nature sustainability

Resource

https://doi.org/10.1038/s41893-025-01754-y

Global gridded dataset of heating and cooling degree days under climate change scenarios

Received: 17 January 2025

Accepted: 8 December 2025

Check for updates

Jesus Lizana[1,2,3] ✉, Nicole D. Miranda[2,3], Sarah N. Sparrow[4], David C. H. Wallom[1,4], Radhika Khosla[1,2,5] & Malcolm McCulloch[1,2,3]

Accurate projections of heating and cooling demands are crucial for advancing towards the sustainable development goals. Here we present a global dataset of heating degree days (HDDs) and cooling degree days (CDDs) for three levels of global mean temperature rise above pre-industrial conditions—1.0 °C (2006–2016), 1.5 °C and 2.0 °C—regardless of the pathways leading to these warming scenarios. The dataset comprises 30 gridded maps (0.883° × 0.556° resolution) characterizing climate variability through five statistical metrics per variable and scenario over a representative ten-year period. The dataset reveals a widespread decline in HDDs and a pronounced, nonlinear increase in CDDs, with the most significant shifts in climate intensity and adaptation needs emerging early in the warming trajectory. Furthermore, using the 'middle-of-the-road' pathway SSP2–4.5 as a reference, the dataset indicates that the population experiencing extreme heat conditions (exceeding 3,000 CDDs) is projected to nearly double if the 2.0 °C threshold is reached, increasing from 23% (1.54 billion people) in 2010 to 41% (3.79 billion) by 2050, with the largest projected populations affected in India, Nigeria, Indonesia, Bangladesh, Pakistan and the Philippines. This HDD–CDD dataset provides a robust foundation for integrating climate information into sustainability planning and development policy.

Q1 Decarbonizing heating and cooling energy systems is critical as these two end-uses dominate energy demand, are important sources of emissions and are key to a range of sustainability goals[1,2]. Heating currently accounts for approximately 45% of building emissions[3], whereas space cooling is projected to expand more rapidly than any other building end-use, expected to be more than triple by 2050[4]. To inform sustainability and energy policy decisions, it is crucial to understand how climate change may affect building energy use and Q8 associated greenhouse gas emissions across temporal and spatial scales[5]. Developing more effective and resilient community mitigation and adaptation strategies for the built environment is imperative to achieving the global goal of net-zero carbon emissions by 2050[6].

Heating degree days (HDDs) and cooling degree days (CDDs) are widely used indicators to estimate heating and cooling demands globally, serving as key metrics for understanding energy needs across diverse climates and socio-economic contexts[5,7]. They quantify the extent to which the daily mean temperatures deviate from a reference temperature threshold over a given period[8]. HDDs are particularly relevant for assessing the implications of cold conditions in high-latitude and economically vulnerable regions, where energy poverty poses significant challenges. Likewise, CDDs are instrumental in evaluating the impacts of extreme heat, especially in low-income areas where cooling access is limited and vulnerability to heat stress is pronounced. Emerging research seeks to enhance these metrics by incorporating additional Q2 Q3 Q4 Q5 Q6 Q7

[1]ZERO Institute, University of Oxford, Oxford, UK. [2]Future of Cooling Programme, Oxford Martin School, University of Oxford, Oxford, UK. [3]Energy and Power Group, Department of Engineering Science, University of Oxford, Oxford, UK. [4]Oxford e-Research Centre, University of Oxford, Oxford, UK. [5]Smith School of Enterprise and the Environment, School of Geography and the Environment, University of Oxford, Oxford, UK. ✉e-mail: jesus.lizana@eng.ox.ac.uk

 https://doi.org/10.1038/s41893-025-01754-y

variables such as humidity, adaptive comfort thresholds and behavioural factors to improve local relevance[4]. Despite these advancements, HDDs and CDDs remain indispensable, consistent and scalable indicators for evaluating heating and cooling demands. Moreover, they enable comparability across existing studies, enhancing the usefulness of data for adaptation planning by providing more relevant and actionable insights.

Previous research on HDDs and CDDs has predominantly focused on global mapping using historical data[9,10], with some employing model-based climate projections to assess the climate change impacts in specific regions[11–14] or globally under specific time frames and emissions pathways[15,16]. The most recent global mapping of HDDs and CDDs under different climate change scenarios was produced by Spinoni et al.[16]. They generated global maps at a 0.44° × 0.44° resolution using outputs from 34 Coordinated Regional Climate Downscaling Experiment simulations based on regional climate models driven by 20 global climate models from the Coupled Model Intercomparison Project Phase 5 (CMIP5). However, this dataset was not bias corrected, lacked a historical baseline scenario (covering only 1.5 °C, 2 °C, 3 °C and 4 °C above pre-industrial levels) and reported only ensemble medians and spreads—without capturing climate variability (for example, P10, P90 or standard deviation). Moreover, the remaining previous studies have been mainly constrained to specific temporal contexts and emissions pathways, making it challenging to compare datasets and scenarios due to the diverse range of methodologies and assumptions. This variability has created a substantial gap in forecasting and comparing current and future heating and cooling demands across global warming levels—from 1 °C (2006–2016) to 1.5 °C and 2.0 °C—independently of the timing of these changes. Key questions remain for adaptation planning, such as whether trends in HDDs and CDDs progress linearly or nonlinearly and whether these trends follow consistent patterns across countries or exhibit significant regional variations.

This study generates a global dataset of HDDs and CDDs for three global warming levels above pre-industrial conditions—1.0 °C (based on 2006–2016 observations), 1.5 °C and 2.0 °C—regardless of when these occur, to evaluate the climate change implications for the heating and cooling sector globally. The temperature ensemble used to generate this dataset is characterized by (1) a high temporal resolution (6-hourly mean temperatures simulated with the HadAM4 climate model[17,18]), (2) a large ensemble size (70 members over ten years), (3) bias-corrected outputs, (4) multiple statistical descriptors per grid cell to illustrate climate variability with 30 gridded maps and (5) the representation of global mean temperature rise levels of 1.5 °C and 2.0 °C independently of the specific time at which these thresholds are reached. The HadAM4 climate model[19] is particularly well suited to the goals of this study, offering specific advantages over CMIP5 or CMIP6 models. Whereas HadAM4 lacks interactive coupling to ocean and aerosol components, it is sufficiently memory efficient to run on personal computers of volunteers using the climateprediction.net distributed computing platform[20]. This computational efficiency enables the generation of very large, high-resolution ensembles using prescribed sea surface temperatures and greenhouse gas concentrations, an approach that would be prohibitively expensive to run on a standard supercomputer with most fully coupled Earth system models[21]. Its configuration is comparable to that of many CMIP6 and CMIP5 models, and its warming patterns are similar to the CMIP6 multi-model mean as reported by Lizana et al.[17], ensuring a credible representation of climate dynamics. The HadAM4 configuration was selected for its efficiency in simulating stable global mean temperature states[17] or its demonstrated ability to represent extreme-season variability[21]. Moreover, the bias correction is also necessary because, unlike other studies such as Spinoni et al.[16], it ensures that the results are not systematically skewed by model-specific errors, thereby improving the reliability and comparability of the findings. As a result, the bias-corrected HadAM4-based temperature ensemble used in this study features a large ensemble size (more than double those typically available in CMIP5 or CMIP6), high spatio-temporal resolution (6-hourly mean temperatures rather than daily variables) and the ability to represent global mean temperature rise levels of 1.5 °C and 2.0 °C above pre-industrial conditions independently of the specific timing at which these thresholds are reached. By decoupling the analysis from specific time horizons and focusing on global mean temperature rise thresholds, the dataset offers a unique, policy-relevant perspective on climate impacts. This approach allows decision makers and researchers to assess adaptation needs and infrastructure resilience irrespective of when these warming levels are reached, making it particularly valuable for long-term planning under uncertainty.

The three global warming levels adhere to the half a degree additional warming, prognosis and projected impacts (HAPPI) experimental design protocol[22], with the historical scenario between 2006 and 2016 representing a global mean temperature rise of 1.0 °C. The general dataset builds upon recent contributions[4,9,15,16,23], generating here an enhanced, comprehensive statistical gridded dataset of 30 maps that capture climate variability through five statistical descriptors for each variable and scenario over a 10-year representative period: mean, median, 10th percentile, 90th percentile and standard deviation. The resulting global maps of HDDs and CDDs were calculated using the dry-bulb temperature, following the standard approach[8]. The final global gridded maps have a spatial resolution of 0.833° × 0.556° (longitude × latitude), covering the land surface area. They are available in NetCDF-4 file format (*.nc) at the Oxford University Research Archive (ORA) repository[24].

These maps serve as a key resource for estimating evolving thermal demands under various global warming levels and assessing adaptation priorities, including energy infrastructure and policy needs. The dataset also facilitates the evaluation of energy equity, understanding of socio-economic impacts and informed guidance on investments in renewable energy systems and climate-resilient designs. By integrating these data with variables such as population growth, urbanization and technological advancements, it supports the development of targeted and sustainable solutions for a warming world.

The following sections detail the generated dataset and examine its immediate implications. First, the 30 global maps are described, and subregional changes in mean HDDs and CDDs are statistically demonstrated. Second, the countries anticipated to witness the most significant variations in HDDs and CDDs are identified. Third, the rate of change in CDDs and HDDs across all countries is normalized and compared. Finally, the implications of these findings for the population are explored using the 'middle-of-the-road' projection scenario (SSP2–4.5) as an example. Q9

