

Disentangling the Evolving Effects of Climate Change and Technology Diffusion on Building Electricity Demand

Mai Shi

maish@umich.edu

School for Environment and Sustainability, University of Michigan, Ann Arbor, MI, USA.

<https://orcid.org/0000-0002-6430-0315>

Ziqi Wei

Department of Civil and Environmental Engineering, Massachusetts Institute of Technology, Cambridge, MA, USA

Michael Craig

School for Environment and Sustainability, University of Michigan, Ann Arbor, MI, USA.

Research Article

Keywords: Peak demand, Climate change, Technology diffusion, Energy system, Climate adaptation

Posted Date: October 14th, 2025

DOI: <https://doi.org/10.21203/rs.3.rs-7819501/v1>

License: © ⓘ This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Additional Declarations: The authors declare no competing interests.

1
2 **Main Manuscript for**

3 **Disentangling the Evolving Effects of Climate Change and Technology Diffusion on**
4 **Building Electricity Demand**

5 Mai Shi^{a,*}, Ziqi Wei^b, Michael T. Craig^{a,c*}

6 ^a *School for Environment and Sustainability, University of Michigan, Ann Arbor, MI, USA.*

7 ^b *Department of Civil and Environmental Engineering, Massachusetts Institute of Technology, Cambridge, MA, USA.*

8 ^c *Department of Industrial and Operations Engineering, University of Michigan, Ann Arbor, MI, USA.*

9 **Mai Shi; Michael T. Craig.*

10 **Email:** maish@umich.edu; mtcraig@umich.edu

11 **Author Contributions:** Mai Shi. formed the research concept, designed and performed the analysis, collected data,
12 wrote the code and drafted the paper. Ziqi Wei contributed to methodology in climate data processing. Michael T. Craig.
13 contributed to the concept. methodology and revised the narrative structure and language of the paper.

14 **Competing Interest Statement:** The authors declare no competing interests.

15 **Classification:** Physical Sciences—Engineering+ Social Sciences—Sustainability Science

16 **Keywords:** Peak demand; Climate change; Technology diffusion; Energy system; Climate adaptation.

17 **This PDF file includes:**

18 Main Text

19 Figures 1 to 5

20

Disentangling the Evolving Effects of Climate Change and Technology Diffusion on Building Electricity Demand

Abstract:

Climate change and technology diffusion will interact to drive future electricity demand of buildings. That interaction will evolve over time based on rates of climate change and technology diffusion, a phenomenon not previously studied but crucial for planning reliable power systems. We estimate electricity demand from residential and commercial buildings under climate change and/or technology diffusion across 111 cities in the United States through 2060. Our framework drives 159,840 machine learning models of building electricity demand with 40 climate realizations and 18 technology diffusion pathways of air source heat pumps and insulation. We find interactions between climate change and technology diffusion generate peak load trajectories that diverge substantially from those driven by either factor alone, with patterns differing between hot and cold grid regions. In cold regions, climate change and technology diffusion drive roughly up to 3 and 20 times larger peak demand growth than climate change alone by 2040 and 2060, respectively. Conversely, in hot regions, technology diffusion counteracts climate-change-driven peak demand growth. Across regions, climate-change-induced warming reduces or eliminates a shift towards winter peaking driven by technology diffusion. Via uncertainty partitioning, we find climate-related uncertainty dominates near-term peak demand uncertainty, while technology-diffusion-related uncertainty grows to contribute 10-60% of uncertainty by 2060. Our results highlight the importance of capturing interactions between climate change and technology diffusion over time for resilient power-system design.

Significance:

Climate change and technology diffusion interact to drive building electricity demand, and this interaction evolves with their rates of change. We target building peak demand, a crucial point for future reliable power systems planning, and build the first high-resolution framework that couples 40 climate trajectories with 18 technology-diffusion pathways across 111 U.S. cities to project its dynamics through 2060. Combined effects are larger than either driver alone and are non-additive. In cold regions they amplify peak growth and shift seasonality toward winter versus climate-only; in hot regions they mitigate climate-driven increases. By separating uncertainty from climate versus technology-diffusion, we find climate dominates near-term risk while technology-diffusion grows in later decades. These insights enable targeted, time-phased reliability and investment strategies.

Introduction

In the coming decades, energy systems worldwide will be shaped by climate change and decarbonization. Anthropogenic climate change will increasingly affect mean and extreme weather^{1,2}, which in turn can affect energy systems through diverse pathways^{3,4}. Uncertainty regarding future weather will increase^{5,6} driven by internal unforced variability^{7,8}, climate response uncertainty in different climate models⁹ and radiative forcing uncertainty among different scenarios¹. Changes and attendant uncertainty in mean and extreme changes has profound implications for climate adaptation of energy infrastructure¹⁰⁻¹⁴, especially since existing and new infrastructure with multi-decadal lifetimes must contend with a spectrum of climatic futures. Alongside climate change, the global transition to low-carbon technologies¹⁵⁻¹⁹ will unfold with increasing deployment or diffusion of low-carbon technologies. But technology diffusion rates remain uncertain²⁰, so significant uncertainty surrounds low-carbon infrastructure deployment.

Uncertainty in low-carbon diffusion could amplify or mitigate climate-driven uncertainty for adaptation planning^{21,22}. Creating robust and resilient climate adaptation strategies therefore requires integrating climate

and technology diffusion uncertainties. Capturing these combined uncertainties remains largely overlooked, as most current researches incorporate climate^{23–25} or technology diffusion uncertainties^{26–28} in isolation. While some integrated assessment models (IAM) frameworks address both climate and technology diffusion uncertainties^{29,30}, they depend on a handful of broad scenarios that offer only a coarse, incomplete portrayal of uncertainty rather than high-fidelity modeling of their interactions.

Uncertainties between climate change and low carbon technology diffusion are not static, but rather evolve over time. A stream of literature in the climate sciences examines rates of change in extremes, which is crucial to inform by when adaptation investments must occur^{31,32}. This literature often uses large climate ensembles, given their unique ability to capture extreme (or tail) events over time by leveraging large numbers of climate transients. Such a perspective on the rate of climate change and its implications for when adaptation must occur is lacking in the energy system. This lack leaves energy system planners without guidance as to when to make adaptation investments, ultimately risking system reliability and human wellbeing. This lack also means the joint uncertainty across space and time arising from climate change and technology diffusion remain poorly characterized, further inhibiting effective system planning.

Buildings, which consume nearly one third of global primary energy³³, are an especially important sector in which to capture interactions between climate change and technology diffusion. A significant driver of building energy consumption in many global regions is heating, ventilation, and air conditioning (HVAC). Building decarbonization targets weather-dependent HVAC energy demand through electrification^{34,35} and efficiency gains.³⁶ Rising temperatures may increase summer cooling totals and peaks while reducing winter heating demand^{10,11,37–39}; widespread heat pump adoption may elevate winter electricity peaks when displacing non-electric heating^{40–43}; and insulation upgrades may reduce heating and cooling loads⁴⁴. Capturing the evolution of building electricity demand is crucial for power system planning, as HVAC loads drive system peak magnitude and timing^{45–48}. Misestimating how these forces interact over time can lead to electricity shortfalls, or rolling outages. For instance, the California Independent System Operator under-forecasted cooling peaks during an August 2020 heatwave⁴⁹, contributing to rolling outages.

Existing literature separately investigates how rates of climate change and technology diffusion affect building power demand. Existing methods for analyzing future building energy demand at regional to national scales use top-down statistical models^{40,50–52} on total system energy demand. Such methods exclude heterogeneous stocks and demand patterns in buildings, so cannot capture building-level technology diffusion. Other recent literature quantifies net load impacts from heating electrification and climate change via bottom-up analysis in a case-study region^{51,52}. But these papers only examine a boundary condition of 100% heating electrification, so do not capture technology diffusion over time, and use climate datasets that do not capture most climate-related uncertainty in the near term^{51,52}. As a result, these papers ignore the evolution of demand over years and attendant uncertainty, limiting their utility for near- and mid-term planning.

In summary, no framework has emerged to quantify the evolving effect of interacting uncertainties between climate change and low-carbon technology diffusion on energy system planning. We construct such a framework, and apply it to quantify electricity demand of the U.S. building sector, which is crucial for maintaining reliable electricity systems and pursuing decarbonization goals. We specifically quantify future electricity demand under climate change and diffusion of heat pumps and household insulation for 250,000 commercial and residential buildings in 111 cities across the United States (Figure S2, Table S1). We trained 159,840 machine-learning based regression models for different types and technology sets of buildings, then fed them with downscaled weather data from 40 climate transients and 18 technology diffusion pathways to predict future demand. Our 40 climate transients span 10 climate models and 4 initial conditions under the

Shared Socioeconomic Pathway (SSP) 3-70 scenario from the CESM2 large ensemble⁵³. Large ensembles are designed to capture many sources of climate uncertainty, including internal variability, model uncertainty, and parametric uncertainty^{54,55}, and are widely used to study extreme weather events^{31,54,56}, which are particularly relevant to our results. While our climate data only captures one SSP scenario, internal and model variability dominates near-term climate-related uncertainty⁵⁵, which is well captured by our 40 ensemble members. To create technology diffusion pathways, we use logistic diffusion model (S-curves) rooted in sets of historic analogs (Methods), and sample homes as adopters based on them. Our results identify the separate and combined effects over time of technology diffusion and climate change on peak electricity demand, and decompose the contribution of each to the total uncertainty in future peak demand.

