Constructing climate change scenarios of urban heat island intensity and air quality

Robert L Wilby
Department of Geography, Lancaster University, Farrer Avenue, Lancaster LA1 4YQ, England;
e-mail: r.wilby@lancaster.ac.uk
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Abstract. As the global population becomes increasingly urbanised, so interest has grown in the potential climate change impacts on city infrastructure, services, and environmental quality. However, urban areas are only beginning to be represented explicitly in the land-surface schemes of dynamical climate models through modified energy and moisture budgets. This paper summarises recent evidence of urban impacts on climate and vice versa. The technique of statistical downscaling is then introduced through exemplar studies of London's future urban heat island and peak ozone concentrations. Projections of both indices are derived from atmospheric variables supplied by four general circulation models, driven by a medium-high (A2) emissions scenario for the 2050s. The results show further intensification of the nocturnal heat island and higher ozone concentrations that are most pronounced in summer. These changes reflect sensitivity to variations in regional climate alone, so omit other factors such as changes in land use, emissions, climate feedbacks, or synergies between air quality and heat islands. Nonetheless, the downscaled scenarios are consistent with an emerging picture of increasing risks to human health in urban areas unless appropriate adaptation measures are taken.

1 Introduction
Studies of the meteorology of cities are enjoying a renaissance, thanks partly to the continued urbanisation of the world's population and a growing realisation that built environments are potentially vulnerable to climate change. Extreme weather events such as Hurricane Katrina (figure 1) have stimulated much discussion about possible changes in the destructiveness of storms (Emanuel, 2005), and have exposed the fragility of critical urban infrastructures and supporting resource systems. Likewise, the devastating European summer heat wave of 2003 raised important questions about our understanding of the human health and social implications of urban thermal stress (McGregor et al, 2006). In these cases the built form and land-cover characteristics of cities were recognised as factors that exacerbated a ‘natural’ hazard. Hence we may consider urban areas as both a driver and receptor of climate change impacts.

1.1 Impacts of urbanisation on climate
Recent progress in urban climatology was reviewed in detail by Arnfield (2003). Since Luke Howard's classic study of London's urban heat island (UHI) in the early 19th century (Howard, 1833), it has been known that urban centres can be up to several degrees warmer than the surrounding countryside. Compared with vegetated surfaces, building materials retain more solar energy during the day, and have lower rates of radiant cooling during the night. Urban areas also have lower wind speeds, less convective heat losses, and less evapotranspiration, yielding more energy for surface warming. Artificial space heating, air conditioning, transportation, cooking, and industrial processes introduce additional sources of heat into the urban canopy layer, as shown by distinct weekly cycles in UHI intensity (figure 2).
Figure 1. Infrared image of hurricane Katrina prior to landfall on 29 August 2005 (source: UK Met Office, http://www.metoffice.com/satpics/namerica_IR.html).

Figure 2. Weekly variations in London's urban heat island intensity derived from temperature differences between St James's Park and Wisley, 1959–2000: taken during (a) the night (minimum temperatures) and (b) the day (maximum temperatures). The vertical bars denote the standard error of the mean estimates for each day of the week (source: Wilby, 2003b).
After numerous field studies the most important determinants of UHI character and behaviour are now well understood (table 1). For example, detailed monitoring has revealed that London’s UHI is a highly mobile phenomenon with the location of the thermal maximum shifting day to day in response to variations in wind direction (Graves et al, 2001). Other studies have emphasised the control exerted by underlying land-use features, such as the built-up ratio, on the pattern of mean maximum UHI intensity (Bottya¨n et al, 2005). This implies that, as the density of development and/or area of continuous built cover increases, so does the strength of the UHI. Long-term records show that London’s nocturnal UHI has indeed become more intense since the 1960s (table 2), especially during spring and summer (Lee, 1992; Wilby, 2003a).

Table 1. Controls of urban heat island (UHI) magnitude and structure. Adapted from Oke (1982) and Arnfield (2003).

<table>
<thead>
<tr>
<th>Controls</th>
</tr>
</thead>
<tbody>
<tr>
<td>UHI intensity decreases with increasing wind speed.</td>
</tr>
<tr>
<td>UHI intensity decreases with increasing cloud cover.</td>
</tr>
<tr>
<td>UHI intensity is greatest during anticyclonic conditions.</td>
</tr>
<tr>
<td>UHI intensity is best developed in the summer or warm half of the year.</td>
</tr>
<tr>
<td>UHI intensity tends to increase with increasing city size and/or population.</td>
</tr>
<tr>
<td>UHI intensity is greatest at night.</td>
</tr>
<tr>
<td>UHI may disappear by day or the city may be cooler than the rural environs.</td>
</tr>
<tr>
<td>Rates of heating and cooling are greater at rural sites than the city.</td>
</tr>
</tbody>
</table>

Table 2. Seasonal trends in London’s nocturnal and daytime urban heat island intensity (°C per decade) 1959–98 (source: Wilby, 2003a).

