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Modeled temperature, mortality impact and external benefits of cool roofs and rooftop photovoltaics in London

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Population exposure to high temperatures poses health risks and increases mortality. 'Cool roofs' (high-albedo roofs) and rooftop photovoltaics (RPV) may reduce temperatures in urban areas. Here, using advanced urban climate modeling, we model impacts of these measures on air temperature and heat-related mortality in London during the record-breaking hot summer of 2018. We estimate changes in mean near-surface air temperature of −0.3 °C in the RPV scenario and −0.8 °C in the cool roof scenario. We find that the heat-related mortality in this period (estimated 655–920) could have been reduced by 96 (12%) by RPV, or 249 (32%) by cool roofs, in scenarios where all roofs have these measures. Monetized using value of statistical life, we estimate benefits for RPV and cool roofs of £237 M and £615 M, respectively. We estimate that up to 20 TWh of electrical energy would be generated in the full RPV scenario. We show that, for conditions such as in London June–August 2018, RPV or cool roofs may reduce near-surface air temperatures and associated heat-related mortality, with cool roofs having a larger effect.

Heat is an increasing concern in the UK, with thousands of deaths attributed to heat in recent years (https://www.ons.gov.uk/peoplepopulationandcommunity/birthsdeathsandmarriages/deaths/articles/climaterelatedmortalityandhospitaladmissionsenglandandwales/1988to2022, last accessed 21 December 2023) and climate change increasing the frequency and intensity of heatwaves[1,2]. The summer (June, July and August) of 2018 was the hottest on record in England (highest average temperature), but the UK Met Office's climate projections suggest that a summer with an average temperature as high as this might occur in more than half of years by mid-century under a high-emissions scenario[1].

The built environment of urban areas alters the energy balance of the land surface, leading to cities having their own climate, distinct from nearby rural areas[3,4]. Typically, this leads to higher air temperatures in urban areas, especially at night, known as the urban heat island effect[3]. This is of interest because 83% of the UK population lives in urban areas (https://www.gov.uk/government/statistics/key-findings-statistical-digest-of-rural-england/key-findings-statistical-digest-of-rural-england, last accessed 11 March 2024) and is therefore exposed to higher temperatures, which worsens summer thermal comfort and may increase heat-related mortality[5]. It also points to the possibility of reducing exposure to excessive heat through changes to the urban environment.

Increasing the albedo of urban surfaces reduces absorption of solar radiation and, therefore, the temperature of those surfaces; applying high-albedo materials to roofs can reduce heat flux into buildings, thereby passively reducing indoor temperature and cooling demand[6]. This can also reduce the amount of solar radiation converted into sensible heat flux and, therefore, the outdoor air temperature[7]. Typical urban neighborhood albedo (that is, the albedo of an urban area as a whole, rather than single facets such as roofs or walls[4] is often estimated at around 0.2, and cool roofs are usually modeled with a range of albedo from 0.5 to 0.9, with the resultant change in neighborhood albedo

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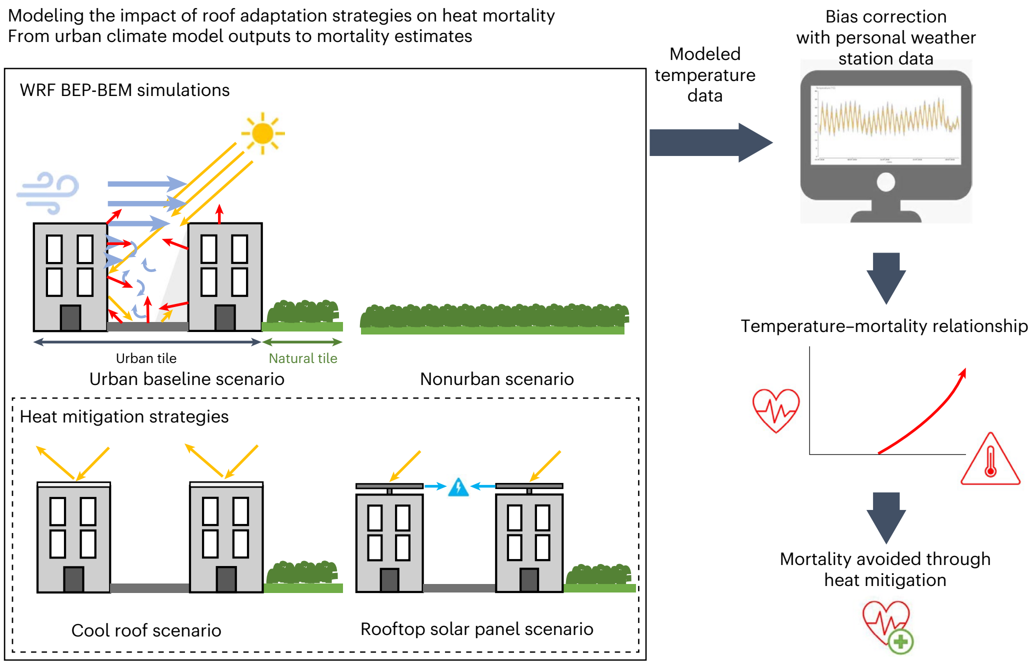

Fig. 1 | Illustration of the analysis process. Four scenarios are modeled in an urban climate model (WRF BEP-BEM), including heat mitigation scenarios. Modeled temperature data from these simulations are then post-processed by bias adjusting to PWS data. A temperature–mortality relationship is applied to estimate mortality differences between the scenarios and, therefore, the heat-related mortality avoidable through the use of the heat-mitigation strategies.

depending on the plan-area fraction of roof surface. Previous urban climate modeling studies have found that a 0.1 increase in neighborhood albedo leads to a 0.2–0.6 °C decrease in near-surface air temperature in clear-sky afternoon conditions[7]. In a modeling study of the West Midlands region of the UK, Macintyre and Heaviside[8] found that cool roofs may reduce daytime average 2 m outdoor air temperatures by 0.5 °C, and by applying exposure–response functions (ERFs) derived from epidemiological studies, they estimated that this could have reduced heat-related deaths in June, July and August of 2006 by 6–12%.

