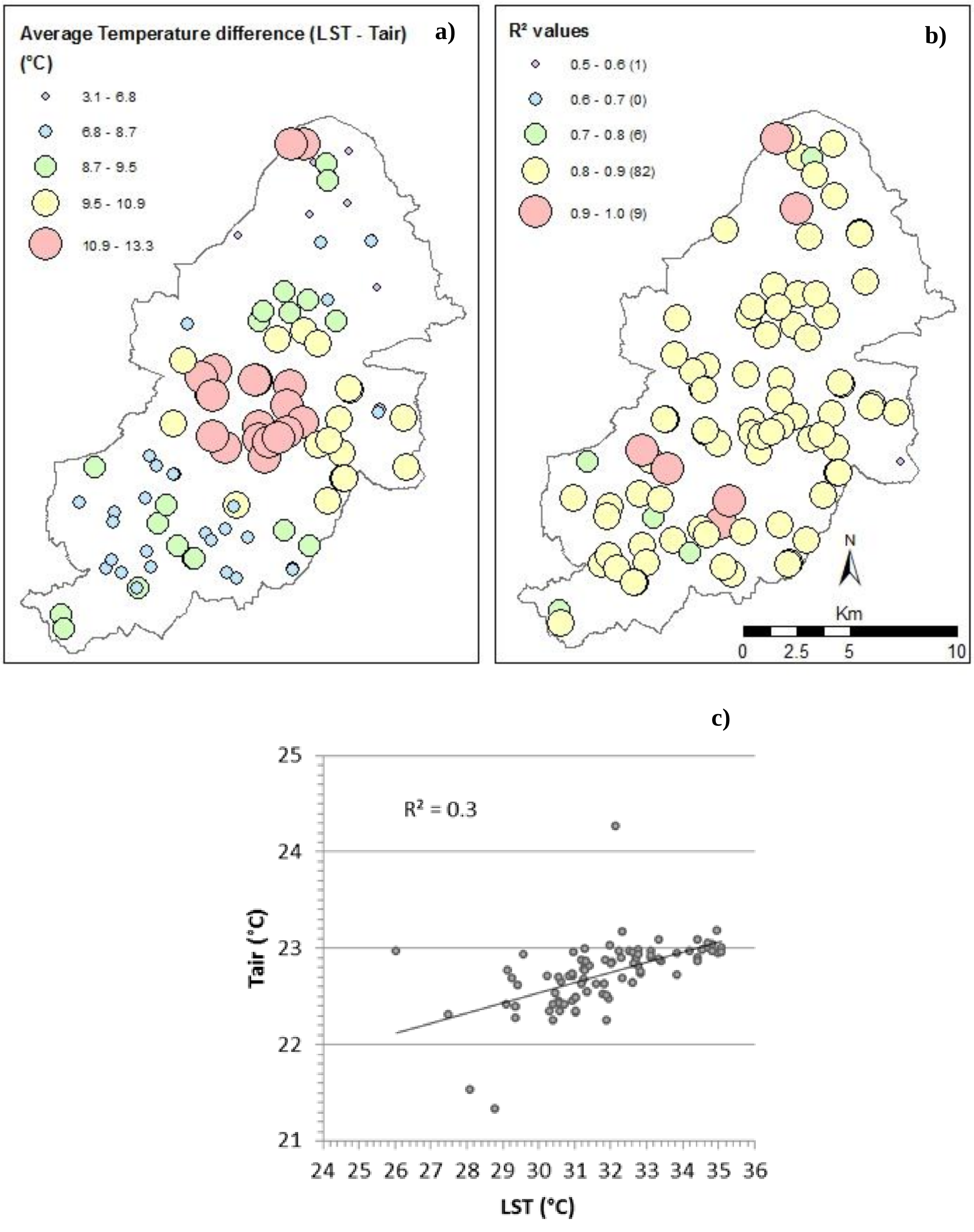

Figure 3.6. LST and T_{air} daytime comparison at 13:30. **a)** LST-T_{air} difference (MODIS-BUCL), **b)** R^2 values at sensors and weather stations location and **c)** R^2 values for city scale (all sensors and weather stations).

Table 3.7. Temperature difference (LST - T_{air}) at 13:30 and Land use (EEA, 2010)

Temperature difference (°C)	Land use
10.9 – 13.3	Industrial and commercial
9.5 – 10.9	Continuous urban fabric; and discontinuous dense urban fabric
8.7 – 9.5	Discontinuous low density urban fabric
6.8 – 8.7	Discontinuous low density urban fabric
3.1 – 6.8	Discontinuous low density urban fabric and green urban area

The result is that up to 91% of the variation in T_{air} at sites across Birmingham can be explained by LST (Figure 3.6.b). With a couple of outliers as exceptions (e.g., one sensor site with a R^2 of 0.5), this relationship is consistent across the city at the neighbourhood scale. However, when the analysis is extended to cover all sites at the city scale, the results and relationship are not consistent, and highlights the challenges in producing a simple relationship between T_{air} and LST (Figure 3.6.c).

As correlations found were consistent, slope was also applied to the analyses for verification. Slope indicates gradient of a line, describing its direction and steepness. Slope results can either indicate a line that is increasing ($m > 0$), decreasing ($m < 0$), or neutral ($m = 0$). During daytime slope varied from 0.70 to 1.31. During the day 6 sensors had slope varying from 0.96 to 0.99 and only 1 at 0.70 (same sensor that had anomalous R^2 value). All the others (88 sensors) had increasing values. These results are in line and consistent with results found for R^2.

3.4.2. Night-time

Direct comparisons between T_{air} and LST at night, show that T_{air} is consistently higher than LST across the city, ranging from 0.7 to 3.2 °C (Figure 3.7.a). Temperature differences again vary with land use (Table 3.8) with the lowest temperatures differences between LST and T_{air} in the city centre, likely because of the increased thermal capacity of urbanised surfaces. In contrast, the largest differences are in areas with more vegetation (i.e., Sutton Park and Woodgate Valley Country Park).

As per Chapter 1, the energy balance is determined by solar gains (absorbed and transformed into sensible heat) and heat loss (emitted via longwave radiation). In the urban areas the urban geometry plays an import role in this process as it relates to the availability of sunlight (solar energy gains) on building facades. Later the urban structure emits long wave radiation to the sky after sunset, once again this is related to the urban geometry. The openness of an area is important while absorbing and emitting energy.

Intensity of the emitted radiation depends on the view factor of the surface regarding the sky, known as the Sky View Factor (SVF). The higher the SVF (closer or equal 1 or 100%) the more radiation emitted, the lower the SVF (closer or equal to 0) the lower the long wave radiation emitted. Higher values of SVF are found in rural areas decreasing towards suburbs and city centre, since urban canyons usually become more enclosed towards the city centre (Bradley *et al*., 2002).

Vegetated areas and parks tend to have higher SVF, as it is usually more ‘open’, therefore the SVF of Sutton Park might be an important reason for identifying such high difference in temperature between surface and air during night-time (Figure 3.7.a).

Site specific R^2 values are consistently high between the two datasets (R^2 = 0.8-1) with less outliers than during the daytime (Figure 3.7.b); 8 sensors ranged between 0.8 and 0.9, and 90 sensors between 0.9 and 1. Furthermore, the relationship at the city scale is improved at night (Figure 3.7.c) and is to be expected given the less complex radiation processes operating after sunset. These results are greatly improved from a previous pilot study in Birmingham that compared 13 MODIS night-time summer LST images with 28 low-cost, unshielded, iButton loggers. In this study, R^2 values were not as consistently high (R^2 = 0.5-0.9) and no clear spatial pattern in the results was found (Tomlinson *et al.*, 2012b). Similarly, they show improvement on transect studies in Szeged which yielded correlations in the range of 0.6-0.7 depending on the size of the sample radius (Unger *et al.*, 2010b).

During night-time slope was also applied due to the admittedly high correlation values. These varied from 0.88 to 1.11. During the night 66 sensors were above 1 indicating increasing values, and 32 below 0 indicating decreasing values. Again the results were in line with results found for R^2.

The improved results in this study in comparison to the previous one in Birmingham (Tomlinson *et al.*, 2012) and Szeged (Unger *et al.*, 2010b) are attributed to the improved quality controlled/assured T_{air} dataset derived from BUCL (Chapman *et al*., 2014). Therefore, it highlights the importance of metadata and specific protocols when deploying sensors. Furthermore, correlations in all of these studies could have been different if correction of vertical surfaces were included. However, the aim was to observe direct correlations between the values.

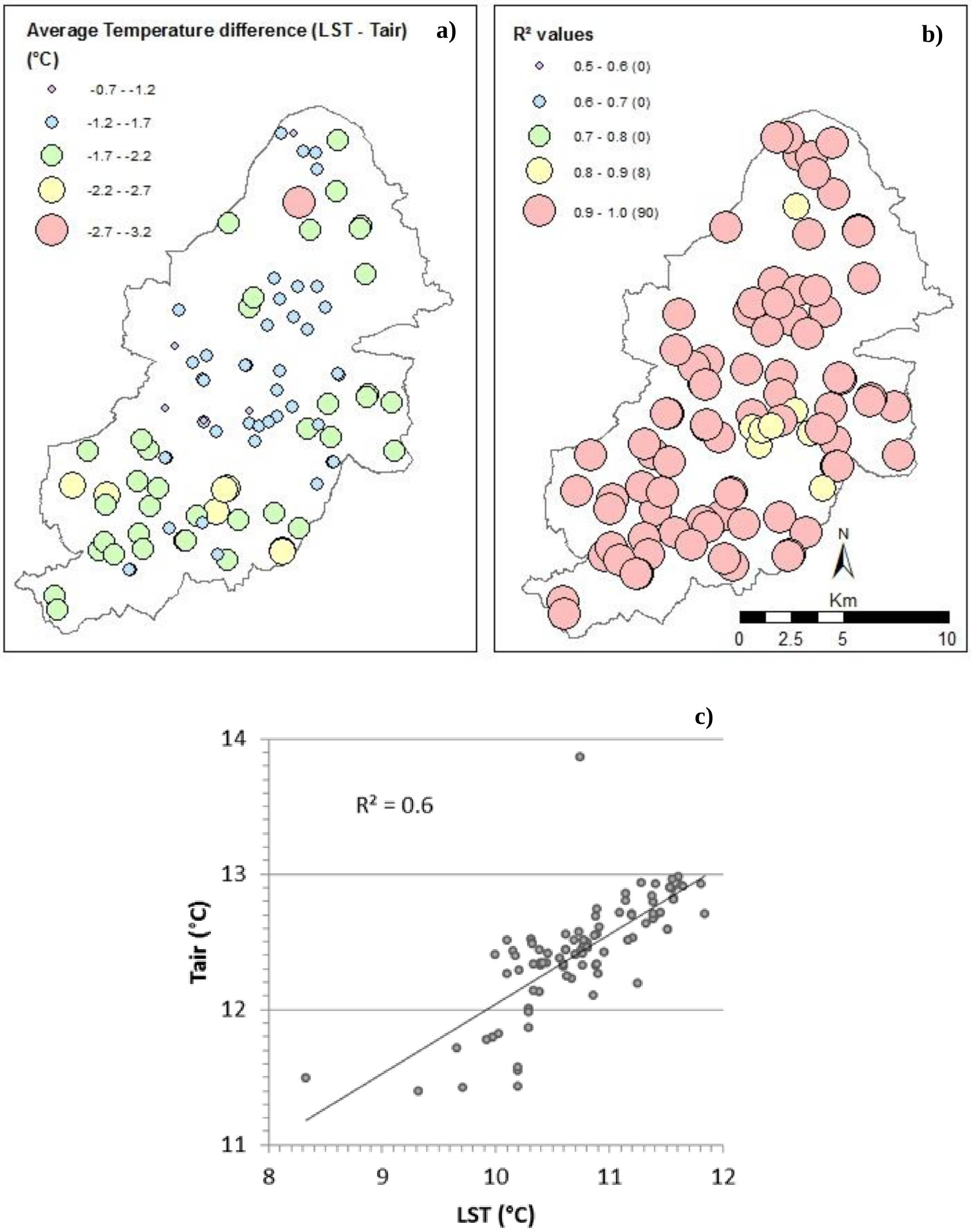

Figure 3.7. LST and T_{air} night-time comparison at 1:30. **a)** LST-T_{air} difference (MODIS-BUCL), **b)** R^2 values at sensors and weather stations location and **c)** R^2 values for city scale (all sensors and weather stations).

