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SUPPLEMENTARY INFORMATION

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Heat exposure and global air conditioning

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Supplementary Information
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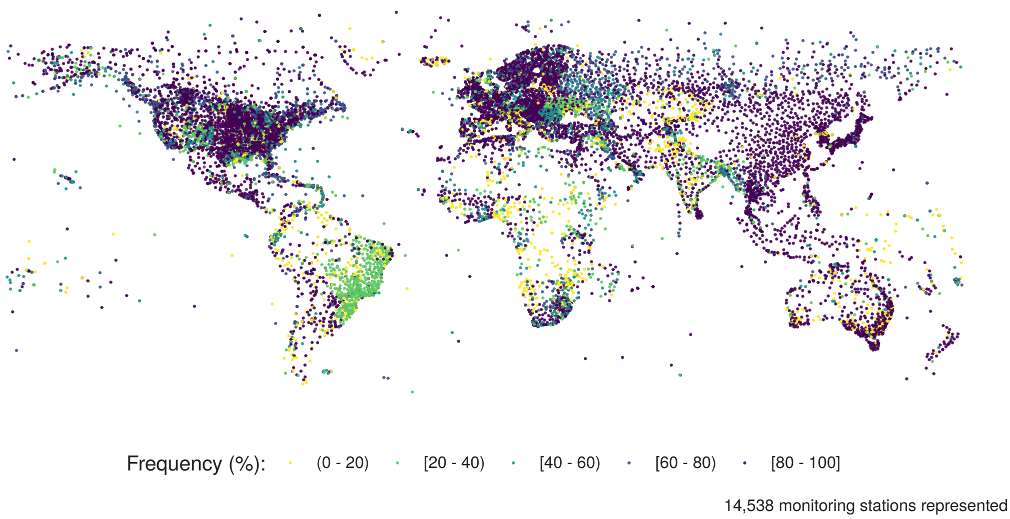
1 Supplementary Methods

In this appendix, we provide a detailed description of all data sources and methodologies. Our calculations proceed in several steps. First, we use weather data 2009-2018 to construct cooling degree days (CDDs) using 14,500+ temperature monitoring stations around the world. Second, we merge this information with gridded global population estimates at the 5km by 5km level. Third, we combine this merged dataset with data on the geographic boundaries of the world's countries, along with UN population estimates for cities around the world to calculate population-weighted measures at the region, country, and city-level.

1.1 Weather Data

We collected weather information from the U.S. National Climatic Data Center (NCDC) "Global Summary of the Day" database. These data describe daily weather data recorded at 14,500+ monitoring stations around the world. Stations typically report daily mean, minimum, and maximum temperature, as well as relative humidity, precipitation, and wind speed. For our analysis we use daily mean temperature only.

We base all of our calculations on data from 2009-2018. Our selection of this time period reflects several objectives. We wanted to use recent data because global mean temperatures are increasing, so older data are less comparable. At the same time, we also wanted to include an entire decade of data to reduce the impact of idiosyncratic year-to-year variation.



Supplementary Figure 1: Reporting Frequencies for Monitoring Stations

The geographical breakdown of the monitoring stations is shown in Figure 1. Overall the dataset offers a rich coverage of the world. While 14,538 stations record at least once over the period, the number of stations recording on any given day is systematically lower. Recording frequency is also shown in Figure 1. While the great majority of stations in Brazil report between 20% and 40% of the days in 2009-2018, the stations in India, China, and South-East Asia tend to report more than 80% of the time over the entire period. More generally, half the 14,538 stations report at least 92% of the time while the typical station reports 73% of the time.

We take several steps to minimize any impact that missing weather data might have on our estimates. Most importantly, our approach for measuring temperature at individual locations takes advantage of all stations for which there is non-missing data. In particular, when data are not available for a given station, the approach incorporates information from stations farther away. While stations farther away are not a perfect substitute, this approach allows us to impute temperatures for all days in the sample, avoiding introducing compositional changes in the sample.

As we discuss in the paper, we measure total CDD exposure using cooling degree days (CDDs), a widely-used measure of cooling demand calculated as the sum of daily mean temperatures above 18.3°C (65°F). This particular threshold, 18.3°C, has been widely used in previous studies (see, e.g. Sailor and Muñoz, 1997; Shorr et al., 2009; Alberini and Filippini, 2011; Petri and Caldeira, 2015), with at least one other study using a very similar 18.0°C threshold (Baumert and Selman, 2003).

After calculating CDDs for each day, we sum across all days in the calendar year to calculate annual CDDs. The annual measure thus reflects both the number of days with hot weather and the intensity of heat on those days. We exclude ocean-based measures to avoid any possible biases from ships and buoys (Karl et al., 2015).

1.2 Population Data

We collected population data from the *Gridded Population of the World* (GPW) project at Columbia University's *Center for International Earth Science Information Network* (CIESIN). We are using data from the fourth version (GPWv4) which provides global population estimates at approximately the 1km by 1km level for 2000, 2005, 2010, 2015, and 2020. See `http://sedac.ciesin.columbia.edu/data/collection/gpw-v4` for details. Our calculations are based on the estimates for 2015.

The GPW estimates are based on population censuses that were performed around the world between 2005 and 2014. The GPW estimates are created using the most detailed geographic units available in each census. For most countries, this means population measures at the city- or municipality- level. The GPW estimates assume a uniform distribution of population within geographic units when mapping population to the 1 km grid. Finally the GPW estimates incorporate population projections from the United Nations' *World Population Prospects*, to project the global distribution of population in 2015.

The advantage of the GPW estimates is that they provide high-quality measures of where people live within each country. This doesn't matter much for small countries, but it matters a great deal for many of the countries with the largest total CDD exposure. CDDs vary massively within India, for example, from the relatively cool Northern mountainous areas to the blistering hot Southern areas.

We aggregate these data to a 5km by 5km grid, which reduces the total number of cells from 780 million to a more manageable 30 million. This is still computationally burdensome but we prefer not to further aggregate the data because of within-cell climate variation.

1.3 Imputing Temperatures for Global Grid

We impute daily average temperatures for our 5km by 5km grid of the world using inverse distance weighting. In particular, we weigh temperature observations from nearby temperature monitoring stations using $1/d^2$ where d is the distance between the monitoring station and the cell centroid. With inverse distance weighting, the weight given to data points decreases with distance.[1] Inverse distance weighting with weights equal to the inverse of squared distance has been widely used in the academic literature (see, e.g., Deschênes and Greenstone, 2011).

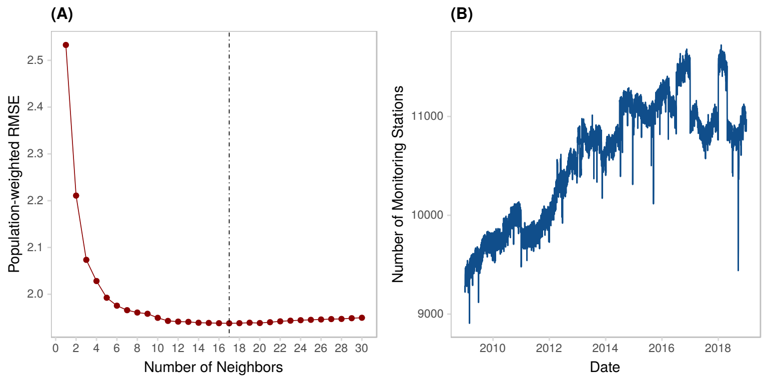
In addition to selecting this weighting function, we must decide how many nearby monitoring stations to use. The closest stations have the most information content and as one moves to more distant stations they have less information content and more noise. To determine the optimal number of nearby monitoring stations to include, we run a simulation on the 14,538 monitoring stations available in our sample. We use the following steps.

1. We randomly select with replacement 100,000 days from the 3,641 days available over the period 2009 to 2018.
2. For each day, we randomly select a monitoring station, hide its temperature report and extract from GPW the population living in the 5km by 5km cell the station is located in.
3. We interpolate the temperature for that station using a number of neighbors that varies from 1 to 30. For each of these 30 we record the difference between the prediction and the temperature that was actually recorded by that station.
4. We select the number of neighbors that minimizes the population-weighted root mean squared error (RMSE) over the 100,000 station-days of the simulation.

That is, this procedure allows us to determine how many nearby monitoring stations is optimal from the perspective of minimizing RMSE. The results of the simulation

[1] For example, consider the case in which there are two stations, one 2 kilometers away and another 4 kilometers away. In this case, 80% of the weight is put on the nearest station, with only 20% on the farther away station.

described above can be seen in the Panel **(A)** of Figure 2. The population-weighted RMSE decreases substantially when the first few neighbors are added, only to stabilize slightly below 2 °C for n = 10 and beyond. RMSE is minimized for n = 17, so we use the nearest 17 monitoring stations for all calculations. Panel **(B)** of Figure 2 shows the number of stations recording on each day over the period 2009-2018.



