

Inequalities in global residential cooling energy use to 2050

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 Check for updatesGiacomo Falchetta ^{1,2,3} ✉, Enrica De Cian ^{1,3,4}, Filippo Pavanello^{1,3,5} & Ian Sue Wing ⁶

Intersecting socio-demographic transformations and warming climates portend increasing worldwide heat exposures and health sequelae. Cooling adaptation via air conditioning (AC) is effective, but energy-intensive and constrained by household-level differences in income and adaptive capacity. Using statistical models trained on a large multi-country household survey dataset ($n = 673,215$), we project AC adoption and energy use to mid-century at fine spatial resolution worldwide. Globally, the share of households with residential AC could grow from 27% to 41% (range of scenarios assessed: 33–48%), implying up to a doubling of residential cooling electricity consumption, from 1220 to 1940 (scenarios range: 1590–2377) terawatt-hours yr⁻¹, emitting between 590 and 1,365 million tons of carbon dioxide equivalent (MtCO₂e). AC access and utilization will remain highly unequal within and across countries and income groups, with significant regressive impacts. Up to 4 billion people may lack air-conditioning in 2050. Our global gridded projections facilitate incorporation of AC's vulnerability, health, and decarbonization effects into integrated assessments of climate change.

Climate change impacts are increasingly being felt^{1,2}, with increased heat exposures being a ubiquitous outcome^{3,4}, leading to serious negative health consequences^{5–9}. Adoption of cooling, in particular air conditioning (AC), as an adaptation to heat is rapidly expanding^{10–13}, but it is characterized by stark inequalities—across countries and regions¹⁴ as well as among households that differ in their capacity to adapt¹⁵. While AC's shielding effects confer potentially large health benefits^{16,17}, its use can increase the demand for energy in ways that can adversely affect electricity systems stability and planning^{18,19}, environmental pollution—including feedback emission of greenhouse gases and climate policy^{20–22}, and households' energy burdens and economic well-being²³. These challenges are projected to become increasingly significant as the climate warms. Cooling appliances already account for nearly 20% of global electricity use by buildings¹². In turn, the operations of the building sector represents 30% of global final energy consumption and cause 26% of global energy sector carbon dioxide

(CO₂) emissions²⁴. About two thirds of the 1.6 billion AC units installed globally are in residential buildings, accounting for about half of the total 1,200 terawatt (TW) of installed cooling capacity.

A growing literature investigates AC adoption as a heat adaptation strategy. Prior studies differ in their methodology (e.g., empirical models^{10,25–28} or bottom-up engineering simulations^{22,29,30}), context and spatial scale (e.g. city^{31,32} or country-level^{33–35}) and/or geographic scope (e.g. multi-country^{10,14,26,36} or global^{25,27} analysis, see Supplementary Table 1 for key features of globally-relevant projection studies on AC and utilization). Nevertheless, a comprehensive global picture of the potential inequalities in the future expansion of AC, and attendant energy poverty implications of increased cooling electricity use, remains elusive^{37–39}. Because income constraints may limit households' operation of available residential AC^{40–42}, it is critical to elucidate the intensive margin of adaptation (i.e., utilization), and its conditional dependence on technology adoption on the extensive margin^{33,43}.

¹Centro Euro-Mediterraneo sui Cambiamenti Climatici, 30133 Venice, Italy. ²International Institute for Applied Systems Analysis, Schlossplatz, 1, Laxenburg A-2361, Austria. ³RFF-CMCC European Institute on Economics and the Environment, Venice, Italy. ⁴Ca' Foscari University of Venice, Department of Economics, 30121 Venice, Italy. ⁵University of Bologna, Department of Economics, Piazza Scaravilli 2, 40125 Bologna, Italy. ⁶Boston University, Dept. of Earth & Environment, Boston 02215, USA. ✉ e-mail: giacomo.falchetta@cmcc.it

Additionally, local climates, community-level institutions and infrastructures, and households' demographic and socioeconomic characteristics influence these joint adaptation decisions, but in ways that could potentially be context-specific. The latter possibility points to the need to account for heterogeneity in household responses as a driver of inequality in future access to space cooling, energy demand consequences and environmental implications within and across countries and world regions.

Here, we rise to this challenge by assembling and analyzing a multi-country database of household-level microdata covering more than 500 sub-national administrative units in 25 countries (see Supplementary Fig. 1 and Supplementary Table 2). These countries represent 62% of the world's population and account for 73% of the global electricity consumption. The dataset describes a rich set of characteristics (see Supplementary Table 3 for a complete list of variables) of 673,215 households. We augment the microdata with country- or sub-national-level external data on electricity prices and use external gridded data on urbanization to characterize the degree of urbanization of the region in which a household lives, as well as historical meteorological reanalysis data to construct climate variables (see Methods). We use the resulting dataset to train two-stage classification and regression models of AC adoption and AC impact on residential electricity use (Fig. 1a). We evaluate different model specifications (Supplementary Tables 6-7) to show why our preferred prediction framework is a random forests (RF) machine learning (ML) model, which uses regression tree algorithms to implement flexible non-parametric estimations which capture non-linear relations among variables (see Methods). The estimated non-linear conditional probabilities of AC ownership (1st stage model) and expected values of electricity consumption (2nd stage) are illustrated by examining partial dependence and elasticities (Fig. 1d-e; see Methods), with the aim of connecting econometric estimation goals and ML prediction methods⁴⁴. We demonstrate the ability of the trained models to assess the probability of AC ownership and the level of AC electricity use in unsampled locations conditional on local household and geographical characteristics. We then use the validated models (Supplementary Figs. 4 and 5) to generate global gridded predictions and projections of current and future AC uptake and use under an array of socio-economic and climate change scenarios (see Supplementary Table 5 for a description of the assumed future evolution of socio-economic, demographic, and climate drivers in each scenario) based on the validated models (Fig. 1c). We leverage the global coverage and high granularity of our estimates to study the current and projected inequalities in the distribution of AC and its usage and identify critical areas of vulnerability in need of actions to increase adaptive capacity. We also draw implications for energy use and carbon dioxide equivalent emissions. Our results can support decision makers at the intersection of public health, infrastructure planning, and energy and climate policy. The resulting datasets are publicly available⁴⁵ and can be the basis for more informed heat vulnerability and impact assessments.

Results

Inequitable air-conditioning access and use worldwide

Our model-based validated (Supplementary Figs. 4 and 5) predictions for 2020 for the world show a high heterogeneity in the distribution of AC across and within regions and countries based on sub-national units defined over a regular global grid with a spatial resolution of 0.5 arc-degrees (Fig. 2a), reflecting the interaction of different climatic conditions and the distribution of population and its socio-economic attributes (Supplementary Figs. 3, 8). Existing areas of high concentration of household AC ownership (>50%) are clearly visible in North America, Southern Europe and North Africa, the Middle East, South Africa, Southern Latin America, Japan, Eastern China, and Australia. Looking at 2050 (Fig. 2b displaying Shared Socioeconomic

Pathway (SSP) 2(45) scenario; refer to Supplementary Fig. 11 for SSP1(26), SSP3(70), and SSP5(85) scenarios), areas with high AC ownership rates will expand as a result of a warmer climate, rising affluence levels and socio-demographic change (see Supplementary Table 5). Such growth is particularly strong in areas with currently low levels of AC penetration, such as South-East Asia (+96 million households, scenario mean), e.g. Indonesia, and Eastern Asia (+41 millions), e.g. Northern India, sub-Saharan Africa (+72 millions), while it will grow more slowly in Central Europe (+30 millions), North Africa and the Middle East (+24 millions) and portions of Latin America (+33 millions) because of already higher current AC prevalence rates (North America), climate heterogeneity and low propensity to use AC (Europe).

In terms of electricity consumption for AC use, the maps in Fig. 2c, d suggest that the total electricity use for AC tends to be strongly correlated with population density only in areas of high AC penetration, such as the United States, Eastern Asia, and Mediterranean countries. In the rest of the world, AC electricity use tends to be more concentrated in the proximity of larger urban centers. By 2050, new areas with high concentration of demand are projected to emerge in India, Mexico, and East and South-East Asia. In per-household (HH) terms, we estimate that in 2020 families owning AC consumed an average of 2000 kilowatt-hours $\text{HH}^{-1} \text{yr}^{-1}$ for cooling, noting that such figure has very large differences across regions: for instance, in North America it stands at 5,445 kilowatt-hours $\text{HH}^{-1} \text{yr}^{-1}$, while in sub-Saharan Africa at 985 kilowatt-hours $\text{HH}^{-1} \text{yr}^{-1}$. By 2050, we project the average consumption to range between 1,967 - 2289 kilowatt-hours $\text{HH}^{-1} \text{yr}^{-1}$, depending on the scenario considered. Supplementary Fig. 14 provides a summary of regional trajectories, while Supplementary Tables 8, 9 report country-level statistics for the projected AC ownership and AC electricity consumption, as well as the corresponding Gini indexes of within-country inequality.