Table 3.8. Temperature difference (LST - T_{air}) at 1:30 and Land use (EEA, 2010)

Temperature difference (°C)	Land use
-0.7 – -1.2	Industrial and commercial; continuous urban fabric; discontinuous dense urban fabric
-1.2 – -1.7	Industrial and commercial; continuous urban fabric; discontinuous dense urban fabric
-1.7 – -2.2	Discontinuous low density urban fabric; continuous and discontinuous urban fabric; and small proportion of industrial and commercial
-2.2 – -2.7	Discontinuous low density urban fabric and green urban area
-2.7 – -3.2	Green urban area

3.5. Conclusions

This Chapter has compared the $UHI_{surface}$ and UHI_{canopy} in Birmingham using MODIS LST and a unique, high resolution, T_{air} dataset. The UHI is clearly present in both datasets, both day and night, and over a range of atmospheric stability classes. During the day, LSTs in the city can be up to several degrees warmer than the rural reference, with the greatest variations occurring in class B (moderately unstable) reinforcing the findings of other similar studies (e.g., Kolokotroni and Giridharan, 2008). During the night, UHI intensity increases in line with atmospheric stability and is greatest in class G. During both the day and night, the $UHI_{surface}$ was greater than UHI_{canopy}.

A key finding of this Chapter is the differences in the spatial patterns for $UHI_{surface}$ and UHI_{canopy}. With respect to $UHI_{canopy,}$ there is a tendency for a larger core of urban heat to spread to the east of the city, which is hypothesised to be a result of advective processes, in line with other published results (Heaviside *et al.*, 2015). In contrast, $UHI_{surface}$ extends more to the west of the city, suggesting that the $UHI_{surface}$ pattern is more clearly linked with land use, and that advection does not play a significant role. This difference is particularly distinct at night, and underlines the need to use high resolution datasets to further investigate advective process in the urban canopy. To this end, the 25 BUCL weather stations equipped for measuring wind speed and direction provide data for future investigation of advection, including its pattern and intensity.

Although strong relationships were found between T_{air} and LST during both the day and night at a neighbourhood scale, it is clear that, even with higher resolution datasets such as BUCL, it is presently unlikely that a simple statistical model could be obtained between LST and T_{air} at the city scale. However, quality controlled higher spatial and temporal resolution T_{air} datasets remain an important way in evaluating and validating T_{air} physically derived from LST.

To conclude, it is clear that the use of high resolution data from UMNs greatly facilitates work of this nature, and given extended periods of study, then general relationships and physical process-based numerical models could become more realistic. Indeed, the greatest potential in this area perhaps comes from co-located IR surface temperature monitoring devices at BUCL sites. These will enable surface temperature to be measured in the same vertical profile as air temperature and will potentially enable unprecedented direct ground truthing of LST datasets. If used in sufficient numbers per pixel (i.e., 1 km), this approach will provide high quality data for comparison studies simplifying the complexities of the wider environment/variable T_{air} source areas contained within a pixel. Overall, as this Chapter has shown, improvements in measuring T_{air} across the urban environment are beneficial to not only understanding UHI_{canopy}, but also $UHI_{surface}$.

3.6. Chapter Summary

A significant finding of this chapter is that it demonstrates that the distribution of the surface UHI appears to be clearly linked to land use, whereas for canopy UHI, advective processes appear to play an increasingly important role. Since energy consumption is linked to T_{air} and not LST, the consumption pattern could be wrongly estimated if assumptions are made using LST patterns. Indeed the advective process seems to play a very important role in the Birmingham UHI, however that was beyond the scope of this research and advective processes will not be investigated.

BUCL data is ideal for energy consumption estimations at intra-urban level, due to its temporal and spatial resolution. It is important to highlight that energy consumption does not occur only on ideal circumstances, but every minute of the day, every day, therefore, the analyses for each stability class will not be addressed further in this research as well, although the results can be used to estimate consumption in ideal scenarios or spatial risk assessments. However, given this new unprecedented high resolution dataset, there is a need to see how this can be utilized to explore consumption using established techniques. This thesis will now explore and critique the standard approaches used.

Chapter 4

Critique and suggested modifications on the degree days methodology to enable long-term electricity consumption assessments

4.1. Introduction

The onset of climate change will lead to increasingly elevated temperatures over large regions of the world. Higher outdoor ambient temperatures will significantly influence energy consumption by increasing demand for refrigeration and air conditioning (Papakostas *et al.*, 2010). For example, in the United States it has been shown that increases in air temperature can explain 5-10% of urban peak electric demand, with a typical rise of 2-4% for every 1 °C rise in daily maximum temperature over 15-20 °C (Akbari, 2005). Air conditioning usage is expected to increase significantly in the short term (de Munck *et al*., 2013), not only because of the increased cooling required by a warming climate, but due to such goods no longer being seen as a luxury item (De Cian *et al*., 2012).

In temperate climates, an increase in energy consumption for cooling in summer will potentially be offset with reduced energy use for winter heating (McGilligan *et al*., 2011; De Cian *et al*., 2012; Golombek *et al*., 2012; Santamouris, 2013). Although regional climatology will be a key driver in energy use, subtle variations in consumption will also be apparent dependent on energy efficiency measures (Li *et al*., 2012), availability of passive cooling, building construction (Semmler *et al*., 2010; Kolokotroni *et al*., 2012) as well as changes in social attitudes (Semmler *et al*., 2010). The associated switch of energy requirements from heating to cooling could also be problematic. Oil and gas are traditionally used for heating, whereas electricity is more commonly used for cooling. As electricity has a tendency to be less efficient, and therefore more expensive, current estimates indicate additional expenditure of energy on cooling in summer will probably outweigh winter energy savings (McGilligan *et al*., 2011). Furthermore, electricity also has higher CO_2 emissions per unit of consumption, meaning that the switch from heating to cooling, could potentially further exacerbate climate change and global warming (De Cian *et al*., 2012; Li *et al*., 2012). Overall, the result will be increasing pressure on electricity networks during times of peak demand, which has the potential to be a bigger problem in the longer term if part of the future energy mix is provided by renewables, such as hydropower, which are also vulnerable to climate change (Vine, 2012).

4.1.2. Background to Degree Days

Degree days are a climate statistic originally developed by US utility companies in the 1930's for estimating demand for coal and gas based upon typical energy usage. There have been efforts to improve the precision of the technique (e.g., degree hours, used by Tselepidaki *et al*., 1994; Satman and Yalcinkaya, 1999; Kolokotroni *et al*., 2010; Dimoudi *et al*., 2013), however the original methodology remains the most common approach used in scientific studies. By definition, degree days are based on the principle that energy balance is achieved when heat inputs in a building are equal to overall heat loss, resulting in no latent load (McGilligan *et al*., 2011). Hence, a Balance Point Temperature (BPT) exists where the outdoor ambient temperature is sufficiently high (or low) enough to ensure that there will be no need for additional heating (or cooling). It is this BPT that is used to define the base temperature which is integral to the degree days methodology (ASHRAE, 2001).

Two indices are frequently used; Heating Degree Days (HDD), which approximate space heating demand, and Cooling Degree Days (CDD) which approximate demand for refrigeration and air conditioning. HDD are calculated by subtracting the mean daily temperature from a pre-determined base temperature and summing up any positive values over a set time period (1). Similarly, CDD are calculated by subtracting the base temperature from the mean daily temperature and summing up only positive values over a determined time period (2) (Thom, 1952; 1954).

$$
\begin{aligned}
&T_{average} = \frac{(T_{\max} - T_{\min})}{2} \\
&x = T_{base} - (T_{average}) \\
&HDD = \Sigma(x \geq 0)
\end{aligned}
\tag{1}
$$

$$
\begin{aligned}
&T_{average} = \frac{(T_{\max} - T_{\min})}{2} \\
&x = T_{average} - T_{base} \\
&CDD = \Sigma(x \geq 0)
\end{aligned}
\tag{2}
$$

Sailor and Pavlova (2003) used CDD to demonstrate that a 1 °C increment in temperature corresponded to an average increase in energy consumption of 8% (with air conditioning being the primary cause of this increase). Other studies have attempted to use the approach to assess the impact of a changing climate on the energy industry. For example, a decreasing trend in HDD and a subsequent rise in CDD across Spain was observed over the period of 1983-1998 (Valor *et al.*, 2001). Similar results were found in Greece for HDD and CDD between 2 time periods; 1993–2002 and 1983–1992 (Papakostas *et al*., 2010). Examples of longer term studies include Christenson *et al.* (2006) who noted a significant reduction in HDD, and subsequent increase in CDD, in a number of central European cities over the 20th century and Castañeda and Claus (2013) who observed local trends in HDD across Argentina over an extended time period of 108 years.

4.1.3. Critique to the use of Degree Days

There are three main criticisms that should be highlighted with the use of CDD and HDD. These are the input data that uses outdoors temperatures in the calculations, the selection of base temperatures and finally the applicability of the methodology over longer time scales.

4.1.3.1. Input data: the use of outdoor air temperatures in calculations

Arguably the biggest limitation of the degree days methodology is the use of outdoor ambient temperatures in the calculations. The 'set point' temperature is defined as a comfortable indoor temperature - i.e., the temperature at which air conditioning and space heating are typically switched on by users. Unfortunately, widespread measurements of 'set-point' temperature have not been historically available and as such outdoor air temperatures have to be used instead. McGilligan *et al.* (2011) argued that the way the degree days methodology is calculated, it assumes steady state conditions, where each degree rise would result in an equal indoor temperature rise. Clearly, outdoor ambient temperatures will be quite different from comfort levels experienced in buildings, each with varying levels of insulation and heating/cooling technologies (Kadioğlu *et al*., 2001). This limitation can only realistically be overcome by obtaining detailed indoor temperature data across a large sample of the housing stock.