Results

The evolution of peak demand under climate change and technology diffusion

To quantify diffusion of air source heat pumps and building insulation, our main results use a logistic S-curve based on the historic diffusion of home air conditioners in the U.S., or 10.0% per year as the S-curve diffusion rate. (We test the sensitivity of our results to lower and higher diffusion rates in following sections.) We quantify future building peak demand under three scenarios: climate change only, technology diffusion only, and their combined effects. The climate change only scenario quantifies building demand for the current building stock across our 40 future climate realizations; the technology diffusion only scenario quantifies building demand for annually updated heat pump and insulation penetrations under a 2020 climate (for which we have 40 realizations); and the combined effects scenario quantifies building demand for annually updated technology penetrations under our 40 future climate realizations. For each scenario, we focus on annual peak demand, which determines power system capacity investment needs, defined as the 95th percentile of all 40 annual max demand values across climate realizations ($Extreme_{year} = P_{95}(Max(Demand_{year}))$). To capture rates of change in peak demand across years, we use the Thiel-Sen (TS) slope, which robustly quantifies the long-term trends of peak demand (detailed in Methods and Table S8).

Under climate change only impacts, peak load increases by 2%–5% from 2020 to 2060 in every region except the Northwest (Figure 1). Peak load increases are driven by increasing extreme heat driving increasing peak cooling demand (Figure S4). In the Northwest, peaks are heating driven, so climate change reduces peak demand by 11% from 2020 to 2060. Peak seasonality (or in which season peak demand occurs) does not change under climate change only (Figure 2a). All regions except the Northwest remain summer peaking, while the Northwest remains mostly winter peaking.

Technology diffusion only produces larger increases in peak demand than climate change only. Technology-driven peak increases significantly differ between cold regions (New England (ISO-NE), New York (NYISO), Midwest (MISO), Mid-Atlantic (PJM), Northwest, and Great Plains (SPP)) and hot regions (California (CAISO), Southwest, Southeast, and Texas (ERCOT)). Peak demands overall increase by 56-100% in cold regions (Figure 1), as increasing penetration of heat pumps continually grows the heating peak demand by substituting current non-electric heating and shifts peak seasonality from mostly (>95%) summertime to mostly (>95%) wintertime (Figure 2b). Conversely, peak demands overall decrease by 2-9% from 2020 to 2060 in hot regions, where peak demands mostly stay in summer (despite seldom winter peaks may emerge in Southwest and Southeast region in later 2050s (Figure 2b)). Therefore, the substitution of current air conditioners to higher efficiency heat pumps and insulation upgrades increase the overall cooling efficiency and reduce the peak.

In the combined effects scenario, peak demand changes fall between those in the climate- and technology-

only scenarios for most regions. Interactions between climate change and technology diffusion vary in direction based on climate zone. In cold regions, warmer winters reduce peak demand growth from technology diffusion by up to 57%, resulting in overall peak demand growth of 18%-68% through 2060 (Figure 1). Warming also reduces the frequency of winter peaks, delaying the transition from summer to winter peaks, relative to technology diffusion only. For instance, PJM sees a higher frequency of winter than summer peaks in 2035 under technology diffusion only, but that transition is delayed to 2043 under the combined scenario. The overall average winter peak frequency in PJM from 2040 to 2060 is also reduced from 89% under technology diffusion to 68% under combined effects (Figure 2c). In hot regions, peak demand grows less in the combined effects scenario than under climate change only, as technology diffusion efficiency gains offset climate-induced peak growth. Under combined effects, peak demand tends to decline by 0-7% through 2060, relative to 3%-5% increases under climate change only. Combined effects also largely maintain summer peaking and eliminate winter peaks observed under technology diffusion only. CAISO is an exception: under combined impacts, peak increases exceed those in either individual scenario, as both warming temperatures and widespread heat-pump adoption (which replaces current room-ACs and expands conditioned floor area) drive cooling peaks higher (Figure S23-24).

The evolution of peak demand over time differs significantly between our scenarios. Under climate change only, peak demand changes accrue steadily across regions. Under technology diffusion only, cold regions see modest near-term peak increases followed by significant acceleration in peak increases in the mid-term, while most hot regions experience a peak decrease in the near-term followed by a rebound in the mid-term. When combining both effects, the peak demand trajectory of cold regions follows that of technology diffusion only but with notably subdued growth during the acceleration phase (Figure 1a-f). In MISO, climate change only increases peak demand by roughly 1.2% per decade, while technology diffusion only increases peak demand by 0.1% and 2.0% in the 2020s and 2030s, respectively, followed by a 28% and 37% increase in the 2040s and 2050s, respectively. Under combined effects, warming winters moderate the peaks' rise in the 2040s, and 2050s to 14% and 21%, respectively. In hot regions, technology diffusion offsets the peak growth from climate warming, resulting in a constant neutral (Southwest) or decrease (Southeast, ERCOT) in demand peaks towards mid-century (Figure 1h-i). Southeast, for instance, sees steady decadal changes of +1.2% under climate change only and steady -1.0% decadal changes before a rebound in 2050 under technology diffusion only. This rebound is driven by the emergence of heating peaks during cold extremes driven by heat pump adoption. Under combined effects of climate change and technology diffusion, Southeast sees a constant -1.2% decrease in peaks per decade towards mid-century. The mid-term rebound in the technology diffusion only scenario disappears under combined effects, as warmer futures reduce cold extremes.

We quantify uncertainties in future peak dynamics through modelling the range of future annual peaks (Figure S21) and their TS growth rates (Figure 3) in all climate realizations. We find that climate change only tends to produce narrower long-term uncertainty in peak demand growth than combined effects in cold regions. In ISO-NE for example, climate change yields an equalized peak load increase through 2060 of 1-9%, while combined effects result in an equalized peak growth at 17-58%, respectively (Figure 3a). Conversely, in a typical hot region like the Southeast, climate change only increases peaks by 1-9% through 2060, while combined effects yields similar uncertainty, but for a decrease of 1-7%(Figure 3a) . We also capture the time-evolving climate uncertainty, through the coefficients of variation (CV) of peak demand across climates in different decades (Figure 3c&d). Results show that climate only impacts tend to not influence the peak deviation, as the CV of all decades remain no 10% more than CV in 2020 across all regions. However, tech-diffusion significantly increase the peak uncertainty from 2040s especially in cold regions, where the CVs of peak in 2040s and 2050s swiftly increase up to 2-3 and 3-4 times than that in 2020 under combined impacts. A key driver for larger peak uncertainties in cold regions is that their peak seasonality tends to shift from

summer to winter along with the tech-diffusion, and cold extremes usually bring much larger heating peak demand than that of cooling in their hot extremes. In hot regions, while diffusion impacts only may induce larger climate uncertainty in later decades in Southwest and Southeast regions, the peak CVs rather constant under combined effects across all decades.

Peak demand driven by technology diffusion uncertainty

Our prior results assume a diffusion rate for heat pumps and building insulation based on a close historic analog, air conditioners (diffusion rate per year of 10%). Here, we quantify peak demand growth under alternative diffusion rates drawn from a wider set of historic technologies. Specifically, we classify 18 historic analogs into three categories based on their shared similarities with our technologies: 1) home appliances with large energy use intensity ($r \sim 7$ to 15%); 2) other home appliances related to lifestyle improvement ($r \sim 4$ to 27%); and 3) infrastructures related with resource supply of daily life ($r \sim 2$ to 36%). Table S7 details each technology and their historic diffusion rates.

Varying diffusion rates lead to markedly different future peak load dynamics, especially on the magnitude and year of the largest peak demand between 2020 and 2060 ($max_{2020-2060}(Extreme_{year})$), which we define here as “maximum peak load (MPL)”. In most cold regions, MPL continually increases with more rapid diffusion rates. In warm regions, MPL either decreases (ERCOT) or decreases then increases (Southeast, Southwest) with increasing diffusion rates. In ISO-NE, a cold region, MPL rises to between 1.1–3.2 times their respective 2020 peak loads as diffusion rates accelerate from 2.0 % (vacuum cleaners) to 36.3 % (cell phones) (Figure 4a). In ERCOT, increasing diffusion rates moderate the 12% increase of MPL under climate change only to as low as 5% in the fastest-diffusion scenario. (Figure 4b) In the Southwest case, MPL changes with two phases as diffusion rates increase: it first decreases when the diffusion rates are lower than 10% then substantially increases. The two-phase dynamics in the Southwest reflects the different interactions between climate change and diffusion under different rates. A warmer climate is able to moderate heating peak growth with increasing electrification, keeping heating peaks lower than cooling peaks when the diffusion rates are low enough. But with faster diffusion of heat pumps, heating peaks grows rapidly with less warming moderation, shifting peak seasonality to winter and resulting in even higher MPL.

