nature sustainability

Brief Communication

https://doi.org/10.1038/s41893-023-01155-z

Change in cooling degree days with global mean temperature rise increasing from 1.5 °C to 2.0 °C

Received: 21 December 2022

Accepted: 24 May 2023

Published online: 13 July 2023

Check for updates

Nicole D. Miranda[1,2,6], Jesus Lizana[1,2,6], Sarah N. Sparrow[3], Miriam Zachau-Walker[2], Peter A. G. Watson[4], David C. H. Wallom[3], Radhika Khosla[1,5] & Malcolm McCulloch[1,2]

Limiting global mean temperature rise to 1.5 °C is increasingly out of reach. Here we show the impact on global cooling demand in moving from 1.5 °C to 2.0 °C of global warming. African countries have the highest increase in cooling requirements. Switzerland, the United Kingdom and Norway (traditionally unprepared for heat) will suffer the largest relative cooling demand surges. Immediate and unprecedented adaptation interventions are required worldwide to be prepared for a hotter world.

This work identifies regions of high cooling needs using 2,100 simulation runs of global mean surface temperature through the HadAM4 model[1,2] across three global warming scenarios: historical (2006–2016), 1.5 °C and 2 °C. Rising extreme heat is already driving an unprecedented surge in cooling demand, with the energy required for cooling by 2050 predicted to be equivalent to the combined electricity capacity of the United States, European Union and Japan in 2016[3]. But how much more cooling would be required if the Paris Agreement's preferred 1.5 °C limit[4] is overshot, and global mean temperature increases to 2.0 °C? The question is crucial, given the growing consensus that there is currently 'no credible pathway to avoid warming to 1.5 °C'[5].

Cooling degree days (CDDs) are a widely used indicator to examine warming and quantify cooling demand. CDDs measure how warm a given location is, by comparing the mean outdoor temperatures recorded each day with a standard temperature (usually 65 °F or 18 °C)[3]. For example, a day with a mean outdoor temperature of 30 °C has 12 CDDs. In this Article, we map annual CDDs and examine the most affected countries by warming from 1.5 °C to 2.0 °C projections. These are identified by absolute and relative cooling demand increases between these two scenarios. Absolute changes (abs-ΔCDD) show where human exposure to hotter weather will be severe. Relative changes (rel-ΔCDD) indicate large adaptation challenges in regions not traditionally prepared for increasing heat.

Previous work has mainly reported CDDs using historical data[6,7]. Model-based studies for specific areas of the world have also been reported[8–11]. Global model data, however, have only been analysed for specific years, leaving an important gap in predicting and preparing for cooling demand in fast approaching 1.5 °C and 2.0 °C scenarios. To calculate CDDs, we simulate 700 members per scenario using the citizen-science project climate*prediction*.net (CPDN), obtaining 6-hourly mean temperatures at a spatial resolution of 0.883° × 0.556°.

The findings of this study are summarized in Fig. 1 and Table 1. Figure 1a maps the difference in CDDs between the 1.5 °C and 2.0 °C scenarios, and Table 1a highlights the top ten countries with more than 5 million inhabitants that will experience, and subsequently need to respond to, the largest changes. Extended Data Table 1 includes the top 50 countries with a population of more than 2 million. A more extended list is provided in Supplementary Note 4. To examine variability, we map the standard deviation of results in Supplementary Note 3.