<table>
<thead>
<tr>
<th>Season</th>
<th>Nocturnal $T_{\text{min}}$</th>
<th>Daytime $T_{\text{max}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Winter</td>
<td>$-0.023^a$</td>
<td>$-0.081^{**}$</td>
</tr>
<tr>
<td>Spring</td>
<td>$+0.131^{**}$</td>
<td>$+0.015^a$</td>
</tr>
<tr>
<td>Summer</td>
<td>$+0.120^{**}$</td>
<td>$+0.036^*$</td>
</tr>
<tr>
<td>Autumn</td>
<td>$+0.077^*$</td>
<td>$-0.046^*$</td>
</tr>
</tbody>
</table>

$^a$ Not significant; $^*$ significant at $p = 0.05$; $^{**}$ significant at $p = 0.01$.

UHIs have also figured prominently in debates about global warming. Given the above trends, much discussion has understandably surrounded the influence of urbanisation (and other land-cover changes) on long-term surface-air temperature trends (Kalnay and Cai, 2003). The possible contamination of surface-air temperature records by urban heat advection is, indeed, consistent with observed decreases in diurnal temperature ranges (IPCC, 2001). However, recent analyses of trends of global annual average minimum temperatures for windy, calm, and all conditions show identical trends of 0.19 °C ± 0.06 °C per decade since 1950 (Parker, 2004). If significant urban effects were present they would have emerged in the record for calm days. Even where urban heat advection has been detected at individual stations, such as De Bilt in the Netherlands, the effect is of the order of approximately 10% of observed temperature rise over the last century (Brandsma et al, 2003).

1.2 Impacts of climate change on urban areas

To date, there has been relatively little research into climate change impacts on the built environment, but this situation is changing in the UK thanks to dedicated programmes (such as Building Knowledge for a Changing Climate). Previous work
has tended to focus on managing existing weather-related risks, rather than on addressing future climate change impacts. Typical measures for mitigating high temperatures include implementing heat health warning systems (e.g., Philadelphia, Shanghai, and Lisbon) or reducing the intensity of the UHI using cool roofs, green-space, and water features (e.g., Tokyo, Basel, and Newark). However, it is generally recognised that the most important potential impacts of climate change on cities include fewer periods of extreme winter cold; an increased frequency of heat waves, air and water pollution episodes; rising sea levels and increased risk of storm surge; and changes in the timing, frequency, and severity of urban flooding associated with more intense precipitation events (IPCC, 2001; Wilby, 2007).

One of the first climate change impact studies for a world city was undertaken by the London Climate Change Partnership (LCCP, 2002). Table 3 provides a summary of the main findings by key sector. Subsequent work has focused more specifically on impacts on London’s biodiversity (Wilby and Perry, 2006), transport system (GLA, 2005a), and the identification of adaptation measures for developers and planners (GLA, 2005b; 2006; LCCP, 2006). Elsewhere, adaptation scenarios for addressing the UHI of Newark and Camden, New Jersey have highlighted the benefits of urban trees both for the present and for year 2020 (Rosenzweig et al., 2005; Solecki et al., 2005). Models show that urban vegetation can deliver lower energy demands for air conditioning, as well as reduced health hazards through removal of air pollutants.

Climate change is expected to affect the outdoor air quality of large urban areas. This is because future weather will have a major influence on the production, transport, dispersal, and deposition of pollutants. For instance, any increase in the frequency of hot, anticyclonic weather in summer will favour the creation of more temperature inversions trapping pollutants in the near-surface layer of the atmosphere. Lee (1993) estimates that a 1°C rise in summer air temperatures (a proxy for the amount of catalysing sunshine) is associated with a 14% increase in surface ozone concentrations in London. This partly explains the poor air quality that contributed to significant mortality during the European summer heat wave of 2003 (Stedman, 2004). The exceptional temperatures stimulated emissions of natural volatile organic compounds (VOCs), such as isoprene, from vegetation, leading to the highest recorded ozone concentrations experienced in the UK for over a decade.

