MODELLING AND MONITORING TOOLS TO EVALUATE THE URBAN HEAT ISLAND'S CONTRIBUTION TO THE RISK OF INDOOR OVERHEATING

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ABSTRACT

The growth of cities increases urban surface areas and anthropogenic heat generation, causing an Urban Heat Island (UHI) effect. In the UK, UHI effects may cause positive (winter) and negative (summer) health, comfort and energy consumption consequences. With the increasing focus on climate change-related heat exposure and consequent increased mortality risk, there is a need to better investigate the UHI during hot seasons. This paper reviews the current literature regarding UHI characterisation using monitoring, modelling, and remote sensing approaches, their limitations, and applications in building simulation and population heat exposure models. Ongoing and future research is briefly introduced in which downscaling techniques are proposed that provide higher temporal and spatial information to assess and locate heat-associated health risk in London.

INTRODUCTION

An increase in urbanisation is leading to greater population densities, reductions in greenspace, and an increase in anthropogenic heat sources in cities worldwide. The Urban Heat Island (UHI), a phenomenon where the temperature in urban areas is elevated compared to surrounding rural areas, is one of the consequences of increased urbanisation (Grimmond et al., 2016), with the temperature increase an indicator of UHI intensity. While the UHI may be beneficial in reducing winter mortality risks due to cold (Voogt, 2000) and winter energy use for heating (Mavrogianni et al., 2009), it may exacerbate exposure to high temperatures during periods of hot weather, thereby increasing the risk of heat-related mortality (Tomlinson et al., 2011; Taylor et al., 2015).

The interaction between the UHI and buildings is complex, with the contribution of buildings to the UHI dependent on their energy interaction with the urban environment, which is in turn driven by building construction characteristics, and occupant behaviour. Buildings may contribute to the UHI during their operation, emitting heat from air conditioning systems and central heating systems, depending on the energy efficiency of the building envelope; conversely, UHI temperatures may increase building heat exposure. Therefore, the indoor overheating risk will be dependent on outdoor temperatures, which may vary at a local or neighbourhood scale across an urban area.

UHIs may be evaluated using urban meteorological networks, modelling tools, or remotely-sensed imagery, all of which have advantages and disadvantages. This paper reviews the relevant literature about monitored, modelled and remotely-sensed weather data used as inputs into building simulation and heat exposure modelling, and describes how downscaling may improve spatial resolution. Ongoing and future research is introduced that aims to bridge the gap between what climate models and remote sensing provide and what building simulation models require, through monitoring, modelling and downscaling techniques. The methodology proposed may be applied to other cities that do not have appropriate sources of weather measurements. This work will supply city planners, urban engineers and architects with satisfactory temperature coverage of London to assess and locate heat-associated health risk in London. These data would also be of use to epidemiologists and public health officials aiming to understand and reduce heat-related mortality through the mitigation of heat exposure due to the UHI and building performance.

UHI, Heat, and Health

Exposure to even modest heat has been shown to lead to an increased mortality risk in temperate climates (Armstrong et al., 2011; Hajat et al., 2010). In the UK, there is no official definition of a heat wave, but it may be described using the definition of the World Meteorological Organization as a period "*when the daily maximum temperature of more than five consecutive days exceeds the average maximum temperature by 5 °C, the normal period being 1961-1990*" (Met Office, 2016). Extreme temperature events have been labelled as the most dangerous hazard for human health in Europe (EEA, 2010), and hot weather can be intensified by the UHI. In the UK, two recent extreme temperature events in 2003 and 2006 (GLA, 2006; Zhang et al., 2014) have been extensively reported in the literature. The 2003 European heat wave led to around 600 excess deaths in London and the UHI intensity reached up to 6–9 ºC (GLA, 2006). Extreme temperature events are predicted to become more frequent in the UK and along with it the risk of heat-related mortality (Jenkins et al., 2014).

Most British dwellings are free running during the summer, and their relative overheating performance is determined by a number of factors, including building fabric and geometry characteristics, orientation, local weather, and occupant behaviour. As the UK population spends the majority of their time indoors, the possibility to estimate indoor heat exposures inside individual urban dwellings, placed within a high-resolution UHI map would enable the understanding of intra-urban variations in the risk to human health.

