

Electrification can trigger rapid growth in peak demand uncertainty

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Abstract

Electrification of space heating shifts weather-sensitive energy use onto power systems, driving peak electricity demand and its uncertainty. We quantify uncertainty in residential and commercial peak electricity demand across the contiguous United States by generating 256,200 county-level, hourly demand simulations across 14 heat pump penetration levels and 100 climate trajectories. As penetrations rise, the relative spread between median and extreme realizations of annual peak demand grows nonlinearly. Across northern regions, a critical transition period spanning only a 10-20% increase in heat-pump penetration, typically around 20-40% penetration, drives more than 60% of total uncertainty growth. This transition occurs when systems shift from summer-only to summer or winter peaking, and increases underestimation risk when using historic weather. Preparing for this transition period is critical for planning reliable systems.

Introduction

Anthropogenic climate change is reshaping energy systems through decarbonization and adaptation to intensifying weather-related stresses¹⁻⁵. Electrification, or the substitution of electricity for direct fossil-fuel use, is central to deep decarbonization. This shift is especially pronounced in buildings, where heat pumps are emerging as a central technology for decarbonizing space conditioning⁶⁻⁹. U.S. heat-pump prevalence rose by roughly 50% between 2015 and 2020, to nearly 18 million units, while high-electrification pathways imply around 170 million heat pumps by mid-century^{10,11}.

Because heating and cooling are highly weather sensitive, their electrification couples electricity demand more tightly to temperature variability, long-term warming, and extreme heat and cold¹²⁻¹⁷. These changing sensitivities matter most at peak demand, the few hours or days that determine whether generation, transmission and operational flexibility can meet demand^{16,18-20}. Peak demand forecasts therefore anchor long-term resource-adequacy and network-planning decisions^{21,22}. Planning depends not only on a central forecast of peak demand, but also on uncertainty in that forecast, as tail estimates indicate how far rare but physically plausible outcomes may exceed typical peak conditions at a given electrification state²³⁻²⁵. Underestimating this tail can leave a system that appears adequate under normal weather exposed during an extreme heat wave or cold spell^{26,27}. This risk was evident during the February 2021 rolling blackouts in Texas, when estimated demand absent load shedding exceeded ERCOT's extreme-winter forecast by 14% due to the cold spell²⁸⁻³⁰. Characterizing plausible peak extremes is therefore a first-order problem for reliable and cost-effective system design³¹.

For long-lived power infrastructure, the magnitude of peak demand uncertainty is only part of the problem. Its rate of change determines how much advance warning planners have^{32,33}. Generation, transmission, and major demand-side investments are committed years before they become operational, requiring resource-adequacy assessments to anticipate the distribution of future loads rather than respond after its change³⁴. In practice, utilities and system operators often represent this weather uncertainty through historical weather years to inform capacity and reliability needs^{35,36}. This approach can remain informative when peak uncertainty widens gradually, allowing forecasts and planning margins to be updated as conditions evolve^{37,38}. But if that gap expands rapidly over a narrow stage of electrification, historical weather samples may lag the risk they are intended to represent^{35,39}. In this case, new assets could enter service against a peak-demand distribution substantially different from the one used to plan them^{31,40}. The central planning question is therefore not only how large future peak uncertainty becomes, but whether it evolves gradually enough for historical-weather-based planning to keep pace, or instead accelerates over a narrow interval, requiring reliability investments to be committed before the emerging risk is fully apparent.

However, existing research does not resolve how uncertainty in peak demand evolves along the electrification pathway^{6,11,41,42}. Most projections collapse weather variability into an expected or representative load trajectory, enabling comparisons of peak levels and dominant peak seasons across electrification scenarios but not of the spread between typical and extreme outcomes^{6,11,41,42}. Studies that retain multiple weather years and explicitly quantify peak uncertainty examine fixed technology states (often fully electrified) using historical weather records^{31,43–46}. They therefore reveal variability at an electrification endpoint, but not its trajectory through intermediate adoption levels^{43,47,48}, while historical records alone do not capture how the upper tail may change under future climate conditions^{23,43}. This literature also focuses on individual regions or power systems, limiting generalized understanding of growth dynamics in peak demand uncertainty^{44,47–49}.

It therefore remains unknown when the most vulnerable period of peak uncertainty growth is, whether peak uncertainty dynamics are consistent across climate-diverse regions, and when historical weather samples have limited utility in resolving future extremes. We therefore ask whether and when electrification triggers a rapid transition in peak uncertainty across climates, and how that transition reshapes uncertainty sources and weather-sampling requirements. We combine hourly building-demand simulations for 183 counties in ten U.S. grid regions with 100 climate trajectories spanning four climate models, three emissions pathways and internal variability. We quantify climate-conditioned peak uncertainty as the relative spread between median and 95th-percentile annual peaks across heat pump adoption pathways. We then trace how this uncertainty evolves across the electrification pathway and examine its seasonal dynamics, climatic sources and implications for weather sampling.

We show that uncertainty changes little while summer peaks dominate, expands rapidly when either season can set the annual maximum, and grows more slowly after winter peaking is established. Across five northern regions completing this shift to winter peaking, a mixed-season window spanning only approximately 20% of the pathway accounts for more than 60% of the total increase in peak demand uncertainty, with the fastest growth near the point at which winter sets the annual maximum in half of climate realizations. This crossover in when peaking occurs elevates the relative role of internal variability, weakens the benefit of spatially aggregating demand, and rapidly raises the number of weather realizations needed to estimate peak extremes.

Results

Electrification widens peak demand distributions unevenly across the seasonal transition

To examine how building electrification reshapes weather-driven peak-demand risk, we combined hourly building-demand simulations across 183 counties in ten U.S. grid regions with 500 annual weather samples nested within 100 climate trajectories that sample internal climate variability, climate-model response and emissions-scenario uncertainty. The ensemble spans four climate models (CanESM5, CESM2-LENS2, ACCESS-ESM1-5 and MPI-ESM1-2-LR) and three pathways (SSP2-4.5, SSP3-7.0 and SSP5–8.5), with 50 members per model-scenario combination (Supplementary Table S7 and Note 3). We evaluate 14 electrification ratios from 0 to 1, specifying target heat pump penetration in residential and commercial stocks while retaining any county- and sector-specific initial penetration above the target to

avoid artificial de-electrification. We define peak demand uncertainty as the relative upper-tail spread, $U = \frac{P_{95} - P_{50}}{P_{50}}$, where (P_{50}) and (P_{95}) denote the median and 95th-percentile annual peaks across the full climate ensemble. Estimating this metric consistently across the large ensemble traces how rare but plausible peaks extend above typical peaks as electrification increases.

Under 2060 climate conditions, electrification extends the annual peak tail and widens its distribution in most regions. In Northern regions except Northwest, (i.e. ISO-NE, NYISO, MISO, PJM and SPP), peak demand uncertainty begins

near 6–9%, rises rapidly at intermediate heat-pump penetration, and then grows more gradually to 27-40% under full electrification. The Northwest rises steadily from approximately 33% to 52%. In Southern regions, the Southwest and Southeast show little initial change but stronger growth at higher penetration, whereas CAISO and ERCOT retain narrow and weakly changing peak distributions. These trajectories align with a shift in peak seasonality. We classify a region as summer dominated when winter peaks exceed summer peaks in less than 20% of realizations, mixed season at 20–80%, and winter dominated at greater than 80%. In ISO-NE, NYISO, MISO, PJM and SPP, uncertainty increases by up to 2% before the mixed-season interval, increases by 13–21% during it, and increases by a further 6-10% from its end to full electrification. Thus, across these regions, the mixed-season interval spans only 13-27% of the pathway but accounts for 58-68% of the total uncertainty increase (Figure S17). Therefore, most electrification-driven widening is concentrated in a narrow penetration interval rather than distributed uniformly across the pathway.

The electrification ratio of fastest uncertainty growth is within 7% of the ratio at which winter supplies the annual peaks in half of realizations. (Figure S17) Near this crossover, small penetration increases switch many realizations from summer to winter peaks; after the crossover, seasonality changes in fewer realizations and marginal uncertainty growth slows. Regional exceptions support this relationship. For example, Northwest is already winter peaking in approximately 78% of initial realizations and therefore starts with high uncertainty without a distinct acceleration; the Southeast transitions later and shows delayed growth; and CAISO and ERCOT change little in either seasonality or uncertainty. Thus, uncertainty growth depends more on whether and when electrification changes the peaking season than on penetration alone.

Power-system planners increasingly recognize the value of coordinating resources across larger regions to improve short-run operations and long-run investment planning⁵⁰. However, we find that electrification weakens the value of spatial aggregation in reducing peak demand uncertainty (Fig. 2). Along with the electrification process, regional peak demand uncertainty tends to shift from lower to higher percentile of county-scale estimates, e.g. 36th to the 64th percentile of county-scale estimates in ISO-NE and from the 12th to the 63rd percentile in MISO. To assess aggregation against an additive county-level benchmark, we further quantify relative margin attenuation using $R_r = M_r / \sum_{c \in r} M_c$, where M_r and M_c are the differences between the 95th and 50th percentiles of regional and county annual peak demand, respectively. Values below one indicate a regional margin smaller than the sum of separately estimated county margins, whereas increasing values indicate weaker attenuation relative to this benchmark. R_r increases from 0.41-0.67 to 0.67-0.90 across MISO, PJM, SPP, the Southwest and the Southeast. The ratio approaches or exceeds one in ISO-NE, NYISO, MISO and SPP at intermediate penetration rates of 25-35%, indicating that regional margins can become comparable to or larger than the sum of county margins in transitioning periods.

The weakening of this mitigating effect is consistent with increasing spatial and seasonal alignment of county-level peak outcomes (Figure S18). Spatial aggregation is most effective when local peak extremes occur under different weather conditions or at different times, allowing their contributions to the regional peak to partly offset one another. Heating electrification increases the common sensitivity of county demand to geographically extensive cold events and shifts annual peaks towards the same winter weather regime across counties. As a result, a larger share of county-level upper-tail variability persists after aggregation, causing regional uncertainty to rise relative to the county-level distribution. Electrification therefore not only widens the annual peak-demand tail, but also reduces the extent to which county-level uncertainty is attenuated through regional aggregation, with both changes concentrating around the seasonal transition.

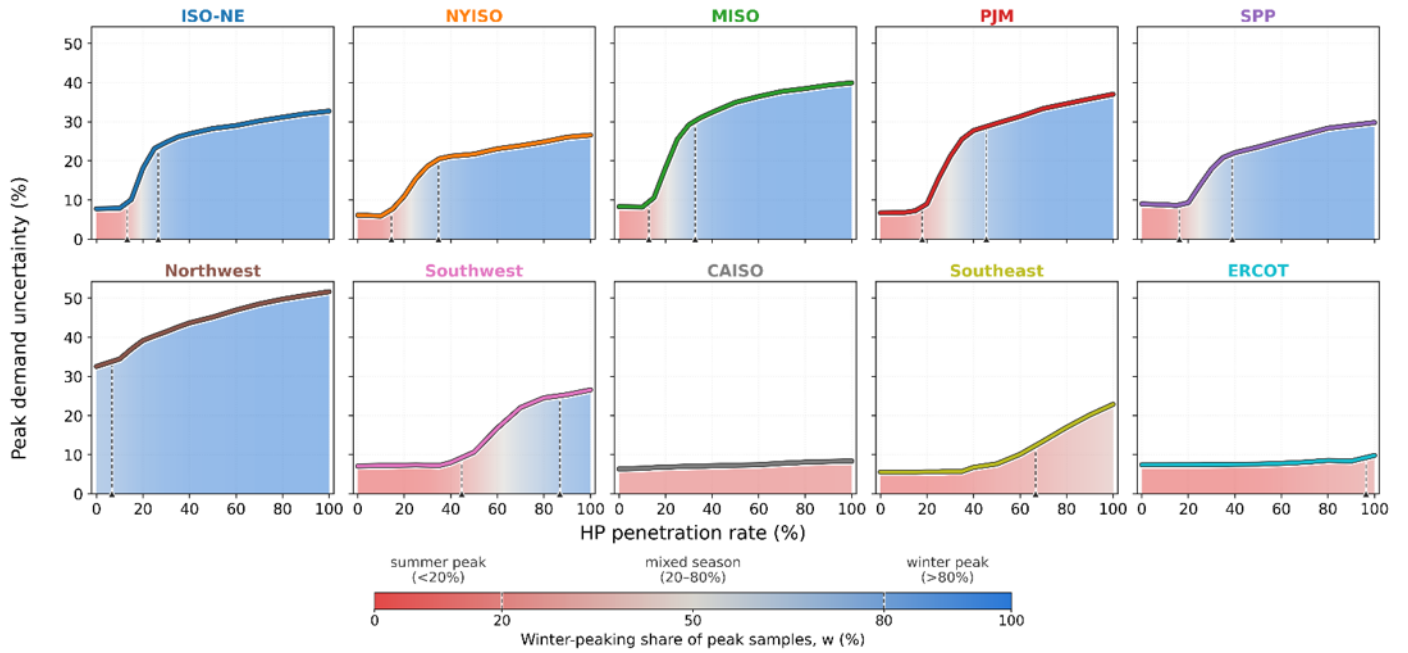


Fig. 1 Annual peak-demand uncertainty and peak seasonality across electrification ratios.

Annual peak-demand uncertainty and the seasonality of annual peaks for ten U.S. grid regions under 2060 climate. Peak-demand uncertainty is defined as $(U = (P_{95} - P_{50})/P_{50})$, where (P_{50}) and (P_{95}) are the median and 95th-percentile annual peaks across the full 500-realization climate ensemble. Solid curves show annual peak-demand uncertainty. The color of the shaded area beneath each curve indicates the fraction of annual weather samples in which winter supplies the annual peak. The electrification ratio specifies the target heat-pump penetration in both residential and commercial building stocks; county- and sector-specific initial penetration is retained where it exceeds the target. Summer-dominated, mixed-season and winter-dominated conditions correspond to winter-peaking shares below 20%, between 20% and 80%, and above 80%, respectively.

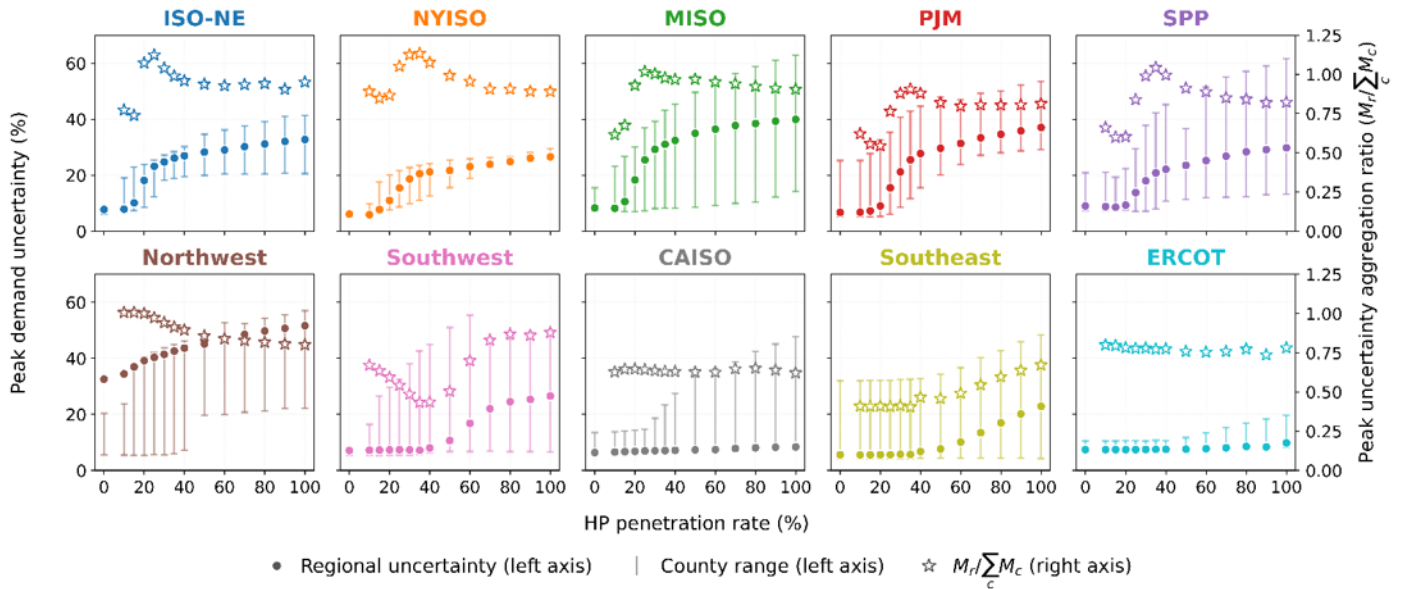


Figure 2 | Spatial aggregation of annual peak-demand uncertainty across electrification levels. Annual peak-demand uncertainty at county and grid-region scales under 2060 climate conditions. On the left axis, uncertainty is expressed as $100(P_{95} - P_{50})/P_{50}\%$, where P_{95} and P_{50} are the 95th and 50th percentiles of the annual peak-demand ensemble. Filled circles show uncertainty calculated from spatially aggregated regional demand, and vertical capped bars show the range of county-level uncertainty within each region. Bars show Tukey whiskers, extending to the most extreme county values within 1.5 interquartile ranges below the first quartile and above the third quartile. For NYISO,

CAISO and ERCOT whose representative counties are less than 10, bars span their full minimum–maximum range. Open five-point stars indicate the regional-to-summed-county margin ratio, $R_r = M_r / \sum_{c \in r} M_c$, on the right axis, where each absolute uncertainty margin is defined as $M = P_{95} - P_{50}$. Ratios below one indicate a smaller regional margin than the sum of separately estimated county margins; increasing ratios indicate weaker attenuation relative to this benchmark.