4.1.3.2. Parameterisation: selection of base temperatures

Base temperature is presently the only parameter in the degree days methodology, which can be varied to take into account local conditions. Base temperatures are based on BPT and take into account building size, building configuration and available technology for a specific geographical region (Kadioğlu *et al*., 2001). Hence, in order to compensate for the use of outdoor temperature data in the analysis, base temperatures are often several degrees lower than expected 'set points'. For example, the first adopted base temperature was 18.3 °C (Thom, 1952). This was calculated based on the assumption that 21.1 °C was a typical indoor comfort temperature, of which 2.8 °C could be attributed to solar heat gain, occupants and other internal processes.

The base temperatures used for HDD are frequently different from those used for CDD, as it can be assumed that a range of comfortable temperatures exist between the two (De Cian *et al*., 2012). For example, for uninsulated buildings in the USA, HDD and CDD have traditionally been calculated using a base temperature of 18 °C and 22 °C, respectively, thus indicating a non-sensitive 'comfort zone' temperature interval of 4 °C (Valor *et al*., 2001). However, base temperatures can often be varied due to both personal preferences (Sailor and Pavlova, 2003) and the specific building characteristics controlling BPT. This lack of objectivity means that it is not surprising to find a wide range of base temperatures evident in the literature (Table 4.1). The result is that standardisation often is not evident even when the technique is applied in the same country. Whilst this may be appropriate in large countries (e.g., USA), a lack of standardisation in smaller territories (e.g., Greece) is questionable. Overall, the choice of base value (i.e., based on an outline of building standards) is rarely justified in the literature, and highlights a need for improved rigour in the general application of the methodology.

Table 4.1. Summary table of base temperatures used in the literature for the degree days methodology

Country and City	Base Temperature		Justification for Base Temperature	Reference
	HDD	CDD		
Argentina	18.3 °C	-	Thom (1954)	Castañeda and Claus (2013)
Australia	18 °C	-	-	Badescu and Zamfir (1999)
China	18 °C	26 °C	-	Xiao *et al.* (2012)
Greece (Athens and Thessaloniki)	15 °C	24 °C	"These temperatures are the most common balance temperatures of normally insulated buildings without especially large heat gains from internal heat sources and solar radiation."	Papakostas *et al.* (2010)
Greece (Athens)	-	25 °C and 28 °C	-	Tselepidaki *et al.* (1994)
Greece (Penteli, Ilioupolis, Aigaleo, Athens)	-	23.7 °C	-	Hassid *et al.* (2000)
Greece	14 °C	-	"With experimental and empirical methods of trial and error, a value of 14 °C was fixed as the basic temperature Tb"	Matzarakis and Balafoutis (2004)
Ireland	18 °C	18 °C	Thom (1954)	Semmler *et al.* (2010)
Israel	10 °C	25 °C	-	Beenstock *et al.* (1999)
Jordan	15.5 °C	-	-	Kodah and El-Shaarawi (1990) and El-Shaarawi and

				Al-Masri (1996)
Macedonia	20 °C	20 °C	-	Taseska *et al.* (2012)
Netherlands	18 °C	18 °C	-	Hekkenberg *et al.* (2009)
New Zealand	15.6 °C and 16 °C	-	-	Badescu and Zamfir (1999)
Romania	18 °C	-	-	Badescu and Zamfir (1999)
Saudi Arabia	17.8 °C, 21.1 °C	-	-	El-Shaarawi and Al-Masri (1996)
Saudi Arabia	18 °C and 21 °C	23 °C and 25.5 °C used for buildings without insulation; and 25.5 °C and 27.8 °C was used for well-insulated buildings	-	Said (1992)
Spain	15 °C	21 °C	Within these two limits a comfort zone was established and no heating or cooling is required	Valor *et al.* (2001)
Spain	18 °C	18 °C	"Standard reference commonly used to calculate heating and cooling degree-days, especially in the analysis of the impact of weather on energy consumption"	Valor *et al.* (2001)
Switzerland (Lugano)	8 °C, 10 °C and 12 °C	18.3 °C, 20 °C and 22 °C	"Outdoor air temperature (for a specified internal temperature) at which the total heat loss is equal to the internal	Christenson *et al.* (2006)

			and solar heat gains"	
Turkey	14 °C, 16 °C, 18 °C, 20 °C and 22 °C	18 °C, 20 °C, 22 °C, 24 °C, 26 °C and 28 °C	-	Büyükalaca *et al.* (2001)
Turkey	15 °C	24 °C	-	Kadioğlu *et al.* (2001)
Turkey	15 °C	-	-	Kadıoğlu *et al.* (1999)
UK	15.6 °C and 16 °C	-	-	Badescu and Zamfir (1999)
UK (Edinburgh, Manchester and London)	20 °C	26 °C	-	McGilligan *et al.* (2011)
UK(London)	15.5 °C	-	-	Kolokotroni *et al.* (2009) and Kolokotroni *et al.* (2010)
UK	15.5 °C	22 °C	-	UKMO (2009)
USA (California)	18 °C	18 °C	-	Xu *et al.* (2012)
USA (39 cities)	18.3 °C	18.3 °C	"Base temperature was selected after an optimization study revealed that alternative definitions would not improve upon the models in a statistically significant way"	Sailor and Pavlova (2003)
USA	18 °C	18 °C	"18°C is due to the additional heat generated by occupants and their activities, resulting in an average indoor temperature of 21°C"	Sivak (2008)
USA (Los Angeles, Washington, St Louis, New York, Baltimore, Seattle, Detroit, Chicago and Denver)	18.3 °C	18.3 °C	-	Taha (1997)
USA	18.3 °C	-	-	Badescu and

				Zamfir (1999)
USA	18.3 °C	-	-	Thom (1952) and Thom (1954)
USA (Ohio, Louisiana and Washington)	18.3 °C	18.3 °C	-	Sailor and Muñoz (1997)
USA (Florida)	21 °C	21 °C	-	Sailor and Muñoz (1997)
Western Europe	18 °C	22 °C	-	Golombek *et al.* (2012)

4.1.3.3. Acclimatisation: applicability over longer timescales

The simplicity of the degree days methodology remains a key advantage of the approach. However the technique relies on generalised assumptions to approximate BPT as well as uniform perceptions of thermal comfort independent of age, health and activity levels (Ormandy and Ezratty, 2012). For this reason, it is inappropriate to assume that these factors will remain constant over an extended study period. As the impacts of climate change begin to manifest, local temperatures will change and as such, the local population will begin to acclimatise and adapt (Sailor and Pavlova, 2003). In a warming climate, people's perception of comfort will change and subsequently so will 'set point' temperatures. As such, when dealing with long-term datasets (especially over large geographical regions, e.g., the USA), there is a need to carefully consider how methodologies can evolve to account for such adaptation. Whilst detailed computer simulations are capable of this at the building scale (e.g., DOE-2: Akbari, 2005), larger scale studies are still reliant on the degree day methodology.

This Chapter now aims to highlight how these limitations can be overcome by conducting a study into electricity consumption patterns over a 9 year period in Birmingham.

4.2. Methodology

4.2.1. Energy data

Ordinary domestic electricity data were obtained from DECC (DECC, 2013), for the city over the time period 2005-2013 (Table 4.2).

Table 4.2. Variation in annual and seasonal temperatures, and ordinary domestic electricity consumption

Year	Annual			December, January and February			June, July and August			Ordinary Domestic Electricity Consumption (kWh)
	Average Temperature (ºC)	Average Maximum Temperature (ºC)	Average Minimum Temperature (ºC)	Average Temperature (ºC)	Average Maximum Temperature (ºC)	Average Minimum Temperature (ºC)	Average Temperature (ºC)	Average Maximum Temperature (ºC)	Average Minimum Temperature (ºC)	
2005	10.34	13.97	6.65	5.18	7.90	2.64	16.17	20.80	11.53	1,362,304,701.30
2006	10.79	14.40	7.24	4.08	6.43	1.72	17.49	22.46	12.52	1,400,455,171.50
2007	10.38	14.00	6.78	6.36	8.93	3.80	15.20	19.24	11.15	1,391,909,032.00
2008	9.87	13.30	6.35	5.54	8.61	2.47	15.57	19.57	11.57	1,346,568,783.00
2009	9.94	13.54	6.30	3.62	6.17	1.07	15.63	19.95	11.31	1,350,824,020.90
2010	8.76	12.51	5.02	2.21	4.64	-0.23	15.97	20.54	11.41	1,367,259,041.30
2011	10.73	14.72	6.75	3.03	5.64	0.41	15.14	19.92	10.36	1,361,442,469.30
2012	9.25	12.93	5.58	4.35	7.29	1.42	14.83	18.78	10.88	1,339,389,853.00
2013	9.21	12.79	5.63	4.12	6.57	1.68	15.59	20.23	10.94	1,347,649,532.00

4.2.2. Base temperature

In order to demonstrate the methodological sensitivity of the choice of base temperature in the degree day methodology, CDD and HDD were calculated from Equations 1 and 2 for each year of the study period. Hourly temperature data from Coleshill weather station were used (located ~ 10 km to the east of Birmingham city centre) (UKMO, 2013). A range of values between 8-24 °C were then used to test the sensitivity of the technique to a range of base temperatures proposed for the UK in the literature (Table 4.1). Finally, Spearman Rank correlation coefficients were calculated between degree days and energy consumption for each of the base temperatures used (Figure 4.1.).

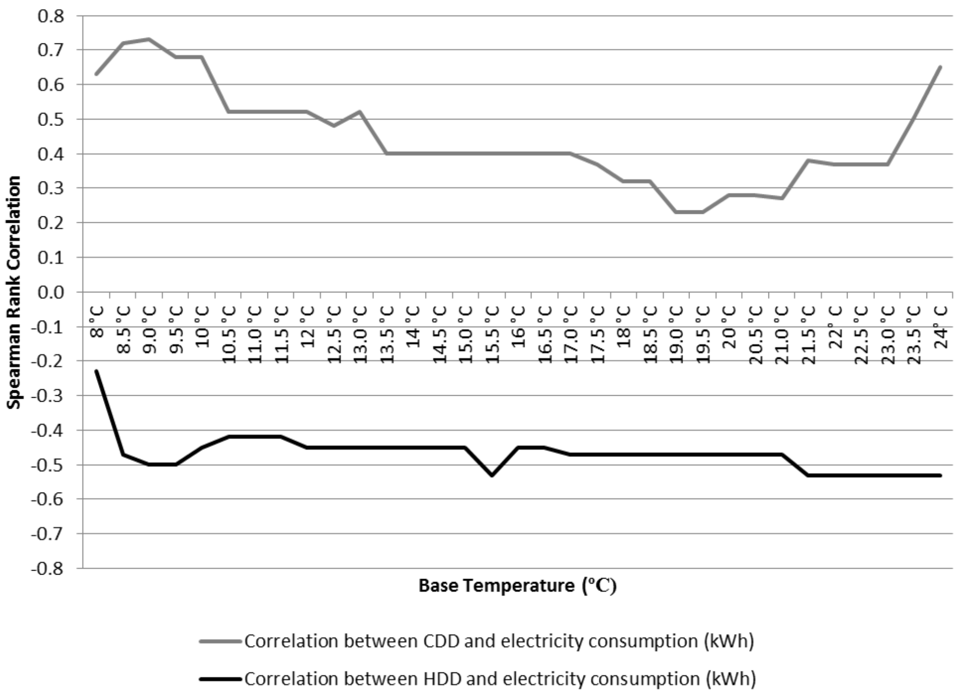

Figure 4.1. Spearman Rank Correlation between CDD and HDD and ordinary electricity consumption, for different base values, for the studied time series (2005-2013).