Exposure to heat can be particularly dangerous to vulnerable segments of the population, such as people with limited mobility (elderly, babies and individuals with chemical and alcohol dependence), chronic or severe disease (obesity, respiratory diseases and cardiovascular conditions) and homeless people (Department of Health, 2015). While the UHI phenomenon is present year-round, it is during the summer that the increased temperature may exacerbate heat-related mortality. The UHI effects are estimated to lead to significant excess mortality during hot periods, including heat-related illnesses (Department of Health, 2015). For example, a recent paper by Heaviside et al. (2016) suggested that the UHI was responsible for 50% of the excess heat-related deaths in the West Midlands during the 2003 heat wave (Heaviside et al, 2016).

The role of housing on temperature exposure has been investigated in a number of studies, showing that overheating risk can vary across different UK dwelling types. These include building simulation studies which highlight, for example, bungalows and top-floor flats as being among the most at-risk of overheating (Mavrogianni et al., 2012; Taylor et al., 2015). Building on an improved understanding of the role of housing on heat exposure, a number of recent studies have sought to combine UHI estimates with simulated or assumed building overheating risks to estimate indoor temperature exposures and heat-related mortality risks. Approaches have included, for example: 1) using a combination of monitored and modelled temperature data to create weather files for building simulation (Oikonomou et al., 2012), 2) using regional climate model-derived weather files at 5 km^2 resolution to use with building simulation (Kershaw et al., 2010; Lee and Levermore, 2012), 3) using 1 km^2 modelled UHI temperatures as a post-hoc adjustment for simulated indoor temperatures (Taylor et al., 2015), or 4) overlaying remote-sensed UHI imagery with a principle components analysis of heat vulnerability that includes housing type as a factor (Wolf and McGregor, 2013). There is, therefore, an increasing research interest in combining three layers (UHI distribution, housing stock and vulnerable individuals) to estimate the spatial variation of heat risk and evaluate the relative importance of housing and UHI on heat exposure. It is likely, however, that there are important temperature variations that occur at smaller spatial extents due to local microclimatic processes (Kolokotroni and Giridharan, 2008).

OBSERVED WEATHER DATA

Field Measurements

Urban temperature data may be available from networks of meteorological stations (Zakšek and Oštir, 2012; Huth et al., 2015; Jiang et al., 2015). These stations have advantages, in that they provide direct meteorological data, such as measured air temperature, at regular time intervals. These field measurements are frequently used to quantify the UHI intensity (Marzari and Haghighat, 2010). Due to the elevated cost of installation and maintenance of the measurement equipment, the density of fixed stations inside the city is typically inadequate to characterise the local spatial variation in UHI intensities, limiting the ability of many studies to properly investigate neighbourhood temperatures using measured data. The use of weather data from meteorological stations for building simulation is most suitable when the building is located close to the monitoring site. Measured data also can be appropriate for validation of modelled UHI temperatures (Mirzaei and Haghighat, 2010). Additionally, the variability of air temperature in cities may be acquired by performing transects across urban areas using, for example, sensors installed on cars (Nichol et al., 2009).

There are a number of examples of monitored temperature data used in building simulation for indoor overheating analysis. For example, Virk et al. (2015a) evaluated building overheating in London using EnergyPlus and monitored weather data from the Chartered Institute of Building Services Engineers (CIBSE) in the form of Design Summer Years (DSY) for three baseline years (1976, 1989 and 2003). Three locations were considered: urban (London Weather Centre), semi-urban (London Heathrow and rural (London Gatwick).

The HiTemp project in Birmingham sought to increase spatial coverage of monitoring stations using a dense meteorological network of more than 150 Wi-Fi sensors, located in each Middle Level Super Output Area (MSOA), and 100 Wi-Fi sensors on lampposts, in the commercial area of the city. These sensors measured air temperature, precipitation, relative humidity, wind speed and direction, pressure and solar radiation, with the aim of analysing climate impacts on household electricity consumption and assess the heat health risk across the city (HiTemp, 2016). In London, the London Site-Specific Air Temperature Model (LSSAT) provides hourly air temperature estimates for 77 fixed temperature stations across London, which may be interpolated to a radial grid with 52 location points (Kolokotroni et al., 2009). These data were developed as part of the

LUCID (the development of a Local Urban Climate model and its application to the Intelligent Design of cities) project. Weather data from LSSAT was used by Oikonomou et al. (2012) from the centre and edge of London to examine the relative role of building characteristics and UHI on overheating risk using EnergyPlus.