Electrification shifts peak-demand uncertainty towards internal climate variability

Electrification alters not only the magnitude of peak-demand uncertainty, but also its composition across internal climate variability, climate-model uncertainty and emissions-scenario uncertainty (Fig. 3a). Internal variability generally contributes the largest share of annual peak-demand variance, followed by climate-model uncertainty and then emissions-scenario uncertainty. In regions undergoing a summer-to-winter peak transition, however, the internal-variability fraction rises non-monotonically from approximately 43-62% in summer-dominated conditions to 80%-95% during the mixed-season interval, then declines to 71%-90% after winter peaking is established. Model uncertainty generally follows the opposite pattern that its share falls from 30%-51% under summer-dominated conditions to a minimum of 4-14% during the mixed-season interval, then rebounds to 8-26% after winter peaking is established. Scenario uncertainty remains below approximately 12% in most regions. The transition-centered maximum is clearest in ISO-NE, NYISO, MISO, PJM and SPP; the Northwest begins high and stable because it is already winter dominated, whereas the Southwest and Southeast increase later with their seasonal transitions. Internal variability is thus amplified most strongly during the mixed-season interval rather than increasing monotonically with penetration.

Decomposition of temperature extremes explains this pattern. Before the transition, cooling-driven annual peaks have an internal-variability fraction closer to that of maximum temperature ($T_{\max}$). As winter peaks emerge, minimum temperature ($T_{\min}$), whose uncertainty is more strongly dominated by internal variability, becomes more influential. During the mixed-season interval, the demand-based fraction exceeds the $T_{\min}$ benchmark by approximately 4-18% in six regions because internal variability affects both seasonal peak magnitudes and which season supplies the annual maximum. Once winter peaks dominate most realizations, this seasonal-selection effect weakens and the fraction approaches the ($T_{\min}$) contribution. The transition-period internal-variability contribution maximum therefore combines uncertainty in when peaking occurs with a shift from lower-internal-variability summer extremes to higher-internal-variability winter extremes.

Absolute contributions show that the post-transition decline in internal variability's share is not due to a decline in its absolute magnitude (Fig. 3b). Across transitioning regions, the internal-variability-attributed spread increases from approximately 2.9-4.5% before the transition to 11.1%-18.1% during it and remains near this elevated level after winter dominance. Model uncertainty can also increase in absolute terms after the transition despite a smaller variance share because the total distribution widens substantially. Scenario uncertainty remains the smallest component in most regions, contributing approximately 0.9-4.9% under full electrification in 2060. The Northwest retains a large internal-variability contribution whereas the corresponding contribution in Southeast increases beginning at higher penetration. In CAISO and ERCOT, the internal-variability-attributed component of peak-demand uncertainty remains below 6% despite their relatively high internal-variability shares in total variance. Internal variability therefore peaks in relative importance during the transition and remains the largest absolute contributor afterward.

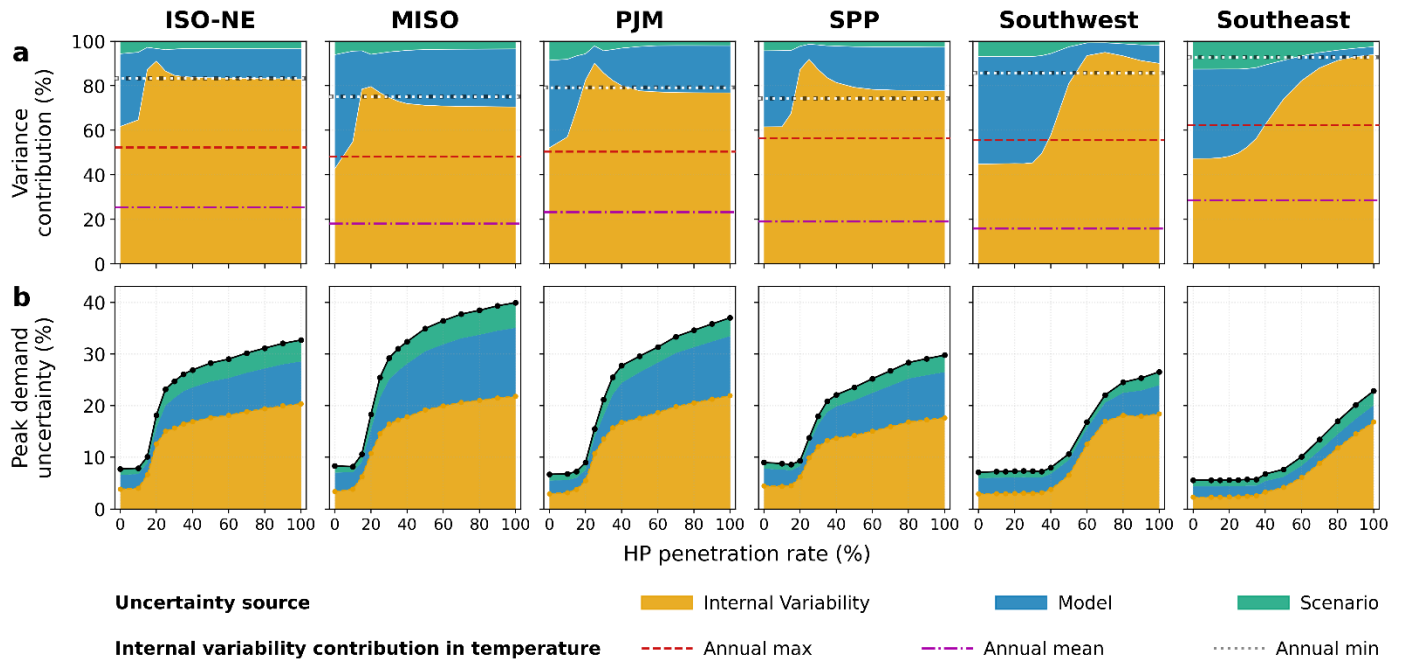


Fig. 3 Climate-uncertainty contributions to annual peak-demand variance and peak demand uncertainty. **a**, Fractional contributions of internal climate variability (orange), climate-model uncertainty (blue) and emissions-scenario uncertainty (green) to annual peak-demand variance across heat-pump penetration rates under 2060 climate conditions. The stacked areas sum to 100% at each penetration rate. Horizontal reference lines show the internal-variability fractions of annual maximum temperature ($(T_{\max})$; red dashed), mean temperature ((T_{mean}) ; magenta dash-dotted) and minimum temperature ($(T_{\min})$; white dotted), calculated from the same climate ensemble. **b**, Source-attributed contributions of the same three components to annual peak-demand uncertainty, defined as $(U = (P_{95} - P_{50})/P_{50})$ and expressed in percentage points. The stacked areas sum to total peak-demand uncertainty, shown by the solid black line. The orange dotted line shows peak-demand uncertainty calculated from the internal-variability-only ensemble. Columns show the six grid regions that undergo a transition from summer- to winter-dominated annual peaking. Six regions with peak seasonality transitions are selected in this figure, while Figure S19 contains information for other regions.

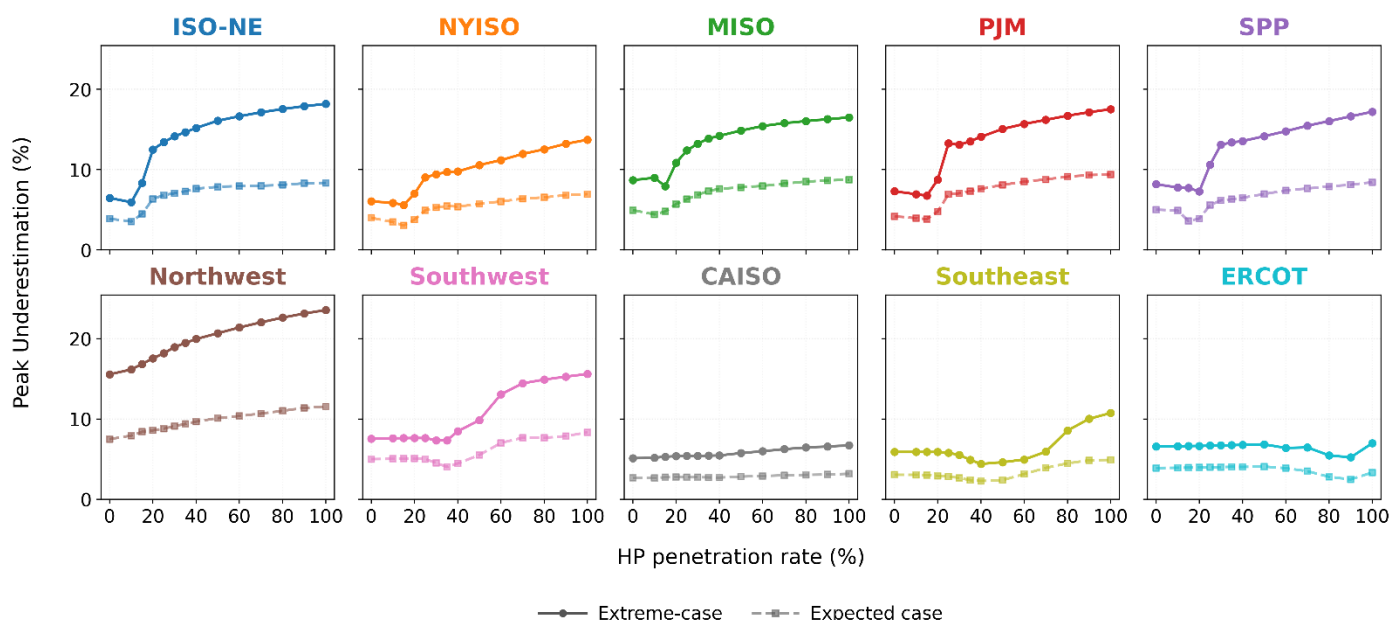
Electrification increases underestimation risk and sample sizes needed to resolve peak extremes

With internal variability remaining the largest absolute contributor to the widened peak-demand tail, accurately characterizing future peak extremes increasingly depends on sampling a sufficiently broad range of weather conditions. We compare P_{95} peak estimates from 20-year weather records with the full-ensemble benchmark across the electrification pathway under SSP3–7.0, averaging across 2055–2060 to reduce single-year sensitivity (Fig. 4). We quantify underestimation using the mean error among estimates below the benchmark and the magnitude of the fifth-percentile error as a more adverse sampling outcome. Initially, historical records underestimate P_{95} by approximately 3–5% on average and 5–8% in adverse outcomes across most regions. Both measures increase substantially with electrification in regions undergoing a summer-to-winter peak transition, indicating that a historical weather record of fixed length became progressively less able to represent the expanding upper tail of future peak demand.

In the six regions completing the seasonal transition (ISO-NE, NYISO, MISO, PJM, SPP and Southwest), adverse underestimation rises from 6–9% initially to 14–18% under full electrification, while mean underestimation increases from 4–5% to 7–9%. The initially winter-dominated Northwest rises from approximately 15% adverse and 8% mean error to 24% and 12%. The error growth of Southeast starts at high-electrification, and its adverse error reaches 10% at full electrification. CAISO and ERCOT remain near 5–7% adverse error and below 4% mean error through most of the

224 pathway. Across transitioning regions, 52%-75% of the total error increase in adverse underestimation and 61-85% of
 225 the increase in expected underestimation occurs during the mixed-season interval. Historical-record bias therefore
 226 follows the same regional timing as tail widening and the shift toward winter peaks.
 227

228 The ensemble needed to limit underestimation to 5% also increases several-fold, especially for P95 peak extremes (Fig.
 229 5). We identify the smallest tested ensemble required to keep peak underestimation within 5% of the full-ensemble
 230 benchmark (Fig. 5). ISO-NE requires about 10 realizations initially, approximately 60 near the start of its transition and
 231 more than 80 at higher penetration, while NYISO, MISO and SPP follow similar trajectories. The Northwest begins
 232 near 65 and reaches the largest tested size. Requirements in the Southwest and Southeast rise from about 10 and 5,
 233 respectively, to approximately 70 and 65, respectively, once winter peaks become influential. CAISO stays below
 234 approximately 10, while ERCOT remains near 10 before reaching about 20 under full electrification. In regions
 235 completing a seasonal transition, the sharpest increase occurs within or just after the mixed-season interval, and the
 236 requirement rises earlier and more strongly for P95 than for P50. Thus, electrification simultaneously increases
 237 historical-record underestimation and the weather ensemble needed for stable peak estimation.
 238
 239



240

241 **Fig. 4 Underestimation of future extreme peak demand from 20-year weather records.**

242 Average underestimation of the 95th-percentile annual peak in late-2050s, under SSP3-7.0 when estimated from
 243 preceding 20-year weather records, relative to the full-ensemble benchmark. Solid lines with circles show adverse
 244 underestimation, defined as the magnitude of the fifth-percentile relative error across repeated estimates. Dashed lines
 245 with squares show expected underestimation, defined as the mean relative error among estimates below the full-
 246 ensemble benchmark. Each panel represents one grid region, and the horizontal axis shows the heat-pump penetration
 247 rate.
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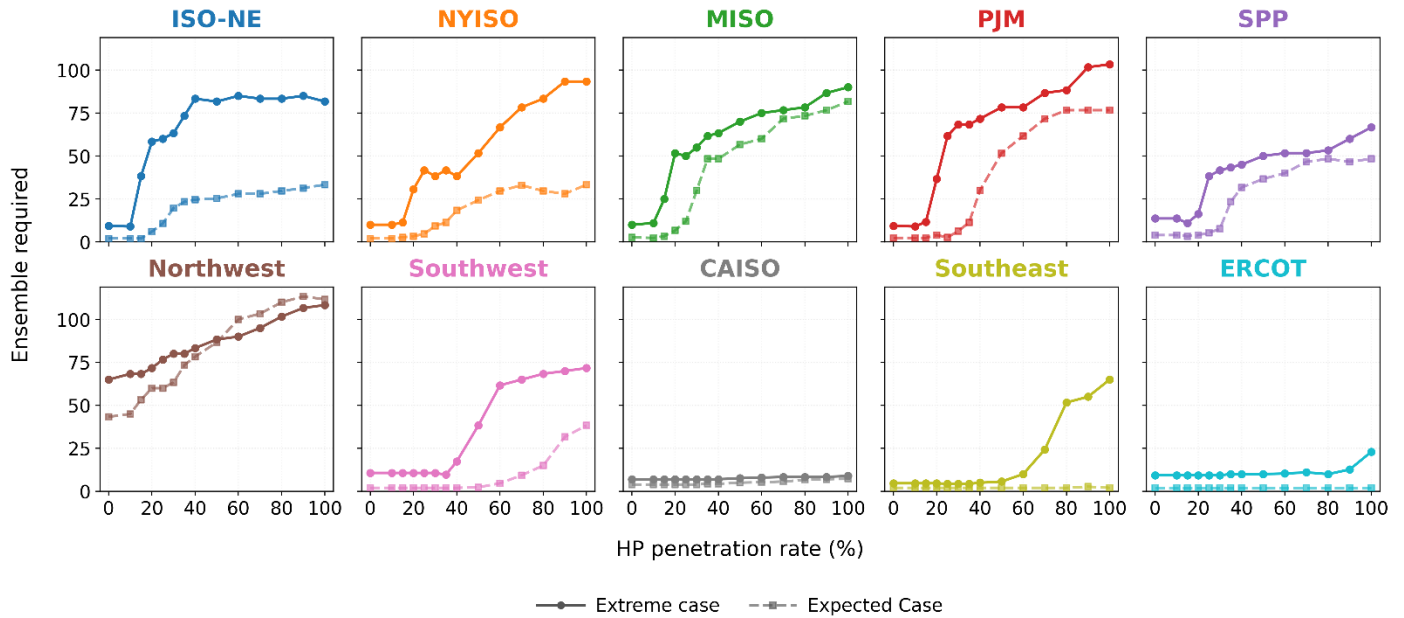


Fig. 5 Minimum weather-ensemble size for median and extreme annual peak estimation.

Minimum number of climate realizations required to limit underestimation of the full-ensemble benchmark to 5% under SSP3-7.0. For each region, electrification ratio and analysis year, (P_{50}) and (P_{95}) were re-estimated from 1,000 random subsets of size N , sampled without replacement from the full ensemble. The minimum ensemble size is the smallest tested N for which the fifth percentile of the relative-error distribution is no lower than -5%, with this criterion remaining satisfied for all larger tested ensemble sizes. Equivalently, at least 95% of repeated estimates underestimate the full-ensemble benchmark by no more than 5%. Solid lines with circles show the requirement for peak extremes (P_{95}), and dashed lines with squares show that for median peaks (P_{50}). Values are averaged across analysis years in late-2050s. Candidate ensemble sizes range from 2 to 200.

Discussion

Our results show that heating electrification reshapes weather-driven peak-demand risk through a concentrated seasonal transition rather than by uniformly scaling an existing demand distribution. In regions shifting from summer- to winter-dominated peaking, uncertainty changes little at low penetration, expands rapidly while both seasons remain plausible annual maxima, and grows more slowly once winter peaking is established. The mixed-season interval occupies only approximately 20% of the electrification pathway but accounts for more than 60% of the total increase in peak uncertainty. The shift from ($T_{\max}$)-driven summer peaks toward ($T_{\min}$)-driven winter peaks raise the uncertainty share related to internal variability, which is further amplified during the transition because internal variability also determines the peak season. In the SSP3-7.0 sampling analysis, a fixed 20-year weather record increasingly underestimates (P_{95}) as electrification progresses, while the number of weather realizations required to limit underestimation to 5% increases several-fold, particularly near the seasonal transition. Spatial aggregation provides less attenuation near the seasonal transition. Electrification therefore changes the trajectory, climatic sources and spatial expression of peak uncertainty, rather than simply raising its central level. These results are also robust to sensitivity analysis on ultra-high efficiency heat pumps, different target years and extreme demand percentiles (Supplementary Note 6).

The distinction between the rate of uncertainty growth and its eventual level has important planning implications. During the early summer-dominated phase, uncertainty changes slowly, but the rising fraction of winter-peaking realizations can serve as an early indicator that the system is approaching a more rapid transition. Because capacity, transmission and major demand-side programs have long lead times⁵¹, planners can use this stage to test winter resource performance, examine fuel and transmission constraints, and preserve investment flexibility before uncertainty accelerates. During

the mixed-season interval, assumptions become outdated fastest since the tail widens, historical records lose representativeness and spatial diversification benefits weaken. Forecasts should therefore be updated more frequently, summer and winter stresses assessed jointly, and weather ensembles enlarged before the crossover. Scalable or reversible measures, including managed heating, demand response, storage and weatherization, are especially valuable while uncertainty evolves rapidly. After winter peaking is established, change slows but a wider, internally variable winter tail persists, shifting the priority from transition flexibility to sustained winter adequacy.