Rooftop photovoltaics (RPV) can provide renewable energy without taking up additional land. Urban roof space is limited, so choices must be made between roof types, solar photovoltaics (PV) and cool roofs, as well as rooftop vegetation and building services such as air conditioning units, all of which entail consideration of construction, installation and maintenance costs. This could be seen as a trade-off between climate adaptation and emissions mitigation, but comparison of the relative benefits may point toward what mix is most appropriate.

RPV often has a lower albedo than typical roof surfaces, but a proportion of absorbed radiation is converted to electrical energy and therefore not emitted as sensible heat. Previous studies into the urban climate effects of RPV have found a mix of cooling effects and heating effects depending in part on whether they were compared with high- or low-albedo surfaces, on whether nighttime or daytime temperatures were compared, and on climatic conditions[9]. Some studies have been criticized for not modeling heat exchange between the bottom side of the panel and the roof; assuming unrealistically high conversion efficiency; or neglecting the effect of temperature on conversion efficiency[9]. These effects are modeled realistically in the present study. Previous studies have not estimated the impact on heat-related mortality of outdoor air temperature changes resulting from widespread RPV (for example, refs. 9–11).

Urban climate models enable the estimation of thermal effects of roofing technologies at the city scale: detailed models of the energy balance of the urban environment are coupled with an atmospheric model, which enables analysis beyond the effect on single buildings and in a more physically consistent way than the bulk scheme used in some regional- to global-scale climate models[12]. Some urban climate modeling studies have relied on single-layer urban canopy parameterization[13] ('urban canopy' refers to the layer of air below the mean height of buildings in an urban area), which does not incorporate simulation of detailed urban structure in three dimensions; this is important because heat transport between roofs and the urban canyon means that changes to the energy balance at the roof level are not equivalent to changes within the urban canopy. While simpler urban parameterizations can perform well in simulating urban boundary-layer air temperatures, more complex, three-dimensional (3D) models of the urban environment are necessary to simulate the effects of changes to specific elements of the urban environment such as roof albedo and RPV[12–15]. Our preliminary work in Brousse et al.[16] indicated that cool roofs and RPV both have potential for reducing air temperatures in London, with a larger effect from cool roofs.

Monetary valuation is used to present mortality impacts in economic terms[17]. In the field of heat and health, this method has been used previously to evaluate interventions such as heat-health action plans[18,19]. In the present study, we use value of life years (£79,000 per life year) and value of statistical life (£2.5 million per life) set out in UK Government guidance[20,21]. In this context, the health benefits of temperature reduction could be seen as a beneficial externality of solar and cool roof adoption.

We use urban climate modeling to estimate the effect that cool roofs and RPV could have had on urban-canopy air temperature in London during the extremely hot summer of 2018 (Fig. 1). To contextualize the impact of these interventions, we estimate how many deaths attributable to heat could be avoided, based on the results of an ecological time-series analysis of temperature and mortality[22]. We further apply value of statistical life methods to convert mortality impacts into monetary values, to enable comparisons of the costs of these interventions with their benefits.

Results

Modeled urban air temperature

We compared outputs from four runs of the urban climate model (Methods). The 'baseline' scenario is intended to represent the actual urban

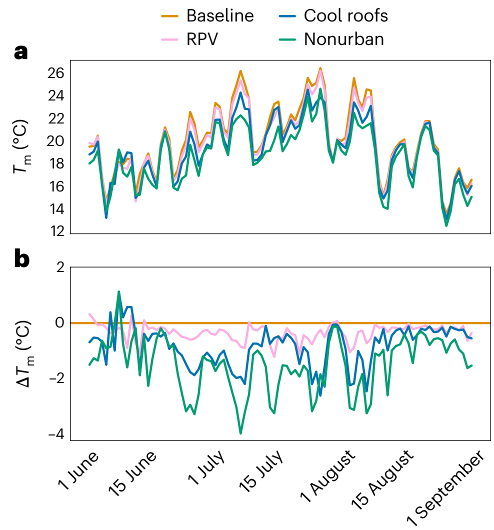

Fig. 2 | Population weighted mean temperature. a,**b**, Population-weighted daily mean urban-canopy air temperature time series in three scenarios (**a**), and temperature difference from the baseline scenario (**b**).

environment during the study period, while three other alternative scenarios have modifications to the landscape or buildings: (1) all buildings having full coverage with RPV panels, (2) all buildings having full coverage with high-albedo roofs ('cool roofs') and (3) a 'nonurban' scenario in which all urban land cover is replaced by natural (that is, vegetated) land cover. The nonurban scenario is intended to contrast with the baseline scenario to illustrate how urban land cover affects the local climate, while the RPV and cool roof scenarios are intended to explore the physical limits of plausible interventions against excessive urban temperatures.