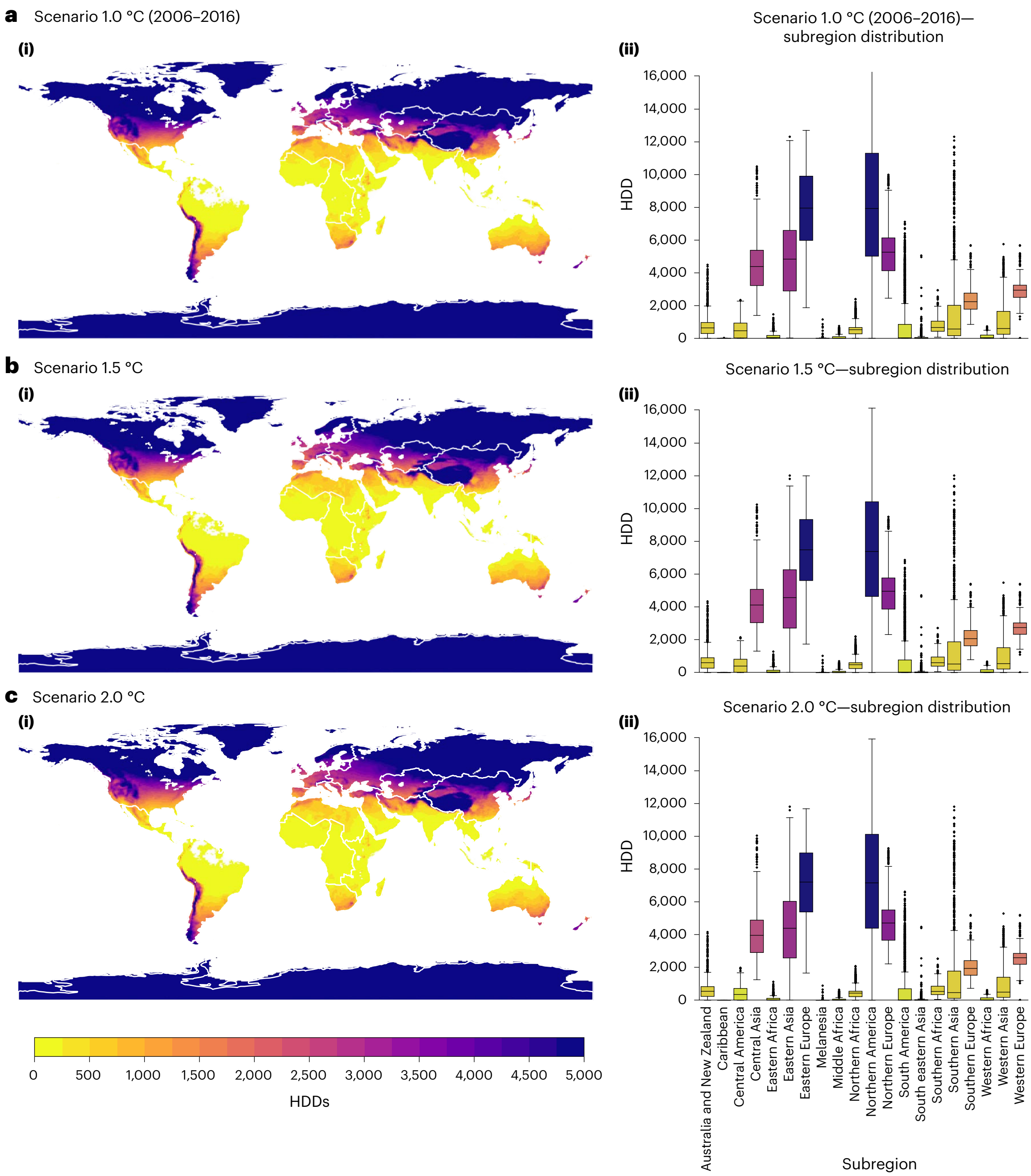
Global gridded maps of HDDs and CDDs under three global warming levels

Understanding changes in future heating and cooling needs is crucial for forecasting energy demand, optimizing energy systems and supporting climate adaptation efforts. Reliable data are essential for effective resource allocation and advancing sustainability initiatives.

The complete dataset produced in this study is summarized in Extended Data Table 1. It comprises 30 global gridded maps, covering two variables—HDD and CDD—across three global mean temperature rise scenarios: 1.0 °C (based on 2006–2016 observations), 1.5 °C and 2.0 °C. For each variable and scenario, five statistical descriptors of the model ensemble are provided: mean, median, 10th percentile, 90th percentile and standard deviation. This dataset represents the most comprehensive global mapping to date of heating and cooling needs, capturing the ensemble-based climate variability across global warming levels. All maps are provided at a spatial resolution of 0.833° × 0.556° (longitude × latitude) over the land surface, approximately 60 km at mid-latitudes.

Figure 1 illustrates and statistically analyses the spatial distribution of mean HDD. Left panels in Fig. 1 show global maps of mean HDDs for each climate scenario, calculated as the annual mean per grid cell using

 https://doi.org/10.1038/s41893-025-01754-y



Q11 **Fig. 1 | Global mean HDDs for three global warming scenarios. a**, Global mean HDDs for 1.0 °C (historical scenario) (i). **b**, Global mean HDDs for 1.5 °C (i). **c**, Global mean HDDs for 2.0 °C (i). Values are calculated as the annual mean HDDs per grid across the ensemble of 70 members for 10 years per scenario, resulting in a total of 700 annual runs. Spatial resolution: 0.833 longitude and 0.556 latitude. The boxplot shows the distribution of data by region, indicating the median (centre line), the interquartile range (IQR) (box, 25th–75th percentiles), whiskers extending to 1.5 × IQR, and points beyond are plotted as outliers: boxplot of HDD distribution under the 1.0 °C scenario (2006–2016) (**a**(ii)); boxplot of HDD distribution under the 1.5 °C scenario (**b**(ii)); boxplot of HDD distribution under the 2.0 °C scenario (**c**(ii)). Basemaps in **a**(i), **b**(i) and **c**(i) from Natural Earth. Q12

a 70-member ensemble over a 10-year period (700 annual simulations per scenario). Right panels in Fig. 1 display boxplots of HDD distributions across world regions, enabling a comparative assessment of
Q10 regional heating demand under progressive global warming.

While the spatial maps provide a global overview of HDD patterns, differences between scenarios may appear subtle given the scale of global change. However, the boxplots clearly demonstrate a consistent decline in HDDs across all regions as global mean temperature rises. This downward trend indicates a widespread reduction in heating demand, with the most pronounced decreases occurring in higher-latitude regions that have historically exhibited the highest HDD values. The ensemble-based approach enhances the robustness of these findings, underscoring the significant impact that even modest global warming can have on regional energy impact for heating.

In a similar approach, Fig. 2 shows and statistically analyses the spatial distribution of mean CDD, with left maps showing global mean CDD maps while right plots present regional boxplots for each warming scenario. Q13

Again, while the spatial maps provide a broad overview of CDD patterns, the boxplots clearly reveal a consistent rise in CDD values across all regions as global temperatures increase. This upward trend signals a growing demand for cooling, particularly in lower-latitude regions already subject to high ambient temperatures. The results also

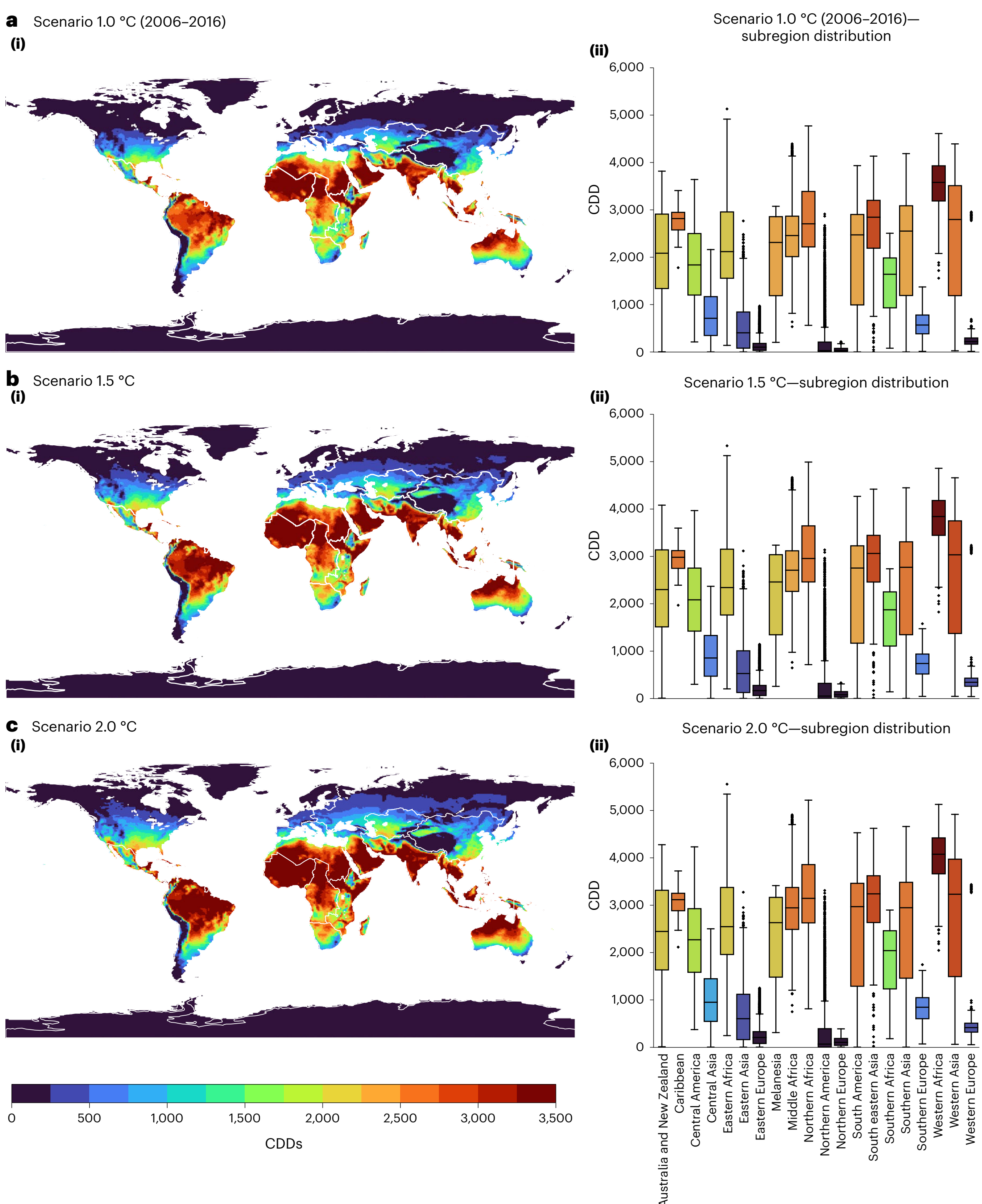


Fig. 2 | Global mean CDDs for three global warming scenarios. a, Global mean CDDs for 1.0 °C (historical scenario). (i) **b**, Global mean CDDs for 1.5 °C (i). **c**, Global mean CDDs for 2.0 °C (i). Values are calculated as the annual mean CDDs per grid across the ensemble of 70 members for 10 years per scenario, resulting in a total of 700 annual runs. Spatial resolution: 0.833 longitude and 0.556 latitude. The boxplot shows the distribution of data by region, indicating the median (centre line), the IQR (box, 25th–75th percentiles), whiskers extending to 1.5 × IQR, and points beyond are plotted as outliers: boxplot of CDD distribution under the 1.0 °C scenario (2006–2016) (**a**(ii)); boxplot of CDD distribution under the 1.5 °C scenario (**b**(ii)); boxplot of CDD distribution under the 2.0 °C scenario (**c**(ii)). Basemaps in **a**(i), **b**(i) and **c**(i) from Natural Earth.

indicate increasing disparities in cooling needs between regions. As with HDD, the ensemble-based methodology enhances the robustness of these findings, demonstrating that even modest warming can lead to significant changes in regional cooling requirements.

Additional descriptive statistics for the complete dataset are provided in Extended Data Table 1.

