Climate change will impact the value and optimal adoption of residential rooftop solar

Mai Shi[1,2], Xi Lu[1,3*], Michael T. Craig[2,4*]

Affiliations

[1] *School of Environment, State Key Joint Laboratory of Environment Simulation and Pollution Control, Tsinghua University, Beijing 100084, China.*

[2] *School for Environment and Sustainability, University of Michigan, Ann Arbor, MI, USA.*

[3] *Institute for Carbon Neutrality, Tsinghua University, Beijing 10084, China.*

[4] *Department of Industrial and Operations Engineering, University of Michigan, Ann Arbor, MI, USA.*

List of corresponding authors:

Xi Lu. (xilu@tsinghua.edu.cn)

Michael T. Craig. (mtcraig@umich.edu)

Abstract

Rooftop solar adoption is critical for residential decarbonization and hinges on its value to households. Climate change will likely affect the value of rooftop solar through impacts on rooftop solar generation and cooling demand, but no studies have quantified this effect. We quantify household-level effects of climate change on rooftop solar value and technoeconomically optimal capacities by integrating empirical demand data for over 2,000 U.S. households across 17 cities, household-level simulation and optimization models, and downscaled weather data for historic and future climates. We find climate change will increase the value of rooftop solar to households by up to 19% and increase technoeconomically optimal household capacities by up to 25% by end-of-century in an RCP-4.5 scenario. This increased value is robust across cities, households, across future warming scenarios, and retail tariff structures. Researchers, installers, and policymakers should capture this increasing value to maximize household and system value of rooftop solar.

Main

Anthropogenic climate change has caused the world's temperature to increase by approximately 1.1℃ since preindustrial times, and additional warming is expected through midcentury[1]. Climate change will not only affect air temperatures, but also other meteorological conditions and variability, thus bringing a series of climate-change-related risks[2]. To limit climate change, decarbonization of the global economy, particularly through renewable energy deployment in the energy sector, is critical. Studies have emphasized the necessity for rapid renewable growth to reach the net-zero future, both nationally or globally[3-5]. A key part of current and future renewable energy portfolios is residential rooftop solar photovoltaics (RSPV). The US Department of Energy has projected that by 2050, almost 200 GW of RSPV will be installed as part of a national decarbonization strategy, relative an 8-fold increase from 2022’s installed capacity of 26 GW[6].

Increasing RSPV deployment requires increasing adoption by residential consumers. Among the many factors that affect RSPV investments, economic feasibility is the most important[7-11]. Value of solar (VOS) is a commonly used index for RSPV economic feasibility that covers various categories of RSPV benefits, including financial, grid and environmental benefits[12,13]. In this study, we specifically consider VOS as household-level financial benefits from RSPV installation, or RSPV earnings (electricity bill savings plus revenues from selling excess RSPV electricity) minus investment costs[14-18]. In the early stage of RSPV development, policymakers tend to stimulate RSPV uptake by increasing the VOS through subsidy, tariff design, and tax exemption[19,20]. But for RSPV to achieve high penetrations and play a major role in future decarbonized systems, RSPV must achieve grid-parity[21,22] through better economic competitiveness[23,24]. RSPV economic competitiveness can improve through either lower costs or higher earnings. Technological innovation has significantly reduced PV hardware costs, such that soft costs currently account for roughly 65% of US RSPV costs, the highest ratio among all PV types[25]. While technological innovation will continue to reduce hardware costs, soft costs will pose an increasingly large barrier to significant future RSPV cost reductions. Given declining net metering compensation across the US, future RSPV earnings will increasingly depend on RSPV generation offsetting household electricity demand rather than being exported to the grid[14].

Meteorological changes driven by climate change will likely affect the future value and investments of RSPV by affecting household RSPV earnings. On the supply side, changes in solar radiation and ambient air temperatures under climate change will likely reduce PV generation across large parts of the world, potentially reducing the value of RSPV[26-30]. On the demand side, rising air temperatures under climate change will shift household electricity demand patterns, particularly through increasing space cooling loads. Climate change could increase household total cooling energy by 40 -100%[31] and peak cooling by around 20%[32] for cities in U.S. Increasing electricity demand from cooling loads could increase the VOS by increasing household demand offset by, and consequently earnings from, RSPV, as cooling loads are one of the most temporally synergistic electric loads with PV output[16,33,34]. Transmission-scale studies indicate increasing electricity demand under climate change in developing regions will incentive expansion of utility-scale PV[35-37].

Collectively, this existing research suggests climate change could have a large impact on the future value of RSPV at the household level, which could in turn have large consequences on its deployment and contribution to achieving decarbonized power systems. Here, we quantify the future household value of RSPV under climate change for over 2,000 households in 17 cities across the United States. We use empirical household cooling data[38] to capture interactions between future RSPV value and household space cooling needs given heterogeneity in climate conditions, building stocks, and user behavior. To project hourly household cooling demand under alternative climates (Methods), we train a series of household-specific regression models on empirical data. We simulate hourly household RSPV generation potential using city-specific radiation and temperature. To estimate the VOS and optimal RSPV deployment per household, we use a technoeconomic optimization model that maximizes RSPV net value, or earnings minus costs. By quantifying VOS and optimal RSPV deployment for historic versus future climates, we quantify the effect of climate change on each value. We obtain county-level hourly downscaled climate data for the historic climate (1980-2019) and four future climates for mid-century (2020-2059) and end-of-century (2060-2099) from the Thermodynamic Global Warming (TGW) dataset[39]. (Figure S1) The four future climates include cooler and hotter versions of Representative Concentration Pathways (RCPs) 4.5 and 8.5 that use warming signals with low and high climate sensitivity from global climate models (GCMs), respectively.

Effects on residential cooling demand and RSPV potential

Throughout our main results, we present results for the hotter RCP-4.5 ("RCP-4.5-Hotter") climate scenario as a representative climate pathway, then detail the sensitivity of our results to other climate scenarios. Under the RCP-4.5-Hotter scenario, electricity demand for space cooling increases across all households by 35% and 64% on average by mid and end-of century (Figure 1). Across households in cold, mild and hot cities, cooling intensity (or the annual cooling consumption per floor area) will increase from 5, 11 and 24 kWh/m^2, respectively, under the historic climate to 7, 14 and 28 kWh/m^2, respectively, by mid-century and 9, 16 and 31 kWh/m^2, respectively, by end-of-century. Cooling electricity demand increases more in percentage terms in cold cities (Figure 1b) for two reasons: (1) cooling increases are more significant for homes with lower historic cooling intensity (Figure S11,12) and (2) houses in cold cities tend to have a longer extension of the cooling season than hotter cities (Figure S13). Significant differences also exist among houses within each city. For instance, household level cooling increase ranges between 45%-190% in Boston and 6%-52% in Miami by end-of-century.

Unlike cooling loads, which increase across all cities and climate scenarios, RSPV capacity factors exhibit differing trends across cities and future scenarios. (Figure 1c) Solar capacity factors vary positively with solar radiation (due to increased panel-received energy) and negatively with air temperatures (due to declining panel efficiency) (Figure S14). While climate change increases surface temperatures across our cities, it has heterogeneous effects on ground received radiation intensity due to interactions between temperature, moisture and precipitation changes[27,40]. In Miami, Orlando and Atlanta, solar capacity factors increase across climate scenarios, as impacts from increasing solar radiation outweigh impacts from increasing air temperatures. For Ann Arbor, Austin, Chicago, Dallas, Detroit, Houston, Louisville and Milwaukee, solar capacity factors have mixed effects across climate scenarios, as changes due to temperatures and solar radiation are opposing but roughly comparable. For Baltimore, Boston, Los Angeles, Minneapolis, New York City and Phoenix, solar capacity factors significantly decrease, driven by increasing temperatures and decreasing radiation.

Effects on households' value of solar

Household cooling and solar generation potential changes driven by climate change can affect the value of solar (VOS) in two ways: (1) affect the VOS per unit of deployed RSPV capacity, and (2) affect the technoeconomically optimal capacity of RSPV that a household could deploy. In the next two sections, we examine each effect in turn. To quantify changes in VOS per unit of deployed RSPV capacity, we maximize each household's VOS by optimizing its RSPV capacity under historic climate, then quantify the VOS of that same RSPV capacity under future climates. As detailed in the methods, this RSPV optimization model accounts for city-specific retail electricity prices, a solar feed-in price, households' electricity demand and RSPV generation potential profiles (see Methods). The change in VOS per unit of deployed RSPV capacity is composed of two parts, the revenue per unit of RSPV electricity generation ($/kWh) and the RSPV capacity factor (kWh/W).