The sampling analysis reinforces this distinction. Internal variability cannot be removed by choosing a preferred climate model or emissions scenario, whose upper tail must be sampled⁵². A fixed historic year record that is adequate at low electrification increasingly misses extremes as cold-sensitive demand enters the annual tail. Extending the record further into the past may not solve the problem because older weather can be less representative of future climate and the emerging temperature-load relationship. Peak assessment instead requires samples that are both sufficiently large and relevant to the electrification state. In transitioning regions, ensemble requirements increase several-fold and rise earlier for extreme than median peaks. Resource-adequacy studies should therefore expand and update weather ensembles as electrification progresses and rapidly evolve especially at transition periods.

Where large physical climate-demand ensembles are unavailable, generative models may complement process-based simulations. Rather than directly resampling a small ensemble, a fitted model can generate conditional realizations for tail estimation^{53,54}. Used alongside physical simulations, generative models could support more frequent updates of peak-risk distributions and better-resolved tails in computationally intensive adequacy assessments.

Our main analysis is indexed by electrification penetration rather than calendar time. Actual heat-pump adoption may accelerate through intermediate penetration, as in an S-shaped diffusion pathway⁵⁵, compressing the uncertainty transition into a shorter and more operationally challenging period. Linking the identified penetration thresholds to region-specific adoption pathways would reveal when the transition occurs and how quickly planning assumptions must adjust. Our research also isolates the building electrification impacts on future peak extreme uncertainty. Future research could combine concurrent insulation upgrades, thermostat behavior and managed demand adoption to test how interactions between these technologies drive sensitivity of peak uncertainty trajectories^{56,57}. Future research could also extend current single-hour based peak into duration or recurrence of high-demand conditions, which may create different stresses for storage, fuel supply, demand response and generator performance. Extending the framework from demand extremes to resource adequacy will require joint modelling of high-load duration, renewable output, outages, storage and transmission constraints^{39,58}. Finally, although our ensemble spans multiple models, scenarios and internal-variability members, it does not cover the full range of climate models. Broader large ensembles and improved representation of spatially coherent events would strengthen estimates of rare outcomes and regional aggregation⁵⁹.

We show heating electrification not only increases peak demand, but structurally changes the risk profile of electricity systems to climate. The most consequential period will likely be a transitional period, when peak uncertainty, sampling requirements and spatial-aggregation benefits all change fastest. Planning for electrification should therefore anticipate the pathway to winter peaking, not only the fully electrified endpoint.

Methods

We use a controlled heat-pump penetration experiment to quantify how the distribution of annual building electricity peaks changes across electrification states under future climates. The analysis builds on the building-demand and weather-generation framework described by Shi et al⁶⁰. Here, we evaluate fixed penetration levels against matched weather realizations and characterize the distribution of uncertainty growth around seasonal peak transitions, its persistence after spatial aggregation, and the weather samples required to estimate peak extremes.

Building-demand simulations and climate ensemble

We perform regressions for residential and commercial electricity demand in 183 representative counties across the contiguous United States using ResStock⁶¹ and ComStock⁶² building characteristics and simulated end-use profiles. The selected samples contain 215,312 residential and 147,099 commercial buildings. Counties are selected to reproduce the within-state distribution of buildings across weather zones, with an L1 difference below 5% (Table S1). Within each county, buildings sharing heating equipment, cooling equipment and envelope characteristics are grouped to retain differences in temperature sensitivity while reducing the number of regressions. We ultimately distinguish 76 residential and 32 commercial building groups in each county, for which ResStock and ComStock contains current and heat-pump-upgrade configurations.

Separate multilayer perceptron (MLP) regressions estimate heating and cooling electricity demand for each county, building group and equipment configuration. Each MLP comprises two hidden layers with 128 and 16 neurons, respectively. Nine predictors describe outdoor temperature, its mean over the preceding 24 hours, the preceding 24-hour mean temperature increment, sine and cosine encodings of hour of day, interactions between these encodings and temperature, season, and weekend versus weekday. Together, these predictors represent the immediate thermal response, recent thermal history and recurring occupancy-related load patterns. We ultimately develop 53,436 individual models on temperature-demand relationship for base-efficiency heat pump adoption.

The regressions are trained on 15-minute heating and cooling electricity profiles simulated for 2018, paired with Actual Meteorological Year 2018 weather supplied with the building simulations. Hourly temperatures are linearly interpolated to align with the load records. Observations are divided into a 90% training subset and a 10% test subset using ten temperature-quantile strata, preserving coverage of the temperature distribution in both subsets. Training observations above its 95th load percentile are included a second time to place greater emphasis on high-demand conditions.

We assess regression performance using held-out coefficients of determination and signed symmetric percentage (SSPE) errors in peak demand. Across the grid regions, median hourly R^2 values range approximately from 0.95 to 0.98 for residential heating and from 0.98 to 0.99 for residential cooling; the corresponding commercial ranges are 0.94-0.97 and 0.97-0.99, respectively (Figs. S5 and S6). The plotted regional median SSPEs for annual total building-group peaks range approximately from -1% to 0% for residential buildings and from -0.6% to 0.6% for commercial buildings (Figs. S7 and S8). We also test the reliability of these regressions on future currently unseen hot extremes by climate change. Through exclusion of the hottest 2% hours from training data, the median SSPE error of cooling-peak estimates stays within $\pm 10\%$ across all grid regions, suggesting no systematic bias toward over- or underprediction under OOD extremes (Figure S9).

We use the regressions to construct hourly building-demand profiles, with non-HVAC electricity use retained at its baseline profile. Representative-building loads are scaled using state residential and commercial electricity totals from the Residential Energy Consumption Survey (RECS)⁶³ and Commercial Buildings Energy Consumption Survey (CBECS)⁶⁴, allocated to counties according to their simulated consumption shares. County profiles were then summed synchronously within ten grid regions: ISO-NE, NYISO, MISO, PJM, Northwest, SPP, CAISO, Southwest, Southeast and ERCOT (Figure S2 and Table S2).

Climate ensemble data and hourly weather reconstruction

Weather inputs are generated using the LOCA2-based ensemble framework described in our preceding study⁶⁰. LOCA2 provides bias-corrected daily maximum and minimum temperatures at approximately 6-km resolution⁶⁵. From LOCA2, we use CanESM5, CESM2-LENS2, ACCESS-ESM1-5 and MPI-ESM1-2-LR under SSP2-4.5, SSP3-7.0 and SSP5-8.5. CESM2-LENS2 contributes only under SSP3-7.0, yielding ten model-scenario combinations (Supplementary Table S7).

Daily records for 2018-2062 support the construction of weather trajectories and the five-year window around the 2060 target climate. County locations were matched to the nearest climate grid point.

For each model-scenario combination, we estimated a smoothly evolving forced response separately for daily maximum and minimum temperature, following the methods in previous literature⁶⁶. We first construct a five-year moving-average annual temperature cycle and represent it using the first three Fourier harmonics. This smoothed seasonal cycle approximates the externally forced component of temperature evolution. Member-specific departures from the corresponding forced response define internal-variability residuals. Separating these components allows the ensemble to combine differences in the forced response across climate models and emissions scenarios with repeated samples of internal variability.

We use ten CESM2 ensemble members under SSP3-7.0 as the donor pool for internal variability. For each target model-scenario combination, we generate ten synthetic temperature trajectories by sampling one CESM2-LENS member and one donor year for each two-year target block. The selected donor-year residual sequence is mapped by month and day to both target years and added to their respective forced responses. For a given synthetic member, the same sequence of donor-member identities and source-year blocks is applied across counties and to both daily maximum and minimum temperature. This construction retains spatially coherent temperature anomalies, and their association between daily extrema and temporal persistence within resampled blocks. The use of a common donor pool standardizes the sampling of internal variability across target combinations; model-specific differences in internal-variability structure are not separately represented.

We reconstruct hourly temperatures with county-specific random forest models trained against ERA5. The models predict residual departures from a baseline diurnal temperature profile using daily extrema from the previous, current and following days, together with cyclical calendar and hour-of-day features. ERA5 records for 1980-2015 were used for training, and 2016-2024 were held out for evaluation. The reconstructed hourly profiles are rescaled to match each day's supplied minimum and maximum. Across distinct county reconstruction models in the validation archive, mean hourly MAE, RMSE and R² were 0.84 °C, 1.29 °C and 0.98, respectively (Table S8). The fitted models are then applied to the synthetic LOCA2 daily sequences.

Our main experiment uses a five-year window centered on 2060 to more fully represent internal climate variability near the target year. Each of the ten model-scenario combinations includes ten synthetic climate trajectories, and each trajectory contributes five annual weather samples, one from each year between 2058 and 2062. Together, these two dimensions of sampling yield 50 annual samples per model-scenario combination and 500 annual samples nested within 100 synthetic trajectories across the full ensemble. To test the sensitivity of our results to climate year, we also test 2030, 2040 and 2050 in the sensitivity analysis.

Modelling the building electrification dynamics

We evaluated target air-source heat-pump penetration of 0%, 10%, 15%, 20%, 25%, 30%, 35%, 40%, 50%, 60%, 70%, 80%, 90% and 100% in both residential and commercial stocks. Penetration was an experimental control, with climate conditions held fixed across the sweep. To isolate the effect of heat-pump adoption on peak-demand uncertainty, we therefore keep building-stock size, non-HVAC load profiles, envelope characteristics and equipment-performance assumptions fixed.

Existing heat pumps were retained when the initial county- and sector-specific penetration exceeded the target. For county c and sector k , realized penetration was therefore defined as

$$e^{real}_{c,k} = \max(e, e^0_{c,k}).$$

Here, e denotes the target heat-pump penetration, and the superscript 0 denotes the initial penetration in each county and

sector. Consequently, the 0% target scenario retains all existing heat pumps, and adoption increases only when the target exceeds the initial share. For targets above the initial share, the composition of the building stock was updated to attain the required heat-pump penetration. Technology assignments at a given penetration were held fixed across weather realizations, so that climate-conditioned distributions did not include variation from reassigning technologies between weather samples.

The selected heat-pump package determines heating electricity use under cold conditions as well as cooling efficiency. The reference residential package in the underlying framework is rated at 16 SEER (Seasonal Energy Efficiency Ratio) and 9.2 HSPF (Heating Seasonal Performance Factor), retaining 50% of rated heating capacity at 5 °F. We also test the sensitivity of our results to adoption of ultra-high efficiency (UHE) heat pumps, which are rated at 24 SEER and 13 HSPF and 90% capacity retention.

Peak demand uncertainty transition and spatial aggregation

For region r , target penetration e and annual weather sample i , we calculated annual peak demand from the hourly (h) regional profile L :

$$P_{r,e,i} = \max_h L_{r,e,i,h}.$$

The empirical distribution of these annual maxima defines the climate-conditioned peak distribution at each penetration. We summarized its central value by the median and its upper tail by the 95th percentile. Relative peak uncertainty was quantified as

$$U_{r,e} = \frac{Q_{0.95}(P_{r,e}) - Q_{0.50}(P_{r,e})}{Q_{0.50}(P_{r,e})} \times 100\%.$$

This measure expresses the upper-tail spread relative to typical annual peak demand. Differences in U are reported in percentage points. County uncertainty was calculated using the same definition applied to each county's own annual maxima.

We characterized peak seasonality by the fraction of weather realizations in which winter peak demand exceeded summer peak demand. Summer-dominated, mixed-season and winter-dominated conditions corresponded to winter-peaking shares below 20%, between 20% and 80%, and above 80%, respectively. The seasonal crossover occurred when this share reached 50%.

We evaluate how spatial aggregation mitigates the peak demand uncertainty, through comparison of regional and county uncertainty. We first calculate the absolute peak uncertainty margin as:

$$M_{x,e} = Q_{0.95}(P_{x,e}) - Q_{0.50}(P_{x,e}).$$

where x indicates spatial unit (either region r or county c), e indicates electrification ratio, and $M_{x,e}$ is the absolute peak uncertainty margin. The peak uncertainty aggregation ratio $R_{r,e}$ is then defined as

$$R_{r,e} = \frac{M_{r,e}}{\sum_{c \in r} M_{c,e}}$$

where the denominator is the sum of separate peak uncertainty margin in county level. For $R_{r,e}$, values below one indicate attenuation relative to the summed county margins, increasing values indicate weaker attenuation, and values above one indicate a regional margin exceeding this benchmark

Partitioning the climate-related peak demand uncertainty

We partitioned climate-related uncertainty in annual peak demand into contributions from internal variability, climate-model uncertainty and emissions-scenario uncertainty, following the variance-partitioning framework of Lehner et al⁶⁷. For each region r , target year t and heat-pump penetration e , we represented the ensemble variance as

$$V_{\text{total}}(r, t, e) = \text{Var}_{s,m,i}[P_{r,t,e,s,m,i}] = V_{\text{internal}}(r, t, e) + V_{\text{model}}(r, t, e) + V_{\text{scenario}}(r, t, e),$$

where P is annual peak demand, and s , m and i indicate emissions scenarios, climate models and annual weather

realizations within the target-year analysis window. As suggested by the literature⁶⁷, we assumed these three climate uncertainty are mutually independent with each other. Statistical interactions among the three sources were therefore not included.

Specifically, internal variability was estimated from variation among realizations within each model-scenario combination. Model uncertainty was estimated from differences among realization-mean peaks across climate models, and scenario uncertainty from differences among multi-model mean peaks across emissions scenarios. Each component was divided by the total variance to obtain its fractional contribution.

To express source contributions on the scale of relative peak-demand uncertainty U , we converted the variance components to standard deviations and used their normalized values to allocate the observed upper-tail spread:

$$U_k = U \times \frac{\sqrt{V_k}}{\sqrt{V_{\text{internal}}} + \sqrt{V_{\text{model}}} + \sqrt{V_{\text{scenario}}}}$$

Here, U_k is the contribution allocated to source k , expressed in percentage points.

Weather-record underestimation and sampling requirements

We use repeated weather sampling to quantify the risk of underestimating peak demand and the ensemble size needed to constrain this risk across electrification levels. For each region and heat-pump penetration, the peak-demand distribution from the full climate ensemble serves as the reference. We compare quantiles estimated from limited weather samples with the corresponding full-ensemble quantiles, defining relative estimation error as

$$\frac{\hat{Q}_q^{(b)} - Q_q^{\text{ref}}}{Q_q^{\text{ref}}} \times 100$$

where $\hat{Q}_q^{(b)}$ is the estimated quantile from weather sample b , and Q_q^{ref} is the reference quantile. Negative values indicate underestimation.

We first evaluate the adequacy of a fixed-length weather record by estimating P95 from the previous 20 weather years along each climate trajectory. Comparing these estimates with the target-period reference produces a distribution of errors across trajectories. We summarize underestimation using the magnitude of the mean error among estimates below the reference and the magnitude of the fifth-percentile error, representing average and adverse underestimation, respectively.

We then estimate the weather-ensemble size required to constrain underestimation of P50 and P95. We repeatedly draw subsets of increasing size without replacement from the target-period ensemble and calculate the quantile error for each subset. The required ensemble size is the smallest tested size for which the fifth-percentile error is no lower than -5%, with this criterion remaining satisfied at all larger tested sizes. This threshold requires at least 95% of repeated estimates to underestimate the reference by no more than 5%. We repeat the analysis across penetration levels to quantify how weather-sampling requirements change through electrification.

In the main analysis, we use SSP3-7.0, which includes all four climate models and provides 200 annual peak samples per target-year reference ensemble. We evaluate subset sizes from 2 to 200 using 1,000 repeated draws per size. Underestimation measures and required ensemble sizes are averaged across the analyzed years in the late-2050s to reduce sensitivity to individual target years.

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Supplementary Information

Electrification can trigger rapid growth in peak demand uncertainty

Supplementary Note 1 Methodological framework and data preparation

1.1 Study design and scope

We evaluated how heat-pump adoption changes the magnitude, seasonality, and climatic uncertainty of peak electricity demand in residential and commercial buildings. The framework combines building-stock data and temperature-dependent demand models with a large ensemble of hourly climate realizations, then aggregates building loads to county and grid-region scales (Fig. S1). The modeled boundary includes electricity used for space heating, space cooling, and non-HVAC building end uses. Industrial and transportation loads are outside this boundary.

The experiment isolated the impacts of heat-pump penetration while holding the building stock, envelope characteristics, non-HVAC profiles, and reference equipment package fixed. The main analysis represents climate conditions around 2060 using annual weather records from 2058–2062. Ten available climate-model–emissions-scenario combinations each contain ten synthetic trajectories, and each trajectory contributes five annual records. The resulting ensemble comprises 500 annual weather samples nested within 100 trajectories. These annual records retain their trajectory and year identities throughout the demand analysis. Building-demand regressions and climate-ensemble construction are described in Supplementary Notes 2 and 3, respectively.

1.2 County selection and representativeness

The study includes 183 selected counties across the 48 contiguous states and the District of Columbia. County selection uses the distribution of simulated residential buildings among ASHRAE/IECC 2004 climate zones within each state. The 183 representative counties were selected to cover the range of different states, weather zones and power grid regions. For each state, the proportional distribution of buildings across in-state weather

Figure S2 shows the geographical distribution of the selected counties, their climate-zone composition, and their assignment to the ten study regions. Table S2 lists the selected counties, their region assignments, and the numbers of simulated residential and commercial buildings.

1.3 Building-stock data and technology packages

We used ResStock 2024.2¹ and ComStock 2023² building characteristics and simulated electricity profiles. Within each county, residential buildings are grouped by heating equipment, cooling equipment, and envelope insulation status; commercial buildings are grouped by heating and cooling equipment. Tables S3 and S4 list the classification schemes. Grouping retains equipment-dependent temperature responses while keeping the computational burden manageable. The 2018 baseline simulations provide the heating, cooling, and non-HVAC end-use profiles used to construct the demand model.

Table S5 lists the technology packages. The reference residential adoption case uses the ENERGY STAR air-to-air heat-pump package with electric backup, and the residential ultra-high-efficiency (UHE) package is evaluated separately as a sensitivity test. UHE heat-pump package rated at 24 SEER (Seasonal Energy Efficiency Ratio) and 13 HSPF (Heating Seasonal Performance Factor) and retaining 90% of its rated heating capacity at 5°F, compared with 16 SEER, 9.2 HSPF, and 50% capacity retention for the ENERGY STAR package. Commercial adoption uses the HP-RTU and ASHP-Boiler package. Existing heat-pump buildings retain their baseline equipment configuration, whereas newly adopting buildings receive the specified upgrade package. Envelope characteristics remain fixed during the main penetration experiment. Non-HVAC electricity follows the baseline profile and receives the same stock-scaling factor as heating and cooling electricity.