Global changes in HDDs

To gain an initial understanding of the dataset's implications, it is essential to identify the countries most likely to experience the most significant shifts in heating and cooling requirements. Table 1 lists the top 20 countries with populations exceeding 2 million that are projected to experience the most substantial changes in HDDs from 1.0 to 2.0 °C.

https://doi.org/10.1038/s41893-025-01754-y

Q14 **Table 1 | Countries with the highest absolute change in area-weighted mean HDDs from 1.0 °C to 2.0 °C scenario**

	Top countries by ΔHDD_{18}	ΔHDD18 from 1.0 to 1.5 °C	ΔHDD18 from 1.5 to 2.0 °C	ΔHDD18 from 1.0 to 2.0 °C	Relative Change (%) from 1.0 to 1.5 °C	Relative Change (%) from 1.5 to 2.0 °C	Relative Change (%) from 1.0 to 2.0 °C
1	Canada	−594	−256	**−850**	−7.0%	−3.3%	−10.0%
2	Russian Federation	−456	−296	**−752**	−5.6%	−3.9%	−9.3%
3	Finland	−337	−278	**−614**	−6.2%	−5.5%	−11.3%
4	Sweden	−312	−254	**−566**	−5.9%	−5.1%	−10.7%
5	Norway	−311	−242	**−554**	−5.5%	−4.6%	−9.9%
6	Mongolia	−263	−223	**−486**	−4.2%	−3.7%	−7.8%
7	USA	−278	−206	**−484**	−6.6%	−5.2%	−11.4%
8	Kyrgyzstan	−258	−195	**−453**	−4.2%	−3.3%	−7.4%
9	Austria	−249	−202	**−451**	−6.3%	−5.4%	−11.3%
10	Belarus	−242	−207	**−449**	−6.1%	−5.5%	−11.3%
11	Switzerland	−247	−201	**−448**	−5.7%	−4.9%	−10.3%
12	Armenia	−252	−184	**−436**	−6.3%	−4.9%	−10.9%
13	Lithuania	−231	−204	**−436**	−5.9%	−5.5%	−11.0%
14	North Korea	−246	−177	**−423**	−5.8%	−4.4%	−9.9%
15	China	−241	−181	**−422**	−5.3%	−4.2%	−9.3%
16	Kazakhstan	−250	−172	**−421**	−5.5%	−4.0%	−9.2%
17	Georgia	−244	−171	**−415**	−6.6%	−4.9%	−11.2%
18	Slovakia	−226	−183	**−409**	−6.7%	−5.9%	−12.2%
19	Czechia	−219	−187	**−406**	−6.4%	−5.8%	−11.8%
20	Tajikistan	−226	−179	**−405**	−3.5%	−2.9%	−6.3%

Countries with more than 2 million inhabitants in 2020 are listed. Annual HDDs were calculated using a temperature baseline of 18 °C. Delta (Δ) refers to the incremental (+) or decremental (−) change in the variable. The relative change (%) per country was calculated using area-weighted mean values rather than grid-based values. The bold column denotes the metric used for country ranking. The countries are ranked by the absolute change in their heating needs between the 1.0 °C and 2.0 °C scenarios. Delta HDD (ΔHDD) refers to the incremental/decremental change in area-weighted mean HDDs per country.

Extended Data Fig. 1 illustrates the difference between historical mean HDDs at 1.0 °C and 1.5 °C (Extended Data Fig. 1a), between 1.5 °C and 2.0 °C (Extended Data Fig. 1b) and between 1.0 °C and 2.0 °C (Extended Data Fig. 1c) global warming levels.

When analysing the top-20 countries with the largest change in heating needs as the world warms to 2.0 °C, several key points are worth noting. Most of these 20 countries (18 out of 20) are among the coolest Q15 regions in the world, as listed in Supplementary Note 3. In this context, Slovakia and Czechia take the place of Chile and Ukraine.

They are all regions from three main continents: North America, Europe and Asia. The most considerable changes in area-weighted mean HDDs are found in Canada, the Russian Federation, Finland, Sweden and Norway, with reductions ranging from 554 to 850 HDDs.

The decrease in heating needs is not linear in these regions. Most of the decrease in heating demand occurs before reaching the 1.5 °C threshold, indicating that the most significant shifts in energy requirements happen in the early stages of warming rather than in a steady progression. This is evident in the comparison of Extended Data Figs. 1a,b, where the yellow areas are more widespread at the first Q16 warming threshold.

Changes in CDDs

Table 2 ranks the top 20 countries with more than 2 million inhabitants that will experience the most significant absolute increase in area-weighted mean CDDs from 1.0 to 2.0 °C. Extended Data Fig. 2 illustrates the differences between historical mean CDD at 1.0 °C and 1.5 °C (Extended Data Fig. 2a), between 1.5 °C and 2.0 °C (Extended Data Fig. 2b) and between 1.0 °C and 2.0 °C (Extended Data Fig. 2c).

When analysing the top-20 countries with the largest increase in cooling needs under a 2.0 °C rise in global mean temperature, several key points should be noted. In contrast to the changes in HDDs, here only 7 out of 20 countries are located in some of the hottest regions in the world (all countries in Supplementary Note 4). These regions are in Africa (Mali, Burkina Faso, Chad, South Sudan, Benin, Nigeria) and Asia (Cambodia).

The 20 countries with the most significant changes in CDDs are also developing nations. They are all located near the equator or within tropical and subtropical latitudes, resulting in warm climates with high temperatures throughout the year. These shifts are expected to further strain the socio-economic development of these regions. Most of these countries are in Africa (Central African Republic, Nigeria, South Sudan, Burkina Faso, Mali, Chad, the Democratic Republic of the Congo, Cameroon, Uganda, Benin, Congo), whereas others are in South America (Brazil, Venezuela, Paraguay), Central America (Honduras, Guatemala, Nicaragua) and Southeast Asia (Laos, Thailand, Cambodia).

The largest increases in area-weighted mean CDDs are observed in the Central African Republic, Nigeria, South Sudan, Laos and Brazil, with increases of 524–560 CDDs. These regions are projected to experience the most dramatic increase in cooling needs from 1.0 °C to 2.0 °C, as shown in Extended Data Fig. 2, necessitating substantial adaptation efforts.

Like HDDs, most CDD changes occur before reaching the 1.5 °C threshold across the top 20 countries, indicating that the most significant shifts in adaptation requirements to higher temperatures occur in the early stages of warming rather than in a steady progression. This is evident in the comparison of Extended Data Fig. 2a,b, where the red areas are more widespread at the first warming threshold. Q17

The rate of change in heating and cooling needs

This section examines the linear or nonlinear nature of changes in CDDs and HDDs across global warming levels for all countries. The earlier analysis indicates that among the 20 countries most impacted by

Table 2 | Countries with the highest absolute change in area-weighted mean CDDs from 1.0 °C to 2.0 °C scenario

	Top countries by ΔCDD_{18}	ΔCDD18 from 1.0 to 1.5 °C	ΔCDD18 from 1.5 to 2.0 °C	ΔCDD18 from 1.0 to 2.0 °C	Relative Change (%) from 1.0 to 1.5 °C	Relative Change (%) from 1.5 to 2.0 °C	Relative Change (%) from 1.0 to 2.0 °C
1	Central African Republic	293	266	**560**	+10.3%	8.5%	+19.6%
2	Nigeria	295	245	**540**	+8.9%	6.8%	+16.3%
3	South Sudan	285	251	**536**	+8.2%	6.7%	+15.4%
4	Laos	334	196	**530**	+15.6%	7.9%	+24.7%
5	Brazil	297	227	**524**	+11.4%	7.8%	+20.0%
6	Honduras	303	216	**519**	+14.4%	9.0%	+24.6%
7	Guatemala	292	225	**516**	+13.0%	8.9%	+23.0%
8	Burkina Faso	262	254	**516**	+6.8%	6.2%	+13.5%
9	Venezuela	294	214	**508**	+10.6%	6.9%	+18.3%
10	Paraguay	294	210	**503**	+11.9%	7.6%	+20.3%
11	Mali	250	253	**503**	+6.4%	6.0%	+12.8%
12	Thailand	303	197	**499**	+9.5%	5.6%	+15.7%
13	Chad	263	236	**498**	+7.3%	6.1%	+13.8%
14	Democratic Republic of The Congo	253	240	**493**	+11.1%	9.5%	+21.7%
15	Cameroon	264	228	**491**	+10.8%	8.4%	+20.0%
16	Benin	266	220	**486**	+7.8%	6.0%	+14.2%
17	Nicaragua	284	200	**484**	+10.5%	6.7%	+17.9%
18	Cambodia	294	189	**482**	+8.4%	5.0%	+13.8%
19	Congo	240	241	**481**	+9.5%	8.7%	+19.1%
20	Uganda	249	232	**480**	+12.8%	10.6%	+24.7%

Countries with more than 2 million inhabitants in 2020 are listed. Annual CDDs were calculated using a temperature baseline of 18 °C. Delta (Δ) refers to the incremental (+) or decremental (−) change in the variable. The relative value per country was calculated using area-weighted mean values rather than grid-based values. The bold column denotes the metric used for country ranking. The countries are ranked by the absolute change in their cooling needs between the 1.0 °C and 2.0 °C scenarios. Delta CDD (ΔCDD) refers to the incremental/decremental change in area-weighted mean CDD per country.

changes in HDDs and CDDs, the transition from the 1.0 °C (2006–2016) to the 1.5 °C warming scenario represents the most significant shift. However, a key question remains: will this short-term acceleration in HDD and CDD trends follow a similar pattern across all countries or will regional variations emerge?

Figure 3 answers the question, illustrating all countries' normalized changes in CDDs (Fig. 3a) and HDDs (Fig. 53b). It compares the CDD–HDD observations from 2006–2016, a period with a global mean temperature rise of 1.0 °C, to the projected CDD–HDD scenarios, with a global mean temperature rise of 1.5 °C and 2.0 °C.

The results clearly demonstrate how the warming rate is accelerating the increase in CDDs during the current decade for all countries, as the world approaches a global mean temperature rise of 1.5 °C. This trend shows that even regions with historically moderate cooling demands (low CDD values) are experiencing sharper increases in CDDs as temperatures rise. Consequently, this leads to a significant increase in energy demand for cooling systems, posing challenges for energy infrastructure and sustainable development. Additionally, this rapid shift underscores the need for more resilient, energy efficient building designs and cooling technologies to mitigate the growing reliance on air conditioning systems.

In the case of HDDs, results reveal a more complex and varied pattern across countries. Some countries, particularly those in colder regions, experience a notably higher decrease in HDDs as temperatures warm during the current decade before the global mean temperature reaches 1.5 °C, as discussed in the previous section. In contrast, other countries show the opposite trend, with less significant or delayed changes in HDDs. This divergence underscores regional differences in climate sensitivity and the interplay of local geography, seasonal patterns and baseline temperatures. Regions experiencing significant changes earlier will need to adapt their heating strategies, which may operate at partial load more frequently and for more extended periods, whereas those with delayed changes may have more time to adjust. These findings emphasize the importance of region-specific policies to address heating demands, improve energy efficiency, and optimize building services in response to climate change.

Implications under the SSP2–4.5 pathway

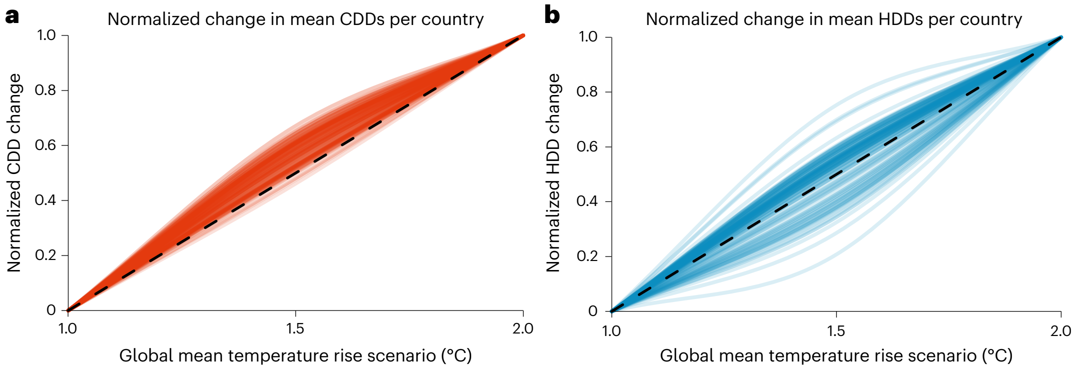
The dataset's independence from specific emissions or socio-economic pathways enables its application in various policy and planning contexts. In this section, we explore the implications of our dataset using a specific Shared Socioeconomic Pathway (SSP) scenario as an illustrative example.

