

Urban heat and residential electricity consumption: A preliminary study



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ABSTRACT

The Urban Heat Island (UHI) is a well-documented phenomenon occurring in cities across the world resulting in city centres often being several degrees warmer than their surroundings. This local elevation in temperatures could potentially impact upon local energy consumption, with residents in the warmer central section of the city using more energy to cool their homes in summer and less energy to warm them in winter. This study uses a combination of Geographical Information System techniques and Remote Sensing data (MODIS LST and NDVI), as a preliminary investigation, to assess the spatial relationship between UHI, urban greenspace, household income and electricity consumption in Birmingham, UK. It provides 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 show that, the present impact of the UHI is limited and instead highlights the dominance of household income over local climate in explaining consumption patterns across Birmingham.

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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 & Assis, 2013). The electricity consumption by sectors in the UK can be observed in Fig. 1, domestic consumption has maintained itself as the larger consuming sector almost throughout the whole period from 1965 to 2013.

Household size, income, building design characteristics and local climatic conditions are all key factors in determining residential energy consumption (Santamouris et al. 2007). 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, Ortiz, & Pout, 2008). Similarly, household income is an important factor, with a strong correlation evident between daily electricity consumption and earnings (Ghisi, Gosch, & Lamberts, 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 & Assis, 2013).

With respect to climatic factors, the Urban Heat Island (UHI) is a potentially important localised phenomenon to take into account when assessing consumption in cities. The UHI is described as the difference in temperature between an urban area and the surrounding rural area of the conurbation. It is 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). The overall result is that cities are generally warmer than their rural surroundings, reaching a maximum under "ideal" conditions (e.g., clear skies and light winds). For small cities, the effect can be minimal, for example, differences of 1 °C in Ljutomer, Slovenia (Ivajnsič, Kaligarič, & Žiberna, 2014) where as differences of more than 7 °C are not uncommon for large cities (e.g. Paris, France: Lac et al. 2013). The subtle changes in temperature caused by UHI can impact on many aspects of everyday life, such as critical infrastructure (Chapman, Azevedo, & Prieto-Lopez, 2013), health (Tomlinson, Chapman, Thornes, & Baker, 2011) and energy consumption (Santamouris

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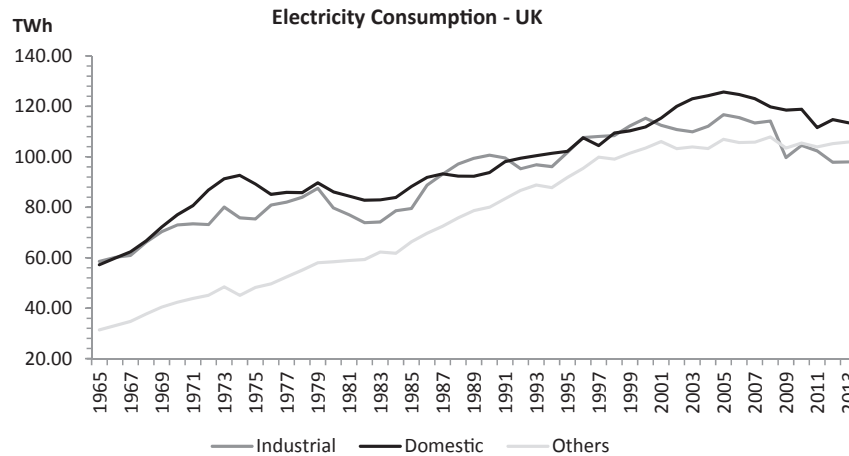


Fig. 1. Electricity consumption in the UK by sector. Others: Public administration, transport, agricultural and commercial sectors.

et al. 2001), with such impacts becoming exacerbated under heatwave events. It is hypothesised that the UHI should have a direct impact on energy consumption, particularly in the warmer core of the city (Akbari, Pomerantz, & Taha 2001; Hassid et al. 2000; Kolokotroni, Davies, Croxford, Bhuiyan, & Mavrogianni, 2010; Taha, Akbari, Rosenfeld, & Huang, 1988) where higher energy loads will be required for cooling in summer, and in winter consumption will reduce for heating. 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). Therefore, by not considering the UHI, energy consumption and peak power should be significantly underestimated (Hassid et al. 2000).