The results show that regions surrounding the Equator, particularly the Sub-Saharan region, will experience the largest increase in cooling demand (Fig. 1a). Table 1a shows that ten African countries are the nations with the largest change in CDDs, with important implications for their planning and building climate resilience. These countries align in a west–east band in central Africa. They mainly border Mauritania, Niger and Sudan, identified in ref. 6 to have the highest extreme heat historically. Mali and Chad were also previously reported

[1]Future of Cooling Programme, Oxford Martin School, University of Oxford, Oxford, UK. [2]Energy and Power Group, Department of Engineering Science, University of Oxford, Oxford, UK. [3]Oxford e-Research Centre, University of Oxford, Oxford, UK. [4]School of Geographical Sciences, University of Bristol, Bristol, UK. [5]Smith School of Enterprise and the Environment, School of Geography and the Environment, University of Oxford, Oxford, UK. [6]These authors contributed equally: Nicole D. Miranda, Jesus Lizana. e-mail: jesus.lizana@eng.ox.ac.uk

https://doi.org/10.1038/s41893-023-01155-z

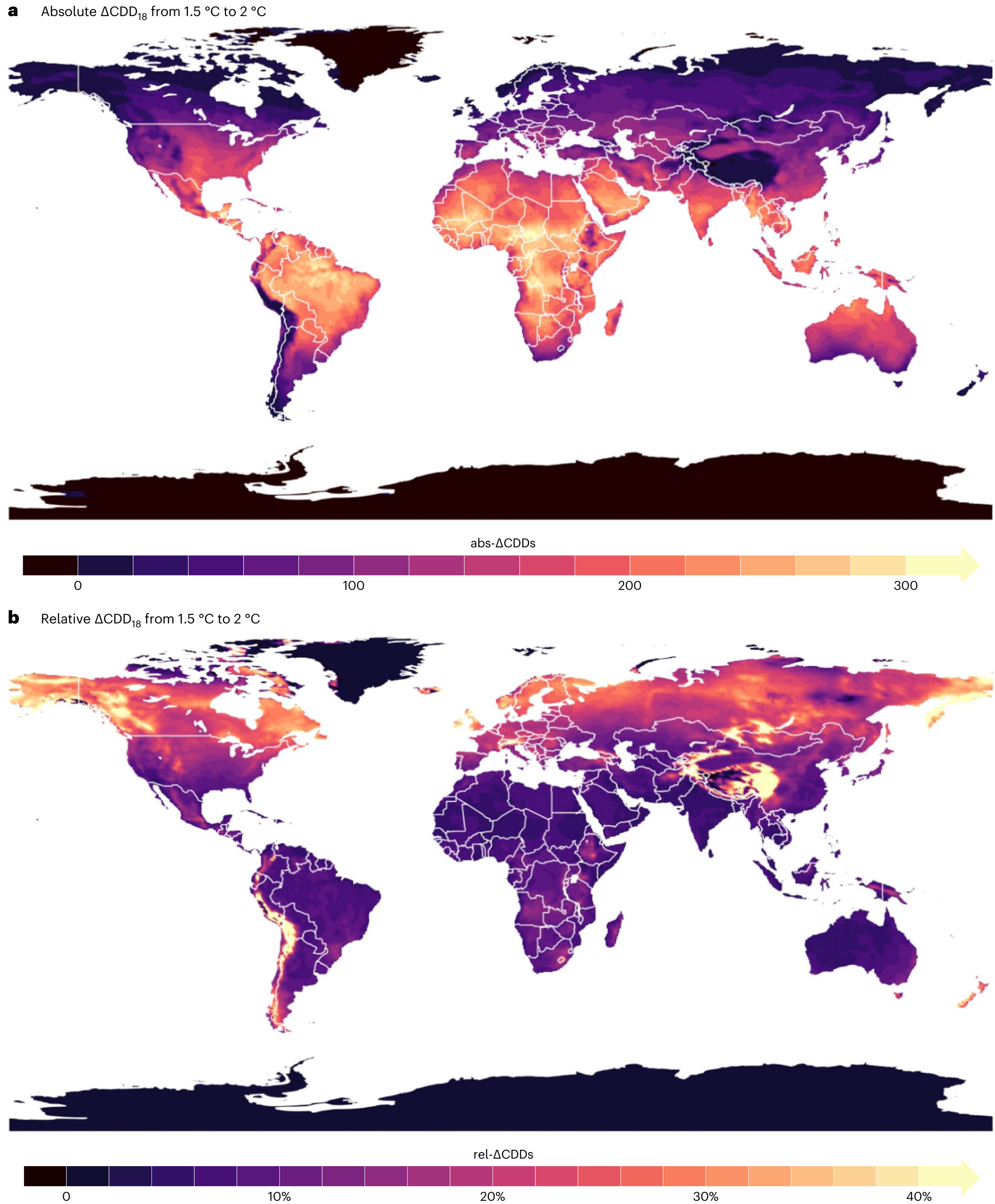

Fig. 1 | Global CDD difference between 1.5 °C and 2 °C global warming scenarios. a, Absolute delta cooling degree days (abs-ΔCDD) from 1.5° to 2 °C global warming scenarios. **b**, Relative delta cooling degree days (rel-ΔCDD) from 1.5 °C to 2 °C global warming scenarios. Delta (Δ) refers to the incremental change in the variable. The absolute and relative delta from 1.5 °C to 2 °C scenarios were calculated using the mean annual CDDs per coordinate across ensemble members per scenario, involving 700 simulations each. Administrative boundaries were used from EuroGeographics.

https://doi.org/10.1038/s41893-023-01155-z

Table 1 | Ranking of the top ten countries that will suffer the highest increase (absolute and relative) in area-weighted mean CDDs from 1.5 °C to 2.0 °C

Top ten countries by absolute change	abs-ΔCDD_{18}	Top ten countries by relative change	rel-ΔCDD_{18}
Central African Republic	266	Switzerland	30%
Burkina Faso	254	United Kingdom	30%
Mali	253	Norway	28%
South Sudan	251	Finland	28%
Nigeria	245	Sweden	28%
Congo	241	Austria	24%
Democratic Republic of The Congo	240	Canada	24%
Chad	236	Denmark	24%
Uganda	232	New Zealand	24%
Cameroon	228	Belgium	21%