Zooming in and looking at within-region and within-country patterns, we observe that growing inequalities will affect the African continent, where AC gains prominence in North African countries and areas of Southern Africa, while it will remain less available to the majority of the population of the sub-Saharan African region. A similar pattern is projected in India, Indonesia and South East Asia: irrespective of a considerable growth in the national AC penetrations, large fractions of the population will remain vulnerable to acute heat. In China, AC use will also soar, with a very strong growth in the intensive margin. Looking at Central and Latin America, strong inequalities are found irrespective of similar heat exposure. For instance, the highest AC penetration rates are projected in Argentina and coastal areas of central Brazil, while populations in the highly exposed northern part of South America will reach significantly lower AC access. Conversely, AC penetration and use are projected to grow more homogeneously across Southern European and Mediterranean countries, another key hotspot of chronic heat exposure. Penetration in the United States, Australia, and Japan, being already close to saturation, will grow more moderately.

While these inequalities may also derive from differences in local climates, our analysis shows that within each region and country AC prevalence is and will persistently be unequally distributed across income groups in SSP2(45), as seen in Fig. 3a (see Supplementary Figs. 15-17 for additional scenarios). This income-stratified assessment reveals inequalities are observed in all regions: such differences are explained both by income availability inequalities, and by geographical correlations between income levels and heat exposure (noting that both globally and within each of the seven macro-regions considered, countries with highly different income levels exist). Globally, the lowest quintile of income AC penetration is expected to grow from a mean of about 17% to 21-39% by 2050, whilst in the highest our projections suggest a growth in the mean value from 52% to about 56-60%. It is worth noting, as seen from Supplementary Fig. 19, that the AC

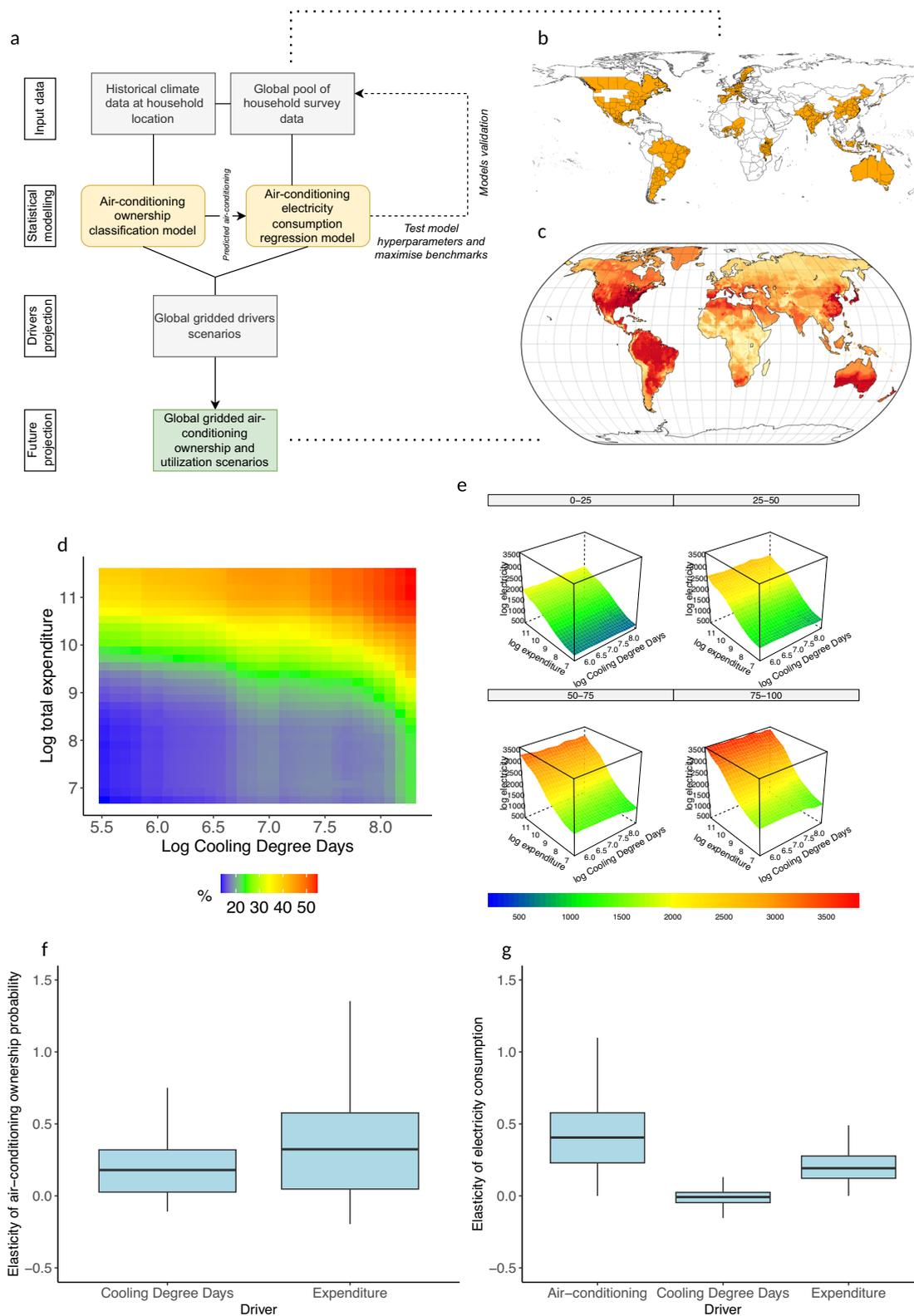


Fig. 1 | Statistical framework and estimated prediction ranges of the analysis presented in this paper. **a** Flowchart of the residential air-conditioning (AC) analysis. **b** Countries covered in the household survey global pool database. **c** Representative example of output gridded projections. **d, e** Partial dependence

plots (conditional probabilities for the 1st stage AC ownership model; expected values for the 2nd stage electricity consumption model, by AC ownership probability bins). **f, g** Box plots of the distribution of the estimated partial elasticities derived from the models' partial dependences.

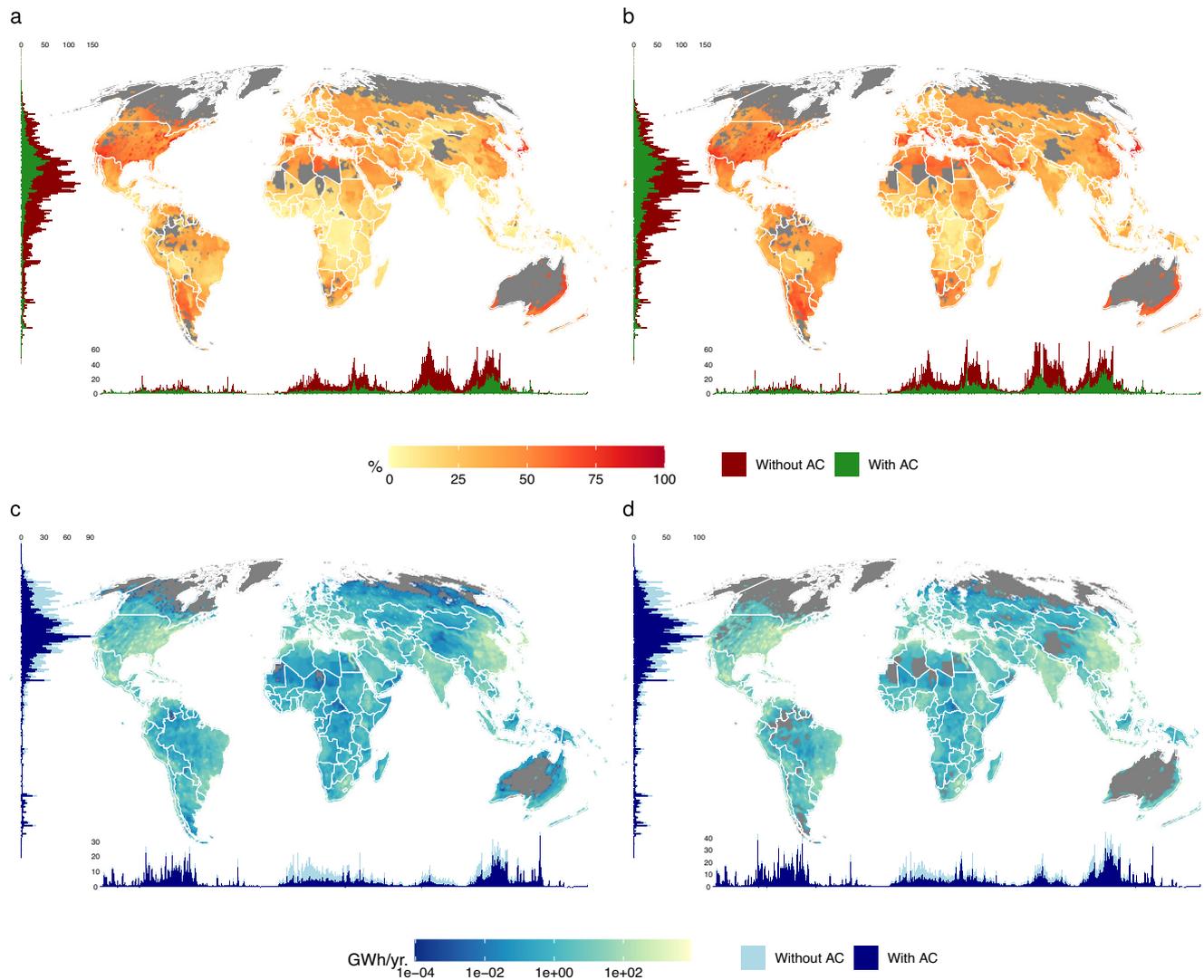


Fig. 2 | Global gridded projections for residential air-conditioning (AC) ownership and use inequality. Maps and bar charts of AC ownership (% and count of households) (a, b) and (c, d) household AC electricity consumption (gigawatt-hours yr^{-1} and terawatt-hours yr^{-1}), historical (2020 and 2050 for Shared Socioeconomic

Pathway (SSP) scenario 2(45). Coupled Model Intercomparison Project Phase 6 (CMIP6) Global Climate Models (GCM) ensemble median (excluding 'hot models'⁶²). Supplementary Figs. 11–13 in the Supplementary Information provide similar maps and bar charts for SSP scenarios 1(26), 3(70) and 5(85).

availability gap between the top and lowest income quintiles is projected to enlarge in sub-Saharan Africa and South Asia, where we observe the largest increase in AC adoption among the richest households belonging to the fourth and fifth quintile of the income distribution, while in the other regions it is expected to shrink or remain similar.