Figure S3 summarizes initial heat-pump penetration in the sampled residential and commercial stocks. These initial-stock shares provide context for the lower bounds on adoption; the sector-specific eligibility rules used to impose the experimental targets are described below.

1.4 Requested versus realized penetration

We prescribed heat-pump penetration levels of 0%, 10%, 15%, 20%, 25%, 30%, 35%, 40%, 50%, 60%, 70%, 80%, 90%, and 100%. For a given county and sector, let N denote the relevant adoption-pool size, H_0 the existing heat-pump count, C the available non-heat-pump candidate count, and e the requested fraction. The number of additional adopters and the resulting share are

$$H_{add}(e) = \min\{C, \max[0, \text{round}(eN) - H_0]\} \quad \text{Eq.S1}$$

$$e_{real}(e) = \frac{H_0 + H_{add}(e)}{N} \quad \text{Eq.S2}$$

Existing heat pumps are retained whenever their initial share exceeds the target, so a requested penetration of 0% preserves the existing stock. Candidate availability can also limit attainment of a target, particularly for commercial buildings without an eligible heating system. Accordingly, the commercial experimental denominator differs from the all-sampled-building denominator used to summarize initial penetration in Fig. S3.

The reference allocation selects additional adopters with a fixed random seed of 2020. For each county, sector, and penetration level, the resulting technology assignment is held constant across climate realizations and weather years. Thus, variation across the weather ensemble reflects climate-driven changes in demand rather than repeated random reassignment of heating equipment.

1.5 Scaling and synchronous aggregation

Here, we aggregate the COUNTY-scale simulated results in ResStock and ComStock into hourly demand of total building sector, through weighting them based on state-level statistical power consumption data in Residential Energy Consumption Survey (RECS) and Commercial Building Energy Consumption survey (CBECS), as shown in EqS3-S5:

$$Res_{county,i} = ResStock_{county,i} \times \frac{RECS_{state,2020}}{ResStock_{state,2020}} \quad \text{Eq.S3}$$

$$Com_{county,i} = ComStock_{county,i} \times \frac{CBECS_{state,2018}}{ComStock_{state,2018}} \quad \text{Eq.S4}$$

$$Total_{grid,i} = \sum_{city \in grid} (Res_{county,i} + Com_{county,i}) \quad \text{Eq.S5}$$

where $ResStock_{county,i}$, $ComStock_{county,i}$ indicate the model prediction results of residential and building electricity consumption in year i in each city, respectively; $Res_{county,i}$, $Com_{county,i}$ indicate the weighted results of residential and building electricity consumption in year i in each city, respectively; $RECS_{state,2020}$, $CBECS_{state,2018}$ indicate the statistical results of state-level electricity consumption in each state, recorded in 2020 RECS and 2018 CBECS, respectively; $ResStock_{state,2020}$ and $ComStock_{state,2018}$ indicate the simulated total state-level building consumption in 2020 and 2018, respectively, as a comparison with statistical data.

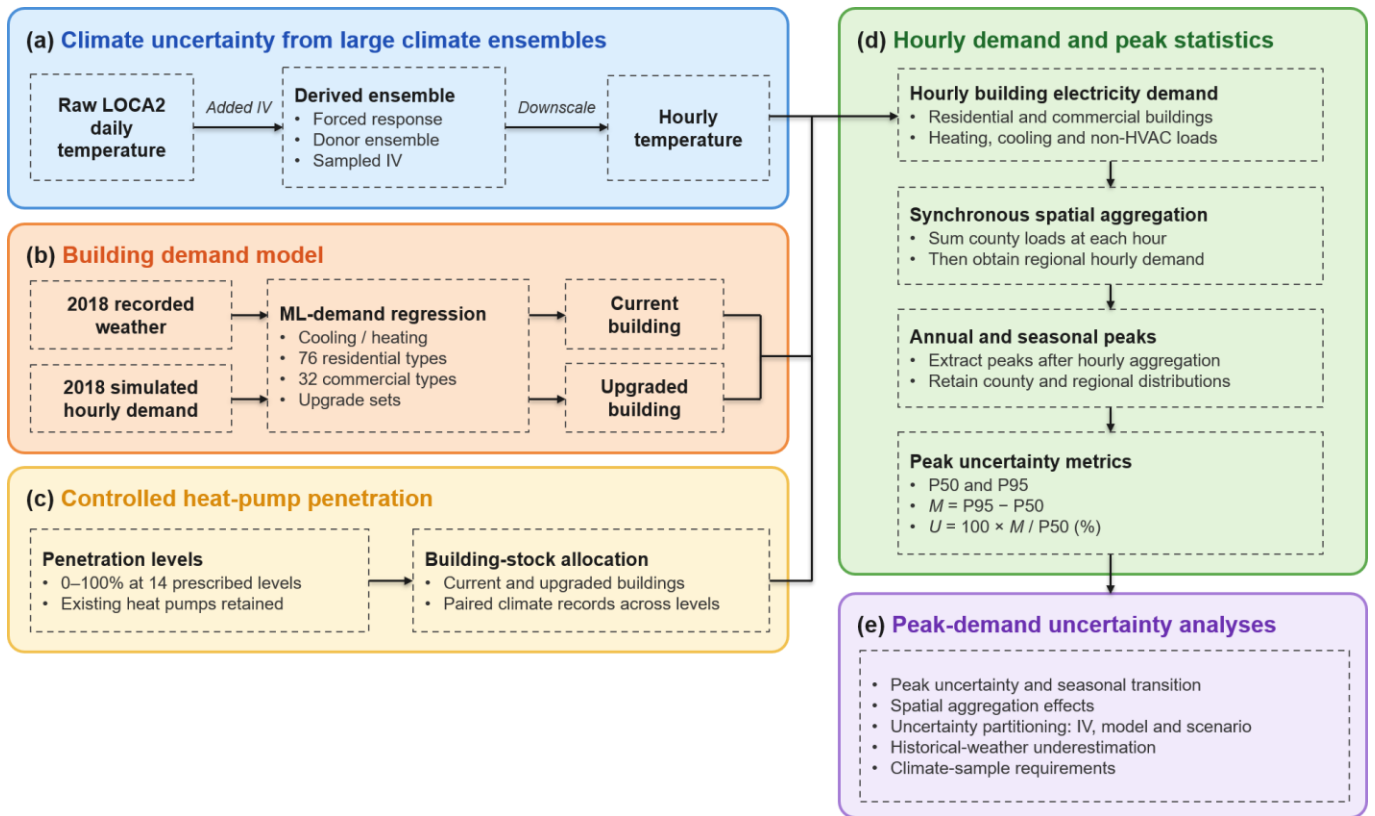
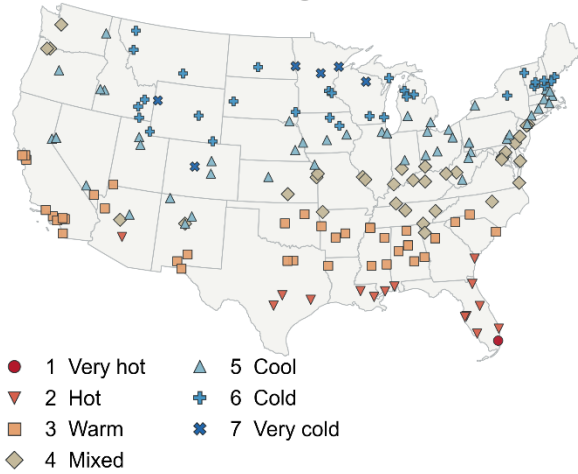


Figure S1. Overview of methodology framework

a Climate-zone coverage



b Study-region membership

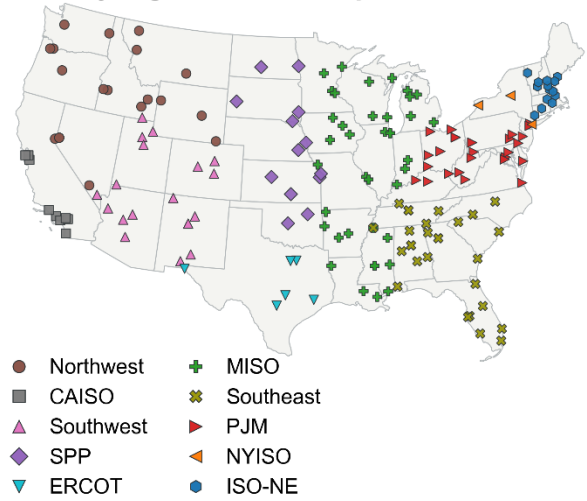
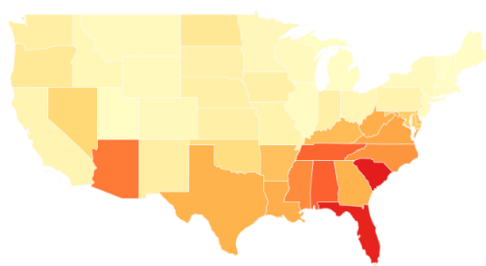


Figure S2. Spatial distribution and climatic coverage of the selected counties across U.S. study regions.

a Initial residential HP share



b Initial commercial HP share

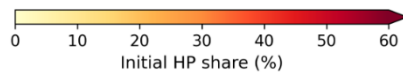
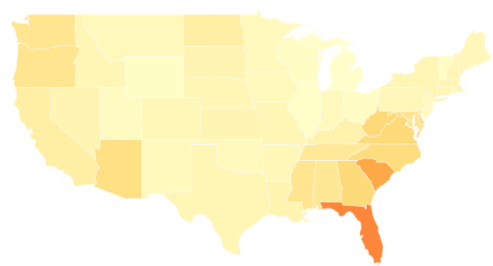


Figure S3. Initial heat-pump penetration in residential (a) and commercial (b) sampled buildings.

Table S1 L1 difference of distribution of buildings in weather zones between selected counties and state total

State	Weather zones	L1 difference (%)	State	Weather zones	L1 difference (%)
AL	2A, 3A	2.32	NC	3A, 4A, 5A	2.16
AR	3A, 4A	1.05	ND	6A, 7A	2.47
AZ	2B, 3B, 4B, 5B	0.83	NE	5A	0.00
CA	2B, 3B, 3C, 4B, 4C 5B, 6B	1.01	NH	5A, 6A	0.70
CO	4B, 5B, 6B, 7B	2.64	NJ	4A, 5A	0.33
CT	5A	0.00	NM	3B, 4B, 5B	0.17
DC	4A	0.00	NV	3B, 5B	2.28
DE	4A	0.00	NY	4A, 5A, 6A	0.36
FL	1A, 2A	1.56	OH	4A, 5A	2.30
GA	2A, 3A, 4A	0.18	OK	3A, 4B	0.74
IA	5A, 6A	0.70	OR	4C, 5B	1.18
ID	5B, 6B	2.15	PA	4A, 5A, 6A	2.04
IL	4A, 5A	1.91	RI	5A	0.00
IN	4A, 5A	0.73	SC	3A	0.00
KS	4A, 5A	2.43	SD	5A, 6A	0.46
KY	4A	0.00	TN	3A, 4A	2.11
LA	2A, 3A	0.51	TX	2A, 2B, 3A, 3B, 4B	2.36
MA	5A	0.00	UT	3B, 5B, 6B	1.55
MD	4A, 5A	0.79	VA	4A	0.00
ME	6A, 7A	4.44	VT	6A	0.00
MI	5A, 6A, 7A	2.65	WA	4C, 5B, 6B	1.78
MN	6A, 7A	0.13	WI	6A, 7A	0.17
MO	4A, 5A	1.91	WV	4A, 5A	1.11
MS	2A, 3A	2.41	WY	5B, 6B, 7B	2.72
MT	6B	0.00			

Table S2 Detailed information of select counties

County	State	Grid region	Res_number	Com_number
Jefferson County	AL	Southeast	1259	1127
Mobile County	AL	Southeast	750	671
Madison County	AL	Southeast	637	378
Montgomery County	AL	Southeast	427	382
Tuscaloosa County	AL	Southeast	363	241
Shelby County	AL	Southeast	344	269
Lee County	AL	Southeast	269	109
Benton County	AR	MISO	405	286
Pulaski County	AR	MISO	748	869
Sebastian County	AR	MISO	231	191
Garland County	AR	MISO	209	177
Yavapai County	AZ	Southwest	465	199
Mohave County	AZ	Southwest	462	178
Maricopa County	AZ	Southwest	6938	3674
Coconino County	AZ	Southwest	266	111
Santa Clara County	CA	CAISO	2692	1852
Los Angeles County	CA	CAISO	14399	10370

San Diego County	CA	CAISO	4898	2968
Orange County	CA	CAISO	4427	3159
Riverside County	CA	CAISO	3386	1833
San Bernardino County	CA	CAISO	2922	2267
Alameda County	CA	CAISO	2443	1877
San Francisco County	CA	CAISO	1586	1404
Ventura County	CA	CAISO	1176	835
Denver County	CO	Southwest	1235	963
El Paso County	CO	Southwest	1096	785
Summit County	CO	Southwest	125	40
Hartford County	CT	ISO-NE	1546	1155
Fairfield County	CT	ISO-NE	1505	992
District of Columbia	DC	PJM	1265	773
New Castle County	DE	PJM	910	500
Sussex County	DE	PJM	534	167
Orange County	FL	Southeast	2100	1423
Miami-Dade County	FL	Southeast	4146	2598
Palm Beach County	FL	Southeast	2779	1273
Hillsborough County	FL	Southeast	2286	1601
Pinellas County	FL	Southeast	2074	1330
Duval County	FL	Southeast	1630	1295
Lee County	FL	Southeast	1552	864
Fulton County	GA	Southeast	1856	1381
DeKalb County	GA	Southeast	1269	794
Chatham County	GA	Southeast	503	483
Hall County	GA	Southeast	288	239
Black Hawk County	IA	MISO	235	131
Polk County	IA	MISO	787	512
Linn County	IA	MISO	391	275
Cerro Gordo County	IA	MISO	92	41
Bonneville County	ID	Northwest	168	132
Ada County	ID	Northwest	691	660
Canyon County	ID	Northwest	295	266
Bannock County	ID	Northwest	138	63
Bonner County	ID	Northwest	101	94
Cook County	IL	MISO	8985	4982
DuPage County	IL	MISO	1478	1019
Madison County	IL	MISO	488	288
St. Clair County	IL	MISO	488	268
Marion County	IN	MISO	1732	1424
Lake County	IN	MISO	869	516
Monroe County	IN	MISO	247	122
Vanderburgh County	IN	MISO	343	279
Johnson County	KS	SPP	962	619
Sedgwick County	KS	SPP	887	773
Ellis County	KS	SPP	54	24
Jefferson County	KY	PJM	1411	1221
Fayette County	KY	PJM	573	412
Orleans Parish	LA	MISO	794	746
East Baton Rouge Parish	LA	MISO	791	675
Caddo Parish	LA	MISO	466	309
Middlesex County	MA	ISO-NE	2557	1436
Worcester County	MA	ISO-NE	1360	731

Montgomery County	MD	PJM	1592	535
Baltimore County	MD	PJM	1390	801
Cumberland County	ME	ISO-NE	580	457
York County	ME	ISO-NE	442	312
Wayne County	MI	MISO	3367	2275
Kent County	MI	MISO	1027	954
Grand Traverse County	MI	MISO	175	138
Marquette County	MI	MISO	142	49
Isabella County	MI	MISO	117	50
Newaygo County	MI	MISO	103	38
St. Louis County	MN	MISO	425	251
Hennepin County	MN	MISO	2147	1093
Ramsey County	MN	MISO	900	529
Crow Wing County	MN	MISO	169	83
St. Louis County	MO	MISO	1810	1112
Jackson County	MO	SPP	1302	1115
Buchanan County	MO	MISO	159	79
Hinds County	MS	MISO	430	393
Harrison County	MS	MISO	370	212
DeSoto County	MS	MISO	264	230
Rankin County	MS	MISO	240	173
Madison County	MS	MISO	169	165
Lee County	MS	MISO	150	90
Lauderdale County	MS	MISO	144	69
Yellowstone County	MT	Northwest	275	183
Missoula County	MT	Northwest	212	115
Wake County	NC	Southeast	1657	1068
Mecklenburg County	NC	Southeast	1732	1397
Cass County	ND	SPP	311	181
Burleigh County	ND	SPP	163	87
Douglas County	NE	SPP	938	703
Lancaster County	NE	SPP	517	412
Hillsborough County	NH	ISO-NE	690	441
Rockingham County	NH	ISO-NE	531	446
Merrimack County	NH	ISO-NE	261	161
Grafton County	NH	ISO-NE	213	85
Carroll County	NH	ISO-NE	165	75
Bergen County	NJ	PJM	1464	1122
Essex County	NJ	PJM	1297	1073
Middlesex County	NJ	PJM	1233	814
Bernalillo County	NM	Southwest	1189	1059
Dona Ana County	NM	Southwest	348	185
Santa Fe County	NM	Southwest	295	192
Sandoval County	NM	Southwest	223	113
San Juan County	NM	Southwest	205	84
Otero County	NM	Southwest	128	62
Washoe County	NV	Northwest	774	588
Clark County	NV	Southwest	3566	1783
Douglas County	NV	Northwest	98	37
Carson City	NV	Northwest	97	78
Lyon County	NV	Northwest	93	40
Nye County	NV	Northwest	90	32
Erie County	NY	NYISO	1739	920