Climate change increases VOS on a per-capacity basis for most households and cities (Figure 2). Across all cities except Minneapolis, the city-average VOS per W increases by 1-14% (or up to $0.20 per W) and 0-19% (or up to $0.36 per W) by mid- and end-of-century, respectively, under RCP-4.5-Hotter climate(Figure 2, Figure S16). In many of these cities, the VOS increases despite decreasing RSPV generation potential due to greater revenue per unit of RSPV electricity generation. For instance, by end-of-century, greater household cooling demand increases the average household VOS per unit of deployed RSPV capacity by 2-8% across cities, since greater cooling demand increases the ratio of locally consumed RSPV generation (more valuable) to exported RSPV generation (less valuable) (Figure S15). In contrast, by end-of-century, changes in RSPV generation potential change the average household VOS per unit of deployed RSPV capacity by -19% to +12% across cities. The largest increase across cities in household average VOS occurs in Miami, where a 19% VOS increase is driven by a 7% VOS increase due to greater household cooling demand and a 12% VOS increase due to greater RSPV generation. Conversely, in Minneapolis, the household average VOS decreases by roughly 17%, as a 2% VOS increase from greater household cooling demand is countered by a -17% VOS decrease due to less RSPV generation. Besides the limited cooling amount and decreasing solar potential, low electricity retail prices in Minneapolis contributes to its reduced VOS (Supplementary R2). Significant heterogeneity in VOS changes exists between households within each city due to differences in demand profiles and responses to climate change (Figure S17). By end-of-century under our RCP-4.5-Hotter scenario relative to historic, households see a 20% decrease to 30% increase in VOS across cities and see a 5% decrease to 20% increase in VOS within LA.

Effects on technoeconomically optimal solar capacity

Climate change will affect not only households' VOS per unit of deployed RSPV capacity, but also households' technoeconomically optimal solar capacity. To quantify such changes, we optimize household RSPV capacity to maximize household VOS under future as well as historic climates (see Methods).

Technoeconomically optimal household RSPV capacities increase under climate change in 99% of households. Under RCP-4.5-Hotter, the average optimal household RSPV capacity increases by 2-15% and by 3-25% across households by mid- and end-of-century, respectively. (Figure S18) Climate change generally enhances the technoeconomically optimal RSPV deployments continuously, as the optimal RSPV capacity increases across all cities from cooler to hotter RCP scenarios and from mid-century to end-of-century. (Figure S19, Figure S37) Households with larger solar radiation and particularly cooling intensity increases under climate change tend to have larger increases in optimal RSPV capacity (Figure 3 (a,b,c)). Different retail electricity prices in cities drive the economic value of RSPV in offsetting demand increases. Cities with higher power retail prices (e.g., Boston, NYC, LA, Miami, and Orlando) within each climate zone tend to have larger RSPV capacity increases per demand increases than cities with lower retail prices (Minneapolis, Louisville, and Phoenix).

How much RSPV a household deploys will affect its VOS, i.e. the net economic value provided to the household by the RSPV. We separate the effects of larger future RSPV capacities ("capacity effect") from load and PV generation changes assuming a fixed RSPV capacity ("direct climate effect"). (Figure 4) In general, the capacity effect (or deploying more RSPV under climate change) increases the VOS, but has a smaller effect across cities than the direct climate effect (Figure 4). From mid- to end-of-century, the capacity effect plays a larger (but still secondary) role in driving the total VOS increase. (Figure 4, Figure S21).

Sensitivity analysis

Across analyzed climate scenarios, household VOS and technoeconomically optimal capacities tend to increase under climate change. But these relationships are not uniformly increasing with warming level (Figure 5), as higher warming levels increase cooling demand but decrease RSPV panel efficiency and generation (Figure S35-S38). For instance, average household VOS increases by end-of-century are 7-109% larger under RCP-4.5-Hotter than RCP-4.5-Cooler across cities. But 12 of 17 cities have a lower VOS increase by end-of-century under RCP-8.5-Hotter than RCP-4.5-Hotter, since the consequences of panel efficiency reductions (driven by panel output efficiency to temperature) outweigh those of cooling demand increases (driven by household cooling sensitivity to temperature). VOS increases with warming level in hot cities (e.g., Orlando and Miami) and high-power-price cities (Boston, LA) (Figure 5a), where the panel efficiency losses are outweighed by more locally-consumed power increases and higher revenues per kWh cooling increase, respectively. However, future climates increase RSPV technoeconomically optimal capacities across households (Figure 5b). Our finding of climate change increasing rooftop VOS except in Minneapolis is robust across pairwise combinations of 5 PV tilt and 5 PV azimuth scenarios (Supplementary R8, Figure S44-45). Changes in azimuth have a larger influence on VOS increases under climate change than changes in tilts. For most cities, households encounter the highest VOS for per W panel on roof azimuths toward south or southwest and flat tilts.

We also test the sensitivity of our results to a series of policy- and technology-related economic model input parameters, including a TOU price with lower off-peak prices during hours with high solar generation; lower and higher solar feed-in prices; and lower RSPV investment costs (see Methods). Under a TOU rate based on a current Southern California Edison TOU tariff design, the household average VOS per W panel across cities would be reduced by 15%-20% under historic weather (Figure S26), and all cities except Minneapolis see an increase of VOS under climate change holds under a TOU tariff (Figure S27). Our finding that the technoeconomically optimal solar capacity increases under climate change also holds under TOU tariffs. Higher feed-in prices generally yield higher optimal investment capacities and VOS under historic and future climates (Figure S24). Lower RSPV panel costs also generally increase the optimal investment capacity and VOS for residents. Furthermore, lower panel costs yield a greater increase in VOS due to climate change, such that Minneapolis shifts from a declining to increasing VOS under climate change (Figure S25).

Discussions and Conclusions

As the first known research quantifying climate-induced changes in the value of residential rooftop solar photovoltaics (RSPV), our assessment provides an important step forward for the evolving value of RSPV, integrating climate-driven analysis on both RSPV supply and power demand. We found the value of RSPV would increase by 5% -20% in a wide range of U.S. cities under climate change. Changing climate conditions would also increase the technoeconomically optimal capacity by 5%-25%. Given an RSPV lifetime of around 30 years, RSPV investments today will operate through 2050, which will be a mid-century climate. Thus, installers and policymakers should plan for future, not historic, climates in considering the value and sizing of RSPV to maximize RSPV value for households and the power system.

Increasing RSPV value and technoeconomically optimal capacities for households driven by climate change could lead to greater RSPV electricity penetration in the residential sector, furthering decarbonization goals. If all of our analyzed households deployed their optimal RSPV capacity, they would generate annually 10.0, 10.9 and 11.6 kWh per m^2 of floor area on average under historic, RCP-4.5-Hotter mid-century and end-of-century climates, respectively. This generation would reduce CO_2 emissions by 3.6, 3.9 and 4.1 kg/(yr-m^2) CO_2 emission reduction per floor area based on state-level grid emission factors[41]. (Figure S30) If we scale our households' results to represent all households within the same census division, technoeconomically optimal deployment and generation changes driven by climate change would increase solar generation by 12 and 20 GWh per year and reduce CO_2 emissions by 4.3 and 7.1 Mt per year (Supplementary R6), with greater generation and CO_2 benefits in warmer scenarios (Figure S40). Thus, climate change will drive greater decarbonization benefits from RSPV deployment.

Globally, climate change will increase cooling demand in many regions, particularly in areas with mild current climates[31], and have mixed effects on PV generation potential, with most regions seeing slight (less than 10%) decreases[26,28,42-44] but some regions, e.g. Southern Europe, Southwest China, and northern South America, seeing increases. We find the VOS of RSPV increases under climate change in U.S. cities that have increases or decreases in PV generation potential as long as cooling demand also increases. This suggests the VOS of RSPV could increase across global regions, except in regions with limited future cooling demand and significant PV potential loss, such as in Minneapolis in our results and potentially Scandinavia in another global region. Increasing VOS could increase RSPV adoption globally, accelerating decarbonization. Our results also suggest utility-scale PV would experience increased value under climate change across most of the United States. For utility-scale PV, aggregated rather than household-level cooling demand increases would affect its future value[35-37], moderated by regional changes in PV potential.

RSPV adoption will be influenced by many non-technoeconomic factors. Policy frameworks and technological advancements aiming at a low-carbon future will influence retail rates, feed-in tariffs, and panel costs. Our sensitivity analysis captures their multifaceted impacts on evolving RSPV value. A probable future scenario features declining grid rates and feed-in tariffs, which could counterbalance the VOS enhancements induced by climate change. Conversely, decreasing panel costs due to technological innovations could reinforce RSPV value, especially with a warming climate. As individuals adapt to warmer climates, their habits and behaviors may evolve. They might set lower cooling setpoints during peak solar hours to fully use the local solar power or pre-cool homes in the afternoon to reduce evening consumption[45]. They may also make extra investments on employing demand-response and integrating storage to maximize local energy use. These adaptations, which could lead to higher household PV self-consumption, might enhance the value of household RSPV and alter climate-related effects. Adjustments in cooling behaviors could intensify the alignment between cooling demand and PV outputs, amplifying the climate-influenced VOS rise. Conversely, integrating storage changes this alignment, moving the temporal synergy from an emphasis on cooling demand to an overall demand shift. Therefore, the climate-induced VOS increase might be mitigated by the incorporation of battery storage. Still, many of these behavioral shifts remain uncommon in the current U.S. landscape, introducing considerable uncertainty due to evolving practices and varied user habits. For instance, future reductions in battery costs will crucially determine their role in bolstering RSPV value, paralleling the trajectory seen with panel costs. Individual receptiveness to behavioral adjustments also introduces variability, which may further amplify the difference among households on their VOS increase along with climate change.