Higher diffusion rates also advance the year in which the MPL occurs across most regions, an important indicator for power system planning. In cold regions, the MPL year shifts from the 2050s to 2040s in ISO-NE, MISO when diffusion rates are higher than 18% and 27% respectively, as higher rates advance saturation of electric heating(Figure 4a). In hot regions, the MPL of cooling loads in ERCOT could also be advanced from 2040s to 2020s with a $>8.9\%$ diffusion rate (Figure 4b), as rapid cooling efficiency improvement could offset the climate warming impact and continually reduce the future cooling peak.

Partitioning peak demand uncertainty between climate change and technology diffusion uncertainty

Our prior results demonstrate significant differences in how climate change and technology diffusion affect future peak demands. To better characterize drivers of future peak demand uncertainty, we statistically decompose the contributions of climate and technology diffusion uncertainty to peak demand uncertainty on an annual regional basis using a variance-decomposition method (Methods). Under base technology diffusion rates, climate-driven uncertainty shifts from driving nearly all peak demand uncertainty in the 2020s to 38%-98% in the 2050s. Climate-driven uncertainty drives most uncertainty and remains the dominant driver in Southwest, Northwest, SPP and CAISO regions, accounting for 90%-98% in the 2050s, while technology-diffusion-driven uncertainty drives more peak demand uncertainty ($>60\%$) in Northeast cold regions (ISO-NE, NYISO) in the 2050s. Across most regions, the share of technology-diffusion uncertainty rises steeply through the 2030s and 2040s before leveling off (e.g., in ISO-NE) or even declining (e.g., in PJM) in the 2050s.

Introducing a broader range of diffusion trajectories amplifies the technology contribution further and shifts the inflection point, when most uncertainty shifts from climate change to technology diffusion, to earlier decades without altering relative differences across space (Fig. 5 b,c). For example, in the enriched diffusion ensembles, ISO-NE still exhibits the highest technology-driven share in the 2050s (74 % and 77 % under the second and third sets, respectively), while climate uncertainty continues to dominate overall uncertainty (>75 %) in Southwest, Northwest, SPP, and CAISO. Accordingly, the inflection years advance from around 2045-2050 under the base scenarios to roughly 2035-2040 and 2030-2035 under the second and third diffusion ensembles, respectively.

Discussion and Conclusion

While rising demand peaks driven by climate warming and by the diffusion of electrification technologies have each been studied in isolation, their joint impact remains poorly understood. In this work, we bridge that gap by coupling 40 ensemble projections from downscaled climate models (SSP3-7.0) with 18 residential heat-pump and envelope-retrofit diffusion scenarios, and applying them to machine-learning-based, hourly load models for 256,840 buildings. Our integrated projections to 2060 reveal that combined climate-and-technology effects can produce peak loads trajectories that diverge substantially from those driven by either factor alone. We also highlight and decompose the substantial uncertainty in future peak trajectories arising from both climate change and technology diffusion, showing that while climate-driven uncertainty dominates in the near term, the influence of technology-diffusion uncertainty grows over time and becomes the principal contributor in some regions in later decades.

Our models and findings provide key implication for future energy-system resilience and planning. First, different peak load increases under climate change and technology diffusion effects across regions indicate different targets for future power infrastructure expansion planning. Peak growth under climate change only requires steady expansion of power grid at 1-2% per decade across all regions, while its combination with technology diffusion greatly enlarges the difference across decades and regions. In northern cold regions, grid operators should anticipate swift growth in winter peak demand starting from late 2030s, which will increase the overall peak in mid-century by 30%-60% larger than the current peaks. This necessitates large power capacity expansions in these regions, and winter capacity procurement as peaks shift to winter. In hot regions, technology diffusion would partially or fully counteract climate-change-induced peak growth, suggesting that planners would not need to procure significantly more peaking capacity. Second, the amplified peak uncertainty and intra-year variability, especially in cold regions, call for a strategic shift toward enhanced flexibility in both planning and operations. System planners should deploy and size fast-response resources, including utility-scale batteries, peaking gas turbines and demand-response programs, to absorb sudden peak excursions. Third, our distinguishing between semi-controllable uncertainties (driven by technology diffusion) and uncontrollable uncertainties (driven by climate change) (where controllable is defined from the perspective of the local utility) enables region-tailored strategies. In areas where technology diffusion accounts for the majority of future peak demand uncertainty (ISO-NE, MISO, NYISO), planners can commit to firm capacity expansions (e.g., new generation and storage assets) aligned with incentives they provide for adoption of heat pumps, household insulation, and other household technologies. Conversely, in regions where uncontrollable climate uncertainty prevails (SPP, Southwest, CAISO), emphasis should shift toward bolstering reserve margins and deploying demand-side flexibility (e.g., demand response programs, quick-start units) to buffer against uncertainty in demand growth. The temporal evolution of peak uncertainty sources underscores the need for near-term climate-resilience planning, as climate-driven uncertainty dominates total peak uncertainty in the coming decades, countering the notion that such planning can be deferred until climate change intensifies in the longer term. Policymakers could also incorporate administrative tools or subsidies to

support high-efficiency heat pumps or support the heat pump diffusion first on current electric-resistance heating users, to mitigate the intensive growth especially in early decades.

We suggest several opportunities for further improving the building loads prediction to future researchers. Our technology scenarios capture diffusion pathways but assume static performance, ignoring continual efficiency gains in heat pumps and envelope measures, as well as demand-side flexibility options (e.g., thermal storage, smart controls) that could mitigate peak stress⁵⁷. We also focus solely on thermal end-uses, whereas future shifts in appliance ownership and non-thermal loads (e.g., electric vehicle charging⁵⁸, process loads⁵⁹) will further reshape demand patterns. Incorporating such technology advancement other than only tech-diffusion, potentially through the application of integrated assessment models, would better reflect the evolvement of future building load dynamics. We test alternative efficiencies of residential heat pumps as a sensitivity example, and find next-generation ultra-high-efficiency (UHE) units could deliver further savings in peak demand, especially in cold climates (Figure S30-31). Assuming UHE rather than Energy-Star units in ISO-NE, the 40-year Theil–Sen median growth rate for peak loads falls from 31.5% to 10.3%. Meanwhile, we assume random uptake of technology diffusion among potential adopters without considering their behavioral heterogeneities. We therefore perform a sensitivity analysis with two alternative scenarios: prioritizing adoption of current fuel heat users or electric-resistance heating users. We found the former will increase ISO-NE’s 40-year TS growth rates to 46.8% while the latter lowers it to 14.4% (Figure S32-33). Besides, we represent climate uncertainty with different models and initial conditions under a single climate pathway (SSP-3.70). Evaluating multiple greenhouse-gas scenarios and incorporating bias-corrected would yield more robust projections of the dynamic combined impacts of climate change and tech-diffusion.

In sum, our coupled climate-and-technology framework demonstrates that neither driver alone can capture the full spectrum of future load dynamics. Moreover, this dual-driver perspective should extend well beyond building-load forecasting. For example, future energy supply will face analogous joint uncertainties: climate change will alter renewable output profiles (through shifting wind patterns and solar irradiance¹²), while next-generation technologies—high-efficiency wind turbines⁶⁰, advanced PV panels⁶¹, grid-scale batteries⁶² and hydrogen systems⁶³—will diffuse at different rates across regions. Consequently, capacity-expansion planning, resource-adequacy assessments and integrated resource planning studies must likewise adopt models that jointly represent both climate impacts and technology diffusion, ensuring that investment and operational decisions remain robust under deep, co-evolving uncertainties.

Methods

In this study, we capture interactions over time between climate change and technology adoption (i.e. air source heat pump adoption and insulation upgrades) in driving peak demand in building sector. To quantify building peak demand, we first build machine learning models on the relationship between hourly electric cooling and heating demand and temperature, based on the simulated consumption results for current and upgraded building stocks. To capture climate change impacts, we run the trained temperature-driven models under 40 different future climate transients. To capture technology diffusion impacts, we project future technology uptake dynamics by fitting it into logistic-growth curves with different growth rate scenarios. Each set of methods is discussed in detail below. Figure S1 illustrates the integrated methodology framework.