Remote sensing

Remote sensing is the science of obtaining information about an object without physical contact using sensors that register the interaction between the radiation (emitted, reflected and absorbed) and the target (Schneider dos Santos et al., 2015). Infrared sensors on-board satellites or aircraft can generate thermal images of land surface temperatures during the day and night, thereby enabling the mapping and monitoring thermal urban characteristics. Additionally, sensors may capture data that enable land use classification, which can be used to supplement thermal imagery. Sensors may capture data at different resolutions (spatial, temporal and radiometric) and accuracy levels. While remote-sensed thermal imagery is of land surface temperature (LST), it may be used to grid surface energy fluxes and get an estimation of air temperature (Zakšek and Oštir, 2012; Jiang et al., 2015).

There are many satellites capable of providing LST measurements as well as wide geographical coverage. Geostationary satellites provide a geosynchronous orbit over Earth. These satellite types are valuable for climate monitoring (such as cloud cover and wind) since they provide a constant view of the same surface area. Geostationary satellites, such as Spinning Enhanced Visible Infra-Red Imager (SEVIRI), on board Meteosat Second Generation (MSG); and the Geostationary Operational Environmental Satellite (GOES) (Kustas et al., 2003; Jiang et al., 2015), are used in UHI and heat wave analysis, because they have high frequency of observation (every 15 min), although with poor spatial resolution (around 4 km).

Polar-orbiting satellites are closer to the earth's surface than geostationary satellites and have an orbiting period of around 1.5 hours. The spatial resolution and revisit time varies depending on the swath width of the satellite (Bechtel et al., 2013). Two daily images are offered by wide swath sensors, such as the MODerate resolution Imaging Spectroradiometer (MODIS), on board the Terra and Aqua satellites and the Advanced Very High Resolution Radiometer (AVHRR), on board National Oceanic and Atmospheric Administration (NOAA). Sensors with low swath have lower overpass frequency, such as the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) and Landsat sensors.

Table 1 shows satellites that provide LST data for urban thermal analysis. Each data source presents a trade-off between resolution and revisit frequency. It is, therefore, not possible to obtain LST data at high temporal and spatial resolutions via a single satellite (Atkinson, 2013). Additionally, overpass must coincide with cloud-free conditions to gather clear imagery.

Table 1
Technical characteristics of different satellite sensor for UHI and heat wave studies.
(VNIR: Visible and Near Infrared; TIR: Thermal Infrared).

SENSOR/ SATELLITE	**SPATIAL RESOLUTION**		**TEMPORAL RESOLUTION**
	VNIR Bands	TIR Bands	
TM/ Landsat 5	30 m	120 m	16 days
ETM+/ Landsat 7	30 m	60 m	16 days
OLI & TIRS/ Landsat 8	30 m	100 m	16 days
ASTER/ Terra	15 m	90 m	16 days
MODIS/ Aqua | Terra	250 m	1000 m	1-2/days
AVHRR/ NOAA	1000 m	1000 m	2/days
SEVIRI/ MSG	1000 m	3000 m	5-15 min
GOES imager/ GOES	-	5000 m	15 min

Remote sensing equipment on board aircraft may also capture UHI data. The spatial and temporal resolution can be controlled, but surveys are expensive and flights are typically made to order. Data from NASA's Advanced Thermal and Land Applications Sensor (ATLAS) instrument, on board the NASA Stennis Lear Jet, have been extensively used for UHI analysis in the USA (Gluch et al., 2006; Dominguez et al., 2011). ATLAS has 15 bands covering the visible, near-InfraRed (IR), mid-IR and thermal-IR wavelengths, with spatial resolution of up to two meters per pixel, but multispectral/thermal data are usually used at 10 m (Gluch et al., 2006).

There are a number of examples of remote-sensed UHI data being used alongside dwelling overheating risk estimates in heat risk assessments. For London, Wolf and McGregor (2013) combined remote-sensed UHI imagery with a principle components analysis of heat vulnerability to estimate the spatial variation in heat vulnerability. In Birmingham, Tomlinson et al. (2011) used an UHI derived from MODIS imagery to predict spatial heat risk. However, due to the limited spatial or temporal resolution, remotely-sensed UHI data has not been used to generate weather files for direct use in building simulation.

MODELLED WEATHER DATA

Weather modelling is a useful tool to estimate the distribution of UHI temperatures since it can address past, present and future scenarios, helping researchers to better understand processes on different scales. These models can generate grids of meteorological data at varying resolutions.