Countries with more than 5 million inhabitants in 2020 are listed. Annual CDDs were calculated using a temperature baseline of 18 °C. Delta (Δ) refers to the incremental change in the variable. The rankings use the area-weighted mean values per country rather than grid-specific relative values, as the latter can distort results with large percentage values for specific latitude–longitudes that go from no/negligible CDDs in a 1.5 °C to having notable CDDs in a 2.0 °C. The full list of countries with more than 2 M population is provided in Supplementary Notes 4 and 5, following different statistical criteria.

to have the highest historical CDD[6], and here we show that they will also experience a large increment in CDDs from a 1.5 °C to a 2.0 °C scenario. Indeed, the central African population not only had the highest requirements for cooling historically (2009–2018) but would also experience the highest surge in heat exposure and wide-ranging adaptation requirements.

Notably, the results of relative changes in CDDs (Fig. 1b and Table 1b) show that the Global North will experience dramatic relative increases in the number of days that require cooling. Table 1b is the first to rank the top ten most affected countries by their relative increases in CDDs globally. Eight of ten are European nations, which are traditionally unprepared for high temperatures and will require large-scale adaptation to heat resilience.

Globally, Switzerland and the United Kingdom will see the largest relative variation in cooling demand (30%). This is relevant, as current cooling studies for Switzerland and the United Kingdom are, at best, limited. For Switzerland, only two studies in 2006 and 2021 were found[12,13], which warned of the accelerating demand for cooling (compared with heating demand). In the case of the United Kingdom, the country with the second-largest relative increase in CDDs, only one 2009 predictive study is found[14]. The latter aligns with the large relative change of our results (but for different temperature increases), reporting that the energy (and emissions) from air conditioners almost doubles from 2004 to 2030 in London. However, these 2009 study results were not set in the global context we provide. Additional statistics on the relative (and absolute) increase in CDDs in countries with more than 2 million inhabitants are provided in Supplementary Note 5, this time exclusively considering urban areas. This urban area-weighted analysis identifies Ireland, the United Kingdom and Finland as the top three most affected countries—foreshadowing important questions about prioritizing sustainable cooling access and heat resilience strategies in their cities.