Green spaces are a widely adopted strategy to mitigate UHI intensity (Lambert-Habib, Hidalgo, Fedele, Lemonsu, & Bernard, 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, Lindley, & Levermore, 2014). For example, the highest cooling loads in Athens are seen in the western area of the city where there is limited greenspace (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 at midday (Skelhorn, Lindley, & Levermore, 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, Akbari, Taha, & Rosenfeld, 1987).

The UHI can be largely subdivided into three different types: the surface UHI, the canopy UHI (i.e. 2 m) and the boundary layer UHI (Azevedo, Chapman, & Muller, 2016). Air temperature measurements are used to quantify both the canopy and boundary UHI, whereas land surface temperature (LST) is used for the surface UHI. Traditional ways in which canopy UHI are measured include station pairs (e.g. Wilby, 2003) or the use of transects (e.g. Smith, Webb, Levermore, Lindley, & Beswick, 2011). However, these usually have limited spatial (Muller, Chapman, Grimmond, Young, & Cai, 2013; Smith et al. 2011) and temporal resolution, and therefore there has been an ongoing challenge to quantify the intensity and spatial extent of the canopy UHI.

Due to the wide spatial coverage and availability of data, thermal remote sensing is one of the most popular techniques used for the evaluation of UHI (Azevedo, Chapman, & Muller, 2016; Dousset, 1989; Dousset, Laaidi, & Zeghnoun, 2011; Keramitsoglou,

Kiranoudis, Ceriola, Weng, & Rajasekar, 2011; Roth, Oke, & Emery, 1989; Smith et al. 2011; Schwarz, Lautenbach, & Seppelt, 2011; Tomlinson, Chapman, Thornes, & Baker, 2012; Weng, Lu, & Schubring, 2004; Yuan & Bauer, 2007). The main advantage is that remote sensing provides a consistent, repeatable methodology for the end-user (Tomlinson et al. 2011). However, thermal remote sensing observes LST which restricts studies to just the surface UHI. Although LST plays a major role in urban climatological processes as surface temperature modulates the air temperature of the urban canopy layer, and therefore influences the internal climate of buildings and general thermal comfort (Voogt & Oke, 2003), it can only provide an indication of air temperatures and therefore the canopy UHI. Furthermore, remote sensing isn't ideal to evaluate the UHI in small cities, since the spatial resolution of the sensor can often be too coarse (Ivajnsić, Kaligarić, & Žiberna, 2014).

Vegetation abundance is an influential factor controlling UHI (Weng, Lu, & Schubring, 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 & Bauer, 2007). Other studies which have included energy consumption data in the analysis (Akbari, Pomerantz & Taha, 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 (e.g. Pereira & Assis, 2013; Santamouris et al. 2007). Hence, this article aims to combine energy and income data with LST and NDVI data to assess the relationship between income, UHI,¹ vegetation and residential electricity consumption in Birmingham, UK. It also focuses on simple and repeatable steps, based on freely available datasets. The results could be used to inform current residential electricity consumption modelling due to the UHI effect.

2. Study area

Birmingham is the second largest urban area in the UK with an estimated population of over 1 million people (Birmingham City Council, 2014). It is a post-industrial city with a distinct range of land use zones (e.g. the central business district, eastern industrial areas with the majority of residential areas straddling this belt of

¹ Since LST data is being analysed, only surface UHI is being addressed, however the general term UHI will be used.

commerce and industry to the north and south). Some large parks can be found closer to the wealthier neighbourhoods (Fig. 2a).

Tomlinson, Chapman, Thornes, and Baker (2012) used night-time MODIS imagery for the summer of 2003–2009 and identified that during periods of high atmospheric stability, the surface UHI magnitude in Birmingham can reach up to 5–7 °C. The cooling effect of large areas of greenspace in Birmingham was evident, particularly in Sutton Park, Woodgate Valley and the Lickey Hills (mentioned locations in Fig. 2b), with a significant temperature gradient 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).

3. Methodology, datasets & analysis

3.1. 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 don't have consistent physical size, but are instead based on established ranges of population and households for Census purposes (Table 1 – ONS, 2011a). Income data is not available for the lower level (LSOA), hence middle level data (MSOA) is the universal unit considered for this study.