Global and Regional Climate Models

Global Climate Models (GCM) are used for climate predictions and run weather data at low spatial resolution (100-250 km) with high temporal resolution (e.g. hourly). Due to the low spatial resolution, they are not adequate to supply temperature information at local scale (Wilby and Wigley, 1997; Huth et al., 2015) and therefore Regional Climate models (RCM) are widely used for more local temperature estimates. RCMs are capable to run climate variables at better resolution (25-50 km).

Mesoscale models are climate models able to be run at more local levels using inputs of land use and weather conditions to estimate urban temperatures at 1 km² or less. Land use and city characteristics may be informed by an urban surface scheme, which offers an appropriate two-dimensional representation of the building types and the energy fluxes from the urban surfaces. Two examples of the climate models with the combination of urban canopy schemes are: Weather Research Forecasting (WRF) model and the UK Met Office's Unified model (MetUM).

WRF, a regional meteorological model, was used by Heaviside et al. (2015), for example, in Birmingham and the West Midlands Metropolitan region to model the UHI impact on air temperature to assess the heat-related health risk at 1 km^2 resolution, during the 2003 heat wave. The model used weather data in combination with an urban canyon scheme and a detailed land use data to generate results, with observations from four weather stations used to validate the model.

The MetUM model is a tool that combines Numerical Weather Prediction (NWP) and climate models, to improve the understanding of the urban areas effect for weather forecasting and regional climate modelling. The MetUM model has been used with the Met Office–Reading Urban Surface Exchange Scheme (MORUSES) to estimate UHI temperature data at 1 km² for London (Porson et al., 2010). These combined models, referred to as the London Unified Model (LondUM), were used to generate UHI estimates for the LUCID project (Porson et al., 2010; Bohnenstengel et al., 2011). Taylor et al. (2015) used the 1 km^2 air temperature outputs from this project, in conjunction with modelled individual-building indoor temperatures, as modifiers of heat exposure and subsequent mortality across London.

Microclimate Models

In contrast with mesoscale models, microscale models are not generally applied to an entire city, but instead at neighbourhood scales due to high computational cost, since the energy flux interactions and canyon configurations are more detailed. At the same time, such models simplify atmospheric interactions, since they do not include atmospheric vertical mixing or Coriolis effects (Mirzaei and Haghighat, 2010). The spatial resolution of these models is usually 1-50 m² and they can offer two and three-dimensional representations of the buildings. Microclimate models are a useful tool to estimate heat effects at a scale of up to few hundreds of meters, since the local weather can change considerably from the original weather forecasting, due to the energy flux interactions of urban surfaces.

The Atmospheric Dispersion Modelling System Temperature and Humidity (ADMS T&H) is one such tool that assesses the spatial variation of temperature over the urban system at high spatial resolution (1-50 m²). This tool was used by Virk et al. (2015a) to investigate the impact of retrofitted green and cool roofs on the variation of air temperature near to the building. These outdoor temperatures were used to estimate internal temperatures using dynamic building thermal simulation (EnergyPlus).

Another such tool is ENVI-met, designed to simulate detailed surface-plant-air interactions within an urban environment. The spatial resolution is from 0.5 to 10m and it offers three-dimensional representations of the buildings. O'Malley et al. (2014) developed successful scenarios of UHI mitigation strategies using ENVI-met modelling for West Kensington and North Fulham, London.

Computational Fluid Dynamics (CFD) models provide simulation of thermal conditions and airflow inside and above the urban canopy (Somarathne et al., 2005). CFD is capable of providing detailed three-dimensional information on temperature, wind velocity and other fluid properties in local urban environments. CFD is, therefore, considered to be better than Urban Surface Schemes, which are based on the relationship of the energy exchanges between buildings and ambient air within urban canopy (Mirzaei and Haghighat, 2010). Nonetheless, CFD requires high computational power and a complex input dataset, making it inappropriate for modelling a large area. Somarathne et al. (2005) used a dynamic thermal modelling (DTM) procedure within CFD, to simulate indoor-outdoor temperature exchange in a typical UK office, based on CIBSE template for well-insulated airtight building.

DOWNSCALING TECHNIQUES

Downscaling is a generic term that refers to methods for increasing the temporal and spatial resolution of

GCM, RCM and satellite images through auxiliary data with higher resolution (Zakšek and Oštir, 2012).