Several opportunities for future research exist. First, we assume a static building stock, but upgrades and renovations, e.g. through heat pump adoption or increased building insulation, would affect the relationship between household electricity demand and ambient air temperatures. Future research could capture this effect through building simulation tools or simplified building models. Second, we assume users to be perfect rational on RSPV adoption, while future study could capture how behavioral variability (e.g. the adoption of load management) may alter the climate effect on solar investments. Researchers could also model the evolving value of RSPV with distributed storage under climate change[46]. Third, climate change will affect more than rooftop solar and cooling demand in power systems, affecting utility-scale investment decisions and operations[47]. These changes could affect retail rate structures in the future, which could in turn affect the future value of rooftop solar. In particular, increasing value in utility-scale solar as noted above could increase utility-scale solar investments, which would likely reduce the alignment of high TOU rates with rooftop solar output. To capture these dynamics, future studies could combine household-level models like ours with transmission-scale planning to model future potential rate structures. Fourth, the evolving value of RSPV were predicted based on moderate (RCP-4.5) and radical warming pathways (RCP-8.5), and the VOS increase impact may mitigate under a conservative carbon-neutral pathway (e.g. RCP-2.6). Meanwhile, the RCP-4.5-cooler version could partially reflect a carbon-neutral future, as it has average 1.30 and 2.12 °C temperature increase across cities in mid- and end-of-century, slightly higher than a lowest emission future (i.e. RCP-2.6) with an average temperature increase at about 1.6°C[48]. We also recommend a more reliable RSPV potential modelling under climate change with an ideal climate datasets that doesn't require radiation decomposition, which is not available currently as pointed as a common challenge at the interface of energy system and climate analyses[49]. Despite these limitations, our results indicate that climate change will improve the economic value and deployment potential of rooftop solar, which could accelerate climate mitigation efforts.

Acknowledgements

This work was supported by the National Key R&D Program of China 2023YFE0204600, National Natural Science Foundation of China (No. 72025401, 71722003, 71974108, and 71690244), Tsinghua University-INDITEX Sustainable Development Fund. We thank Pamela Wildstein on building modelling and grid tariff analysis, and Ritvik Jain on building simulation.

Author Contributions Statement

Author and affiliations

School of Environment, State Key Joint Laboratory of Environment Simulation and Pollution Control, Tsinghua

University, Beijing 100084, China
Mai Shi, Xi Lu
School for Environment and Sustainability, University of Michigan, Ann Arbor, MI, USA.
Mai Shi, Michael T. Craig
Institute for Carbon Neutrality, Tsinghua University, Beijing 10084, China.
Xi Lu
Department of Industrial and Operations Engineering, University of Michigan, Ann Arbor, MI, USA.
Michael T. Craig

Contributions

M.S. formed the research concept, designed and performed the analysis, collected data, wrote the code and drafted the paper. M.T.C contributed to the project concept, reviewed the codes and revised the narrative structure and language of the paper. X.L contributed to paper draft and revision.

Competing Interests Statement

The authors declare no competing interests.

Tables

No tables in the main text

Figure Legends/Captions

Figure 1

Boxplots of climate change induced residential cooling and solar potential change. (a) Boxplots of cooling power intensity across households for 40-year average in RCP-4.5-Hotter in historic, mid-century and end-of-century, sample size (n) for each city equals to the number of effective houses in each city in Table S1; **(b)** Boxplots of cooling power increase across households for 40-year average in RCP-4.5-Hotter in historic, mid-century and end-of-century, sample size (n) for each city equals to the number of effective houses in each city in Table S1; **(c)** Boxplots for residential solar capacity factor in each city for the distribution of 40 years in RCP 4.5 Hotter in historic, mid-century and end-of-century (n = 40) . Boxplots indicate variability between households by cities. In all boxplots, we present median (notch), first and third quantile (lower and upper hinges of boxes) and 1.5 times the inter-quartile range (whiskers). City labels are as follows: AA – Ann Arbor, BOS – Boston, CHI – Chicago, DET – Detroit, MIL – Milwaukee, MIN – Minneapolis, ATL – Atlanta, BAL – Baltimore, LA – Los Angeles, LOU - Louisville, NYC – New York City, AUS – Austin, DAL – Dallas, HOU – Houston, MIA – Miami, ORL – Orlando, PHX – Phoenix.

Figure 2

Waterfall charts showing the average changing ratio of VOS per W across households by city under RCP-4.5-Hotter. (a) Mid-century relative to historic (b) End-of-century relative to historic. The blue columns indicate the VOS change driven by the household cooling increase, which are calculated using residential loads in mid- or end-of-century and hourly historic PV generation. The purple columns are the total household average VOS change, which are calculated using both loads and generation profiles in mid-century and end-of-century. The orange columns are the difference between the blue and purple columns, indicating the VOS effect of PV generation changes under climate change.

Figure 3

Household level technoeconomically optimal RSPV capacity increase and VOS per W increase by end-of-century under RCP-4.5-Hotter scenario relative to historic climate. (a-c) Scatter plot of technoeconomically optimal RSPV capacities increase versus annual cooling demand increase in cold (a), mild (b) and hot (c) cities; **(d-f)** Scatter plot of household VOS increase versus power demand increase in cold (d), mild (e) and hot (f) cities. Differences in trends between cities within subplots are mainly driven by electricity retail price differences between cities, with higher retail price cities (e.g., Boston and New York City) having larger investments and VOS increases than cities with lower retail prices.

Figure 4

Scatter plot of household VOS increase due to direct climate effect versus due to capacity effect in mid-century and end-of-century under RCP-4.5-Hotter scenario. Only houses with increasing VOS are included here, so Minneapolis is excluded. Direct climate effect indicates the VOS increase due to meteorological changes under climate change, while capacity effect indicates the VOS increase due to greater RSPV investments.

Figure 5

Average household VOS and technoecomically optimal capacities increase across cities among climate scenarios. (a) comparison of average household VOS per unit RSPV increase across cities by mid-century under RCP-4.5-Cooler, RCP-4.5-Hotter and RCP-8.5-Hotter scenarios relative to historic; (b) comparison of average household technoecomically optimal capacities across cities by mid-century under RCP-4.5-Cooler, RCP-4.5-Hotter and RCP-8.5-Hotter scenarios relative to historic.

Reference

1 Masson-Delmotte, V. M.-D., V.; Zhai, P.; Portner, H.-O.; Roberts, D.; Skea, J.; Shukla, P. R.; Pirani, A.; Moufouma-Okia, W.; Pean, C.; Pidcock, R.; Connors, S.; Matthews, J. B. R.; Chen, Y.; Zhou, X.; Gomis, M. I.; Lonnoy, E.; Maycock, T.; Tignor, M.; Waterfield, T., Eds. Global Warming of 1.5°C: An IPCC Special Report on the Impacts of Global Warming of 1.5°C above Pre-industrial Levels and Related Global Greenhouse Gas Emission Pathways, in the Context of Strengthening the Global Response to the Threat of Climate Change, Sustainable Development, and Efforts to Eradicate Poverty. (Intergovernmental Panel on Climate Change, 2018).

2 Hans-Otto Pörtner, Debra C. Roberts. Climate Change 2022: Impacts, Adaptation and Vulnerability. (Working Group II for the Sixth Assessment Report of the Intergovernmental Panel on Climate Change, 2022).

3 Stéphanie Bouckaert, Christophe McGlade, Uwe Remme, Brent Wanner. Net Zero by 2050: A Raodmap for the Global Energy Sector. (2021).

4 Larson, E., *et. al*. Net-Zero America: Potential Pathways, Infrastructure, and Impacts. (Princeton University, 2021).

5 Zhang, S. & Chen, W. Assessing the energy transition in China towards carbon neutrality with a probabilistic framework. *Nature Communications* **13**, 87, doi:10.1038/s41467-021-27671-0 (2022).

6 Becca Jones-Albertus., *et.al*. Solar Futures Study. (Office of Energy Efficiency & Renewable Energy, US Department of Energy, 2021).

7 Schulte, E., Scheller, F., Sloot, D. & Bruckner, T. A meta-analysis of residential PV adoption: the important role of perceived benefits, intentions and antecedents in solar energy acceptance. *Energy Research & Social Science* **84**, 102339, doi:https://doi.org/10.1016/j.erss.2021.102339 (2022).

8 Alipour, M., Salim, H., Stewart, R. A. & Sahin, O. Residential solar photovoltaic adoption behaviour: End-to-end review of theories, methods and approaches. *Renewable Energy* **170**, 471-486, doi:https://doi.org/10.1016/j.renene.2021.01.128 (2021).

9 Ashraf Fauzi, M., Hanis Zainal Abidin, N., Mohd Suki, N. & Mokhtar Albshir Budiea, A. Residential rooftop solar panel adoption behavior: Bibliometric analysis of the past and future trends. *Renewable Energy Focus* **45**, 1-9, doi:https://doi.org/10.1016/j.ref.2023.02.002 (2023).

10 Shimada, H. & Honda, T. What drives households' choices of residential solar photovoltaic capacity? *Energy Policy* **168**, 113120, doi:https://doi.org/10.1016/j.enpol.2022.113120 (2022).

11 Jacksohn, A., Grösche, P., Rehdanz, K. & Schröder, C. Drivers of renewable technology adoption in the household sector. *Energy Economics* **81**, 216-226, doi:https://doi.org/10.1016/j.eneco.2019.04.001 (2019).

12 Hansen, L., *et. al*. A review of solar PV benefit & cost studies. (Rocky Mountain Institute, 2013).

13 Sexton, S., Kirkpatrick, A. J., Harris, R. I. & Muller, N. Z. Heterogeneous Solar Capacity Benefits, Appropriability, and the Costs of Suboptimal Siting. *Journal of the Association of Environmental and Resource Economists* **8**, 1209-1244, doi:10.1086/714970 (2021).