New York County	NY	NYISO	3578	1137
Oneida County	NY	NYISO	429	310
Cuyahoga County	OH	PJM	2552	1586
Hamilton County	OH	PJM	1557	1314
Franklin County	OH	PJM	2230	1617
Montgomery County	OH	PJM	1048	945
Summit County	OH	PJM	1011	809
Lucas County	OH	PJM	835	745
Stark County	OH	PJM	684	553
Oklahoma County	OK	SPP	1363	1527
Tulsa County	OK	SPP	1142	1148
Deschutes County	OR	Northwest	342	228
Multnomah County	OR	Northwest	1371	1291
Washington County	OR	Northwest	907	548
Allegheny County	PA	PJM	2432	2023
Philadelphia County	PA	PJM	2768	1924
Lancaster County	PA	PJM	851	479
Westmoreland County	PA	PJM	693	465
Berks County	PA	PJM	678	339
Providence County	RI	ISO-NE	1088	908
Greenville County	SC	Southeast	831	955
Horry County	SC	Southeast	800	644
Minnehaha County	SD	SPP	314	159
Pennington County	SD	SPP	193	110
Yankton County	SD	SPP	40	20
Davidson County	TN	Southeast	1217	1173
Shelby County	TN	Southeast	1664	1355
Knox County	TN	Southeast	820	795
Hamilton County	TN	Southeast	639	513
Rutherford County	TN	Southeast	451	290
Montgomery County	TN	Southeast	316	149
Williamson County	TN	Southeast	305	191
Dallas County	TX	ERCOT	4028	3238
Harris County	TX	ERCOT	6967	4862
Tarrant County	TX	ERCOT	3055	2328
Bexar County	TX	ERCOT	2803	2005
Travis County	TX	ERCOT	1961	1421
El Paso County	TX	ERCOT	1179	1050
Salt Lake County	UT	Southwest	1555	1364
Utah County	UT	Southwest	654	483
Washington County	UT	Southwest	258	122
Cache County	UT	Southwest	162	81
Summit County	UT	Southwest	112	60
Fairfax County	VA	PJM	1697	551
Virginia Beach city	VA	PJM	752	417
Chittenden County	VT	ISO-NE	279	161
Windsor County	VT	ISO-NE	141	36
Spokane County	WA	Northwest	856	831
King County	WA	Northwest	3644	2036
Milwaukee County	WI	MISO	1722	1251
Dane County	WI	MISO	920	635
Oneida County	WI	MISO	126	56
Kanawha County	WV	PJM	381	377

Cabell County	WV	PJM	192	199
Monongalia County	WV	PJM	182	64
Raleigh County	WV	PJM	149	134
Harrison County	WV	PJM	130	58
Laramie County	WY	Northwest	172	87
Natrona County	WY	Northwest	147	91
Lincoln County	WY	Northwest	37	11

Table S3 Aggregated type of all residential buildings

Heating	Cooling	Enhanced Insulation
ASHP	ASHP	FALSE
ASHP	ASHP	TRUE
Electric Baseboard	AC	FALSE
Electric Baseboard	AC	TRUE
Electric Baseboard	None	FALSE
Electric Baseboard	None	TRUE
Electric Baseboard	Room AC	FALSE
Electric Baseboard	Room AC	TRUE
Electric Baseboard	Shared Cooling	FALSE
Electric Baseboard	Shared Cooling	TRUE
Electric Boiler	AC	FALSE
Electric Boiler	AC	TRUE
Electric Boiler	None	FALSE
Electric Boiler	None	TRUE
Electric Boiler	Room AC	FALSE
Electric Boiler	Room AC	TRUE
Electric Boiler	Shared Cooling	FALSE
Electric Boiler	Shared Cooling	TRUE
Electric Furnace	AC	FALSE
Electric Furnace	AC	TRUE
Electric Furnace	None	FALSE
Electric Furnace	None	TRUE
Electric Furnace	Room AC	FALSE
Electric Furnace	Room AC	TRUE
Electric Furnace	Shared Cooling	FALSE
Electric Furnace	Shared Cooling	TRUE
Electric Wall Furnace	AC	FALSE
Electric Wall Furnace	AC	TRUE
Electric Wall Furnace	None	FALSE
Electric Wall Furnace	None	TRUE
Electric Wall Furnace	Room AC	FALSE
Electric Wall Furnace	Room AC	TRUE
Electric Wall Furnace	Shared Cooling	FALSE
Electric Wall Furnace	Shared Cooling	TRUE
Fuel Boiler	AC	FALSE
Fuel Boiler	AC	TRUE
Fuel Boiler	None	FALSE
Fuel Boiler	None	TRUE
Fuel Boiler	Room AC	FALSE
Fuel Boiler	Room AC	TRUE

Fuel Boiler	Shared Cooling	FALSE
Fuel Boiler	Shared Cooling	TRUE
Fuel Furnace	AC	FALSE
Fuel Furnace	AC	TRUE
Fuel Furnace	None	FALSE
Fuel Furnace	None	TRUE
Fuel Furnace	Room AC	FALSE
Fuel Furnace	Room AC	TRUE
Fuel Furnace	Shared Cooling	FALSE
Fuel Furnace	Shared Cooling	TRUE
Fuel Wall/Floor Furnace	AC	FALSE
Fuel Wall/Floor Furnace	AC	TRUE
Fuel Wall/Floor Furnace	None	FALSE
Fuel Wall/Floor Furnace	None	TRUE
Fuel Wall/Floor Furnace	Room AC	FALSE
Fuel Wall/Floor Furnace	Room AC	TRUE
Fuel Wall/Floor Furnace	Shared Cooling	FALSE
Fuel Wall/Floor Furnace	Shared Cooling	TRUE
MSHP	MSHP	FALSE
MSHP	MSHP	TRUE
None	AC	FALSE
None	AC	TRUE
None	None	FALSE
None	None	TRUE
None	Room AC	FALSE
None	Room AC	TRUE
None	Shared Cooling	FALSE
None	Shared Cooling	TRUE
Shared Heating	AC	FALSE
Shared Heating	AC	TRUE
Shared Heating	None	FALSE
Shared Heating	None	TRUE
Shared Heating	Room AC	FALSE
Shared Heating	Room AC	TRUE
Shared Heating	Shared Cooling	FALSE
Shared Heating	Shared Cooling	TRUE

Table S4 Aggregated type of all commercial buildings

Heating	Cooling
District Heating	ACC
District Heating	DX
District Heating	District
District Heating	WCC
ASHP	ASHP
Electric Resistance	ACC
Electric Resistance	DX
Electric Resistance	District
Electric Resistance	Evaporative Cooling
Electric Resistance	None
Electric Resistance	WCC
Electricity Furnace	DX
GSHP	GSHP

WSHP	WSHP
FuelOil Boiler	ACC
FuelOil Boiler	DX
FuelOil Boiler	WCC
FuelOil Furnace	DX
FuelOil Furnace	Evaporative Cooling
FuelOil Furnace	None
NaturalGas Boiler	ACC
NaturalGas Boiler	DX
NaturalGas Boiler	District
NaturalGas Boiler	WCC
NaturalGas Furnace	DX
NaturalGas Furnace	Evaporative Cooling
NaturalGas Furnace	None
Propane Boiler	DX
Propane Boiler	WCC
Propane Furnace	DX
Propane Furnace	Evaporative Cooling
Propane Furnace	None

Table S5 Technology upgrade packages in ResStock and ComStock used in this study

Building	Version	Package
ResStock	2024.2	Baseline
ResStock	2024.2	ENERGY STAR Air-to-Air Heat Pump With Electric Backup
ResStock	2024.2	Ultra High Efficiency Air-to-Air Heat Pump With Electric Backup (Sensitivity test)
ComStock	2023	Baseline
ComStock	2023	HP-RTU and ASHP-Boiler

Supplementary Note 2 Building demand regression and validation

S2.1 Regression targets and training data

We fitted separate multilayer perceptron (MLP) models for heating and cooling electricity consumption for each county, building group, and equipment package. The building classifications and technology packages are described in Supplementary Note 1 and Tables S3–S5. Within each group, the simulated electricity-consumption records of the constituent buildings were summed at each 15-min interval. The regression target is therefore the group total, rather than an average building profile. Empty county–group combinations were skipped. An end use with zero consumption throughout the training year was represented by zero output, and its R^2 was not reported.

The training targets were constructed from the 2018 ResStock and ComStock simulations. Residential heating combines the heating and associated fan/pump end uses with electric heat-pump backup; cooling includes the cooling and cooling fan/pump end uses. Commercial heating combines heating and heat-recovery electricity, and commercial cooling combines cooling and heat-rejection electricity. The corresponding county weather record supplies outdoor dry-bulb temperature. Hourly weather observations were linearly interpolated to the 15-min simulation timestamps.

S2.2 Predictors and model training

Nine predictors describe the temperature response and its dependence on time: outdoor dry-bulb temperature T_t ; the mean temperature over the preceding 24 h; the mean 15-min temperature increment over the preceding 24 h; $\sin(2\pi h/24)$ and $\cos(2\pi h/24)$; their respective products with T_t ; season; and weekend status. The two history variables use a trailing 96-record window shifted by one 15-min interval. Specifically, the temperature-history feature averages T_{t-1} through T_{t-96} , and the trend feature averages the preceding 96 values of $\Delta T_t = T_t - T_{t-1}$. At the start of the record, each rolling average uses the available preceding observations; the initial missing value is filled from the next available rolling value.

The hour h is the integer hour on the fixed UTC–5 axis. Seasons are entered as integer codes 1–4 for DJF, MAM, JJA, and SON, respectively. Weekend status is a binary indicator derived from the county-local date. These predictors retain short-term temperature history and recurring temporal patterns while allowing the temperature response to vary over the day.

For each regression, observations were assigned to ten temperature-quantile strata, dropping duplicate quantile boundaries when necessary. A stratified random split allocated 90% of the 15-min records to training and 10% to an external test set. This procedure preserves similar temperature distributions in the two subsets.

To emphasize high-load conditions, training observations with target consumption strictly above the training-set 95th percentile were duplicated once. This increases their representation in model fitting while leaving the external test set unchanged. The final MLP has hidden layers of 128 and 16 units with ReLU activation, Adam optimization, and an L2 regularization parameter of 10^{-4} . Training was limited to 200 iterations and used early stopping with a 20% internal validation fraction and a patience of 20 iterations. The internal validation subset is drawn from the augmented training records and is distinct from the external 10% test set. Table S6 summarizes these settings.

Table S6. Configuration of the principal heating and cooling demand regressions.

Setting	Implementation
Training reference	2018 building simulations; group-total electricity at 15-min resolution
Model indexing	County $\times$ building group $\times$ equipment package $\times$ heating or cooling
Predictors	Nine temperature, temperature-history, diurnal, season, and weekend variables
External split	90% training / 10% test; random split stratified by up to ten temperature quantiles
Random seed	51 for splitting and MLP initialization

Setting	Implementation
Scaling	Separate MinMaxScaler transformations for predictors and target; fitted on training records
Peak emphasis	Duplicate once each training record above the target's training-set 95th percentile
Hidden layers and activation	128 and 16 units; ReLU
Optimizer and regularization	Adam; L2 parameter $\alpha = 10^{-4}$
Training stop	At most 200 iterations; early stopping enabled
Internal validation	20% of augmented training records; no improvement for 20 iterations
Absent end uses	Zero-output representation; undefined R^2 excluded from summaries
Evaluation resolutions	15-min external test; hourly reconstruction after summing interval consumption

S2.3 Exploratory feature sensitivity

further verified the contribution of each input feature using permutation analysis of the contribution from each variable on peak estimation, taking Dallas as an example (Fig. S4). For each feature, its values were randomly permuted across the full simulation-year input series while the other inputs were held fixed. Predictions were aggregated to hourly consumption, and the annual peak was compared with the reference peak using symmetric absolute percentage error. The feature-specific change, ΔSMAPE , is the error after permutation minus the error with the unpermuted inputs, expressed in percentage points. Result shows that all input features contribute to at least 5% improvement on Symmetric Mean Absolute Percentage Error of either cooling and heating hourly peak.

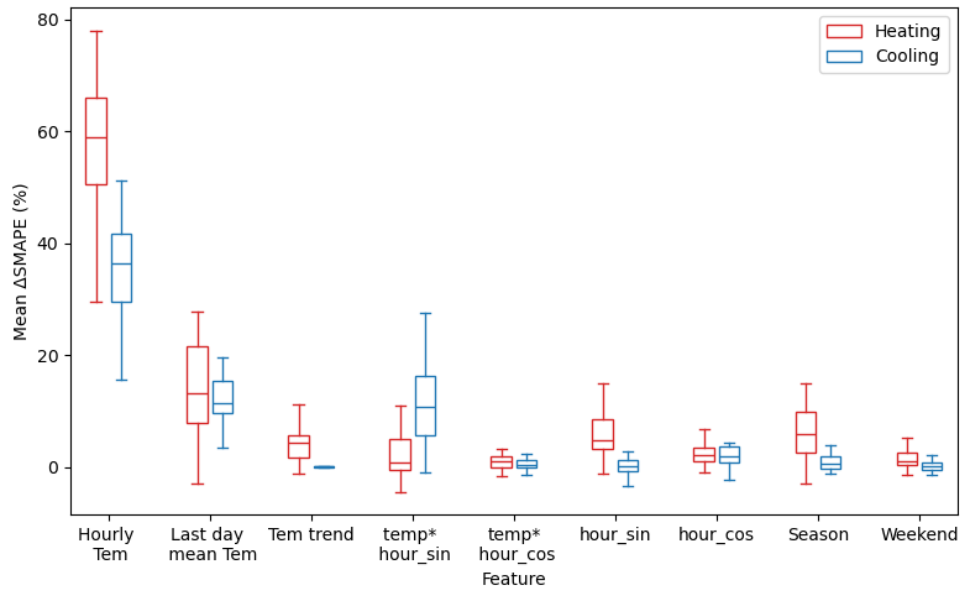


Figure S4. Exploratory feature sensitivity in Dallas. Boxes show the distribution across residential building groups of the mean increase in annual-peak SMAPE after permuting one predictor, averaged over ten permutations. Heating and cooling results are shown separately. The vertical axis is ΔSMAPE in percentage points. This auxiliary analysis uses a 64-16 MLP; the principal demand regressions use the configuration in Table S6.

S2.4 Hourly reconstruction and peak error

We distinguish performance on the external 15-min test records from reconstruction of the full simulation year. Figures S5 and S6 show the distributions of hourly R^2 for residential and commercial demand, respectively. Across the ten grid regions, the plotted median R^2 values range approximately from 0.95 to 0.98 for residential heating and from 0.98 to 0.99 for residential cooling. The corresponding commercial medians range approximately from 0.94 to 0.97 for heating and from 0.97 to 0.99 for cooling.

Figures S7 and S8 show the distributions of symmetric signed percentage error (SSPE) in annual heating, cooling, and total-demand peaks for residential and commercial buildings, respectively. Across the grid regions, the plotted residential median SSPEs are approximately 0% for heating, 0% to 0.8% for cooling, and -1% to 0% for total demand. The corresponding commercial medians are approximately 0% for heating, -2.1% to 1.9% for cooling, and -0.6% to 0.6% for total demand. Negative SSPE values indicate underestimation of the annual peak relative to the simulation reference, whereas positive values indicate overestimation.

S2.5 Temperature extremes and comparison with other studies

We further conduct an out-of-distribution (OOD) test to assess model reliability under unseen hot extremes, as future temperatures may extend beyond the range covered by the training data. Specifically, we exclude the hottest 2% of temperature hours from model training and then evaluate model performance on these withheld out-of-bound conditions, focusing on cooling-peak prediction. As shown in Fig. S9, the median symmetric signed percentage error of cooling-peak estimates stays within $\pm 10\%$ across all grid regions, suggesting no systematic bias toward over- or underprediction under OOD extremes. While the error spread is moderately larger for OOD cases in some regions, the overall magnitude remains limited, with most errors staying below about 10%. Together, these results indicate that our model retains good extrapolative skill for cooling peaks under extreme heat conditions.

We also compared the modeled demand changes with prior building-energy studies as a check on their plausibility. Previous research on the effects of climate change on total residential electricity peak demand projects increases of 4%-8% by 2060 in California and the U.S. Southwest^{3,4}, which is consistent with our corresponding estimate of 3%-9%. In addition, a ResStock-based study for ERCOT examining peak-demand impacts of base-efficiency heat pump electrification found that winter peak demand could rise to 25% above the historical summer peak under a scenario in which heat pumps replace all existing non-electric and fuel-based heating systems⁵, while homes with electric-resistance heating remain unchanged. Because our main scenario assumes random heat-pump adoption across both electric-resistance and fuel-heating households, we conducted an additional ERCOT sensitivity analysis in which heat pumps are adopted only by current non-electric-heating users. Under this comparable setup, our model projects that the winter peak extreme would rise to 17% above the previous summer peak; this somewhat lower estimate may partly reflect our assumption of a higher heat-pump heating seasonal performance factor (HSPF; 9.2 versus 8.5 in the reference study). Taken together, these comparisons suggest that our modeled estimates of climate-change and technology-diffusion impacts fall within the plausible range reported in the existing literature.

