Estimating heat-related mortality burden changes under type-specific green and blue space scenarios in China

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The authors declare they have nothing to disclose.

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Abstract

Background: Green and blue spaces (GBS) are assumed to mitigate heat-induced health risks. However, few studies have explored the impact of type-specific GBS changes on heat-related mortality burden.

Objectives: This study aimed to investigate the effect modifications of different GBS types on heat-related mortality risks, and to estimate the changes in mortality burden in multiple GBS scenarios.

Methods: A case time-series study design was utilized based on the daily data on all-cause mortality and temperatures from 2009 to 2020 in 1,085 sub-districts in China. Mortality count data were obtained from the Zhejiang Center for Disease Control and Prevention. Meteorological data on temperature and relative humidity were acquired from the Zhejiang Meteorological Bureau. GBS exposure was assessed by integrating fine-scale population density, GBS boundary from Baidu and OpenStreetMap, and street-view image data from Baidu. Conditional Poisson regression analyses were conducted with the distributed lag non-linear model, incorporating modifiers of type-specific GBS exposure. Changes in heat-attributable mortality under different GBS scenarios were also assessed.

Results: Heat-related mortality risks were lower for populations with high exposure (95%) than for those with low exposure (5%) (1) to overall green spaces, forests, parks, nature reserves, and street greenery, rather than to grasses, farms, and scrubs; and (2) to overall blue spaces, lakes, and rivers, rather than reservoirs, wetlands, or coasts. An increase of 10%, 20%, and 30% exposure to overall green spaces are expected to avoid heat-related mortality burden by 1.6% (95% empirical confidence interval [eCI]: 1.4, 1.9), 3.2% (2.5, 3.9), and 4.8% (3.5, 6.2), respectively, whereas corresponding estimates for overall blue spaces are 5.4% (4.4, 6.4), 10.8% (8.5, 13.3), and 16.2% (12.3, 20.5), respectively. Conversely, a 30% decrease in overall green and blue space exposure will increase the heat-related mortality burden by 4.8% (4.3, 5.2) and 15.9% (15.2, 16.7), respectively.

Discussion: Our study revealed differences in the capacity of various GBS types to mitigate heat-related mortality risks. While the protective effects of GBS may be moderate, targeted planning strategies should prioritize their implementation for maximum benefits in mitigating heat-related health risks. The continuous shrinkage of the GBS would render other efforts futile, such as heat-health action plans.

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Introduction

Increasing heat extremes are considered a primary global environmental challenge of the 21st century, driving numerous negative implications for human health and well-being. [1-3] According to a latest multi-country study, nearly 490,000 deaths per year can be directly or indirectly attributed to excessive natural heat. Asia and China are the most affected continent and country, respectively, accounting for 45% and 15% of heat-related deaths worldwide, respectively.[3] The effects of climate change and urbanization, combined with a rapidly aging population, require innovative strategies to combat heat stress. This is particularly important in cities where urban heat island (UHI) effects are anticipated to cause unprecedented temperatures.[4,5] Heat preparedness and response action plans for individuals and communities (e.g., education, health care infrastructure, and early warning system) are costly and labor-intensive to implement.[6,7] Nature-based solutions have been increasingly identified as cost-effective and promising methods for building climate-resilient cities in a long-term efficient and adaptable manner.[8,9]

Green-blue space (GBS) is an essential nature-based solution for regulating micro-climates through shading and evapotranspiration.[4,10-14] Recent studies have demonstrated that GBSs have a protective effect against heat-related mortality risks.[15-17] However, conflicting findings have been reported, suggesting the absence of discernible benefits.[9] The cooling effects of various types of GBSs depend on their size, shape, landscape composition, and configuration.[17-19] Furthermore, the impact of GBSs on individual outdoor activities and heat exposure during summer may vary by their

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types.[20,21] Therefore, the heterogeneity in previous findings has been speculated to be associated with the region-specific components of GBS types by directly driving thermal comfort and indirectly influencing human exposure.[20,22] Nevertheless, comparative epidemiological evidence on the combined health effects of different GBS types on potentially increased outdoor exposure time and decreased heat stress are lacking. A limited understanding of the relationships between different types of GBS and the impacts of heat on health hinders the development of effective GBS planning and design strategies to mitigate adverse heat-related health effects.

Although the effect modifications of green or blue space on heat-related mortality risks have been examined recently,[15-17] the changes in heat-attributable mortality burden via an increase in GBS exposure have not been assessed extensively. This information can inform the government of the health benefits of maintaining and developing green and blue spaces, and encourage them to take action. Furthermore, although some cities have been successful in maintaining or expanding their GBS in recent years, others have experienced degradation and destruction of natural vegetation and water bodies due to rapid urban expansion and construction.[23] This prompts an inquiry into the impact of potential GBS degradation and destruction on heat-attributable mortality burden, particularly in China, a rapidly urbanizing country.

In this ecological study, exposure indices were developed to reflect residential exposure to overall and type-specific GBS. This was achieved by combining fine-scale

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population distribution data with the GBS maps of nature reserves, forests, parks, farms, scrubs, grasses, coasts, rivers, lakes, wetlands, and reservoirs. Because street greenery has been identified as a significant contributor to cooling,[24] and tree planting is a prevalent method of urban greening, we included street greenery as a type of green space. Exposure to street greenery was assessed using street view images and a convolutional neural network model because of the scarcity of data sources for measuring street greenery. To investigate the potential impacts of GBS on heat-related health risks, we comprehensively quantified the effect modifications of overall green space, overall blue space, and 12 GBS types on heat–mortality associations in Zhejiang province, China, between 2009 and 2020. We further estimated the changes in the mortality fraction attributable to heat under different GBS scenarios. This provides the mortality burden that could be prevented through green and blue infrastructure planning strategies or that may be increased due to a decrease in GBS. Our ultimate goal was to provide policy-makers and decision-makers with scientific evidence to integrate type-specific GBS planning into climate change adaptation and mitigation measures to build sustainable, climate-resilient, and healthy urban environments.

Methods

Study area

The study was conducted in Zhejiang Province in China, which had a population of 64.56 million in 2020 and a total area of 105,500 km^2 (Figure 1). Zhejiang is located in the middle of the subtropical zone, and its summer climate is characterized by

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prolonged high temperatures and humidity. Zhejiang comprises 11 cities, with 90 districts under its jurisdiction, and each district is comprised several sub-districts. For this study, we selected a sub-district as the analysis unit because it is the smallest administrative unit in the death reporting system. We excluded sub-districts whose names or boundaries changed during the study period and thereby their daily mortality was not recorded continuously. Ultimately, 1,085 sub-districts were included in the analysis (Figure S1). The mean population of these sub-districts was 46,386 (standard deviation [SD]: 51,349), and the average area was 76.1 (SD: 60.5) km^2.