14 Meriläinen, A., Puranen, P., Kosonen, A. & Ahola, J. Optimization of rooftop photovoltaic installations to maximize revenue in Finland based on customer class load profiles and simulated generation. *Solar Energy* **240**, 422-434, doi:https://doi.org/10.1016/j.solener.2022.05.057 (2022).

15 Beuse, M., Dirksmeier, M., Steffen, B. & Schmidt, T. S. Profitability of commercial and industrial photovoltaics and battery projects in South-East-Asia. *Applied Energy* **271**, 115218, doi:https://doi.org/10.1016/j.apenergy.2020.115218 (2020).

16 Shi, M. *et al.* Opportunity of rooftop solar photovoltaic as a cost-effective and environment-friendly power source in megacities. *iScience* **25**, 104890, doi:https://doi.org/10.1016/j.isci.2022.104890 (2022).

17 Tongsopit, S. *et al.* The economics of solar PV self-consumption in Thailand. *Renewable Energy* **138**, 395-408, doi:https://doi.org/10.1016/j.renene.2019.01.087 (2019).

18 Mike Taylor, J. M., Karlynn Cory,Ted Davidovich, John Sterling, Miriam Makhyoun. Value of Solar: Program Design and Implementation Considerations. (National Renewable Energy Laboratory, 2015).

19 Ossenbrink, J. How feed-in remuneration design shapes residential PV prosumer paradigms. *Energy Policy* **108**, 239-255, doi:https://doi.org/10.1016/j.enpol.2017.05.030 (2017).

20 O'Shaughnessy, E., Barbose, G., Wiser, R., Forrester, S. & Darghouth, N. The impact of policies and business models on income equity in rooftop solar adoption. *Nature Energy* **6**, 84-91, doi:10.1038/s41560-020-00724-2 (2021).

21 Lu, X. *et al.* Combined solar power and storage as cost-competitive and grid-compatible supply for China's future carbon-neutral electricity system. *Proceedings of the National Academy of Sciences* **118**, e2103471118, doi:10.1073/pnas.2103471118 (2021).

22 Adeyemi-Kayode, T. M., Misra, S., Maskeliunas, R. & Damasevicius, R. A bibliometric review of grid parity, energy transition and electricity cost research for sustainable development. *Heliyon* **9**, e15532, doi:https://doi.org/10.1016/j.heliyon.2023.e15532 (2023).

23 Lang, T., Ammann, D. & Girod, B. Profitability in absence of subsidies: A techno-economic analysis of rooftop photovoltaic self-consumption in residential and commercial buildings. *Renewable Energy* **87**, 77-87, doi:https://doi.org/10.1016/j.renene.2015.09.059 (2016).

24 Waibel, C., Hsieh, S. & Schlueter, A. in *Carbon Neutral Cities – Energy Efficiency & Renewables in the Digital Era (CISBAT 2021), Lausanne, Switzerland, September 8–10, 2021* Vol. 2042 (The Electrochemical Society, 2021).

25 Vignesh Ramasamy, J. Z., Eric O'Shaughnessy, David Feldman, Jal Desai, Michael Woodhouse, Paul Basore, and Robert Margolis. U.S. Solar Photovoltaic System and Energy Storage Cost Benchmarks, With Minimum Sustainable Price Analysis. (National Renewable Energy Lab, 2022).

26 Feron, S., Cordero, R. R., Damiani, A. & Jackson, R. B. Climate change extremes and photovoltaic power output. *Nature Sustainability* **4**, 270-276, doi:10.1038/s41893-020-00643-w (2021).

27 Crook, J. A., Jones, L. A., Forster, P. M. & Crook, R. Climate change impacts on future photovoltaic and concentrated solar power energy output. *Energy & Environmental Science* **4**, 3101-3109, doi:10.1039/C1EE01495A (2011).

28 Jerez, S. *et al.* The impact of climate change on photovoltaic power generation in Europe. *Nature Communications* **6**, 10014, doi:10.1038/ncomms10014 (2015).

29 Wild, M., Folini, D., Henschel, F., Fischer, N. & Müller, B. Projections of long-term changes in solar radiation based on CMIP5 climate models and their influence on energy yields of photovoltaic systems. *Solar Energy* **116**, 12-24, doi:https://doi.org/10.1016/j.solener.2015.03.039 (2015).

30 Gernaat, D. E. H. J. *et al.* Climate change impacts on renewable energy supply. *Nature Climate Change* **11**, 119-125, doi:10.1038/s41558-020-00949-9 (2021).

31 Deroubaix, A. *et al.* Large uncertainties in trends of energy demand for heating and cooling under climate change. *Nature Communications* **12**, 5197, doi:10.1038/s41467-021-25504-8 (2021).

32 Ortiz, L., González, J. E. & Lin, W. Climate change impacts on peak building cooling energy demand in a coastal megacity.

Environmental Research Letters **13**, 094008, doi:10.1088/1748-9326/aad8d0 (2018).
33 Laine, H. S. *et al.* Meeting global cooling demand with photovoltaics during the 21st century. *Energy & Environmental Science* **12**, 2706-2716, doi:10.1039/C9EE00002J (2019).
34 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, doi:https://doi.org/10.1016/j.enpol.2008.09.051 (2009).
35 Kan, X., Hedenus, F., Reichenberg, L. & Hohmeyer, O. Into a cooler future with electricity generated from solar photovoltaic. *iScience* **25**, 104208, doi:https://doi.org/10.1016/j.isci.2022.104208 (2022).
36 Wang, H. *et al.* Optimization of Clustering Analysis of Residential Electricity Consumption Behavio. *14th IEEE Conference on Industrial Electronics and Applications (ICIEA).* 418-423. (2019).
37 Zhu, K., Victoria, M., Andresen, G. B. & Greiner, M. Impact of climatic, technical and economic uncertainties on the optimal design of a coupled fossil-free electricity, heating and cooling system in Europe. *Applied Energy* **262**, 114500, doi:https://doi.org/10.1016/j.apenergy.2020.114500 (2020).
38 Ecobee Inc. *Donate your data researcher handbook*. (2019).
39 Jones, A. D., Rastogi, D., Vahmani, P., Stansfield, A., Reed, K., Thurber, T., Ullrich, P., & Rice, J. S. . IM3/HyperFACETS Thermodynamic Global Warming (TGW) Simulation Datasets (v1.0.0) [Data set]. (MSD-LIVE Data Repository.) (2022).
40 Dessler, A. E. A Determination of the Cloud Feedback from Climate Variations over the Past Decade. *Science* **330**, 1523-1527, doi:10.1126/science.1192546 (2010).
41 Scott Institute for Energy Innovation. (2017). Power Sector Carbon Index. Carnegie Mellon University, Pittsburgh, PA. Retrieved from https://www.emissionsindex.org.
42 Narvaez. G., *et al.*Climate change impact on photovoltaic power potential in South America *arXiv:2304.13668v1 [physics.ao-ph] for this version) https://doi.org/10.48550/arXiv.2304.13668* (2023).
43 Zhang, J., You, Q. & Ullah, S. Changes in photovoltaic potential over China in a warmer future. *Environmental Research Letters* **17**, 114032, doi:10.1088/1748-9326/ac9e0b (2022).
44 Lei, Y. *et al.* Co-benefits of carbon neutrality in enhancing and stabilizing solar and wind energy. *Nature Climate Change*, doi:10.1038/s41558-023-01692-7 (2023).
45 Naderi, S., Pignatta, G., Heslop, S., MacGill, I. & Chen, D. Demand response via pre-cooling and solar pre-cooling: A review. *Energy and Buildings* **272**, 112340, doi:https://doi.org/10.1016/j.enbuild.2022.112340 (2022).
46 Hunter, C. A. *et al.* Techno-economic analysis of long-duration energy storage and flexible power generation technologies to support high-variable renewable energy grids. *Joule* **5**, 2077-2101, doi:https://doi.org/10.1016/j.joule.2021.06.018 (2021).
47 Craig, M. T. *et al.* A review of the potential impacts of climate change on bulk power system planning and operations in the United States. *Renewable and Sustainable Energy Reviews* **98**, 255-267, doi:https://doi.org/10.1016/j.rser.2018.09.022 (2018).
48 Hayhoe, K., D.J. Wuebbles, D.R. Easterling, D.W. Fahey, S. Doherty, J. Kossin, W. Sweet, R. Vose, and M. Wehner,. Our Changing Climate. In Impacts, Risks, and Adaptation in the United States: Fourth National Climate Assessment, Volume II U.S. Global Change Research Program, Washington, DC, USA, pp. 72–144., (2018).
49 Craig, M. T. *et al.* Overcoming the disconnect between energy system and climate modeling. *Joule* **6**, 1405-1417, doi:https://doi.org/10.1016/j.joule.2022.05.010 (2022).

Methods

We integrate household electricity demand and RSPV generation models to quantify the effect of climate change on the value of RSPV. We first describe how we estimate hourly household electricity demand and PV generation potential for historic and future climates, then formulate our household optimization model for quantifying the value of and technoeconomically optimal deployment of RSPV.