Building energy demand regression model

We use the individual building information and their simulated power consumption profiles in ResStock and ComStock database, for residential and commercial building loads training and prediction. ResStock and ComStock database contains 549,718 and 336,149 buildings, respectively, which are sampled and assigned

with housing properties based on the national and local surveys^{64,65}. We extract 178,587 residential and 122,006 commercial buildings in our selected 111 cities across the United States (Figure S2, Table S1). For each individual building, ResStock and ComStock contains several technology sets including different building upgrades scenarios, from which we select those related with air source heat pump adoption and building insulation upgrades (8 ResStock and 4 ComStock upgrades sets) (Table S4).

Instead of establishing cooling and heating consumption models on individual buildings, we aggregate the cooling and heating consumption for buildings which share the same cooling (e.g. no cooling, room air conditioners, central cooling, etc.), heating (e.g. no heating, gas-boilers, fuel-furnaces, electric boiler, heat pumps, etc.) and insulation (higher or lower than targeted insulation level) type in each city, in order to reduce the computation burden. Specifically, we aggregate the current stock of residential and commercial buildings into 74 and 32 types (detail in Table S2&S3), respectively, assuming that they share same dynamics with temperature changes. Consequently, we in total develop 159,840 machine learning models, which consists of 2 different end-use (cooling OR heating), 111 cities and 720 different type-upgrades combination groups (Residential: 592 (74 type $\times$ 8 upgrades) and Commercial: 128 (32 type $\times$ 4 upgrades))

For each individual aggregated group of buildings, we then train and predict their 15-min consumption using a multilayer perceptron (MLP) model, because its feed-forward architecture of stacked nonlinear layers can flexibly learn complex consumption–temperature relationships and reliably extrapolate to future temperature conditions beyond the historical training range. We use an MLP architecture with 2 hidden layers each with 64×16 neurons, based on hyperparameter tuning in case regions. The input features include real-time outdoor temperature, daily average temperature, 24-h rolling mean hourly temperature difference, sinusoidal encodings of hour-of-day (sine and cosine)⁶⁶ and their multiple value with hourly outdoor temperature, and categorical indicators for season (winter or summer) and weekend-or-weekday. In principle, these features capture both instantaneous thermal drivers (current hourly temperature and its hour-to-hour change) and cumulative thermal drivers (daily mean temperature and the 24-h rolling mean temperature difference), while also incorporating building’s thermal and behavioral dynamics (diurnal cycles and their interactions with temperature, seasonal and weekend-or-weekday indicators). For the training datasets, we use 15-minute building-level cooling and heating electricity consumption in 2018 from the ResStock and ComStock simulation profiles. The associated weather data are derived from the Actual Meteorological Year 2018 (AMY-2018) dataset released together with the simulations. AMY-2018 provides county-level hourly meteorological variables generated from National Oceanic and Atmospheric Administration (NOAA) surface weather observations. We downscale these hourly records to 15-minute resolution through statistical interpolation to align them with the temporal resolution of the load data.

Our cross-validation of ablation analysis confirms the appropriateness of the selected input features (Figure S3). To ensure the model sees enough extreme events, we performed stratified sampling by temperature: the training set was sampled to have roughly uniform coverage of low, medium, and high outdoor temperatures. Further, observations with the top 5% of loads were up-weighted in the loss function to emphasize correct prediction of peak demand⁶⁷.

The MLP regressions for cooling and heating power demand produced robust performances. For residential buildings, the coefficient of determination (R^2) for hourly cooling and heating demand is approximately 0.98 and 0.97–0.98, respectively. For commercial buildings, the corresponding R^2 values are 0.97–0.98 and 0.95–0.97. Peak load prediction accuracy, evaluated using the Symmetric Mean Absolute Percentage Error (SMAPE), shows errors of 0.02–0.03, 0.02–0.06, and 0.01–0.02 for residential heating, cooling, and total peak loads, respectively. For commercial buildings, the SMAPE ranges are 0.03–0.04, 0.04–0.06, and 0.01–0.02

for heating, cooling, and total peak loads, respectively (Figure S4-S7).

Weather under future climate realizations

To capture the evolution and uncertainty of climate change over time, we create and use a large ensemble of 40-year future hourly temperatures from 2020-2060 by downscaling the CESM2 large ensemble (LENS2) dataset. LENS2 comprises 100 distinct transient realizations differentiated by climate model formulation and initial conditions under SSP3-70 scenario. From this pool, we select 40 transient realizations at three-hour resolution to drive our analysis. We then build a machine-learning (ML) downscaling method that converts the coarse three-hour means of air temperature to hourly values.

We use hourly temperature data from ERA-5 as the high-resolution “truth” in downscaling. For each day, we derive four baseline climate descriptors---the eight three-hour mean temperatures, the daily maximum and minimum temperatures, and the daily mean specific humidity. We then augment them with ten auxiliary features: sinusoidal encodings of hour, week-day and year-day; 3-day running mean and standard deviation of temperature; two physically motivated interaction terms (temperature $\times$ sinusoidal hours, humidity $\times$ sinusoidal hours); and quadratic terms in temperature and humidity. These auxiliary features enable the downscaler to learn key temporal patterns and dependencies beyond the four baseline descriptors, including diurnal, week and season cycles, short-term persistence, state-dependent modulation of cycles and nonlinear sensitivities.

Based on the comparison across multiple models, we fit a random forest for each county location and select its specific configuration via parameter estimation within the ranges $n\text{-estimators} \in \{100, 200, 500\}$; $\text{max-depth} \in \{\text{None}, 10, 20\}$ and $\text{min-sample split} \in \{2, 5\}$, using year-blocked 5-fold cross-validation (1980-2015 training, 2016-2024 validation), on the target variable hourly anomaly $\Delta T_{d,h}$.

$$\Delta T_{d,h} = T_{d,h}^{\text{ERA5}} - \overline{T_{3h,d,h}^{\text{ERA5}}} \quad \text{Eq.1}$$

where $T_{d,h}^{\text{ERA5}}$ and $\overline{T_{3h,d,h}^{\text{ERA5}}}$ is the ERA5 hourly temperature and temperature averaged over the three-hour window centred on hour h day d , respectively. The validation results show the regression achieves a RMSE within 0.12-0.29 °C and MAE within 0.07-0.18°C, respectively. (Table S6, Figure S9-S10) The biases at the 95th percentile of hourly temperature stays within 0.5% for all cities.

For each ensemble member we predict $\widehat{\Delta T_{d,h}}$ and reconstruct hourly temperature $\widehat{T_{d,h}}$ via

$$\widehat{T_{d,h}} = \overline{T_{3h,d,h}^{\text{LENS2}}} + \widehat{\Delta T_{d,h}} \quad \text{Eq.2}$$

where $\overline{T_{3h,d,h}^{\text{LENS2}}}$ is the model-derived three-hour mean temperature in the LENS2 dataset.

Technology diffusion

To capture technology diffusion over time, we project adoption of technologies by residential and commercial buildings using the logistic substitution model²⁰, which assumes that technology adoption starts exponentially but gradually flattens out to follow an S-shaped curve as it approaches saturation. The logistic substitution model is widely used to provide a good representation of observed data in a variety of technologies, from large infrastructure projects to consumer goods, and energy technologies are also expected to follow the same pattern⁶⁸. Therefore, we adopt it to predict the future diffusion of building-energy-related technologies, of which heat pump adoption and insulation upgrades are two major drivers. The logistic substitution model assumes an S-curve for future technology diffusion processes. It can be used to project the total number of

adopters at each time interval based on the number of adopters at last interval and tech-diffusion rate, as shown in Eq.3:

$$C_{t+1} = C_t(1 + k(1 - \frac{C_t}{L})) \quad \text{Eq.3}$$

where C_{t+1} and C_t indicate the percentage of new technology adopters, respectively; k is the growth rate, which were taken from history analogs; and L is the saturation level, which is determined as 100% in this study in the main scenario towards a fully electrified heating and cooling future with higher insulation efficiency. The initial installation numbers at 2018 (C_{2018}) of heat pump and insulation upgrades users are adopted from the building-level baseline information for each city in ResStock and ComStock, respectively (Figure S16-18); more recent data on city-level penetrations of these technologies are not available.

We apply different values of k to capture the uncertainty of technology diffusion, based on different historical analogs. Specifically, we apply SHARD methods⁶⁹ to identify 18 technologies in the HATCH database⁷⁰, and classify these 18 technologies into 3 categories due to their similarities to reflect lower to higher diffusion uncertainties. The three categories are: 1) home appliances with large energy use intensity ($r \sim 7.1\% - 15.4\%$), including laundry dryers, washing machines, home air conditioning, refrigerators and stoves; 2) other individual or home used appliances on life improvements ($r \sim 4.2\% - 27.1\%$), including passenger cars, bicycles, telephones, microcomputers, color TV and compact fluorescent light bulbs; and 3) other technologies related with individual living, energy transition and decarbonizations ($r \sim 2.0\% - 36.3\%$), including vacuums, electricity, running water, solar thermal energy, solar PV and cellphones. The detailed information of each analog technology is listed in Table S7. The historic diffusion rate of home air conditioning in the U.S. is adopted as the main diffusion scenario in this study.