We employ SSP2–4.5, which represents a 'middle-of-the-road' socio-economic context, to illustrate how our dataset can be incorporated into a particular pathway in which global development trends follow historical trajectories (refer to Fig. 4a, orange line)[25]. Under this scenario, the global population is projected to increase from approximately 6.81 billion in 2010 to 8.32 billion by 2030 and 9.24 billion by 2050 (Fig. 4b, orange line)[25,26]. This example provides a concrete case for interpreting the impact of projected changes in heating and cooling demand, illustrating the relevance of our dataset for informing sectoral adaptation strategies under plausible future conditions.

For this 'middle-of-the-road' socio-economic pathway (or intermediate pathway, SSP2–4.5), Fig. 4c analyses the global population's exposure to HDDs and CDDs under the SSP2 pathway for 1 °C (historical, 2006–2016), 1.5 °C and 2.0 °C scenarios. Global population data are Q21
grouped in increments of 100 CDDs and HDDs.

Figure 4c shows the total distribution of the population under different heat exposures, aggregated in 100 CDD intervals. The figure

 https://doi.org/10.1038/s41893-025-01754-y



Q18 **Fig. 3 | Normalized changes in area-weighted mean CDDs and HDDs for all countries. a**, CDDs. **b**, HDDs. The comparison is drawn between the historical scenario—based on observations from 2006 to 2016, with a global mean temperature rise of 1.0 °C following the HAPPI protocol[22]—and the projected scenarios for a global mean temperature rise of 1.5 °C and 2.0 °C.

highlights how people living in extreme heat regions (> 3,000 CDD) are projected to increase from 23% (1.54 billion, blue line) in 2010 to 34% (2.80 billion, orange line) by 2030 and to 41% (3.79 billion, red line) by 2050. The countries with the largest populations affected by these extremes are, and will continue to be, India, Nigeria, Indonesia, Bangladesh, Pakistan and the Philippines. Also, global people × CDD (people-CDD) is expected to increase by 42% if the global warming level reaches 1.5 °C. This figure will extend to 74% if we reach 2.0 °C.

From a different perspective, in SSP2–4.5, the total distribution of the population by heating need is illustrated in Fig. 4d, aggregated into 100 HDD intervals. Here people living in extremely cool regions (> 3,000 HDDs) are projected to decrease from 14% (0.93 billion, blue line) to 10% (0.80 billion, orange line) by 2030 and to 7% (0.68 billion, red line) by 2050. Globally, global people × HDD (people-HDD) will increase by 1% if the global warming level reaches 1.5 °C, mainly due to population growth, but decrease by 4% if it reaches 2.0 °C.

Discussion

The global gridded dataset of HDDs and CDDs developed in this study captures how global warming levels of 1.5 °C and 2.0 °C above pre-industrial levels influence thermal energy demand worldwide. Beyond quantifying spatial variations in heating and cooling needs, the dataset provides a foundation for assessing regional disparities in climate hazards, vulnerability and coping capacity, offering valuable insights for adaptation planning and risk management.

The statistical analysis of the dataset also highlights several key insights of broader relevance that should be carefully considered, including the nonlinear rate of increase in climate intensity, the countries most affected and the projected increase in the number of people living under extreme heat conditions, as discussed below.

The warming rate is not linear between 1.0 °C (2006–2016), 1.5 °C and 2.0 °C. Cooling needs are changing faster in the current decade as the world approaches a 1.5 °C global temperature rise, with CDD increases from 1.0 °C to 1.5 °C surpassing those expected between 1.5 °C and 2.0 °C. This has important implications for adaptation to warming temperatures, including the need for rigorous, immediate, sustainable solutions. In terms of heating needs, these rapid changes are particularly evident in the coolest regions.

Countries with significant implications for a global mean temperature rise of 2.0 °C are also identified. Canada, the Russian Federation, Finland, Sweden and Norway will experience a significant decrease in area-weighted mean HDDs, ranging from 554 to 850 HDDs, drastically reducing future heating needs per capita. Analogously, the Central African Republic, Nigeria, South Sudan, Laos and Brazil will experience a significant rise in area-weighted mean CDDs per country, increasing by 524–560 CDDs, drastically increasing cooling needs per capita. The countries experiencing the most significant changes in CDD are predominantly developing nations in tropical and subtropical regions. These regions, characterized by warm year-round climates and high temperatures, are primarily found in Africa, with additional representation from South America, Central America and Southeast Asia. As these shifts in CDDs continue, they are expected to place additional pressure on the socio-economic development of these countries, exacerbating existing challenges and hindering their growth and resilience.

It should also be noted that the impact of temperature-related climate change on people, energy, infrastructure, the economy and the environment is determined not only by absolute values but also by the relative changes compared to historical conditions. This principle is particularly important for future CDDs or cooling needs, especially in countries lacking the infrastructure to manage cooling demand. Given that these countries' built environment and infrastructure are predominantly prepared for cold seasons (for example, homes that maximize solar gains and minimize ventilation, public transport without air conditioning systems and so on), the anticipated temperature increase, though moderate, will probably have a severe impact compared to regions with the resources, capacity and embodied capital to manage heat[23].

These findings also reveal how, under a 'middle-of-the-road' shared socio-economic pathway scenario (SSP2–4.5), the population living in extreme heat regions (>3,000 CDDs) is projected to increase from 23% (1.54 billion) in 2010 to 34% (2.80 billion) by 2030 and to 41% (3.79 billion) by 2050. The results underscore the rapidly growing vulnerability of populations to extreme heat and emphasize the need for targeted adaptation and mitigation strategies to address the impacts of rising temperatures. Additionally, they highlight that global population × CDD (people-CDD) is expected to increase by 74% if the global mean temperature increases to 2.0 °C, while global population × HDD (people-HDD) is expected to decrease by 4% if we reach 2.0 °C.

This open-source dataset offers valuable insights for anticipating future energy demand, optimizing energy systems and advancing climate adaptation and sustainable development goals. To ensure the practical relevance of these findings, it is essential to demonstrate how they can support decision-making across key sectors. The projections of heating and cooling degree days (HDDs and CDDs) can be directly applied to inform early-stage building design, regional energy system planning and public health preparedness.

For instance, in the building sector, the gridded HDD and CDD data can guide climate-responsive planning by identifying regions where cooling demand is projected to increase most significantly in the coming decades[27]. In areas shifting from heating-dominated to mixed or cooling-dominated climates, architects and engineers can prioritize adaptation strategies for sustainable cooling[28]—such as shading, ventilation or thermal mass—and revise building standards to align with emerging needs.

https://doi.org/10.1038/s41893-025-01754-y

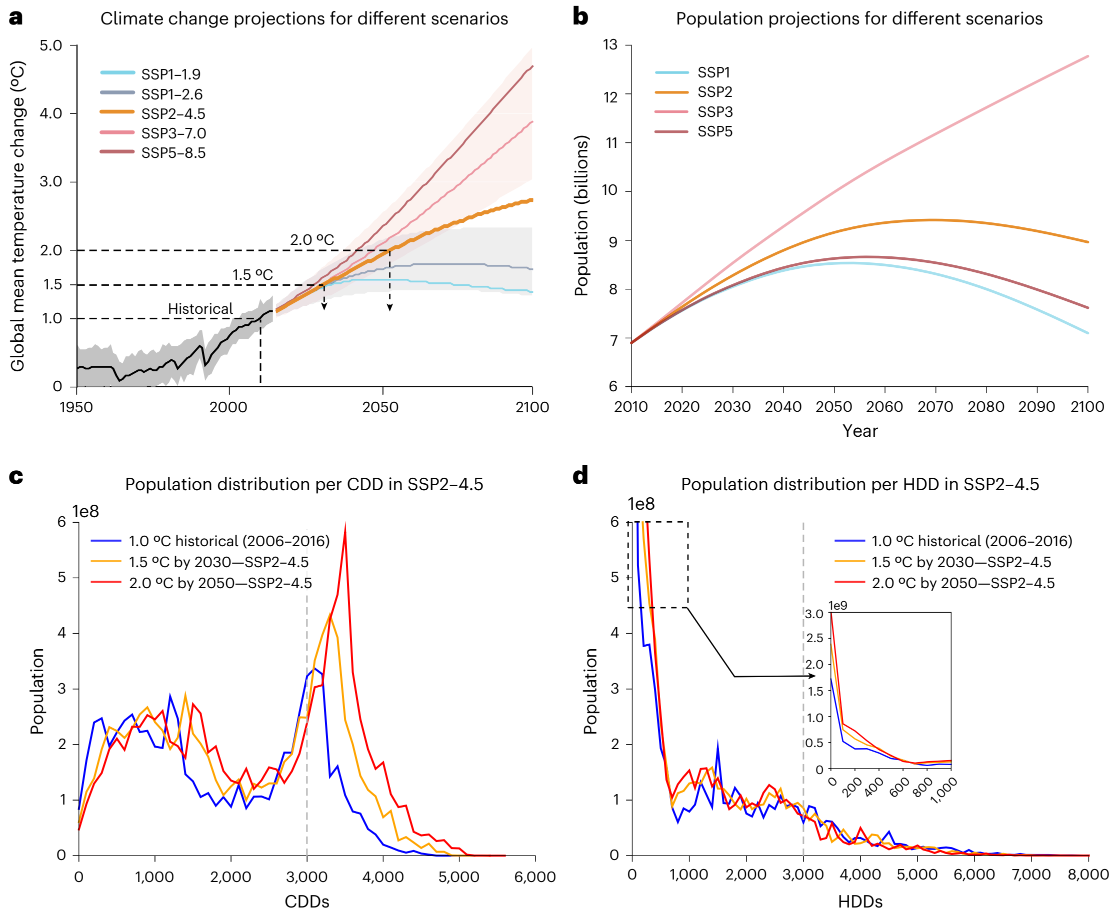


Fig. 4 | Implications of CDDs and HDDs for the Intergovernmental Panel on Climate Change scenario SSP2–4.5. a, Climate change projections across Intergovernmental Panel on Climate Change (IPCC) scenarios, with identification of the generated CDD and HDD datasets used for SSP2–4.5 (dashed lines). Colour shading shows the uncertainty ranges for the low- and high-emissions scenarios (SSP1–2.6 and SSP3–7.0). **b**, Population projections for different SSPs. **c**, Population distribution over CDDs in SSP2–4.5, with the total number of population in 2010 aggregated in 100 CDD intervals. **d**, Population distribution per HDD in SSP2–4.5, with the total population in 2010 aggregated in 100 HDD intervals. Q19 Q20

In energy system planning, spatially resolved HDD and CDD trends offer critical inputs for forecasting future energy loads, enabling planners and utilities to anticipate changes in peak demand and to consider centralized and/or decentralized energy solutions, such as demand flexibility[29,30] or district heating and cooling networks[31]. These data are beneficial for scenario analysis and long-term planning at both the regional and national levels.

