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Supplementary Information for

Humidity-driven divergence and extremes in global air-conditioning energy response under climate change

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Supplementary Text 1 | Deriving AC energy use fractions

To obtain anthropogenic heat flux (AHF) due to AC for validation, we follow a similar procedure as described in ref.[1] We start with a gridded AHF dataset, then multiply it with the country- or region-specific fractions of AC energy use over total energy consumption, which we define as AC energy use fractions (f). In this study, we collaborated with the authors of Varquez et al. dataset[2] and obtained an updated AHF dataset, which represents AHF from the commercial, residential, and transport sectors only. This is one of the components that make up the original Varquez et al. dataset. This allowed us to correct some of the biases introduced from industry or point sources (such as power plants) that lead to high AHF on sparsely built/populated areas.

Because of this change, the AC energy fractions now need to represent AC energy use as a fraction of commercial, residential, and transport energy consumption. Therefore, we modify the calculations to reflect this change as well as leverage updated versions of the relevant datasets, as detailed below.

Country-level data come from two free IEA datasets in their latest versions: 1) Energy Efficiency Indicators Highlights (EEI) November 2023 edition (https://www.iea.org/data-and-statistics/data-product/energy-efficiency-indicators-highlights), which contains final end-use energy consumption that includes AC energy consumption for residential and commercial sectors for select countries; and 2) World Energy Balances Highlights (WEB) 2024 edition (https://www.iea.org/data-and-statistics/data-product/world-energy-balances-highlights), which contains annual sectoral total energy consumption for select countries. A total of 15 countries/regions (including the U.S.) have AC energy consumption data in EEI. These countries/regions are: United States, South Korea, Germany, Japan, France, Portugal, New Zealand, Italy, Morocco, Netherlands, Canada, Spain, Uruguay, Taiwan, and Hong Kong. The f for the 14 countries/regions excluding the U.S. are calculated as:

$$f = \frac{E_{AC,res} + E_{AC,com}}{E_{res} + E_{com} + E_{tra}}, \quad \text{(S1)}$$

where $E_{AC,res}$ and $E_{AC,com}$ are average annual AC energy consumption for residential and commercial sectors, respectively, obtained from EEI, and E_{res}, E_{com}, and E_{tra} are average annual total energy consumption for residential, commercial, and transport sectors, respectively, obtained from WEB. The average is computed for 2010 – 2019 ignoring missing years.

For the U.S., we compute f for each state by leveraging U.S. subnational-level data from three EIA datasets: 1) 2015 Residential Energy Consumption Survey (RECS) (https://www.eia.gov/consumption/residential/data/2015/), which include the annual final end-use (including AC) energy consumption in the residential sector at the census division level (the 50 U.S. states are grouped into 9 census divisions); 2) 2018 Commercial Buildings Energy Consumption Survey (CBECS) (https://www.eia.gov/consumption/commercial/data/2018/), which include the annual final end-use (including AC) energy consumption in the commercial sector at the census division level, and 3) 2022 State Profiles and Energy Estimates (https://www.eia.gov/state/), which include annual total primary energy consumption for all sectors (including residential, commercial, transportation, and industrial) at the state level.

We combine the three datasets and calculate f for each state as:

$$f = \frac{E'_{AC,res}}{E'_{res}} \cdot \frac{E_{res}}{E_{crt,tot}} + \frac{E'_{AC,com}}{E'_{com}} \cdot \frac{E_{com}}{E_{crt,tot}}, \quad \text{(S2)}$$

where $E_{crt,tot}$ is annual total energy consumption for commercial, residential, and transport sectors, and the prime symbol denotes the census-division value of the respective quantity is used. In this equation, $\frac{E'_{AC,res}}{E'_{res}}$ is calculated from 2015 RECS for each census division, $\frac{E'_{AC,com}}{E'_{com}}$ is calculated from 2018 CBECS for each census division, and $\frac{E_{res}}{E_{crt,tot}}$ and $\frac{E_{com}}{E_{crt,tot}}$ are calculated from 2022 State Profiles and Energy Estimates for each state. This allows us to obtain state-level estimates of f by leveraging census-division level statistics where state-level information is missing.

Supplementary Table 1 | The U-Surf dataset[3] helps correct anthropogenic heat overestimation. The observed value is derived from the Varquez et al. dataset[2], following ref.[4] Both simulations are run with the original modeling scheme (i.e., no dehumidification), with the same urban extent as defined in U-Surf. The AHF result for default surface data is much larger than that presented in ref.[4] because the urban extent in U-Surf is used, which is much larger than the default urban extent used in ref.[4]

Annual average global total AHF due to heating and air conditioning for 2010 – 2014	**Value (terawatts)**
Observed estimates (derived from ref.[2])	3.1
Simulated with default surface data	9.7
Simulated with U-Surf	3.3

Supplementary Table 2 | Condensate produced from the new dehumidification scheme has minimal effect on river flow. Annual average volumetric flow rates of world's 50 largest rivers simulated under the new dehumidification scheme and under the original scheme for 2081 – 2100, and the increase due to condensate from dehumidification. The simulation run under the original scheme is otherwise identical to the one analyzed in the study.