We apply the logistic substitution model to develop an annual list of the number of new adopters for heat pump and building insulation in each city (Figure S19-20). Given the number of new adopters, we then assign those new adopters to users that have not adopted heat pumps and insulation upgrades. The new insulation upgrades adopters are always randomly assigned within the not-yet-upgraded buildings. The new heat-pump adopters are randomly assigned among those without heat-pump in main scenario, while in fuel- or electric-resistance-prioritized scenarios the new adopters follow the order by their current heating sources. For instance, in fuel-prioritized scenario, the current electric-resistance heating users start heat-pump adoption only after all previous fuel-heating users already upgrade to heat pumps. Through the annual assignment of new heat pumps and insulation upgrades adopters, each aggregated building type in each city will have a dynamic composition ratio among four upgrades sets (no upgrades, heat pump upgrade only, insulation upgrade only, and heat pump & insulation upgrades).

Scenario analysis of peak demand and its uncertainty partitioning

Based on the trained building energy demand regressions, downscaled future climate and technology diffusion projections, we quantify how peak demand evolves under climate change only, technology diffusion only, and both. For climate effects only, we fed hourly downscaled LENS2 temperature in each city into MLP models to predict future hourly cooling and heating electricity consumption. We assume other appliance loads remain constant along with future climates, and then calculate the annual peak demand trajectories across all 40 different climate transients. For diffusion effects only, we use 40 different climate realizations in 2020 (essentially assuming a stationary climate) and adopt the annual dynamic composition ratio among four upgrades sets for all types of buildings. Then annual peak demand profiles are then calculated by aggregating the hourly energy demand of four upgrades sets based on their relevant ratios for each type building in each city. The combined effects are quantified through the combination of weather data and dynamic upgrade sets through 2060.

For each trajectory, we compute their Theil–Sen estimator of slope on annual time series of peak demand for each county and scenario, to robustly quantify long-term trends in building loads under different scenarios. The Theil–Sen slope was estimated as the median of all pairwise slopes, as shown in Eq.4-5:

$$\beta_k = \text{median} \frac{L_k(t_y) - L_k(t_x)}{t_y - t_x} : 2020 \leq t_x \leq t_y \leq 2060 \quad \text{Eq.4}$$

$$\beta_k^\delta = \beta_k * 40 \quad \text{Eq.5}$$

where β_k indicate the annual Theil–Sen growth for building loads L_k from 2020-2060 in city k ; and β_k^δ indicates the Theil–Sen estimator for 40-year growth in the Result section.

To quantify how much of the spread in projected annual peak and total demand arises from climate variability versus technology diffusion, we treat our full simulation ensemble as a two-factor experiment, with one factor being the climate realization (across 40 LENS2 members) and the other being the diffusion rate ensemble (18 historic technology diffusion rates). For each county and year, we first computed the total variance of demand across all climate-diffusion combinations. We then partitioned that variance into two main components by attributing the sum of squared deviations associated with either climate or technology diffusion scenarios. Each driver’s contribution was expressed as its component variance divided by the total variance, so that the climate and technology shares sum to one. Finally, we summarized these annual contributions across all power regions to identify whether future uncertainty in building loads is dominated by climatic or diffusion-driven effects, as shown in Figure 5.

Load profiles aggregation

In this study, we aggregated building-level residential and commercial load profiles to power-region–scale total load profiles through a four-step procedure (see Supplementary M5 for details). First, we collected historical annual electricity consumption of residential and commercial buildings at the state level from the Residential Energy Consumption Survey (RECS)⁷¹ and the Commercial Building Energy Consumption Survey (CBECS)⁷². Second, we allocated these state-level totals to cities by applying proportional weights derived from the ratio of simulated total consumption in each city to the corresponding state total. Third, we scaled the predicted future hourly loads of representative buildings to real-world consumption using the historical relationship between simulated and recorded totals. Finally, we aggregated the city-level loads into ten power grid regions of the continental United States: New England (ISO-NE), New York (NYISO), Midwest (MISO), Mid-Atlantic (PJM), Northwest, Great Plains (SPP), California (CAISO), Southwest, Southeast, and Texas (ERCOT) (Figure S2b).

Acknowledgments

For funding, we thank the U.S. National Science Foundation under Award Number 2142421, and the University of Michigan Graham Sustainability Institute.

Reference

1. Intergovernmental Panel On Climate Change (Ipcc). *Climate Change 2021 – The Physical Science Basis: Working Group I Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. (Cambridge University Press, 2023). doi:10.1017/9781009157896.
2. Summary for policymakers. in *Climate Change 2022: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (eds Pörtner, H.-O. et al.)

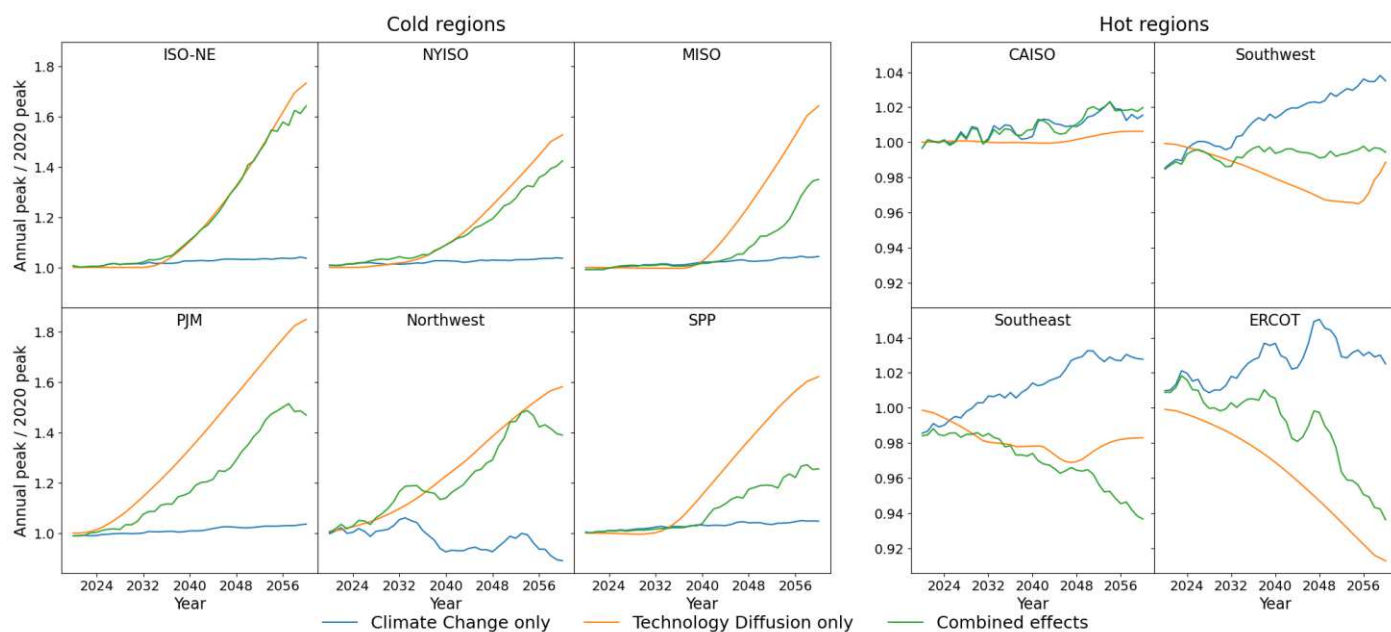
(Cambridge University Press, 2022).