The UK government subsequently commissioned a comprehensive review of potential impacts of climate change on outdoor air quality (Defra, 2006). The Air Quality Expert Group anticipates fewer poor air quality episodes in winter under the assumption of increased ventilation associated with greater winter storminess. However, an increase is expected for summer photochemical smog episodes and ozone precursor biogenic VOCs—both linked to rising temperatures and solar radiation. This has implications for the future selection of species used for biofuels or urban tree planting (see Stewart et al., 2003).

The remainder of this paper will illustrate methods for constructing climate change scenarios of UHI intensity and air quality (ozone) using case studies for London. These indicators of climate change were chosen because of their paramount significance to human comfort and health in urban areas (DOH, 2001; Patz et al., 2005). Section 2 reviews the options for deriving scenarios, given that neither UHI nor air quality can be obtained directly from general circulation model (GCM) output. Section 3 outlines the statistical downscaling method used to develop UHI and air quality scenarios for London, described in sections 4 and 5, respectively. Finally, section 6 briefly considers the key uncertainties and priorities for future research.
### Table 3. Potential climate change impacts for London (source: LCCP, 2002).

<table>
<thead>
<tr>
<th>Issue</th>
<th>Main impacts</th>
</tr>
</thead>
<tbody>
<tr>
<td>Higher temperatures</td>
<td>Intensified urban heat island, especially during summer nights. Increased demand for cooling (and thus electricity) in summer. Reduced demand for space heating in winter.</td>
</tr>
<tr>
<td>Flooding</td>
<td>More frequent and intense winter rainfalls, leading to riverine flooding and overwhelming of urban drainage systems. Rising sea levels, storminess, and tidal surges require more closures of the Thames Barrier.</td>
</tr>
<tr>
<td>Water resources</td>
<td>Heightened water demand in hot, dry summers. Reduced soil moisture and groundwater replenishment. River flows higher in winter and lower in summer. Water-quality problems in summer associated with increased water temperatures and discharges from stormwater outflows.</td>
</tr>
<tr>
<td>Health</td>
<td>Poorer air quality affects asthmatics and causes damage to plants and buildings. Higher mortality rates in summer due to heat stress. Lower mortality rates in winter due to reduction in cold spells.</td>
</tr>
<tr>
<td>Biodiversity</td>
<td>Increased competition from exotic species, spread of disease and pests, affecting both fauna and flora. Rare saltmarsh habitats threatened by sea-level rise. Increased summer droughts cause stress to wetlands and beech woodlands. Earlier springs and longer frost-free seasons affect dates of bird egg-laying, leaf emergence, and flowering of plants.</td>
</tr>
<tr>
<td>Built environment</td>
<td>Increased likelihood of building subsidence on clay soils. Increased ground movement in winter affecting underground pipes and cables. Reduced comfort and productivity of workers.</td>
</tr>
<tr>
<td>Transport</td>
<td>Increased disruption to transport system from extreme weather. Higher temperatures and reduced passenger comfort on the London Underground. Damage to infrastructure through buckled rails and rutted roads. Reduction in cold-weather-related disruption.</td>
</tr>
<tr>
<td>Business and finance</td>
<td>Increased exposure of insurance industry to extreme weather claims. Increased cost and difficulty for households and business of obtaining flood insurance cover. Risk management may provide significant business opportunity.</td>
</tr>
<tr>
<td>Tourism and lifestyle</td>
<td>Increased temperatures could attract more visitors to London. High temperatures encourage residents to leave London for more frequent holidays or breaks. Outdoor living, dining, and entertainment may be more favoured. Green and open spaces will be used more intensively.</td>
</tr>
</tbody>
</table>

**2 Methods for constructing climate change scenarios for urban areas**

Approaches to the generation of building-scale climate change scenarios have already been reviewed by Hacker et al (2008). Various downscaling methods are suitable for obtaining future series of primary variables, such as temperature and precipitation, at length scales finer than the typical 300 km grid resolution of GCMs. But additional work is needed to explicitly represent urban surfaces or to derive ‘exotic’ variables such as heat island or air quality indices. Nonetheless, the required techniques may still be
conveniently grouped into dynamical and statistical downscaling methods. This section gives a few examples of each approach.

### 2.1 Dynamical downscaling

The UK Climate Impacts Programme (UKCIP02) scenarios are a good example of dynamical downscaling, being derived from a regional climate model (RCM) with a spatial resolution of around 50 km (Hulme et al., 2002). However, the UKCIP02 scenarios are indicative of climate change for vegetated surfaces, even where grid boxes cover large urban areas such as London and Manchester. This is a major limitation because built areas exert significant influences on local surface energy and moisture budgets, and would be expected to respond differently to the radiative forcing of increased greenhouse gas concentrations. As has already been shown, artificial heat sources exert additional influence on urban temperature regimes (figure 2).

