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Research paper

Assessing the impact of changes in surface cover, human behaviour and climate on energy partitioning across Greater London

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ABSTRACT

Climate-sensitive urban design is an increasingly important consideration for city planners and policy makers. This study demonstrates the use of a biophysical model to assess the response of urban climate to various changes, including population growth, reduced energy use, urban development and urban greening initiatives. Model inputs are intentionally derived using only publicly available information and assumptions involved in collating the data are discussed. Results are summarised in terms of the energy partitioning which captures changes in meteorology, surface characteristics and human behaviour. The model has been recently evaluated for the region, and those findings are drawn upon here to discuss the model's capabilities and limitations. Model simulations demonstrate how both intentional and inadvertent changes to the urban landscape can alter the urban climate. For example, the impact of population growth depends on where, and how, people are housed, and recent changes in garden composition have reduced evaporation. This study has been designed so that model output could be combined with socio-economic data in future, enabling both risk and vulnerability to be considered together.

1. Introduction

Growth in urban populations puts increasing pressure on city planners, policy makers and society to develop in a sustainable and resilient manner. Cities must have the capacity to mitigate the impacts of extreme weather in order to minimise damage to human health, the environment and the economy. Urban climate-related risks include, but are not limited to, thermal stress, flooding, air quality events and extreme wind (e.g. Bell et al., 2007; Chen, Hill, & Urbano, 2009; Dessai, 2002; Hsieh & Wu, 2012). In many cases the urban environment enhances these risks. For example, urban areas are known to exacerbate heat stress for the following reasons:

- The relatively limited amount of vegetation reduces the opportunity for evaporation and its associated cooling effects, contributing to city temperatures that are typically a few degrees higher than in the surrounding countryside (Howard, 1833; Oke, 1982).
- Paved and built surfaces (e.g. roads, carparks, roofs) are fairly impermeable to water so rainfall is quickly routed into drainage systems and directed away from the surface, thus removing the source of moisture for evaporation (Grimmond & Oke, 1986; Grimmond, Oke, & Steyn, 1986; Oke, 1982; Xiao, McPherson, Simpson, & Ustin, 2007).
- Buildings and roads absorb and store a large proportion of heat during the day and the release of this heat after sunset means temperatures may remain high throughout the night (e.g. Grimmond & Oke, 1999b; Kotthaus & Grimmond, 2014a; Offerle, Grimmond, & Fortuniak, 2005; Roberts, Oke, Grimmond, & Voogt, 2006).
- Dark surfaces (such as asphalt) absorb solar radiation well, and the arrangement of buildings and roads can trap energy, further increasing the heat available (Sailor, 1995; Taha, 1997).
- Human activities provide additional energy: directly through heating buildings and as waste heat from air-conditioning units, electrical appliances, cooking, transportation and human metabolism (e.g. Bergeron & Strachan, 2010; Hamilton et al., 2009; Sailor, 2011). In densely populated areas, this anthropogenic energy supply can be substantial (Ichinose, Shimodozono, & Hanaki, 1999; Klysik, 1996).

Urban design options to moderate heat stress include increasing vegetation cover (e.g. parks, street trees, green roofs), incorporating water bodies or using high albedo building materials (e.g. Lee, Mayer, & Chen, 2016; Nakayama & Fujita, 2010; Ng, Chen, Wang, & Yuan, 2012; Sailor, 1995). Decisions may sometimes have unforeseen and/or detrimental effects. For example, increased use of

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air-conditioning in warm conditions releases additional waste heat into the environment, further augmenting temperatures and exacerbating heat stress, and putting pressure on power supplies (de Munck et al., 2013; Ohashi et al., 2007; Ramamurthy, Li, & Bou-Zeid, 2015). To lower carbon emissions, one way to encourage use of public transport over private cars is to increase the cost of residents' parking permits. In London, this has led to more people paving over their front gardens so they can park off-road (GLA, 2005b). Vegetation and pervious gravel/soil surfaces have been replaced by impervious concrete or asphalt, enhancing runoff and reducing infiltration of rain water, with the result that evaporation is restricted.

Biophysical models use information about the urban surface (e.g. land cover, building height, radiative properties such as albedo or reflectivity) and inhabitants (population density, energy use), along with past, present or predicted meteorological data to simulate components of the energy balance and/or water balance and thus inform about the environmental conditions. In addition to identifying regions with the greatest risk of exposure, models can also indicate how the risk may change over time. The physical processes represented in models enable us to understand why the risk may be greater under certain conditions and, conversely, to identify measures that may be used to reduce exposure. Models permit the advantages and disadvantages to be explored to better inform planning decisions before investments are made. For example, the impact of several urban cooling measures (including water, vegetation, high albedo surfaces and building dimensions) on pedestrian thermal comfort was assessed for a district in Toulouse that will soon undergo redevelopment (Martins et al., 2016). Potential feedbacks resulting from decisions (made by citizens or government) can be assessed. In the Toulouse study, the high albedo scenario was found to negatively impact pedestrian comfort as more radiation was reflected from walls towards pedestrians.