A key output of the urban climate model is the near-surface air temperature within the urban canopy, that is, the temperature of the air 2 m above the street. Population-weighted mean temperatures were calculated as the spatial mean of temperature weighted by census population. Figure 2 shows the time series of modeled population-weighted daily mean urban-canopy air temperature (T_m) in each of the scenarios. Descriptive statistics for each of the temperature series used in this analysis are given in Supplementary Table 1. Mean differences from the baseline scenario in population-weighted mean urban-canopy temperature were −0.3 °C in the RPV scenario, −0.8 °C in the cool roof scenario and −1.9 °C in the nonurban scenario. Based on comparisons between the modeled output and observations, we estimate a root mean squared error on the modeled urban temperature of 1.0 °C (Methods).

Figures 3 and 4 show how the differences in temperature between the scenarios are distributed across the population of London. Averaged across June, July and August, the whole population of Greater London would experience a lower mean temperature in both the cool roof and RPV scenarios. In the RPV and cool roof scenarios, we observe reduced mean daily maximum temperature but little difference in mean daily minimum temperature; this contrasts with the nonurban scenario, which shows greatly reduced daily minimum temperature but little difference in daily maximum temperature. The spatial pattern (Fig. 3) is substantially different between the cool roof and nonurban scenarios, emphasizing the conceptual difference between minimizing the urban heat island intensity (that is, minimizing urban–rural nighttime differences) and mitigating heat (reducing the high temperatures to which the population are exposed)[23].

Estimated heat-related mortality

Using the population-weighted daily mean temperature, we estimate how many deaths and how many years of life lost (YLL) would be attributable to heat in each scenario. YLL is calculated summing average remaining life expectancy by age group. When deaths or YLL are lower than in the baseline scenario, we interpret these impacts as being avoidable by use of the intervention in that scenario.

Table 1 gives estimates for deaths and YLL attributable to heat under baseline conditions, and avoidable deaths and YLL estimates for the interventions. Table 2 gives estimates for the costs of mortality attributable to heat, and benefits of the interventions.

Modeled electricity generation

The urban climate model estimated electrical energy output at 20 TWh in June–August 2018 under a full RPV coverage scenario in Greater London. This is comparable in order of magnitude to London's total electricity usage in 2018 (37.8 TWh) (https://www.london.gov.uk/who-we-are/what-london-assembly-does/questions-mayor/find-an-answer/london-annual-energy-usage, last accessed 21 December 2023). Based on variations in efficiency, we estimate that in practice this would vary between 9.5 and 20 TWh. Based on a range of electrical energy prices, we estimate that the value of this energy would be between £550 million and £7.3 billion (see 'Electric power generation' section in Methods). The full range of our estimates is presented in Supplementary Table 4.

Within the urban climate model, we assume that 100% of buildings have either a cool roof or RPV depending on the scenario. Considering that a mix of rooftop technologies is likely to be adopted, we here consider the effect of combining the scenarios by assuming that the modeled changes scale linearly with the area of the interventions. We estimate that 65% of roof area would be the suitable for RPV given the characteristic of existing buildings, whereas RPV on 2% of roof area is approximately in line with the targets set by the Greater London Authority (see 'Solar panel suitability' section in Methods). If 2% of all buildings had RPV and the remaining 98% cool roofs, then temperatures and heat-related mortality would be very similar to the results of modeling under the cool roof scenario (248 deaths avoided compared with baseline) but would provide the additional benefit of between 200 and 400 GWh of electrical energy generated (worth between £11 million and £146 million). If 65% of all buildings had RPV and the remaining 35% cool roofs, 150 deaths would be avoided compared with baseline, with between 6.2 and 13 TWh of electrical energy generated worth between £357 million and £4.7 billion. For the full range of our estimates, see Supplementary Table 4.

Summary

We estimate that 786 (95% confidence interval (CI) 655–920) deaths in Greater London in June, July and August of 2018 were attributable to heat (Table 1). Of these deaths, we estimate that 96 (95% CI 85–107) (12%) could have been avoided by full adoption of RPV, or 249 (95% CI 219–277) (32%) by full adoption of cool roofs. Most deaths attributed to heat take place among people 75 years and older. Based on life tables, we estimate 9,810 (95% CI 7,620–12,020) YLL to heat in London during June–August 2018, of which 1,200 (95% CI 990–1,430) could have been avoided by RPV, or 3,100 (95% CI 2,520–3,650) by cool roofs. Based on modeled differences in attributable mortality in Greater London for June, July and August of 2018 only, we estimate that the monetized value of heat-related mortality avoidable by RPV is £237 million (95% CI £211–265 million), and by cool roofs is £615 million (95% CI £541–684 million), relative to a standard low-albedo roof scenario. Similarly, the monetized value of YLL avoidable by RPV is £108 million (95% CI £89–129 million), and by cool roofs is £280 million (95% CI £228–329 million). We estimate that 9.5–20 TWh of electrical energy would be generated in the full coverage RPV scenario during the same period, worth between £550 million and £7.3 billion.