As part of the BETWIXT (Built Environment: Weather scenarios for investigation of Impacts and eXTremes) project, the UK Hadley Centre developed a new land-surface ‘tiling’ scheme to represent subgrid surface heterogeneity in a GCM (Betts and Best, 2004). Separate energy and water budgets were simulated for different land surfaces, including urban areas (figure 3). Tiles representing built areas incorporate physical characteristics such as heat storage in buildings, partitioning between sensible and latent heat fluxes, frictional drag on the atmosphere, and direct anthropogenic heat sources. Several experiments were then conducted, considering presence/absence of urban areas, the extent of artificial heat sources (equivalent to 0, 20, or 60 Wm$^{-2}$), under current and doubled atmospheric CO$_2$ concentrations. The various simulations enabled preliminary analyses of the effects of land-surface feedbacks, climate change, and anthropogenic heat sources on UHIs. Experimental results for New York signal fewer occurrences of near neutral daytime heat islands and a greater frequency of more intense nocturnal UHIs.

![Figure 3. Representation of the new land surface scheme implemented in the Hadley Centre regional climate model, with explicit ‘tiled’ representation of the temperatures $T$ and heat fluxes $H$ on different landscape types, including urban areas (source: Betts and Best, 2004).](image-url)

Dynamical downscaling has also been used to investigate the effects of climate change on continental-scale air quality. For example, Leung and Gustafson (2005) used the Penn State/NCAR mesoscale model (MM5) to investigate potential changes in atmospheric conditions related to air quality over the US, parts of Canada, and Mexico. The results show that, during summer, Texas experiences marked warming, increased downward solar radiation, less frequent rainfall, and more frequent stagnation of air masses—all of which favour an increase in ozone concentrations by the 2050s. Comparable changes emerge for central and southern Europe, owing to decreased precipitation scavenging of oxidised nitrogen compounds, increased temperatures favouring biogenic precursors of ozone, and increased radiation driving the photochemical...
production of ozone (Langner et al, 2005). Rising peak ambient ozone concentrations are, in turn, expected to translate into increased morbidity and mortality. For instance, MM5 and the Community Multiscale Air Quality atmospheric chemistry model showed a median 4.5% increase in ozone-related acute mortality across the thirty-one county New York metropolitan region by the 2050s (Knowlton et al, 2004).

2.2 Statistical downscaling
As shown above, dynamical downscaling can provide useful insights into the physical mechanisms affecting future heat stress and ambient air quality in urban areas. However, such modelling is very resource intensive and so is normally undertaken for a single driving GCM, small number of emission scenarios, and/or a few decades in the future. The alternative strategy involves statistically downscaling climate and air quality indices of interest for individual sites. As explained by Hacker et al (2008), statistical downscaling uses empirical relationships between large-scale atmospheric driving variables (such as pressure fields) and local-scale weather (such as maximum temperature) to estimate how the smaller-scale properties will change in the future, given changes in the larger-scale climate. For a detailed description of various statistical downscaling methods and their assumptions see Wilby et al (2004).

A key advantage of statistical downscaling over dynamical downscaling is that a large number of uncertainties affecting future scenarios can be evaluated, such as different heat island and air quality scenarios emerging from different driving GCMs and/or emission scenarios. For example, Hayhoe et al (2004) scaled station-scale temperatures by several GCM temperature projections to investigate future extreme heat and heat-related mortality in four cities (Los Angeles, Sacramento, Fresno, and Shasta Dam). The annual number of days classified as heatwave conditions increased under all simulations. Using known relationships between extreme heat and summer excess mortality for the Los Angeles metropolitan area, heat-related deaths were shown to increase by up to seven times by the 2090s, even with acclimatization.

A further benefit of statistical downscaling is the ability to construct scenarios for indices that are not directly available from either GCMs or RCMs. For example, in a previous paper (Wilby, 2003a) I used information on regional airflows, pressure, and humidity supplied by a GCM to investigate future changes in the intensity of London’s UHI under two emission scenarios. The results suggest further intensification of the mean nocturnal UHI, by as much as ~1°C in summer by the 2080s, even when excluding possible changes in anthropogenic heat sources, population density, and infrastructure. Although this might seem a modest amount of urban warming it is in addition to the present average (~2°C), and peak (~10°C) UHI intensity. Furthermore, there would be a disproportionate increase in the number of nights with peak intensity events, and this is all before the regional warming projected by the UKCIP02 scenarios is factored into the absolute temperatures experienced in the centre of London. This early work is extended in following sections by considering UHI behaviour under a wider range of GCMs, and by exploring associated changes in peak ozone concentrations.