Estimation of daily population-weighted meteorological variables

Meteorological data on hourly temperature and relative humidity from January 1st, 2009, to June 30th, 2020, were acquired from the Zhejiang Meteorological Bureau and were subjected to a thoroughly automated quality control process to remove random errors. The data were gathered from a highly dense observational network of 4,007 automatic weather stations in the Zhejiang Province and its neighboring provinces (Figure S2). The European Centre for Medium Range Weather Forecast (ECMWF) Interim Reanalysis (ERA-Interim), the global atmospheric reanalysis dataset, was used to generate gridded three-dimensional (3D) temperature and relative humidity data at a resolution of 0.75°.[25] Based on meteorological observations, ERA-interim, and a digital elevation model (DEM), the hourly temperature and humidity data were interpolated to 1 km resolution using a method described in Hu et al..[26] Five-fold cross validation was

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performed for the predicted daily mean temperature to confirm that the interpolation method yielded reliable predictions with negligible bias (R^2 = 0.93, RMSE = 0.48°C).

Daily $PM_{2.5}$ concentrations from January 1st, 2009, to June 30th, 2020, were obtained from the Tracking Air Pollution in China (TAP) dataset (http://tapdata.org.cn). This product was generated using machine learning techniques based on multi-source data, including the data from ground-based observations, remote-sensing, atmospheric reanalysis, land use, and model simulations. High-quality data for $PM_{2.5}$ with a spatial resolution of 1 km (R^2=0.80–0.88, RMSE=13.9–22.1 μg/m^3) were retrieved from the TAP dataset.[27-29]

The population density in 2010 was estimated at 1 km resolution (Figure S1) using a random forest algorithm based on points-of-interest (POIs), road networks, DEM, and other multi-source remote-sensing data, such as those of nighttime light and enhanced vegetation index. The details of these methods have been published by Ye et al..[30] Subsequently, to accurately measure population exposure, the population-weighted averages of the daily 24-hour mean temperature, relative humidity, and $PM_{2.5}$ in each sub-district were calculated.[26]

Green and blue space exposure assessments

We developed a green space exposure index to reflect sub-district-level residents' exposure to overall green spaces (Figure 1) and green spaces based on the type, namely,

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farms, nature reserves, forests, scrubs, grasses, parks, or street greenery. Polygon green space map data in 2020 for the boundary of farms, nature reserves, scrubs, grasses, and parks were derived from OpenStreetMap (OSM, www.openstreetmap.org), a collaborative project for creating a free global geographic database. OSM provides fairly complete and accurate geographical information of GBS with good quality (Figure S3-S4, compared with another three frequently-used data sources of Baidu map (map.baidu.com, overlap rate=99.98%), Amap (ditu.amap.com, overlap rate=81.79%), and China Land Use/Cover Dataset (CLUD, https://doi.org/10.5281/zenodo.4417810, overlap rate=95.18%). Polygon green space map data in 2020 for the boundary of forests were obtained from the Baidu area-of-interest (AOI) dataset, which is the Chinese equivalent of Google Map. First, buffer zones were created around the input polygons of green spaces (Figure S5) to a specified maximum attraction distance (Table S1, 0.15–10 km) corresponding to different sizes of green spaces.[31-39] The maximum attraction distance represents the maximum range within which the cooling service capacity of green or blue spaces can extend,[31] and it was derived based on the findings from previous studies on the cooling effects of GBS.[32-39] A higher maximum attraction distance was set for larger green space areas. The green space exposure index was generated by calculating the ratio the number of people residing in the buffer zone of a specific type of green space to the total population of a certain sub-district.

The green space exposure index of street greenery was assessed using the green view index (GVI), calculated by semantic segmentation of Baidu street-view images. First,

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the sampling points were selected at 50 m intervals along the urban road network from OpenStreetMap (Figure S6). We only chose the road network in 524 urban sub-districts as the street view images were scarce in rural sub-districts. Thereafter, 3,314,028 Baidu street-view images were downloaded for the 828,507 sampling points from four angles (0°, 90°, 180°, and 270°) during 2017–2020. The majority (64.6%) of street-view images were captured in summer, when the trees and plants were at their greenest. Other street-view images (35.4%) were captured in spring and autumn, and the images captured in winter were excluded. Although we used full year's data in statistical analyses to identify the minimum mortality temperature, our main focus was on the effect modifications of GBS on the mortality risks at high temperatures during summer. Therefore, the collection time of street view images was assumed not to substantially affect our main findings. GVI was derived from street-view images through semantic segmentation using Google's third-generation DeepLab convolutional neural network series, DeepLab V3+.[40] The CityScapes dataset was used to train DeepLab V3+, and the xception71_dpc_cityscapes_trainval model (http://download.tensorflow.org/models/deeplab_cityscapes_xception71_trainvalfine_2018_09_08.tar.gz) was applied. GVI was derived by calculating the mean proportion of vegetation pixels present in the four matched images at each sampling point. The GVI varied between 0 and 1, with a higher value indicating greater street greenery. The mean intersection over union (MIoU), which was often used to measure the accuracy of vegetation pixels being correctly labeled,[41] was estimated to be 87.8%, which indicated a good accuracy of classification results. To determine the green space

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exposure index for street greenery at the sub-district level, we first interpolated all point data of GVI values using the kriging method at a spatial resolution of 1 km, and calculated the population-weighted GVI in each sub-district.

The normalized difference vegetation index (NDVI) is a commonly used satellite-derived index for measuring green coverage, and is defined as the ratio of the difference between the reflectance in the near-infrared region and red reflectance to the sum of these two measures.[42] Here we used NDVI as a proxy for exposure to overall green space for the sensitivity analysis. All available 2,535 images from Landsat 8 Collection 2 Tier 1 from 2013 to 2020 and 610 images from Landsat 5 Collection 2 Tier 1 from 2009 to 2011 with a resolution of 30 m were downloaded.[43] The annual NDVI composite was generated using the maximum value compositing (MVC) technique, preserving the maximum NDVI value of all available Landsat images for each pixel within each year.[44] The yearly NDVI was selected to account for the temporal variations in green spaces. The mean NDVI values for 2011 and 2013 were used as proxies for the 2012 NDVI value, because there were no Landsat satellite images for 2012. The values of NDVI ranged from –1 to 1, and negative values were excluded before the next calculation. The NDVI data were first resampled to a resolution of 1 km, and the population-weighted NDVI of each sub-district was calculated.