Discussion

In this study we modeled the effect of RPV and cool roofs on summer temperatures in London. We found that either RPV or cool roofs would

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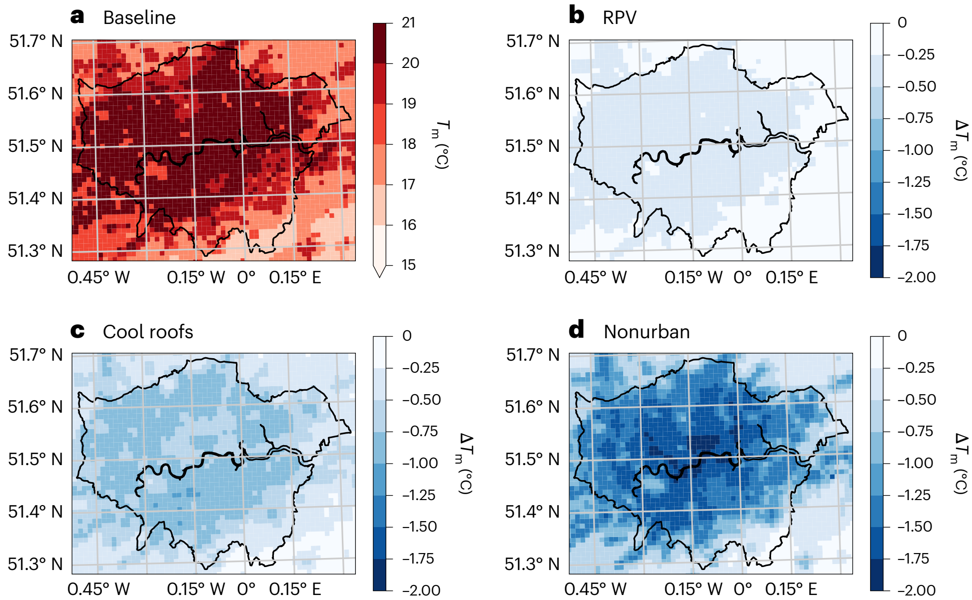

Fig. 3 | Spatial distributions of mean urban-canopy air temperature in the scenarios. a–d, The mean temperature is shown for the baseline scenario (**a**), and differences from the baseline are shown for the other scenarios (**b**–**d**). Temperature differences from the baseline scenario are shown for the rooftop PV scenario (**b**), cool roof scenario (**c**) and nonurban scenario (**d**). Boundaries are from Office for National Statistics licensed under the Open Government Licence v.3.0 (https://www.nationalarchives.gov.uk/doc/open-government-licence/version/3/). Contains OS data © Crown copyright and database right 2024.

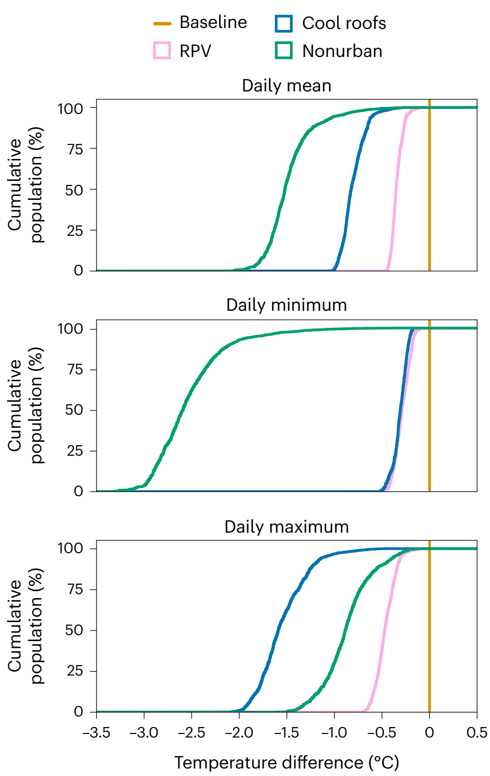

Fig. 4 | Percentage of the population experiencing temperature differences between scenarios in RPV, cool roof and nonurban scenarios, compared with the baseline scenario. The mean daily mean (top), daily minimum (middle) and daily maximum (bottom) temperatures are shown.

reduce mean summer outdoor air temperatures in London under similar conditions to June–August 2018, and could therefore reduce heat-related mortality, with cool roofs having a larger effect. The economic value of mortality avoided in both scenarios are large and are of a similar order of magnitude to the consumer price of the electricity that would be generated, suggesting that the health-related externalities could be an important part of the strategic and wider economic case for cool roofs and solar panels.

Temperature changes are generally consistent with comparable studies. The albedo cooling effectiveness—defined as the temperature change per 0.1 change in albedo[7]—is estimated at 0.3 °C per 0.1 change in albedo, which is in the middle of the range of high-quality urban climate modeling studies (0.2–0.6 °C per 0.1 change in albedo) identified by Krayenhoff et al.[7]. Compared with our preliminary work in Brousse et al.[16], which simulated the two hottest days of 2018 (26th–27th July) using the same urban climate model setup as the present study, mean temperature differences between the cool roof and baseline scenarios were greater in the present study than in the preliminary work during the common simulation period (Supplementary Fig. 1), which is thought to be due to differences in cloudiness that often occur between model runs with different initialization times[24].

Mean temperature and mortality reductions by cool roofs modeled in the present study are larger than were found for the West Midlands for summer 2006 by Macintyre and Heaviside[8]; this is probably because the atmospheric conditions modeled in the present study are generally hotter, London is more urbanized than the West Midlands, and the modeled albedo change is larger.