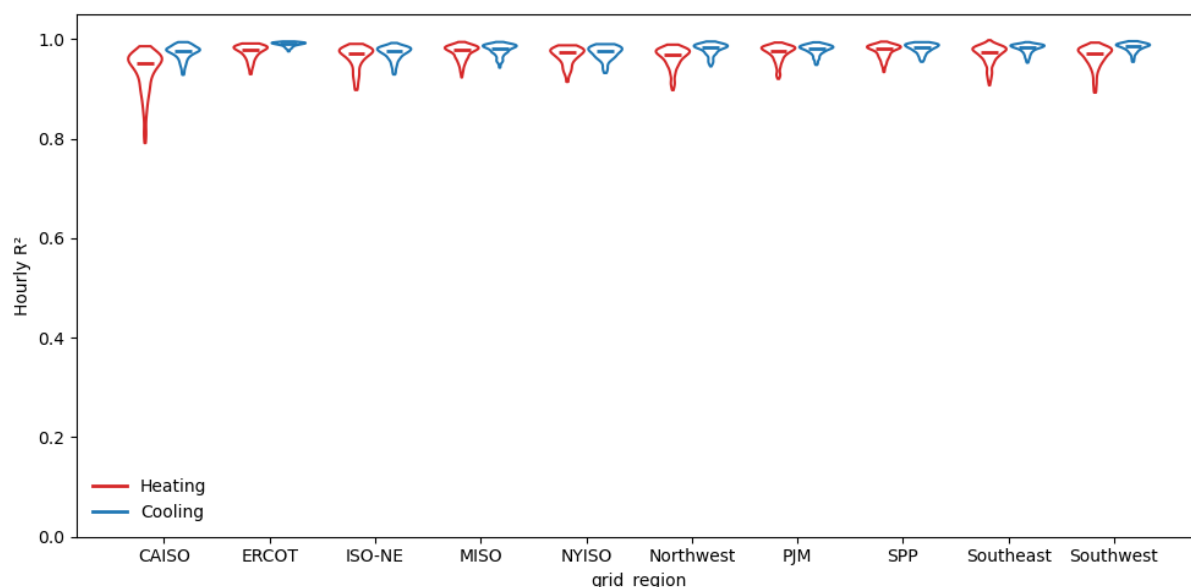


Figure S5 Violin plot of the distribution of R^2 of MLP building regression for residential buildings. *X-axis indicate different regions. Each violin includes n_{county} (county_number in region) * 76 (aggregated residential type)*3 (upgrades packages) points for its R^2 estimation. The violin plots don't include outliers.*

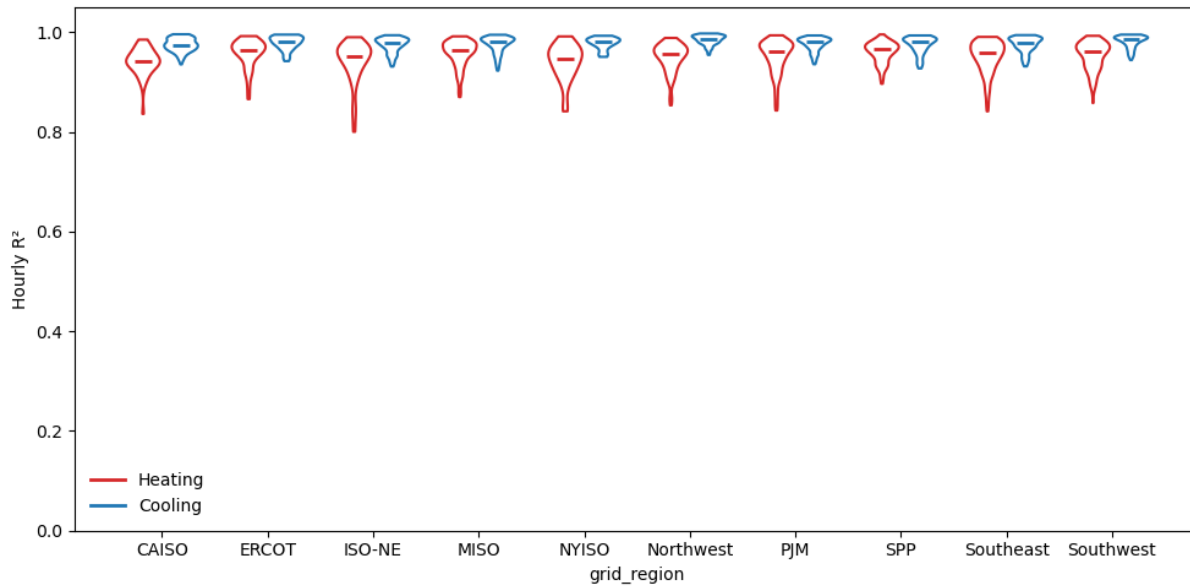


Figure S6 Violin plot of the distribution of R^2 of MLP building regression for commercial buildings. *X-axis indicate different regions. Each violin includes n_{county} (county_number in region) * 32 (aggregated residential type)*2 (upgrades packages) points for its R^2 estimation. The violin plots don't include outliers.*

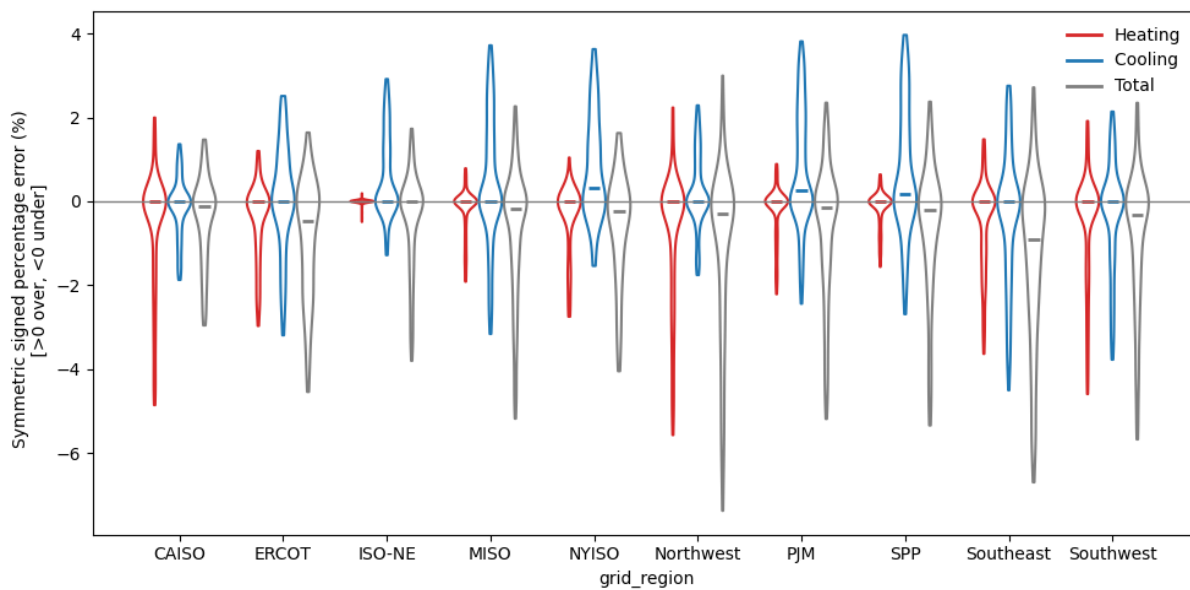


Figure S7 Violin plot of the distribution of Symmetric Signed Percentage Error (SSPE) of MLP building regression for residential buildings. *X-axis indicate different regions. Each violin includes n_{county} (county_number in region) * 76 (aggregated residential type)*3 (upgrades packages) points for its SSPE estimation. Different boxes indicate the SSPE for heating, cooling and total peak. The violin plots don't include outliers.*

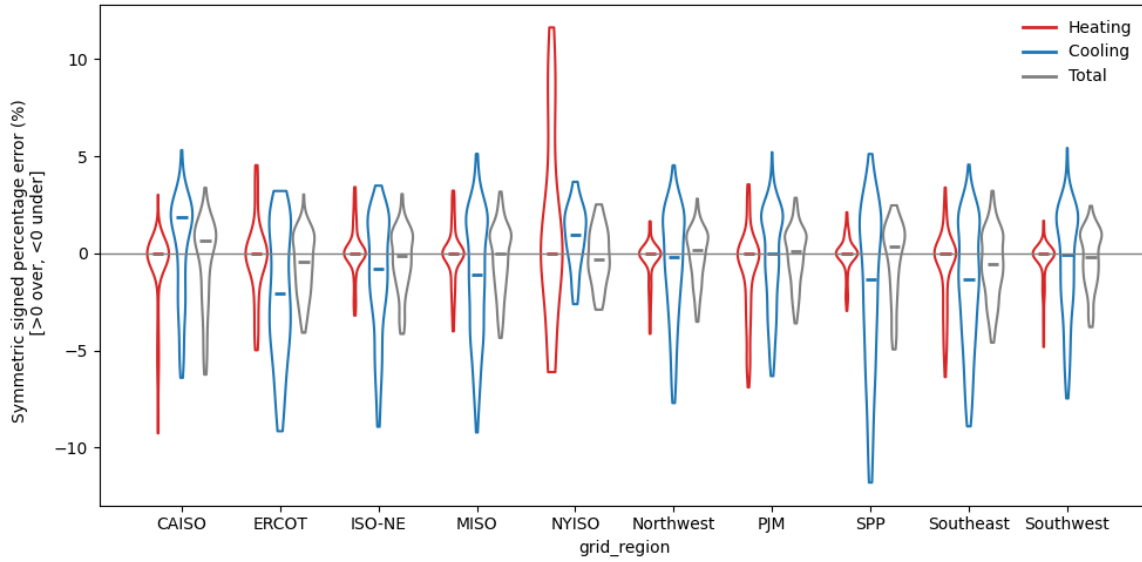


Figure S8 Violin plot of the distribution of Symmetric Signed Percentage Error (SSPE) of MLP building regression for commercial buildings. *X-axis indicate different regions. Each violin includes n_{county} (county_number in region) * 32 (aggregated commercial type) * 4 (upgrades packages) points for its SSPE estimation. Different boxes indicate the SSPE for heating, cooling and total peak. The violin plots don't include outliers.*

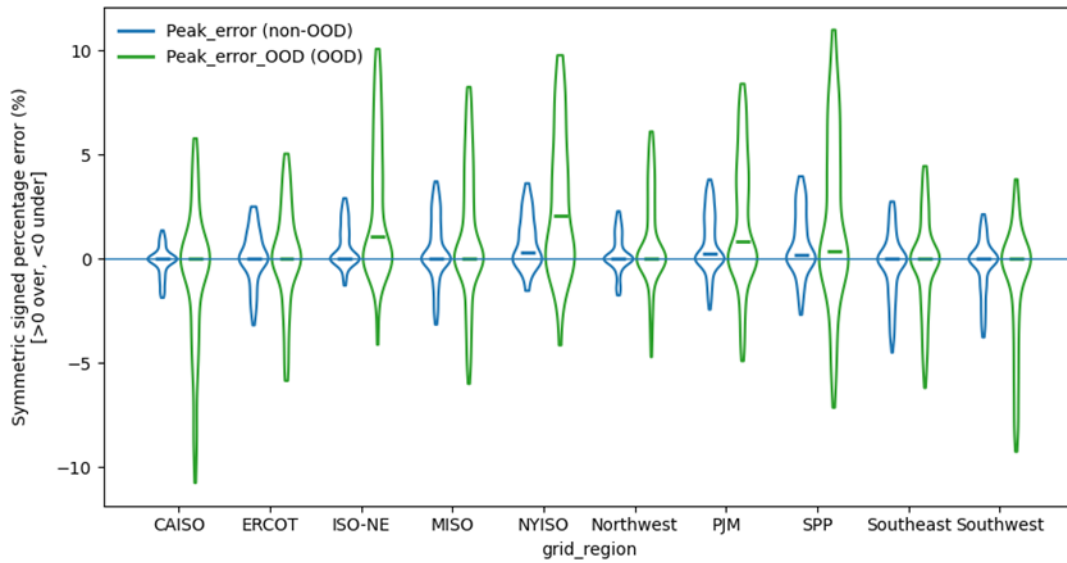


Figure S9 Comparison between the original trainset and without top 2% hottest temperature on residential cooling peak estimation. *X-axis indicate different regions. Each violin includes n_{county} (county_number in region) * 76 (aggregated commercial type) * 3 (upgrades packages) points for its SSPE estimation.*

Supplementary Note 3 Climate ensemble construction and hourly reconstruction

S3.1 Climate ensemble construction and sampling

The climate inputs combine LOCA2 daily temperature projections from four climate models and three emissions scenarios. The available model–scenario combinations are CanESM5, ACCESS-ESM1-5, and MPI-ESM1-2-LR under SSP2-4.5, SSP3-7.0, and SSP5-8.5, together with CESM2-LENS under SSP3-7.0.

Table S7. Ensemble sizes for climate model and emission scenario in LOCA2 raw dataset.

Climate model	Raw members used SSP2-4.5	Raw members used SSP3-7.0	Raw members used SSP5-8.5
CanESM5	7	7	7
CESM2-LENS	—	10	—
ACCESS-ESM1-5	5	5	5
MPI-ESM1-2-LR	9	9	9

We separated daily temperature into a forced response and an internal-variability component. The forced response was estimated separately for each county and model–scenario combination. For each calendar date, daily maximum and minimum temperatures were averaged separately across the available ensemble members. For each target year, the resulting ensemble-mean series was used to calculate a day-of-year climatology over a centered five-year window, using the available years at the endpoints. This seasonal cycle was then fitted with an intercept and the first three Fourier harmonics. Repeating this procedure for successive target years produced an evolving forced response for daily maximum and minimum temperature. Calculations used a 365-day calendar, with 29 February omitted.

Internal variability was extracted from the ten CESM2-LENS members under SSP3-7.0. For each county, member, and calendar date, we subtracted the CESM2-LENS forced response, estimated using the same procedure, from the member’s daily temperature. The resulting residuals describe departures from the CESM2-LENS forced response and provide the donor sequences used to construct the synthetic ensembles.

For each of the other nine model–scenario combinations, we generated ten synthetic trajectories by adding sampled CESM2-LENS residuals to that combination’s own forced response. Sampling was performed in blocks of two target years. For each block, one CESM2-LENS member and one donor year were selected, and that donor year’s daily residual sequence was mapped by month and day to both target years. The same selection was applied across counties and jointly to maximum and minimum temperature. Thus, each synthetic trajectory combines the target model–scenario’s evolving forced response with a spatially coordinated CESM2-LENS weather-residual sequence. Residuals were added without amplitude rescaling. The CESM2-LENS SSP3-7.0 combination retained its ten original member trajectories directly

The main experiment uses the five calendar years 2058–2062 to represent climate conditions around 2060. Ten combinations, ten trajectories per combination, and five annual records per trajectory yield 500 annual weather samples nested within 100 trajectories. The pool contains 150 records under SSP2-4.5, 200 under SSP3-7.0, and 150 under SSP5-8.5.

S3.2 Temperature distributions and uncertainty representation

Figure S10 illustrates the temperature distribution across climate models and emission scenarios, taking ISO-NE and ERCOT as an example. Annual mean and maximum temperatures generally separate more clearly by climate model and emissions scenario as the century progresses, whereas annual minimum temperatures retain substantial overlap among realizations. The ordering of regional responses need not be identical across regions: for example, the relative warming of CESM2-LENS and ACCESS-ESM1-5 differs between the two examples.

Figure S11 shows the uncertainty partitioning results for temperature from internal variability, climate models and emission scenarios. Results show that for max and mean temperature, the uncertainty from climate model and emission scenarios tend to increase, while internal variability tend to keep as the major uncertainty contribution for min temperature.

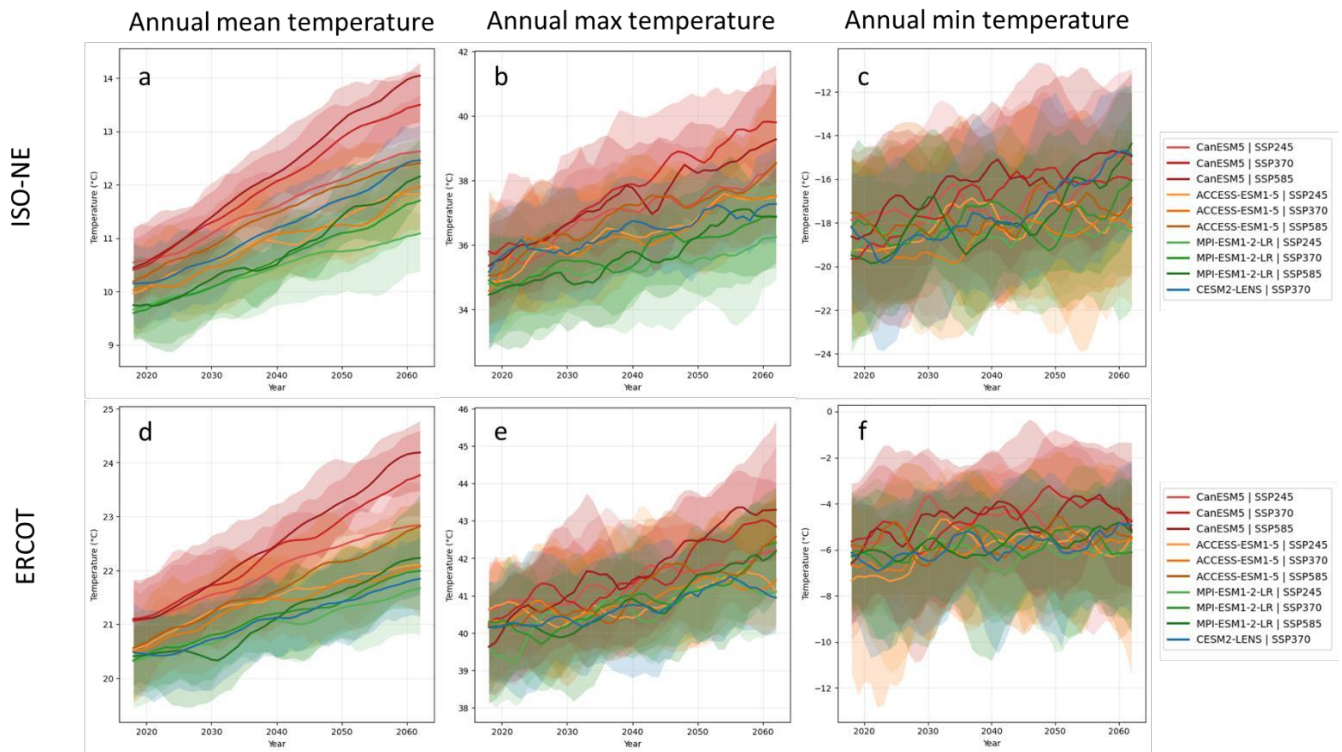


Figure S10. Temperature distribution across models and scenarios in the derived climate ensembles from LOCA2, taken ISO-NE and ERCOT region as an example. *The line plots indicate forced response in the annual mean temperature plots (a&d), and median across ensemble members in others. Band plots indicate the distribution across all internal variability members.*

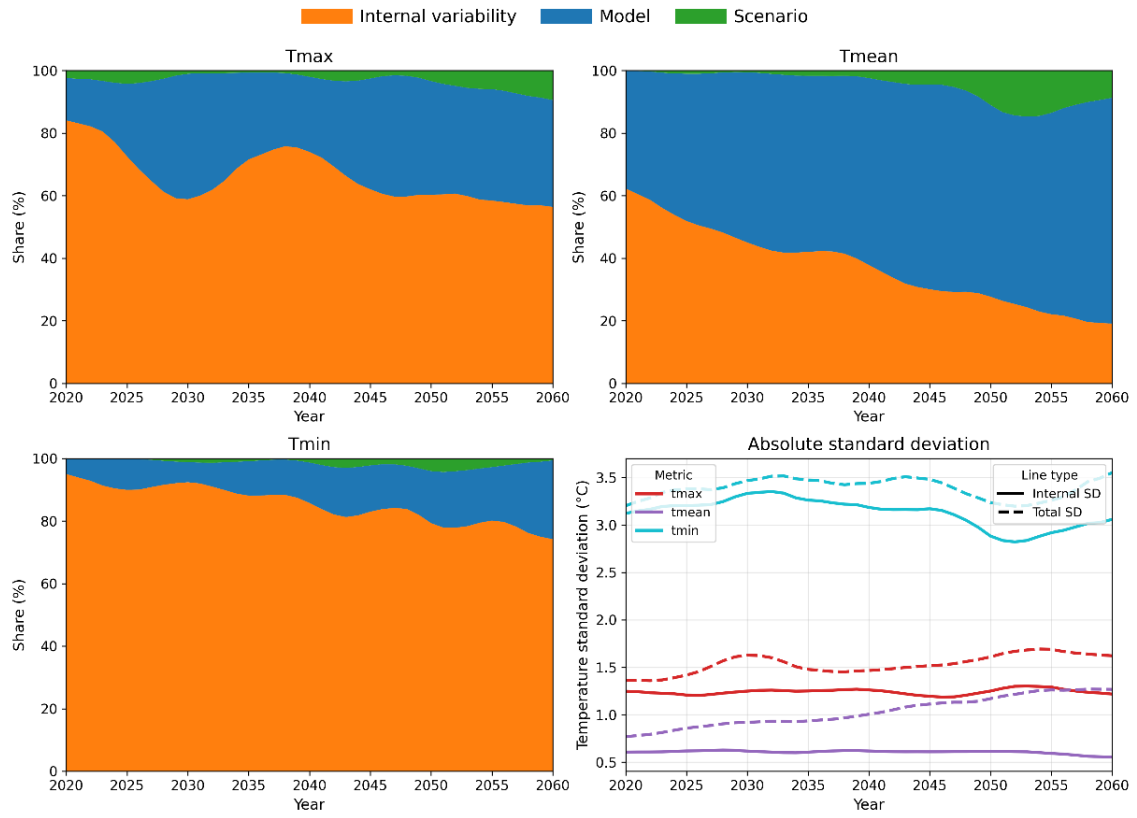


Figure S11. Uncertainty partitioning of temperature from internal variability, climate model and emission scenario, ISO-NE example. (a-c) contribution of total variance from internal variability, climate model and emission scenario for annual max, mean and min temperature; (d) Absolute standard deviation in Celsius degree for max, mean and min temperature across all realizations (dashed line) or from internal variability (solid line)..