Our results enhance and complement the existing literature. A previous study examining predictions of CDDs in Europe[9] reports changes in CDDs between Representative Concentration Pathways (RCP4.5 and RCP8.5) in different years from historical (1981–2010) to the period 1981–2100. It models temperature at different years rather than forcing specific global warming scenarios, as in our analysis. While the results are analogous regarding the highest absolute increase in Europe to be in Mediterranean countries, no relative changes are reported. Another study reports European CDDs (that is, Mediterranean) in a 2.0 °C scenario (with spatial resolution >200 km^2)[15], showing that the further south, the more the absolute change of CDD increases.

In our study, other large regions of high CDD relative increase are found in the mountain ranges of the Andes in South America, crossing the continent from North to South, and the Himalayas in Central Asia, which extend into the Southwest of China. This brings additional insight for sustainability planning as previous CDD predictions[16,17] for China under different RCP scenarios did not highlight this region for its relative increase in cooling demand. Further research on changing climate in these regions is needed as no additional studies have been found.

Supported by these results, we argue how immediate and unprecedented climate adaptation interventions are required worldwide to be prepared for a hotter world. An increasing number of stocktake studies[4,5] make clear that limiting a surge in global mean temperature to 1.5 °C is increasingly out of reach. We show that moving from a 1.5 °C to 2.0 °C warmer planet would dramatically exacerbate heat exposure and energy demand for cooling. There has already been an increase in global surface temperature of 1.09 °C above pre-industrial levels between 2011 and 2020[4,18]. The total difference in cooling demand from today to a 2.0 °C warmer planet would be greater than our analysis maps, requiring a key focus on an issue that has traditionally been a blind spot for sustainability debates[19].

For this study, the differences in CDDs reported are built on the largest ensemble of 700 simulations for each scenario to ensure internal climate variability and at the current highest available temporal resolution of temperatures. The 6-hourly mean temperature predictions result in high granularity of cooling demand variations. The geographical resolution of 0.833° × 0.556° allows examination of the whole planet under one lens while managing the computational intensity of large datasets.

The absolute change in CDDs values shows that African countries will experience the highest increase in cooling demand. These conditions will pose further stress to the continent's socio-economic development and energy networks, and their implications for equitable access to cooling, issues that require much additional research given the limited studies of this rising threat in the African context[20]. Further, the results on relative changes indicate that countries that will experience the most drastic increases in CDDs are traditionally prepared for heating, not cooling. These countries will require acute and long-term adaptation to make their populations and the built environment more heat resilient, including broad cooling access through sustainable pathways[21]. Much can be shared and learnt from countries across the world as they tackle this global challenge.

Overall, CDDs are a valuable indicator of normalized temperature exposure, and are useful to enable a top-down comparison of global warming scenarios between regions. As research grows, additional socio-economic, technical and environmental variables, such as humidity, solar irradiance and wind speed, are needed for more precise cooling demand estimations. It should also be noted that individual thermal comfort expectations differ across communities and countries, depending on conventions, physiology and cultural norms, among others[3].

Several important policy implications stem from these results. First, this work clearly indicates that every small increase in global warming will affect heat exposure and cooling demand worldwide, driving the need for immediate, unprecedented and localized adaptation. Second, it is in the national interest of all Global North and South countries to work towards the 1.5 °C target, given that they will be the most affected by the relative and absolute change in CDDs, respectively. Current planning and implementation of energy and climate policies across countries must be designed to be prepared for and build resilience to a hotter local climate. It is important to recognize that the dramatic, and often inequitable, rise in cooling demand can no longer be ignored but rather be addressed through socio-technical levers of change[19], which support holistic sustainable solutions.