We also developed a blue space exposure index to assess residents' exposure to overall blue spaces and blue spaces by the type, namely lakes, rivers, wetlands, reservoirs, or

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coast. Polygon data on the inland blue space types of rivers, lakes, wetlands, and reservoirs in 2020 were derived from the Chinese river system and river basin datasets (https://www.rserforum.com/thread/212, Figure S7). The blue space exposure index was generated by calculating the ratio of the number of residents in the buffer zone of a specific type of blue space to the total population of a certain sub-district. The buffer zones of inland blue spaces were created around the input polygons of blue spaces to a specified maximum attraction distance (1–5 km) corresponding to different types of blue space (Table S2), based on previous research on the cooling effects of blue spaces.[45-54] A buffer zone of the coast was created around the coastline of Zhejiang Province at 5 km.[52]

Mortality and socio-economic data

Daily sub-district-level mortality count data from January 1st, 2009, to June 30th, 2020, were obtained from the Zhejiang Center for Disease Control and Prevention. All deaths in Zhejiang must be reported to the surveillance system, which has stringent quality control measures to ensure data quality[55]. The sub-district-level percentages of population aged over 65 years, sex ratios, and illiteracy rates in people above 15 years of age were obtained from the 2020 China National Census. District-level per capita disposable income for 2015 was obtained from the Statistical Yearbook of Zhejiang Province and 11 cities of Zhejiang (e.g., Hangzhou). The socioeconomic status (SES) indicator was measured by adding the Z-score normalized values of per capita disposable income to the illiteracy rates in population aged over 15 years, as described

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in previous research.[56]

Statistical analysis

Time-series daily data on all-cause mortality and ambient mean temperature were collected for 1,085 sub-districts across Zhejiang Province, China from January 1, 2009, to June 30, 2020. The associations between high temperature and all-cause mortality were explored using a novel case time-series design developed by Gasparrini,[57] modeling a sub-district-specific series via a fixed-effects conditional quasi-Poisson regression. This design reduces exposure misclassification by allowing exposure and outcomes to be aggregated in a small geographical unit. The regression controlled for the long-term and seasonal trends and the day-of-the-week effect by using strata to match the case and control days within the same sub-district, year, month, and day of the week. Temperature-mortality associations were modeled using cross-basis functions through distributed lag non-linear models (DLNMs), which provided a flexible modeling framework to estimate complex non-linear and delayed effects.[58] A cross-basis function was first defined using a natural cubic spline with two internal nodes at the 33th and 66th percentiles of the mean temperature, and a natural cubic spline for the space of 21 lag days with three degrees of freedom. The lag-response association indicated that it was the heat exposure on the same day and the previous two days (lag 0–2) that was significantly associated with the increase in mortality risk (Figure S8 and Supplemental Excel file S1). Thus, the maximum lag day of high temperatures was then defined as 3 days in cross basis function in DLNM. Minimum mortality temperature

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(MMT, 18.0°C) was derived from the lowest point of the temperature-mortality association curve (Figure S9 and Supplemental Excel file S2),[26] reflecting the most optimum temperature. The effect modifications of green and blue space on heat-related mortality risk were assessed by adding a linear interaction between the cross-basis function and the green or blue space exposure index.[57,59] Heat temperature was defined using the 95th percentile of daily population-weighted 24-hour temperature, as in previous studies. [60,61,62] Subsequently, RRs (95th percentile temperature vs. MMT) at low (5%) and high (95%) levels of green or blue space exposure index were predicted. The 5th and 95th percentiles of GBS exposure index were set for defining high and low exposure levels mainly considering the potential non-normal distributions of GBS exposure indices, and meanwhile allowing for a comparison across different studies on effect modifiers of GBS.[62,64] To compare RRs at low and high levels of green or blue spaces exposure indices, the ratios of relative risks (RRRs) were calculated using the method detailed in Altman and Bland's study,[65] with the Z test as the significance test for the effect modifications of green and blue spaces.

For specific types of green–blue spaces with a significant effect modification (P<0.05 for Z test) on heat-related mortality, we calculated the attributable fractions (AFs) resulting from temperatures above the MMT in different green–blue-space scenarios. The empirical confidence intervals (95% eCIs) of AF were obtained by 1,000 Monte Carlo simulations, assuming a multivariate normal distribution for the estimated spline model coefficients.[66] The absolute AF changes and percentages of AF changes were

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then computed under type-specific green or blue space scenarios: 10%, 20%, or 30% increase, or decrease in the mean value of the green or blue space exposure index.

Next, we conducted sensitivity analyses to verify the robustness of the potential differences in mortality changes at different levels of GBS by (1) using both time-independent and time-varying annual average NDVI to represent the green space exposure; (2) reporting RRs at the 10^{th}, 25^{th}, 50^{th}, 75^{th} and 90^{th} percentiles of the type-specific GBS exposure index; (3) using half of the original maximum attraction distances and also limited the maximum distances to 5 km, 2 km, and 1 km for green spaces (Table S3) and 2.5 km, 2 km, and 1 km for blue spaces in GBS exposure measurement (Table S4); (4) additionally adjusting for potential confounders of the percentage of adults aged over 65 years, sex ratio, and socio-economic status by adding interactive terms in the regression models, separately; or (5) additionally adjusting for daily population-weighted 24-hour mean $PM_{2.5}$ at 0–1 lag days or for daily population-weighted 24-hour mean relative humidity at 0–3 lag days.

Additionally, we explored the effect modifications of type-specific GBS on cold-related mortality risk to further investigate the potential underlying mechanism of the influence of GBS on heat-related mortality risks. Cold temperature was defined using the 5^{th} percentile of daily population-weighted 24-hour mean temperatures.

All statistical analyses were performed in R 4.2.0 and the R packages of *dlnm, gnm,*

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and *MASS* were used. For all statistical tests, the significance level was set at $P<0.05$ (two-tailed). All maps were produced by ArcGIS 10.5, and the baselayers of the maps were obtained by ArcGIS online.

Results

Descriptive statistics

This study included 2,778,865 all-cause deaths in the 1,085 sub-districts of Zhejiang Province, China, with an average of 241,640 deaths per year. The average daily mean temperature was 16.9°C ranging between –11.3°C and 36.2°C during the study period (Table 1). The 90th, 95th, and 99th percentiles of the daily mean temperature were 27.7°C, 29.3°C, and 31.7°C, respectively. The average daily relative humidity was 76.6%. Zhejiang Province, one of China's most mountainous regions, possesses abundant green spaces and water bodies. Consequently, exposure indices for these spaces—representing the proportion of the population within their service buffer zones—are generally high. The mean (SD) values of green space exposure indices were 0.63 (0.40), 0.57 (0.41), 0.21 (0.10), 0.14 (0.28), 0.14 (0.31), 0.02 (0.12), 0.11 (0.26), and 0.02 (0.10) for overall green spaces, forest, street greenery, parks, nature reserves, grasses, farms, and scrubs, respectively. The mean (SD) values of blue space exposure indices were 0.70 (0.35), 0.24 (0.28), 0.28 (0.37), 0.38 (0.39), 0.04 (0.14), and 0.51 (0.49) for overall blue spaces, lakes, rivers, reservoirs, wetlands, and coast, respectively. The distributions of green and blue space exposure indices were provided in Figure S10–S11 and Table S5.