Estimated heat-attributable mortality is consistent with regional average for the years 2018–2022 presented by the Office for National Statistics (https://www.ons.gov.uk/peoplepopulationandcommunity/birthsdeathsandmarriages/deaths/articles/climaterelatedmortalityandhospitaladmissionsenglandandwales/1988to2022, last accessed 9 November 2023).

This is the first study to present estimated monetized values of reduced mortality resulting from solar and cool roofs. Strengths of the present study include its use of advanced urban climate modeling at high spatiotemporal resolution (hourly outputs and 1 km grid horizontal resolution) and evaluated against a dense network of weather stations (see Brousse et al.[25]). The 3D urban parameterization used maintains distinctions between changes in surface temperature, air temperature at roof level and at urban canopy level; represents fluid

Table 1 | Modeled mortality attributable to heat in London in June, July and August of 2018, and differences between scenarios

	Total	Age groups		
		64 years and under	65–75 years	75 years and over
Basic statistics				
Total deaths (June, July and August of 2018)	11,170	2,288	1,933	6,949
Population	10,244,007	979,470	467,939	8,796,598
Deaths per 100,000 population	726	234	413	79
Total YLL	636,540	30,730	101,310	504,500
Deaths				
Attributable to heat	786	95	88	603
	(655–920)	(62–128)	(60–116)	(533–676)
Avoidable by solar roofs	96	12	11	73
	(85–107)	(8–16)	(8–14)	(69–77)
Avoidable by cool roofs	249	30	28	191
	(219–277)	(20–39)	(20–36)	(179–202)
YLL				
Attributable to heat	9,810	3,280	1,460	5,070
	(7,620–12,020)	(2,140–4,420)	(1,000–1,920)	(4,480–5,680)
Avoidable by solar roofs	1,200	410	180	610
	(990–1,430)	(280–550)	(130–230)	(580–650)
Avoidable by cool roofs	3,100	1,040	460	1,600
	(2,520–3,650)	(690–1,350)	(330–600)	(1,500–1,700)

The parentheses contain CIs based on the CIs of the ERF and the estimated uncertainty on the modeled temperature. Basic statistics are from the Office for National Statistics.

Table 2 | Monetary values of modeled mortality attributable to heat, and avoidable by interventions in London in June, July and August of 2018

Mortality outcome/ valuation method	Cost or benefit item	Total	Age groups		
			64 years and under	65–75 years	75 years and over
Value of statistical life	Cost of heat in baseline scenario	1,944	235	218	1,491
		(1,619–2,274)	(153–316)	(148–287)	(1,318–1,671)
	Avoidable by solar roofs	237	30	27	180
		(211–265)	(20–40)	(20–35)	(171–190)
	Avoidable by cool roofs	615	74	69	472
		(541–684)	(49–96)	(49–89)	(443–499)
Value of life years	Cost of heat in baseline scenario	884	296	132	456
		(686–1,084)	(193–399)	(90–173)	(403–512)
	Avoidable by solar roofs	108	37	16	55
		(89–129)	(25–50)	(12–21)	(52–58)
	Avoidable by cool roofs	280	93	42	145
		(228–329)	(62–122)	(30–54)	(136–153)

The CIs are based on the CIs of the ERF and the estimated uncertainty on the modeled temperature. Costs are in millions of pounds in 2023 prices.

dynamic and radiation trapping effects in detail within the urban environment; and models in detail the heat balance of RPV[14,15]. The 3D urban parameterization presents advantages over other urban climate modeling methods because it integrates in detail all energy fluxes happening within the urban canyons and between the urban canopy and the atmosphere. It also permits a change of urban surfaces properties at the building level (roof, walls or street) that are then physically integrated in the urban climate model instead of applying an estimated average value of physical and radiative changes at the grid level, which would result in the creation of unrealistic average elements. Lastly, the 3D model used in this study represents the kinetic energy exchanges happening within the urban canyons and within the urban canopy layer rather than simply considering the urban surface as a natural element with altered roughness.

Several limitations apply to the present study. Mortality is assumed to depend on outdoor air temperature, but the interventions modeled also affect indoor air temperature; however, research linking indoor high temperatures directly with mortality is extremely limited as most epidemiological studies rely on outdoor temperature as a proxy[26]. We assume that the relationship between outdoor temperature and mortality is static, but heat-health action plans[18], acclimatization[27] or increasing air conditioning use[28] may reduce the dependence of mortality on outdoor temperature, which would lessen the effect of the modeled interventions on mortality. We assume that all roof area is converted either to cool roof or RPV to investigate the maximum possible effect of the interventions, which is likely to be achieved in practice; the findings of Lu et al.[29] support the assumption that temperature differences scale roughly linearly with the plan area to which interventions are applied.

The uncertainty of the regional climate model is difficult to quantify; however, we used a large number of urban temperature observations provided through crowdsourcing to validate the model output, meaning that modeling is better scrutinized in urban areas compared with if only sparse official data had been used[25]. Validation with reference to observations in the baseline simulation does not tell the whole story, and while the parameterization of the energy balance of cool roofs and RPV used in the present study is physically sound, validation under all conditions is impossible. Therefore, results from this study have to be considered representative of a single urban climate model output, and we assume that the accuracy of the model is similar between scenarios. Results will be different with a different climate, built environment or baseline albedo for comparison; for example, studies in locations where typical roof albedo is high may find that RPV increases temperatures[9]. Over time, soiling and weathering can reduce the albedo of cool roofs and the ability of PV to generate electricity.