From a public health perspective, rising CDD values highlight regions at growing risk of extreme heat exposure, especially in areas with historically low cooling demand. These insights can support the design of heat-health early warning systems, the strategic placement of cooling shelters and the development of heatwave response plans—particularly in regions with vulnerable populations[32].

By applying these metrics across disciplines, stakeholders can better prepare for climate-induced changes in temperature patterns, supporting more resilient and adaptive systems.

Methods

In this section, we describe the data and methods used to generate the global gridded maps of CDDs and HDDs and perform the geospatial statistical analysis.

Climate data and selection criteria

The global gridded CDD and HDD maps were generated using a large bias-corrected HadAM4-based temperature ensemble for three global warming levels (1 °C, 1.5 °C and 2.0 °C) generated by Lizana et al.[17] and available at the CEDA repository[18]. This climate dataset was produced using the HadAM4 Atmosphere-only General Circulation Model[33,34] from the UK Met Office Hadley Centre. The simulations were conducted within the climateprediction.net (CPDN) climate modelling environment[20], which employs the Berkeley Open Infrastructure for Network Computing framework to distribute numerous computational tasks across a global network of volunteer computers Q22

This temperature ensemble was chosen for four reasons: (1) its large ensemble size of 70 members over ten years per scenario, (2) its high spatio-temporal resolution with 6-hourly mean temperatures at 0.883° × 0.556°, (3) its bias-corrected simulations and (4) its capability to represent global mean temperature rise scenarios by 1.5 °C and 2.0 °C independently of when these thresholds are achieved. This ensemble size is significantly larger than those typically available in other model intercomparison projects (for example, CMIP6), where most models provide only 10–30 ensemble members per scenario. The use of the HadAM4 model within the CPDN framework also allows for output at a 6-hourly temporal resolution, significantly finer than the daily output commonly available from recent climate model ensembles. Also, the model focuses on global mean temperature rise levels of 1.5 °C and 2.0 °C, independent of when or under which pathway these temperature thresholds are reached. This framing enables a policy-relevant, scenario-agnostic assessment of climate impacts that aligns directly with the temperature goals of the Paris Agreement. The climate modelling aligns with the HAPPI protocol, which prescribes constant forcing levels consistent with 1.5 °C and 2.0 °C of Q23

https://doi.org/10.1038/s41893-025-01754-y

global warming above pre-industrial levels. All ensemble members were run with these fixed forcings over a 10-year period to sample the climate system's internal variability. Consequently, the simulations are not designed to reach 1.5 °C or 2.0 °C at a specific point in time; rather, they represent stabilized climate states corresponding to these warming levels. Any temporal differences observed across ensemble members reflect internal model variability, not differences in when the warming thresholds were reached.

Bias correction

The temperature ensembles generated by Lizana et al.[17] were corrected for bias using a quantile-mapping method, which adjusts the full distribution of modelled temperatures to match observed data. This method corrects systematic biases at each percentile, ensuring a representation of both average conditions and extremes while preserving the ensemble's internal variability. For this process, the ERA5 reanalysis dataset[35,36] with a spatial resolution of 0.25° was re-gridded to a 0.833° × 0.556° grid to match the model resolution. Biases were calculated at each percentile by comparing the cumulative distribution functions of the historical model output and ERA5 observations. The calculated biases were added to the 1 °C (2006–2016), 1.5 °C and 2.0 °C temperature scenarios at their corresponding percentiles, assuming that the bias remains constant across scenarios. The bias correction was applied to the combined ensemble, comprising 70 individual members over a 10-year period, thereby preserving the internal variability of the multi-member ensemble after correction. More details can be found in Lizana et al.[17].

Validation and uncertainty

The validation and reliability of the bias-corrected HadAM4-based temperature ensemble used in this study were assessed by comparing the bias-corrected HadAM4-based temperature ensemble with ERA5 (for the historical period between 2006 and 2016) and with the CMIP6 multi-model mean for future projections[17]. Details from this analysis are provided in Supplementary Note 6. The analysis shows that the ensemble used to generate the historical maps aligns perfectly with ERA5 observations, indicating the good performance of the bias-corrected historical model output. Comparing future projections for 1.5 °C and 2.0 °C scenarios with the CMIP6 model mean shows similar overall warming, with most temperature differences within ± 0.5 °C and slightly higher warming (0.5–1 °C) in some high northern latitudes. These differences are within the range of differences seen between other models and lie within the range of credible projections produced by contemporary climate models[37].

Other datasets used

Other datasets were used to provide an example on how to use this dataset under a specific Shared Socioeconomic Pathway (SSP) scenario: the SSP2–4.5 pathway defined by IPCC[25]. The global gridded population datasets for this SSP2–4.5 scenario across different temporal periods were obtained from Wang et al.[38] and are available in the Figshare repository[39]. These datasets were used to quantify the implications of CDDs and HDDs in the population, illustrated in Fig. 4.

Calculation of HDDs and CDDs

HDD and CDD measure how much the dry-bulb temperature exceeds (above or below) a reference temperature threshold ($T_{\text{Threshold}}$) each day over a given period.

The calculation of HDD and CDD can follow different methodologies depending on the available data, context and intended application[8]. Commonly used reference temperature thresholds for calculating HDD and CDD are 65 °F (18.0 °C) (refs. 4,40–43). Some studies adopt 18.3 °C as a direct conversion from 65 °F (refs. 9,15), whereas others apply even higher thresholds[9,42]. Temperature data used in these calculations may vary in temporal resolution, from daily to sub-daily records. Although finer resolutions tend to improve accuracy, the difference between daily and hourly estimates is usually minor[8].

In this study, HDD and CDD are calculated using 6-hourly temperature data following the approach previously used in Nicole et al.[23] and described in equations (1) and (2). This sub-daily resolution captures part of the diurnal temperature variability, which is particularly important in regions with large day–night temperature ranges. Both $T_{\text{threshold}}$ and T_{base} were set to 18 °C.

$$\text{HDD} = \frac{\sum_{t=0}^{t=m} (T_{\text{base}} - T_t)}{n}, T_t < T_{\text{threshold}} \tag{1}$$

$$\text{CDD} = \frac{\sum_{t=0}^{t=m} (T_t - T_{\text{base}})}{n}, T_t > T_{\text{threshold}} \tag{2}$$

Where:

t = time step

m = last time step of the year

n = number of time steps in one day (n = 4 for 6-hourly data)

T_t = mean outdoor temperature at time t

T_{base} = reference temperature used to calculate the temperature difference.

$T_{\text{threshold}}$ = outdoor temperature above which temperature differences are calculated.

Global gridded maps of HDDs and CDDs

The global gridded maps of HDDs and CDDs were obtained as follows. First, HDDs and CDDs were calculated annually across 700 annual periods per scenario (70 temperature members per scenario over a 10-year period). Here we obtained 700 CDD and HDD global gridded maps per global warming level: 1.0 °C (historical, 2006–2016), 1.5 °C and 2.0 °C above pre-industrial levels. Second, five statistical indices across these large ensembles of HDDs and CDDs are obtained per coordinate (longitude × latitude) and scenario to capture the climate variability. These statistical indices are mean, median, 10th percentile, 90th percentile and standard deviation. Third, the final statistical results of HDDs and CDDs were stored in five different global gridded maps per scenario as NetCDF V4 files (*.nc). These global gridded maps have a spatial resolution of 0.833° × 0.556° (longitude × latitude) over the land surface and are available at the ORA repository[24].

Geospatial statistics and visualization

The spatial visualizations and area-weighted statistics for each subregion and country presented in this manuscript were produced utilizing Python programming and the QGIS geographic information system. The Python code is available on GitHub (https://github.com/lizanafj/python_examples_with_CDDandHDD_files). The administrative boundaries used to perform these geospatial statistics were obtained from EuroGeographics and Natural Earth. Area-weighted statistics for all countries with populations exceeding 2 million are detailed in the Supplementary Information (Supplementary Note 3 and Supplementary Note 4).

Limitations

HDD and CDD were calculated using the dry-bulb temperature, following the standard approach to enable comparison with previous studies[8]. These indices are directly related to heat and cooling exposure but do not account for other social, economic and environmental factors influencing heating and cooling energy demand. These factors include the existing building stock and its thermal performance, socio-technical behaviours and usage patterns, access to energy resources, the availability of heating and cooling technologies and other variables influencing thermal comfort, such as humidity.

The dataset was generated from HadAM4 climate model outputs. HadAM4 lacks interactive coupling to ocean and aerosol components. When compared with the CMIP6 multi-model mean, most temperature differences are below ± 0.5 °C and the largest differences, generally within 0.5–1 °C, occurring in mid to high northern latitudes. The greater warming projected by HadAM4 may lead to underestimation of HDDs and overestimation of CDDs in these regions, indicating a potential warm bias in derived indicators. However, these differences remain within the range observed among other models and lie within the credible projections produced by contemporary climate models[37]. It is also important to note that direct comparisons between HadAM4 and CMIP6 ensembles should be interpreted with caution, as differences in ensemble size, temporal sampling and model formulation can influence the results. Further details are provided in Supplementary Note 6.

Additionally, because the global climate dataset used does not account for urban heat island effects, HDD values are probably overestimated and CDD values are underestimated in urban areas.

The use of other datasets associated with SSP2–4.5 served to demonstrate how our CDD and HDD datasets can be integrated into a 'middle-of-the-road' socio-economic context. It is important to note, however, that the SSP2–4.5 projections carry inherent uncertainties (for example, regional downscaling methods), which should be considered when interpreting the results.

Reporting summary

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

Data availability

The global gridded dataset of HDDs and CDDs under the three climate change scenarios (1 °C, 1.5 °C and 2 °C) is available in the Oxford University Research Archive (ORA) repository at https://doi.org/10.5287/ora-w4qpqy522. Five maps are available for HDDs and CDDs per scenario: mean, median, 10th percentile, 90th percentile and standard deviation. The complete list of maps for each global warming level is provided in Extended Data Table 1. The spatial resolution is 0.833° × 0.556° (longitude latitude) over the land surface. Further data are available from the authors on request.

Code availability

The code to calculate HDDs and CDDs from the temperature ensemble is available via Github at https://github.com/lizanafj/cdd_hdd_mapping. The code for data visualization and statistical analysis is available via Github at https://github.com/lizanafj/python_examples_with_CDDandHDD_files. Examples of how to use the Python code are provided in Supplementary Note 7.