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Effect modifications of green and blue spaces

The V-shape curve of temperature and mortality showed that both high and low temperatures increased the risk of mortality (Figure S9). The relative risk (RR) at 95th percentile of temperature versus MMT was 1.15 (95%CI: 1.14, 1.16). Significantly lower heat-related mortality risks were found for sub-districts with high levels of green space exposure index for overall green spaces, forests, parks, nature reserves, and street greenery (*P*s<0.01, Figure 2). For instance, for overall green spaces, the RRs (P95 vs. MMT) for specific sub-districts with low and high levels of green space exposure index were 1.18 (95%CI: 1.16, 1.21) and 1.13 (95%CI: 1.12, 1.15), respectively, with the RRR estimated to be 1.05 (95%CI: 1.02, 1.07) (Table S6). However, the effect modification of the green space exposure index of grasses, farms, or scrubs on heat-related mortality risk was not observed.

Differences in heat-related mortality risks were observed for blue space as well, i.e., among sub-districts with low and high exposure levels of overall blue spaces, lakes, and rivers (*P*s<0.01, Figure 3). For example, the RRs (P95 vs. MMT) for specific sub-district with low and high exposure levels to lakes were 1.18 (95%CI: 1.17, 1.20) and 1.09 (95%CI: 1.06, 1.11), respectively, with an RRR of 1.09 (95%CI: 1.06, 1.12) (Table S7). In contrast, sub-districts with low and high exposure to reservoirs, wetlands, or coasts did not have different heat-related mortality risks.

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Attributable mortality fractions under different GBS scenarios

The mortality fractions attributable to temperatures above the MMT in Zhejiang Province, China was 2.64% (95% eCI: 2.42, 2.84). The decreases in absolute AFs are expected to be 0.13% (95% eCI: 0.10, 0.15), 0.04% (95% eCI: 0.04, 0.05), 0.16% (95% eCI: 0.14, 0.17), 0.04% (95% eCI: 0.03, 0.04), and 0.08% (95% eCI: 0.07, 0.09) for a 30% increase in the exposure to overall green spaces, nature reserves, forests, parks, and street greenery (Figure 4), respectively; the corresponding to the percentages decreases in AFs as 4.81% (95% eCI: 3.50, 6.22), 1.60% (95% eCI: 1.29, 1.98), 6.06% (95% eCI: 7.36, 4.86), 1.35% (95% eCI: 1.19, 1.53), and 1.88% (95% eCI: 1.65, 2.13) (Table S10), respectively. Similarly, 10% and 20% increases in the exposure to overall green spaces in all sub-districts is expected to decrease the heat-related AF by 1.60% (95% eCI: 1.35, 1.87) and 3.20% (95% eCI: 2.51, 3.94), respectively, whereas the AF will increase by 1.60% (95% eCI: 1.55, 1.65) and 3.19% (95% eCI: 3.06, 3.29) with 10% and 20% decreases in the exposure to overall green spaces, respectively.

Figure 5 shows a similar pattern that AFs decreased as the exposure to the overall blue spaces, rivers, and lakes increased. Absolute AFs will substantially decrease by 0.14% (95% eCI: 0.13, 0.15), 0.28% (95% eCI: 0.25, 0.32), or 0.42% (95% eCI: 0.39, 0.45), if the exposure to overall blue spaces is increased by 10%, 20%, or 30%, respectively; similarly, the corresponding percentages decreases in AFs will be 5.37% (95% eCI: 4.41, 6.44), 10.77% (95% eCI: 8.52, 13.27), or 16.20% (95% eCI: 12.33, 20.49), respectively (Table S11). A 30% increase in the exposure to rivers is expected to

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decrease the AF by 3.16% (95% eCI: 2.48, 4.00), while a 30% increase in the exposure to lakes is expected to decrease the AF by 6.44% (95% eCI: 5.21, 7.94).

Sensitivity analyses

The heat–mortality associations at high and low levels of the overall green space exposure index and both time-varying and time-independent population-weighted NDVI were consistent, indicating that the green space exposure index can represent greenness exposure as well as NDVI (Figure S12 and Supplemental Excel file S3). The analyses reporting RRs at the 10^{th}, 25^{th}, 50^{th}, 75^{th}, and 90^{th} percentiles of the type-specific GBS exposure index (Figure S13-S14 and Supplemental Excel file S4-S5) provided valuable insights into the health effects associated with varying levels of GBS exposure and demonstrate a clear trend: decreasing exposure to various types of green and blue space exposure (e.g., forest, street greenery, park, natural reserve, river, and lake) is associated with an increasing risk of heat-related mortality across the exposure spectrum. Sensitivity analyses using changed maximum attraction distances in GBS exposure measurement (Tables S12-S19), or additionally adjusting for the confounders of the percentage of people aged over 65 years, sex ratio, SES, relative humidity, or $PM_{2.5}$ did not alter the effect modifications of specific types of green and blue spaces (Figures S15–S24). These sensitivity analyses reinforce the robustness of our main conclusions.

Discussion

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To our knowledge, this is the first study to assess heat-attributable mortality burden under multiple type-specific GBS scenarios. We observed that in Zhejiang Province, China, heat-induced premature deaths could be prevented by higher exposure to both green and blue spaces, in accordance with existing evidence from Europe[67], China[68], South Korea[69], and Portugal[15]. Although the cooling effects delivered by various GBS types have been much extensively discussed,[13,20,70,71] it was unclear which type of GBS can preserve the lives of populations in coping with heat. Our findings support that specific GBS types, namely, nature reserves, forests, parks, street greenery, rivers, and lakes, but not grasses, farms, scrubs, reservoirs, wetlands, or coasts, can alleviate the short-term effects of high temperatures on mortality.

Our study highlights that an unevenly distributed GBS may be an important contributor to the spatial heterogeneity in the health impacts of high temperatures. We found that the heat-related mortality risks at extremely high temperatures were 5% (95%CI: 2, 7) and 9% (95%CI: 6, 12) higher in the sub-districts with less green and less blue spaces, respectively. This estimate is consistent with an earlier literature review that concluded that heat-related mortality risk was approximately 5% (95%CI: 0, 11) higher in less vegetated areas.[72] Additionally, a multi-country study provided clear evidence that the environmental injustice to retain greenness exposure significantly modified city-level vulnerability to heat, with its relative contribution being greater than that of the proportion of older adults.[73] It also emphasizes the ethical concern that the creation or improvement of GBS in previously dense GBS areas may worsen health inequity, which

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is especially harmful to vulnerable and disadvantaged groups that often suffer from a lack of high-quality GBS.[2,74] Therefore, targeted efforts to reduce inequalities in GBS access are required to maximize the health benefits of adaptable GBS planning.