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 have been extensively reviewed, and a number of different techniques are available to overcome bias (Jacobs-Crisioni, Rietveld, & Koomen, 2014). For example, Bayes adjustment (Assunção, Schmertmann, Potter, & Cavenaghi, 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 & 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

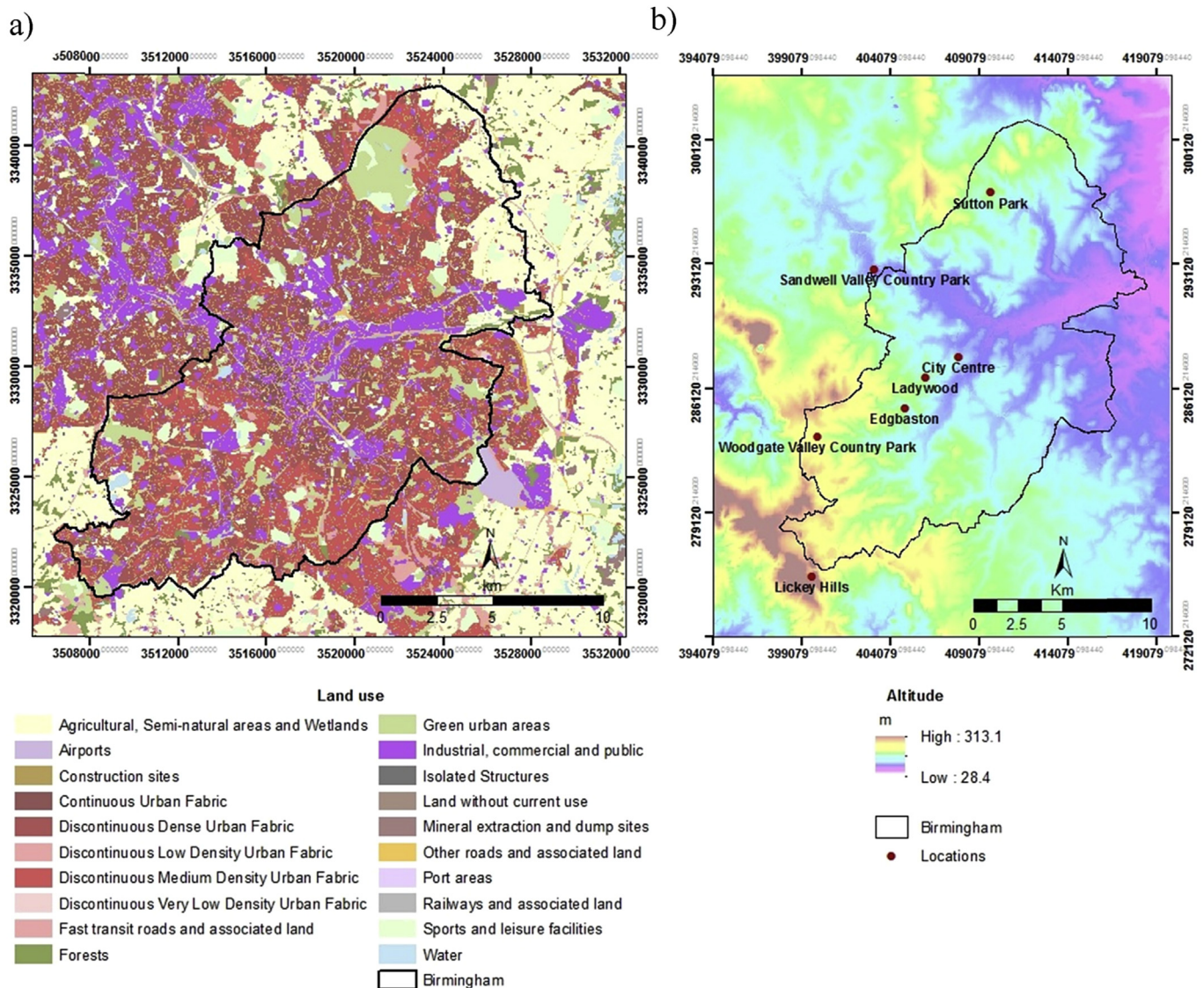


Fig. 2. a) Landuse classes in Birmingham, b) Map of the Birmingham urban area and locations.