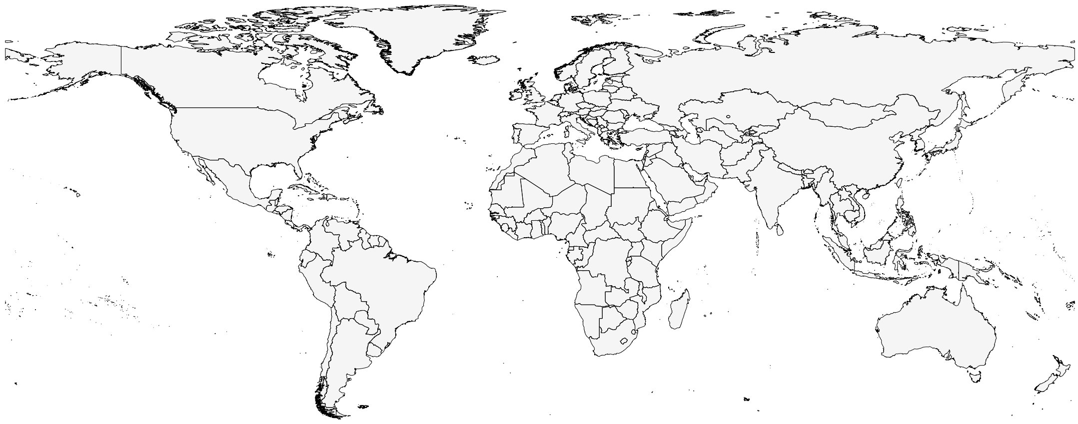
Supplementary Figure 2: **(A)**: Simulation results showing that the optimal number of neighboring stations to use for the inverse distance interpolation is n = 17. **(B)**: Number of monitoring stations recording each day from 2009 to 2018. 10,580 stations report each day on average.

Imputing temperatures for 30,000,000+ cells using the 17 closest monitoring stations for each of 3,641 days is a daunting computational task. In order to significantly speed up the nearest-neighbor search, we rely on a *k-dimensional tree* (k-d tree), a space-partitioning data structure for organizing points in a k-dimensional space. In the case of a nearest-neighbor search, the algorithm seeks the point in the tree that is closest to the given input location. Doing so allows the search for randomly distributed points to be performed in $\mathcal{O}(\log n)$ time by using the tree properties to eliminate large irrelevant portions of the search space. Since the available k-d tree packages available in R use Euclidean distances to build the binary tree, we convert the WGS84 coordinates of our stations and the cells of our empty grid of the world to "Earth-Centered, Earth-Fixed" (ECEF) coordinates. ECEF is a geographic coordinate system that also stands as a Cartesian coordinate system. It represents positions (in meters) as X, Y, and Z coordinates. Using ECEF coordinates allows Euclidean distances in that plane to mimic great circle distances, i.e. accounting for the fact the Earth's surface is curved. Conversion from WGS84 coordinates to ECEF coordinates is done using standard formulas.

1.4 Geographic Boundaries

To calculate daily cooling degrees for each cell, we take the difference between daily mean temperature and 18.3°C, or zero, whichever is greater. Thus, a day with average temperature of 15°C has zero cooling degrees whereas a day with average temperature of 28.3°C has 10 cooling degrees. This particular threshold, 18.3°C (65°F) has been widely used in previous studies including Baumert and Selman (2003). After calculating CDDs for each day, we sum across all days in the calendar year to calculate annual CDDs, and average across the ten years in our data.

These calculations yield annual average CDDs for a 5km by 5km grid of the global landmass. These estimates are plotted in Figure 1. We next calculate population-weighted average CDDs at the region- and country-level. This requires us to categorize cells by region and country. We collected the 1:10m "Cultural Vectors" shapefile (Figure 3) from *Natural Earth* `http://www.naturalearthdata.com/`, a public domain map dataset supported by the *North American Cartographic Information Society*.



Supplementary Figure 3: *Natural Earth*'s 1:10m Cultural Vectors shapefile cropped at 85.0°N and 60.0°S.

This shapefile tells us the region and country corresponding to each 5km by 5km cell. We then calculate population-weighted CDDs by region and country by taking a weighted average of all cells in each region and country, using GPW populations as weights.[2] Finally for cities we use imputed CDDs for the 5km by 5km cell corresponding to the city centroid as reported by United Nations (2014). Then we multiply CDDs by the

[2]As a check on our results, we also take a sum of the weights to compare the implied country-level populations to country populations in United Nations (2017). Overall, the population estimates are extremely close except for a few countries with highly irregular coastlines (e.g. Philippines, Aruba, French Polynesia). To avoid any ambiguity we use population county from United Nations (2017) in Table 1 of the paper and throughout the paper for our country-level calculations of total CDD exposure, though results using populations measured using GPW data are essentially identical.

population for each "urban agglomeration" from (United Nations, 2014) for our measures of total CDD exposure by city.

1.5 U.S. Data on Air Conditioning Use

We report in the paper that air conditioning in the United States uses 400 terawatt-hours of electricity annually, representing 17% of total residential electricity consumption and 12% of total commercial electricity consumption. The 400 terawatt-hours comes from the U.S. Department of Energy and reflects total residential and commercial electricity consumption for space cooling.[3] The 17% and 12% shares are then calculated by dividing by total delivered electricity in each sector.[4] It is also worth noting that in the United States, 87% and 80% of residential and non-residential buildings have air conditioning, respectively.[5]

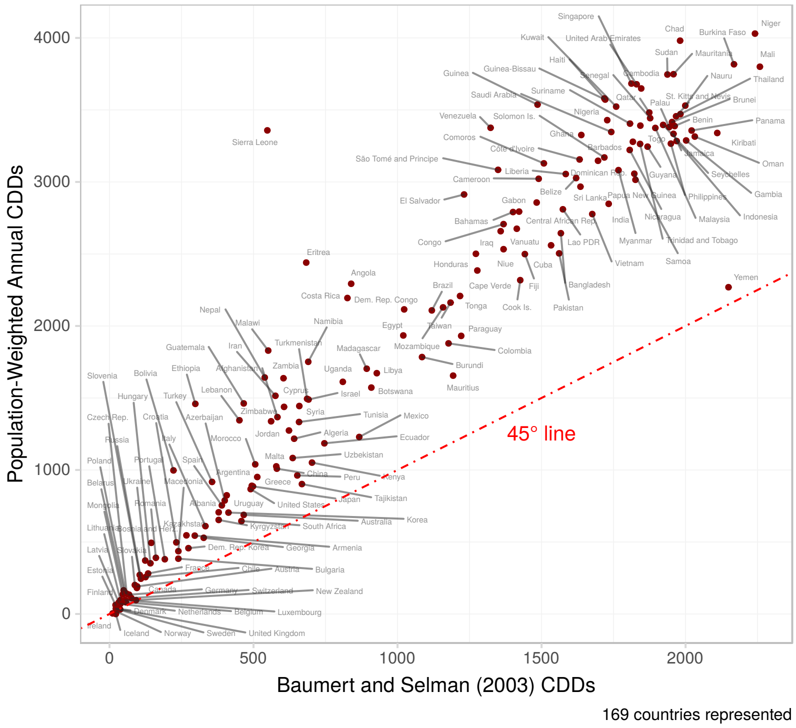
2 Supplementary Discussion

2.1 Region Rankings

Supplementary Table 1: Total CDD Exposure By Region

	Region	Population (in millions)	Share of World Population	Total CDD Exposure (in billions)	Share of Global Total CDD Exposure
1.	South Asia	1,744	23.8%	4,785.3	35.5%
2.	East Asia & Pacific	2,309	31.6%	3,730.7	27.7%
3.	Sub-Saharan Africa	952	13.0%	2,352.8	17.5%
4.	Latin America & Caribbean	631	8.6%	1,148.5	8.5%
5.	Middle East & North Africa	425	5.8%	812.9	6.0%
6.	Europe & Central Asia	901	12.3%	358.3	2.7%
7.	North America	356	4.9%	284.0	2.1%

Notes: This table ranks regions by total CDD exposure. We use the World Bank classification of regions. Populations are aggregated from country-level populations from United Nations (2017). Total CDD exposure is defined as in Table 1.



Supplementary Figure 4: Comparing Our Estimates to Previous Estimates

2.2 Comparing Our Results to Previous Estimates

Figure 4 compares our CDD estimates to the estimates from the World Resources Report (Baumert and Selman, 2003). Virtually all countries are above the 45 degree line (in red), reflecting the global warming that has occurred during the period between which the two datasets were constructed. According to NOAA, the ten hottest years in recorded history globally all have occurred since 1991, so incorporating recent temperature data is crucial.