Household cooling electricity demand model

To estimate hourly electricity demand for space cooling for each household in historic and future climates, we couple 3 models including 1) a timeseries regression to predict hourly indoor air temperatures; 2) a control algorithm for determining whether air conditioning (AC) turns on or off based on predicted indoor air temperatures; and 3) regressions to predict AC capacity per household and power consumption when the AC is running. Meanwhile, we defined dynamic cooling seasons for AC cooling operation each year at different cities, whose beginning and ending are the first and last week with an average outdoor temperature above 65°F, respectively. The indoor temperature regression predicts the indoor temperature for each 5-minute interval given the outdoor temperature, latest indoor temperature, and AC operation status (Figure S3). The AC control algorithm then predicts whether the AC runs in each hour based on the individual user habit and the predicted indoor temperature. Specifically, the user habits include the hourly cooling setpoint, AC opening threshold (Supplementary M2) and hourly schedule (Home, Away and Sleep). Once AC system parameters were sized through a regression-based household capacity prediction, the AC electricity consumption regression model generated estimates of electricity usage for each AC operation time interval.

Multiple datasets are utilized in the household AC cooling consumption (HHAC) model. First, we trained the indoor temperature regression and regressed the AC operation time for each household with Ecobee Donate Your Data dataset and historic weather data from NOAA weather station[50]. Ecobee data is collected and publicized by Ecobee Inc., a Toronto-headquartered smart thermostat manufacturer whose products are widely used in US and Canada, and it contains high quality and frequency household level energy usage data.[38] From the Ecobee data, we specifically obtain the AC cooling setpoint, indoor temperature, hourly schedule (Home, Away or Sleep) and cooling running time in 5-minute intervals for 2121 households spanning 2019-2020 years. The Ecobee dataset also contains a self-reported metadata document for household characteristics, including city, number of floors, and square footage, which we use to estimate household solar potential. After filtering our dataset, we obtain data for 20-300 households across 17 cities (see SI). (Table S1). We also use ResStock database[51] to provide information not included in the Ecobee data on two aspects. First, we used the relationship between building floor area and AC capacity for millions of single-family houses in ResStock to estimate the AC capacity for each Ecobee house. Second, we select 400 ResStock samples in each city and simulate their other electric device demands (i.e. indoor lighting, outdoor lighting and interior electric equipment consumption). We assume these demands are insensitive to ambient air temperatures and would not vary between history consumption and climate scenarios. (Supplementary M3). Finally, to estimate AC electricity consumption in our HHAC model, we construct linear regressions from the Goodman's AC product specifications catalog[52], which contains observed AC electricity usage in kW for different AC capacities under different indoor and outdoor temperatures. This linear regression specifically estimates electricity consumption as a function of AC run time and indoor and outdoor temperatures. We apply this regression to each time interval in which the AC runs to estimate AC electricity consumption in each interval[53] (Supplementary M3) The additional details and the mathematical formulation of household cooling demand model are listed in Supplementary M3. The regressions in the household cooling demand model produce robust performances. Specifically, the indoor temperature regression has a range of average R-square from 0.97-0.99 across cities (Figure S6), while the R-square range for hourly and daily cooling demand are 0.68-0.80 and 0.83-0.92, respectively. (Figure S7-S8)

Household solar generation and deployment potential model

For each household, we estimate hourly RSPV per unit generation potentials (or capacity factors) and the maximum potential RSPV deployed capacity. We calculate each household's maximum RSPV deployment capacity as:

$$CAPP_i = RF_i \times ST_i \times PF_i \times \frac{P}{A} \qquad \text{Eq.1}$$

where $CAPP_i$ is the solar capacity potential for Ecobee house i; RF_i is rooftop area, which equals the household floor area divide by the number of floors; ST_i is the city-specific fraction of rooftop area suitable for PV panel installation [54]; PF_i is the packing factor, which quantifies the percentage of panel area to total suitable area; and P and A are the rated power and area for the PV panel. We assume panels are installed at its optimal angle correlated with latitude on flat roofs, and alongside half the roofs facing closer to south on tilted roofs. In the main results, the roofs are considered as southward with 28° incident angle, which is the most common rooftop observed by NREL[54]. 20 other scenarios with different azimuth and rooftop tilt are also detected (Supplementary R8). Taking the main scenario as an example, PF equals the half of the cosine of 28°, yielding a PF of 0.56. Meanwhile, we use a 375 W, 1.94 m^2 PV panel per specifications of a modern Longi panel[55] (Table S3), the largest PV manufacturer globally.

We estimate hourly RSPV capacity factors by processing city-level meteorology in the PVlib Python package[55]. First, we decomposed hourly total shortwave downward radiation (i.e. global horizontal irradiance (GHI)) into direct normal irradiance (DNI) and diffuse horizontal irradiance (DHI) using the Erbs model and solar altitude and azimuth[56] (Supplementary M4). Second, the hourly panel-received radiation was developed through PVlib package using the hourly decomposed radiation, considering the azimuth and incident angle for PV panels. Finally, the hourly PV capacity factor were calculated based on the panel-received radiation and the hourly temperature effect of panels, on a household-by-household basis.

Household value of solar model

To estimate the value of RSPV for each household, we use an optimization model that maximizes the value of solar (VOS), or solar earnings minus costs, by sizing the solar array (Equations 2-8). After setting the optimization RSPV capacity in historic, the Equation 3-7 could then calculate the dynamic VOS across climate change with changing input of hourly load and solar capacity factor. Given that each year within TGW 40-year spans manifests distinct weather patterns, while only climate signals inform variations with 40- and 80-year offsets, we allocated the optimization model on each 40-year TGW climate period to prevent biases linked to intra-annual weather fluctuations and the start year of investments. Notably, while the 40-year period is earmarked for climate categorization, our model respects the widely accepted 25-year PV panel lifespan. This distinction is underscored by the 'yr' variable in Equation 5, set at 25 years[57], to transpose the lump-sum investment into its corresponding cost annuity.

$$maximize\ \ \mathrm{vos}_i \qquad \text{Eq.2}$$

$$\mathrm{vos}_i = \sum_{y=0}^{40} SE_{i,y} - SC_{i,y} \qquad \text{Eq.3}$$

$$SE_{i,y} = \sum_{t=0}^{8760} ((L_{i,t,y} - ND_{i,t,y}) \times P_{grid} + EXSOL_{i,t,y} \times P_{feedin}) \qquad \text{Eq.4}$$

$$SC_{i,y} = cap_i \times C \times ((r + (\frac{r}{(1+r)^{YR} - 1})) \qquad \text{Eq.5}$$

$$ND_{i,t,y} = \begin{cases} (L_{i,t,y} - CF_{i,t,y} \times cap_i), \forall L_{i,t,y} > CF_{i,t,y} \times cap_i \\ 0, \forall L_{i,t,y} \le CF_{i,t,y} \times cap_i \end{cases} \qquad \text{Eq.6}$$

$$EXSOL_{i,t,y} = \begin{cases} CF_{i,t,y} \times cap_i - L_{i,t,y}, \forall CF_{i,t,y} \times cap_i > L_{i,t,y} \\ 0, \forall CF_{i,t,y} \times cap_i \le L_{i,t,y} \end{cases} \qquad \text{Eq.7}$$

$$\mathrm{s.t.} \quad 0 \le cap_i \le CAPP_i \qquad \text{Eq.8}$$

where vos_i is the value of solar over a 40-year TGW climate cycle (historic, mid- or end-of-century) for house i. $SE_{i,y}$ and $SC_{i,y}$ represents the total solar earnings and solar cost for house i in year y in each TGW climate period, respectively. $SE_{i,y}$ consists of the saving of power expense from net demand load reduction and the revenue by selling excess solar to grid. $SC_{i,y}$ is the solar PV panel investment cost annuity across its lifetime year YR. This value is adjusted for the time value of money from the initial panel investment, making it directly comparable to the annual RSPV revenue $SE_{i,y}$. For solar revenue, $L_{i,t,y}$, $ND_{i,t,y}$ and $EXSOL_{i,t,y}$ represents total power consumption, power net demand and excess solar power in kW for house i at hour t in year y, respectively. $CF_{i,t,y}$ is the hourly solar capacity factor house i at hour t in year y. P_{grid} and P_{feedin} represent the unit price ($/kWh) of purchasing power from grid (Table S1) and feed excess solar into grid. For solar cost, variable cap_i represents the capacity (kW) of the PV installation in home i, C is the PV panel investment cost ($/kW), YR is PV panel lifetime taken as 25 years for the quantification on the financial time effect of PV investment and r is the interest rate at 4.5%[57]. The optimization considers the constraint that the PV capacity installed by each home, cap_i, should not exceed its total solar potential, $CAPP_i$.