Table 1
Ranges of lower and middle Super Output Areas.

| Geography | Minimum population | Maximum population | Minimum number of households | Maximum number of households |
|-----------|--------------------|--------------------|------------------------------|------------------------------|
| LSOA | 1000 | 3000 | 400 | 1200 |
| MSOA | 5000 | 15,000 | 2000 | 6000 |

of the research (Pereira & Assis, 2013; Tomlinson et al. 2011).

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. 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 h period at night (for example, the charging of night storage heaters) where as ordinary consumption is the remainder of other tariffs. Total electricity consumption is simply the combination of the two. This study 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. For the analysis, MSOA consumption data for 2006 was 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).

3.2. LST data

Satellite data, also from 2006, was aggregated to produce an annual summary. LSTs were analysed for both daytime and night–night 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 paper. Data was obtained from MODIS Aqua, with an overpass in the study area, ~01:30 and ~13:30 (UTM). The product used was MYD11A1 (V5) – MODIS/Aqua Land Surface Temperature and Emissivity Daily L3 Global 1 km Grid SIN (LPDAAC, 2015a). This product does present a compromise in spatial resolution (e.g. when compared to the 60 m thermal band of Landsat 7 – i.e. after February 25th, 2010, Landsat 7 thermal band is collected at 60 m but resampled to 30 m (USGS, 2010)), but the vastly improved temporal resolution of Aqua greatly increases image availability for the study. This is an important factor for studies in the UK, where cloud cover is a frequent and prohibitive problem when using Landsat, which overpasses the study area just once every 16 days.

The MODIS LST product uses a split window algorithm to correct for atmospheric effects (LPDAAC, 2015a) and surface emissivity (Tomlinson, Chapman, Thornes, & Baker, 2012) and has been used in Birmingham in previous studies (Azevedo, Chapman, & Muller, 2016; Tomlinson, Chapman, Thornes, Baker, & Prieto-Lopez, 2012; Tomlinson, Chapman, Thornes, & Baker, 2012). The MODIS Reprojection Tool (MRT) (LPDAAC, 2014) was used to convert images to GeoTIFF format at UTM, and subsequently converted to British National Grid (BNG) in ArcGIS (MODIS products are released at Sinusoidal Projection). For the night-time analysis, 45 cloud free images were available and for daytime, 27 images were retained. In both cases the largest amount of images available were during

summer and autumn, because of the more stable weather conditions on those seasons with decreasing cloud cover. 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 (Fig. 3a) and one for night-time LST (Fig. 3b).

3.3. NDVI dataset

The NDVI dataset was also obtained from Aqua MODIS products, MYD13Q1 (V5) – MODIS/Aqua Vegetation Indices 16-Day L3 Global 250 m 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, Lu, & Schubring, 2004; Yuan & Bauer, 2007). NDVI ranges from –1 to 1, being positive values increasing amount of vegetation in a pixel (Yuan & Bauer, 2007), while 0 and negative values indicate rock, asphalt, clouds, snow, ice and water.

As per the LST product, the data was downloaded and converted in MODIS MRT to GeoTIFF format at UTM, and subsequently to British National Grid (BNG) in ArcGIS. All NDVI images available for 2006 were used, resulting in 23 images for the study period (one every 16 days). 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 (Fig. 3c).

3.4. Data aggregation and analysis

As income and residential electricity consumption data is available by MSOA, for analysis purposes, there was a need to average and aggregate LST and NDVI into MSOAs (Fig. 4). 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. Direct correlations between the variables was then calculated by using Pearson correlation coefficients (Table 2). Direct Pearson correlation was also carried between the MSOA consumption by household normalized by the income data and the aggregated LST and NDVI by MSOAs (Table 3). *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 Fig. 5.