3. Craig, M. T. *et al.* Overcoming the disconnect between energy system and climate modeling. *Joule* **6**, 1405–1417 (2022).
4. Yalew, S. G. *et al.* Impacts of climate change on energy systems in global and regional scenarios. *Nat. Energy* **5**, 794–802 (2020).
5. Knutti, R. & Sedláček, J. Robustness and uncertainties in the new CMIP5 climate model projections. *Nat. Clim. Change* **3**, 369–373 (2013).
6. Hawkins, E. & Sutton, R. The Potential to Narrow Uncertainty in Regional Climate Predictions. (2009) doi:10.1175/2009BAMS2607.1.
7. Brown, P. T., Ming, Y., Li, W. & Hill, S. A. Change in the magnitude and mechanisms of global temperature variability with warming. *Nat. Clim. Change* **7**, 743–748 (2017).
8. Deser, C., Phillips, A., Bourdette, V. & Teng, H. Uncertainty in climate change projections: the role of internal variability. *Clim. Dyn.* **38**, 527–546 (2012).
9. Roe, G. H. & Baker, M. B. Why Is Climate Sensitivity So Unpredictable? *Science* **318**, 629–632 (2007).
10. Deroubaix, A. *et al.* Large uncertainties in trends of energy demand for heating and cooling under climate change. *Nat. Commun.* **12**, 5197 (2021).
11. Amonkar, Y., Doss-Gollin, J., Farnham, D. J., Modi, V. & Lall, U. Differential effects of climate change on average and peak demand for heating and cooling across the contiguous USA. *Commun. Earth Environ.* **4**, 402 (2023).
12. Gernaat, D. E. H. J. *et al.* Climate change impacts on renewable energy supply. *Nat. Clim. Change* **11**, 119–125 (2021).
13. Pryor, S. C., Barthelmie, R. J., Bukovsky, M. S., Leung, L. R. & Sakaguchi, K. Climate change impacts on wind power generation. *Nat. Rev. Earth Environ.* **1**, 627–643 (2020).
14. Feron, S., Cordero, R. R., Damiani, A. & Jackson, R. B. Climate change extremes and photovoltaic power output. *Nat. Sustain.* **4**, 270–276 (2021).
15. Staadecker, M., Szinai, J., Sánchez-Pérez, P. A., Kurtz, S. & Hidalgo-Gonzalez, P. The value of long-duration energy storage under various grid conditions in a zero-emissions future. *Nat. Commun.* **15**, 9501 (2024).
16. Sepulveda, N. A., Jenkins, J. D., Edington, A., Mallapragada, D. S. & Lester, R. K. The design space for long-duration energy storage in decarbonized power systems. *Nat. Energy* **6**, 506–516 (2021).
17. Cherp, A., Vinichenko, V., Tosun, J., Gordon, J. A. & Jewell, J. National growth dynamics of wind and solar power compared to the growth required for global climate targets. *Nat. Energy* **6**, 742–754 (2021).
18. Edwards, M. R. *et al.* Modeling direct air carbon capture and storage in a 1.5 °C climate future using historical analogs. *Proc. Natl. Acad. Sci.* **121**, e2215679121 (2024).
19. Kazlou, T., Cherp, A. & Jewell, J. Feasible deployment of carbon capture and storage and the requirements of climate targets. *Nat. Clim. Change* **14**, 1047–1055 (2024).
20. Rogers, E. M., Hagerstrand, T. & Pred, A. Innovation Diffusion as a Spatial Process. *Technol. Cult.* **10**, 480 (1969).
21. Morris, J. *et al.* Quantifying both socioeconomic and climate uncertainty in coupled human–Earth systems analysis. *Nat. Commun.* **16**, 2703 (2025).
22. Labriet, M., Kanudia, A. & Loulou, R. Climate mitigation under an uncertain technology future: A TIAM-World analysis. *Energy Econ.* **34**, S366–S377 (2012).
23. Zheng, D. *et al.* Strategies for climate-resilient global wind and solar power systems. *Nature* 1–3 (2025) doi:10.1038/s41586-025-09266-7.
24. Sundar, S., Lehner, F., Voisin, N. & Craig, M. T. Identifying Robust Decarbonization Pathways for the Western U.S. Electric Power System Under Deep Climate Uncertainty. *Earths Future* **12**, e2024EF004769 (2024).
25. Plaga, L. S. & Bertsch, V. Methods for assessing climate uncertainty in energy system models — A systematic literature review. *Appl. Energy* **331**, 120384 (2023).
26. van Heerden, R. *et al.* Demand-side strategies enable rapid and deep cuts in buildings and transport emissions to 2050. *Nat. Energy* **10**, 380–394 (2025).
27. Duan, L. & Caldeira, K. Implications of uncertainty in technology cost projections for least-cost decarbonized electricity systems. *iScience* **27**, 108685 (2024).

28. Way, R., Ives, M. C., Mealy, P. & Farmer, J. D. Empirically grounded technology forecasts and the energy transition. *Joule* **6**, 2057–2082 (2022).
29. Kucuksayacigil, F., Zhang, Z. & Davidson, M. R. Coordinating power sector climate transitions under policy uncertainty. *Nat. Commun.* **16**, 3786 (2025).
30. Gillingham, K. *et al.* Modeling Uncertainty in Integrated Assessment of Climate Change: A Multimodel Comparison. *J. Assoc. Environ. Resour. Econ.* **5**, 791–826 (2018).
31. Fischer, E. M., Sippel, S. & Knutti, R. Increasing probability of record-shattering climate extremes. *Nat. Clim. Change* **11**, 689–695 (2021).
32. Fischer, E. M. *et al.* Record-breaking extremes in a warming climate. *Nat. Rev. Earth Environ.* **6**, 456–470 (2025).
33. World Energy Outlook 2024 – Analysis. *IEA* <https://www.iea.org/reports/world-energy-outlook-2024> (2024).
34. Levesque, A., Pietzcker, R. C., Baumstark, L. & Luderer, G. Deep decarbonisation of buildings energy services through demand and supply transformations in a 1.5°C scenario. *Environ. Res. Lett.* **16**, 054071 (2021).
35. Jacobson, M. Z. *et al.* 100% Clean and Renewable Wind, Water, and Sunlight All-Sector Energy Roadmaps for 139 Countries of the World. *Joule* **1**, 108–121 (2017).
36. Ibrahim, M., Harkouss, F., Biwole, P., Fardoun, F. & Ouldboukhite, S. Building retrofitting towards net zero energy: A review. *Energy Build.* **322**, 114707 (2024).
37. 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).
38. Wang, C. *et al.* Impacts of climate change, population growth, and power sector decarbonization on urban building energy use. *Nat. Commun.* **14**, 6434 (2023).
39. 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).
40. Waite, M. & Modi, V. Electricity Load Implications of Space Heating Decarbonization Pathways. *Joule* **4**, 376–394 (2020).
41. Roth, A., Gaete-Morales, C., Kirchem, D. & Schill, W.-P. Power sector benefits of flexible heat pumps in 2030 scenarios. *Commun. Earth Environ.* **5**, 718 (2024).
42. Liang, J., Qiu, Y. (Lucy) & Xing, B. Impacts of electric-driven heat pumps on residential electricity consumption: An empirical analysis from Arizona, USA. *Clean. Responsible Consum.* **4**, 100045 (2022).
43. Bistline, J. E. T., Roney, C. W., McCollum, D. L. & Blanford, G. J. Deep decarbonization impacts on electric load shapes and peak demand. *Environ. Res. Lett.* **16**, 094054 (2021).
44. Reyna, J. L. & Chester, M. V. Energy efficiency to reduce residential electricity and natural gas use under climate change. *Nat. Commun.* **8**, 14916 (2017).
45. Net Zero by 2050 – Analysis. *IEA* <https://www.iea.org/reports/net-zero-by-2050> (2021).
46. Camarasa, C. *et al.* A global comparison of building decarbonization scenarios by 2050 towards 1.5–2 °C targets. *Nat. Commun.* **13**, 3077 (2022).
47. Ürge-Vorsatz, D. *et al.* Advances Toward a Net-Zero Global Building Sector. *Annu. Rev. Environ. Resour.* **45**, 227–269 (2020).
48. Sugiyama, M. Climate change mitigation and electrification. *Energy Policy* **44**, 464–468 (2012).
49. CPUC, CAISO, & CEC. *Root Cause Analysis: Mid-August 2020 Extreme Heat Wave*. <http://www.caiso.com/Documents/Final-Root-Cause-Analysis-Mid-August-2020-Extreme-Heat-Wave.pdf> (2021).
50. Romitti, Y. & Sue Wing, I. Heterogeneous climate change impacts on electricity demand in world cities circa mid-century. *Sci. Rep.* **12**, 4280 (2022).
51. Tarroja, B. *et al.* Translating climate change and heating system electrification impacts on building energy use to future greenhouse gas emissions and electric grid capacity requirements in California. *Appl. Energy* **225**, 522–534 (2018).
52. Ssembatya, H. *et al.* Dual Impacts of Space Heating Electrification and Climate Change Increase Uncertainties in Peak Load Behavior and Grid Capacity Requirements in Texas. *Earths Future* **12**, e2024EF004443 (2024).
53. Rodgers, K. B. *et al.* Ubiquity of human-induced changes in climate variability. *Earth Syst. Dyn.* **12**, 1393–1411 (2021).
54. Deser, C. *et al.* Insights from Earth system model initial-condition large ensembles and future prospects. *Nat. Clim. Change*