3 The Statistical DownScaling Model (SDSM)
As in the previous case study, climate change scenarios for London were generated via the SDSM version 3.1 (Wilby et al, 2002). SDSM is best described as a hybrid of regression-based and stochastic weather generator downscaling methods, because daily atmospheric circulation patterns and moisture variables are used to condition local-scale predictands at target sites (in this case UHI and air quality indices). Unexplained variance is reproduced by adding stochastically resampled residuals from the predictor–predictand regression relationships. This enables the generation
of multiple realisations with slightly different time series attributes, but the same overall statistical properties. An advantage over conventional time series adjustment (‘change factor’ or ‘morphing’) methods is that new temporal sequences of (extreme or more persistent) events can be generated under future climate forcing (Diaz-Nieto and Wilby, 2005). A further strength of SDSM is that scenarios can be produced in seconds using a desktop computer. As noted before, this means that it is feasible to evaluate a range of GCMs and/or emission scenarios—both important sources of uncertainty affecting climate change assessments. The tool is also extremely versatile as is evidenced by the breadth of recent applications (table 4).

3.1 Large-scale climate information

Atmospheric predictor variables used to calibrate SDSM were obtained from the National Center for Environmental Prediction (NCEP) reanalysis. Future climate change scenarios were downscaled from four GCMs: the Canadian Centre for Climate Modelling and Analysis model (CGCM2); the Commonwealth Scientific and Industrial Research Organisation model (CSIRO Mk2); the Max-Planck-Institut for Meteorology model (ECHAM4); and the Hadley Centre’s coupled ocean/atmosphere climate model (HadCM3). The archive of NCEP and GCM output contains twenty-nine daily predictors (describing atmospheric circulation, thickness, and moisture content at the surface, 850 hPa and 500 hPa levels), for nine grid boxes covering the British Isles, for the period 1961 – 2100 (figure 4). The present study uses predictors taken from the grid boxes centred on eastern (EE) and southwest (SW) England under the A2 (medium-high emissions) scenario of the IPCC Special Report on Emission Scenarios.

Table 4. Examples of Statistical DownScaling Model applications to climate change impact assessment.

<table>
<thead>
<tr>
<th>Study</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Precipitation and temperature scenarios for water balance modelling of Lake Ziway, Ethiopia</td>
<td>Abraham (2006)</td>
</tr>
<tr>
<td>Evaluation of links between synoptic climatology and glacier mass balances, Norway</td>
<td>Fealy (2004)</td>
</tr>
<tr>
<td>Modelling the effects of climate and land-use change on flood risk in the Alzette basin, Luxembourg</td>
<td>Guangul (2003)</td>
</tr>
<tr>
<td>Evaluation of daily precipitation and temperature simulations for different downsampling techniques in a Quebec watershed, Canada</td>
<td>Khan et al (2006)</td>
</tr>
<tr>
<td>Future mass balance and meltwater yields from glaciers in the Alps, Switzerland</td>
<td>MacDonald (2004)</td>
</tr>
<tr>
<td>Evaluation of daily precipitation simulations for different downsampling techniques, China</td>
<td>Wetterhall et al (2007)</td>
</tr>
<tr>
<td>Scenarios of wet season precipitation occurrence and amounts for the Anti Atlas, Morocco</td>
<td>Wilby (2005)</td>
</tr>
<tr>
<td>Transient scenarios of nitrogen concentrations and evaluation of adaptation options for a lowland chalk stream, UK</td>
<td>Whitehead et al (2006)</td>
</tr>
</tbody>
</table>
3.2 Application of SDSM

Downscaling using SDSM involved two main steps. First, statistical relationships must be established between the variables of interest (i.e., daily UHI intensity and ozone concentrations) and large-scale indices of regional weather over the target region obtained from the NCEP reanalysis for the current climate. Table 5 shows the correlation coefficient for significant predictor–predictand relationships. These illustrate the strength of association between the variables for August. Second, the empirical predictor–predictand relationships for the observed climate were used to downscale ensembles of the same local variables for the future climate, using data supplied by four GCMs driven by the A2 emission scenario for the period 1961–2100.

Table 5. Large-scale atmospheric predictor variables (from the National Center for Environmental Prediction reanalysis) used to downscale daily urban heat island (UHI) and air quality for London. The correlation coefficients ($r$) are given for the strength of association between variables in August. All variables included in the downscaling model are significant at the $p = 0.01$ level.