Climate data and sensitivity analyses

We obtain hourly, county-level downscaled meteorological variables for historic and future climates from Casey et.al[58], who performed climate projections and spatial analysis on county level based on the Thermodynamic Global Warming (TGW) raw data[39] and methodology from Jones, Andrew D et. al[59]. The TGW raw data is generated through dynamically downscaling a 40-year sequence of past weather from 1980-2019 in ERA5 atmospheric re-analysis data to 12km^2, and then repeating this 40-year sequence using a range of time-evolving thermodynamic warming signals that follow future warming trajectories from mid-century (2020-2058) to end-of-century (2060-2099). (Figure S9). The county-level TGW data is generated from the 12km^2 TGW raw data through spatial averaging of each of six meteorological variables (temperature, specific humidity, shortwave radiation, longwave radiation, and east-west and north-south components of wind speed). For future climate scenarios, it contains four climate simulations corresponding to cooler and hotter versions of Representative Concentration Pathways 4.5 and 8.5 that sample variability across 8 global climate models (GCMs) (Figure S31). Specifically, the cooler 4.5 and 8.5 pathways use warming signals from GCMs with low climate sensitivity (and consequently low warming relative to other GCMs), while the hotter 4.5 and 8.5 pathways use warming signals from GCMs with high climate sensitivity (and consequently high warming relative to other GCMs) (Figure S10). Average mid- and end-of-century temperature increase across cities are 1.30°C and 2.12°C in RCP-4.5-Cooler scenario, while in RCP-8.5-Hotter scenario they are 2.23°C and 5.14°C, respectively. As the input for HHAC and VOS models, we obtain surface air temperatures and downward shortwave radiation intensity for counties that includes each city for which we have household data. As the TGW dataset has not been bias corrected, we use quantile mapping[60] to bias correct temperature and radiation data in the historic and future TGW datasets based on the relationship between the historic TGW data and observed weather data (i.e. weather station data[50] for temperature and National Solar Radiation Database (NSRDB) for radiation[61]). Quantile mapping implements a statistical transformation on the modelled climate data so that they agree with the distribution of observed data distribution of modelled climate variables to observational ones. This bias correction allows us to use of TGW modelled data to predict the historic and future building energy consumption based on with our regressions from fit on historic observational data.

In addition to alternative climates, we test the sensitivity of our results to rooftop shape variety, time-of-use (TOU) rates, RSPV investment costs and feed-in prices, key technology- and policy-related uncertainties that will affect the value of RSVP vis-à-vis earnings and cost impacts. Our main results assume feed-in prices of 0.04 $/kWh[62] and RSVP investment costs of 2.55 $/W[63], while we consider a series of feed-in price scenarios (0.08, 0.06, 0.02, 0 $/kWh) and declining investment costs scenarios (2.0, 1.6 $/W). Meanwhile, we regard a constant grid power retail price for each city from the monthly average price for each state in the main results (Table S1), and we set two TOU rates scenarios in sensitivity analysis for each city based a tariff by South California Edison[64] to reflect the potential influence of higher utility-solar penetration in the grid.(Supplementary M7) While the shapes of roof are considered as most common at southward with 28° incident angle in the main results, we also test their uncertainty with a series of 21 scenarios including flat roofs and pitched roofs with 5 azimuths (Eastward, Southeastward, Southward, Southwestward and Westward) and 4 tilts (15°, 28°, 41°, 54°).

Data availability

The data containing individual hourly cooling behavior is from Ecobee inc upon requests[38]. The data with future TGW climate scenarios is from U.S. Department of Energy Office of Scientific and Technical Information[39] and publicly available. Other data sources are provided in the Methods and Supplementary Information. We provided the household-level VOS, optimal solar capacity data through Figshare[65].

Code availability

The codes (python scripts) are available at Figshare[65], including model codes (HHAC model, solar potential mapping and value of solar optimization) and figure production codes (Figure 1-5).

Methods-only References

50 Local Climatological Data (LCD), (National Oceanic and Atmospheric Administration, 2023) https://www.ncei.noaa.gov/data/local-climatological-data/access/.

51 Janet Reyna, E. W., Andrew Parker, Aven Satre-Meloy, Amy Egerter, Carlo Bianchi, Marlena Praprost, Andrew Speake, Lixi Liu, Ry Horsey, Matthew Dahlhausen, Christopher CaraDonna and Stacey Rothgeb. U.S. Building Stock Characterization Study: A National Typology for Decarbonizing U.S. Buildings. (National Renewable Energy Laboratory, 2022).

52 "Literature Library," Goodman Air Conditioning and Heating, 2023. https://www.goodmanmfg.com/support/literature-library (accessed April 20, 2023).

53 Wildstein, P. J., Craig, M. T. & Vaishnav, P. Participant overrides can halve the reliability value of direct load control programs. *Energy and Buildings* **299**, 113606, doi:https://doi.org/10.1016/j.enbuild.2023.113606 (2023).

54 Pieter Gagnon, Robert Margolis, Jennifer Melius, Caleb Phillips & Elmore, R. Rooftop Solar Photovoltaic Technical Potential in the United States: A Detailed Assessment. 70 (National Renewable Energy Laboratory, 2016).

55 Holmgren, W., Hansen, C. & Mikofski, M. pvlib python: a python package for modeling solar energy systems. *Journal of Open Source Software* **3**, 884, doi:10.21105/joss.00884 (2018).

56 Erbs, D. G., Klein, S. A. & Duffie, J. A. Estimation of the diffuse radiation fraction for hourly, daily and monthly-average global radiation. *Solar Energy* **28**, 293-302, doi:https://doi.org/10.1016/0038-092X(82)90302-4 (1982).

57 NREL (National Renewable Energy Laboratory). *"2021 Annual Technology Baseline."* Golden, CO: National Renewable Energy Laboratory. *https://atb.nrel.gov/*.(2021)

58 Burleyson, C., Thurber, T., & Vernon, C. (2023). Projections of Hourly Meteorology by County Based on the IM3/HyperFACETS Thermodynamic Global Warming (TGW) Simulations (v1.0.0) [Data set]. MSD-LIVE Data Repository. https://doi.org/10.57931/1960548.

59 Jones, A. D. *et al.* Continental United States climate projections based on thermodynamic modification of historical weather. *Scientific Data* **10**, 664, doi:10.1038/s41597-023-02485-5 (2023).

60 Bias-correction 0.4 https://pypi.org/project/bias-correction/ (2022).

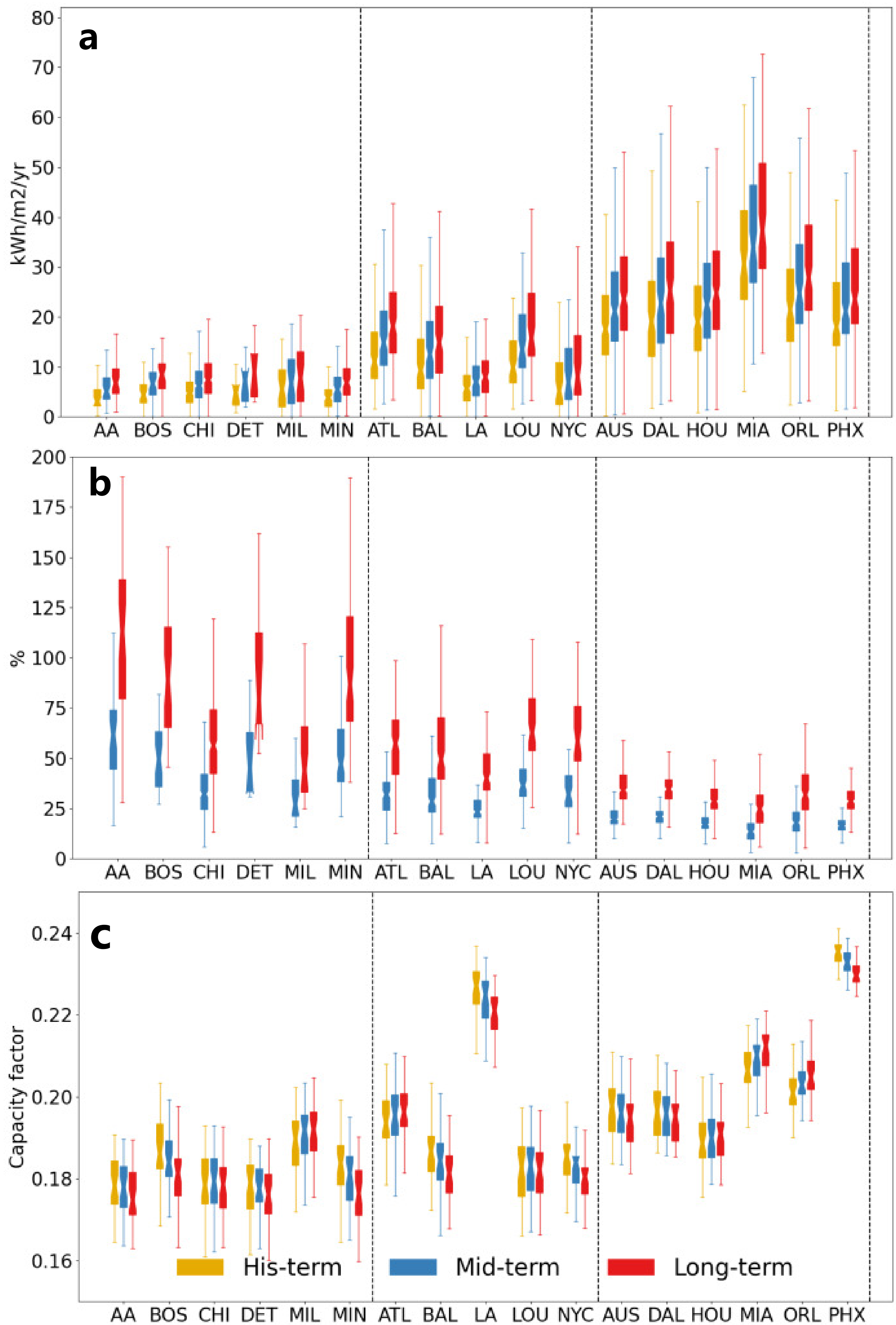
61 Sengupta, M. *et al.* The National Solar Radiation Data Base (NSRDB). *Renewable and Sustainable Energy Reviews* **89**, 51-60, doi:https://doi.org/10.1016/j.rser.2018.03.003 (2018).