Despite growing evidence on the health benefits of green spaces, the mechanisms governing the association between green spaces and heat-related health risks have not been fully elucidated. The protective effects of green space may be related to cooling through direct shading and indirectly through evaporation during the daytime.[75] The absence of an observable effect of green spaces on cold mortality (Table S20) supports this view, as green spaces are more effective at regulating temperatures in summer than in winter.[76,77] The effectiveness of green space cooling is determined by its size, shape, landscape composition, and configuration.[17-19] The size of green spaces has been speculated to be a major factor affecting effect modification. In our analysis, the large green spaces of parks, nature reserves, and forests produced stronger effect than those produced by the small green spaces of grasses, farms, or scrubs. This supports previous findings that heat mitigation requires a minimum area of green space to be effective, and that a larger green space would achieve greater cooling effect transport into the surrounding environments.[22,78,79] In addition, green space have also been linked to positive behaviors such as increased physical activity and social cohesion, which could promote human health and improve people's adaptive capacity to heat stress.[80-82] This pathway may be closely related to street greenery and recreational green spaces such as urban parks.[83] Our findings suggest that green spaces generally have a beneficial effect

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on heat-related mortality, which could alleviate concerns regarding increased health risks related to potentially enhanced outdoor exposure. In summary, the addition of specific types of green infrastructural networks may aid in achieving the public health goals to address urban heat stress.

Blue spaces have long been considered vital components of adaptation strategies for providing cooling benefits through evaporation.[84] The ability of a blue space to modify thermal comfort is largely determined by its patch area.[17-19] Larger water bodies (e.g., oceans, lakes, and rivers) often absorb more heat radiation than do smaller bodies (e.g., reservoirs and ponds).[17,18] It could explain why the reservoir did not present a protective effect in our analysis. However, we found that higher exposure to the coast did not reduce the risk of heat-related mortality, which challenges the findings in Canada[85] and Portugal[15] but is in agreement with the findings in Hong Kong[9]. Based on the inconsistent results for cold-related mortality risks (Table S21), the potential reasons for this should be further explored. Additionally, the wetlands were not found to modify the heat–mortality associations. Possible reasons may include only a small proportion of residences covered by the cooling buffer of the wetland, however, further investigation is required.

The scenario analysis predicted moderate decreases (1.6–3.2% for overall green space, and 5.4–10.8% for overall blue space) in heat-related mortality burden benefiting from the 10–20% increases in GBS exposures. Under an ambitious greening scenario with a

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30% increase, 4.8% of the total heat-induced mortality was avoided. Although management strategies of developing green and blue spaces can only reduce a moderate proportion of heat-related mortality, as estimated by a French study,[67] this approach should nevertheless be prioritized considering the multiple health benefits (e.g., reduced stress and enhanced physical activity) offered by GBS exposure. To maximize the benefits of green space on heat-related health risks, practices such as the protection of nature reserves and forests are needed, and actions to build new or enhance existing parks and street greenery should be taken, for example, to optimize the spatial configuration of urban parks and expand the tree canopy of street greenery.[22,86] Blue space planning decisions for artificial rivers and lakes should be informed by assessing the cooling effectiveness of spaces with different sizes and shapes.[17,18] Furthermore, the increased mortality in scenarios of decreased GBS exposure emphasizes that policymakers should pay close attention to the health threat of human-made losses to GBSs. For example, the continuous shrinkage of GBS would render other efforts, such as heat-health action plans, futile.

The primary strength of our study is the addition of an epidemiological perspective to the existing literature beyond linking GBS types and their cooling effects to heat-related mortality based on a large sample of nearly 3 million deaths during a relatively long study period. The predominant approach in ecological studies investigating the effects of GBS on health risks is to use area-averaged satellite-derived indices (e.g., NDVI), the coverage of GBS, or the proximity to GBS (e.g., the distance to a water body) to

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assess green or blue space exposure.[9,21,82] However, this makes it difficult to distinguish between various GBS types; further, such area-level aggregation processes do not consider the spatial distribution of the population and are confronted with the modifiable areal unit problem (MAUP), potentially leading to bias or errors in the exposure measurement.[87] The GBS exposure index developed in our study overcomes the MAUP and exposes it to the effects of type-specific GBS. Additionally, a scenario-based analysis is worthwhile for understanding how much of the heat-related mortality burden can be prevented by GBS planning, which could provide scientific evidence for supporting future climate change adaptation and mitigation policies.

Our study had some limitations. First, although we modelled the temperature–mortality associations at a relatively smaller geographical level than those used in previous ecological studies,[69,88,89] owing to private policies, we were unable to obtain information on residential addresses and population's movements. Therefore, the relatively large average area of the sub-districts (76 km²) still introduces a substantial degree of measurement error in individual green/blue space exposure, as individuals residing within the same sub-district are assigned the same exposure value despite potential variations in their actual access. Second, although the study considered several demographic and socioeconomic confounders, uncontrolled confounding factors (e.g., noise and the use of air conditioning), owing to the unavailability of appropriate data, may have biased the results.[6,7] Third, in our GBS exposure assessment, the applied maximum attraction distance only considered the size of the GBS; however, the spatial

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extent of the GBS's impact may also vary by GBS type. Future studies should use size-type-specific maximum attraction distances. Fourth, to maximize statistical power, we did not stratify mortality by the cause of death, age, or sex. This limited us from exploring the effect modification of GBS types in different age groups, sexes, and specific-causes of death.

In summary, this study revealed differences in the capacity of various GBS types to mitigate heat-related mortality risks. The findings can provide evidence-based guidelines for type-specific GBS planning strategies in cities to foster resilience in the face of warming climates. Importantly, this study suggests that the benefits of other heat health action plans can easily be outweighed by the shrinking GBS. Therefore, although the protective effects of GBS may be moderate, targeted planning strategies should prioritize their implementation for maximum benefits in mitigating heat-related health risks.