References

1. IPCC in *Climate Change 2022: Mitigation of Climate Change* (eds Shukla, P. R. et al.) 953–1048 (Cambridge Univ. Press, 2023); https://doi.org/10.1017/9781009157926.011
2. Khosla, R. et al. Cooling for sustainable development. *Nat. Sustain.* **4**, 201–208 (2021).
3. Abergel, T. & Delmastro, C. Is cooling the future of heating? *IEA* https://www.iea.org/commentaries/is-cooling-the-future-of-heating (2020).
4. IEA. *The Future of Cooling. Opportunities for Energy-Efficient Air Conditioning* (IEA Publications, 2018).
5. Reinhart, C. Linking energy use to local climate. *Nat. Energy* **8**, 1311–1312 (2023).
6. *Global Status Report for Buildings and Construction: Beyond foundations: Mainstreaming Sustainable Solutions to Cut Emissions from the Buildings Sector* (UNEP, 2024); https://doi.org/10.59117/20.500.11822/45095
7. Staffell, I., Pfenninger, S. & Johnson, N. A global model of hourly space heating and cooling demand at multiple spatial scales. *Nat. Energy* https://doi.org/10.1038/s41560-023-01341-5 (2023).
8. CIBSE *Degree-Days: Theory and Application - TM41: 2006* (CIBSE, 2006).
9. Biardeau, L. T., Davis, L. W., Gertler, P. & Wolfram, C. Heat exposure and global air conditioning. *Nat. Sustain.* **3**, 25–28 (2020).
10. Mistry, M. N. Historical global gridded degree-days: a high-spatial resolution database of CDD and HDD. *Geosci. Data J.* **6**, 214–221 (2019).
11. Petri, Y. & Caldeira, K. Impacts of global warming on residential heating and cooling degree-days in the United States. *Sci. Rep.* **5**, 12427 (2015).
12. Spinoni, J. et al. Changes of heating and cooling degree-days in Europe from 1981 to 2100. *Int. J. Climatol.* **38**, e191–e208 (2018).
13. Almazroui, M., Saeed, S., Saeed, F., Islam, M. N. & Ismail, M. Projections of precipitation and temperature over the South Asian countries in CMIP6. *Earth Syst. Environ.* **4**, 297–320 (2020).
14. Almazroui, M. et al. Projected change in temperature and precipitation over Africa from CMIP6. *Earth Syst. Environ.* **4**, 455–475 (2020).
15. Deroubaix, A. et al. Large uncertainties in trends of energy demand for heating and cooling under climate change. *Nat. Commun.* **12**, 1–8 (2021).
16. Spinoni, J. et al. Global population-weighted degree-day projections for a combination of climate and socio-economic scenarios. *Int. J. Climatol.* **41**, 5447–5464 (2021).
17. Lizana, J. et al. Ensemble of global climate simulations for temperature in historical, 1.5 °C and 2.0 °C scenarios from HadAM4. *Sci. Data* **11**, 578 (2024).
18. Lizana, J. et al. Large ensemble of global mean temperatures: 6-hourly HadAM4 model run data using the Climateprediction.net platform. *CEDA Archive* https://doi.org/10.5285/9c41e3aa67024bbdad796290a861e968 (2023).
19. Watson, P. et al. Multi-thousand member ensemble atmospheric simulations with global 60km resolution using climateprediction.net. Technical Report EGU2020-10895. *Copernicus Meetings* https://doi.org/10.5194/egusphere-egu2020-10895 (2023).
20. Climateprediction.net (CPDN) program (2025); https://www.climateprediction.net/
21. Leach, N. J., Watson, P. A. G., Sparrow, S. N., Wallom, D. C. H. & Sexton, D. M. H. Generating samples of extreme winters to support climate adaptation. *Weather Clim. Extremes* **36**, 100419 (2022).
22. Mitchell, D. et al. Half a degree additional warming, prognosis and projected impacts (HAPPI): background and experimental design. *Geosci. Model Dev.* **10**, 571–583 (2017).
23. Miranda, N. D. et al. Change in cooling degree days with global mean temperature rise increasing from 1.5 °C to 2.0 °C. *Nat. Sustain.* **6**, 1326–1330 (2023).
24. Lizana, J. et al. Global land surface dataset of heating and cooling degree days from a bias-corrected HadAM4-based temperature ensemble under 1.0 °C, 1.5 °C, and 2.0 °C climate scenarios. *ORA* https://doi.org/10.5287/ora-w4qpqy522 (2024).
25. IPCC *Climate Change 2022: Impacts, Adaptation, and Vulnerability* (Cambridge Univ. Press, 2022); https://doi.org/10.1017/9781009325844
26. KC, S. & Lutz, W. The human core of the shared socioeconomic pathways: population scenarios by age, sex and level of education for all countries to 2100. *Glob. Environ. Change* **42**, 181–192 (2017).
27. Mehmood, S., Lizana, J., Núñez-Peiró, M., Maximov, S. A. & Friedrich, D. Resilient cooling pathway for extremely hot climates in southern Asia. *Appl. Energy* **325**, 119811 (2022).

28. Lizana, J. et al. Overcoming the incumbency and barriers to sustainable cooling. *Build. Cities* **3**, 1075–1097 (2022).
29. Franken, L. et al. Power system benefits of simultaneous domestic transport and heating demand flexibility in Great Britain's energy transition. *Appl. Energy* **377**, 124522 (2025).
30. Halloran, C., Lizana, J., Fele, F. & Mcculloch, M. Data-based, high spatiotemporal resolution heat pump demand for power system planning. *Appl. Energy* **355**, 122331 (2024).
31. Lizana, J., Ortiz, C., Soltero, V. M. & Chacartegui, R. District heating systems based on low-carbon energy technologies in Mediterranean areas. *Energy* **120**, 397–416 (2017).
32. Ballester, J. et al. Heat-related mortality in Europe during the summer of 2022. *Nat. Med.* **29**, 1857–1866 (2023).
33. Webb, M., Senior, C., Bony, S. & Morcrette, J.-J. Combining ERBE and ISCCP data to assess clouds in the Hadley Centre, ECMWF and LMD atmospheric climate models. *Clim. Dyn.* **17**, 905–922 (2001).
34. Williams, K. D., Ringer, M. A. & Senior, C. A. Evaluating the cloud response to climate change and current climate variability. *Clim. Dyn.* **20**, 705–721 (2003).
35. Hersbach, H. et al. ERA5 hourly data on single levels from 1940 to present. *Climate Data Store* https://doi.org/10.24381/cds.adbb2d47 (2023).
36. ECMWF. ERA5 hourly data on single levels from 1959 to present. Q29 Climate Data Store https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels?tab=overview
37. Wehner, M. et al. Changes in extremely hot days under stabilized 1.5 and 2.0 °C global warming scenarios as simulated by the HAPPI multi-model ensemble. *Earth Syst. Dyn.* **9**, 299–311 (2018).
38. Wang, X., Meng, X. & Long, Y. Projecting 1 km-grid population distributions from 2020 to 2100 globally under shared socioeconomic pathways. *Sci. Data* **9**, 1–13 (2022).
39. Wang, X., Meng, X. & Long, Y. Projecting 1 km-grid population distributions from 2020 to 2100 globally under shared socioeconomic pathways. *Figshare* https://doi.org/10.6084/m9.figshare.19608594.v2 (2022).
40. Labriet, M. et al. Worldwide impacts of climate change on energy for heating and cooling. *Mitigation Adapt. Strategies Global Change* **20**, 1111–1136 (2015).
41. Isaac, M. & van Vuuren, D. P. Modeling global residential sector energy demand for heating and air conditioning in the context of climate change. *Energy Policy* **37**, 507–521 (2009).
42. Andrijevic, M., Byers, E., Mastrucci, A., Smits, J. & Fuss, S. Future cooling gap in shared socioeconomic pathways. *Environ. Res.* Q30 *Lett.* **16**, (2021).
43. Sivak, M. Where to live in the United States: combined energy demand for heating and cooling in the 50 largest metropolitan areas. *Cities* **25**, 396–398 (2008).

Acknowledgements

This research received support from the University of Oxford Strategic Research Fund and the Oxford Martin School's Future of Cooling Programme. J.L. acknowledges funding from the European Union's Horizon 2020 research and innovation programme (MSCA: 101023241). S.N.S. was funded by UKRI (NE/P002099/1). To ensure open access, we have granted a CC BY licence to any Author Accepted Manuscript resulting from this work. We are also grateful to M. Z. Walker and R. Renaldi for their valuable contributions to the early stages of the research concept.

Author contributions

R.K., D.C.H.W. and M.M. conceptualized the work proposed. J.L. and N.M. coordinated the study. N.M. performed the data extraction and data management. J.L. performed the data pre-processing of the climate model. J.L. calculated and generated the CDD and HDD datasets. J.L. provided the statistics and visualizations available in the manuscript. J.L. wrote the manuscript draft. S.S. and D.C.H.W. led the interpretation and analysis of the data. S.S. provided expertise in data analytics. All authors reviewed the paper.

Competing interests

The authors declare no competing interests.

Additional information

Extended data is available for this paper at https://doi.org/10.1038/s41893-025-01754-y.

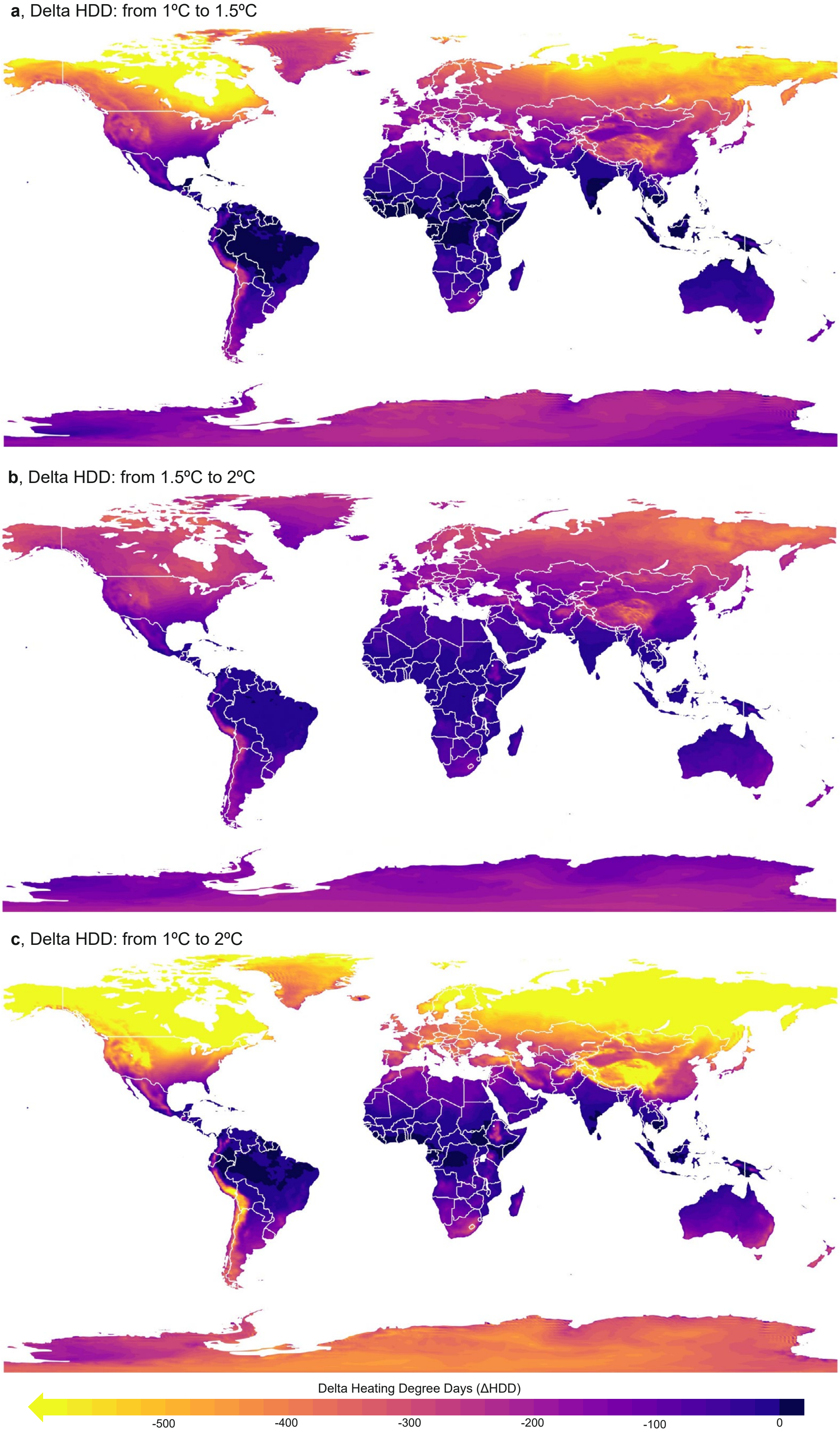
Supplementary information The online version contains supplementary material available at https://doi.org/10.1038/s41893-025-01754-y.