Downscaling techniques, when applied to climate models, rely on a combination of large-scale climatic models (such as GCM outputs combined with RCM data), local climate (climate station information) and local conditions (topography and land use properties) to provide higher spatial and temporal resolution (Wilby and Wigley, 1997). Downscaling methods can be broadly divided into Dynamical Downscaling (DDS) and Statistical Downscaling (SDS). These methods are extensively used to estimate important climate variables, including temperature and precipitation (Wilby and Wigley, 1997; Huth et al., 2015).

DDS may be used to downscale GCM outputs to a RCM to characterise the new climate variables patterns at a resolution of 25-50 km² (Wilby and Fowler, 2010). DDS produces consistent representation of RCM interactions without the need for historical data, however it requires high computational power and has limited scale reduction. This method was used by Lee and Levermore (2012) to produce weather files representative of climate change scenarios from a GMC to RCM (HadRM3) on 25 km² grid. In combination with a weather generator data, 25 km² were downscaled further to 5 km² grid of hourly and daily air temperature. The outputs were used to model overheating risk using EnergyPlus in a typical Manchester dwelling. For Chicago, USA, Conry et al. (2015) applied a combination of DDS with a GCM (Community Atmosphere Model), RCM (WRF) and Microscale (ENVI-met) models to create microscale outputs that were combined with a building energy model to estimate energy demand. The PROMETHEUS project (The use of probabilistic Climate Change Data to Future-proof Design Decisions in the Building Sector) produced weather files in the EnergyPlus weather format to be compatible with common building simulation software, based on the latest UKCP09 projections (PROMETHEUS, 2016). This involved temporally downscaling (from monthly to hourly values) the Met Office's RCM data (HadRM3) (Kershaw et al., 2010)

SDS involves enhancing GCM resolution using local variables through validated empirical relationships. SDS has been widely applied to UHI studies since the tools are easy to implement and do not require the computational power of DDS. However, it requires historical observational data to establish the relationship between global and local-scale processes. These downscaled RCM models output may not be the most appropriate input data for local scale analyses, since the output grids do not provide sufficient resolution to evaluate the UHI's contribution to the risk of indoor overheating at the individual-building level. This method was used, under different statistical techniques, by Poggio and Gimona, et al. (2015) to provide the best estimation for the climate model (HadRM3) data in relation to climate variables.

Remote sensing images may also be spatially downscaled to provide finer spatial resolutions, however with the limitation of providing LST rather than air temperature. Several studies have downscaled satellite data to better understand the spatial and temporal variation of temperatures at local scales (e.g. Jiang et al., 2015). SDS may be used to downscale remotely-sensed LST data by relying on the relationship between LST and auxiliary data. Satellite sensors provide better spatial resolution in the visible and near-infrared regions compared to the thermal region. Those two regions can provide auxiliary datasets, such as vegetation cover, albedo and land use; these data can help in the disaggregation process since LST is influenced by the surface characteristics. The most frequently SDS technique uses the negative correlation between the LST and Normalized Difference Vegetation Index (NDVI) to acquire better LST resolution (Kustas et al., 2003). There are number of examples of downscaling applications grounded in remote sensing data. For example: Zakšek and Oštir (2012) applied multiple regression in SEVIRI images, based on Principal Component Analysis (PCA) to disaggregate LST from 5 km to 250 m; Jiang et al. (2015) used SDS on remote-sensed data as the first step of their methodology to create a risk map to monitor the heat hazard across Los Angeles city (USA), at 1 km resolution with higher repeat cycle (every 15 min); and Dominguez et al. (2011) applied High Resolution Urban Thermal Sharpener (HUTS) to ASTER TIR image (90 m), using VNIR image (10 m) as auxiliary data from NASA's ATLAS airborne to enhance the spatial resolution of ASTER thermal image.

ONGOING AND FUTURE RESEARCH

There are several possibilities for using remote sensing as a substitute for, or to supplement, existing measured and monitored urban climate data. Remote sensing tools do not require a complex input dataset or high computational power; they offer historical data and do not rely on city weather station coverage; and there are data available for cities worldwide. Although air temperature cannot be acquired directly using remote sensing, LST data are useful as a surrogate for air temperature (Jiang et al., 2015). Remote sensing data is limited by the trade-off between high temporal (hourly) or high spatial (less than 1 km²) resolutions via a single satellite (Atkinson, 2013). However, with the addition of downscaling techniques, remote-sensed data can estimate land surface temperatures at an individual-building scale (Dominguez et al., 2011).