Methods

Ensembles of 2,100 global climate simulations for mean temperature for three scenarios were generated using the HadAM4 Atmosphere-only General Circulation Model[1,2] from the UK Met Office Hadley Centre. The scenarios followed the half-a-degree additional warming prognosis and projected impacts experiment design protocol[22], specifically: historical (2006–2016), 1.5 °C and 2 °C above pre-industrial levels. Thus, the model was forced to achieve the increase in temperature for scenarios 1.5 °C and 2.0 °C, regardless of when this occurs. The simulations output 6-hourly mean temperatures at a horizontal resolution of 0.833 longitude and 0.556 latitude, where each scenario involves 70 individual members for a 10 year period (700 runs per scenario), aiming to ensure internal variability. This simulation experiment ran within the CPDN climate simulation environment[23]. CPDN uses the Berkeley Open Infrastructure for Network Computing[24] framework, tasking more than 30,000 globally distributed volunteer members of the public.

Biases in simulated temperature were identified and corrected using a quantile mapping approach. The bias correction was performed in the entire ensemble using reference temperature data from ERA5 for the same timeframe of the historical scenario (2006–2016). Biases are calculated for each percentile in the cumulative distribution function from the historical scenario compared with ERA5 observations. Then, the calculated biases are added to the simulations of the historical, 1.5 °C and 2 °C scenarios to correct the biases of each percentile, assuming that the bias is unchanging between scenarios. This ensures the preservation of the ensemble's internal variability, and the cumulative distribution of the ensemble aligns with the cumulative distribution of the observations. Further details and validation of the climate model are provided in Supplementary Note 1.

CDDs were used to compare global warming scenarios. CDDs are a widely used indicator to measure temperature exposure and cooling demand through dry bulb temperature. Annual CDDs were calculated for the ensemble members per scenario (700 simulated years) in all coordinates according to equation (1):

$$\mathrm{CDD} = \frac{\sum_{t=0}^{t=m}(T_t - T_{\mathrm{base}})}{n}, T_t > T_{\mathrm{threshold}} \tag{1}$$

where t is the time step, m is the last time step of the year, n is the number of time steps in one day ($n = 4$, given 6-hourly data), T_t is the mean outdoor temperature at time t, T_{base} is the reference temperature used to calculate the temperature difference, and $T_{\mathrm{threshold}}$ is the outdoor temperature value above which the temperature differences are calculated. $T_{\mathrm{threshold}}$ and the baseline temperature, T_{base}, was defined as 18 °C, following the most widespread approach in previous studies to enable comparison[3]. However, this methodology can have several modifications depending on available data, context and application (Supplementary Note 2). It should be noted that since we are evaluating the absolute and relative change between scenarios, the modification of CDD calculation criteria has few implications in the findings.

Then, mean annual CDDs and standard deviation per coordinate across ensemble members (700 simulations) were obtained for the 1.5 °C and 2 °C scenarios, and deltas were computed. Finally, the area-weighted statistics per country were calculated using QGIS geographic information system. Supplementary Note 4 lists the top 100 countries with more than 2 M population. Additionally, Supplementary Note 5 also introduces the top 100 countries by considering only urban area-weighted statistics per country to consider the dimension of urban contexts. This last ranking should be considered carefully since 44% of the population still lives in rural areas[25].

This study has the following limitations. CDDs were calculated using the dry bulb temperature following the standard approach, which does not account for the influence of humidity or other environmental variables on perceived thermal comfort. CDDs may also be underestimated in urban areas since the urban heat island effect was ignored.

Supplementary Information provides additional details of the methods and results associated with the climate model (Supplementary Note 1), CDDs (Supplementary Note 2), additional statistical results (Supplementary Note 3) and a more extended ranking of countries according to different criteria (Supplementary Notes 4 and 5).

Reporting summary

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

Data availability

The data of absolute and relative changes in CDDs (to reproduce the maps of this work) are found in the Oxford University Research Archive ORA at https://doi.org/10.5287/ora-9rbzrxxgz. Further data are available from the corresponding author on request.