<table>
<thead>
<tr>
<th>Predictand</th>
<th>Predictors</th>
<th>$r$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nocturnal UHI 1961–90</td>
<td>near-surface airflow strength</td>
<td>−0.40</td>
</tr>
<tr>
<td></td>
<td>near-surface westerly wind component</td>
<td>−0.36</td>
</tr>
<tr>
<td></td>
<td>near-surface vorticity</td>
<td>−0.41</td>
</tr>
<tr>
<td></td>
<td>850 hPa geopotential height</td>
<td>0.48</td>
</tr>
<tr>
<td></td>
<td>near-surface relative humidity</td>
<td>−0.41</td>
</tr>
<tr>
<td>Maximum fifteen-minute ozone concentration 1992–2000</td>
<td>mean sea-level pressure</td>
<td>0.17</td>
</tr>
<tr>
<td></td>
<td>near-surface relative humidity</td>
<td>−0.55</td>
</tr>
<tr>
<td></td>
<td>near-surface westerly wind component</td>
<td>−0.21</td>
</tr>
<tr>
<td></td>
<td>mean regional temperature at 2 m</td>
<td>0.60</td>
</tr>
</tbody>
</table>
Case study 1: nocturnal UHI intensity

As in a previous paper (Wilby, 2003a), the strength of London’s UHI was represented by the temperature gradient between St James’s Park (urban station) and Wisley in Surrey (a rural reference station 30 km from the city centre). The nocturnal UHI is given by the difference in the daily minimum temperature between the two stations, and is on average strongest in August (+2.2°C) and weakest in January (+1.1°C). However, these averages conceal considerable day-to-day variability. For example, the annual mean nocturnal heat island intensity for the period 1961–90 was +1.8°C, but daily values ranged from +10.0°C (on 14 January 1982) to −8.9°C (on 31 May 1970), with 5% of days having an intensity of 5°C or more.

Following a previous paper (Wilby, 2003a), SDSM was calibrated using 1961–90 daily minimum temperature differences between St James’s and Wisley, and NCEP climate variables centred on the EE grid-box (figure 4). Significant correlations were found between the intensity of the heat island and several regional climate indices (most notably strength of airflow, vorticity, and near-surface relative humidity) (table 5). This combination of predictors explains up to 40% of the daily variability in the nocturnal heat island intensity in August. As expected, UHI intensity is greater under clear sky conditions (as implied by low humidity) and low wind speeds (under anticyclonic weather). Interestingly, the nocturnal heat island intensity is only weakly correlated with regional temperatures, suggesting that future intensification of London’s heat island would be largely independent of projected temperature changes.

The limitations of SDSM in reproducing London’s present and projected UHI have been discussed before (Wilby, 2003a). The nocturnal model is known to have a cool bias (~0.2°C), and to underestimate the observed frequency of very intense episodes. Nonetheless, despite the coarse resolution of the input data, and the absence of thermal storage effects or anthropogenic heat sources, the model does emulate the time-varying UHI of notable heatwaves, such as the summer of 1995 (figure 5). Even so, in common with all downscaling methods (statistical and dynamical), the quality of future projections depends on the stationarity of the calibrated predictor–predictand relationships and their accompanying parameterisation.

With the above points in mind, SDSM was used to downscale the UHI using large-scale predictor variables supplied by the four GCMs under present and future (2050s) greenhouse gas forcing. Perfect prognosis results derived from NCEP fully capture the observed seasonal variability in the mean strength of the UHI, but consistently underestimate the frequency of the most intense episodes (figure 6). These outcomes
are repeated by the four GCMs, although CGCM2 tends to overestimate UHI intensity between August and November, whereas ECHAM4 and HadCM3 underplay mean intensities between July and August. All SDSM - GCM combinations underestimate the frequency of intense episodes, owing to the recognised tendency of SDSM to reproduce means at the expense of extreme events, combined with known biases in the GCM output driving the downscaling (see Wilby and Harris, 2006). Nonetheless, for most months, observations fall within the 95% confidence ranges of the GCM-downscaling model uncertainty.

The four GCMs project intensification of the nocturnal UHI by the 2050s between May and October, but show a mixed response during the rest of the year (figure 6). The most rapid warming is shown by ECHAM4 in August (a further 0.5 °C by the 2050s)—approximately half the historic rate observed in summer since the 1960s (table 2). Interestingly, ECHAM4 also shows weakening of the mean UHI intensity in winter, a pattern that is mirrored to a lesser extent by CSIRO. All GCMs suggest more frequent intense UHI episodes, with, on average, seven such events in August, compared with five presently.