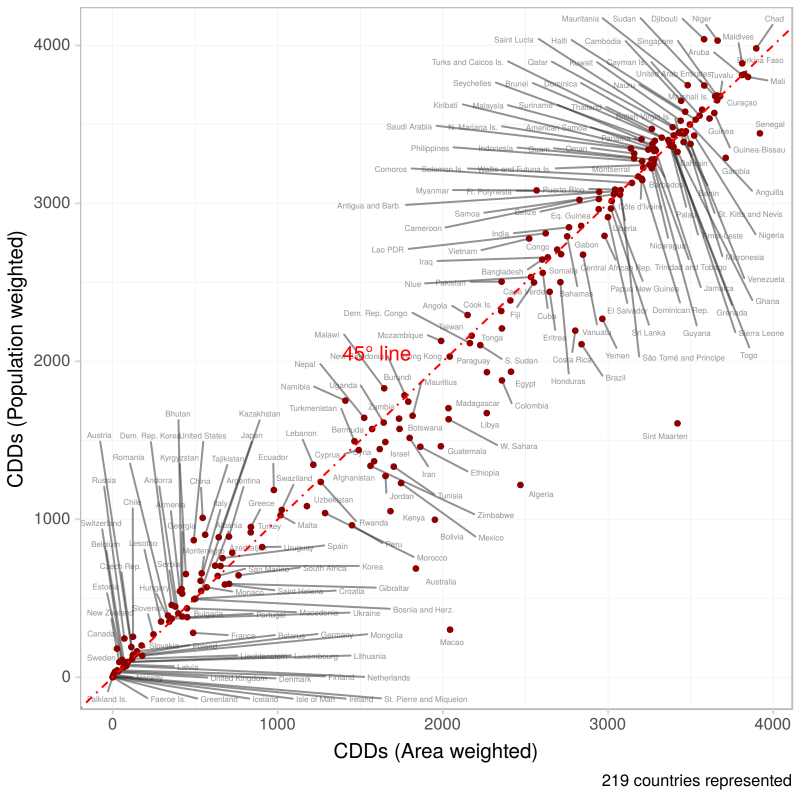
[3] DOE, 2016, Table A4 "Residential Sector Key Indicators and Consumption" and Table A5 "Commercial Sector Key Indicators and Consumption," reports that U.S. households and firms in 2015 used 0.80 and 0.55 quadrillion Btu of electricity for space cooling, respectively. The vast majority of this energy use is for air conditioning, though this also includes electric fans, evaporative coolers, and heat pumps. Each quadrillion Btu is equivalent to 293.1 terawatt-hours (293.1 million megawatt-hours).

[4] Table A4 "Residential Sector Key Indicators and Consumption" and Table A5 "Commercial Sector Key Indicators and Consumption," report that total delivered electricity in 2015 in these two sectors was 4.78 and 4.64 quadrillion Btu, respectively.

[5] DOE, *Residential Energy Consumption Survey (RECS) 2015*, Table HC7.1 "Air Conditioning in U.S. Homes," Released February 2017. DOE, *Commercial Buildings Energy Consumption Survey (CBECS) 2012*, Table B30 "Cooling Energy Sources, Number of Buildings and Floorspace," released May 2016.

2.3 Does Population Weighting Matter?

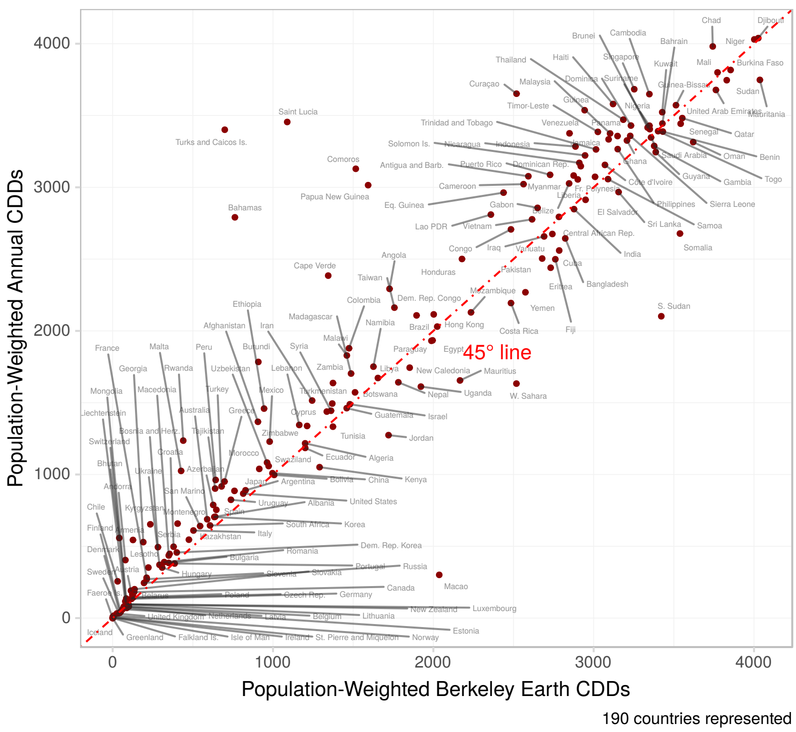
Our CDD estimates are population weighted and thus reflect where people live in each country. An alternative would be to weigh all areas equally. Figure 5 compares these two measures. Deviations between the two measures are relatively small overall, but illustrate the importance of population weighting. For small countries the two measures are essentially identical and, indeed, countries like Hong Kong, Singapore, and Kuwait are right on the 45°-line (in red). For larger countries, however, the population-weighting clearly matters. Brazil, Australia, and Algeria, for example, are well below the 45°-line, showing that people tend to live in relatively cooler areas of these countries. China, Myanmar, and Djibouti, in contrast, are above the 45°-line, meaning that people tend to live in relatively warmer parts of these countries. Overall, there are many more countries below the line than above the line, potentially reflecting a tendency of people to sort into relatively cooler areas. Migration patterns can change over time, however, and, for example, some historians have argued that air conditioning has facilitated migration toward the American South (Arsenault, 1984).



Supplementary Figure 5: Does Population-Weighting Matter?

2.4 Cross-validation

Berkeley Earth offers gridded daily temperature estimates at the 1° by 1° Latitude-Longitude level[6]. We use the estimates for the latest decade available to construct an alternative set of CDDs, which we then weight by population. Figure 6 shows that for the vast majority of countries the two measures are essentially identical, lying very close to the 45 degree line. And, in the few cases where the measures meaningfully differ, they tend to be small island countries (e.g. Turks and Caicos, Saint Lucia, Bahamas), for which Berkeley Earth's 1° by 1° resolution is particularly coarse.



Supplementary Figure 6: Comparing our estimates to estimates derived from *Berkeley Earth* daily temperature data.

2.5 Confidence Intervals

A novel feature of our analysis is that we also report 95% confidence intervals for all estimates. Our analysis does not rely on survey information or other data derived from an explicit sampling of the population. Instead, the sense in which our estimates are a sample is that temperature is observed only for a sample of all possible locations. Even

[6]See See `http://berkeleyearth.org/data/` for details.

with 14,538 total temperature monitoring stations, there are large areas of the planet far from a monitoring station, as well as stations that fail to report temperature data on some days.

We use a bootstrap simulation to assess how much this incomplete coverage matters. First, we use our data to construct 50 bootstrap samples. For each bootstrap sample, we draw with replacement a sample of 14,538 monitoring stations. These bootstrap samples are different from the original sample with different numbers of duplicates of various stations as well as omissions of stations.[7]

Second, we calculate all of our estimates for each bootstrap sample. For example, we calculate population-weighted annual cooling degrees in India for each bootstrap sample. At the end of this, we thus have a different estimate of population-weighted annual cooling degrees in India for each bootstrap sample, in addition to the estimate from the original dataset.

Third, we calculate the standard deviation for these 50 estimates. This standard deviation is our standard error, and we use this to calculate 95% confidence intervals. These confidence intervals reflect the sensitivity of our results to including or excluding particular stations. For parts of the world with large numbers of monitoring stations, this is like having a large sample size and the estimates don't tend to vary much across bootstrap samples. However, for parts of the world with sparse coverage, the estimates can vary significantly depending on which particular stations are included, and this gets reflected in wider confidence intervals.

[7] It is worth clarifying one subtle issue. Because we are sampling with replacement, we have duplicate monitoring stations in all bootstrap samples. In using inverse distance weighting to impute average temperatures for the 5km by 5km grid, we do not drop these duplicates. We include these duplicate measures as if they were coming from multiple stations all the same distance from a given cell.