Correspondence and requests for materials should be addressed to Jesus Lizana.

Peer review information *Nature Sustainability* thanks the anonymous reviewer(s) for their contribution to the peer review of this work.

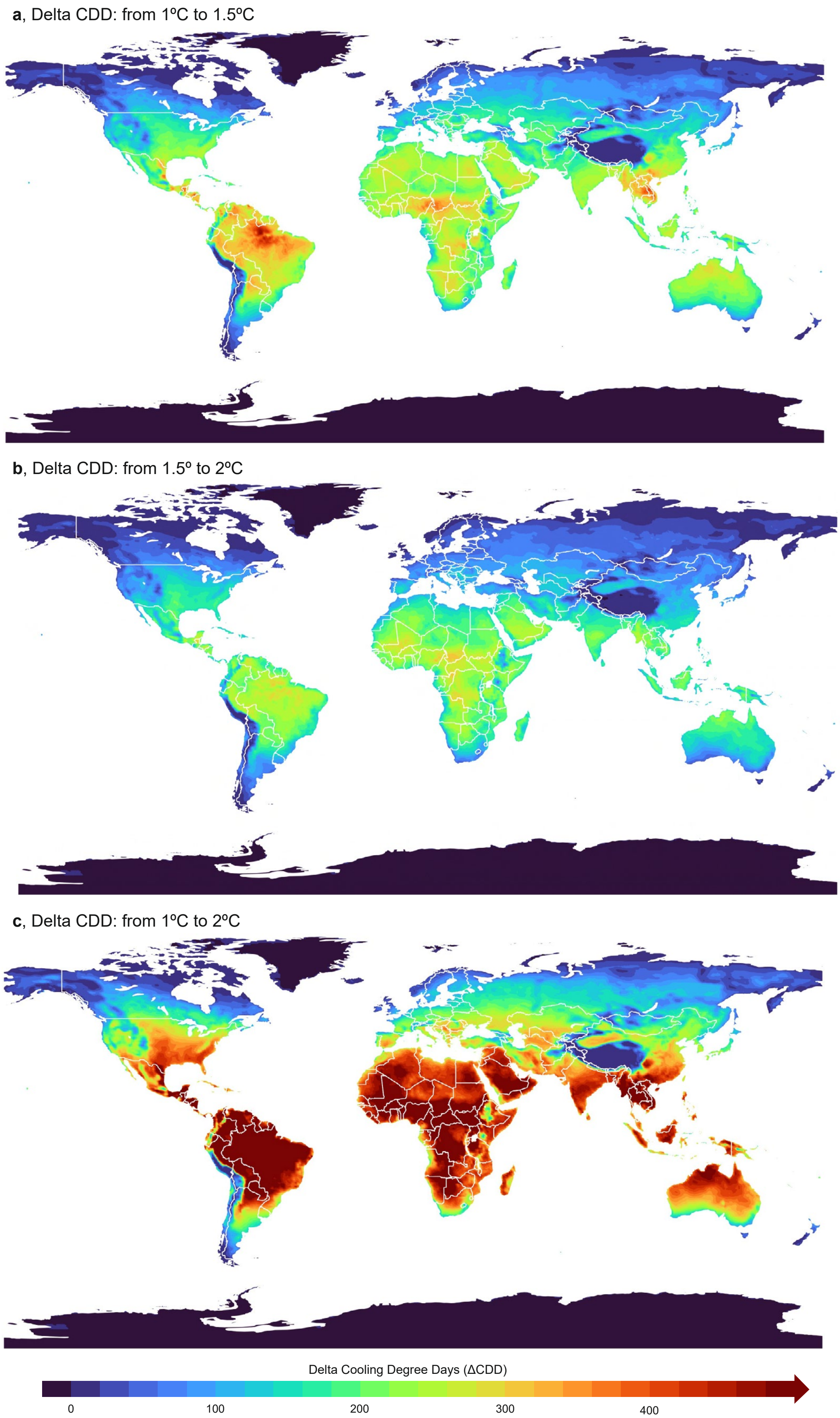
Reprints and permissions information is available at www.nature.com/reprints.

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.



Extended Data Fig. 1 | Global changes in HDD between 1.0 °C (historical, 2006-2016), and future 1.5 °C and 2.0 °C global warming levels. **a**, Absolute change in HDD (Delta HDD) between the 1.0 °C and 1.5 °C scenario. **b**, Absolute change in HDD (Delta HDD) between 1.5 °C and 2.0 °C. **c**, Absolute change in HDD (Delta HDD) between 1.0 °C and 2.0 °C. Delta HDD (ΔHDD) refers to the incremental/decremental change in mean annual HDD per grid. Administrative boundary data © EuroGeographics 2025.

https://doi.org/10.1038/s41893-025-01754-y



Extended Data Fig. 2 | See next page for caption.

https://doi.org/10.1038/s41893-025-01754-y

Extended Data Fig. 2 | Global changes in CDD between 1.0 °C (historical, 2006-2016), and future 1.5 °C and 2.0 °C global warming levels. **a**, Absolute change in CDD (Delta CDD) from 1.0 °C to 1.5 °C scenario. **b**, Absolute change in CDD (Delta CDD) from 1.5 °C to 2.0 °C scenario. **c**, Absolute change in CDD (Delta CDD) between 1.0 °C and 2.0 °C. Delta CDD (ΔCDD) refers to the incremental/decremental change in mean annual CDD per grid. Administrative boundary data © EuroGeographics 2025.

Extended Data Table 1 | Overview of the global gridded maps of HDD and CDD by warming scenario

Maps/Variable	Resolution[a]	Temporal domain[b]	File type	Minimum	10th percentile	Median	90th percentile	Maximum
HEATING DEGREE DAYS								
1.0°C scenario								
Mean HDD	0.833° × 0.556°	2006-2016	NetCDF V4	0	32	6971	22493	25453
Median HDD	0.833° × 0.556°	2006-2016	NetCDF V4	0	30	6932	22525	25358
10th percentile HDD	0.833° × 0.556°	2006-2016	NetCDF V4	0	14	6362	21904	24972
90th percentile HDD	0.833° × 0.556°	2006-2016	NetCDF V4	0	52	7638	23106	26096
Standard deviation HDD	0.833° × 0.556°	2006-2016	NetCDF V4	0	12	240	361	539
1.5°C scenario								
Mean HDD	0.833° × 0.556°	-	NetCDF V4	0	28	6555	22286	25230
Median HDD	0.833° × 0.556°	-	NetCDF V4	0	20	6508	22298	25228
10th percentile HDD	0.833° × 0.556°	-	NetCDF V4	0	4	5430	21206	24175
90th percentile HDD	0.833° × 0.556°	-	NetCDF V4	0	60	7749	23361	26355
Standard deviation HDD	0.833° × 0.556°	-	NetCDF V4	0	20	409	588	814
2.0°C scenario								
Mean HDD	0.833° × 0.556°	-	NetCDF V4	0	19	6297	22096	25040
Median HDD	0.833° × 0.556°	-	NetCDF V4	0	12	6258	22125	25046
10th percentile HDD	0.833° × 0.556°	-	NetCDF V4	0	2	5190	20980	23961
90th percentile HDD	0.833° × 0.556°	-	NetCDF V4	0	43	7469	23178	26158
Standard deviation HDD	0.833° × 0.556°	-	NetCDF V4	0	16	412	590	812
COOLING DEGREE DAYS								
1.0°C scenario (2006-2016)								
Mean CDD	0.833° × 0.556°	2006-2016	NetCDF V4	0	0	78	2904	5125
Median CDD	0.833° × 0.556°	2006-2016	NetCDF V4	0	0	73	2890	5121
10th percentile CDD	0.833° × 0.556°	2006-2016	NetCDF V4	0	0	43	2701	4924
90th percentile CDD	0.833° × 0.556°	2006-2016	NetCDF V4	0	0	115	3105	5308
Standard deviation CDD	0.833° × 0.556°	2006-2016	NetCDF V4	0	0	25	109	217
1.5°C scenario								
Mean CDD	0.833° × 0.556°	-	NetCDF V4	0	0	128	3160	5329
Median CDD	0.833° × 0.556°	-	NetCDF V4	0	0	108	3144	5323
10th percentile CDD	0.833° × 0.556°	-	NetCDF V4	0	0	37	2703	4805
90th percentile CDD	0.833° × 0.556°	-	NetCDF V4	0	0	241	3654	5847
Standard deviation CDD	0.833° × 0.556°	-	NetCDF V4	0	0	71	216	394
2.0°C scenario								
Mean CDD	0.833° × 0.556°	-	NetCDF V4	0	0	161	3367	5547
Median CDD	0.833° × 0.556°	-	NetCDF V4	0	0	139	3351	5545
10th percentile CDD	0.833° × 0.556°	-	NetCDF V4	0	0	51	2892	5037
90th percentile CDD	0.833° × 0.556°	-	NetCDF V4	0	0	293	3876	6062
Standard deviation CDD	0.833° × 0.556°	-	NetCDF V4	0	0	81	227	402

[a] Average spatial resolution at mid-latitudes (~45°) is approximately 60km^2.
[b] The temporal domain of the projections for 1.5°C and 2.0°C is independent of specific timelines or emission pathways, thereby enabling a scenario-independent evaluation explicitly aligned with the temperature targets of the Paris Agreement.

This table lists the global gridded maps generated for three climate change scenarios: 1.0 °C, 1.5 °C, and 2.0 °C. For each variable and scenario, five statistical descriptors of the model ensemble are provided: mean, median, 10th percentile, 90th percentile, and standard deviation. These metrics were calculated from annual CDD and HDD values derived from a temperature ensemble comprising 70 members over a 10-year period, representing a total of 700 simulated years per scenario.

QUERY FORM

Manuscript ID	**[Art. Id: 1754]**
Author	**Jesus Lizana**

AUTHOR:

The following queries have arisen during the editing of your manuscript. Please answer by making the requisite corrections directly in the e.proofing tool rather than marking them up on the PDF. This will ensure that your corrections are incorporated accurately and that your paper is published as quickly as possible.