Figure 3 b reveals that also household AC electricity consumption is also unequally distributed across income quintiles both globally and within most regions. Interestingly, both at a global scale and within a number of regions (and mostly Middle East & North Africa, Europe & Central Asia and Latin America & Caribbean) we find electricity consumption to have a regressive distribution. Families in low-income quintiles - largely because of their geographical distribution with respect to heat exposure - are consuming similar or higher quantities of electricity to families in higher quintiles within that specific region (for reference, Supplementary Fig. 3 provides a bivariate global map of historical Cooling Degree Days (CDD) exposure and income distribution). Due to lower incomes, this has a significant regressive effect on household energy expenditure. Future socio-economic transformations and growing heat exposure as a result of climate change are found to worsen this energy poverty implication (see Supplementary

Fig. 20 for a comparison of the distributions in the AC electricity change between the top and lowest income quintiles). For instance, families in the second income quintile of Middle East & North Africa are projected to consume more than families in any other quintile.

Examining within-region and within-country heterogeneity across quintiles, a decision-relevant scale mirroring the jurisdictions in which policy makers act, we observe that the regressive impact of AC electricity consumption growth is largely a result of income inequality and heat exposure differences within regions. For instance, in the Middle East and North Africa (MENA) region, some of the hottest areas (e.g. regions of the Arabic peninsula or southern Egypt) overlap with the areas with the lowest income levels in the region. A similar pattern can be traced in North America, where the Southern part of the United States and several regions of Mexico are found to be both very hot and poorer than the average; a similar dynamic is found in South Asia, with large areas of Bangladesh and Pakistan being both low-income and heat exposed. Finally, in sub-Saharan Africa - where the highest income difference between the first and the last quintile is found - few countries represent the bulk of the households in the highest income quintile (e.g. South Africa, parts of Angola and the Republic of Congo). Within-country, the Gini indexes of electricity consumption

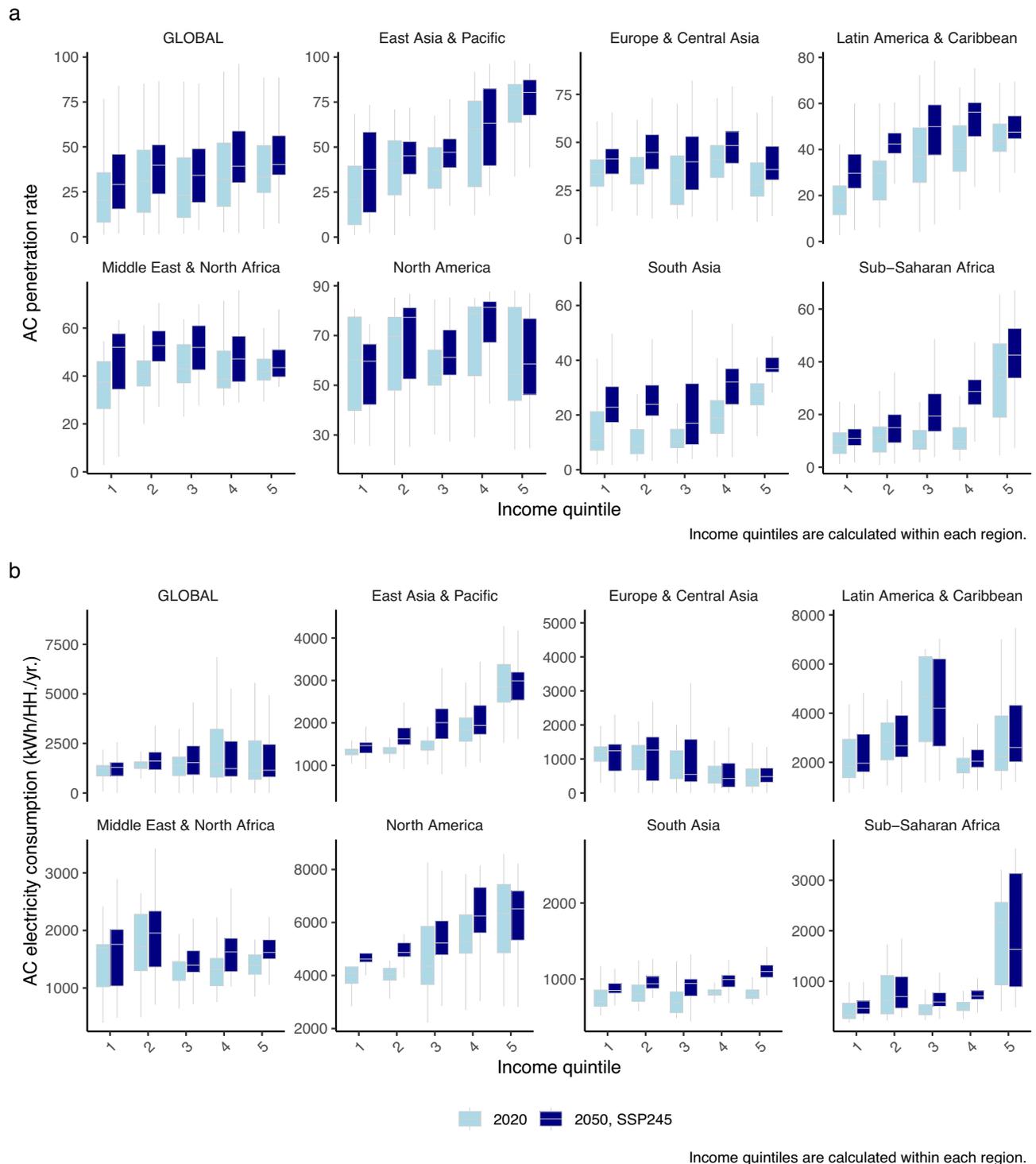


Fig. 3 | Distribution of household air-conditioning (AC) penetration (%) and residential sector average AC electricity consumption (kilowatt-hours/household yr⁻¹, kWh/HH/yr.), by income quintile and region, Shared Socioeconomic Pathway (SSP) scenario 2(45). **a ranges of air-conditioning penetration; **b** ranges of AC electricity consumption. Note that income quintiles are defined based on each specific region's income distribution in year 2020, and therefore the global**

pool panel pools together households belonging to each quintile of different regions. The range of values in each boxplot are based on the projections calculated with the Coupled Model Intercomparison Project Phase 6 (CMIP6) Global Climate Models (GCMs) ensemble median (excluding 'hot models'⁶²). Note: facets have specific y-axis ranges to better emphasize differences among scenarios. Supplementary Figs. 15–17 report quintile-level projections for additional scenarios.

(Supplementary Table 9) reveal that the strongest inequality is found in several low-income countries (we refer to the World Bank 2024 income level country classification⁴⁶), mostly located in sub-Saharan Africa (Kenya, Tanzania, Ethiopia), in a set of upper-middle income

countries (e.g. Fiji, Brazil), but also in some high-income countries (Netherlands, Italy). In most countries, within-country inequalities in AC utilization are expected to decline by 2050, although with large differences across scenarios.