4. Discussion

All MODIS products used in this analyses were obtained for free

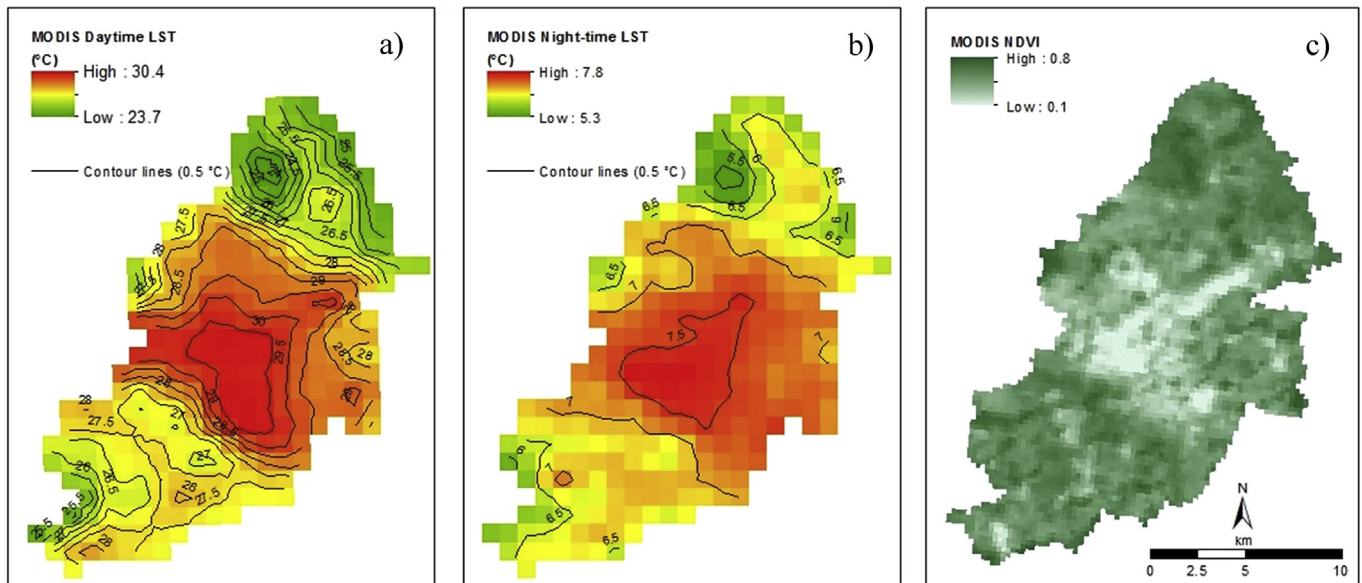


Fig. 3. a) Averaged daytime LST, b) Averaged night-time LST, c) Averaged NDVI for Birmingham in 2006.

online (USGS, 2013) and are available since 2002 with worldwide coverage. The advantage of using the MODIS Aqua dataset is that it is well-suited to non-specialists due to the fact that it is already 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 has good spatial resolution, data is only available as an annual summary per MSOA and therefore doesn't allow for 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.

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 greenspace (Fig. 3a and 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 (Fig. 3c) was also as expected ranging from 0.2 in the city centre to 0.7 in the larger urban greenspaces. As demonstrated in previous studies (Weng, Lu, & Schubring, 2004; Yuan & Bauer, 2007) a strong negative correlation between LST and NDVI exists, with the strongest relationship evident during the daytime ($r = -0.78$ compared to $r = -0.69$ at night). Furthermore, there is a strong positive correlation between income and NDVI ($r = 0.61$) and is explained by increased real estate values surrounding parks and greenspace (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 in with the poor housing stock found in such areas (i.e. less efficient construction and insulation), has implications for not only energy consumption but the general wellbeing and health of the population in these areas (Tomlinson, Chapman, Thornes, & Baker, 2012). 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.

The strongest relationship found with electricity consumption was with income ($r = 0.62$), 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 (Tables 2 and 4). It is primarily for this reason why direct correlations with LST are weaker than would be expected (daytime $r = -0.47$; night-time $r = -0.43$). It was hypothesised that higher temperatures in the city would result in increases electricity consumption by the use of air conditioners and fans, however that was not clearly identified in the first part of the analysis (Table 2).

As a second part of the analysis, the electricity consumption data was normalized by income to attempt to isolate the UHI influence in the electricity consumption, especially with daytime UHI (Table 3). The correlation with the normalized consumption was higher for daytime UHI (daytime $r = 0.52$; night-time $r = 0.41$). A negative correlation with NDVI was observed ($r = -0.53$). In this case, all correlations marginally improved this analysis, but are still limited. Income may be an indirect factor of household size in this case, however such analyses are beyond the scope of this study.