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Supplementary Table 2: Total CDD exposure for the Top 50 Countries

	Country	Population-Weighted Annual Cooling Degree Days	95% Confidence Interval	Total CDD Exposure (in billions)	95% Confidence Interval
1.	India	2,848	[2,762, 2,934]	3728.2	[3615.6, 3840.8]
2.	China	1,009	[970, 1,048]	1409.6	[1355.1, 1464.1]
3.	Indonesia	3,284	[3,096, 3,472]	847.8	[799.3, 896.3]
4.	Nigeria	3,429	[3,311, 3,547]	621.3	[599.9, 642.7]
5.	Pakistan	2,504	[2,316, 2,692]	474.2	[438.6, 509.8]
6.	Brazil	2,108	[2,026, 2,190]	434.2	[417.3, 451.1]
7.	Bangladesh	2,644	[2,494, 2,794]	426.2	[402, 450.4]
8.	Philippines	3,266	[3,101, 3,431]	332.2	[315.4, 349]
9.	United States	867	[857, 877]	277.4	[274.2, 280.6]
10.	Vietnam	2,777	[2,654, 2,900]	259.8	[248.3, 271.4]
11.	Thailand	3,471	[3,417, 3,525]	238.3	[234.6, 242]
12.	Egypt	1,934	[1,778, 2,090]	181.4	[166.7, 196]
13.	Myanmar	3,082	[2,915, 3,249]	161.5	[152.8, 170.3]
14.	Dem. Rep. Congo	2,115	[1,938, 2,292]	161.2	[147.7, 174.6]
15.	Mexico	1,229	[1,097, 1,361]	154.7	[138.1, 171.3]
16.	Ethiopia	1,459	[889, 2,029]	145.7	[88.8, 202.6]
17.	Sudan	3,746	[3,209, 4,283]	144.8	[124, 165.5]
18.	Iran	1,515	[1,410, 1,620]	120.2	[111.9, 128.6]
19.	Japan	886	[834, 938]	113.4	[106.7, 120]
20.	Saudi Arabia	3,347	[3,037, 3,657]	105.6	[95.8, 115.4]
21.	Venezuela	3,376	[3,221, 3,531]	105.2	[100.4, 110]
22.	Malaysia	3,375	[3,265, 3,485]	103.7	[100.3, 107.1]
23.	Iraq	2,658	[2,520, 2,796]	96.0	[91, 101]
24.	Ghana	3,326	[3,238, 3,414]	91.7	[89.3, 94.2]
25.	Colombia	1,879	[1,176, 2,582]	90.6	[56.7, 124.5]
26.	Niger	4,030	[3,881, 4,179]	80.2	[77.2, 83.1]
27.	Côte d'Ivoire	3,156	[3,072, 3,240]	72.9	[71, 74.9]
28.	Turkey	917	[868, 966]	71.8	[67.9, 75.6]
29.	Burkina Faso	3,817	[3,734, 3,900]	69.1	[67.6, 70.6]
30.	Cameroon	3,022	[2,664, 3,380]	69.0	[60.8, 77.2]
31.	Mali	3,800	[3,678, 3,922]	66.4	[64.2, 68.5]
32.	Uganda	1,612	[1,309, 1,915]	64.7	[52.5, 76.9]
33.	Angola	2,293	[2,133, 2,453]	63.9	[59.4, 68.3]
34.	Sri Lanka	2,967	[2,216, 3,718]	61.5	[45.9, 77]
35.	Yemen	2,269	[1,523, 3,015]	61.1	[41, 81.2]
36.	Mozambique	2,129	[1,951, 2,307]	59.6	[54.6, 64.6]
37.	Cambodia	3,649	[3,389, 3,909]	56.6	[52.6, 60.7]
38.	Chad	3,981	[3,750, 4,212]	55.8	[52.5, 59]
39.	Senegal	3,443	[3,131, 3,755]	51.6	[46.9, 56.2]
40.	Taiwan	2,162	[1,984, 2,340]	50.8	[46.6, 55]
41.	Kenya	1,051	[786, 1,316]	49.6	[37.1, 62.2]
42.	Algeria	1,217	[1,108, 1,326]	48.5	[44.2, 52.9]
43.	Nepal	1,642	[1,162, 2,122]	47.1	[33.3, 60.8]
44.	Afghanistan	1,367	[1,194, 1,540]	46.1	[40.3, 52]
45.	Guinea	3,537	[3,368, 3,706]	42.8	[40.7, 44.8]
46.	Madagascar	1,703	[928, 2,478]	41.3	[22.5, 60.1]
47.	Argentina	890	[843, 937]	38.6	[36.6, 40.7]
48.	Haiti	3,580	[3,126, 4,034]	38.3	[33.5, 43.2]
49.	Somalia	2,678	[2,177, 3,179]	37.2	[30.3, 44.2]
50.	Italy	610	[546, 674]	36.3	[32.5, 40.1]

Notes: This table ranks the top 50 countries worldwide by total CDD exposure. Annual cooling degree days (CDD) and CDD exposure are defined as in Table 1.

Supplementary Table 3: Total CDD exposure for Countries Ranked 51 to 100

	Country	Population-Weighted Annual Cooling Degree Days	95% Confidence Interval	Total CDD Exposure (in billions)	95% Confidence Interval
51.	Morocco	1,039	[888, 1,190]	36.2	[30.9, 41.4]
52.	Benin	3,388	[3,268, 3,508]	35.8	[34.6, 37.1]
53.	South Africa	645	[598, 692]	35.7	[33.1, 38.3]
54.	Korea	704	[673, 735]	35.6	[34, 37.2]
55.	Russia	245	[237, 253]	35.3	[34.1, 36.4]
56.	Spain	754	[697, 811]	35.0	[32.3, 37.6]
57.	United Arab Emirates	3,678	[3,512, 3,844]	33.7	[32.1, 35.2]
58.	Uzbekistan	1,083	[960, 1,206]	33.5	[29.7, 37.4]
59.	Dominican Rep.	3,147	[2,915, 3,379]	33.1	[30.7, 35.6]
60.	Malawi	1,829	[1,425, 2,233]	32.1	[25, 39.2]
61.	Peru	962	[572, 1,352]	30.2	[17.9, 42.4]
62.	Cuba	2,560	[2,424, 2,696]	29.3	[27.8, 30.9]
63.	Syria	1,444	[1,350, 1,538]	27.1	[25.3, 28.8]
64.	Zambia	1,637	[1,327, 1,947]	26.4	[21.4, 31.3]
65.	Togo	3,391	[3,322, 3,460]	25.2	[24.6, 25.7]
66.	S. Sudan	2,102	[1,577, 2,627]	25.0	[18.7, 31.2]
67.	Sierra Leone	3,358	[3,200, 3,516]	24.3	[23.2, 25.4]
68.	Papua New Guinea	3,015	[2,688, 3,342]	23.9	[21.3, 26.5]
69.	Guatemala	1,462	[640, 2,284]	23.8	[10.4, 37.1]
70.	Honduras	2,501	[1,861, 3,141]	22.4	[16.7, 28.1]
71.	Zimbabwe	1,338	[1,060, 1,616]	21.1	[16.7, 25.5]
72.	Singapore	3,683	[3,578, 3,788]	20.4	[19.8, 21]
73.	Nicaragua	3,222	[2,746, 3,698]	19.6	[16.7, 22.5]
74.	Ecuador	1,185	[615, 1,755]	19.1	[9.9, 28.3]
75.	Lao PDR	2,810	[2,676, 2,944]	18.7	[17.8, 19.6]
76.	El Salvador	2,913	[2,522, 3,304]	18.4	[15.9, 20.9]
77.	Burundi	1,784	[1,250, 2,318]	18.2	[12.7, 23.6]
78.	France	281	[268, 294]	18.1	[17.3, 19]
79.	Ukraine	371	[361, 381]	16.6	[16.1, 17]
80.	Australia	688	[666, 710]	16.4	[15.9, 16.9]
81.	Mauritania	3,748	[3,358, 4,138]	15.7	[14, 17.3]
82.	Tunisia	1,333	[1,245, 1,421]	15.0	[14, 16]
83.	Hong Kong	2,030	[2,019, 2,041]	14.7	[14.6, 14.8]
84.	Rwanda	1,236	[940, 1,532]	14.4	[10.9, 17.8]
85.	Oman	3,315	[2,687, 3,943]	13.9	[11.3, 16.6]
86.	Kuwait	3,523	[3,461, 3,585]	13.9	[13.6, 14.1]
87.	Liberia	3,055	[2,952, 3,158]	13.7	[13.3, 14.2]
88.	Congo	2,707	[2,587, 2,827]	13.5	[12.9, 14.1]
89.	Panama	3,357	[2,944, 3,770]	13.3	[11.7, 15]
90.	Paraguay	1,931	[1,829, 2,033]	12.8	[12.1, 13.5]
91.	Central African Rep.	2,794	[2,528, 3,060]	12.7	[11.5, 13.9]
92.	Israel	1,489	[1,253, 1,725]	12.0	[10.1, 13.9]
93.	Eritrea	2,440	[1,958, 2,922]	11.8	[9.5, 14.2]
94.	Jordan	1,274	[1,079, 1,469]	11.7	[9.9, 13.5]
95.	Dem. Rep. Korea	457	[417, 497]	11.5	[10.5, 12.5]
96.	Puerto Rico	3,087	[3,000, 3,174]	11.3	[11, 11.7]
97.	Germany	134	[123, 145]	10.9	[10.1, 11.8]
98.	Bolivia	997	[534, 1,460]	10.7	[5.7, 15.7]
99.	Greece	951	[872, 1,030]	10.7	[9.8, 11.6]
100.	Costa Rica	2,194	[1,237, 3,151]	10.5	[5.9, 15.2]