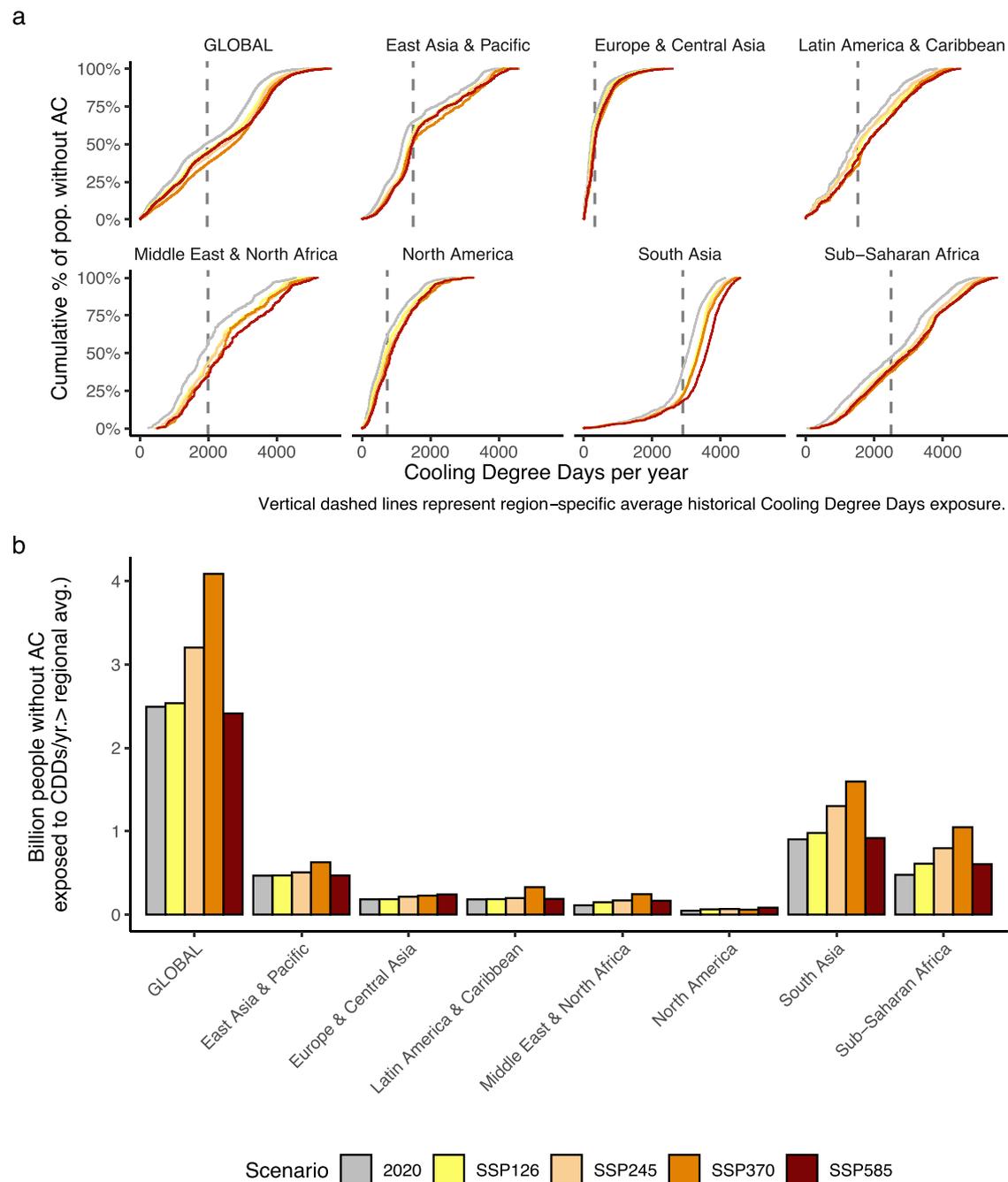


Fig. 4 | The global adaptation cooling deficit. **a** Cumulative share of the population (pop.) without air-conditioning (AC) in 2050 as a function of Cooling Degree Days yr^{-1} (CDDs/yr) exposure, by global region and scenario. Vertical dashed lines highlight the population-weighted average CDDs yr^{-1} in each region under historical climate (1995–2014). **b** Count of people exposed to more CDDs yr^{-1} than the

regional historical average value and living without AC, by global region and scenario. The numbers refer to projections calculated with the Coupled Model Inter-comparison Project Phase 6 (CMIP6) Global Climate Models (GCMs) ensemble median (excluding 'hot models'⁶²).

The global adaptation cooling deficit

An consequence of AC ownership inequality, a large number of individuals are projected to remain without AC by year 2050 (mainly due to income constraints) despite living in climates with considerable heat exposure. To analyze this deprivation dimension of cooling poverty^{26,47}, we leverage the high spatial granularity of our global projections to estimate that, globally, the number of heat-exposed vulnerable people (defined as people without AC exposed to more CDDs yr^{-1} than the regional historical average value) will change from around 2.5 billion today to 3.2 billion by 2050 in

SSP2(45), see Fig. 4. We find that higher exposure will be observed in the low AC and high warming future of SSP3(70), with 4.1 billion exposed people. These numbers are consistent with the cooling gap estimates of ref. 25, who estimate a range of 2–5 billion people in 2050.

Interestingly, we observe that SSP5(85), the scenario with the warmest climate, is projected to be the future with the smallest global adaptation cooling deficit, at 2.4 billion. While this is the result of high economic growth, it also implies the starkest heat exposure for those not gaining access to AC, as seen in Fig. 4a. The figure visualizes—

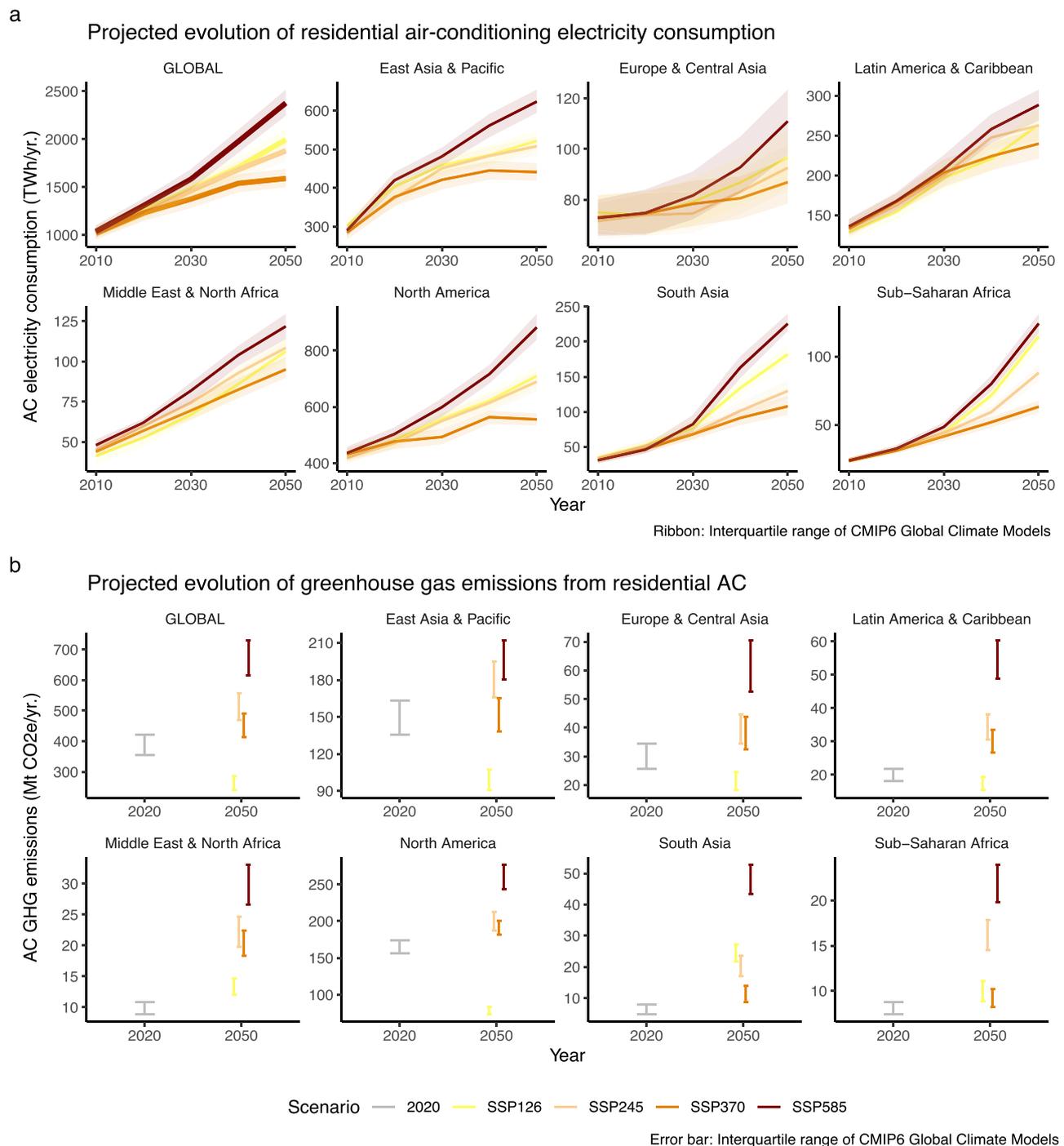


Fig. 5 | Regional aggregated trajectories of residential air-conditioning (AC) electricity consumption and consequent greenhouse gas emissions.

a Projected global residential AC electricity consumption in 2020–2050 in terawatt-hours yr^{-1} (TWh/yr), Shared Socioeconomic Pathway (SSP) scenario 1(26), 2(45), 3(70), and 5(85). **b** Projected global residential AC greenhouse gas emissions in

2020 and 2050 in million tons CO₂ equivalent (MtCO₂e), SSP 1(26), 2(45), 3(70), and 5(85). The ribbon represents the Coupled Model Intercomparison Project Phase 6 (CMIP6) Global Climate Models (GCMs) interquartile range, whilst the solid line depicts the model ensemble median (excluding ‘hot models’⁶²). Note: facets have specific y-axis ranges to better emphasize differences among scenarios.

globally and for each major world region - the cumulative fraction of people exposed to a certain cumulative heat exposure (quantified in CDDs yr^{-1}) who are estimated not to have AC by year 2050 in the four scenarios considered. In addition, the increases or only moderate decreases in the gap figure is explained by the expected global demographic growth in highly exposed but adaptation capacity-constrained areas, which may partially or more than counterbalance the projected growth in the global AC penetration rates. As a

consequence, the deprivation is and will increasingly be concentrated in Africa and in South Asia. In relative terms, this implies that in 2050 36% [scenarios range: 30–51%] of the global population living in areas experiencing higher CDD exposure than their regional population-weighted mean is projected to remain without AC, compared to the current estimate of 2.5 billion people (35% of the global population). Hence, while the share of people affected by the global adaptation cooling deficit will remain more or less constant (in the scenario-mean

pathway), in absolute terms it will increase by 500 million people [−100 +1600 million].