Query No.	*Nature of Query*
Q1:	Please define 'SSP' in the sentence beginning "Furthermore, using the 'middle..." in the Abstract.
Q2:	Please check your article carefully, coordinate with any co-authors and enter all final edits clearly in the eproof, remembering to save frequently. Once corrections are submitted, we cannot routinely make further changes to the article.
Q3:	Note that the eproof should be amended in only one browser window at any one time; otherwise changes will be overwritten.
Q4:	Author surnames have been highlighted. Please check these carefully and adjust if the first name or surname is marked up incorrectly, as this will affect indexing of your article in public repositories such as PubMed. Also, carefully check the spelling and numbering of all author names and affiliations, and the corresponding author(s) email address(es). Please note that email addresses should only be included for designated corresponding authors, and you cannot change corresponding authors at this stage except to correct errors made during typesetting.
Q5:	You cannot alter accepted Supplementary Information files except for critical changes to scientific content. If you do resupply any files, please also provide a brief (but complete) list of changes. If these are not considered scientific changes, any altered Supplementary files will not be used, only the originally accepted version will be published.
Q6:	Please check Figures for accuracy as they have been relabelled. Please markup minor changes in the eProof. For major changes, please provide revised figures. (Please note that in the eProof the figure resolution will appear at lower resolution than in the pdf and html versions of your paper.)
Q7:	If applicable, please ensure that any accession codes and datasets whose DOIs or other identifiers are mentioned in the paper are scheduled for public release as soon as possible, we recommend within a few days of submitting your proof, and update the database record with publication details from this article once available.
Q8:	Please note, we reserve 'significant' and its derivatives for statistical significance. Please reword where this is not the intended meaning (for example to important, notable, substantial); there are 22 instances throughout your text.

QUERY FORM

Manuscript ID	**[Art. Id: 1754]**
Author	**Jesus Lizana**

AUTHOR:

The following queries have arisen during the editing of your manuscript. Please answer by making the requisite corrections directly in the e.proofing tool rather than marking them up on the PDF. This will ensure that your corrections are incorporated accurately and that your paper is published as quickly as possible.

Query No.	*Nature of Query*
Q9:	Please define 'SSP' in the sentence beginning "Finally, the implications of these...".
Q10:	Please note, citations to Fig. 1 in the paragraph beginning 'Figure 1 illustrates and statistically...' have been edited according to style. Please check.
Q11:	Please note, our style does not allow for special characters in figure caption titles, so they have been removed from the titles for Figs. 1 and 2. Please check, and feel free to add information to the captions if needed.
Q12:	Please note, panel labels have been edited in Figs. 1 and 2 and their captions according to style. Please check.
Q13:	Please confirm that edits to the Fig. 2 citations in the sentence beginning "In a similar approach, Fig...." have retained the intended meaning.
Q14:	Please note, our style does not allow for special characters in table titles, so they have been removed from Tables 1 and 2.
Q15:	Please confirm that edits to the supplementary information citation in the sentence beginning "Most of these 20 countries (18..." and similar changes throughout are accurate.
Q16:	Please confirm that edits to the figure citation in the sentence beginning "This is evident in the comparison..." are accurate. Or did you mean to cite Extended Data Fig. 1a and main text Fig. 1b?
Q17:	Please confirm that edits to the figure citation in the sentence beginning "This is evident in the comparison..." are accurate. Or did you mean to cite Extended Data Fig. 2a and main text Fig. 2b?
Q18:	Please confirm that edits to move the parentheses from the Fig. 3 title to the caption are accurate.
Q19:	Please confirm the insertion of 'Year' as an x-axis label in Fig. 4b.

QUERY FORM

Manuscript ID	**[Art. Id: 1754]**
Author	**Jesus Lizana**

AUTHOR:

The following queries have arisen during the editing of your manuscript. Please answer by making the requisite corrections directly in the e.proofing tool rather than marking them up on the PDF. This will ensure that your corrections are incorporated accurately and that your paper is published as quickly as possible.

Query No.	*Nature of Query*
Q20:	Please confirm the insertion of 'Intergovernmental Panel on Climate Change' as a definition for 'IPCC' in the Fig. 4 caption.
Q21:	Please confirm that edits to the figure citation in the sentence beginning "For this 'middle-of-the-road' socio-economic..." are accurate.
Q22:	Please define 'CEDA' in the sentence beginning "The global gridded CDD and...".
Q23:	Please confirm that edits to the sentence beginning "This temperature ensemble was chosen..." have retained the intended meaning.
Q24:	Please define 'UKRI' and 'MSCA' in the Acknowledgements section.
Q25:	In ref. 3, please confirm that edits to the authors' names are accurate.
Q26:	In refs. 15 and 38, please provide the article numbers rather than the page ranges.
Q27:	In refs. 18, 24 and 35, please confirm that edits to the repository names are accurate.
Q28:	In ref. 20, please confirm that edits to the publication date are accurate.
Q29:	In ref. 36, please confirm that edits to the repository name are accurate. Please also provide the publication year.
Q30:	In ref. 42, please provide the page range or article number.

nature portfolio

Corresponding author(s): Jesus Lizana

Last updated by author(s): Nov 1, 2025

Reporting Summary

Nature Portfolio wishes to improve the reproducibility of the work that we publish. This form provides structure for consistency and transparency in reporting. For further information on Nature Portfolio policies, see our Editorial Policies and the Editorial Policy Checklist.

Statistics

For all statistical analyses, confirm that the following items are present in the figure legend, table legend, main text, or Methods section.

n/a	Confirmed	
☐	☒	The exact sample size (n) for each experimental group/condition, given as a discrete number and unit of measurement
☐	☒	A statement on whether measurements were taken from distinct samples or whether the same sample was measured repeatedly
☒	☐	The statistical test(s) used AND whether they are one- or two-sided *Only common tests should be described solely by name; describe more complex techniques in the Methods section.*
☒	☐	A description of all covariates tested
☐	☒	A description of any assumptions or corrections, such as tests of normality and adjustment for multiple comparisons
☐	☒	A full description of the statistical parameters including central tendency (e.g. means) or other basic estimates (e.g. regression coefficient) AND variation (e.g. standard deviation) or associated estimates of uncertainty (e.g. confidence intervals)
☒	☐	For null hypothesis testing, the test statistic (e.g. F, t, r) with confidence intervals, effect sizes, degrees of freedom and P value noted *Give P values as exact values whenever suitable.*
☒	☐	For Bayesian analysis, information on the choice of priors and Markov chain Monte Carlo settings
☒	☐	For hierarchical and complex designs, identification of the appropriate level for tests and full reporting of outcomes
☒	☐	Estimates of effect sizes (e.g. Cohen's d, Pearson's r), indicating how they were calculated

Our web collection on statistics for biologists contains articles on many of the points above.

Software and code

Policy information about availability of computer code

Data collection	n/a
Data analysis	Data analysis was conducted in Python (v3.9) and QGIS (3.28). The code to calculate HDD and CDD from the temperature ensembles is available at https://github.com/lizanafj/cdd_hdd_mapping. The code for data visualisation and statistical analysis can be found at https://github.com/lizanafj/python_examples_with_CDDandHDD_files.

For manuscripts utilizing custom algorithms or software that are central to the research but not yet described in published literature, software must be made available to editors and reviewers. We strongly encourage code deposition in a community repository (e.g. GitHub). See the Nature Portfolio guidelines for submitting code & software for further information.

Data

Policy information about availability of data

All manuscripts must include a data availability statement. This statement should provide the following information, where applicable:

- Accession codes, unique identifiers, or web links for publicly available datasets
- A description of any restrictions on data availability
- For clinical datasets or third party data, please ensure that the statement adheres to our policy

The dataset generated in this study are available at the Oxford University Research Archive (ORA) repository: https://ora.ox.ac.uk/objects/uuid:6fced8c0-5c64-44af-b38e-e99785b2db90 or https://doi.org/10.5287/ora-w4qpqy522.

Research involving human participants, their data, or biological material

Policy information about studies with human participants or human data. See also policy information about sex, gender (identity/presentation), and sexual orientation and race, ethnicity and racism.

Reporting on sex and gender	n/a
Reporting on race, ethnicity, or other socially relevant groupings	n/a
Population characteristics	n/a
Recruitment	n/a
Ethics oversight	n/a

Note that full information on the approval of the study protocol must also be provided in the manuscript.

Field-specific reporting

Please select the one below that is the best fit for your research. If you are not sure, read the appropriate sections before making your selection.

☐ Life sciences ☐ Behavioural & social sciences ☒ Ecological, evolutionary & environmental sciences

For a reference copy of the document with all sections, see nature.com/documents/nr-reporting-summary-flat.pdf

Ecological, evolutionary & environmental sciences study design

All studies must disclose on these points even when the disclosure is negative.

Study description	This study generates and analyses a global gridded dataset of Heating Degree Days (HDD) and Cooling Degree Days (CDD) for three global mean temperature rise scenarios: 1.0°C (2006-2016), 1.5°C, and 2.0°C. The analysis employs a bias-corrected HadAM4-based temperature ensemble with high spatiotemporal resolution (six-hourly mean temperatures on a 0.883º × 0.556º grid)
Research sample	The global dataset was derived from temperature ensembles representing three global mean temperature rise scenarios, generated using the HadAM4 Atmosphere-only General Circulation Model (AGCM) developed by the UK Met Office Hadley Centre. The simulations were conducted within the climateprediction.net (CPDN) distributed climate modelling framework. The temperature ensembles were published by Lizana et al. (2024) and are available through the CEDA repository (DOI: 10.1038/s41597-024-03400-2)
Sampling strategy	The scenarios followed the half a degree additional warming, prognosis and projected impacts (HAPPI) experimental design protocol, being: 1°C (historical, 2006-2016), 1.5°C and 2°C above pre-industrial levels.
Data collection	Data was stored and processed in JASMIN, the UK's data analysis facility for environmental science: https://jasmin.ac.uk/
Timing and spatial scale	The generated global gridded dataset comprises 30 maps that capture annual climate variability using five statistical descriptors (mean, median, 10th percentile, 90th percentile, and standard deviation) for each variable (HDD and CDD) and scenario (1.0°C, 1.5°C, and 2.0°C) over a representative 10-year period.
Data exclusions	The completed bias-corrected HadAM4-based temperature ensemble generated by Lizana et al. (2024) was used without data exclusions.
Reproducibility	All methods follow standardised protocols.
Randomization	n/a
Blinding	n/a

Did the study involve field work? ☐ Yes ☒ No

Reporting for specific materials, systems and methods

We require information from authors about some types of materials, experimental systems and methods used in many studies. Here, indicate whether each material, system or method listed is relevant to your study. If you are not sure if a list item applies to your research, read the appropriate section before selecting a response.

Materials & experimental systems

n/a	Involved in the study
☒	☐ Antibodies
☒	☐ Eukaryotic cell lines
☒	☐ Palaeontology and archaeology
☒	☐ Animals and other organisms
☒	☐ Clinical data
☒	☐ Dual use research of concern
☒	☐ Plants

Methods

n/a	Involved in the study
☒	☐ ChIP-seq
☒	☐ Flow cytometry
☒	☐ MRI-based neuroimaging

Plants

Seed stocks	n/a
Novel plant genotypes	n/a
Authentication	n/a