Although there are subtle differences between the GCM projections, overall the scenarios are qualitatively similar. All point to continued intensification of London’s nocturnal UHI and a greater frequency of intense heat island episodes in summer. These changes are set against a background of more persistent and intense heatwaves over much of Europe and the USA signalled by other studies (eg Meehl and Tebaldi, 2004). Because SDSM makes an instantaneous connection between synoptic conditions and the UHI, compounding effects from long-duration heatwaves are underestimated in the present analysis. However, even a conservative outlook supports the view that there will be an increase in the risk of morbidity and mortality due to more extreme future heatwaves combined with more intense UHIs (Patz et al, 2005; Rooney et al, 1998).

Figure 6. London’s observed and downscaled nocturnal urban heat island for 1961-90 (a) and changes projected for the 2050s (b). The T-bars denote the upper limit of the 95% confidence band due to the variance unexplained by the statistical downscaling model. Intense nocturnal heat island episodes (right column) are arbitrarily defined as nights with temperature differences (between the urban and rural reference stations) exceeding 4 °C. For a description of the models, see text.
5 Case study 2: ozone pollution episodes

As noted previously, atmospheric circulation patterns are a major determinant of ambient air quality and pollution episodes (eg Gardner and Dorling, 2000; McGregor and Bamzelis, 1995; O’Hare and Wilby, 1995), and, hence, the health of urban populations (eg Anderson et al, 1996; Stedman, 2004). Future air pollution concentrations in London will reflect local and regional patterns of emissions, as well as the frequency of high-pressure systems over southeast England. Whereas vigorous westerly airflows favour the dispersal of pollutants, stagnant anticyclonic weather provides ideal conditions for in situ pollution episodes. Whilst it is beyond the scope of this study to model the complex interactions between pollutant emissions, photochemistry, transport, and dispersal, it is possible to speculate about the future frequency of ‘pollution-favouring’ weather patterns. For example, figure 7 shows changes in the frequency of high-pressure systems centred on the EE grid box projected by HadCM3 under the A2 and B2 (medium-low) emissions scenarios (LCCP, 2002). Under A2 emissions there is a projected increase in the frequency of stagnant air masses favouring pollution episodes of over four days per summer by the 2080s, compared with 1961–90. Changes under the B2 emissions lead to an increase of more than two days per summer by 2080s. However, both plots show considerable interannual variability in the frequency of summer pollution episodes.

The above analysis is extended by investigating the influence of regional-scale atmospheric predictor variables on site-specific ozone concentrations. Multivariate linear and nonlinear regression analyses have been used before to disaggregate long-term trends in urban ozone concentrations into climatic and nonclimatic components (eg Gardner and Dorling, 2000; Wise and Comrie, 2005). In this case SDSM was calibrated using 1992–2000 daily maximum fifteen-minute ozone concentrations at Russell Square in London, and NCEP predictor variables centred on the SW grid box but covering SE and EE (figure 4). Peak ozone concentrations were found to be associated most strongly with mean sea level pressure, near-surface westerly wind speeds, relative humidity, and temperature (table 5). These predictor variables explain up to 58% of the daily variability in ozone at the site.

Despite a large difference in spatial and temporal scales between the predictors and predictand, the downscaling yields a good approximation of the overall distribution of peak ozone concentrations at the site [figure 8(a)]. Closer inspection of the daily concentrations during the 1995 summer pollution episode reveals that SDSM faithfully captures the timing of individual peaks but, as in the case of the UHI, underestimates the severity of the very highest concentrations [figure 8(b)]. The unexplained variance may be due to missing factors, such as the release of natural VOCs during intense heatwaves, accumulative effects, or chemical reactions.

Figure 7. Projected change in the number of summer weather patterns centred on the EE grid box (see figure 4) favouring pollution episodes in London under A2 (medium-high) emissions (a) and B2 (medium-low) emissions (b), with respect to the 1961–90 average (source: LCCP, 2002). Annual data are shown in black, with trendlines in grey.
As with the nocturnal UHI, SDSM was used to downscale peak ozone concentrations at the site using predictor variables supplied by the four GCMs for present (1992–2000) and future (2050s) climate conditions. As before, comparison of observed concentrations with results derived from NCEP predictors provides a means of assessing biases due to the downscaling technique per se, as well as the information content of the atmospheric predictor variables. Differences between NCEP and the GCMs are due only to biases in each model’s climatology under present greenhouse gas concentrations. Overall, downscaling using NCEP predictors faithfully captures seasonal variations in mean ozone concentrations, but underestimates the 95th percentile concentration in summer, most notably in July and August (figure 9). Downscaling using predictors supplied by ECHAM4 and HadCM3 tends to overestimate mean concentrations in summer, but compensates for biases in the peak concentrations, giving a close match to observations, especially for ECHAM4. In contrast, downscaling from CGCM2 and CSIRO consistently underestimates both mean and peak ozone concentrations in summer months.