- 10, 277–286 (2020).
55. Lehner, F. *et al.* Partitioning climate projection uncertainty with multiple large ensembles and CMIP5/6. *Earth Syst. Dyn.* **11**, 491–508 (2020).
56. McKinnon, K. A. & Simpson, I. R. How Unexpected Was the 2021 Pacific Northwest Heatwave? *Geophys. Res. Lett.* **49**, e2022GL100380 (2022).
57. van Heerden, R. *et al.* Demand-side strategies enable rapid and deep cuts in buildings and transport emissions to 2050. *Nat. Energy* **10**, 380–394 (2025).
58. Wang, H., Guo, F. & Sivakumar, A. Analysing the impact of electric vehicle charging on households: An interrelated load profile generation approach. *Energy Build.* **335**, 115558 (2025).
59. Weinold, M. P., Kolesnikov, S. & Anadón, L. D. Rapid technological progress in white light-emitting diodes and its source in innovation and technology spillovers. *Nat. Energy* **10**, 616–629 (2025).
60. Wiser, R. *et al.* Expert elicitation survey predicts 37% to 49% declines in wind energy costs by 2050. *Nat. Energy* **6**, 555–565 (2021).
61. Way, R., Ives, M. C., Mealy, P. & Farmer, J. D. Empirically grounded technology forecasts and the energy transition. *Joule* **6**, 2057–2082 (2022).
62. Schmidt, O., Melchior, S., Hawkes, A. & Staffell, I. Projecting the Future Levelized Cost of Electricity Storage Technologies. *Joule* **3**, 81–100 (2019).
63. Odenweller, A., Ueckerdt, F., Nemet, G. F., Jensterle, M. & Luderer, G. Probabilistic feasibility space of scaling up green hydrogen supply. *Nat. Energy* **7**, 854–865 (2022).
64. Present, E. *et al.* *ResStock Dataset 2024.1 Documentation*. NREL/TP-5500-88109, 2319195, MainId:88884 <https://www.osti.gov/servlets/purl/2319195/> (2024) doi:10.2172/2319195.
65. Adams, L. *et al.* *Introduction to ComStock*. NREL/PR--5500-86634, 1999776, MainId:87407 <https://www.osti.gov/servlets/purl/1999776/> (2023) doi:10.2172/1999776.
66. Sudasinghe, P., Herath, D., Karunaratne, I., Weeratunge, H. & Jayasuriya, L. Forecasting renewable energy for microgrids using machine learning. *Discov. Appl. Sci.* **7**, 449 (2025).
67. Wang, C., Zhou, Y., Wen, Q. & Wang, Y. Improving Load Forecasting Performance via Sample Reweighting. *IEEE Trans. Smart Grid* **14**, 3317–3320 (2023).
68. Baumgärtner, C. L., Way, R., Ives, M. C. & Farmer, J. D. The need for better statistical testing in data-driven energy technology modeling. *Joule* **8**, 2453–2466 (2024).
69. Roberts, C. & Nemet, G. Systematic Historical Analogue Research for Decision-making (SHARD): Introducing a new methodology for using historical case studies to inform low-carbon transitions. *Energy Res. Soc. Sci.* **93**, 102768 (2022).
70. CDR Knowledge Hub. *IIASA Scenario Services App* <https://new.apps.ece.iiasa.ac.at/story/hatch>.
71. U.S. Energy Information Administration (EIA). 2020 Residential Energy Consumption Survey (RECS) [Microdata and Consumption & Expenditures Tables]. (2024).
72. U.S. Energy Information Administration (EIA). 2018 Commercial Buildings Energy Consumption Survey (CBECS) Final Results. (2024).

650 **Figure**



651
652 Figure 1 Dynamics of peak hourly building power demand across 2020-2060 under climate, tech-diffusion and combined
653 effects on power-region level. *Y-axis indicates the 5-year rolling average of the ratio between annual peak demand and 2020*
654 *peak.*
655

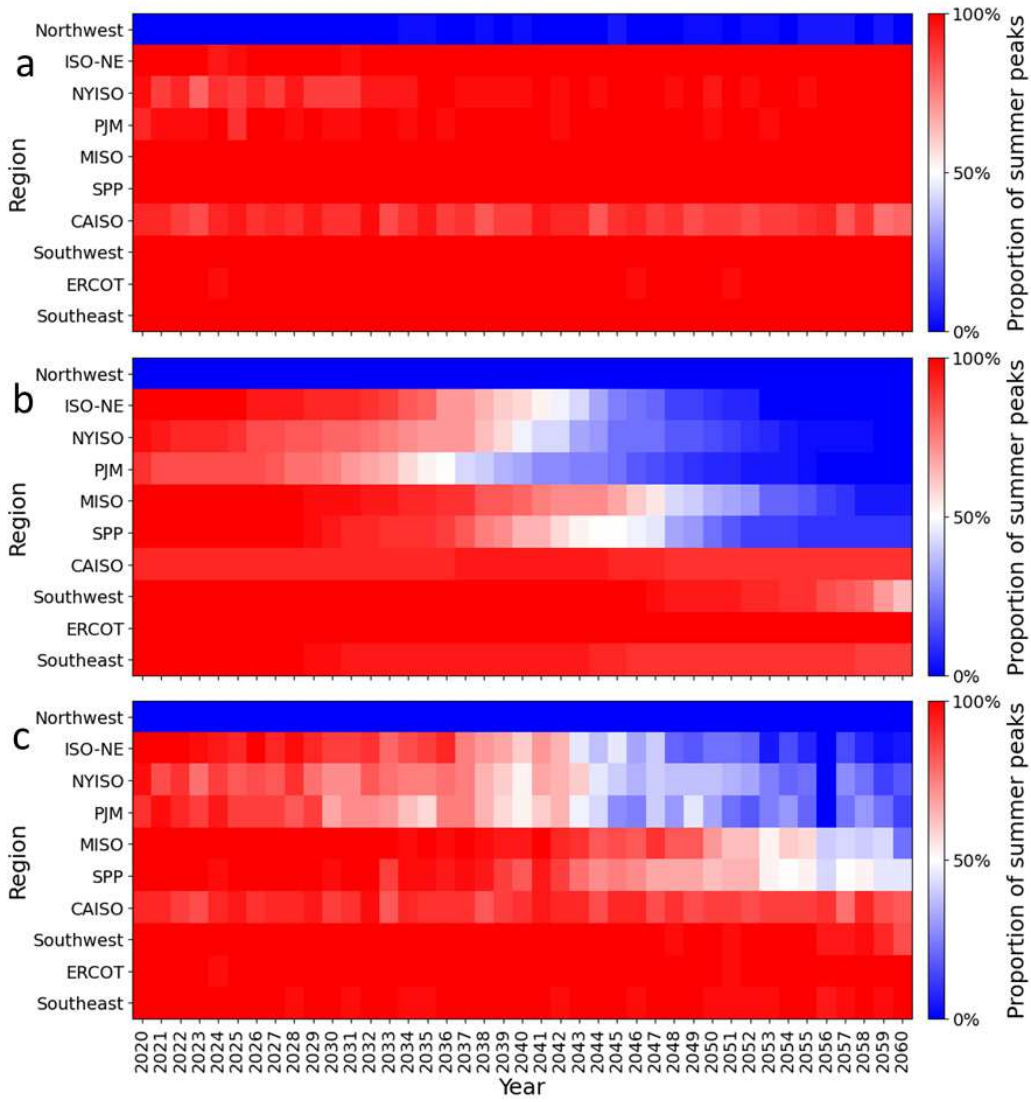


Figure 2 Effects of climate change only (a), technology diffusion only (b), and their combined effects (c) on peak seasonality, defined as the proportion of maximum hourly demand that occur in the summer across 40 climate realizations from 2020 to 2060.