Although the relationships were consistently significant, low correlations were obtained in some of the analyses (Fig. 5). This can be attributed to other factors that may influence consumption, as well as the resolution and aggregation level of the variables. 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

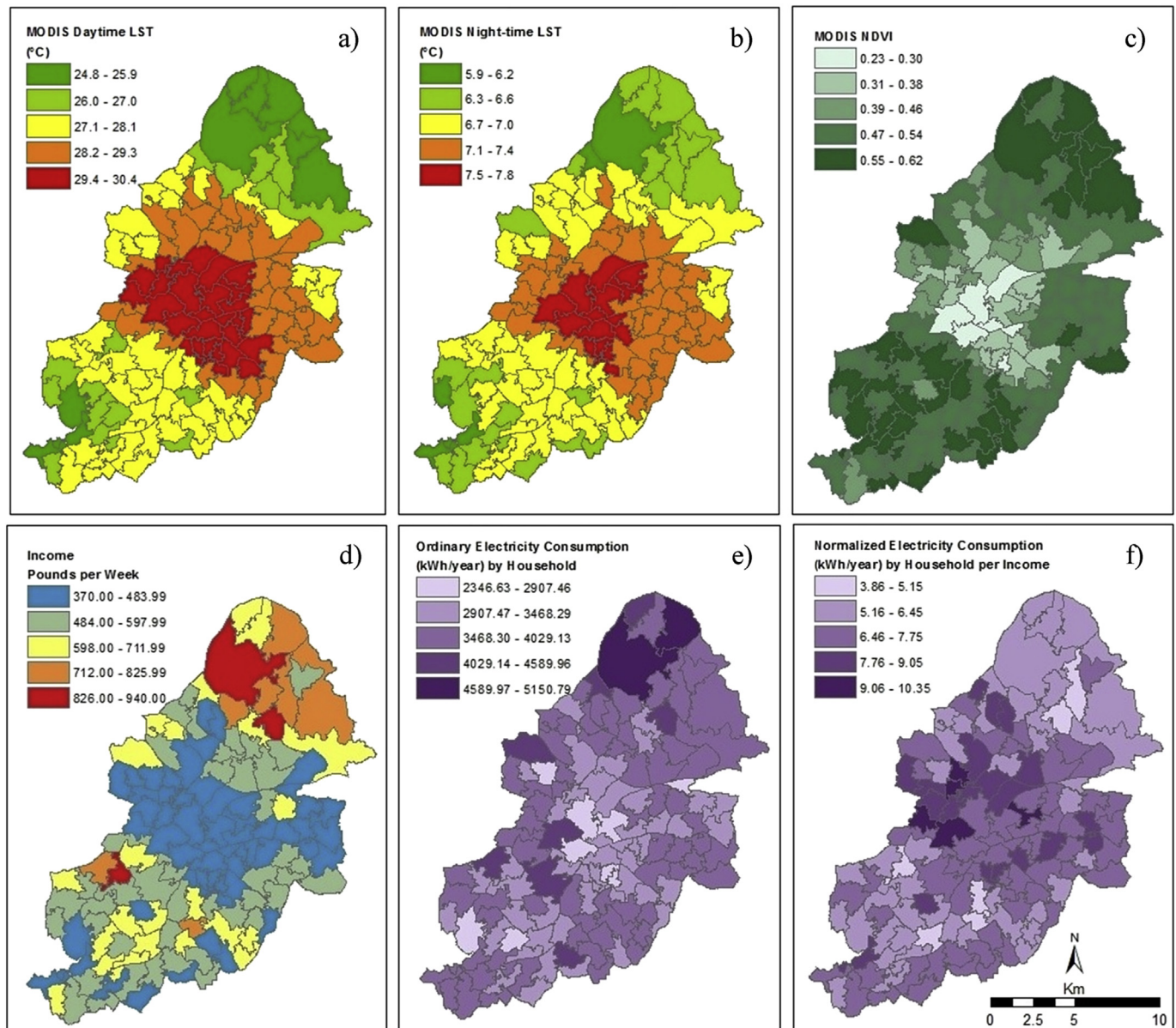


Fig. 4. Aggregated data to MSAO for a) UHI (day), b) UHI (night), c) NDVI, d) Income, e) Residential Electricity Consumption and f) Normalized Residential Electricity Consumption.