Notes: This table shows countries ranked 51 to 100 worldwide by total CDD exposure. Annual cooling degree days (CDD) and CDD exposure are defined as in Table 1.

Supplementary Table 4: Total CDD exposure for Countries Ranked 101 to 150

	Country	Population-Weighted Annual Cooling Degree Days	95% Confidence Interval	Total CDD Exposure (in billions)	95% Confidence Interval
101.	Libya	1,672	[1,548, 1,796]	10.4	[9.7, 11.2]
102.	Kazakhstan	546	[510, 582]	9.7	[9.1, 10.3]
103.	Jamaica	3,334	[2,895, 3,773]	9.6	[8.3, 10.8]
104.	Qatar	3,482	[3,299, 3,665]	8.6	[8.2, 9.1]
105.	Turkmenistan	1,494	[1,392, 1,596]	8.3	[7.7, 8.9]
106.	Lebanon	1,345	[742, 1,948]	7.9	[4.3, 11.4]
107.	Romania	390	[347, 433]	7.8	[6.9, 8.6]
108.	Tajikistan	902	[713, 1,091]	7.7	[6.1, 9.3]
109.	Azerbaijan	788	[688, 888]	7.6	[6.6, 8.5]
110.	Canada	181	[168, 194]	6.5	[6, 7]
111.	Gambia	3,288	[2,192, 4,384]	6.5	[4.3, 8.7]
112.	Guinea-Bissau	3,572	[3,381, 3,763]	6.3	[6, 6.7]
113.	Poland	145	[132, 158]	5.5	[5.1, 6]
114.	Gabon	2,857	[2,768, 2,946]	5.5	[5.3, 5.7]
115.	Bahrain	3,444	[3,421, 3,467]	4.7	[4.7, 4.8]
116.	Chile	256	[186, 326]	4.5	[3.3, 5.8]
117.	Trinidad and Tobago	3,264	[3,119, 3,409]	4.4	[4.2, 4.6]
118.	Namibia	1,751	[1,512, 1,990]	4.2	[3.7, 4.8]
119.	Timor-Leste	3,386	[3,254, 3,518]	4.2	[4, 4.4]
120.	Portugal	380	[308, 452]	4.0	[3.2, 4.7]
121.	Serbia	447	[414, 480]	4.0	[3.7, 4.2]
122.	Kyrgyzstan	653	[582, 724]	3.8	[3.4, 4.2]
123.	Djibouti	4,039	[2,404, 5,674]	3.7	[2.2, 5.3]
124.	Eq. Guinea	2,963	[2,842, 3,084]	3.5	[3.3, 3.6]
125.	Botswana	1,572	[1,482, 1,662]	3.5	[3.3, 3.7]
126.	Hungary	352	[320, 384]	3.4	[3.1, 3.8]
127.	Uruguay	824	[689, 959]	2.8	[2.4, 3.3]
128.	Bulgaria	384	[289, 479]	2.8	[2.1, 3.4]
129.	Guyana	3,245	[2,408, 4,082]	2.5	[1.9, 3.1]
130.	Comoros	3,129	[2,959, 3,299]	2.4	[2.3, 2.6]
131.	Fiji	2,499	[1,815, 3,183]	2.2	[1.6, 2.8]
132.	Croatia	497	[443, 551]	2.1	[1.9, 2.3]
133.	United Kingdom	32	[27, 37]	2.1	[1.8, 2.4]
134.	Georgia	529	[390, 668]	2.1	[1.5, 2.6]
135.	Mauritius	1,655	[873, 2,437]	2.1	[1.1, 3.1]
136.	Albania	706	[615, 797]	2.1	[1.8, 2.3]
137.	Suriname	3,405	[2,904, 3,906]	1.9	[1.6, 2.2]
138.	Solomon Is.	3,170	[2,952, 3,388]	1.9	[1.7, 2]
139.	Bosnia and Herz.	494	[410, 578]	1.7	[1.4, 2]
140.	Cyprus	1,438	[1,386, 1,490]	1.7	[1.6, 1.7]
141.	Austria	191	[170, 212]	1.7	[1.5, 1.8]
142.	Maldives	3,886	[3,744, 4,028]	1.6	[1.6, 1.7]
143.	Armenia	544	[381, 707]	1.6	[1.1, 2.1]
144.	Belarus	164	[141, 187]	1.6	[1.3, 1.8]
145.	Czech Rep.	140	[122, 158]	1.5	[1.3, 1.7]
146.	Brunei	3,416	[3,274, 3,558]	1.4	[1.4, 1.5]
147.	Swaziland	1,059	[779, 1,339]	1.4	[1, 1.8]
148.	Cape Verde	2,385	[2,211, 2,559]	1.3	[1.2, 1.4]
149.	Netherlands	71	[65, 77]	1.2	[1.1, 1.3]
150.	Slovakia	201	[172, 230]	1.1	[0.9, 1.3]

Notes: This table shows countries ranked 101 to 150 worldwide by total CDD exposure. Annual cooling degree days (CDD) and CDD exposure are defined as in Table 1.