4.3. Results and discussion

Figure 4.1. shows that regardless of the choice of base temperature, a positive correlation is evident between electricity consumption and CDD in Birmingham. This confirms (as expected) that more electricity is used at higher temperatures due to refrigeration and air conditioning. Subtle differences are apparent in the strength of the relationship at various base temperature values which indicates that some values are perhaps more appropriate than others. UKCP09 uses a base temperature of 22 °C for CDD (Table 4.1) and based upon this analysis, this choice appears to be acceptable, since it results in strong correlation. However, higher correlations were obtained using a much lower base temperatures with the strongest relationship between CDD and electricity consumption occurring at 8.5 °C and 10 °C. Interestingly, the choice of 8.5 °C and 10 °C base is close to the average annual temperature of Birmingham which is 9.95 °C (using 1981-2010 as a baseline at Coleshill Weather Station).

Conversely, the relationships between electricity consumption and HDD show a negative correlation indicative of reduced electricity use for air conditioning and refrigeration during colder periods. Again, the strength of the relationship varies depending on the base temperature value used, but the UK base value of 15.5 °C (Table 4.1: Kolokotroni *et al*., 2010) together with base values equal to or greater than 21.5 °C outperform all other base temperatures with respect to the strength of the correlation with electricity consumption.

Given the strength of the correlations obtained, it confirms that for simple studies, the use of a wide range of base temperatures is equally acceptable. However, there remains scope to improve the approach by using a base value which also reflects adaptation and acclimatisation of the population to a changing climate. As Table 4.3 shows, whilst the existing values of 22 °C and 15.5 °C for CDD and HDD, respectively, are acceptable for use in the present UK climate, these are likely to change in due course as the impacts of climate change become increasingly apparent. Hence, given the results in Figure 4.1., it is proposed that the use of universal base temperature values which directly reflect (or are related to) the baseline average temperature experienced in a region could be a significant improvement on the degree days methodology when dealing with extended time periods. By maintaining this link, it becomes possible to take into account adaptation by society in a changing climate. This would then enable the incorporation of the degree day methodology into climate change risk assessments via the use of weather generators and temporal analogues.

Table 4.3. UKCP09 projections showing **a)** Annual average temperature from Birmingham for the 50th percentile, **b)** Summer average temperature and **c)** Winter average temperature

	2020s (2010-2039)	2030s (2020-2049)	2040s (2030-2059)	2050s (2040-2069)	2060s (2050-2079)	2070s (2060-2089)	2080s (2070-2099)
a) Average annual temperature (°C)							
Low emission scenario	10.6	10.9	11.2	11.3	11.6	11.8	11.9
Medium emission scenario	10.6	10.9	11.3	11.7	12.0	12.3	12.6
High emission scenario	10.6	11.0	11.4	11.9	12.4	13.0	13.5
b) Summer average temperature (°C)							
Low emission scenario	16.8	17.1	17.4	17.6	17.8	17.9	18.0
Medium emission scenario	16.7	17.1	17.4	17.8	18.3	18.6	19.0
High emission scenario	16.6	17.1	17.5	18.2	18.7	19.3	20.0
c) Winter average temperature (°C)							
Low emission scenario	4.9	5.2	5.4	5.5	5.7	5.9	6.2
Medium emission scenario	5.0	5.2	5.5	5.8	6.1	6.3	6.6
High emission scenario	4.9	5.2	5.6	6.0	6.4	6.7	7.1

4.4. A future perspective

The year 2006 was the warmest year in the study period characterised by a heatwave event which, whilst not as severe or prolonged as the much documented 2003 event, extensively covered much of northern Europe. In the UK, the heatwave peaked in July 2006, breaking the previous July temperature record, but falling several degrees short of the of the all-time temperature record attained during the 2003 event (see Rebetez *et al*., 2008 for a fuller quantification of the two events in Europe).

In this section, a temporal analogue approach is used to set this year in the context of a future climate and to provide a perspective for how the impact of a changing climate can be incorporated into the degree days methodology. The temporal analogue approach is a useful method to identify the possible future impacts of climate change, based on the impacts of real events that have already happened (Giles and

Perry, 1998). The method assumes that a past event is an indicative scenario of the future, and that the probability of an event reoccurring in the future can then be determined by using climate change scenario data and a weather generator (e.g., UKCP09). The relative simplicity and versatility of the technique remains a key strength of the approach (Wilby *et al*., 2004) and as such it has been extensively used in a range of different UK applications including tourism (Giles and Perry, 1998), road accidents (Andersson and Chapman, 2011) and economic uncertainties (Hallegatte *et al*., 2007). However, it has not been used in the energy sector to date.

Using UKCP09 Weather Generator projections (UKMO, 2009) were derived annually for average temperature, summer (JJA) and winter (DJF), for three different emission scenarios (A1F1: High, A1B: Medium & B1: Low), detailed information on how this data is derived can be found in Chapter 5, section 5.2.3. All projections are relative to the 1961-1990 baseline and were calculated for seven decadal time slices (Table 4.3). Although the output is probabilistic, the 50th percentile was used in this analysis. Upon inspection of the output, it can be determined that average temperatures of the magnitude experienced in 2006 will become typical by the 2020's (under all emission scenarios). However, the heat waves experienced in the summer of 2006 will be typical of average conditions that will be experienced in 2040 under the high scenario and 2050 under medium and low scenarios. In contrast, winter average temperatures were representative of current conditions.

The climate change scenario data used in this approach can then be linked to the degree days methodology to help include acclimatisation in the analysis. It is at this point that the advantage of using a standardised base value based on mean temperatures becomes apparent (Figure 4.1.). As the population acclimatises to a warmer climate, it can be assumed that the 'set point' temperature will increase in line with average temperatures and hence, the base temperature used in analyses will also need to increase accordingly. Therefore, in studies over an extended period of time, acclimatisation can now be incorporated into the study by using a base temperature calculated using a moving average of air temperature. This adjustment, when used with a weather generator then becomes a suitable means to approximate electricity consumption at any point in the future.

4.5. Conclusions

Following a critical review of the degree days methodology, a number of areas for improvement that could potentially be made to the approach have been identified. Fundamentally, there appears to be a need to further standardise the method so that it can be used by policy makers and the energy industry to plan and project energy requirements during a changing climate.

As this Chapter has shown, the calculation of CDD and HDD is sensitive to the choice of base temperature which underlines the caution with which the base must be chosen and justified (Büyükalaca *et al.*, 2001) as well as the manner in which results are interpreted. Currently, it is the difficulty in assessing building standards which leads to most of the subjectivity and this is the cause of substantial inaccuracies (Xu *et al*., 2012). Hence, there is a strong argument to standardise the approach based purely on climate. Although, there is some evidence of previous attempts for standardisation in the literature, with a consensus on the use of 18 °C as the base temperature for CDD and

HDD (as first identified in Thom, 1952), the appropriateness of this value has been frequently challenged. For example, Hekkenberg *et al.* (2009) highlights that for the Netherlands, the daily temperature rarely rises above 18 °C making the use of that value as a base quite limited. This further reinforces the argument made in this Chapter that the base ideally needs to be linked to localised mean temperatures.

It is accepted that adopting this approach may be too simplistic for all climates, particularly those with a large range in annual temperatures, but the improved objectivity is a considerable benefit. A further advantage is the option to easily adjust the base value when performing comparative studies across different regions or over extended time periods in order to account for acclimatisation as part of a climate change risk assessment. However, as with all long term studies of this nature, the biggest difficulties are caused due to confounding factors other than temperature such as energy prices, socioeconomic development and adaptation (Kyselý and Plavcová, 2011). In a pertinent recent example, Santamouris *et al.* (2013) investigated the relation between economic crisis and energy consumption in Greece which resulted in a 37 % reduction in consumption than expected.

4.6. Summary

This Chapter has explained the degree day method and carried a critical review of studies in the scientific literature that have used the degree days method and highlighted its limitations. The limitations regarding the use of external temperatures are particularly pertinent for this thesis, as newly available UMN data can be used.

The base values were questioned and possibly it is a good alternative to use average temperature as a universal base temperature, however for the remainder of this thesis, the 18 °C base value will be used, as it has been well accepted across literature.

It is important to focus on the fact that the results of the methodology (or the amount of degree days) do not necessarily correlate to the overall consumption, since a range of factors can impact on consumption, although several studies have identified good correlation. The degree days indicate exclusively the demand related to T_{air}*, therefore estimates the demand in consumption related to climate. This thesis will now investigate the application of the degree days methodology at the neighbourhood scale.*

Chapter 5

Estimating current and future energy demand with an Urban Meteorological Network

5.1. Introduction

As shown in Chapter 4, the degree days methodology is a simple approach used to relate outdoor temperatures and energy demand. Two indices are frequently used: HDD to approximate space heating demand, and CDD to approximate cooling demand (e.g., by the use of air conditioning and others). Using CDD it has been demonstrated that a 1 °C increment in temperature corresponds to an average increase in energy consumption of 8% (with air conditioning being the primary cause of this increase) (Sailor and Pavlova, 2003). Other studies have also investigated the impact of climate change on degree days and consumption (Valor *et al*., 2001; Christenson *et al*., 2006;

Papakostas *et al*., 2010; Castañeda and Claus, 2013) showing general decreases in HDD and/or increases in CDD.

The methodology is dependent on the selection of a base value which is used as a threshold in calculations. The most widely used value is 18 °C, which considers that for an 18 °C T_{air}, the indoor temperature would be approximately a 'comfortable' 21 °C due to the additional heat generated by occupants and insulation. However, there is a lack of consensus on what base value should actually be used. In the previous Chapter, the sensitivity of the choice of base value was tested, and highlighted that the strongest correlations between CDD and consumption data were when a base value of around 10 °C was used – very close to the average annual temperature for the city of 9.95 °C. This lack of standardisation is one of several limitations of the degree days methodology (other limitations include: not considering other weather parameters, energy efficiency of buildings, insulation patterns), however it still provides a useful first order indicator for differences in energy demand regarding cooling and heating (Sivak, 2008). Furthermore, the simplicity and convenience of the approach remains a key advantage (Cox *et al*., 2015).