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Acknowledgments

Contributions of the authors were as follows: Kejia Hu: Conceptualization, Formal analysis, Investigation, Software, Writing-original draft preparation. Shiyi Wang: Investigation, Software, Writing-Review & Editing. Fangrong Fei: Data curation, Writing–original draft preparation. Jingqiao Fu: Data Curation. Yujie Shen: Data Curation. Feng Chen: Data Curation. Yunquan Zhang: Methodology. Jian Cheng: Methodology. Xuchao Yang: Supervision, Funding acquisition, Writing-Review & Editing. Jieming Zhong: Supervision, Writing-Review & Editing. Yuming Guo: Supervision, Methodology, Writing-Review & Editing. Jiayu Wu: Supervision, Funding acquisition, Methodology, Writing-Review & Editing.

The assistance by Prof. Antonio Gasparrini in study design and statistical processes is greatly appreciated.

The study was supported by the Zhejiang Provincial Natural Science Foundation of China (Y23D050006), the National Natural Science Foundation of China (42001013, 41971019, 32271935), the Key Laboratory of Intelligent Preventive Medicine of Zhejiang Province, China (2020E10004), the Leading Innovative and Entrepreneur Team Introduction Program of Zhejiang (2019R01007), and the Healthy Zhejiang One Million People Cohort (20230085).

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Table

Table 1. Descriptive statistics of sub-district-level (n=1,085) population-weighted daily mean temperature, relative humidity, $PM_{2.5}$, and demographic and socioeconomic variables of percentage of older adults, sex ratio, income, and education in Zhejiang province, China.

	Mean±SD	**Min**	**Percentile**					**Max**
			5	**25**	**50**	**75**	**95**	
Daily mean temperature (°C)	16.89±8.46	-11.32	2.78	9.89	17.78	23.90	29.27	36.23
Daily mean relative humidity (%)	76.56±13.01	14.42	52.85	67.90	77.93	87.04	94.80	100.00
Daily mean $PM_{2.5}$ (μg/m^3)	34.95±23.69	0.01	9.04	17.92	28.91	45.86	81.23	245.86
People aged over 65 years (%)	13.11±5.83	1.34	4.65	8.93	12.61	16.46	23.42	69.66
Sex ratio (female:male)	1.10±0.09	0.89	0.95	1.04	1.09	1.14	1.26	1.85
Per capita disposable income (RMB Yuan)	31,160±8,931	16,678	17,868	24,051	30,924	38,711	47,052	51,201
Illiteracy rate (%)	4.48±2.43	1.18	1.55	2.67	3.93	4.48	9.34	13.56

Note: $PM_{2.5}$ data was obtained from the Tracking Air Pollution in China (TAP) dataset (http://tapdata.org.cn). Data on percentages of population aged over 65 years, sex ratios, and illiteracy rates in people above 15 years of age were obtained from the 2020 China National Census. Data on per capita disposable income was obtained from the Statistical Yearbook of Zhejiang Province and 11 cities of Zhejiang (e.g., Hangzhou).

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Figure Captions

Figure 1:

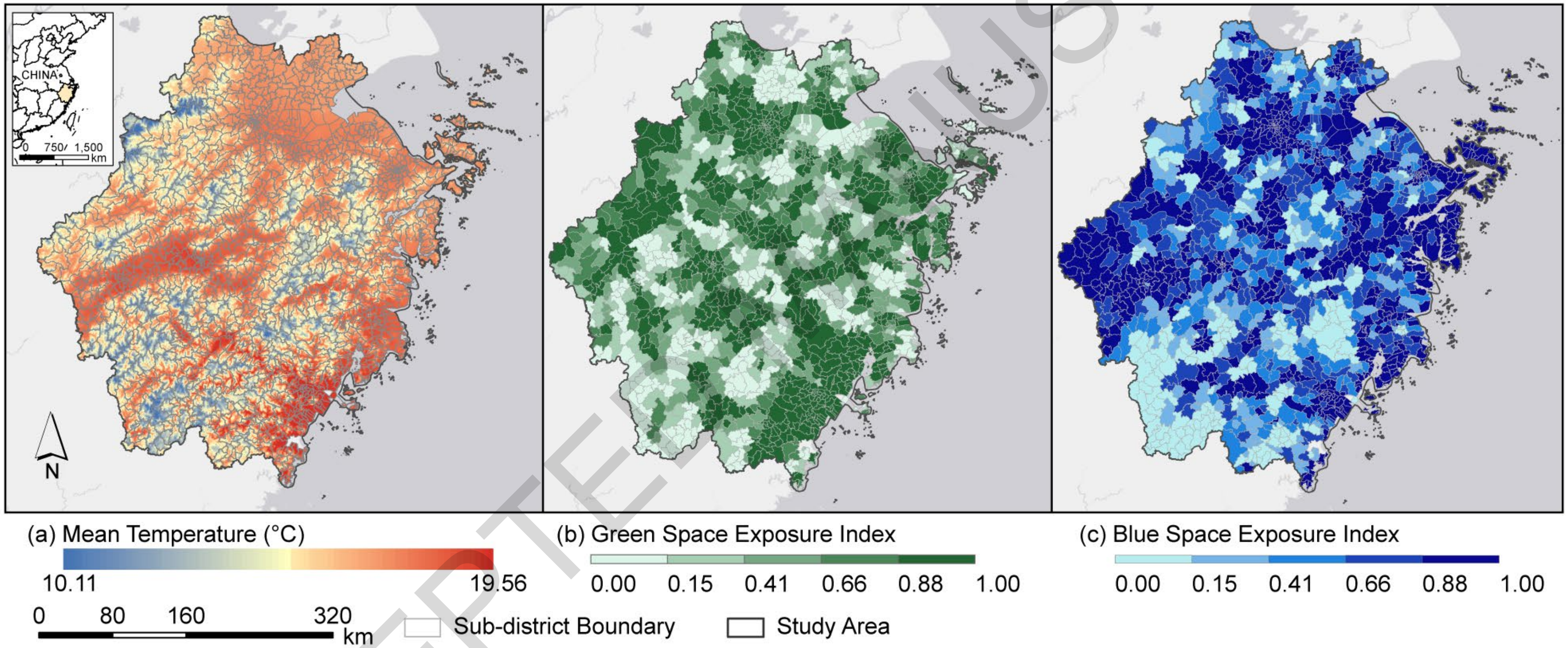

Figure 1. (a) Location of the study area and the averaged daily mean temperature of the area during the study period (2009−2020) of study area. Sub-district-level overall (b) green and (c) blue space exposure index in Zhejiang Province, 2020.