Growing energy and environmental impacts of cooling

When aggregated to the global level (Supplementary Fig. 14), gridded projections (weighted by the number of households per grid cell) for the middle-of-the-road scenario result in a global projected AC penetration rising from the current 27% to a scenario-median of 41%. Households equipped with an AC unit would increase from 620 millions to an estimated median of 900 millions by 2050. Greater AC availability growth translates into a surge in the use of energy and the related environmental impacts. We project global residential AC electricity consumption (Fig. 5a) to grow from the estimated 1220 terawatt-hours yr^{-1} in 2020 to 1940 (1590–2377) terawatt-hours yr^{-1} in 2050. While on a global scale the trajectories are mostly linear (see Supplementary Fig. 18, comparing the projected growth rates in adoption and use of AC), in specific regions, such as East Asia & Pacific, we witness a very rapid growth of AC prevalence and use already in the 2020s, while in other regions, and mainly sub-Saharan Africa and South Asia, such surge is delayed to the decades closer to 2050. This is likely the result of a turning point in the level of available income to access AC. Indeed, a decomposition analysis of the drivers of future AC uptake and utilization growth (Supplementary Fig. 21; see Methods for details and Supplementary Table 5 for the evolution of drivers) reveals that—albeit with some scenario heterogeneity—expenditure growth has the largest relative importance, followed by socio-demographic drivers (including urbanization). The role of climate change, while relevant, is more marginal, consistent with previous evidence¹⁴.

Besides geographical heterogeneity, our results also demonstrate how scenario differences significantly affect AC uptake and energy use projections. Scenarios SSP1(26) and SSP2(45) lead to similar results in most regions, demonstrating how different climate change and socio-economic growth interactions can generate similar impact scenarios. On the other hand, SSP3(70) and SSP5(85) show radically different outcomes irrespective of similar implied radiative forcing. Being SSP3(70) a scenario of regional rivalry, economic stagnation, and high population growth, it results in low AC uptake in the developing world, while SSP5(85) implies strong, fossil-fuel driven economic growth resulting in very high warming and also high cooling energy consumption.

Future changes in the use of AC electricity will feedback on the global warming dynamics through the additional greenhouse gas emissions in a way that will be influenced by degree of decarbonization of world countries. Fig. 5b shows regional CO_2e electricity emissions from the residential use of AC (see Methods for details on the estimation approach), totaling 797 million tons (Mt) in 2020 and—according to our projections—ranging between 590–1365 Mt in 2050, with the lion's share taken by the Americas and Asia (see Supplementary Tables 10, 11 for AC use emission implications by region and by country). For reference, 2021 United States emissions from electric power sector were 1551 Mt. Our estimates hence suggest that future global AC electricity could emit between over one third and almost the equivalent of the current total electricity emissions by the United States⁴⁸. Interestingly, we observe that in regions where the power sector is projected to rapidly decarbonize, rising AC utilization can decouple from emissions in a scenario of deep decarbonization (SSP1(26)).

Discussion

Our analysis indicates that the interaction of anthropogenic climate change and changing socio-economic factors will determine a steep growth in the global uptake and utilization of air-conditioning to cope with heat. We estimate that the share of households owning air-conditioning could grow from 27% to 41% (33–48%) by 2050, implying a surge in global residential AC electricity consumption

from about 1220 terawatt-hours yr^{-1} in 2020 to 1940 (1590–2377) terawatt-hours yr^{-1} in 2050. The growth in residential cooling energy demand could increase CO_2e emissions up to 590–1365 Mt CO_2e by 2050, unless the electricity sector undergo a deep decarbonization as described in SSP1(26). Our projections are in general agreement with the International Energy Agency (IEA)'s The Future of Cooling report¹², though slightly more conservative. The IEA estimates that globally, the share of households with at least one AC will be about 65% in 2050, while our projections reach a maximum of almost 47% of households in SSP5(85), i.e. from the current 1.8 billion individuals to about 3.8 billion. Yet, other scenarios modeled in our study, like the SSP3(70), which is characterized by low economic growth and convergence and high population growth in low income and lower-middle income countries, lead to a significantly slower pace in the global uptake of AC. In addition, in its baseline scenario, the IEA estimates a more than three-fold increase in residential energy use for cooling by 2050, reaching nearly 4000 terawatt-hours yr^{-1} . In the IEA's efficient cooling scenario, this growth is reduced by about 45%, bringing IEA's numbers in line with our residential AC electricity consumption projections range. Emission projections are also comparable. IEA's estimate of current CO_2 emissions associated with the global cooling sector stand at 1130 million tons CO_2 yr^{-1} . This estimate also considers cooling in the commercial and services sectors, which account for about half of the global cooling capacity. Our estimates for 2020 residential AC use carbon dioxide emissions are thus in line, at 797 Mt.

These global aggregate figures have important policy implications for global, regional, and national energy planning as well as for meeting emission reduction targets. Not by chance, during the United Nations Framework Convention on Climate Change (UNFCCC) 28th Conference of the Parties (COP28), sixty-four countries—with some notable exceptions among highly heat-exposed nations—signed the Global Cooling Pledge⁴⁹ with the ambition to reduce cooling-related emissions by 68% by 2050, increase access to sustainable cooling by 2030, and increase the global average efficiency of new air conditioners by half. Despite these ambitious global targets, our analysis demonstrates the importance of considering more granular information if cooling and energy poverty and inequalities are to be tackled. Our sub-national projections show that in the absence of dedicated policies, future growth in AC ownership and use will be highly unequally distributed across regions and income groups. The granularity of our projections is an important contribution that yields new evidence at the scale that matters for policy implementation. For instance, we show that in highly exposed regions, such as South Asia and sub-Saharan Africa, by 2050, AC will only be extensively available (AC availability >50%) to people belonging to the highest income groups, while the vast majority of poorer households will be remaining without access. The high spatial resolution and the global coverage of our projections is of crucial importance to reveal future geographical hotspots of climate adaptation inequalities in different world regions and population sub-groups. Gross Domestic Product (GDP) per-capita is identified as the major driver of growing AC uptake and use (Supplementary Fig. 21), highlighting the large relevance of income as an enabler of autonomous adaptation, as well as the necessity for local regulation of cooling solutions. This is also crucial in relation with energy poverty—which connects with adaptive capacity to climate change⁵⁰—as adapting to higher temperatures would increase the energy burden of less affluent individuals, who are already spending high shares of their income for energy services^{51,52}. In relation to these issues, the granular evidence presented in our study can enable the promotion of more equitable planning of cooling solutions to cope with heat through public subsidies, international donors, building and city planning, and passive cooling solutions. Indeed, emerging evidence is pointing at the framing of access to cooling as a systemic, multi-dimensional issue⁴⁷ that tightly connects to climate change

adaptation justice discussions recently at the center of global climate conferences⁵³.

The study is not without caveats. First, the projected electricity demand and ownership rates only refer to residential cooling demand, and therefore they can be considered as lower-bound estimates, not including cooling energy from commercial, industry, and transport. Second, the empirical approach adopted in this paper is not able to explicitly characterize technological change such as future improvements in the efficiency of appliances, building stock insulation, or other low-energy cooling solutions, as well as the heterogeneous cost of purchasing AC units across world regions. These transformations are partially accounted for by the model non-linearities, which determine highly heterogeneous responses of electricity consumption to AC ownership and utilization, with such responses being mediated by income, education, and geography. These variables and their projected transformations in different areas of the world implicitly encapsulate these technological and efficiency transformations. Third, our projections do not take into account future expansion of electricity access, which in sub-Saharan Africa still stands at less than 50% (more than half a billion people), with important repercussions connecting cooling demand and energy use⁵⁴. Future research could explicitly look at these transformations to assess their potential for reducing future cooling energy demand at a local and global level.

Overall, our dataset contributes to providing the missing input to the modeling community that makes it possible to better assess vulnerability and adaptation assessments when combined with information on the spatial distribution of vulnerable individuals (e.g. the elderly, see refs. 55,56). It can feed into global climate-mortality assessments and characterize the role of adaptation options in mitigating health risks⁶¹. In addition, our output data can be used to evaluate the impact of residential air-conditioning usage on power and grid planning and investments in a context of relation to climate mitigation and development policy.