As illustrated in Chapter 3, given the wide variation in T_{air} across a city, there is a need to consider the UHI in energy demand estimates. However, studies which use the degree days methodology do not currently take into account the UHI effect, since they are frequently based on data taken from a single weather station (often located at a nearby airport or rural area) which are then incorrectly considered to be representative of the city as whole. There is no scientific reason why the degree days approach cannot be scaled up to include UHI, but a significant barrier to doing so previously has been the paucity of high resolution T_{air} data across the city. Fortunately, as shown in Chapter 3, the ever decreasing costs of weather monitoring equipment, data from a new generation of dense UMN (Muller *et al*., 2013b) are now becoming available. Whilst city wide deployments are still quite rare, these have the potential to provide T_{air} data across a city at a high spatial and temporal resolution providing an unprecedented quantification of the UHI and therefore providing consistent real measured data to address current and future energy demand in cities. This Chapter will analyse T_{air} data available from BUCL to estimate energy demand based on CDD across Birmingham. This will enable city scale variations in energy demand to be objectively quantified for use in current and future climate scenarios. Kolokotroni *et al*. (2009) developed a model which generates site specific air temperature for the Greater London Area, and from the model calculated monthly and annual HDD and cooling degree hours (CDH); the difference is that in this research, current CDD across Birmingham will be calculated based on observed temperatures.

5.2. Methods and datasets

5.2.1. T_{air} data acquisition and processing for UHI analyses

This Chapter used the same T_{air} data as Chapter 3 (detailed information on the climate summary for 2013 can be found in Chapter 3, section 3.2.1). It was the warmest summer in the UK since 2006, with a heat wave from 3 to 22 July. It was also a dry and sunny summer.

For the UHI analyses, twice daily meteorological averages were calculated for each site in the network and for Coleshill (Figure 3.1. – Chapter 3), daytime (06:00–17:59) and night-time (18:00–05:59 following day). Using ArcGIS, the data were interpolated for the network, by the Kriging Gaussian method before being averaged and trimmed to the study area, resulting in a daytime (representative of data averaged from 06:00 to 17:59) and night-time (18:00–05:59 the following day) interpolation for each day of the study period. The UHI intensity (T_{urban} - T_{rural}) was then calculated.

5.2.2. T_{air} data acquisition and processing for CDD

For the CDD analyses, a similar procedure regarding the processing of T_{air} was applied. Again T_{air} data from BUCL of the meteorological summer of 2013 was used (Chapman *et al*., 2014). A single meteorological average was then calculated (00:00–23:59) before the data were interpolated in ArcGIS, again by the Kriging Gaussian method, before being averaged and trimmed to the study area resulting in one day average interpolation for each day of the study period.

Interpolations were then averaged for the MSOA area resulting into a unique temperature value per MSOA (details on this geographical unit has been covered on Chapter 2). Finally, CDD was calculated by subtracting the base value (18 °C) from the average day temperature and summing up the positive values (Thom, 1952; 1954).

5.2.3. UKCP09 and weather generator

UKCP09 are the current probabilistic climate change projections used in the UK (UKMO, 2009) and are based upon three IPCC CO_2 emission scenarios. It is based on a Global Climate Model (GCM), which is a mathematical model of the general circulation of the atmosphere or oceans. The GCM used is the HadCM3 developed by the Met Office Hadley Centre and includes ocean and atmosphere processes.

The UKCP09 allows projections either through the Weather Generator or the Met Office Regional Climate Model. The Weather Generator is a stochastic and statistical downscaling of the UKCP09 projections relative to the baseline from 1961-1990 and are available on seven decadal time slices for all emission scenarios, A1FI (High), A1B (Medium) and B1 (Low). The Met Office Regional Climate Model (HadRM3) is a dynamical downscaling model, it downscales GCM projections to a 25 km resolution overland, producing 11 runs of regional climate projections at the medium emission scenarios (A1B) on a daily time scale, however it is not available for user interface. One significant drawback of the use of UKCP09 in this work is that the projections do not include urban-surface schemes, which can underestimate impacts in urban areas.

The Weather Generator is useful for general assessment as it is indicative of more general temperature changes in the region. Based on this assumption, the Weather Generator was used to estimate average JJA temperature for Birmingham for a number of future scenarios. For simplicity, just the 50th percentile was used in this analysis with the results simply added to the averages found for summer 2013 from the network, to create the future weather files considering the UHI.

5.3. Results

5.3.1. 2013 Summer urban heat island and CDD

Figure 5.1. shows the average summer magnitude of the UHI in Birmingham. During the daytime, urban temperatures are typically lower than the rural reference, up to -1.6 °C in the suburban limits of the conurbation. In the city centre, temperatures are closer to the rural reference, but still colder by -0.75 °C. In contrast, for the night-time period, it is found that temperatures are always higher than the rural reference, being on average, 1.2 °C degrees higher in the city centre. These results are in agreement with a large number of studies that have previously investigated the Birmingham UHI (Tomlinson *et al*., 2012a; Tomlinson *et al.*, 2013; Zhang *et al.*, 2014a; Bassett *et al*., 2015; Heaviside *et al*., 2015) and further highlights that a single measurement from a rural reference for a city, which is traditionally done to estimate degree days, is inappropriate and underestimates energy demand in the city.

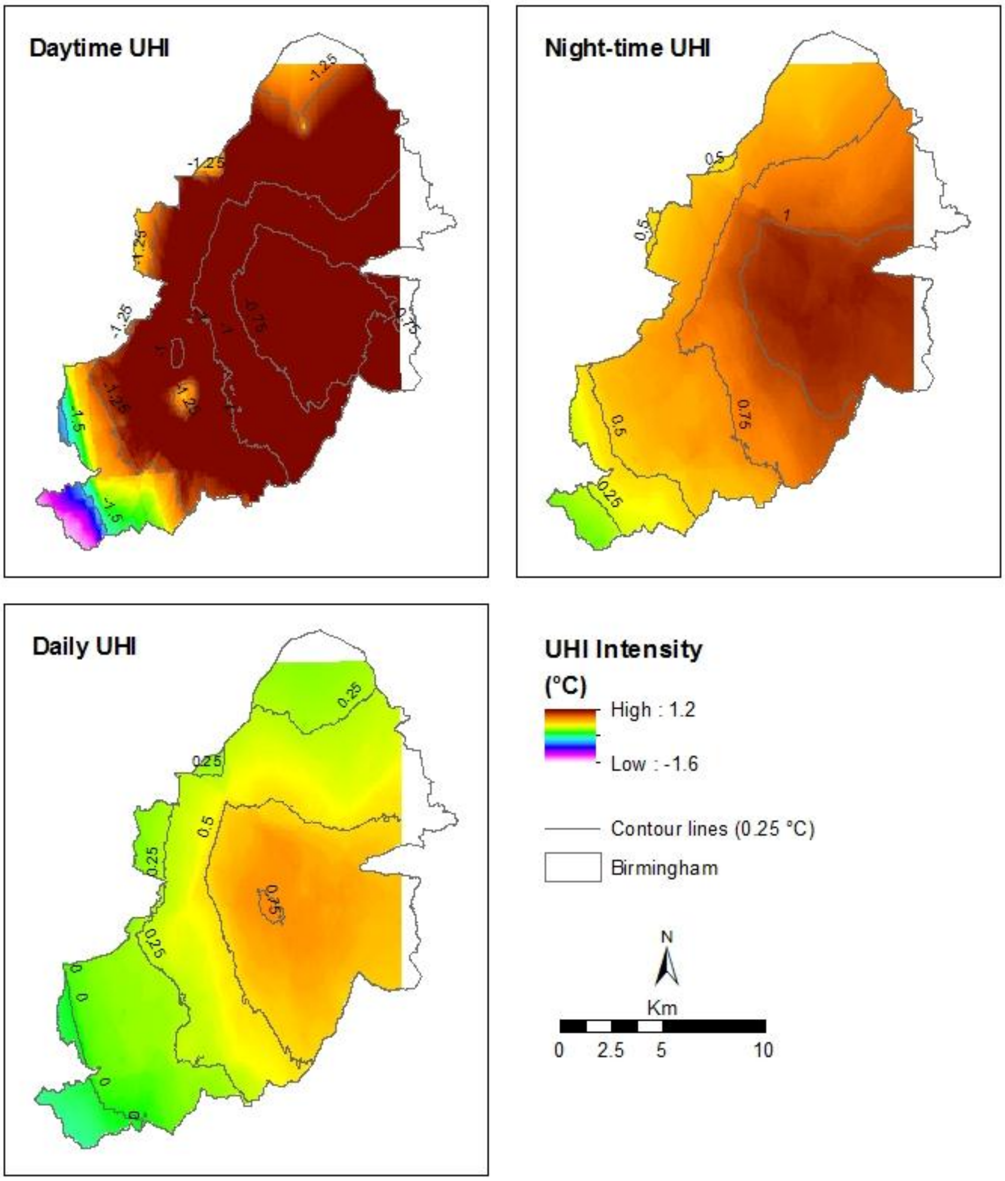

Figure 5.1. UHI intensity: **a)** Daytime UHI (based on average daytime temperature), **b)** Night-time UHI (based on average night-time temperature) and **c)** Daily UHI (based on average day temperature 00:00-23:59).

Using averaged data such as that shown in Figure 5.1., significantly reduces the variance and magnitude of the UHI, which are essential to quantify in energy demand studies. Whilst the average UHI gives an indication of where the impact will be most strongly located, there is a need to investigate the UHI on a daily basis to actually quantify the impact. To this end, the daily average temperature across the city (see example in Figure 5.2.a) was used to calculate the CDD for the base value of 18 °C for each day (see example in Figure 5.2.b), and then summed for the meteorological summer 2013 (Figure 5.2.c). The 19th of July 2013 was used as an example, since it was the warmest day on that summer, and the period involved a prolonged heatwave from July 3rd to 22nd. Note that the slightly different pattern in the UHI is a result of the high atmospheric stability on that day (prevailing winds have a tendency in less stable conditions to advect the UHI eastwards), with temperature differences reaching 2.5 °C in the city core. The resulting range from 45-72 degree days (Figure 5.2.c), does not lead to severe concern with cooling demand at the present time, even in a case which involved a heatwave. Kolokotroni *et al*. (2009) in similar research found that HDD increases and CDH decreases with distance from the urban heat island centre. Therefore, the findings highlight the need to incorporate the UHI in energy demand estimates, since the variation of the CDD is clearly correlated with the UHI pattern.