All four GCMs project increased ozone concentrations throughout much of the year for the 2050s relative to present conditions (figure 9). The largest increases in the mean occur in July and August under the ECHAM4 predictors, and in the 95th percentile concentrations in July under HadCM3 output. Absolute changes in the
mean maximum fifteen-minute concentration in July were up to ~12 ppb, which is comparable to results of dynamical downscaling of ozone in New York City for the 2050s under A2 emissions (Knowlton et al, 2004). The range of uncertainty due to the choice of GCM was 8–13% for the mean, and 3–5% for the 95th percentile concentration. However, it is stressed that the projected changes and model uncertainty reflect only the influence of future atmospheric conditions, thereby excluding other important factors such as future emissions of ozone precursors. In addition, the downscaling does not take into account major feedbacks, such as ozone depletion by the increased water vapour content of a warmer atmosphere, or increased stratospheric influx of ozone to the troposphere (Stevenson et al, 2006).

6 Concluding remarks
This paper has demonstrated some applications of statistical downscaling to climate impact assessments for urban areas. The case studies illustrate potential changes in UHI intensity and ambient air quality in isolation (although some commonality is implied by the shared downscaling predictor variables shown in table 5). Ideally, the various impacts of climate change should be mutually consistent to give plausible narratives of future environmental conditions in built areas. This includes broader considerations such as changes in urban energy consumption, emission controls, growth for the urban area, or future land-use conversions (as in Solecki and Oliveri, 2004). The London case studies show responses to instantaneous, large-scale weather forcing alone; no account is taken of the potential synergy between the heat island and ozone concentrations, or of possible feedback between climate change and atmospheric chemistry (see Defra, 2006).

There is clearly scope for refinement of these analyses. The latest SDSM version 4.1 incorporates new routines for handling serially correlated data and for frequency

![Figure 9. Observed (black line) and downscaled (grey line, NCEP) maximum fifteen-minute ozone concentrations at Russell Square, London for 1992–2000 (a) and changes projected for the 2050s (b). For a description of the models, see text.](image-url)
estimation of extreme events. The former enables more sophisticated treatment of the
time series of downscaled indices (beyond the simple use of lagged predictor variables
in the current version). This could improve the representation of extremes that depend
on cumulative effects, such as thermal storage in the urban fabric, or the build up of
pollutant concentrations in the boundary layer. For example, summer ozone concen-
trations are known to be positively correlated \( r = 0.78 \) with the concentration of the
preceding day (figure 10). Alternatively, greater attention could be paid to the choice of
downscaling predictor variables, by compositing training data into low, medium, and
high-intensity episodes (rather than assuming a common set of predictors and model
weights for all events).

![Figure 10. Evidence of serial correlation in daily maximum fifteen-minute ozone concentrations (ppb) observed in August at Russell Square, London. Points lying above the line signal increasing concentrations between consecutive days.](image)

Given these opportunities, statistical downscaling remains a valuable option for the
rapid production of local-scale climate change information that cannot be obtained
directly from GCMs or dynamical downscaling. The low computational demand of
SDSM also enables the evaluation of key uncertainties affecting future scenarios, such
as the host GCM. This is consistent with wider efforts to undertake multimodel-
ensemble (eg Pryor et al, 2005; Stevenson et al, 2006) or perturbed-physics-ensemble
experiments (eg Murphy et al, 2004), leading to the development of probabilistic
climate change information for impact assessment (eg Benestad, 2004; New et al,
2007; Wilby and Harris, 2006). However, new downscaling frameworks will be required
to translate coarse resolution (space and time) probabilistic information into local
climate change scenarios for impact assessment, not least for urban locations.

The investigation of London’s nocturnal heat island shows qualitatively similar
results regardless of GCM. All models point to further strengthening of the UHI and
increases in the frequency of intense summer episodes owing to projected changes in
weather patterns over southern England. By the 2050s mean nocturnal temperatures
in August could be \(~ 3 \)°C warmer in London than surrounding nonurban landscapes
(which are themselves projected to warm by several degrees). Given that the SDSM
projections are conservative, and that peak intensity episodes are expected to warm by
even more, maximum urban – rural differences could exceed 10 °C. There is also broad
agreement amongst the GCMs that future weather patterns will lead to a deterioration
in London’s air quality, particularly during midsummer. Building designers and spatial
planners will need to factor such information into their long-term strategies to help safeguard the future health and comfort of city dwellers.

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