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Figure 2:

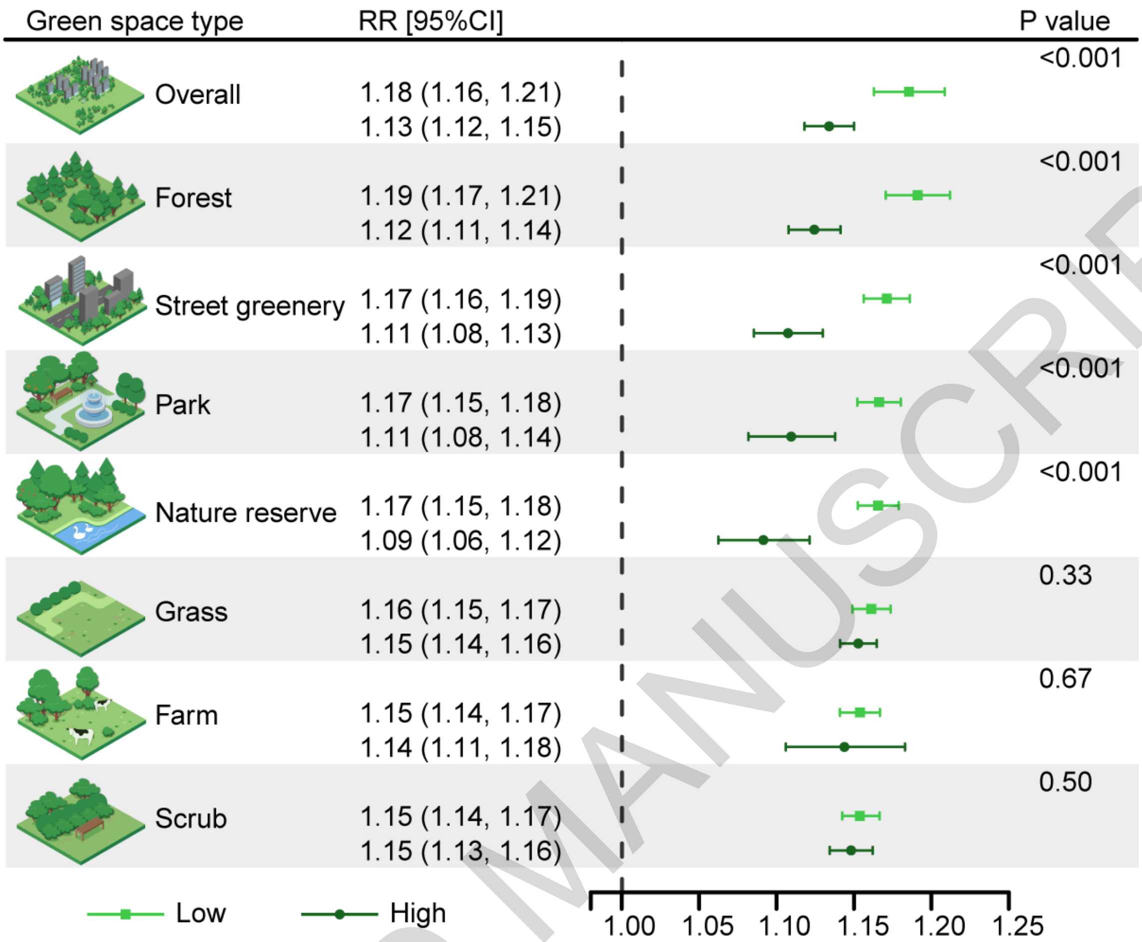

Figure 2. Relative risk (RR) and its 95% confidence interval (95% CI) of all-cause mortality at high temperatures (P95, 29.3°C) predicted for a sub-district with a low (5%, light color) and high (95%, dark color) value of green space exposure index by green space types from case time series study design in 1,085 sub-districts (524 sub-districts for street greenery) in Zhejiang Province, China, 2009−2020.

Note: RRs were derived from fixed-effects conditional quasi-Poisson regressions adjusting for temperature. *P* value refers to the significance of the difference between the RRs at the 95th percentile of the temperature (29.3°C) compared to MMT (18.0°C) at high (95%) and low (5%) levels of green space exposure index using Z test.

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Figure 3:

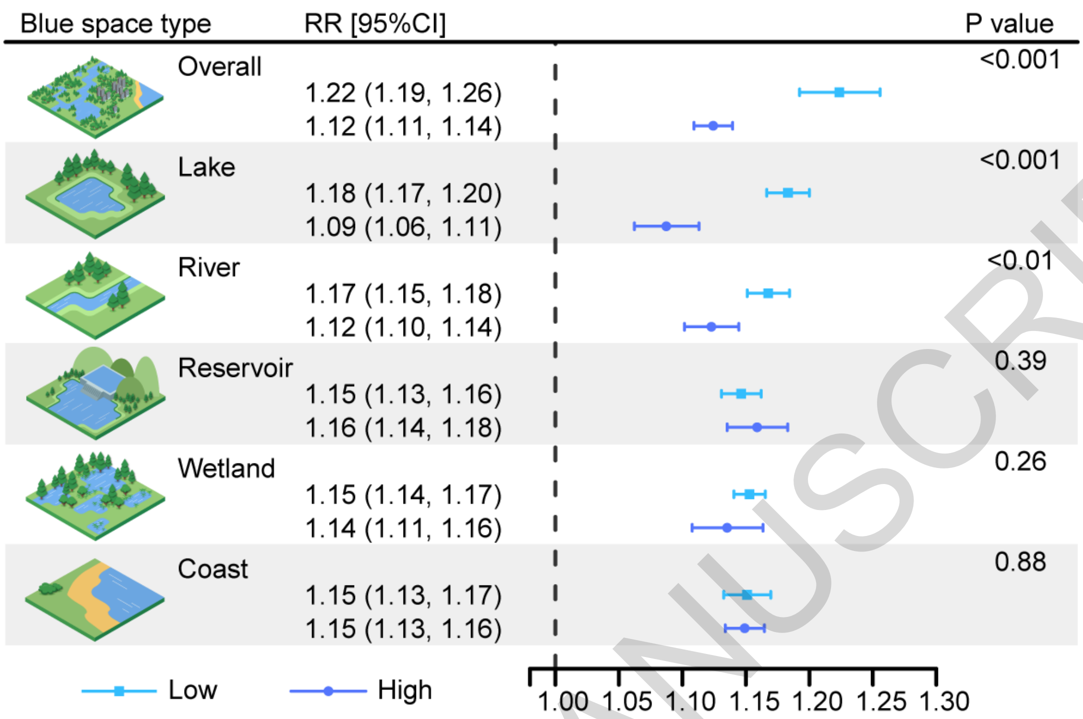

Figure 3. Relative risk (RR) and its 95% confidence interval (95% CI) of all-cause mortality at high temperatures (P95, 29.3°C) predicted for a sub-district with a low (5%, light color) and high (95%, dark color) value of blue space exposure index by blue space types from case time series study design in 1,085 sub-districts in Zhejiang Province, China, 2009–2020.