Methods

Multi-country household survey data

We assemble a globally-relevant household micro data database covering more than 500 sub-national administrative units from 25 countries. Together, these countries represent 62 percent of the world's population and account for 73% of the global electricity consumption. Supplementary Table 2 lists the countries included in the database, the macro-region of belonging, the year(s) when the interviews were carried out, and the number of households included in the final pooled database for each country. Supplementary Fig. 1 shows the spatial distribution and density of surveyed households across the globe.

For each survey we gather information on annual electricity expenditure (also on quantity when available), air-conditioning ownership, total household expenditure, electricity prices, and several socio-economic and demographic variables. We limit our sample to non-missing air-conditioning and non-missing electricity data. This means that our data set excludes households that did not have access to electricity during the survey year. As not all the surveys electricity quantity is available, we enrich our data set with information on average electricity prices. Electricity prices are either directly obtained dividing electricity consumption by quantity or collected at country or sub-national level from external sources. Similarly, the variable indicating whether a household lives in urban or in a rural area is not reported for all countries. For this reason, we also collect gridded data on urbanization from Gao et al.⁵⁷ to construct sub-national shares.

Climate and socio-economic data

Historical climate data is drawn from the European Centre for Medium-Range Weather Forecasts's ERA-5 historical climate reanalysis data

product⁵⁸, covering the period 1970-2019, and having a spatial resolution of 0.25 arc-degrees. We obtain daily average temperature to calculate Cooling and Heating Degree Days (CDDs and HDDs) at each year and pixel, adopting the temperature threshold of 18° C. Both CDDs and HDDs are constructed at the annual level, and they are defined as the cumulative sum of days with daily average temperature above (CDDs) or below (HDDs) the temperature threshold, T^* , as per Eqs. (1) and (2):

$$CDD = \sum_{d=1}^{365} (\gamma_d)(T - T^*) \quad (1)$$

and

$$HDD = \sum_{d=1}^{365} (1 - \gamma_d)(T^* - T) \quad (2)$$

where γ_d is the binary multiplier.

For all pixels we construct both weather and climate CDDs and HDDs. On the one hand, weather CDDs and HDDs are defined during the survey year. On the other hand, climate CDDs and HDDs are the averages of the annual CDDs and HDDs respectively across the period 1970-survey year. Moreover, we also include climate relative humidity (*HURS*), which is a further input to the model given its crucial importance for heat perception and impacts^{59,60}. Household data are then merged with this information using the most disaggregated geographical information available (e.g. provinces or districts) in each survey, and the year in which the survey is conducted. Particularly, we collapse across grid cells within each administrative unit using population weights in order to represent temperature exposure for the average person within a unit.

To project future AC adoption and electricity consumption, we consider Coupled Model Intercomparison Project Phase 6 (CMIP6) climate change projections coming from the NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP-CMIP6) dataset⁶¹ based on from ScenarioMIP bias-corrected model runs, having a native time resolution of one day and a spatial resolution of 0.25 arc-degrees. We process both historical and future periods Global Climate Models (GCM) output data from each CMIP6 GCMs model (excluding 'hot models'⁶²) as well as for the GCMs ensemble median to calculate pixel-wise median values for the 1995-2014 historical and 2041-2060 future periods, respectively, along two scenarios. These, consistently with the CMIP6 logic, are based on SSP-RCP combinations⁶³. In particular, we consider the scenarios SSP126, a combination of SSP1 and Representative Concentration Pathway (RCP) 2.6, a scenario of strong reduction of greenhouse gases concentration implying a radiative forcing of $2.6 \frac{W}{m^2}$; SSP245, a combination of SSP2⁶⁴ and RCP 4.5, an intermediate greenhouse gases concentration scenario implying a radiative forcing of $4.5 \frac{W}{m^2}$; SSP370, a combination of SSP3 and RCP 7.0, an high greenhouse gases concentration scenario implying a radiative forcing of $4.5 \frac{W}{m^2}$; and SSP 585, a combination of SSP5⁶⁵ and RCP 8.5, a very high greenhouse gases concentration scenario implying a radiative forcing of $8.5 \frac{W}{m^2}$.

In addition, to estimate future growth in household expenditure we use yearly per-capita GDP growth rates based on gridded GDP projections compatible with the SSPs⁶⁶. We extract growth rates at the finest level of geographical disaggregation at which survey data are available for each country (e.g., districts or provinces), and we parse each growth rate to household located in the corresponding area. Similarly, SSP-consistent gridded population growth rates⁶⁷ are used to project the growth in the number of households for each geographical disaggregation unit in each country. In addition we exploit SSP-consistent gridded urbanization projections⁵⁷ to assess future change in urban/rural household

status. When it comes to country-wide projections data, we draw information on future distribution of households among age, education and gender groups based on the SSP scenarios⁶⁸. To project future household characteristics and exposure we use both gridded, thus sub-nationally variable data, and national-scale projections. Data on current residential electricity prices (which are assumed to be constant due to the massive uncertainty on their future evolution globally and across countries) is drawn from the Cable.co.uk database <https://www.cable.co.uk/energy/worldwide-pricing/> and adjusted to the 2011 Purchasing Power Parity (PPP) United States dollars unit to match the model training data. Finally, we adopt the Global Administrative Areas (GADM) database⁶⁹ as the standard administrative boundaries for each country.

Model training and validation

We train two random forest models on the pooled household sample (trimming the tails of the within-country distributions at the 1st 99th percentiles for all variables). The first model is a classification probability model to assess whether a household owns at least an AC unit. The second model is a regression model to predict household yearly electricity consumption as reported from the survey data. We test a range of modeling techniques and a broad array of hyperparameters to identify the best performing models. In particular, we train:

- (Generalized) Linear Models [(G)LM] (parametric, linear modeling)
- Generalized Additive Models [GAM] (semi-parametric, non-linear modeling)
- Random Forests [RF] (tree-based, non-parametric, non-linear modeling)

We use 10-fold cross validation to optimize the model hyperparameters selection (Supplementary Figs. 6-7). Among the models tested, the random forests (RF) models reveal to be the most effective (see Supplementary Tables 6-7 and Supplementary Fig. 4), as they achieve maximum training set *Accuracy* and R^2 values of 93% and 85% for AC ownership and electricity consumption, respectively (Fig. 4). We also calculate metrics of Cohen's *Kappa* and *AUC* for the AC ownership classification model. The *Kappa*⁷⁰ metric is preferred as it is more suitable for evaluating binary classification predictions when the two classes (AC/no AC) are unbalanced, such as for the case of global AC ownership, where the global pool dataset mean stands at about 0.25. The two metrics yield 79% and 88%, respectively, indicating very good agreement⁷¹, while the *MSE* (Mean Squared Error) for the electricity consumption regression model yields 0.2. The two trained RF models are then tested on the complementary stratified random sample which was excluded from the training set. Predictions on the test set yield *Accuracy* and R^2 values of 90% and 75% for AC ownership and electricity consumption, respectively. Cohen's *Kappa* and *AUC* metrics for the test set yield 73% and 86%, respectively (substantial agreement⁷¹). The *MSE* metric yields 0.22 and 0.35 for the training and testing sets, respectively.

Altogether these numbers point at a relatively high accuracy of the models in predicting unseen AC ownership and electricity consumption data, and are thus deemed suitable for producing globally relevant estimates.

Shapely values and partial dependence plots

To provide a set of interpretable metrics to assess the contribution of the predictor variables to the two-stage RF models (otherwise challenging to interpret given their non-parametric, 'black-box' nature), we generate a number of additional metrics and plots.

Our first step is to estimate partial dependence values. Consider an outcome, Y , whose values are determined by a set of predictor variables, $\{X_1, \dots, X_N\}$ through the model relationship, $Y = \Omega[X_1, \dots, X_N]$.

The point partial dependence of the outcome on a focal subset of the inputs, say \mathbf{X}_F , is the expectation of the outputs of the model evaluated at fixed values, $\{x_F\}$, in conjunction with a grid ($\mathcal{G}[\cdot]$) of the non-focal variables (Eq. (3)):

$$\pi(\{x_F\}) = \mathbb{E}_{\mathcal{G}[\mathbf{X}_{-F}]} \Omega(\{x_F\}, \mathcal{G}[\mathbf{X}_{-F}]) \quad (3)$$

In our analytical setting, π represents the conditional expected probabilities for the first stage AC ownership model and conditional expected cooling energy consumption for the second stage electricity demand model. Our focal variables are, in the first stage, cooling degree days and the logarithm of household expenditure, and in the second state, CDDs, log expenditure and the probability of a household owning an AC unit. Figure 1d shows maps of these partial dependence relationships.

The elasticity of the outcome with respect to the focal variable is defined by Eq. (4):

$$\eta = \partial \log Y / \partial \log X_F \quad (4)$$

We combine (3) and (4) to calculate partial elasticities using the discrete arc-elasticity formula in Eq. (5):

$$\{\eta_F\} = \frac{\log \pi(\{x_F\}) - \log \pi(\{x_F^0\})}{\{\log x_F - \log x_F^0\}} \quad (5)$$

where x_F^0 denotes the anchor value of each focal variable. As a practical matter, we use the minimum value of each focal input variable as its anchor point. The distributions of the partial elasticities of AC ownership and electricity consumption to expenditure and climate variables are shown in Fig. 1e.