We only include limited sources of economic value in this analysis. For example, we do not model or value changes to indoor energy associated with cooling that could result from the interventions; only a small fraction of buildings in the UK currently have air conditioning systems[30]. We do not quantify disbenefits that could occur from reduced winter temperatures as a result of the interventions; previous modeling of the West Midlands suggests negligible winter penalty at the urban scale[31], but building modeling suggests increased demand for heating[32], depending on roof insulation[33]. The valuation of the electrical energy from RPV depends on the conversion efficiency assumptions, on the price of electrical energy and especially on the assumption that consumer or wholesale electricity prices can be applied to the full amount of generated electrical energy. It is worth noting that the value of electrical energy would be a direct benefit for RPV owners, whereas the value of life lost is a more indirect cost equivalent, and that the costs and benefits are not necessarily experienced by the same people. Finally, we have not attempted to estimate costs of the intervention scenarios; cool roofs have lower material costs than PV, but cool roofing materials are not widely available in the UK. A recent study commissioned for the Greater London Authority assumed that cool roofing materials have equal material cost to standard roofing materials owing to a lack of real price data[34].

Conclusions

We find that wide adoption of cool roofs would decrease average outdoor air temperature in London during a hot summer like 2018 compared with low-albedo roofs already in place; RPV would also reduce temperatures but not by as much. While previous studies have emphasized the role of cool roofs in reducing building cooling demand, and of RPV in providing renewable energy, we have focused on the potential for additional (in)direct benefits (that is, benefits to health from reduced urban temperature) of these technologies that are less well studied. In doing so, we provide a useful point of comparison between the thermal impact of RPV with cool roofs and contribute to the strategic and economic case for policies incentivizing or enabling the adoption of cool roofs and RPV in urban areas.

Methods

Urban climate modeling

The general weather conditions in England in summer 2018 were dominated by dry and sunny weather May to early August, with record average temperature but peak temperatures lower than some other summers (third warmest for daily maximum temperature behind 1976 and 1995) and substantially less rain than average[35]. The maximum temperature officially recorded was 35.6 °C on 27 July[35]. Summer (June, July and August) 2018 was the warmest on record for England, with the average temperature close to 2 °C higher than the 1981–2010 average in many areas of southern England[35]. The study period (June–August 2018) was chosen due to its record-breaking average temperature. Despite the high temperatures, most days were not cloud-free.

The Weather Research and Forecast (WRF; version 4.3, see 'Note on WRF version' in Supplementary Information)[36] regional climate model is used to simulate urban temperatures in London and Southeast England during June–August 2018. The embedded 3D building effect parameterization model with its coupled building energy model (BEP-BEM)[14,15] is used to simulate the impacts of cities and of urban anthropogenic heat emissions on the local climate. The model was run with three nested domains, with horizontal resolutions of 12, 3 and 1 km, respectively, the latter being the inner domain used in the present study. Boundary conditions used as forcing data for the outer domain of the climate model were taken from ERA5 reanalysis[37]. The model setup is identical to that described in our previous work (Brousse et al.[25]) except for the alteration of the rooftops to be high-albedo or to activate a RPV model considering all roofs to be covered with PV.

Urban morphological parameters and urban land-use categories were derived from the World Urban Database and Access Portal Tool (WUDAPT[38]) European local climate zone (LCZ) map at 100 m resolution[39] following the WUDAPT-TO-WRF strategy[40,41] and using the Python code from Demuzerre et al.[42]. An LCZ map of the study area is shown in Supplementary Fig. 3, and a map of the model domain can be found in Brousse et al.[25], fig. 2. Albedo and other urban radiative and thermal parameters were set per land-use category, here given as LCZ: roof albedo was 0.13 in open-lowrise areas, 0.18 in compact-midrise areas and 0.15 in in compact-lowrise areas[25]. The RPV were assumed to have an albedo of 0.11, lower than the baseline roof albedo in all LCZs; therefore, RPV decreased albedo on average compared with the baseline scenario. The cool roofs were assumed to have an albedo of 0.85, and the mean change in neighborhood albedo was 0.26. The cool roofs were assumed to be represented only as a change in albedo. Descriptions of the scenarios modeled are given at the start of Results.

The RPV were modeled in detail, including convective and radiative heat fluxes from the top and bottom of the panel, and conversion efficiency response to temperature. Sensible heat emission is modeled from both the top and bottom surfaces, which are assumed to be the same temperature. The convective heat fluxes depend on the windspeed at roof level, but air flow over the RPV is not treated fluid dynamically. The temperature of the PV panels is estimated using the prognostic equation from Jones and Underwood[43], and as described by Zonato et al.[44] (for more details, see 'Note on WRF version' in Supplementary Information).

Bias adjustment was applied to the baseline scenario of the inner domain, using data from personal weather stations (PWS). PWS provide a greater density of temperature observations in urban areas where there are few official observations and can identify biases in urban temperature that cannot be observed with official observations[25,45]. Model bias was adjusted by using machine learning regression models to predict daily temperature model biases from the urban model inputs, as described in Brousse et al.[25]. To incorporate bias adjustments into the alternative scenarios (cool roofs, solar PV and nonurban), differences between the temperature outputs in each changed scenario compared with the unadjusted baseline scenario are added to the adjusted baseline scenario temperature outputs, so the same adjustment is applied to each scenario.