62 Marissa P. Gillett., John W. Betkoski III., Michael A. Caron. Annual Residential Renewable Energy Tariff Program Review and Rate Setting (Public Utilities Regulatory Authority State of Connecticut) (2021).

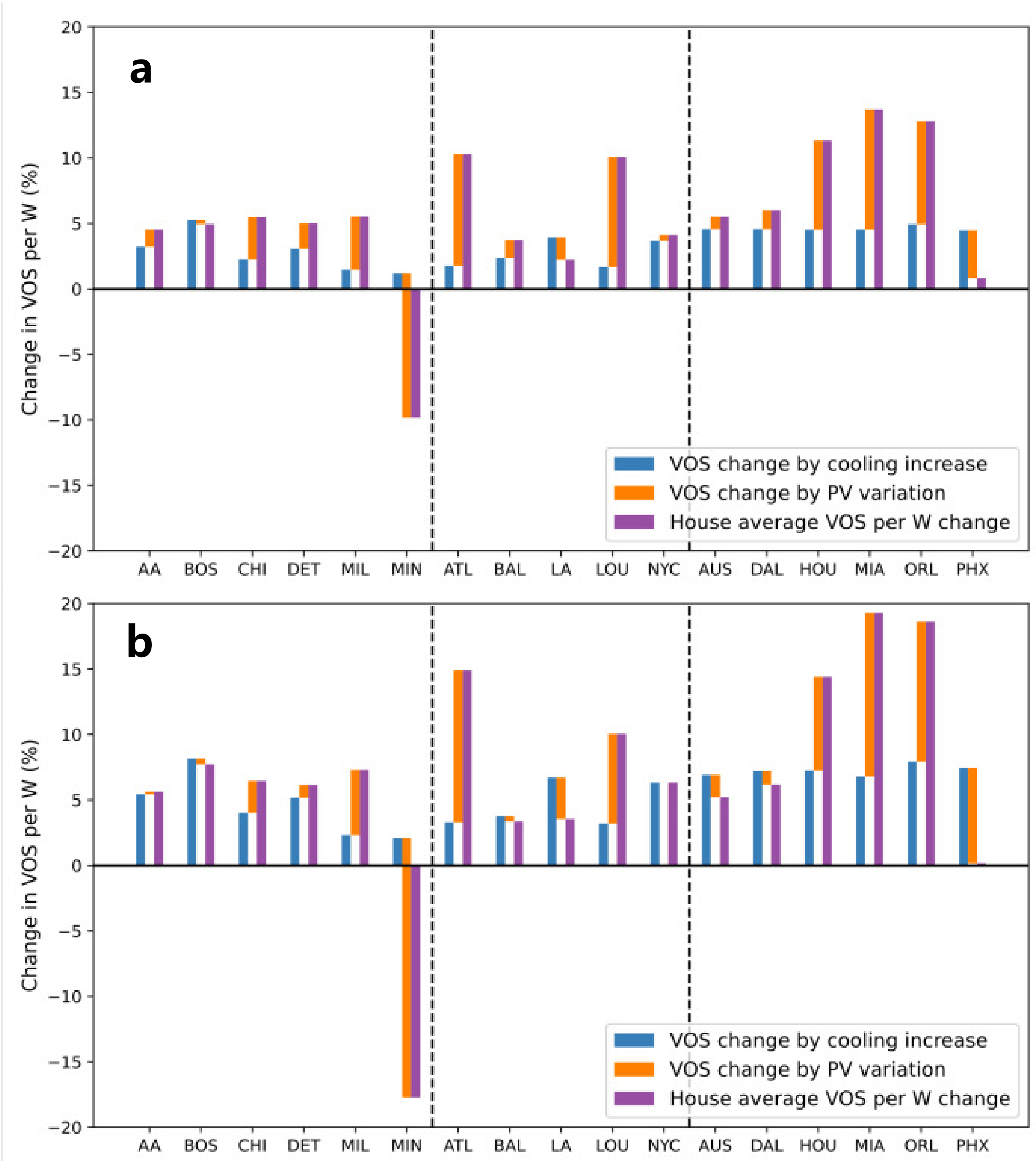
63 Vignesh Ramasamy, J. Z., Eric O'Shaughnessy, David Feldman, Jal Desai, Michael Woodhouse, Paul Basore and Robert Margolis. U.S. Solar Photovoltaic System and Energy Storage Cost Benchmarks, With Minimum Sustainable Price Analysis: Q1 2022. (National Renewable Energy Laboratory, 2022).

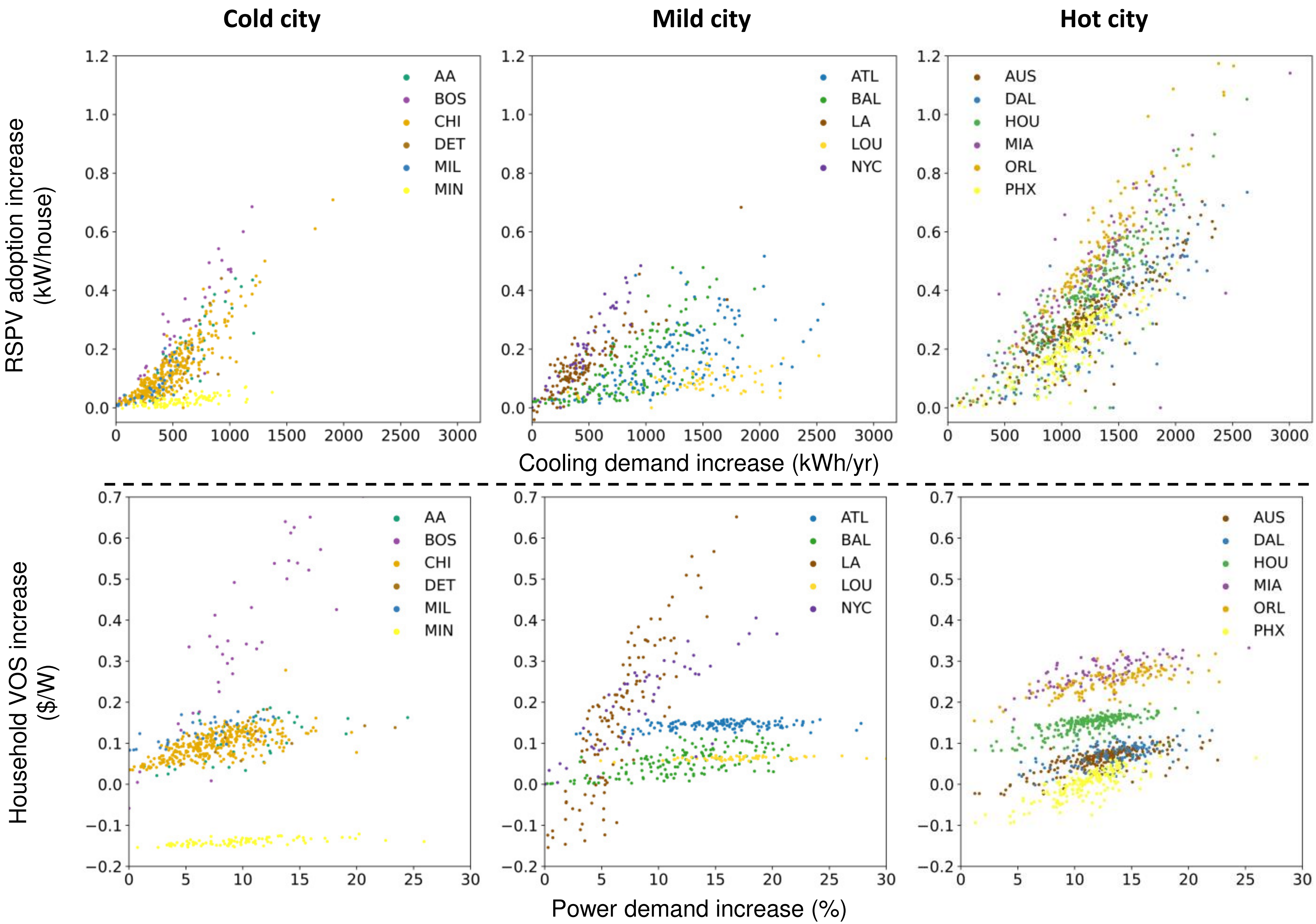
64 South California Edison. Time-Of-Use (TOU) Rate Plans https://www.sce.com/residential/rates/Time-Of-Use-Residential-Rate-Plans. (2023).

65 Shi, M. Shi et.al. Climate change will impact the value and optimal adoption of residential rooftop solar. Nature climate change, 2024. https://doi.org/10.6084/m9.figshare.25296250.v1 (2024).