To gain additional insight into the models' performance, we calculate SHAP (Shapley additive explanations^{72,73}) values that quantify the contribution of each variable to the predicted outcome. SHAP values consider all possible combinations of features and measure their impact on predictions. Supplementary Figs. 8-9 present Shapely values plots, shedding light on the magnitude and direction of features within the RF model and for each specific macro-region considered.

Finally, Supplementary Fig. 10 illustrates a graphical representation of a single decision tree (CART) benchmark model.

Gridded projections

To parse the household surveys to the spatially-explicit datasets described above used to make projections, we refer to the most disaggregated spatial unit available to which each household is assigned in the survey data. This varies by country, but spans from the first level of administrative units (the regions of a country) down to the third level of administrative units (districts). Using these geographical boundaries, we extract raster data and join vector data to calculate the relevant statistics.

Whilst in some instances it is possible to directly parse historical data from the survey variables as their definition and units are consistent (e.g. age, gender), in other instances certain processing steps are required to ensure consistency of the historical data upon which the empirical models are estimated, and the future data used for projections. For instance, as income/expenditure is heterogeneously defined across countries, we first convert it into 2011 PPP United States dollars, and then project the baseline value using the local per-capita GDP growth rates from the downscaled GDP projections⁶⁶ divided by the downscaled population projections⁶⁷.

An additional challenge in making bottom-up model-based projections from disaggregated survey data relates to binary and factor variables, where a set of assumptions need to be made. Finally, for a set of variables (age, gender, education), SSP-consistent projections are only available at a country-level, and thus we assume socio-

demographic transformations to be homogeneous within each country.

External validity and gridded predictions validation

Besides cross-validation at the household level for model training, hyperparameters tuning, and testing, the models output data are also benchmarked against both national AC rates derived from both the household survey training data, and on recent AC ownership statistics from alternative sources^{12,14}. Note that grid-cell level model outputs for the base year 2010 are compared with survey data and statistics which span between 2011–2019 (depending on the country; see Supplementary Table 2 for reference). Thus, part of the observed bias might be owing to different year of reference in the survey and modeled data.

Supplementary Fig. 5 illustrates the results of such comparison. The results (yielding R^2 values of 97% and 92% for aggregated survey data and national statistics, respectively) show that our estimates are broadly consistent with both aggregated training data and national statistics from external sources (including in countries which are not part of our training data pool). This finding provides important evidence for the reliability of our gridded projections, their representativeness at the country-level, and their external validity.

Greenhouse gas emissions estimation

We assess the consequences of increased AC energy use in terms of carbon dioxide emissions by combining the gridded AC electricity consumption projections with country or regional-average (depending on data availability) power sector emission factors of different SSP scenarios from the Intergovernmental Panel on Climate Change (IPCC) Sixth Assessment Report (AR6) Database⁷⁴. Such emission factors are multiplied by the sum of the estimated AC electricity in each country.

Decomposition analysis of projection drivers

To conclude, we carry out a decomposition analysis of the projections by recursively re-estimating the projections changing the input data to the model one driver per time, and letting the other drivers constant at their base year level. Supplementary Fig. 21 illustrates the results of this supplementary analysis for both AC penetration and electricity consumption.

Reporting summary

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

Data availability

The input data required to replicate the analysis and the output data generated in this study and the source data to replicate the figures have been deposited in the Zenodo database under accession code 12697821, <https://doi.org/10.5281/zenodo.12697821>. The output gridded data and the underlying machine learning (ML) model trained on household survey data are made publicly available for future use. In particular, we release global netCDF files with a 0.5 arc-degree spatial resolution (about 55km at the equator) and 10-year time resolution for the period 2010–2050 for the SSP scenarios 1(26), 2(45), 3(70), and 5(85). Dataset for three variables is made available: (i) the AC penetration rate, defined as the fraction of households living at grid cell i in year t owning at least one AC unit; (ii) the population of reference, derived from Gao et al.⁵⁷ which can be used as a weight to aggregate AC penetration rates at different spatial scales; (iii) the total AC electricity consumption (in gigawatt-hours yr^{-1}), defined as the electricity consumed for AC utilization by households at each grid cell i in year t . In addition, source data to replicate figures and tables are provided with this paper. Source data are provided with this paper.

Code availability

The replication code can be accessed through the following Github repository: <https://doi.org/10.5281/zenodo.12671063>.

References

- Intergovernmental Panel on Climate Change. Climate Change 2022 - Impacts, Adaptation and Vulnerability: Working Group II Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (Cambridge University Press, 2023). <https://doi.org/10.1017/9781009325844>.
- Dyer, O. Climate change is outpacing efforts to adapt, warns intergovernmental panel. *BMJ* o541. <https://doi.org/10.1136/bmj.o541> (2022).
- Biardeau, L. T., Davis, L. W., Gertler, P. & Wolfram, C. Heat exposure and global air conditioning. *Nat. Sustain.* **3**, 25–28 (2020).
- Jay, O. et al. Reducing the health effects of hot weather and heat extremes: from personal cooling strategies to green cities. *Lancet* **398**, 709–724 (2021).
- Ballester, J. et al. Heat-related mortality in Europe during the summer of 2022. *Nat. Med.* **29**, 1857–1866 (2023).
- Zhao, Q. et al. Global, regional, and national burden of mortality associated with non-optimal ambient temperatures from 2000 to 2019: a three-stage modelling study. *Lancet Planet. Health* **5**, e415–e425 (2021).
- Lüthi, S. et al. Rapid increase in the risk of heat-related mortality. *Nat. Commun.* **14**. <https://doi.org/10.1038/s41467-023-40599-x> (2023).
- Sun, S. et al. Ambient heat and risks of emergency department visits among adults in the United States: time stratified case crossover study. *BMJ* e065653. <https://doi.org/10.1136/bmj-2021-065653> (2021).
- Vicedo-Cabrera, A. M. et al. The burden of heat-related mortality attributable to recent human-induced climate change. *Nat. Clim. Change* **11**, 492–500 (2021).
- De Cian, E., Pavanello, F., Randazzo, T., Mistry, M. N. & Davide, M. Households' adaptation in a warming climate. air conditioning and thermal insulation choices. *Environ. Sci. Policy* **100**, 136–157 (2019).
- Turek-Hankins, L. L. et al. Climate change adaptation to extreme heat: a global systematic review of implemented action. *Oxf. Open Clim. Change* **1**, kgab005 (2021).
- International Energy Agency. *The Future of Cooling: Opportunities for Energy-efficient Air Conditioning* (International Energy Agency, 2018). <https://www.iea.org/reports/the-future-of-cooling>.
- UNEP. Global Cooling Watch 2023 (UNEP, 2023). <https://www.unep.org/resources/global-cooling-watch-2023>.
- Davis, L., Gertler, P., Jarvis, S. & Wolfram, C. Air conditioning and global inequality. *Glob. Environ. Change* **69**, 102299 (2021).
- Sugden, R. & Sen, A. Commodities and capabilities. *Economic J.* **96**, 820 (1986).
- Barreca, A., Clay, K., Deschenes, O., Greenstone, M. & Shapiro, J. S. Adapting to climate change: the remarkable decline in the us temperature-mortality relationship over the twentieth century. *J. Political Econ.* **124**, 105–159 (2016).
- Sera, F. et al. Air conditioning and heat-related mortality: a multi-country longitudinal study. *Epidemiology* **31**, 779–787 (2020).
- Auffhammer, M., Baylis, P. & Hausman, C. H. Climate change is projected to have severe impacts on the frequency and intensity of peak electricity demand across the United States. *Proc. Natl. Acad. Sci.* **114**, 1886–1891 (2017).
- Auffhammer, M. & Mansur, E. T. Measuring climatic impacts on energy consumption: a review of the empirical literature. *Energy Econ.* **46**, 522–530 (2014).
- Rode, A. et al. Estimating a social cost of carbon for global energy consumption. *Nature* **598**, 308–314 (2021).