Table 2

Correlation matrix showing Pearson Correlation Coefficients between datasets.

| | Income | Ordinary electricity/Household | MODIS night-time LST | MODIS daytime LST | MODIS NDVI |
|--------------------------------|--------|--------------------------------|----------------------|-------------------|------------|
| Income | — | 0.62 | −0.55 | −0.66 | 0.61 |
| Ordinary Electricity/Household | 0.62 | — | −0.43 | −0.47 | 0.39 |
| MODIS night-time LST | −0.55 | −0.43 | — | 0.92 | −0.69 |
| MODIS daytime LST | −0.66 | −0.47 | 0.92 | — | −0.78 |
| MODIS NDVI | 0.61 | 0.39 | −0.69 | −0.78 | — |

detailed research. However, despite these limitations, it is evident that income is the most influential factor in electricity consumption, potentially an indirect factor of household size. 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.

5. Conclusions and final remarks

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, based on simple and repeatable steps with freely available datasets.

Table 3
Correlation matrix showing Pearson Correlation Coefficients between datasets and normalized electricity consumption.

| P | Ordinary electricity/Household – normalized by income | MODIS night-time LST | MODIS daytime LST | MODIS NDVI |
|---|---|----------------------|-------------------|------------|
| Ordinary Electricity/Household – Normalized by Income | – | 0.41 | 0.52 | –0.53 |
| MODIS night-time LST | 0.41 | – | 0.92 | –0.69 |
| MODIS daytime LST | 0.52 | 0.92 | – | –0.78 |
| MODIS NDVI | –0.53 | –0.69 | –0.78 | – |