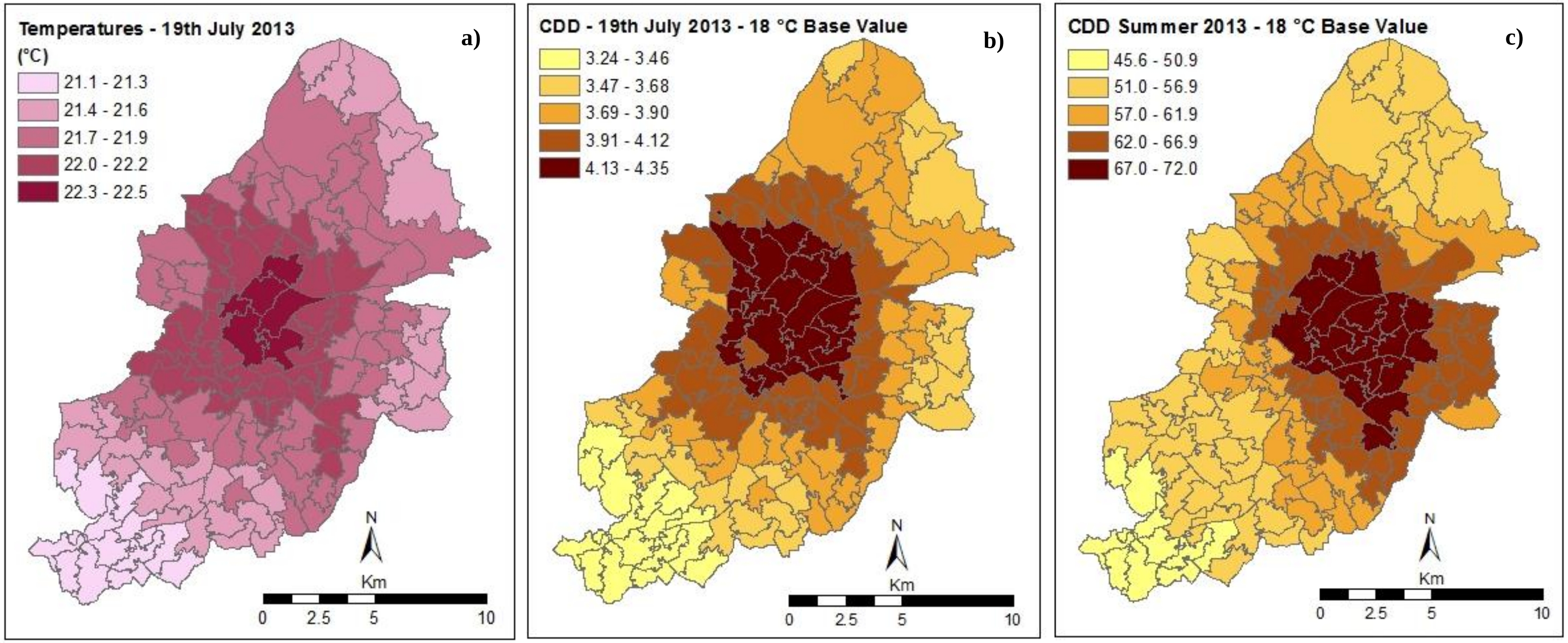

Figure 5.2. a) Average temperatures by MSOA in 19th July 2013, **b)** CDD for 19th July 2013 by MSOA, based on average temperatures for that day and base value of 18 ºC and **c)** Total CDD for Summer (JJA) 2013 by MSOA, based on daily average temperatures and 18 ºC base value.

5.3.2. Future scenarios

The UKCP09 climate change projections indicate that annual average temperature will rise by around 1-4 °C degrees by the 2080's, with temperatures in summer rising up to 5 °C in Birmingham (Table 5.1). When comparing to the 2013 averages it is possible to see that current summer averages are comparable to the expected for the 2020's decadal slice.

Table 5.1. Coleshill 2013 averages and UKCP09 projections for Birmingham using the 50th percentile: **a)** Annual average temperature, **b)** Summer average temperature and **c)** Winter average temperature

	2013	2020's (2010-2039)	2050's (2040-2069)	2080's (2070-2099)
a) Average annual temperature (°C)	9.3			
Low emission scenario		10.6	11.3	11.9
Medium emission scenario		10.6	11.7	12.6
High emission scenario		10.6	11.9	13.5
b) Summer average temperature (°C)	16.4			
Low emission scenario		16.8	17.6	18.0
Medium emission scenario		16.7	17.8	19.0
High emission scenario		16.6	18.2	20.0
c) Winter average temperature (°C)	4.1			
Low emission scenario		4.9	5.5	6.2
Medium emission scenario		5.0	5.8	6.6
High emission scenario		4.9	6.0	7.1

Adding these expected increases in summer average temperature for Birmingham to the BUCL data results in 9 possible scenarios (Figure 5.3.). However, since UKCP09 does not directly include urban effects, it has to be assumed that the UHI intensity will not change over the course of the century. The results show that by the 2050's (even in the low emission scenario) the ranges of CDD in the cooler suburban areas of Birmingham will be as high as those observed in the core of the UHI in 2013. Given these results, whilst this analysis has focussed on just the summer months (JJA), there is potential that the cooling season will also be extended to include a much wider period from March to October.

The quality of the data investigated from UKCP09 Weather Generator should here be commented, in the 2020's, the probabilist results are very close, being different only by decimals, the low scenarios presents higher average temperature than medium and high emissions scenario. When calculating the CDD, the results are more or less close, not causing serious concern, however it is important to acknowledge such fact, and keep in mind that these should be used for risk assessment and are subject to uncertainty.

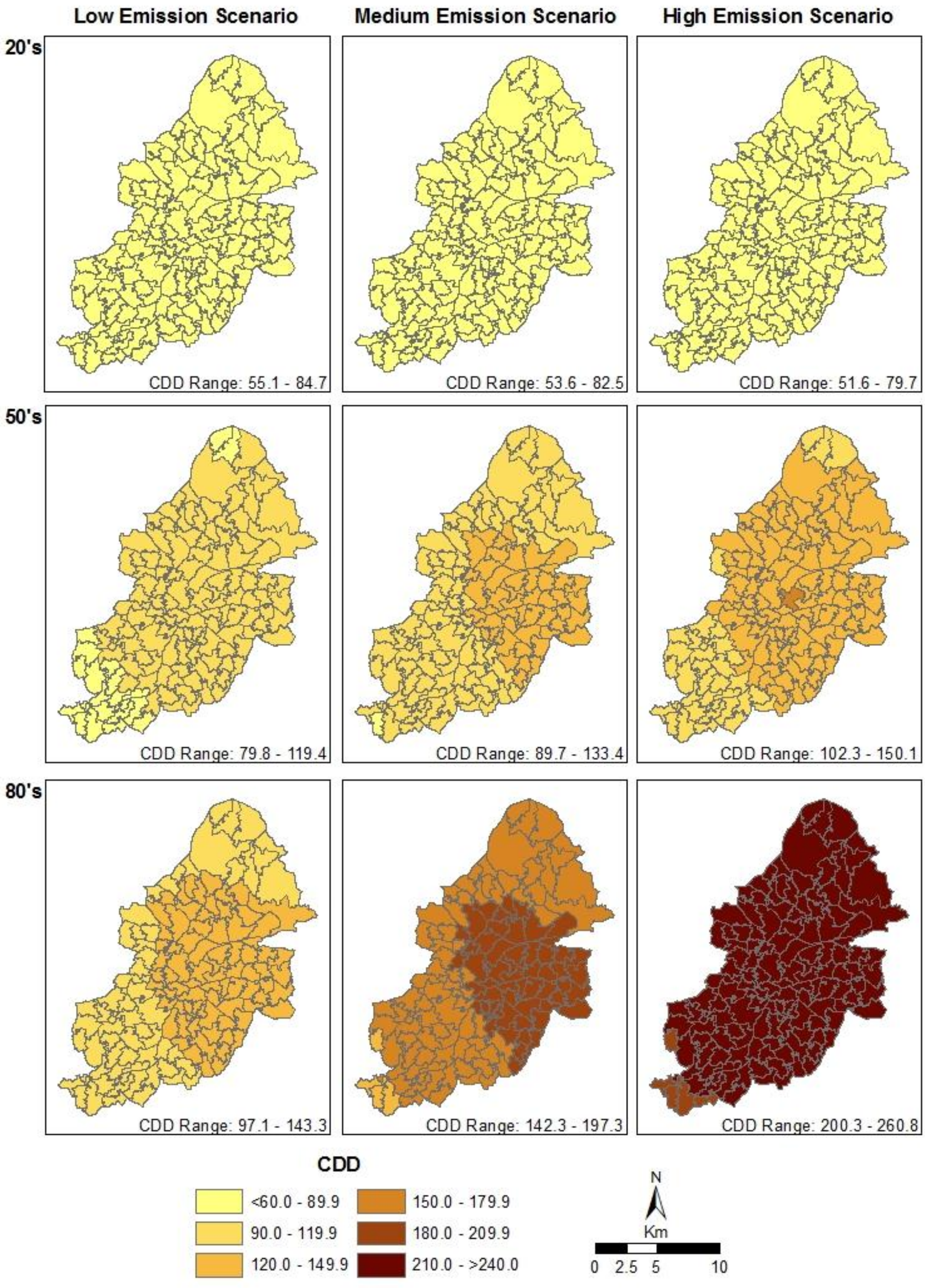

Figure 5.3. CDD for future weather scenarios in Birmingham, using UKCP09 Weather Generator results added to the current UHI effect observed in the summer of 2013, for Birmingham.

5.4. Discussion

The results clearly affirm the need to include the UHI when considering the energy demand for a city. Traditional UHI measurements have previously made this impossible, but the importance of quantifying temperature at a high resolution has been highlighted in this Chapter. Indeed, the UHI also needs be considered when looking at the energy infrastructure within the city. Electricity transformers are one of the most expensive assets in a distribution network, and unplanned replacement or maintenance is expensive (Tomlinson *et al*., 2013). Assets in the UK have an approximate 40 year life, and can cope with internal temperatures of 98 °C; however increasing T_{air} can accelerate ageing and efficiency, therefore temperature increases due to the UHI will impact life expectancy. Transformer loadings due to demand are also an important factor and therefore increasing loadings due to increased cooling needs is another consequence of higher temperatures. In effect, the resilience of urban energy infrastructure faces a double threat from increasing temperatures (Tomlinson *et al*., 2013).

This Chapter also highlights the increase in cooling demand over the coming decades, however the changes in the winter averages from UKCP09 are greater than that predicted for summer and annual averages (Table 5.1). This indicates that HDD will decrease more rapidly than CDD increases in Birmingham and will therefore lead to decreasing energy demand for heating, helping to alleviate fuel poverty (households whose fuel expenditure on all energy services exceeds 10% of their income: Boardman, 1991). However the change from heating to cooling demand will potentially have an impact on the fuel supply (i.e., a switch to electricity from gas) and energy prices in the country.

More generally, in a changing climate, there is a need to further discuss the notion of 'set points'. The set point changes considerably between countries and regions due to different general climate characteristics as well as demographic and socio-economic structures.

As introduced in Chapter 4, as the impacts of climate change begin to manifest, local temperatures will change and population will begin to acclimatize due to physiological adaptation, planned adaptation (mitigation and adaptation of housing) and spontaneous behaviour, altering temperature thresholds (Hajat *et al*., 2014). If such acclimatization takes place, the impacts of temperature projections could potentially be overestimating the increases in cooling demand and decreases in heating demand.