Code availability

The atmosphere-only HadAM4 model was used to generate the data from the Met Office Hadley Centre. In addition, the CPDN project simulation facility is open for collaboration and has an academic licence for the HadAM4 MetOffice software, which can be shared with official collaborators. The code with the ensemble bias correction method using the quantile mapping approach is available at https://github.com/lizanafj/ensemble-bias-correction. Further codes are available from the corresponding author on request.

References

1. Bevacqua, E. et al. Larger spatial footprint of wintertime total precipitation extremes in a warmer climate. *Geophys. Res. Lett.* **48**, e2020GL091990 (2021).
2. Watson, P. et al. *Multi-thousand Member Ensemble Atmospheric Simulations with Global 60km Resolution using climateprediction.net* Technical Report EGU2020-10895 (EGU General Assembly, 2020); https://doi.org/10.5194/egusphere-egu2020-10895
3. *The Future of Cooling—Opportunities for Energy Efficient Air Conditioning* (International Energy Agency, 2018).
4. IPCC *Climate Change 2022: Impacts, Adaptation and Vulnerability* (eds Pörtner, H.-O. et al.) (Cambridge Univ. Press, 2022).
5. United Nations Environmental Programme *Emissions Gap Report 2022*. *New Labor Forum* Vol. 20 (Sage Publications, 2011).
6. Biardeau, L. T., Davis, L. W., Gertler, P. & Wolfram, C. Heat exposure and global air conditioning. *Nat. Sustain.* **3**, 25–28 (2020).
7. Mistry, M. N. Historical global gridded degree-days: a high-spatial resolution database of CDD and HDD. *Geosci. Data J.* **6**, 214–221 (2019).
8. Petri, Y. & Caldeira, K. Impacts of global warming on residential heating and cooling degree-days in the United States. *Sci. Rep.* **5**, 12427 (2015).
9. Spinoni, J. et al. Changes of heating and cooling degree-days in Europe from 1981 to 2100. *Int. J. Climatol.* **38**, e191–e208 (2018).
10. 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).
11. Almazroui, M. et al. Projected change in temperature and precipitation over Africa from CMIP6. *Earth Syst. Environ.* **4**, 455–475 (2020).

12. Mutschler, R., Rüdisüli, M., Heer, P. & Eggimann, S. Benchmarking cooling and heating energy demands considering climate change, population growth and cooling device uptake. *Appl. Energy* **288**, 116636 (2021).
13. Christenson, M., Manz, H. & Gyalistras, D. Climate warming impact on degree-days and building energy demand in Switzerland. *Energy Convers. Manag.* **47**, 671–686 (2006).
14. Day, A. R., Jones, P. G. & Maidment, G. G. Forecasting future cooling demand in London. *Energy Build.* **41**, 942–948 (2009).
15. Giannakopoulos, C. et al. Climatic changes and associated impacts in the Mediterranean resulting from a 2 °C global warming. *Glob. Planet. Change* **68**, 209–224 (2009).
16. Zhou, Y., Eom, J. & Clarke, L. The effect of global climate change, population distribution, and climate mitigation on building energy use in the U.S. and China. *Climatic Change* **119**, 979–992 (2013).
17. Shi, Y., Gao, X., Xu, Y., Giorgi, F. & Chen, D. Effects of climate change on heating and cooling degree days and potential energy demand in the household sector of China. *Clim. Res.* **67**, 135–149 (2016).
18. IPCC *Climate Change 2022: Mitigation of Climate Change* (eds Shukla, P. R. et al.) (Cambridge Univ. Press, 2022).
19. Khosla, R. et al. Cooling for sustainable development. *Nat. Sustain.* **4**, 201–208 (2021).
20. Mulugetta, Y. et al. Africa needs context-relevant evidence to shape its clean energy future. *Nat. Energy* **7**, 1015–1022 (2022).
21. Lizana, J. et al. Overcoming the incumbency and barriers to sustainable cooling. *Build. Cities* **3**, 1075–1097 (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. Stainforth, D. et al. Distributed computing for public-interest climate modeling research. *Comput. Sci. Eng.* **4**, 82–89 (2002).
24. Anderson, D. P. BOINC: a system for public-resource computing and storage. In *Proc. Fifth IEEE/ACM International Workshop on Grid Computing* https://doi.org/10.1109/GRID.2004.14 (2004).
25. World Bank Open Data *Rural Population from 1960 to 2021* (The World Bank Group, 2021); https://data.worldbank.org/indicator/SP.RUR.TOTL.ZS