Model evaluation

Comparison of the modeled baseline scenario with Met Office hourly weather observations from 35 stations gave a mean absolute error of 1.82 °C, a mean bias of −0.56 °C and a mean Pearson R^2 of 0.77, whereas comparison with hourly observations from 402 NetAtmo PWS gave a mean absolute error of 2.19 °C, a mean bias of −1.46 °C and a mean Pearson R^2 of 0.80 (averages across stations for June, July and August of 2018). This indicated that urban temperatures were underestimated, and so bias adjustment was applied. Bias adjustment followed the procedure described in Brousse et al.[25]: bias was estimated for each day of the baseline simulation temperatures at each of the PWS site; then, the bias was gridded using a random-forest regression against the urban canopy parameters used by the WRF model and subtracted from the simulated temperatures.

The mean absolute adjustment applied to the population-weighted temperature was 1.5 °C, although the largest adjustment was applied on 12 June, a cooler day near the start of the study period. The mean absolute adjustment applied on days that were above the threshold for heat-related mortality (that is, on which a fraction of mortality was attributed to heat) was 0.9 °C. After bias adjustment, the root mean squared difference from the urban temperature observations was 1.0 °C, which we treat as the error term of the temperature series. To create bias-adjusted time series for the alternate scenarios, the difference between the unadjusted model output and the baseline scenario is applied to the adjusted baseline scenario.

The urban-canopy air temperature modeled in the alternative scenarios, including the nonurban scenario, is slightly higher than the baseline scenario at the start of the simulation. We believe this is because the convection created by the city alters the modeled weather pattern slightly. Although 7 days of spin-up time was discarded at the start of the run, this may also still be a spin-up effect. The temperature in this period is below the threshold of the exposure–response function (ERF), so including or excluding this period does not have an effect on the mortality impact estimates. Supplementary Fig. 2 shows that the fraction of mortality attributable to heat is at or close to zero for the days before 15 June.

Mortality impacts

The ERF gives the relationship between the exposure (temperature) and a response (risk of mortality). Mortality is assumed to depend on 2-day lagged mean outdoor air temperature following Arbuthnott et al.[22]. To estimate the total number of deaths attributable to heat, the ERF is used to calculate a relative risk (RR) daily time series from the temperature time series $T(t, a)$ using the appropriate coefficient $c(a)$ for each age group a and day t following

$$\mathrm{RR}\,(t,a) = \mathrm{e}^{(c(a)(T(t,a)-T_0))} \quad (1)$$

for temperature above threshold ($T(t) > T_0$), where $c(a)$ is equivalent to the natural log of the RR at 1 °C above threshold. ERFs from Arbuthnott et al.[22] (an ecological time-series analysis of deaths in Greater London between 1996 and 2013) are applied to the population-weighted temperature time series for each scenario to estimate the attributed fraction of mortality for each age group. To population weight the temperature, the population from the 2021 census (https://www.nomisweb.co.uk/sources/census_2021, last accessed 21 December 2023) at the 'output area' level (that is, the smallest census tract type) is used, separately for each age group; only output areas within the Greater London boundary were included. From the RR, the attributable fraction (AF) is calculated as

$$\mathrm{AF}\,(a,t) = \frac{(\mathrm{RR}\,(a,t) - 1)}{(\mathrm{RR}\,(a,t))}. \qquad (2)$$

The AF time series is then multiplied by a daily time series of actual recorded deaths $D(t, a)$ (UK Office for National Statistics) to get the attributable mortality (AM) and is summed over all days of June, July and August of 2018 as

$$\mathrm{AM}\,(a) = \sum_t (\mathrm{AF}\,(t,a) \times D(t,a)). \qquad (3)$$

Mortality is assumed to be equally distributed between male and female for this calculation, as we do not have access to recorded death counts stratified by sex. Then, YLL is given by the difference between life expectancy and median age of death for each age group, based on life tables (https://www.ons.gov.uk/peoplepopulationandcommunity/birthsdeathsandmarriages/lifeexpectancies/datasets/nationallifetablesunitedkingdomreferencetables, accessed 3 April 2023). The attributed mortality calculation is performed for each time series, and the difference in attributable mortality (and attributable YLL) between the scenarios and the baseline are reported as deaths avoided (or YLL avoided). Methods for estimating mortality impacts are the same as in Simpson et al.[17].

Arbuthnott et al.[22] did not find a large effect of adjusting for air pollution or relative humidity and, therefore, did not adjust for the effect of these factors on the mortality time series analysis. Air pollution and the urban heat island intensity are both often higher in stable, low-wind conditions; therefore, our mortality estimate may include some deaths that could equally be attributed to air pollution or to the combined exposure of heat and air pollution.

Uncertainty and sensitivity

Sources of uncertainty included in the analysis were (1) uncertainty on the coefficient of the ERF from Arbuthnott et al.[22] and (2) uncertainty on the modeled outdoor temperature. The two sources of uncertainty were combined using Monte Carlo sampling, with uncertainty in both inputs assumed to have normal distributions.