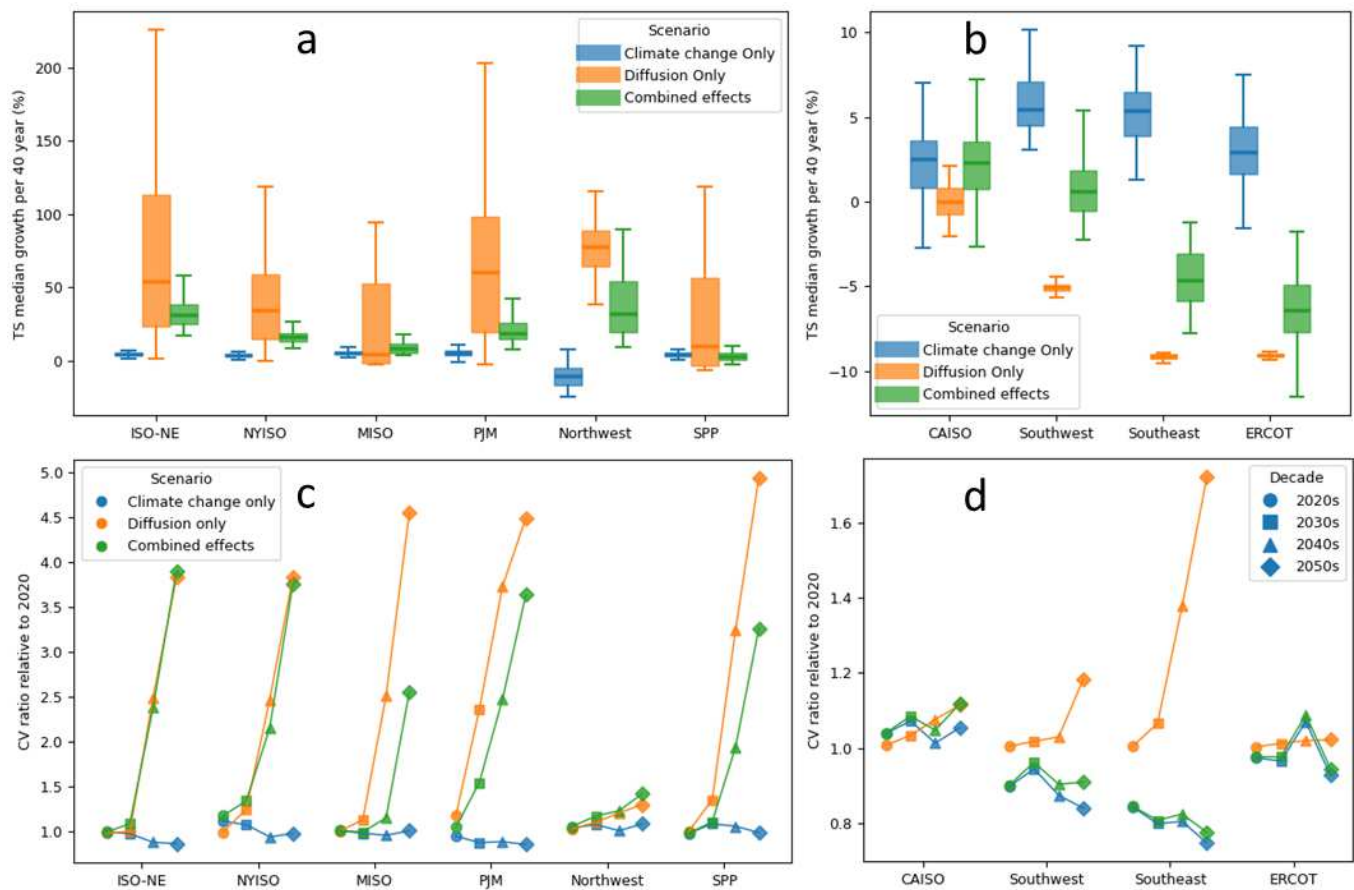


Figure 3 Climate uncertainty on peak dynamics. (a-b) TS growth rate of peak in cold (a) and hot (b) regions; (c-d) Ratio of average annual peak CV across climate realizations across different decades in cold (c) and hot (d) regions.

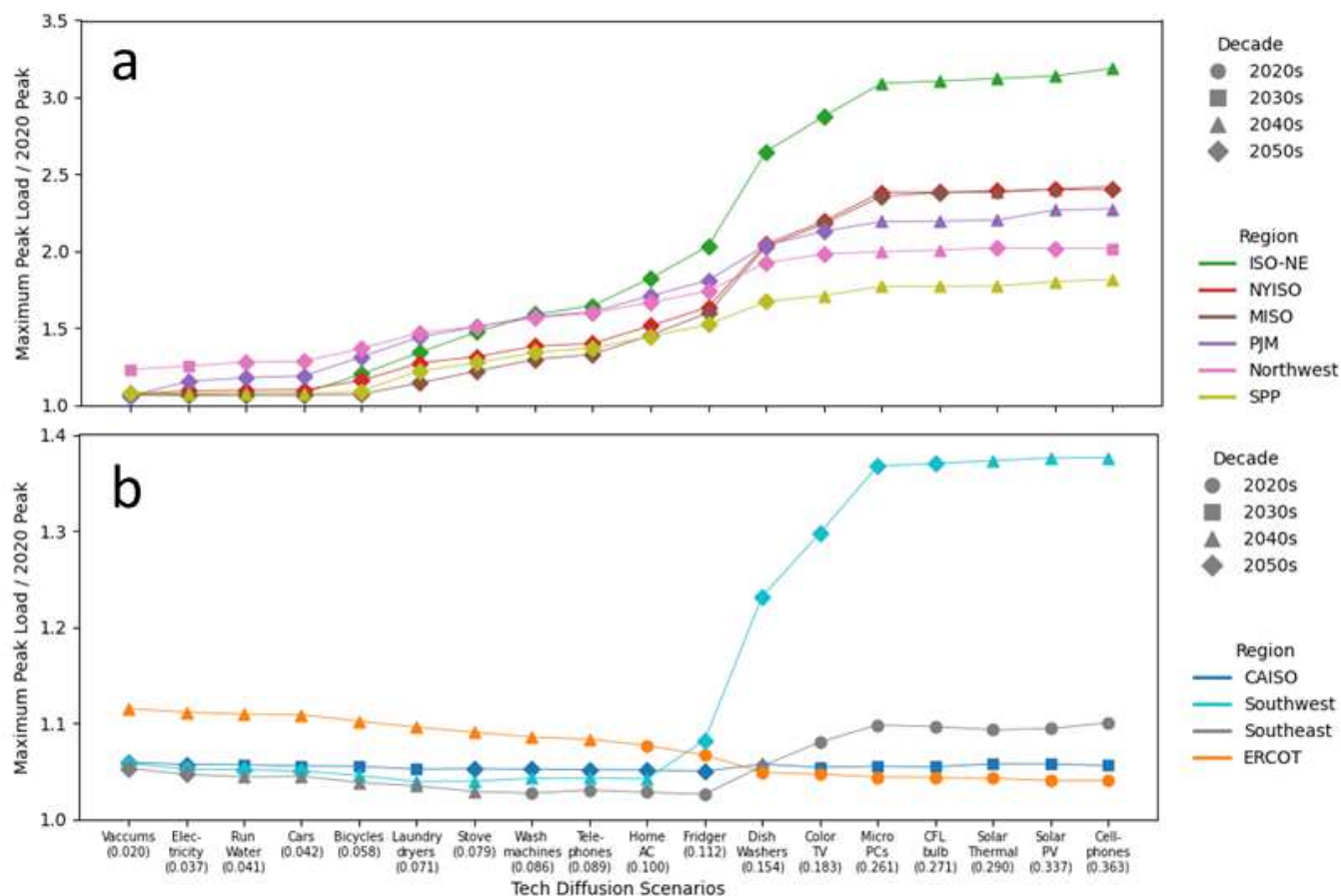


Figure 4 Sensitivity of tech-diffusion rates on peakiest peak loads across power-grid regions. (a,b) Influence of technology-diffusion rates on the magnitude and timing of maximum hourly peak loads across cold regions(a) and warm regions(b) The x-axis ranks diffusion scenarios in ascending order; the y-axis shows the ratio of the 95th PTL of peakiest future peak load across 40 climate realizations to the 95th PTL 2020 peak across 40 climate realizations. Marker shapes denote the decade in which each region's maximum peaks occur most frequently across 40 future climates.

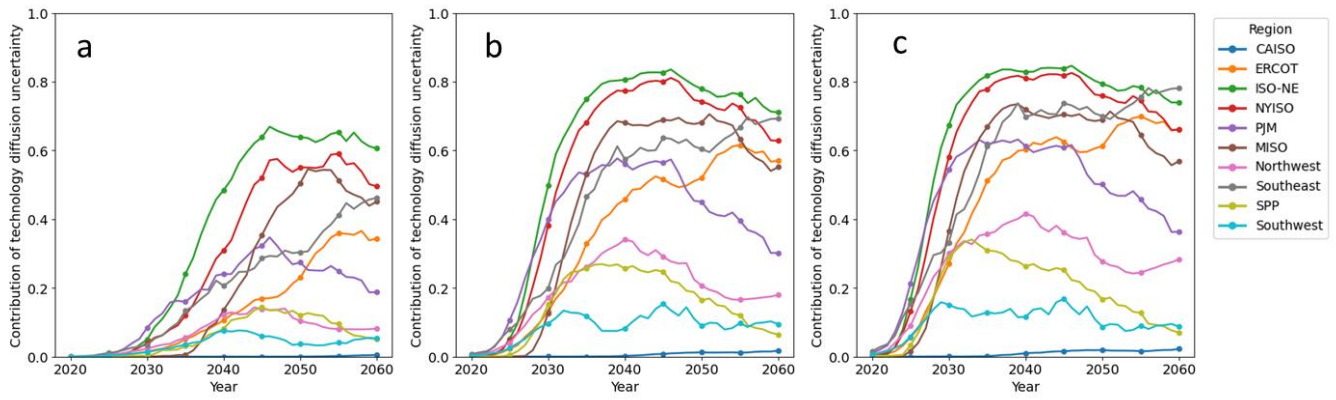


Figure 5 Contribution of the climate and tech-diffusion uncertainty to overall uncertainty from 2020 to 2060 across power grid region level. The y-axis shows the share of uncertainty attributable to technology diffusion. Panels (a–c) use 1, 1–2, and 1–3 historical technology analogs, respectively.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [SIs submission.pdf](#)