21. Kouis, P. et al. Heat-related mortality under climate change and the impact of adaptation through air conditioning: a case study from Thessaloniki, Greece. *Environ. Res.* **199**, 111285 (2021).
22. Staffell, I., Pfenninger, S. & Johnson, N. A global model of hourly space heating and cooling demand at multiple spatial scales. *Nat. Energy* **8**, 1328–1344 (2023).
23. Randazzo, T., De Cian, E. & Mistry, M. N. Air conditioning and electricity expenditure: the role of climate in temperate countries. *Economic Model.* **90**, 273–287 (2020).
24. International Energy Agency. *Buildings* (International Energy Agency, 2022).
25. Andrijevic, M., Byers, E., Mastrucci, A., Smits, J. & Fuss, S. Future cooling gap in shared socioeconomic pathways. *Environ. Res. Lett.* **16**, 094053 (2021).
26. Pavanello, F. et al. Air-conditioning and the adaptation cooling deficit in emerging economies. *Nat. Commun.* **12**, 1–11 (2021).
27. 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).
28. McNeil, M., & Letschert, V. Future Air Conditioning Energy Consumption in Developing Countries and what can be done about it: The Potential of Efficiency in the Residential Sector. Lawrence Berkeley National Laboratory. Retrieved from <https://escholarship.org/uc/item/64f9r6wr> (2008).
29. Mastrucci, A., Byers, E., Pachauri, S. & Rao, N. D. Improving the SDG energy poverty targets: residential cooling needs in the global south. *Energy Build.* **186**, 405–415 (2019).
30. Bezerra, P. et al. Impacts of a warmer world on space cooling demand in Brazilian households. *Energy Build.* **234**, 110696 (2021).
31. Mastrucci, A., Byers, E., Pachauri, S., Rao, N. & van Ruijven, B. Cooling access and energy requirements for adaptation to heat stress in megacities. *Mitig. Adapt. Strateg. Glob. Change* **27**, 1–16 (2022).
32. Romitti, Y. & Sue Wing, I. Heterogeneous climate change impacts on electricity demand in world cities circa mid-century. *Sci. Rep.* **12**, 1–14 (2022).
33. Davis, L. W. & Gertler, P. J. Contribution of air conditioning adoption to future energy use under global warming. *Proc. Natl Acad. Sci.* **112**, 5962–5967 (2015).
34. Zhang, X.-B., Sun, J., Fei, Y. & Wei, C. Cooler rooms on a hotter planet? household coping strategies, climate change, and air conditioning usage in rural china. *Energy Res. Soc. Sci.* **68**, 101605 (2020).
35. Obringer, R. et al. Implications of increasing household air conditioning use across the United States under a warming climate. *Earth's Future* **10**, e2021EF002434 (2022).
36. Colelli, F. P., Wing, I. S. & Cian, E. D. Air-conditioning adoption and electricity demand highlight climate change mitigation–adaptation tradeoffs. *Sci. Rep.* **13**, 4413 (2023).
37. Cong, S., Nock, D., Qiu, Y. L. & Xing, B. Unveiling hidden energy poverty using the energy equity gap. *Nat. Commun.* **13**, 2456 (2022).
38. Wilhelmi, O. V., Howe, P. D., Hayden, M. H. & O’Lenick, C. R. Compounding hazards and intersecting vulnerabilities: experiences and responses to extreme heat during covid-19. *Environ. Res. Lett.* **16**, 084060 (2021).
39. De Cian, E., Falchetta, G., Pavanello, F., Sue Wing, I. & Romitti, Y. The impact of air-conditioning on residential electricity demand across world countries. *SSRN Electron. J.* <https://doi.org/10.2139/ssrn.4604871> (2023).
40. Iverson, S. A. et al. Heat-associated mortality in a hot climate: Maricopa County, Arizona, 2006–2016. *Public Health Rep.* **135**, 631–639 (2020).
41. Huang, L., Nock, D., Cong, S. & Qiu, Y. L. Inequalities across cooling and heating in households: energy equity gaps. *Energy Policy* **182**, 113748 (2023).
42. Kwon, M. et al. Forgone summertime comfort as a function of avoided electricity use. *Energy Policy* **183**, 113813 (2023).
43. Auffhammer, M. Climate Adaptive Response Estimation: Short and long run impacts of climate change on residential electricity and natural gas consumption. *J. Environ. Econ. Manag.* **114**, 102669 (2022).
44. Mullainathan, S. & Spiess, J. Machine learning: an applied econometric approach. *J. Econ. Perspect.* **31**, 87–106 (2017).
45. Falchetta, G., Pavanello, F., De Cian, E. & Sue Wing, I. Global gridded scenarios of residential cooling energy demand to 2050 (2024). <https://zenodo.org/doi/10.5281/zenodo.12697821>.
46. World Bank. World Bank country classifications by income level for 2024–2025—blogs.worldbank.org. <https://blogs.worldbank.org/en/opendata/world-bank-country-classifications-by-income-level-for-2024-2025> (2024).
47. Mazzone, A. et al. Understanding systemic cooling poverty. *Nat. Sustain.* **6**, 1533–1541 (2023).
48. US Energy Information Administration. Monthly energy review (2022). <https://www.eia.gov/totalenergy/data/monthly/>.
49. UN Environment Program. Global Cooling Pledge. <https://www.unep.org/resources/report/global-cooling-pledge> (2023).
50. Andrijevic, M. et al. Towards scenario representation of adaptive capacity for global climate change assessments. *Nat. Clim. Change* **13**, 778–787 (2023).
51. Jones, A., Nock, D., Samaras, C., Qiu, Y. L. & Xing, B. Climate change impacts on future residential electricity consumption and energy burden: A case study in Phoenix, Arizona. *Energy Policy* **183**, 113811 (2023).
52. Jessel, S., Sawyer, S. & Hernández, D. Energy, poverty, and health in climate change: a comprehensive review of an emerging literature. *Front. Public Health* **7**, 357 (2019).
53. News, U. N. Developing countries at COP27 call for ‘climate justice’ in the form of adaptation and loss and damage funds. <https://news.un.org/en/story/2022/11/1130347> (2022).
54. Falchetta, G. & Mistry, M. N. The role of residential air circulation and cooling demand for electrification planning: Implications of climate change in sub-saharan africa. *Energy Econ.* **99**, 105307 (2021).
55. Falchetta, G., De Cian, E., Sue Wing, I. & Carr, D. Global projections of heat exposure of older adults. *Nat. Commun.* <https://doi.org/10.1038/s41467-024-47197-5> (2024).
56. Carr, D., Falchetta, G. & Sue Wing, I. Population aging and heat exposure in the 21st century: Which us regions are at greatest risk and why? *The Gerontologist* **64**, gnad050 (2023).
57. Gao, J. & Pesaresi, M. Downscaling ssp-consistent global spatial urban land projections from 1/8-degree to 1-km resolution 2000–2100. *Sci. Data* **8**, 1–9 (2021).
58. Hersbach, H. et al. The ERA5 global reanalysis. *Q. J. R. Meteorol. Soc.* **146**, 1999–2049 (2020).
59. Cvijanovic, I., Mistry, M. N., Begg, J. D., Gasparrini, A. & Rodó, X. Importance of humidity for characterization and communication of dangerous heatwave conditions. *NPJ Clim. Atmos. Sci.* **6**, 33 (2023).
60. Guo, Q. et al. Significant impacts of humid heat stress on city-level human mortality. In: *ISEE Conference Abstracts Vol. 2023* (2023).
61. Rama Nemani / NASA. Nasa earth exchange global daily down-scaled projections—cmip6. <https://www.nccs.nasa.gov/services/data-collections/land-based-products/nex-gddp-cmip6> (2021).
62. Hausfather, Z., Marvel, K., Schmidt, G. A., Nielsen-Gammon, J. W. & Zelinka, M. Climate simulations: recognize the ‘hot model’ problem. <https://www.nature.com/articles/d41586-022-01192-2> (2022).
63. O’Neill, B. C. et al. The scenario model intercomparison project (scenariomip) for cmip6. *Geosci. Model Dev.* **9**, 3461–3482 (2016).
64. Fricko, O. et al. The marker quantification of the shared socioeconomic pathway 2: A middle-of-the-road scenario for the 21st century. *Glob. Environ. Change* **42**, 251–267 (2017).

65. Kriegler, E. et al. Fossil-fueled development (ssp5): an energy and resource intensive scenario for the 21st century. *Glob. Environ. Change* **42**, 297–315 (2017).
66. Murakami, D., Yoshida, T. & Yamagata, Y. Gridded gdp projections compatible with the five ssp5 (shared socioeconomic pathways). *Front. Built Environ.* **7**, 760306 (2021).
67. Jones, B. & O'Neill, B. C. Spatially explicit global population scenarios consistent with the shared socioeconomic pathways. *Environ. Res. Lett.* **11**, 084003 (2016).
68. Samir, K. & 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).
69. Hijmans, R., Garcia, N. & Wieczorek, J. GADM: database of global administrative areas, version 3.6. *GADM Maps and Data* (2018).
70. Cohen, J. A coefficient of agreement for nominal scales. *Educ. Psychol. Meas.* **20**, 37–46 (1960).
71. Landis, J. R. & Koch, G. G. The measurement of observer agreement for categorical data. *Biometrics* **33**, 159 (1977).
72. Lundberg, S. M. & Lee, S.-I. A unified approach to interpreting model predictions. *Adv. Neural Inform. Process. Syst.* **30** (2017).
73. Aas, K., Jullum, M. & Løland, A. Explaining individual predictions when features are dependent: more accurate approximations to shapley values. *Artif. Intell.* **298**, 103502 (2021).
74. Byers, E. et al. Ar6 scenarios database <https://zenodo.org/record/5886912> (2022).

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Author contributions

G.F. E.D.C., F.P., and I.S.W. conceptualized the paper; G.F. designed the methodological framework; G.F. and F.P. assembled the global household surveys dataset; G.F. performed the statistical analysis and produced the output data; G.F. and I.S.W. produced the figures. G.F. E.D.C., F.P., and I.S.W. contributed to writing and editing the paper.

Competing interests

The authors declare no competing interests.

Additional information

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Correspondence and requests for materials should be addressed to Giacomo Falchetta.

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