The standard deviation of the uncertainty distributions were assumed to be (1) the quarter width of the 5–95% CI of the coefficient and (2) the root mean squared error of the bias-corrected temperature data with reference to urban crowd-sourced observations (see Brousse et al.[25]). For both sources of uncertainty, random values were drawn from the uncertainty distributions and added to the relevant quantities in the health impact calculation; from 100,000 realizations, the 5th, 50th and 95th percentiles of the distribution across realizations of the health impact calculation were taken as the lower, central and upper values of the results, respectively. One draw from the coefficient uncertainty (1) distribution was made for each realization of the health impact calculation, and one draw from the temperature uncertainty (2) distribution was made for each time step, time series and realization of the health impact calculation.

In Supplementary Information, we present the result of translating the entire temperature distribution up or down by up to 1 °C. Supplementary Tables 2 and 3 give the changes produced in the heat-related mortality estimates (Supplementary Table 2) and avoidable heat-related mortality estimates (Supplementary Table 3) when the ERF threshold is changed, showing that the avoidable heat-related mortality estimate is less sensitive to the threshold than the total heat-related mortality estimate is.

Monetization of mortality impacts

Value of statistical life and value of statistical life years were sourced from the UK Government appraisal guidance[20,21] (referred to as the 'value of prevented fatality' therein). These values are based on surveys of willingness to pay to avoid risk of death. Values were converted to 2023 prices. Value of life years was set at £79,000 per life year, and value of statistical life was set at £2.5 million per life. To calculate the economic burden of attributable mortality, the attributable mortality is multiplied by the value of statistical life. Alternatively, the economic burden of YLL is calculated by multiplying the value of life years by the attributable YLL. Our valuation results depend linearly on the assumed value of statistical life and value of life years. The monetization of mortality impacts follows the same methods as Simpson et al.[17].

Solar panel suitability

Targets set by London City Hall in 2018 aim for 1 GW of solar capacity by 2030 and 2 GW by 2050[46]. Assuming a typical power density of 175 $\mathrm{W\,m^{-2}}$, 1 GW of capacity is 5.7 $\mathrm{km^2}$ in area, which is about 2% of the total plan area of buildings in London. Meanwhile, based on the London Solar Opportunity map[47] (https://www.london.gov.uk/programmes-strategies/environment-and-climate-change/energy/energy-buildings/london-solar-opportunity-map, last accessed 21 December 2021), which used light detection and ranging to estimate the available roof area for PV considering overshadowing and roof shape[48], we estimate the total potential area for PV is 166 $\mathrm{km^2}$, which is >65% of the total plan area of buildings in Greater London. To get this number, we divided the total suitable area from the Solar Opportunity Map by the total footprint area of buildings in Greater London.

Electric power generation

Total power generation was calculated from the solar power model included within the urban climate model (BEP-BEM). Within the urban climate model, the RPV conversion efficiency was set at 19%; this is thought to be typical for an RPV system in 2020, although efficiencies are generally increasing[49]. Efficiency was modeled as declining by 0.5% per 1 °C increase in panel temperature over 25 °C. Within the urban climate model, all panels were treated as a horizontal surface over a flat roof, and we were not able to include detailed information about spatial variations in the suitability of rooftops for RPV in the urban climate model. Most RPV in the UK are installed facing south and pitched at around 30° from horizontal, which would lead to differences in the absorption of solar radiation and on sensible heat emission. Given these sources of variation in efficiency in practice, we assume that efficiency (at 25 °C) varies between 9% and 19% for the purpose of the energy calculations[50,51], and rescale the electric power output from BEP-BEM to produce a lower limit.

Electrical energy production for grid cells within the boundary of Greater London were summed. The value of the energy was estimated by multiplying the total energy generated over the study period by an assumed energy price. Energy price assumptions from two sources were considered. While average variable unit prices for electricity in London in 2018 were £150 $\mathrm{MWh^{-1}}$, in 2022 they were £300 $\mathrm{MWh^{-1}}$ (https://www.gov.uk/government/statistical-data-sets/annual-domestic-energy-price-statistics, last accessed 2 October 2023), wholesale day-ahead prices in the UK were £58 $\mathrm{MWh^{-1}}$ in July 2018 and £364 $\mathrm{MWh^{-1}}$ in August 2022 (https://www.ofgem.gov.uk/energy-data-and-research/data-portal/wholesale-market-indicators, last accessed 25 March 2024). We therefore take as low and high estimates £58 $\mathrm{MWh^{-1}}$ and £364 $\mathrm{MWh^{-1}}$. The value estimates for solar power are linearly dependent on the solar panel efficiency and assumed energy price, so we provide high and low estimates rather than a sensitivity analysis. For the full range of our estimates, see Supplementary Table 4.

Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability

Data generated by this study are available via Zenodo at https://doi.org/10.5281/zenodo.13616448 (ref. 52) and are publicly accessible. UK census data are available from https://www.nomisweb.co.uk. The WUDAPT LCZ map for Europe is available via Figshare from https://figshare.com/articles/dataset/European_LCZ_map/13322450.

Code availability

WRF is publicly available via GitHub at https://github.com/wrf-model/WRF. Analysis code used in this study is included in the data archive at Zenodo via https://doi.org/10.5281/zenodo.13616448 (ref. 52). Analysis used Python v3.10 with numpy, matplotlib, seaborn, xarray, geopandas and xarray, which are publicly available via https://conda-forge.org.

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Competing interests

The authors declare no competing interests.

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