For instance there are two known energy consumption scenarios, the current scenario that considers the relationship between energy demand and T_{air} with peaks in energy demand occurring over both summer and winter, explained by the increased use of cooling appliances and space heating, respectively (Hekkenberg *et al*., 2009 – Figure 5.4.a). The second known scenario in which higher temperatures, caused by climate change, will decrease energy demand over winter but increase demand over summer (Papakostas *et al*., 2010; Golombek *et al*., 2012; Jovanović *et al.*, 2015 – Figure 5.4.b). Both of these known consumption scenarios do not consider acclimatization effects, therefore the third possible scenario here proposed, considers that if acclimatization takes place, in an average scenario of more or less 2 °C in the next decades, it is possible that no changes in energy demand regarding only outdoor temperatures will take place (Figure 5.4.c). However, unfortunately there is currently no standard way (method or approach) to account for acclimatization effects (physiological and environmental), which lowers the confidence not of the climate scenarios but of the applicability of their results to energy demand scenarios.

Considering projected increases in the number of people living in cities and socioeconomic changes, exposing more people to climate change and increasing purchasing power of developed and developing countries, other issues should also be kept in mind as part of the larger scenarios of electricity demand in the future, which does not only include climate and acclimatization and adaptation to climate.

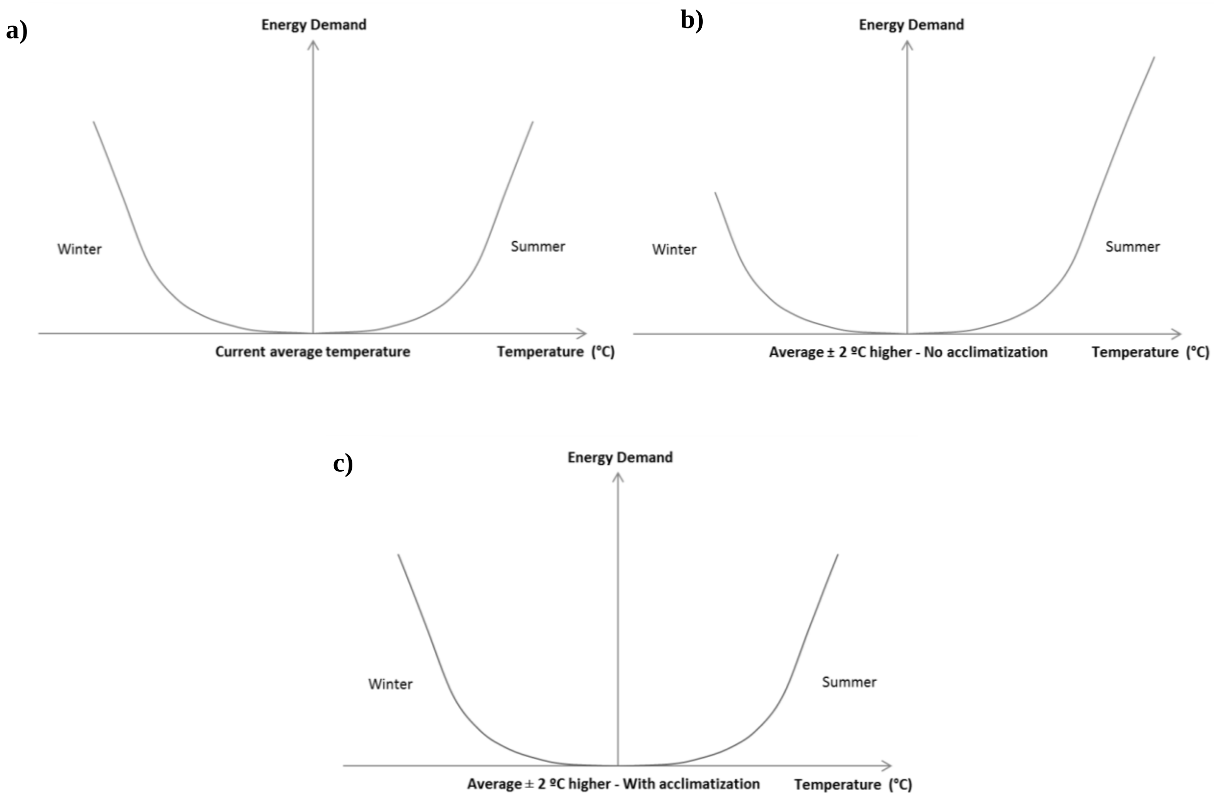

Figure 5.4. a) Energy consumption dependence to temperature – U shape pattern (Hekkenberg *et al*., 2009), **b)** Energy consumption with climate change (Papakostas *et al*., 2010; Golombek *et al*., 2012; Jovanović *et al*., 2015) and **c)** Energy consumption with climate change and possible effect of acclimatization. Figures a and b were derived based on literature findings; Figure c was derived based on the interpretation from the possible impact of acclimatization.

5.5. Conclusion

This Chapter has focused on using T_{air} measurements from an UMN and UKCP09 climate change scenarios to address the impact of the UHI in energy demand over summer, through the degree days method, in current and future scenarios. Despite the limitations of the degree days method, especially uncertainties regarding the 'correct' base value, it remains a simple way to address the temperatures changes impact on energy demand, since it looks at the most important weather parameter regarding consumption and has been correlated with energy consumption data in other studies here mentioned.

T_{air} is the most influential weather parameter in energy demand and therefore it is essential for UHI measurements to be incorporated into energy demand estimates across a city. A non-traditional measurement of the UHI, as the one here presented (every day average T_{air} across the city measured from 00:00–23:59) is an ideal measurement to be used to estimate energy demand to consider the UHI impact. However, more robust analyses of the UHI in specific times of day and weather conditions should be considered as well. There is also possibility of using the analyses to address UHI impact on urban energy infrastructure.

The demand for relevant weather data and information, in both quantity and complexity, in all times and scales possible, provided with quality control flags and uncertainty measurements, delivered, available and accessible in a user friendly manner (Troccoli *et al*., 2013) has been pointed out as crucial to produce effective energy demand estimations, and to avoid overload in the electrical power system (Jovanović *et* *al*., 2015). Addressing future energy demand is important for the purpose of future energy supply planning and economic assessments (Hekkenberg *et al*., 2009), however for such, it is as well necessary future weather files in high temporal resolution (hourly), which are constructed from hourly real, measured data (Cox *et al*., 2015). Ideally, the data should be provided from UMN's, however in the absence of these other sources of high resolution measurements of T_{air} are becoming increasingly available (i.e., crowdsourcing: Muller *et al*., 2015). Such data can further also be applied to calculate other important variables in energy demand, such as Physiologically Equivalent Temperature (PET), which is a measure of thermal comfort, and analyse wind effect, as it is an important parameter in urban thermal comfort (van Hove *et al*., 2015).

The results from the future scenarios demonstrate large changes to CDD across the city, with the current temperatures observed in the city core being common in the suburbs of the city in the future, highlighting an increase in cooling demand for the whole city, as well as possibly extending the cooling period. A decrease in heating demand will also be observed, however it should be taken with caution since it may impact of fuel prices and availability. It is important to acknowledge that UKCP09 projections do not incorporate urban schemes (Jenkins and Projections, 2009) and more consideration is needed for the application of urban schemes models such as JULES (Bassett *et al*., 2015) and MORUSES (Bohnenstengel *et al*., 2011) to be incorporated in the analyses. However, regardless of model limitations for future scenarios, the key problem remains in the fact that there is no established way to account for human acclimatisation, which could lead to several changes in applicability of the results derived from climate change scenarios.

5.6. Chapter Summary

The current climate projections indicate a general increase in air temperatures resulting in more frequent and intense heatwaves as well as the possible exacerbation of the UHI effect (Chapter 1 and details on UHI on Chapter 3). The degree days method has been reviewed in Chapter 4 and applied to city aggregated data. This traditional application of the method has always resulted in a unique value for the city, however this Chapter has shown, that due to the UHI effect, temperature varies across the city and so does the energy demand estimations.

Overall the Chapter demonstrated the importance of high resolution T_{air} *measurements in estimating electricity demand within urban areas and highlights the need to incorporate the UHI in energy demand estimations and other energy issues such as energy infrastructure. It also identified the need to gain a better understanding of the role of human acclimatisation to a changing climate. Through applying the degree day method across the city it has enabled energy demand to be objectively quantified for use in current and future climate scenarios considering the UHI.*

Chapter 6

Conclusions

6.1. Fulfilment of thesis aims

This thesis had 4 specific objectives. These are summarized below.

1. **Assess the relationship between income, $UHI_{surface}$, vegetation and residential electricity consumption in Birmingham for 2006, a year that was warmer than average, identifying which currently is the most relevant variable and the present influence of the UHI on residential electricity consumption.**

Using a combination of Geographical Information System techniques and Remote Sensing data (MODIS LST and NDVI), a preliminary investigation was carried to assess the spatial relationship between UHI, urban green space, household income and electricity consumption in Birmingham. It provided simple and repeatable steps, based on freely available datasets, for urban planners, industry, human and physical geographers, and non-specialists to reproduce the analyses.

The results showed that, the present impact of the UHI is limited and instead highlighted the dominance of household income over local climate in explaining consumption patterns across Birmingham. By isolating income influence through normalization, it was possible to identify the impact of the UHI, however currently a tempered impact.

It is important to acknowledge that although by normalization it is possible to remove the influence of income to understand only the impact of the UHI, none of the variables are mutually exclusive, and should be analysed integrally. Since the overall aim of this thesis was not to analyse all of the variables but the UHI effect on consumption, in the following Chapters a method that only accesses demand based on temperature was used.

The Chapter also highlighted the limitations regarding data available for research, but still provided basic analyses to inform the current residential electricity consumption due to the UHI effect. There is much potential available for such type of analyses to be used by urban planning mapping and spatial risk assessments.

2. **Using data from a high resolution UMN, quantify and compare the spatial pattern of the daytime and night-time UHI, under a range of stability classes, for both $\mathbf{UHI_{surface}}$ and $\mathbf{UHI_{canopy}}$.**

The UHI has been well discussed in the thesis and indeed is the most documented phenomena in urban climatology. Although a range of measurements and modelling techniques are used to assess the UHI, the paucity of traditional meteorological observations in urban areas is still an ongoing limitation for studies, in spite of all the contributions made. The availability of remote sensing data has helped to fill a scientific need by providing high resolution temperature data of our cities, however, satellite-mounted sensors measure LST and not T_{air}. Fortunately, T_{air} data are becoming increasingly available via UMNs, providing opportunities to quantify and compare surface and canopy UHI on unprecedented scale.

Therefore, using BUCL a dense UMN and MODIS LST the spatial pattern of the daytime and night-time UHI was quantified and identified in Birmingham. The analysis was performed under a range of atmospheric stability classes and investigated the relationship between surface and canopy UHI in the city.

A significant finding was that the distribution of the surface UHI appears to be clearly linked to landuse, whereas for canopy UHI, advective processes appear to play an increasingly important role. Strong relationships were found between air temperatures and LST during both the day and night at a neighbourhood scale, but even with the use of higher resolution urban meteorological datasets, relationships at the city scale are still limited.