Supplementary Table 5: Total CDD exposure for the Top 50 Cities

	City	Annual Cooling Degree Days (CDDs)	95% Confidence Interval	Total CDD Exposure (in billions)	95% Confidence Interval
1.	Mumbai, India	3,544	[3,386, 3,702]	74.6	[71.3, 77.9]
2.	Delhi, India	2,831	[2,469, 3,193]	72.8	[63.5, 82.1]
3.	Dhaka, Bangladesh	2,955	[2,656, 3,254]	52.0	[46.7, 57.3]
4.	Karachi, Pakistan	3,108	[2,886, 3,330]	51.6	[48, 55.3]
5.	Manila, Philippines	3,572	[3,261, 3,883]	46.2	[42.2, 50.3]
6.	Kolkata, India	3,047	[2,728, 3,366]	45.3	[40.6, 50]
7.	Lagos, Nigeria	3,227	[3,082, 3,372]	42.3	[40.4, 44.3]
8.	Tokyo, Japan	1,040	[927, 1,153]	39.5	[35.2, 43.8]
9.	Jakarta, Indonesia	3,772	[3,402, 4,142]	38.9	[35.1, 42.8]
10.	Bangkok, Thailand	3,995	[3,746, 4,244]	37.0	[34.7, 39.3]
11.	Chennai, India	3,727	[3,594, 3,860]	36.9	[35.5, 38.2]
12.	Cairo, Egypt	1,941	[1,457, 2,425]	36.4	[27.4, 45.5]
13.	Kinshasa, Dem. Rep. Congo	2,699	[2,615, 2,783]	31.3	[30.3, 32.2]
14.	Shanghai, China	1,246	[988, 1,504]	29.6	[23.5, 35.7]
15.	Rio de Janeiro, Brazil	2,241	[2,159, 2,323]	28.9	[27.9, 30]
16.	Hyderabad, India	3,204	[3,146, 3,262]	28.7	[28.1, 29.2]
17.	Guangzhou, China	2,062	[1,853, 2,271]	25.7	[23.1, 28.3]
18.	Ahmadabad, India	3,478	[3,365, 3,591]	25.5	[24.7, 26.4]
19.	Thành Pho Ho Chí Minh, Vietnam	3,423	[3,284, 3,562]	25.0	[24, 26]
20.	São Paulo, Brazil	1,171	[942, 1,400]	24.7	[19.8, 29.5]
21.	Kuala Lumpur, Malaysia	3,492	[3,192, 3,792]	23.9	[21.8, 25.9]
22.	Lahore, Pakistan	2,687	[2,294, 3,080]	23.5	[20.1, 26.9]
23.	Al-Khartum, Sudan	4,569	[4,456, 4,682]	23.4	[22.9, 24]
24.	Kinki M.M.A., Japan	1,139	[1,037, 1,241]	23.1	[21, 25.1]
25.	Ar-Riyadh, Saudi Arabia	3,572	[3,507, 3,637]	22.8	[22.3, 23.2]
26.	Bangalore, India	2,171	[1,682, 2,660]	21.9	[17, 26.8]
27.	Shenzhen, China	1,996	[1,513, 2,479]	21.5	[16.3, 26.6]
28.	Singapore, Singapore	3,720	[3,508, 3,932]	20.9	[19.7, 22.1]
29.	Surat, India	3,306	[3,002, 3,610]	18.7	[17, 20.4]
30.	Baghdad, Iraq	2,772	[2,643, 2,901]	18.4	[17.6, 19.3]
31.	Beijing, China	807	[539, 1,075]	16.4	[11, 21.9]
32.	Yangon, Myanmar	3,419	[3,178, 3,660]	16.4	[15.3, 17.6]
33.	Chongqing, China	1,223	[990, 1,456]	16.3	[13.2, 19.4]
34.	Jiddah, Saudi Arabia	3,982	[3,868, 4,096]	16.2	[15.8, 16.7]
35.	Abidjan, Côte d'Ivoire	3,190	[3,072, 3,308]	15.5	[14.9, 16.1]
36.	Dongguan, China	2,036	[1,920, 2,152]	15.1	[14.3, 16]
37.	Dar es Salaam, Tanzania	2,956	[2,904, 3,008]	15.1	[14.9, 15.4]
38.	Hong Kong, Hong Kong	2,023	[1,986, 2,060]	14.8	[14.5, 15.1]
39.	Miami, USA	2,502	[2,426, 2,578]	14.6	[14.1, 15]
40.	Luanda, Angola	2,612	[2,530, 2,694]	14.4	[13.9, 14.8]
41.	Foshan, China	2,035	[1,987, 2,083]	14.3	[14, 14.7]
42.	Pune, India	2,358	[2,248, 2,468]	13.5	[12.9, 14.1]
43.	Chittagong, Bangladesh	2,951	[2,803, 3,099]	13.4	[12.7, 14.1]
44.	Tehran, Iran	1,566	[1,278, 1,854]	13.2	[10.8, 15.6]
45.	Buenos Aires, Argentina	826	[673, 979]	12.5	[10.2, 14.9]
46.	Fortaleza, Brazil	3,168	[3,106, 3,230]	12.3	[12.1, 12.5]
47.	Kano, Nigeria	3,419	[3,343, 3,495]	12.3	[12, 12.5]
48.	New York-Newark, USA	661	[484, 838]	12.3	[9, 15.6]
49.	Istanbul, Turkey	805	[485, 1,125]	11.4	[6.9, 15.9]
50.	Tianjin, China	991	[899, 1,083]	11.1	[10.1, 12.1]

Notes: This table ranks the top fifty cities worldwide by total CDD exposure. City populations are from United Nations (2014) and are for "urban agglomerations" as defined by the United Nations. Cooling degree days (CDD) and total CDD exposure are defined as in Table 2.

Supplementary Table 6: Total CDD exposure for Cities ranked 51 to 100

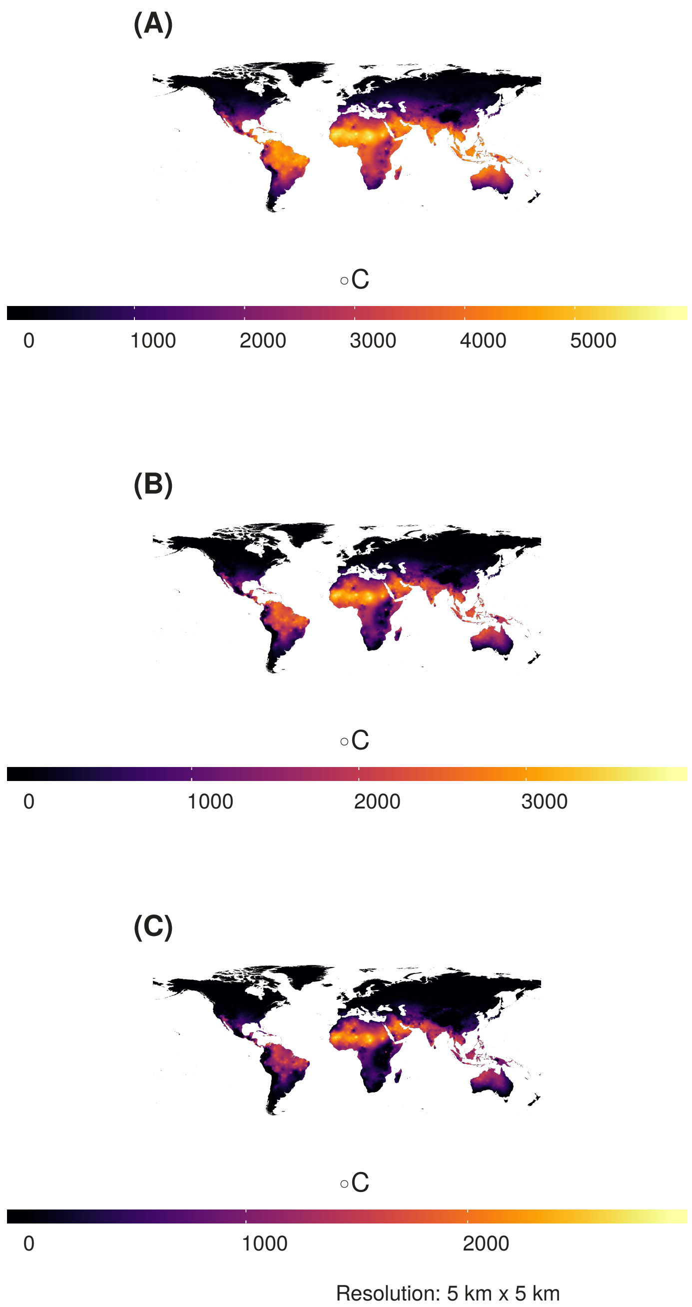
	City	Annual Cooling Degree Days (CDDs)	95% Confidence Interval	Total CDD Exposure (in billions)	95% Confidence Interval
51.	Recife, Brazil	2,952	[2,702, 3,202]	11.0	[10.1, 12]
52.	Phoenix-Mesa, USA	2,684	[2,588, 2,780]	10.9	[10.5, 11.3]
53.	Ouagadougou, Burkina Faso	3,847	[3,635, 4,059]	10.5	[10, 11.1]
54.	Ibadan, Nigeria	3,335	[3,198, 3,472]	10.5	[10.1, 11]
55.	Salvador, Brazil	2,906	[2,447, 3,365]	10.4	[8.8, 12.1]
56.	Surabaya, Indonesia	3,604	[3,374, 3,834]	10.3	[9.6, 10.9]
57.	Belo Horizonte, Brazil	1,789	[1,761, 1,817]	10.2	[10.1, 10.4]
58.	Houston, USA	1,818	[1,758, 1,878]	10.2	[9.9, 10.6]
59.	Jaipur, India	2,932	[2,900, 2,964]	10.1	[10, 10.3]
60.	Al Kuwayt, Kuwait	3,627	[3,543, 3,711]	10.1	[9.8, 10.3]
61.	Wuhan, China	1,261	[1,192, 1,330]	10.0	[9.4, 10.5]
62.	Chukyo M.M.A. (Nagoya), Japan	1,033	[940, 1,126]	9.7	[8.8, 10.6]
63.	Port-au-Prince, Haiti	3,954	[3,932, 3,976]	9.6	[9.6, 9.7]
64.	Monterrey, Mexico	2,102	[2,092, 2,112]	9.5	[9.4, 9.5]
65.	Caracas, Venezuela	3,247	[3,234, 3,260]	9.5	[9.4, 9.5]
66.	Dubayy (Dubai), United Arab Emirates	3,908	[3,899, 3,917]	9.4	[9.4, 9.5]
67.	Dallas-Fort Worth, USA	1,630	[1,597, 1,663]	9.3	[9.1, 9.5]
68.	Douala, Cameroon	3,143	[3,045, 3,241]	9.2	[9, 9.5]
69.	Santo Domingo, Dominican Republic	3,107	[3,003, 3,211]	9.2	[8.8, 9.5]
70.	Faisalabad, Pakistan	2,572	[1,893, 3,251]	9.2	[6.8, 11.6]
71.	Kozhikode, India	3,598	[2,449, 4,747]	8.9	[6.1, 11.8]
72.	Lucknow, India	2,765	[2,003, 3,527]	8.9	[6.5, 11.4]
73.	Nagpur, India	3,251	[2,678, 3,824]	8.7	[7.2, 10.2]
74.	Bamako, Mali	3,451	[3,250, 3,652]	8.7	[8.2, 9.2]
75.	Maracaibo, Venezuela	3,981	[3,436, 4,526]	8.7	[7.5, 9.9]
76.	Makkah, Saudi Arabia	4,804	[4,600, 5,008]	8.5	[8.1, 8.9]
77.	Kanpur, India	2,775	[2,206, 3,344]	8.4	[6.7, 10.1]
78.	Kochi, India	3,473	[3,226, 3,720]	8.4	[7.8, 9]
79.	Hà Noi, Vietnam	2,298	[1,951, 2,645]	8.3	[7.1, 9.6]
80.	Nanjing, Jiangsu, China	1,107	[463, 1,751]	8.2	[3.4, 12.9]
81.	Dakar, Senegal	2,334	[1,975, 2,693]	8.2	[7, 9.5]
82.	Kumasi, Ghana	3,120	[2,949, 3,291]	8.1	[7.7, 8.6]
83.	Abuja, Nigeria	3,310	[2,935, 3,685]	8.1	[7.2, 9]
84.	Hangzhou, China	1,246	[588, 1,904]	8.0	[3.8, 12.2]
85.	Coimbatore, India	3,130	[2,994, 3,266]	8.0	[7.6, 8.3]
86.	San Juan, Puerto Rico	3,243	[3,001, 3,485]	8.0	[7.4, 8.6]
87.	Thrissur, India	3,396	[2,840, 3,952]	7.9	[6.6, 9.2]
88.	Xiamen, China	1,757	[1,412, 2,102]	7.8	[6.3, 9.3]
89.	Lima, Peru	775	[616, 934]	7.7	[6.1, 9.2]
90.	Los Angeles, USA	624	[456, 792]	7.7	[5.6, 9.7]
91.	Zhongshan, China	2,060	[1,562, 2,558]	7.6	[5.8, 9.4]
92.	Guayaquil, Ecuador	2,791	[2,619, 2,963]	7.6	[7.1, 8]
93.	Accra, Ghana	3,319	[3,126, 3,512]	7.6	[7.1, 8]
94.	Malappuram, India	3,424	[2,805, 4,043]	7.6	[6.2, 9]
95.	Shantou, China	1,905	[1,729, 2,081]	7.5	[6.8, 8.2]
96.	Kannur, India	3,477	[2,966, 3,988]	7.5	[6.4, 8.6]
97.	Port Harcourt, Nigeria	3,177	[2,920, 3,434]	7.4	[6.8, 8]
98.	Seoul, Republic of Korea	755	[283, 1,227]	7.4	[2.8, 12]
99.	Medan, Indonesia	3,332	[3,051, 3,613]	7.3	[6.7, 8]
100.	Chengdu, China	926	[381, 1,471]	7.0	[2.9, 11.1]