Understanding and managing climate-related risks in cities is of prime importance, particularly as more variable and more extreme weather is expected in future (IPCC, 2012). The focus of this study is Greater London, home to more than 8 million people (ONS, 2011) and with a daytime population (including workers and tourists) in excess of 10 million (GLA, 2013). The Greater London region is divided into 33 districts: 32 boroughs plus the City of London. For brevity, we refer to all 33 subdivisions as boroughs. There are 12 inner boroughs (plus City of London) and 20 outer boroughs (Fig. 1). Each borough is governed by a borough council (the City of London is governed by the City of London Corporation), responsible for education, provision of services and urban planning. Some planning decisions are also made by the Greater London Authority, responsible for London as a whole. The boroughs represent useful units in terms of governance and the availability of socio-economic data (such as poverty, health status and access to services) which can be used to gauge vulnerability (e.g. Wolf & McGregor, 2013). In future, borough-level risk estimates could be combined with socio-economic data in a move towards interdisciplinary modelling of cities that involves social, economic and biophysical aspects of the city system (Masson et al., 2014). This would enable adaptive or coping strategies to be targeted towards exposed areas that are most vulnerable.

Numerous indicators exist to describe thermal (dis)comfort (de Freitas & Grigorieva, 2015), usually based on temperature and often modified according to some combination of humidity, wind speed, radiation receipt or other variables in an attempt to account for the physiological and psychological effects that translate the physical air temperature to thermal comfort experienced by humans (Johansson, Thorsson, Emmanuel, & Krüger, 2014). Well-known examples include the physiological equivalent temperature (Höppe, 1999), mean radiant temperature (Thorsson et al., 2014) and universal thermal climate index (Jendritzky, de Dear, & Havenith, 2012). Mesoscale modelling studies often rely on 2 m air temperature output, sometimes combined with humidity, to represent human comfort (e.g. Theeuwes, Solcerová, & Steeneveld, 2013). Remotely sensed land surface temperature (Wolf & McGregor, 2013) or urban heat island intensity (Tomlinson, Chapman, Thornes, & Baker, 2011) products are also used. Alexander, Fealy, and Mills (2016) considers the impact of urban development in terms of the surface energy balance. Certain indicators may be more or less suited to particular applications, depending on spatial scale, period of interest and data available. Microscale studies may consider differences between sunlit and shaded areas around individual buildings (e.g. Lindberg, Holmer, & Thorsson, 2008; Middel, Häb, Brazel, Martin, & Guhathakurta, 2014), whereas the computational demands of mesoscale simulations usually restrict the study period to a few days for typical grid-box sizes. A more user-friendly approach is adopted in this study to examine how London's climate responds at the local-scale to changes in meteorology, urban design and policy.

The objectives of this paper are: (i) to assess the response of the urban environment across Greater London to changes in surface characteristics, population and energy use; (ii) to explain the routes by which these changes affect the urban climate; (iii) to demonstrate a methodology which could subsequently be applied to other cities.

2. The biophysical model

2.1. Model description

This study uses the Surface Urban Energy and Water balance Scheme (SUEWS), which has already been evaluated against observational datasets at two urban sites in this region (Ward, Kotthaus, Järvi, & Grimmond, 2016). SUEWS considers the urban surface comprised of seven surface types (paved surfaces, buildings, evergreen trees and shrubs, deciduous trees and shrubs, grass, bare soil and open water) with a single-layer soil store beneath each surface (except water). The exchange of energy at the surface is written (Oke, 1987):

$$Q^* + Q_F = Q_H + Q_E + \Delta Q_S. \quad (1)$$

Q^* is net all-wave radiation; Q_F is anthropogenic heat flux, i.e. the additional energy supplied through human activities. These inputs heat the air (Q_H, turbulent sensible heat flux), evaporate water (Q_E, turbulent latent heat flux) or are stored in (and later released from) the urban volume (ΔQ_S, net storage heat flux). The storage heat flux is calculated using the Objective Hysteresis Model (OHM, Grimmond, Cleugh, and Oke (1991)). Evaporation is calculated using an adapted Penman-Monteith equation (Grimmond & Oke, 1991) with surface conductance formulated after Jarvis (1976) (Ward, Kotthaus et al., 2016). A running water balance is calculated at each time-step, providing soil moisture, runoff and surface wetness. Further details can be found in Järvi, Grimmond, and Christen (2011), Järvi et al. (2014) and Ward, Kotthaus et al. (2016).

One of the advantages of SUEWS is its simplicity. High-performance computing is unnecessary, even when running the model for multiple years or multiple areas. Required inputs include information about the surface characteristics (e.g. land cover, building height, albedo, emissivity) and human behaviour (energy use, water use, population density), along with basic meteorological data: incoming shortwave or solar radiation ($K_\downarrow$), air temperature (T_{air}), relative humidity (RH), barometric pressure (p), wind speed (U) and precipitation (P). The versatility of the model allows additional input information to be accepted if available (Lindberg, Grimmond, Onomura, & Järvi, 2015), otherwise recommended values should provide a reasonable approximation in many cases (Ward, Järvi, Onomura, & Lindberg, 2016). Key site-specific information may need to be derived from other sources (Section 3.1).

The model runs in this study were performed using SUEWS v2016a (Ward, Järvi et al., 2016). Here, we focus on the modelled energy fluxes (Eq. (1)). Results are presented in terms of the energy partitioning using the median midday (1100–1400) Bowen ratio (Q_H/Q_E), β_{MM}. Several