Acknowledgements

The research was supported by the Oxford Martin School, through its Future of Cooling Programme. J.L. was funded by the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement no. 101023241. S.N.S. and P.A.G.W. were supported by the UKRI (NE/P002099/1). For the purpose of open access, the author has applied a CC BY public copyright licence to any author accepted manuscript version arising from this submission. We also thank R. Renaldi for supporting the conceptualization of the research.

Author contributions

N.D.M. and J.L. contributed equally. N.D.M. and J.L. coordinated the study and performed the data pre-processing and data analytics of the models. They developed the bias correction, final statistics and visualizations, and jointly wrote the paper draft. S.N.S. and D.C.H.W. ran the CPDN model, and led the extraction of data. S.N.S. and P.A.G.W. provided expertise in data analytics and bias correction. M.Z.-W. extracted data from the model. R.K., D.C.H.W. and M.M. conceptualized the work, and proposed and reviewed the content of 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/s41893-023-01155-z.

Supplementary information The online version contains supplementary material available at https://doi.org/10.1038/s41893-023-01155-z.

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

Peer review information *Nature Sustainability* thanks Yukihiro Kikegawa, Hussain Athar and Yuya Takane for their contribution to the peer review of this work.

Extended Data Table 1 | Ranking of the top fifty countries with more than 2 million inhabitants that will suffer the highest increase (absolute and relative) in area-weighted mean CDDs from 1.5 °C to 2.0 °C

	a, Countries by absolute change	*abs-ΔCDD₁₈*		b, Countries by relative change	*rel-ΔCDD₁₈*
1	Central African Republic	266.2	1	Ireland	37.9%
2	Burkina Faso	254.5	2	Switzerland	30.3%
3	Mali	252.6	3	United Kingdom	29.8%
4	South Sudan	251.4	4	Norway	28.2%
5	Nigeria	244.9	5	Finland	27.8%
6	Congo	241.0	6	Sweden	27.6%
7	Democratic Republic of The Congo	240.1	7	Austria	24.5%
8	Chad	235.6	8	Canada	24.4%
9	Uganda	231.6	9	Denmark	24.4%
10	Cameroon	227.5	10	New Zealand	23.7%
11	Brazil	226.9	11	Lesotho	21.4%
12	Guatemala	224.9	12	Belgium	20.9%
13	United Arab Emirates	220.4	13	Czechia	20.4%
14	Benin	220.0	14	Germany	20.3%
15	Sudan	219.7	15	Netherlands	20.0%
16	Saudi Arabia	219.5	16	Slovenia	20.0%
17	Côte d'Ivoire	218.6	17	Russian Federation	19.5%
18	Honduras	215.9	18	Slovakia	19.2%
19	Mauritania	214.6	19	Kyrgyzstan	19.2%
20	Venezuela	213.5	20	Bosnia and Herzegovina	18.4%
21	Guinea	212.8	21	Poland	18.3%
22	Togo	212.8	22	Armenia	17.9%
23	Botswana	212.1	23	Lithuania	17.4%
24	Niger	211.5	24	Belarus	17.3%
25	Angola	211.1	25	Serbia	17.3%
26	Paraguay	209.5	26	North Macedonia	16.9%
27	Eritrea	209.2	27	Georgia	16.7%
28	Senegal	207.0	28	Chile	16.7%
29	Sierra Leone	205.9	29	Croatia	16.4%
30	Oman	205.1	30	Hungary	16.3%
31	Liberia	204.8	31	Romania	16.1%
32	Zambia	203.7	32	Mongolia	15.5%
33	United Republic of Tanzania	203.6	33	Albania	15.5%
34	Myanmar/Burma	203.1	34	Rwanda	14.5%
35	Kuwait	202.2	35	Bulgaria	14.3%
36	Colombia	201.6	36	Burundi	14.3%
37	Nicaragua	199.8	37	Ukraine	13.5%
38	Qatar	197.9	38	Moldova	13.4%
39	Thailand	196.7	39	North Korea	13.3%
40	Laos	196.2	40	Italy	13.2%
41	Gabon	194.9	41	Spain	13.1%
42	Ghana	193.3	42	France	12.7%
43	El Salvador	192.6	43	United States	12.7%
44	Kenya	190.6	44	Portugal	11.9%
45	Cambodia	188.5	45	Turkey	11.4%
46	Yemen	188.0	46	Greece	11.2%
47	Algeria	187.9	47	Kazakhstan	11.2%
48	Bangladesh	187.5	48	Zambia	10.9%
49	Ethiopia	187.2	49	China	10.7%
50	Mozambique	185.6	50	South Korea	10.6%