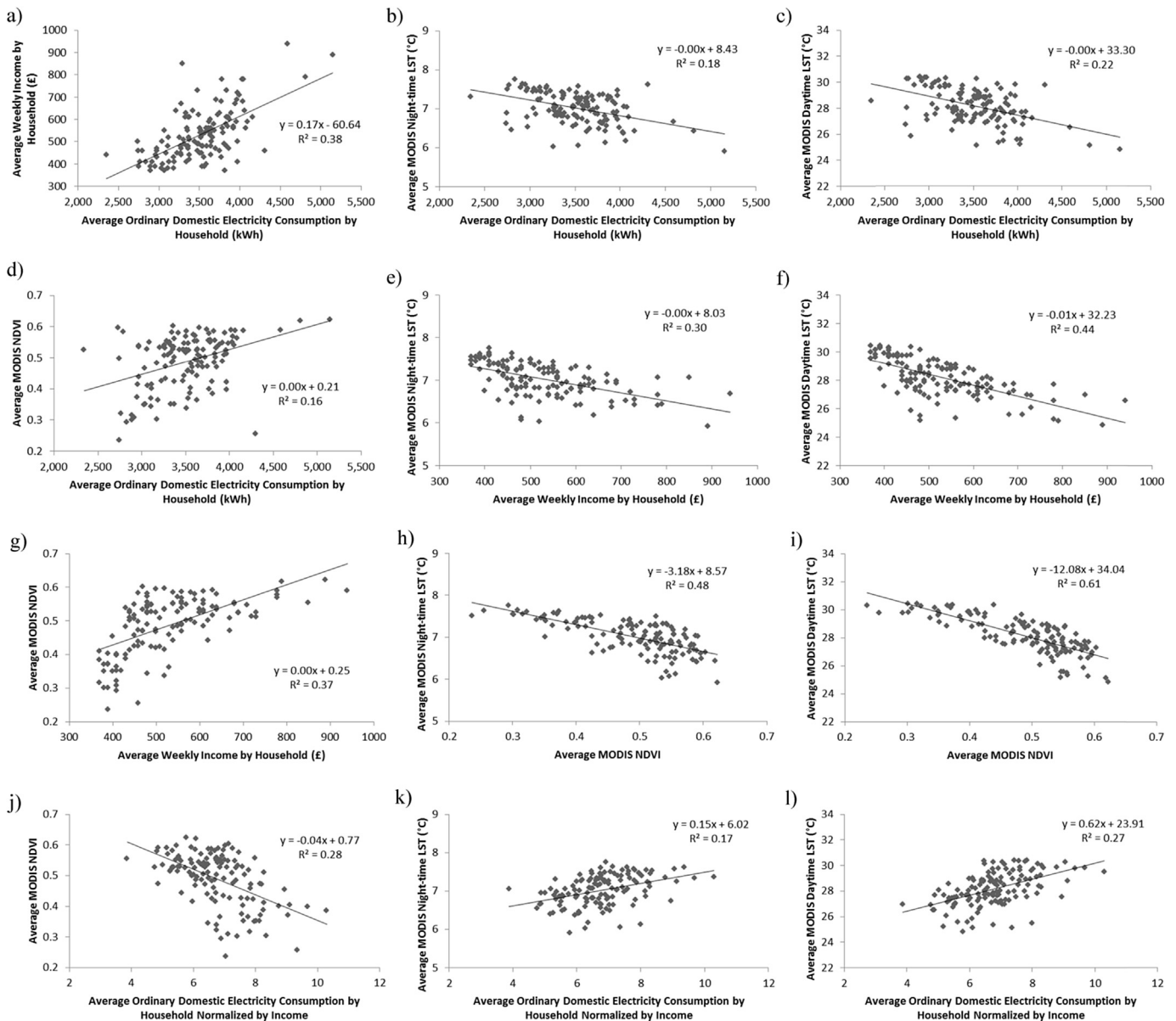


Fig. 5. Scatter plot diagrams with slope, intercept and R^2 a) Income by Consumption, b) Night-time LST by Consumption, c) Daytime LST by Consumption, d) NDVI by Consumption, e) Night-time LST by Income, f) Daytime LST by Income, g) NDVI by Income, h) Night-time LST by NDVI, i) Daytime LST by NDVI, j) Night-time LST by Income Normalized Consumption, k) Daytime LST by Income Normalized Consumption and l) NDVI by Income Normalized Consumption.

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 study, it would

be easy to conclude that electricity consumption due to increasing temperatures does not seem like 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

Table 4

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 | 3900 | 4200 | 4400 | 4700 | 4900 | 5100 | 5200 | 5500 | 6200 | 6700 | 5000 | 4600 |
| 2006 | 3800 | 4000 | 4200 | 4600 | 4800 | 5000 | 5200 | 5400 | 6100 | 6800 | 4900 | 4500 |
| 2007 | 3700 | 4000 | 4200 | 4500 | 4800 | 4900 | 5100 | 5400 | 6100 | 6700 | 4900 | 4500 |
| 2008 | 3500 | 3800 | 4000 | 4300 | 4600 | 4700 | 4900 | 5200 | 5900 | 6600 | 4700 | 4300 |
| 2009 | 3500 | 3700 | 3900 | 4300 | 4500 | 4700 | 4900 | 5200 | 5900 | 6600 | 4700 | 4200 |
| 2010 | 3500 | 3700 | 3900 | 4300 | 4500 | 4700 | 4900 | 5200 | 6000 | 6700 | 4700 | 4200 |
| 2011 | 3400 | 3700 | 3800 | 4200 | 4500 | 4700 | 4900 | 5200 | 5900 | 6700 | 4600 | 4200 |

climate change scenarios in Birmingham, temperatures will increase (Azevedo, Chapman, & Muller, 2015), exacerbating the UHI effect and impacts on electricity consumption. Also, 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.

Higher resolution data would certainly aid analysis, and with the advent of smart metering (i.e. the Internet of Things), consumption data will soon become available at seasonal and even daily scales, allowing better interpretation of LST, NDVI and income with consumption. The Internet of Things is now providing unparalleled opportunities for high resolution weather monitoring in our cities (e.g. crowdsourcing for weather and climate information: (Muller et al. 2015)). Additionally, high resolution vegetation maps and land use maps can be freely extracted from Google Earth Imagery, and used to infer the impacts of different types of greening on temperature. Finally, the emerging Volunteered Geographic Information (Arribas-Bel, 2014; Goodchild, 2007), is available to the aid acquisition and validation of geographical information and variables to improve analyses (Basiouka & Potsiou, 2012; Foody et al. 2013; Hawthorne et al. 2015; Spinsanti & Ostermann, 2013). Hence, moving forward, there is tremendous potential for future research to understand electricity consumption and urban climate at a high temporal and spatial resolution for spatial risk assessment, urban planning and energy industry, for current and future scenarios.

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