S3.3 Daily-to-hourly temperature reconstruction

To match the temporal resolution required by the downstream energy system analysis, we developed a county-specific daily-to-hourly temperature downscaling model and applied it to LOCA2 large-ensemble climate projections. For each county, both the observational training data and the climate projection inputs were extracted using the nearest grid point to the county centroid. ERA5 hourly temperature was mapped to each county by nearest-neighbor matching and used as the observational reference, while LOCA2 daily temperature was matched to the same county locations using the nearest LOCA2 grid cell. This design ensured that both training and inference were carried out at a consistent county-level spatial representation.

For model fitting, the ERA5 record spans 1980-2024. Daily minimum and maximum temperatures are calculated from the hourly reference series. Models are fitted using 1980-2015 and evaluated on the held-out years 2016-2024. The twelve predictors comprise the current day's minimum and maximum temperature, the previous and following days' extrema, and sine/cosine encodings of month, day of week, and UTC hour. Predictor standardization is fitted on training records only. At the boundaries of a record, missing neighboring-day extrema are replaced by the current day's values. Use of the following day is appropriate for reconstruction of a supplied daily climate sequence.

Each fitted model is a random-forest regressor with 400 trees, unrestricted tree depth, and a minimum leaf size of one. The prediction target is the hourly residual relative to the daily midpoint μ , calculated as the average of the prescribed minimum and maximum. For predictor vector X and fitted residual function f , the preliminary temperature at hour h of day d is

$$Z_{d,h} = \mu_d + f(X_{d,h}).$$

A deterministic affine transformation then constrains the 24 reconstructed hourly values within each UTC day to the prescribed daily extrema:

$$\hat{T}_{d,h} = T_{min,d} + (T_{max,d} - T_{min,d}) \times \frac{Z_{d,h} - \min_k Z_{d,k}}{\max_k Z_{d,k} - \min_k Z_{d,k}}$$

Here, k indexes the 24 hours of day d . This transformation retains the ordering of the preliminary hourly values while enforcing the daily minimum and maximum. If the preliminary within-day range is numerically negligible, a deterministic fallback profile is used to satisfy the prescribed extrema. A day with equal prescribed minimum and maximum temperatures has a constant reconstructed profile. Agreement with the supplied daily extrema is therefore imposed by construction; the remaining validation concerns the hourly trajectory, its distribution, and the timing of its extrema.

S3.4 Overall reconstruction performance

We evaluated the county-specific daily-to-hourly temperature downscaling model using both pointwise and distributional metrics. Across counties, the model achieves a mean hourly MAE of 0.8419 °C, mean hourly RMSE of 1.2910 °C, and mean hourly R^2 of 0.9796, together with a mean KS statistic of 0.0087. These results indicate that the model reconstructs hourly temperature accurately from daily inputs while preserving the overall temperature distribution. In addition, the mean timing error for the daily maximum temperature is 1.18 h, and the mean fraction of days for which the maximum hour is recovered within 1 h is 72.4%, further supporting the model's ability to reproduce key diurnal structure relevant to downstream energy-demand analysis.

Relative to published hourly temperature reconstruction studies, the model performs competitively and, in several cases, favorably. The mean hourly MAE is lower than that reported by Felber et al⁶. for a generic diurnal temperature model, and the mean hourly RMSE is lower than the weighted mean RMSE reported by Carrión et al⁷., while the mean R^2 is at the same ~ 0.98 level reported in that study. The small KS statistic also indicates strong distributional fidelity and compares favorably with recent downscaling-based hourly weather generation methods such as that of Shen et al⁸. Overall, these comparisons suggest that the model provides good reconstruction skill while remaining compatible with the practical constraint of using only daily temperature inputs from the LOCA2 large ensembles.

Table S8. Test-period performance of daily-to-hourly temperature reconstruction across 167 fitted models.

Metric	Mean	Minimum	Median	Maximum
Hourly MAE (°C)	0.8419	0.4669	0.8650	1.3820
Hourly RMSE (°C)	1.2910	0.7052	1.3232	2.1221
Hourly R^2	0.9796	0.9235	0.9812	0.9916
KS statistic	0.0087	0.0025	0.0079	0.0366
KS p-value	0.1716	2.74E-46	0.0145	0.9628
Maximum-hour MAE (h)	1.1775	0.3980	1.1340	2.4330
Minimum-hour MAE (h)	2.2878	0.7470	2.2570	3.7100
Fraction within 1 h (maximum)	0.7241	0.4790	0.7330	0.9230
Fraction within 1 h (minimum)	0.5798	0.3680	0.5850	0.9050

These diagnostics evaluate reconstruction of historical ERA5 hourly temperatures from their own daily extrema. They support the use of the reconstructed hourly sequence within that setting, while providing no direct validation of future climate-model bias or a changing diurnal temperature response. Exact preservation of daily extrema should be interpreted separately from the hourly and extremum-timing skill reported above.

S3.5 Representative county-level validation across climate regimes

Table S9 retains the representative county examples from the original validation: New York, Dallas, Los Angeles, Maricopa, Clark, and King counties. Together they span northeastern coastal urban, hot subtropical, Mediterranean coastal, hot desert, and marine west-coast conditions. These examples complement the aggregate distribution by showing both temperature-magnitude and daily-maximum-timing performance at individual locations.

Table S9. Representative county-level reconstruction performance over 2016–2024.

County	Climate regime	Hourly MAE (°C)	Hourly RMSE (°C)	Hourly R ²	KS statistic	Max-hour MAE (h)	Fraction within 1 h (max)
New York, NY	Humid continental / coastal urban	0.8351	1.2669	0.9828	0.0057	1.589	0.606
Dallas, TX	Hot subtropical inland	0.8827	1.3686	0.9773	0.0127	0.856	0.798
Los Angeles, CA	Mediterranean coastal	0.5659	0.8152	0.9766	0.0052	0.788	0.763
Maricopa, AZ	Hot desert	0.6282	0.9582	0.9881	0.0048	0.449	0.904
Clark, NV	Hot desert	0.5796	0.9023	0.9916	0.0066	0.424	0.919
King, WA	Marine west coast	0.6450	0.9462	0.9779	0.0084	0.959	0.820

Hourly MAE is below 0.9 °C in all six examples, with R² ranging from 0.9766 to 0.9916. New York and Dallas have hourly R² values of 0.9828 and 0.9773, respectively. Maricopa and Clark combine hourly MAE below 0.65 °C with daily-maximum timing errors below 0.45 h. King County has an hourly MAE of 0.6450 °C and a within-one-hour maximum-timing fraction of 0.820. The variation among these examples shows why the aggregate temperature-error metrics and the timing metrics are both retained.

S3.6 Propagation of hourly reconstruction error to annual demand peaks

To assess propagation to demand, we compare annual residential heating and cooling peaks under baseline equipment conditions using original ERA5 hourly temperatures and reconstructed ERA5 temperatures over 2016–2024 (Fig. S12). Heating and cooling profiles are summed across building groups within each county at each hour before their annual maxima are calculated. R^2 and MAPE are then computed separately for each of the 48 contiguous states and the District of Columbia, pooling the available county–year peak pairs within that jurisdiction.

Across the 49 jurisdiction-level scores, the retained figure shows median R^2 values of approximately 0.995 for heating and 0.998 for cooling, and median MAPE values of approximately 1.9% and 1.3%, respectively. The displayed interquartile ranges are about 1.4–2.5% for heating MAPE and 1.0–1.7% for cooling MAPE. suggest that hourly temperature downscaling introduces only modest additional error into the annual peak-demand estimates used in this study, with a slightly greater effect on heating peaks.

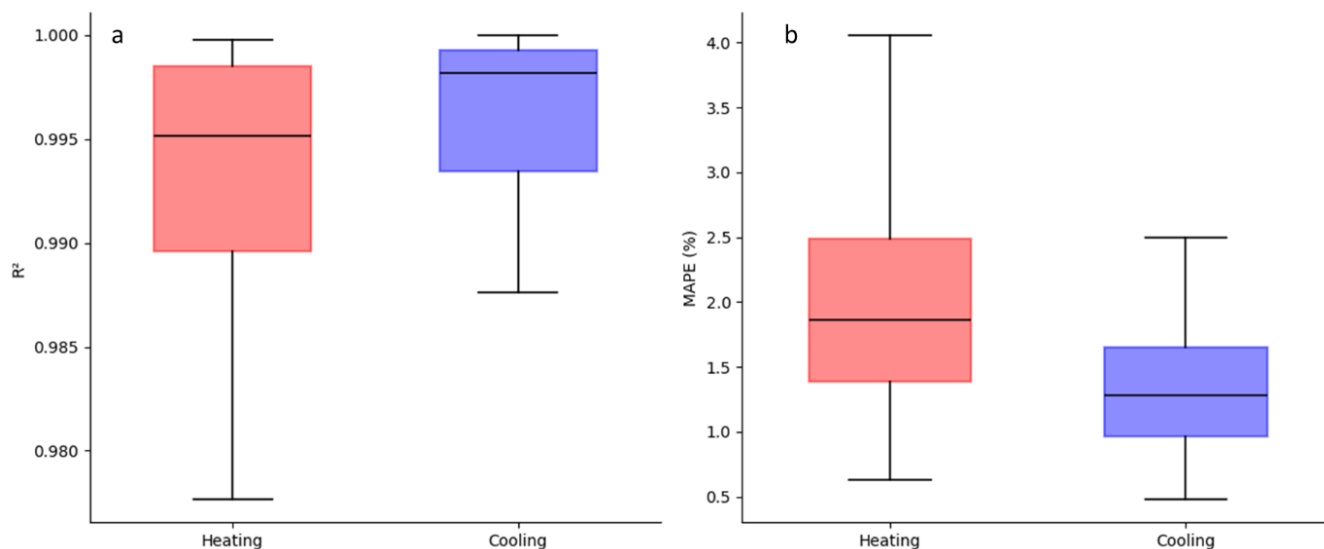


Figure S12. Downscaling-induced uncertainty in annual heating and cooling peak demand, reported by R^2 (a) and MAPE (b), respectively. It's developed through comparing county-level annual heating and cooling peak demands driven by raw ERA5 versus reconstructed ERA5 temperatures over 2016–2024.

Supplementary Note 4 Supplementary results on the rapid transition in peak demand uncertainty

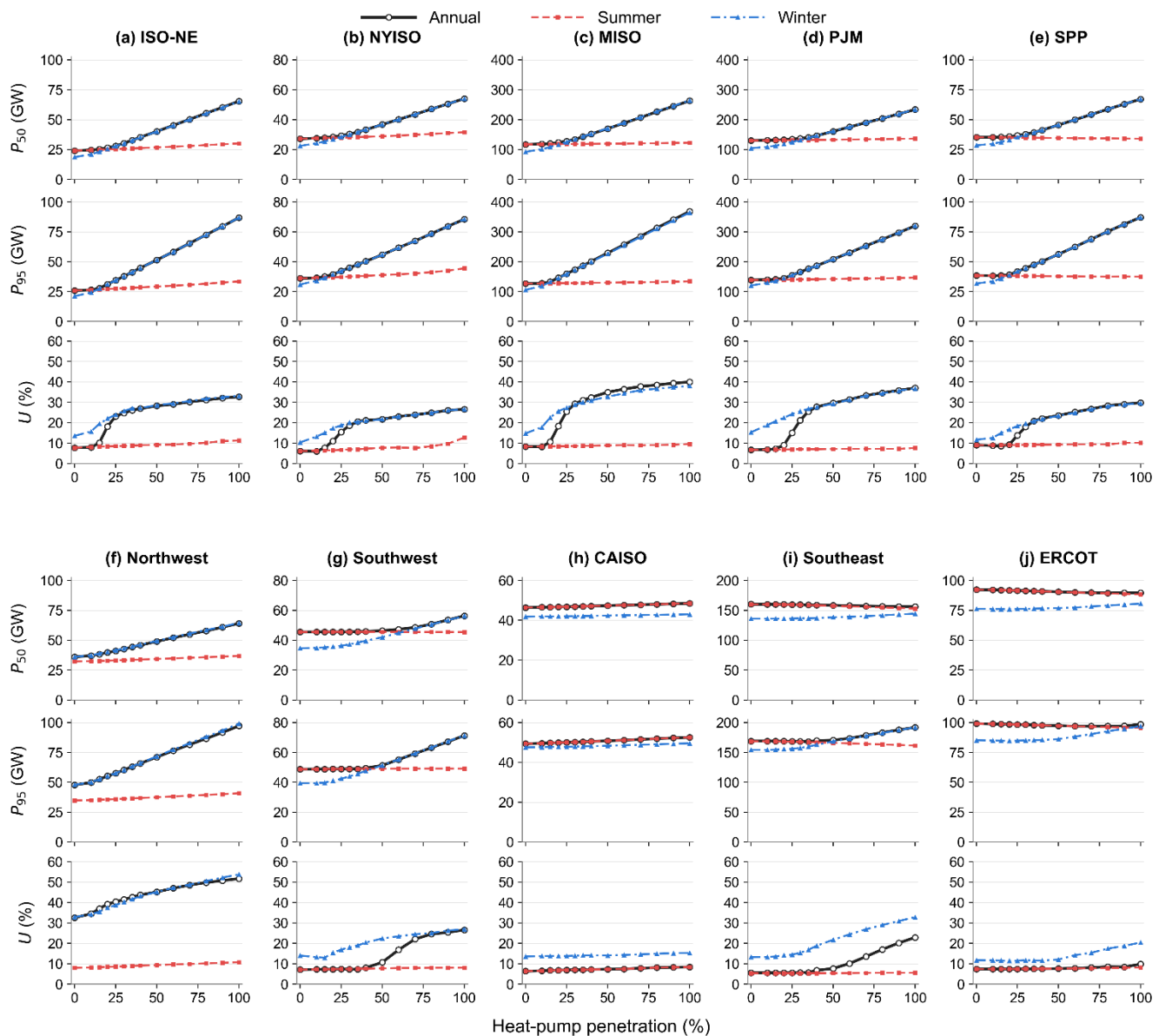


Figure S13. Annual and seasonal peak-demand quantiles and relative uncertainty across heat-pump penetration levels. Supplementary figure for figure 1.