3. Review and critique existing energy consumption methodologies for producing city scale estimates

Energy consumption and T_{air} are inherently related. Low temperatures increase consumption via space heating, whereas high temperatures result in increased demand for refrigeration and air conditioning. The common approach used for investigating this relationship in detail is via the calculation of Degree Days.

Starting with a critical review of studies in the scientific literature that have used this technique, this Chapter highlighted a range of limitations with the methodology, particularly with respect to standardisation which potentially hinders the utility of the technique in climate change risk assessments.

Using an analysis of electricity consumption in Birmingham as an example, the Chapter identified a need for a standardisation of the approach via the use of a universal base temperature calculated using average T_{air}. The adoption of the measure will not only enable meaningful comparisons to be made across regions, but it will also permit a more robust means to account for acclimatisation in longer term analyses such as that required by climate change risk assessments.

4. **Using T_{air} data available from an UMN estimate current and future variations of cooling demand at the neighbourhood scale.**

Current climate projections indicate a general increase in air temperatures resulting in more frequent and intense heat waves as well as the possible exacerbation of the UHI effect.

Degree days are an established methodology used to estimate energy demand, comparing ambient temperatures with a base value considered representative of the city being analysed, and frequently, a single base value is used for the entire city; however, due to the UHI effect, temperatures vary considerably across a city, and therefore so does energy demand. Hence, for degree days (and energy demand) to be estimated across an urban area, highly spatially resolved measurements of T_{air} are required.

Analysing T_{air} data available from BUCL – UMN the cooling demand for JJA 2013 and future climate scenarios were calculated across Birmingham. The results demonstrated the importance of high resolution air temperature measurements in estimating electricity demand within urban areas and highlighted the need to incorporate the UHI in energy demand estimations and other energy issues, such as energy infrastructure. It also identified the need to gain a better understanding of the role of human acclimatisation to a changing climate. This step then enables energy demand to be objectively quantified for use in current and future climate scenarios.

6.2. Critique of the thesis

Overall, this thesis analysed the UHI and estimated current and future cooling demand in Birmingham, using data from an UMN. Many limitations regarding data were found, but it was still possible to address the aim and objectives. However, what also became clear during the period of the research were the enormous opportunities about to become available to overcome data limitations in the near future. Climate and energy are main drivers of concerns in political and environmental discussions, and they both need to be constantly addressed. Intra-urban consumption by the residential sector is very important as it relates to people's vulnerabilities and city management, however data for both climate and energy consumption are rarely available at this scale.

The following are often barriers in the energy data:

1. Data are in general not available by the Government due to security aspects;
2. Energy companies not being able to provide data again due to security issues;
3. Data are available but not at the required temporal or spatial scale; for instance the electricity consumption data analysed in Chapter 2, is only aggregated for a the year period;
4. Data are manipulated to eliminate interference of certain variables, which might actually be the focus of the research; for example, in the gas consumption data available from DECC at MSOA, is weather corrected.

Due to these limitations, energy consumption modelling techniques are frequent alternatives to overcome the issues, however they rely on ‘ideal’ cases, and are usually applied to building scale (micro-scale) or city scale (does not observed the intra-urban patterns).

The process in which public organizations (usually governmental) release some of their internal data in open format (Open governments, open data) is a ‘top-down’ process (Arribas-Bel, 2014). In this process public organizations generate, manage, update and distribute information in accordance to established rules and procedures ensuring reliability and trustworthiness (Spinsanti and Ostermann, 2013).

The main energy consumption dataset available in the UK at an intra-urban level has the advantage of being available for SOAs, and can therefore be compared to other datasets linked to energy that are reported in the same standard unit, such as income, demonstrated in Chapter 2. The sizes of the units also consist of an advantage, since most countries do not report energy data at an intra-urban level.

Electricity consumption estimates data from DECC are available since 2004 for MSOA, and since 2008 for LSOA, divided into domestic and non-domestic users (DECC, 2013). They are divided in Total Consumption, Ordinary Consumption and Economy 7, as explained in Chapter 2. Gas consumption estimates are also available since 2005, at the same level and segmentation as the electricity data, however these are weather corrected and therefore, cannot be used in research that address climate.

Recently another dataset has been made available, Postcode level electricity estimates (DECC, 2015), which at the moment is experimental and only available for 2013. This data will provide even better spatial resolution than the SOA's estimates, however in spite of the good spatial scale of the data and free access to the data, the major problem with this dataset still is the temporal resolution. This dataset is aggregated as well for a yearly period not providing hourly, monthly or seasonal variability of consumption, which are important for several types of energy consumption research.

There is an increasing amount of data emerging through the Internet of Things (IoT); these can be referred to as accidental data, and are collected from internet connected devices and are becoming available as a side effect, since they were created for different purposes but they have become interesting alternative for researchers. For the case of energy data, 'smart meters' are part of this IoT generation and have the potential to revolutionise the data that are available for research.

The smart meters were announced in 2006 outlined as part of the UK Government Energy Review, in which UK energy consumers would soon be able to check their electricity consumption from a device installed in their kitchen, in order to view how much energy they were using and its cost, enabling informed choices, as well as putting an end to estimated bills, enhancing customer service by utility companies, and energy savings potential from the consumers (Venables, 2007). From monitoring energy usage characteristics and collection of energy consumption data from all customers on regular basis utility companies can advise customers on efficient ways to consume energy (Depuru *et al*., 2011). All over the world the deployment of smart meters have been mostly encouraged focusing on energy savings target (Benzi *et al*., 2011). Therefore from the utility companies point view the smart meter is the ideal solution and playing an important role in reducing energy consumption.

Smart meters are advanced energy meters that reads real-time energy consumption information and securely communicates the data in a bidirectional level (Depuru *et al*., 2011). The smart meter system includes a smart meter, communicational infrastructure and control devices, being its communication infrastructure the most import set of the idea. Due to large amount of data being transferred between utility company and smart meter, communication standards are formulated to ensure security (Depuru *et al*., 2011).

There has been an increase in the number of smart meters installed in the UK (Figure 6.1.). As well as, the UK Data Service (ESRC) is recently encouraging researches through events to discuss alternatives to use obtain and use these in a secure manner (Making smarter use of household energy data: opportunities and challenges for scaling up research).

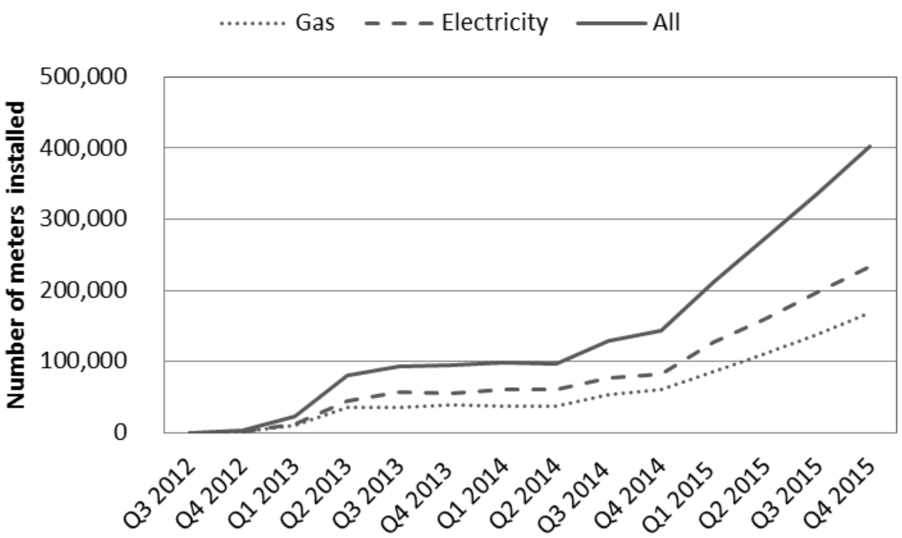

Figure 6.1. Number of domestic smart meters installed by large suppliers from the third quarter of 2012 to fourth quarter of 2015 (DECC, 2016).

Based on this proliferation, it is very likely that smart meter data will be available sometime soon at some level for research, but it is hard to precisely know at what temporal and spatial scale they will be made available.

From a scientific point of view, this large quantity of real time data will be one of the main advances in energy consumption research. However, the availability of the data may still be a barrier and there may be a need to add further complexity to obtain the dataset. It is here where crowdsourcing may play an increasing role.

Crowdsourcing is defined as obtaining data or information from a large number of people, however due to recent innovations and the emergence of these accidental data it can be extended to include data from a range of sensors transmitted via Internet (i.e., sources such as smart phones) (Muller *et al*., 2015). It has potential to provide real time data and information of high temporal and spatial resolution (Muller *et al*., 2015), and information that was impossible or impractical to obtain (Foody *et al*., 2013), through active or passive initiatives. Active crowdsourcing involves citizens in processing the unit that outputs the data to a website, smart apps or web 2.0 platforms (Kamel Boulos *et al*., 2011), and passive crowdsourcing when citizens are only the keeper of their individual sensor and ensures the data are continuously being collected. Volunteered Geographic Information (VGI) is another term being used to reference the acquisition of these accidental data, by citizens collecting and editing spatial data and information (Basiouka and Potsiou, 2012). This approach has been used for crisis events (Spinsanti and Ostermann, 2013) and cadastral mapping (Basiouka and Potsiou, 2012).

With the use of smart phones connected to the internet citizens are freely sharing images, videos, maps, opinions and events, therefore providing environmental information (Spinsanti and Ostermann, 2013). The increasing amount of environmental and human life aspects that are becoming available, when aggregated can revel emerging patterns, redefining the data landscape available to urban researchers (Arribas-Bel, 2014). To this end, there is potential to use smart meters through crowdsourcing and VGI, in which citizens can be actively involved by adding their reading into a web 2.0. platform, or passively by owning the smart meter and keeping the data and releasing them to research if they think it is suitable.

This potential for vast high resolution datasets can also be extended into the collection of climatic data, for cases where an UMN is not available, and therefore this thesis would not be applicable. Indeed, crowdsourcing potential has been highlighted for atmospheric sciences (Muller *et al*., 2015).

Although such datasets may provide the high resolution datasets needed by science, there also needs to be an awareness of their limitations. Unlike data from census or economic survey that are created with specific a purpose, these data were not intended for research. Hence, the challenge with any of these data is quality assurance and control (Kamel Boulos *et al*., 2011; Foody *et al*., 2013; Arribas-Bel, 2014; Muller *et al*., 2015). As well as, the need to maintaining privacy and security of the systems that store these (Depuru *et al*., 2011; Kamel Boulos *et al*., 2011; Foody *et al*., 2013; Arribas-Bel, 2014; Muller *et al*., 2015). However the fact that the smart meters are continuously functioning on households, and quality and assurance are already provided by the utility company, and there is high reliability on what is been measured, problems with quality are very low.

Therefore there is an incredible amount of data emerging, basically from everywhere, as well as new internet connected devices. These provide potential for future research that was unthinkable at the start of this project. Smart meters and high resolution crowdsourced climate data have the potential for the first time to provide good quality data for research in the desired temporal and spatial scale.

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Appendices