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Figure 4:

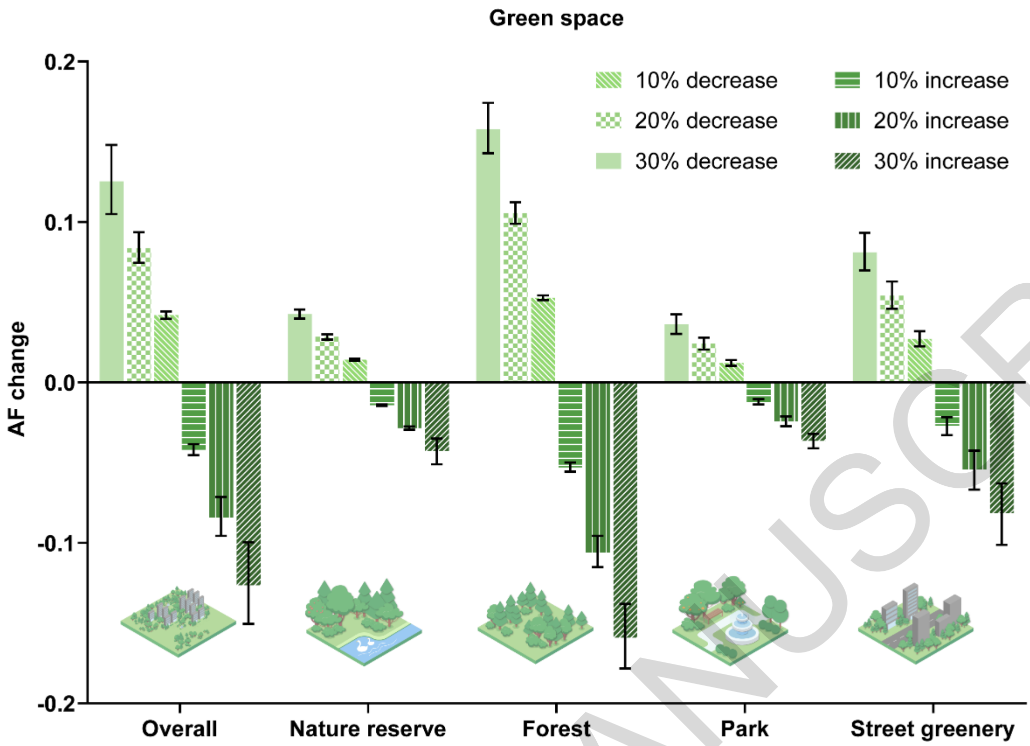

Figure 4. Changes in the absolute value of attributable fraction (AF, %) and their 95% empirical confidence intervals (95% eCIs) of mortality to high temperature above the minimum mortality temperature (MMT) under different green space scenarios: 10%, 20%, and 30% increase and decrease of green space exposure index compared to the current green space exposure index based on the green space types (i.e., overall green spaces, nature reserves, forests, parks, and street greenery) in 1,085 sub-districts (524 sub-districts for street greenery) in Zhejiang Province, China. Corresponding numeric data was provided in supplementary materials Table S8.

Note: The empirical confidence intervals (95% eCIs) of AF were obtained by Monte Carlo simulations, assuming a multivariate normal distribution for the estimated spline model coefficients. The baseline GBS exposure indices originated from the year 2020.

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Figure 5:

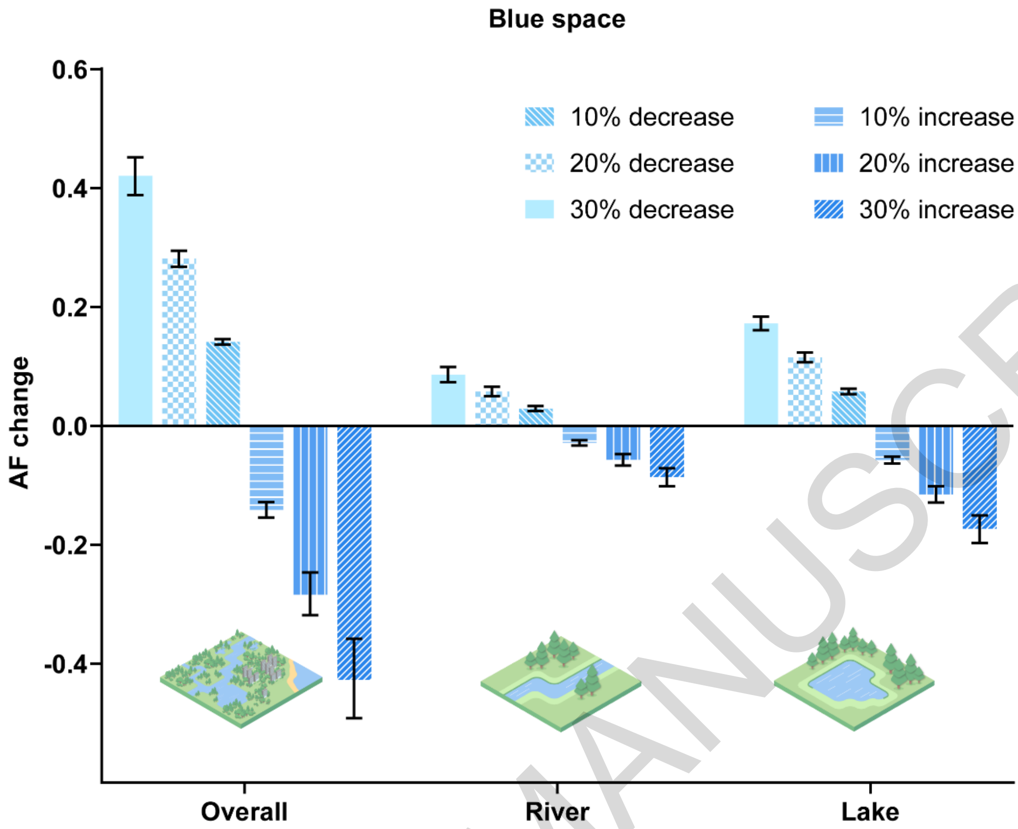

Figure 5. Changes in the absolute value of attributable fraction (AF, %) and their 95% empirical confidence intervals (95% eCIs) of mortality to high temperature above the minimum mortality temperature (MMT) under different blue space scenarios: 10%, 20%, and 30% increase and decrease of blue space exposure index compared to the current blue space exposure index by blue space types (i.e., overall blue spaces, rivers, and lakes) in 1,085 sub-districts in Zhejiang Province, China. Corresponding numeric data was provided in supplementary materials Table S9.

Note: The empirical confidence intervals (95% eCIs) of AF were obtained by Monte Carlo simulations, assuming a multivariate normal distribution for the estimated spline model coefficients. The baseline GBS exposure indices originated from the year 2020.

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