			Volumetric flow rate ($km^3\ yr^{-1}$)			
No.	**River Name**	**Station, country**	**New scheme (with dehumidification)**	**Original scheme (no dehumidification)**	**Increase due to new scheme ($m^3\ yr^{-1}$)**	**Relative increase due to new scheme (%)**
1	Amazon	Obidos, Brazil	2922.365	2922.363	2000	0.000%
2	Congo	Kinshasa, Congo	2763.163	2763.162	1000	0.000%
3	Orinoco	Pte Angostu, Venezuela	764.246	764.244	2000	0.000%
4	Changjiang	Datong, China	1766.562	1766.52	42000	0.002%
5	Brahmaputra	Bahadurabad, Bangladesh	1254.887	1254.887	0	0.000%
6	Mississippi	Vicksburg, MS, USA	712.012	711.99	22000	0.003%
7	Yenisey	Igarka, Russia	820.19	820.19	0	0.000%
8	Parana	Timbues, Argentina	748.066	748.046	20000	0.003%
9	Lena	Kusur, Russia	781.819	781.819	0	0.000%
10	Mekong	Pakse, Laos	412.121	412.112	9000	0.002%
11	Tocantins	Tucurui, Brazil	497.262	497.261	1000	0.000%
12	Tapajos	Jatoba, Brazil	167.063	167.063	0	0.000%
13	Ob	Salekhard, Russia	394.439	394.439	0	0.000%
14	Ganges	Farakka, India	389.709	389.699	10000	0.003%
15	Irrawaddy	Sagaing, Myanmar(Burma)	273.883	273.883	0	0.000%
16	St Lawrence	Cornwall ON, Canada	369.235	369.227	8000	0.002%
17	Amur	Komsomolsk, Russia	610.788	610.786	2000	0.000%
18	Xingu	Altamira, Brazil	71.389	71.389	0	0.000%
19	Mackenzie	Arctic Red, Canada	462.492	462.492	0	0.000%
20	Xijiang	Wuzhou, China	223.535	223.525	10000	0.004%

21	Columbia	The Dalles, OR, USA	226.26	226.26	0	0.000%
22	Magdalena	Calamar, Colombia	304.675	304.675	0	0.000%
23	Uruguay	Concordia, Argentina	154.975	154.973	2000	0.001%
24	Yukon	Pilot Stn, AK, USA	471.407	471.407	0	0.000%
25	Atrato	Tagachi, Colombia	53.659	53.659	0	0.000%
26	Danube	Ceatal Izma, Romania	112.84	112.84	0	0.000%
27	Niger	Gaya, Niger	23.328	23.328	0	0.000%
28	Ogooue	Lambarene, Gabon	209.895	209.895	0	0.000%
29	Essequibo	Plantain Is, Guyana	25.853	25.853	0	0.000%
30	Fraser	Hope, Canada	136.536	136.536	0	0.000%
31	Pechora	Oksino, Russia	144.516	144.516	0	0.000%
32	Nelson	Upstream of Bladder, Canada	1.74	1.74	0	0.000%
33	Khatanga	Khatanga, Russia	116.48	116.48	0	0.000%
34	Sepik	Ambunti, Papua New Guinea	240.695	240.695	0	0.000%
35	Kolyma	Kolymskoye , Russia	236.808	236.808	0	0.000%
36	Zambeze	Matundo-Cai, Mozambique	17.074	17.074	0	0.000%
37	Severnaya Dvina	Ust Pinega, Russia	110.673	110.673	0	0.000%
38	Indus	Kotri, Pakistan	0.22	0.22	0	0.000%
39	Sanaga	Edea, Cameroon	115.492	115.492	0	0.000%
40	Godavari	Polavaram, India	105.002	104.999	3000	0.003%
41	Rajang	Kapit Wharf, Malaysia	120.749	120.749	0	0.000%
42	Sao Francisco	Traipu, Brazil	263.106	263.104	2000	0.001%
43	Usumacinta	Boca del Ce, Mexico	7.725	7.725	0	0.000%
44	Maroni	Langa Tabbe, Suriname	12.332	12.332	0	0.000%

45	Rhine	Lobith, Netherlands	61.687	61.687	0	0.000%
46	Purari	Wabo Dam, Papua New Guinea	173.323	173.323	0	0.000%
47	Caniapiscau	Chute de la, Canada	25.225	25.225	0	0.000%
48	Mahanadi	Kaimundi, India	32.574	32.574	0	0.000%
49	Sacramento	Sacramento, CA, USA	23.848	23.848	0	0.000%
50	Jacui	Passo do Ra, Brazil	58.025	58.024	1000	0.002%

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