In addition, remotely sensed data can be used to generate urban surface and terrain input data to weather and building simulation models, since land use parameters (albedo, thermal admittance and surface resistance to evaporation parameter) and building height are not provided from meteorological networks. These data were used by Virk et al. (2015b) to generate inputs into their microclimate ADMS T&H.

Current research at UCL is investigating the risk of overheating in dwellings and the subsequent risk of mortality to building occupants (Taylor et al., 2015) using 1 km^2 air temperature grids in combination with building thermal simulation models. Ongoing research is building upon this work by investigating variations within these 1km^2 air temperature grids to further refine local estimates of UHI heat exposure. The research hypothesis is that temperature variations within existing grids may be significant, and that a better spatial resolution grid of air temperature is required to estimate accurate predict indoor temperatures, and consequently population mortality risk. The objective of this research is to bridge the gap between the current scale limitation of temperature and the appropriate spatial resolution required from researchers focused on the assessment of heat-associated health risk.

Initially, analyses are focused on existing LST, modelled and monitored air temperature data for London (Figure 1). A 1km^2 grid of modelled air temperature, developed using the LondUM model as part of the LUCID project, provided temperature data from May to August, 2006. This low-resolution data is contrasted with higher-resolution measured and remotely-sensed data to see how the air temperature and LST vary inside of each modelled grid square. Monitored air temperature data, obtained in August 2008 using car transects that recorded air temperature every second, provided high-resolution temperature data within the 1km reference grid squares along the car route (north/south and west/east). In addition, LST was obtained from ASTER for a date within the modelled period (July 28th, 2006) and overlaid on the same grid squares. All data was adjusted to the same geographical reference to be able to apply spatial analysis. By calculating the standard deviation values from all air temperature or LST data contained inside each selected grid cell, it will be possible to explore the air temperature and LST variability across London. The results will help to determine whether there is a requirement to develop urban temperature models at spatial resolutions higher than 1km^2.

If the results indicate high variability within the 1km grid squares, further research will use downscaling techniques to provide higher spatial resolution of air temperature, supported by remote sensing data. The result will provide a temperature data at an appropriate scale to improve our understanding of the contribution of London's UHI on indoor overheating. The final results of this project will be compared with the outputs of more complex high resolution UHI models in order to provide an inter-model validation, evaluating the trade-offs of the models and testing the reliability of the proposed method.

Additionally, this project will develop a downscaling guide as one of its outputs, explaining which technique is more appropriate to obtain the desired results at a local scale. Future work will apply downscaling techniques to other UK cities, providing improved information on urban temperature variations and a higher resolution grid of outdoor temperature. This will, in-turn, help to enhance the understanding of intra-urban variations in the risk to human health.

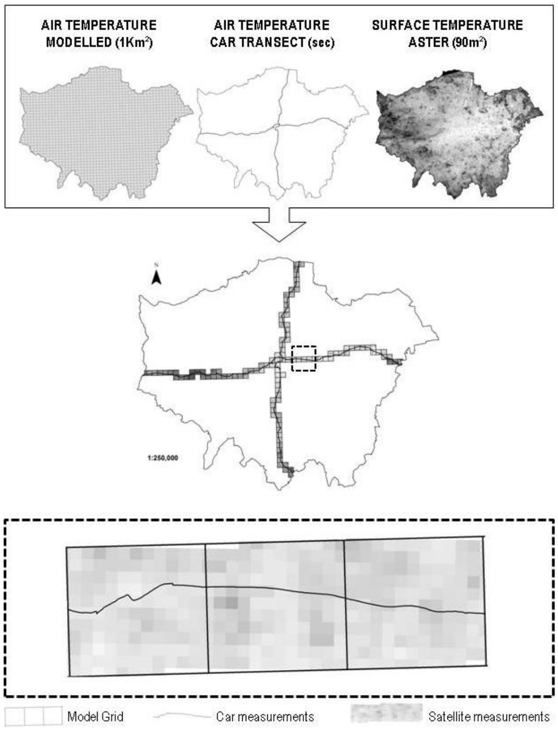

Figure 1 Initial steps of the research structure.

SUMMARY

This paper reviews the data sources commonly used to better understand and substantiate UHI impacts in urban settings and estimate site-specific temperatures. We have addressed the various strengths and limitations of different approaches, and introduced ongoing and future research that seeks to improve on existing UHI data resolution used in existing building overheating and health impact models.

ACKNOWLEDGEMENTS

The authors would like to thank the financial support provided by the Brazilian research-funding agency CNPq (National Council for Scientific and Technological Development).

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