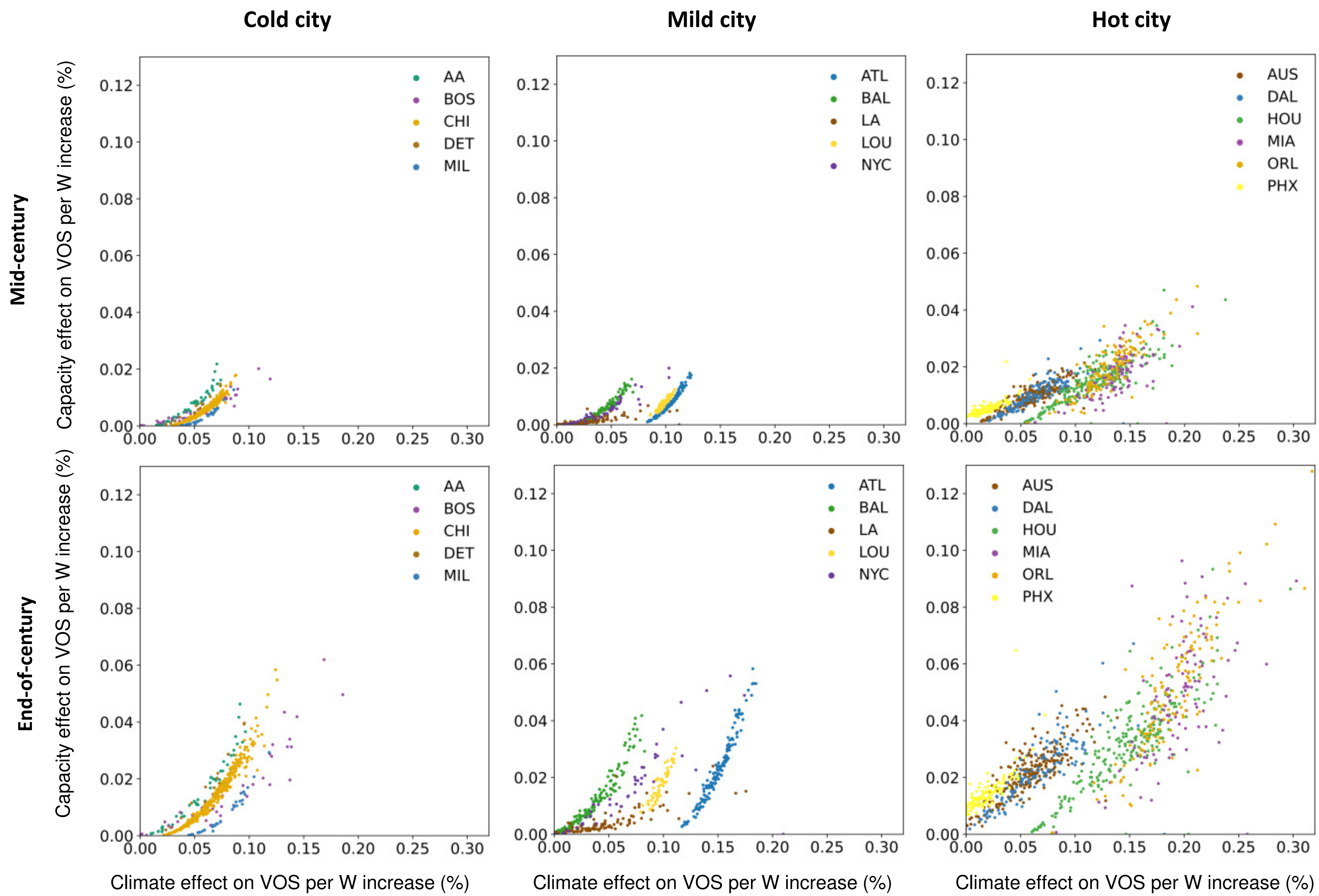


a
kWh/m2/yr
0
10
20
30
40
50
60
70
80
AA BOS CHI DET MIL MIN ATL BAL LA LOU NYC AUS DAL HOU MIA ORL PHX
b
%
0
25
50
75
100
125
150
175
200
AA BOS CHI DET MIL MIN ATL BAL LA LOU NYC AUS DAL HOU MIA ORL PHX
c
Capacity factor
0.16
0.18
0.20
0.22
0.24
His-term
Mid-term
Long-term
AA BOS CHI DET MIL MIN ATL BAL LA LOU NYC AUS DAL HOU MIA ORL PHX

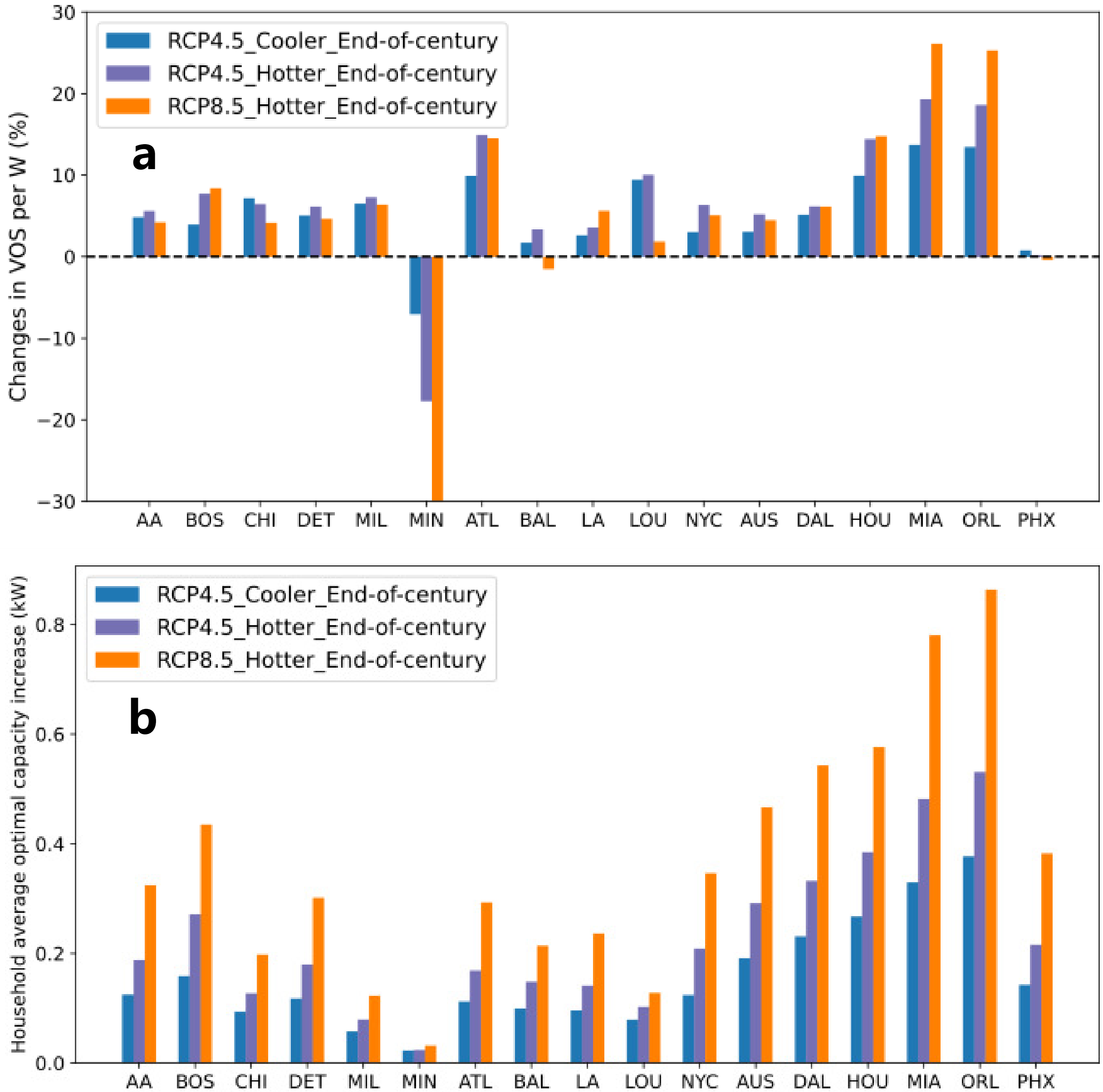

a
b
Change in VOS per W (%)
20
15
10
5
0
−5
−10
−15
−20
VOS change by cooling increase
VOS change by PV variation
House average VOS per W change
AA
BOS
CHI
DET
MIL
MIN
ATL
BAL
LA
LOU
NYC
AUS
DAL
HOU
MIA
ORL
PHX



Cold city
Mild city
Hot city
RSPV adoption increase (kW/house)
AA
BOS
CHI
DET
MIL
MIN
ATL
BAL
LA
LOU
NYC
AUS
DAL
HOU
MIA
ORL
PHX
Cooling demand increase (kWh/yr)
Household VOS increase ($/W)
Power demand increase (%)



Cold city
Mild city
Hot city
Mid-century
End-of-century
Capacity effect on VOS per W increase (%)
Climate effect on VOS per W increase (%)
AA
BOS
CHI
DET
MIL
ATL
BAL
LA
LOU
NYC
AUS
DAL
HOU
MIA
ORL
PHX
0.00
0.02
0.04
0.06
0.08
0.10
0.12
0.05
0.15
0.20
0.25
0.30


a
Changes in VOS per W (%)
RCP4.5_Cooler_End-of-century
RCP4.5_Hotter_End-of-century
RCP8.5_Hotter_End-of-century
30
20
10
0
−10
−20
−30
AA BOS CHI DET MIL MIN ATL BAL LA LOU NYC AUS DAL HOU MIA ORL PHX
b
Household average optimal capacity increase (kW)
RCP4.5_Cooler_End-of-century
RCP4.5_Hotter_End-of-century
RCP8.5_Hotter_End-of-century
0.8
0.6
0.4
0.2
0.0
AA BOS CHI DET MIL MIN ATL BAL LA LOU NYC AUS DAL HOU MIA ORL PHX