Notes: Cooling degree days (CDD) and total CDD exposure are defined as in Table 2.

Supplementary Table 7: Total CDD exposure for Cities ranked 101 to 150

	City	Annual Cooling Degree Days (CDDs)	95% Confidence Interval	Total CDD Exposure (in billions)	95% Confidence Interval
101.	Barranquilla, Colombia	3,520	[3,135, 3,905]	7.0	[6.2, 7.8]
102.	Alexandria, Egypt	1,472	[1,031, 1,913]	7.0	[4.9, 9.1]
103.	Samut Prakan, Thailand	3,875	[3,711, 4,039]	7.0	[6.7, 7.3]
104.	Belém, Brazil	3,103	[2,971, 3,235]	6.8	[6.5, 7.1]
105.	Phnum Pénh, Cambodia	3,946	[3,630, 4,262]	6.8	[6.3, 7.4]
106.	Thiruvananthapuram, India	3,457	[2,984, 3,930]	6.8	[5.9, 7.7]
107.	Visakhapatnam, India	3,540	[3,238, 3,842]	6.8	[6.3, 7.4]
108.	Bandung, Indonesia	2,689	[2,415, 2,963]	6.8	[6.1, 7.5]
109.	Patna, India	2,991	[2,453, 3,529]	6.6	[5.4, 7.8]
110.	Manaus, Brazil	3,190	[2,798, 3,582]	6.5	[5.7, 7.3]
111.	Conakry, Guinea	3,340	[3,235, 3,445]	6.5	[6.3, 6.7]
112.	Indore, India	2,624	[2,306, 2,942]	6.4	[5.6, 7.2]
113.	Vadodara, India	3,220	[3,049, 3,391]	6.4	[6, 6.7]
114.	Suzhou, Jiangsu, China	1,152	[804, 1,500]	6.3	[4.4, 8.2]
115.	Vijayawada, India	3,560	[3,469, 3,651]	6.3	[6.1, 6.4]
116.	Yaoundé, Cameroon	2,033	[1,739, 2,327]	6.2	[5.3, 7.1]
117.	Nanning, China	1,884	[1,590, 2,178]	6.1	[5.1, 7]
118.	Madurai, India	3,743	[3,394, 4,092]	6.0	[5.4, 6.5]
119.	Multan, Pakistan	3,114	[2,746, 3,482]	6.0	[5.3, 6.7]
120.	Semarang, Indonesia	3,640	[3,507, 3,773]	5.9	[5.7, 6.1]
121.	Hyderabad, Pakistan	3,335	[3,055, 3,615]	5.9	[5.4, 6.4]
122.	Ciudad de Panamá, Panama	3,531	[3,401, 3,661]	5.9	[5.7, 6.1]
123.	Davao City, Philippines	3,634	[3,446, 3,822]	5.9	[5.6, 6.2]
124.	Kitakyushu-Fukuoka M.M.A., Japan	1,047	[795, 1,299]	5.8	[4.4, 7.2]
125.	Muqdisho, Somalia	2,709	[2,557, 2,861]	5.8	[5.5, 6.1]
126.	Agra, India	2,875	[2,497, 3,253]	5.7	[4.9, 6.4]
127.	Bhopal, India	2,700	[2,457, 2,943]	5.7	[5.2, 6.2]
128.	Valencia, Venezuela	3,263	[3,010, 3,516]	5.7	[5.2, 6.1]
129.	Brasília, Brazil	1,344	[700, 1,988]	5.6	[2.9, 8.3]
130.	Tel Aviv-Yafo, Israel	1,542	[1,270, 1,814]	5.6	[4.6, 6.5]
131.	Taipei, China	2,066	[1,856, 2,276]	5.5	[4.9, 6.1]
132.	Xi'an, China	903	[682, 1,124]	5.5	[4.1, 6.8]
133.	Madrid, Spain	891	[825, 957]	5.5	[5.1, 5.9]
134.	Santa Cruz, Bolivia	2,544	[2,356, 2,732]	5.4	[5, 5.8]
135.	Rajkot, India	3,330	[3,243, 3,417]	5.3	[5.2, 5.5]
136.	Halab, Syria	1,493	[707, 2,279]	5.3	[2.5, 8.1]
137.	Atlanta, USA	1,025	[527, 1,523]	5.3	[2.7, 7.8]
138.	Tampa-St. Petersburg, USA	2,012	[1,655, 2,369]	5.3	[4.4, 6.3]
139.	Cali, Colombia	1,972	[1,648, 2,296]	5.2	[4.4, 6.1]
140.	La Habana, Cuba	2,420	[2,126, 2,714]	5.2	[4.5, 5.8]
141.	Al-Madinah, Saudi Arabia	4,070	[3,834, 4,306]	5.2	[4.9, 5.5]
142.	Changsha, China	1,369	[1,033, 1,705]	5.1	[3.9, 6.4]
143.	Medellín, Colombia	1,303	[413, 2,193]	5.1	[1.6, 8.6]
144.	Brazzaville, Congo	2,699	[2,683, 2,715]	5.1	[5.1, 5.1]
145.	Makassar, Indonesia	3,445	[3,414, 3,476]	5.1	[5.1, 5.2]
146.	Rawalpindi, Pakistan	2,050	[2,021, 2,079]	5.1	[5.1, 5.2]
147.	N'Djaména, Chad	3,944	[3,897, 3,991]	5.0	[4.9, 5]
148.	Palembang, Indonesia	3,405	[3,316, 3,494]	5.0	[4.8, 5.1]
149.	Benin City, Nigeria	3,313	[3,270, 3,356]	5.0	[4.9, 5]
150.	Gujranwala, Pakistan	2,350	[2,299, 2,401]	5.0	[4.9, 5.1]

Notes: Cooling degree days (CDD) and total CDD exposure are defined as in Table 2.