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 change in the variable. The rankings use the area-weighted mean values per country rather than grid-specific relative values, as the latter can distort results with large percentage values for specific latitude-longitudes that go from no/negligible CDDs in a 1.5C to having notable CDDs in a 2.0 ºC. The full list of countries with more than 2M population is provided in SN4 and SN5, following different statistical criteria.

Ranking of the top fifty countries by absolute and relative changes in CDDs with global mean temperature increasing from 1.5° to 2.0 °C. Only countries with more than 2 million inhabitants in 2020 are listed. Annual CDDs were calculated using a temperature baseline of 18 °C.

nature portfolio

Corresponding author(s): Jesus Lizana

Last updated by author(s): May 5, 2023

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	The software (HadAM4) to generate the data is open source and available in the UK Met Office Hadley Centre webpage.
Data analysis	Data processing and analysis were done in Python (v3.9) and QGIS (3.28). Code for bias correction is available in github: https://github.com/lizanafj/ensemble-bias-correction. Additional code is available upon request.

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

Bias correction was done using ERA5 hourly data: https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels?tab=overview
Data generated in this analysis are available here: https://doi.org/10.5287/ora-9rbzrxxgz
Additional data are available upon request.

Human research participants

Policy information about studies involving human research participants and Sex and Gender in Research.

Reporting on sex and gender	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 paper shows the change on cooling demand with global mean temperature increasing from 1.5ºC to 2.0ºC
Research sample	Ensembles of 700 climate simulations for three global scenarios were generated using the HadAM4 Atmosphere-only General Circulation Model (AGCM) from the UK Met Office Hadley Centre. This simulation experiment ran within the climateprediction.net (CPDN) climate simulation environment.
Sampling strategy	The scenarios followed the half-a-degree additional warming prognosis and projected impacts (HAPPI) experiment design protocol, being: historical (2006-16), 1.5ºC and 2ºC above pre-industrial levels.
Data collection	Data was collected, stored and processed in JASMIN, the UK's data analysis facility for environmental science: https://jasmin.ac.uk/
Timing and spatial scale	The simulations, data extraction, data processing and data analysis took two years. The simulations output 6-hourly mean temperatures at a horizontal resolution of 0.833 longitude and 0.556 latitude, globally.
Data exclusions	700 runs were used per scenario. More data was available but was excluded to keep the same sample per scenario.
Reproducibility	All method follows standardised procedures. HadAM4 model and python codes used are open source and/or available.
Randomization	Randomization is not relevant to this study, as resulting data did not come from experimental samples, but instead from modeling.
Blinding	Blinding is not relevant to this study as resulting data was generated by a well-known validated model

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

Methods

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