Supplementary Figure 7: **(A)**: Global Cooling Degree Days using a 15.6°C (60°F) threshold. **(B)**: Global Cooling Degree Days using a 21.1°C (70°F) threshold. **(C)**: Global Cooling Degree Days using a 23.9°C (75°F) threshold.

Supplementary Table 8: Changes in the Country-level counts of Population-Weighted Cooling Degree Days under the Alternative CDD Thresholds

	Country Ranking using the 18.3°C threshold	Population-Weighted Annual CDDs (15.6°C threshold)	Change in CDDs count	Population-Weighted Annual CDDs (21.1°C threshold)	Change in CDDs count	Population-Weighted Annual CDDs (23.9°C threshold)	Change in CDDs count
1.	India	3,822	+974	2,035	-813	1,257	-1,591
2.	China	1,543	+534	607	-402	299	-710
3.	Indonesia	4,294	+1,010	2,273	-1,011	1,271	-2,013
4.	Nigeria	4,444	+1,015	2,426	-1,003	1,440	-1,989
5.	Pakistan	3,266	+762	1,829	-675	1,234	-1,270
6.	Brazil	3,055	+947	1,254	-854	575	-1,533
7.	Bangladesh	3,653	+1,009	1,827	-817	1,071	-1,573
8.	Philippines	4,290	+1,024	2,272	-994	1,274	-1,992
9.	United States	1,345	+478	492	-375	230	-637
10.	Vietnam	3,746	+969	1,892	-885	1,060	-1,717
11.	Thailand	4,496	+1,025	2,484	-987	1,511	-1,960
12.	Egypt	2,761	+827	1,317	-617	779	-1,155
13.	Myanmar	4,122	+1,040	2,154	-928	1,254	-1,828
14.	Dem. Rep. Congo	3,124	+1,009	1,128	-987	361	-1,754
15.	Mexico	1,998	+769	681	-548	331	-898
16.	Ethiopia	2,432	+973	662	-797	232	-1,227
17.	Sudan	4,733	+987	2,733	-1,013	1,812	-1,934
18.	Iran	2,108	+593	1,079	-436	683	-832
19.	Japan	1,381	+495	519	-367	253	-633
20.	Saudi Arabia	4,298	+951	2,556	-791	1,824	-1,523
21.	Venezuela	4,384	+1,008	2,369	-1,007	1,368	-2,008
22.	Malaysia	4,385	+1,010	2,363	-1,012	1,354	-2,021
23.	Iraq	3,347	+689	2,085	-573	1,560	-1,098
24.	Ghana	4,336	+1,010	2,314	-1,012	1,304	-2,022
25.	Colombia	2,777	+898	1,073	-806	484	-1,395
26.	Niger	5,096	+1,066	3,085	-945	2,128	-1,902
27.	Côte d'Ivoire	4,167	+1,011	2,144	-1,012	1,135	-2,021
28.	Turkey	1,397	+480	560	-357	283	-634
29.	Burkina Faso	4,828	+1,011	2,807	-1,010	1,806	-2,011
30.	Cameroon	4,035	+1,013	2,013	-1,009	1,051	-1,971
31.	Mali	4,809	+1,009	2,791	-1,009	1,805	-1,995
32.	Uganda	2,622	+1,010	667	-945	132	-1,480
33.	Angola	3,292	+999	1,329	-964	532	-1,761
34.	Sri Lanka	3,974	+1,007	1,973	-994	1,025	-1,942
35.	Yemen	3,417	+1,148	1,569	-700	880	-1,389
36.	Mozambique	3,111	+982	1,230	-899	522	-1,607
37.	Cambodia	4,660	+1,011	2,640	-1,009	1,636	-2,013
38.	Chad	5,066	+1,085	3,048	-933	2,059	-1,922
39.	Senegal	4,454	+1,011	2,441	-1,002	1,496	-1,947
40.	Taiwan	3,068	+906	1,417	-745	787	-1,375
41.	Kenya	2,010	+959	411	-640	142	-909
42.	Algeria	1,789	+572	787	-430	441	-776
43.	Nepal	2,430	+788	1,029	-613	509	-1,133
44.	Afghanistan	1,885	+518	896	-471	520	-847
45.	Guinea	4,547	+1,010	2,525	-1,012	1,517	-2,020
46.	Madagascar	2,648	+945	887	-816	324	-1,379
47.	Argentina	1,470	+580	457	-433	179	-711
48.	Haiti	4,590	+1,010	2,569	-1,011	1,560	-2,020
49.	Somalia	3,689	+1,011	1,669	-1,009	733	-1,945
50.	Italy	1,052	+442	327	-283	126	-484

Notes: Changes in the counts of Population-Weighted CDDs are all expressed relative to the counts computed using the 18.3°C threshold.

Supplementary Table 9: Changes in the Country-level ranking of total CDD exposure under the Alternative CDD Thresholds

	Ranking using the 15.6°C threshold	Rank change	Ranking using the 21.1°C threshold	Rank change	Ranking using the 23.9°C threshold	Rank change
1.	India	0	India	0	India	0
2.	China	0	China	0	China	0
3.	Indonesia	0	Indonesia	0	Indonesia	0
4.	Nigeria	0	Nigeria	0	Nigeria	0
5.	Brazil	+1	Pakistan	0	Pakistan	0
6.	Pakistan	-1	Bangladesh	+1	Bangladesh	+1
7.	Bangladesh	0	Brazil	-1	Philippines	+1
8.	Philippines	0	Philippines	0	Brazil	-2
9.	United States	0	Vietnam	+1	Thailand	+2
10.	Vietnam	0	Thailand	+1	Vietnam	0
11.	Thailand	0	United States	-2	United States	-2
12.	Egypt	0	Egypt	0	Egypt	0
13.	Mexico	+2	Myanmar	0	Sudan	+4
14.	Ethiopia	+2	Sudan	+3	Myanmar	-1
15.	Dem. Rep. Congo	-1	Dem. Rep. Congo	-1	Saudi Arabia	+5
16.	Myanmar	-3	Mexico	-1	Iraq	+7
17.	Sudan	0	Iran	+1	Iran	+1
18.	Japan	+1	Saudi Arabia	+2	Venezuela	+3
19.	Iran	-1	Iraq	+4	Niger	+7
20.	Venezuela	+1	Venezuela	+1	Mexico	-5
21.	Saudi Arabia	-1	Malaysia	+1	Malaysia	+1
22.	Malaysia	0	Japan	-3	Ghana	+2
23.	Colombia	+2	Ethiopia	-7	Burkina Faso	+6
24.	Iraq	-1	Ghana	0	Japan	-5
25.	Ghana	-1	Niger	+1	Mali	+6
26.	Turkey	+2	Colombia	-1	Chad	+12
27.	Uganda	+5	Burkina Faso	+2	Dem. Rep. Congo	-13
28.	Niger	-2	Côte d'Ivoire	-1	Côte d'Ivoire	-1
29.	Côte d'Ivoire	-2	Mali	+2	Cambodia	+8
30.	Kenya	+11	Cameroon	0	Cameroon	0
31.	Cameroon	-1	Turkey	-3	Yemen	+4
32.	Yemen	+3	Chad	+6	Colombia	-7
33.	Angola	0	Yemen	+2	Ethiopia	-17
34.	Burkina Faso	-5	Cambodia	+3	Senegal	+5
35.	Mozambique	+1	Sri Lanka	-1	Turkey	-7
36.	Mali	-5	Angola	-3	Sri Lanka	-2
37.	Sri Lanka	-3	Senegal	+2	United Arab Emirates	+20
38.	Cambodia	-1	Mozambique	-2	Taiwan	+2
39.	Taiwan	+1	Taiwan	+1	Guinea	+6
40.	Algeria	+2	Algeria	+2	Algeria	+2
41.	Chad	-3	Guinea	+4	Afghanistan	+3
42.	South Africa	+11	Afghanistan	+2	Haiti	+6
43.	Nepal	0	Nepal	0	Angola	-10
44.	Senegal	-5	Haiti	+4	Mozambique	-8
45.	Russia	+10	Uganda	-13	Nepal	-2
46.	Madagascar	0	United Arab Emirates	+11	Benin	+6
47.	Argentina	0	Benin	+5	Dominican Rep.	+12
48.	Afghanistan	-4	Somalia	+1	Uzbekistan	+10
49.	Italy	+1	Dominican Rep.	+10	Syria	+14
50.	Korea	+4	Madagascar	-4	Somalia	-1

Notes: Changes in ranking are all expressed relative to the ranking derived from using the 18.3°C threshold.