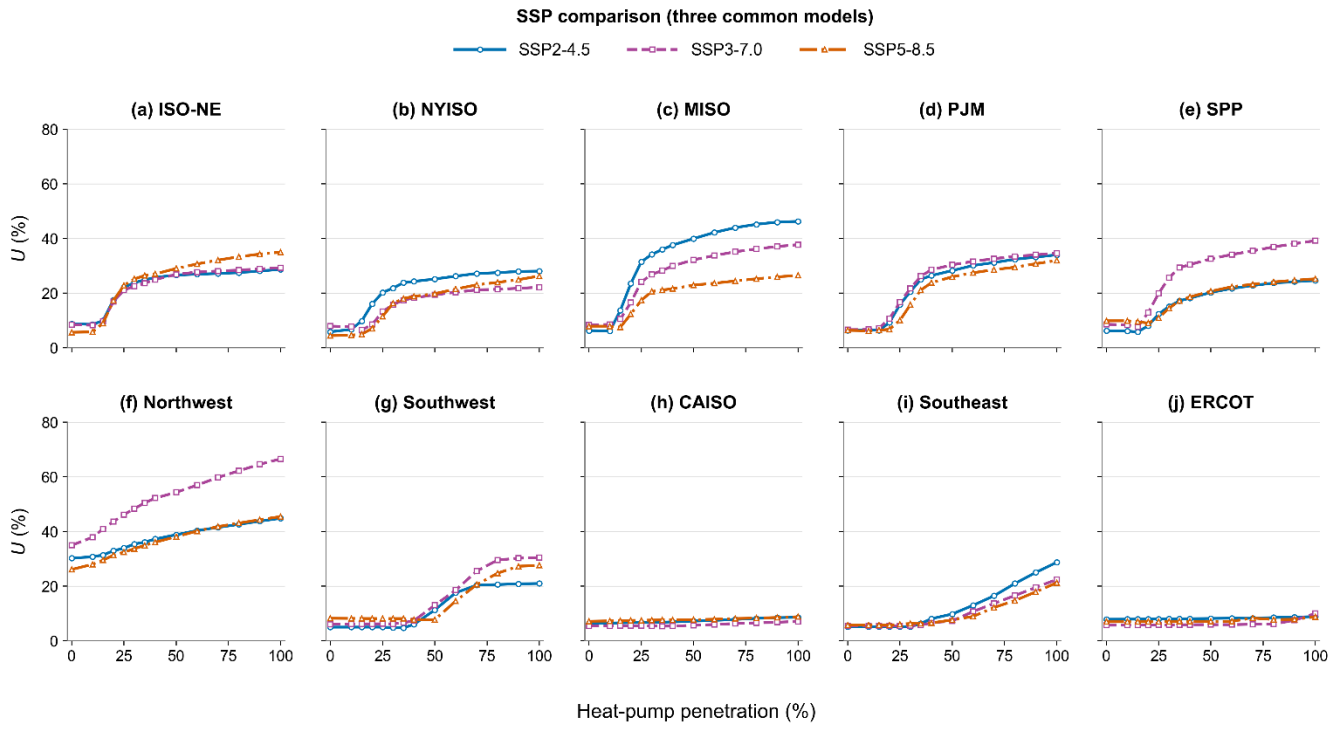


Figure S14 Peak uncertainty across emissions scenarios. Only three common shared models (CanESM5, ACCESS-ESM1-5 and MPI-ESM1-2-LR are used in this analysis)

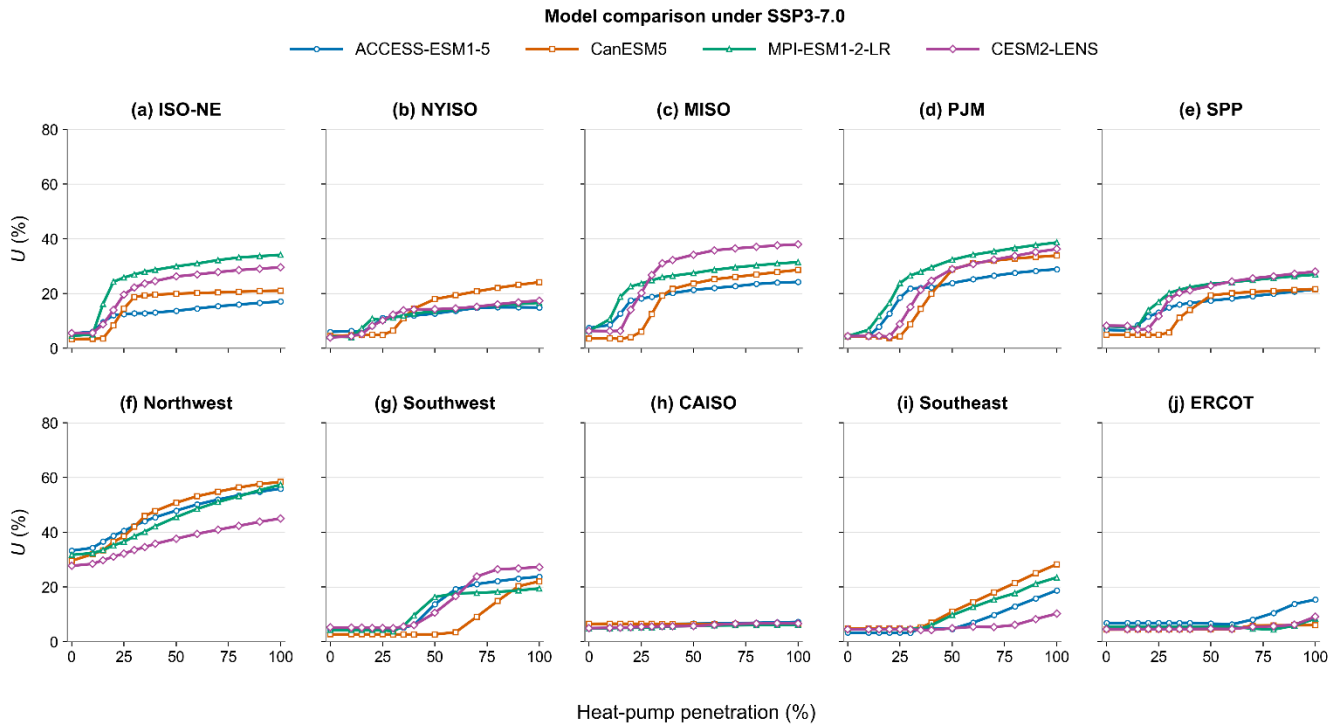


Figure S15 Peak uncertainty across climate models. This analysis is performed for four climate models under SSP-370 scenario.

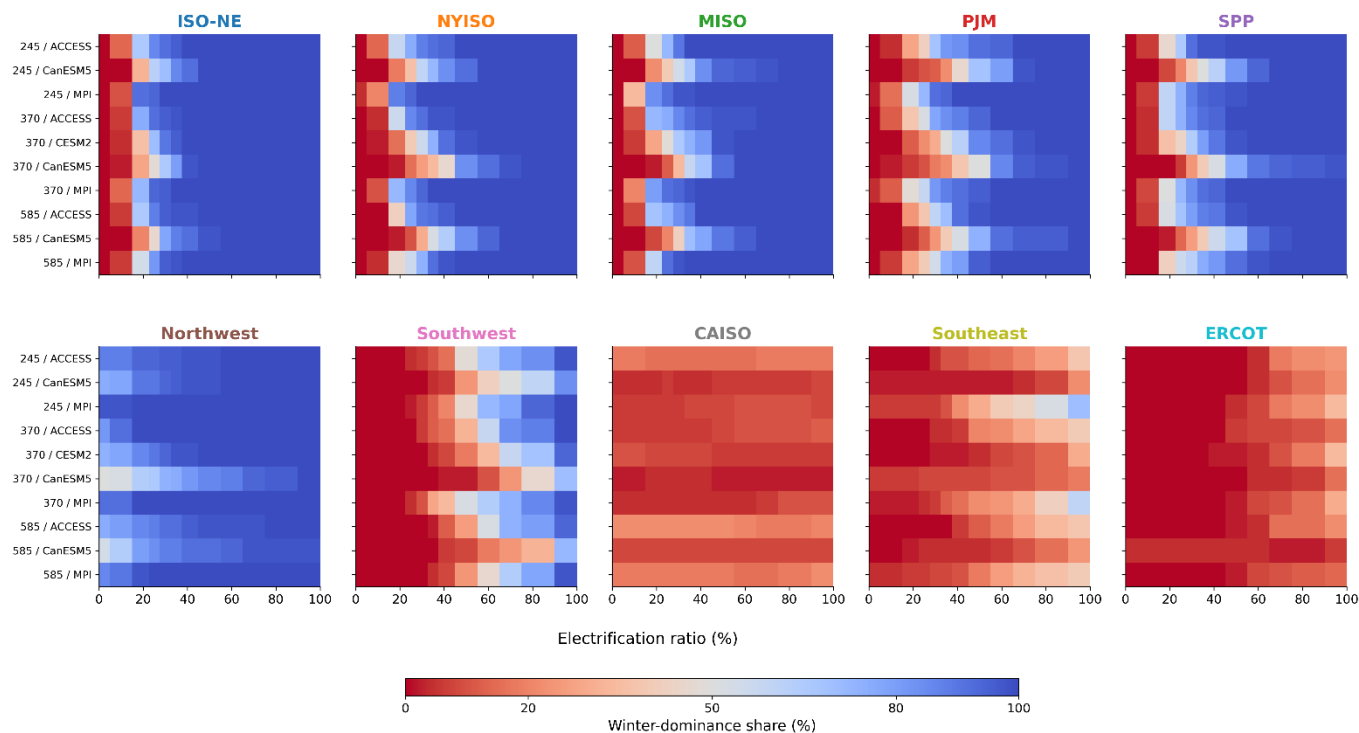


Figure S16 Peak seasonality by climate model and scenario. Supplementary figure for Figure 1.

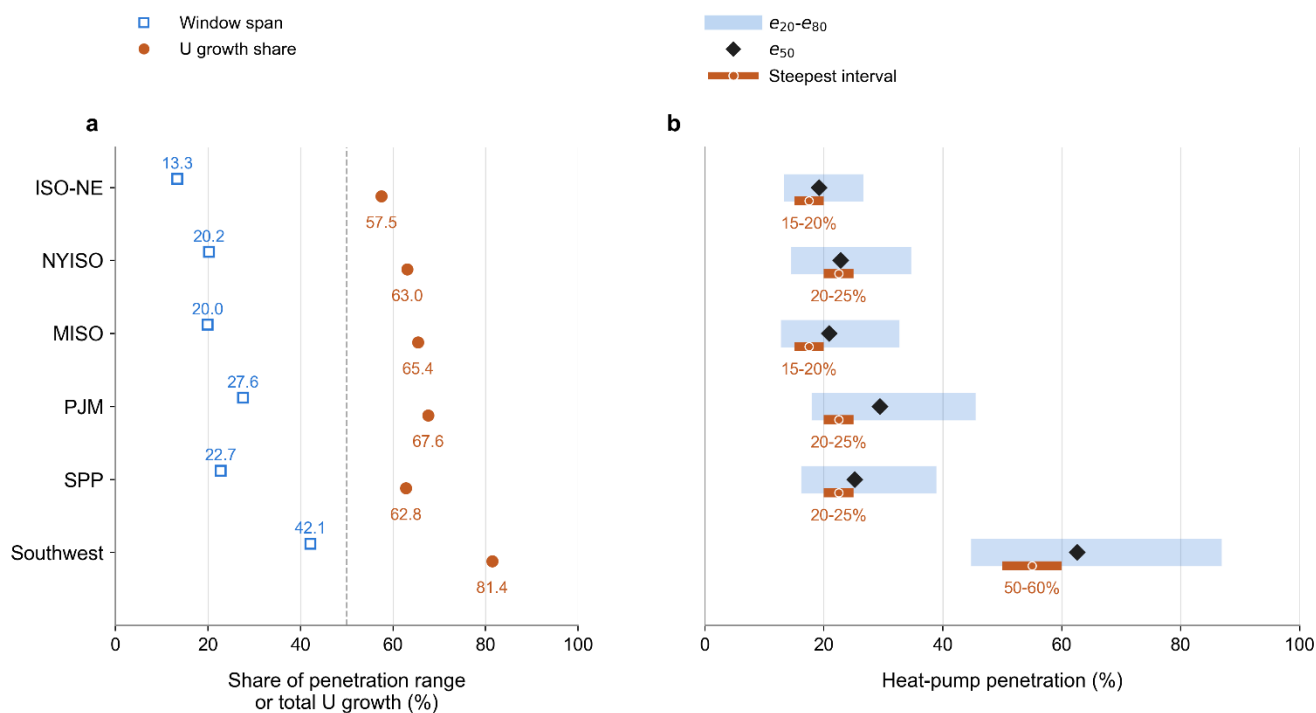


Figure S17. Concentration and location of uncertainty growth during the seasonal transition. Supplementary Information for Figure 1 in the main text (a) Concentration of uncertainty growth. Blue squares show the $e_{20}-e_{80}$ window width as a percentage of the full 0-100% heat-pump penetration range. Orange circles show the share of the total net increase in annual peak-demand uncertainty occurring within that window, $100[U(e_{80}) - U(e_{20})]/[U(100)]$. The dashed vertical line marks 50%. (b) Location of the fastest uncertainty growth. Pale blue segments indicate the $e_{20}-e_{80}$ transition window, black diamonds mark e_{50} , and orange bars show the adjacent simulated penetration interval with the largest increase in U per penetration percentage point. Orange circles mark the interval midpoints, and labels give the interval bounds.

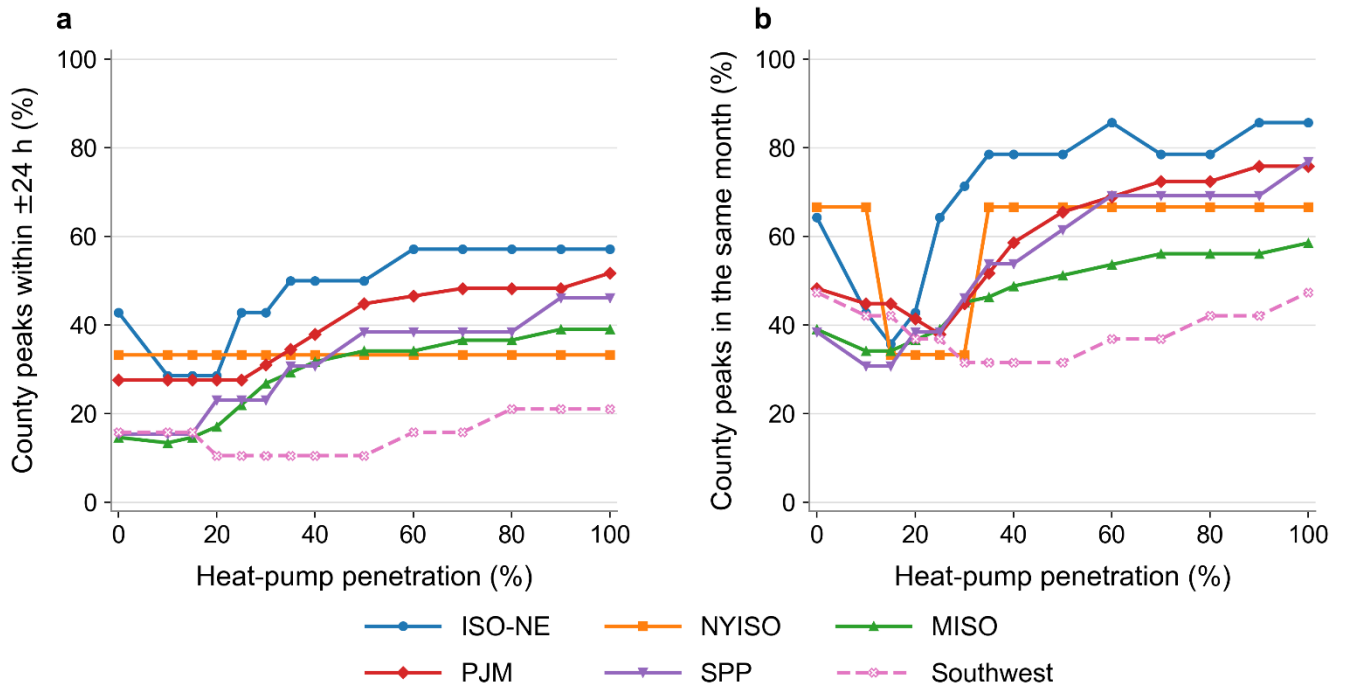


Figure S18. Temporal coincidence of county and regional annual peaks across heat-pump penetration levels. Supplementary figure for Figure 2 **(a) Peak-time coincidence within 24 hours.** Percentage of counties whose annual-peak hour occurs within 24 hours before or after the regional annual-peak hour, including both endpoints. **(b) Peak-month coincidence.** Percentage of counties whose annual maximum occurs in the same UTC calendar month as the regional annual maximum.

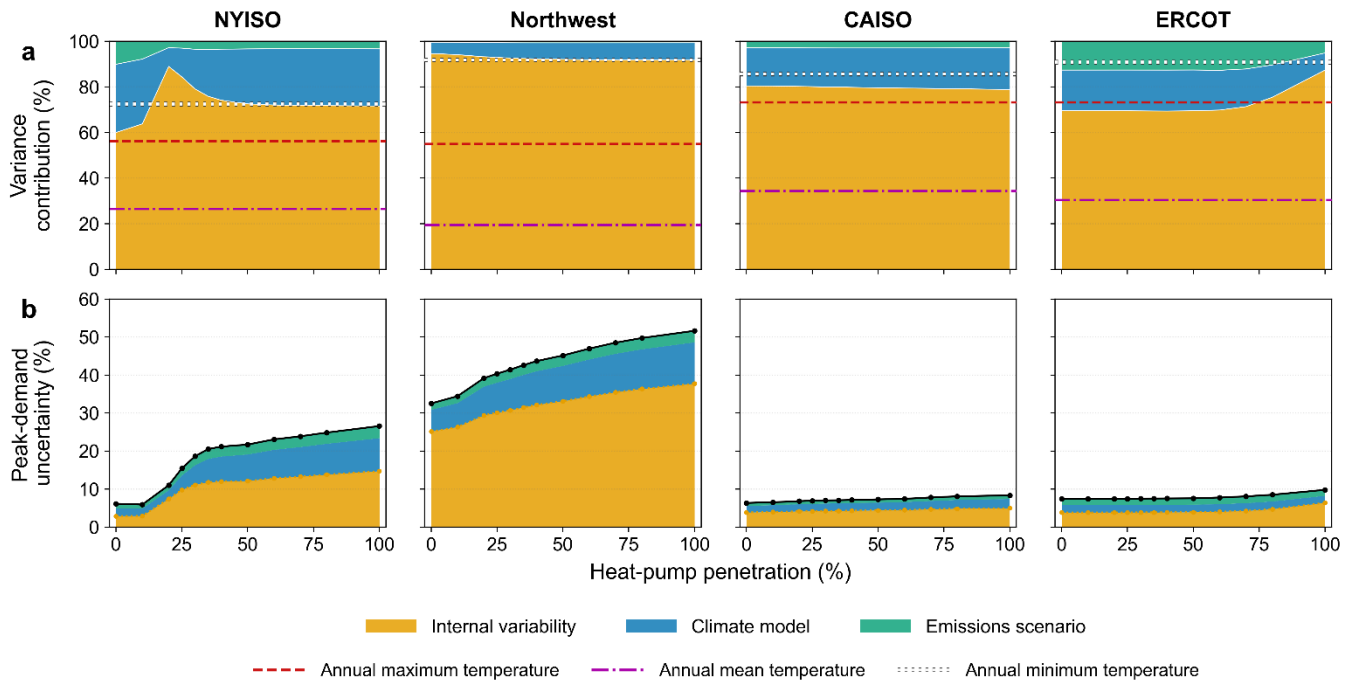


Figure S19. Climate-related uncertainty in annual peak demand for the four regions omitted from Figure 3.

Supplementary Note 5 Historical weather underestimation and climate sample requirement

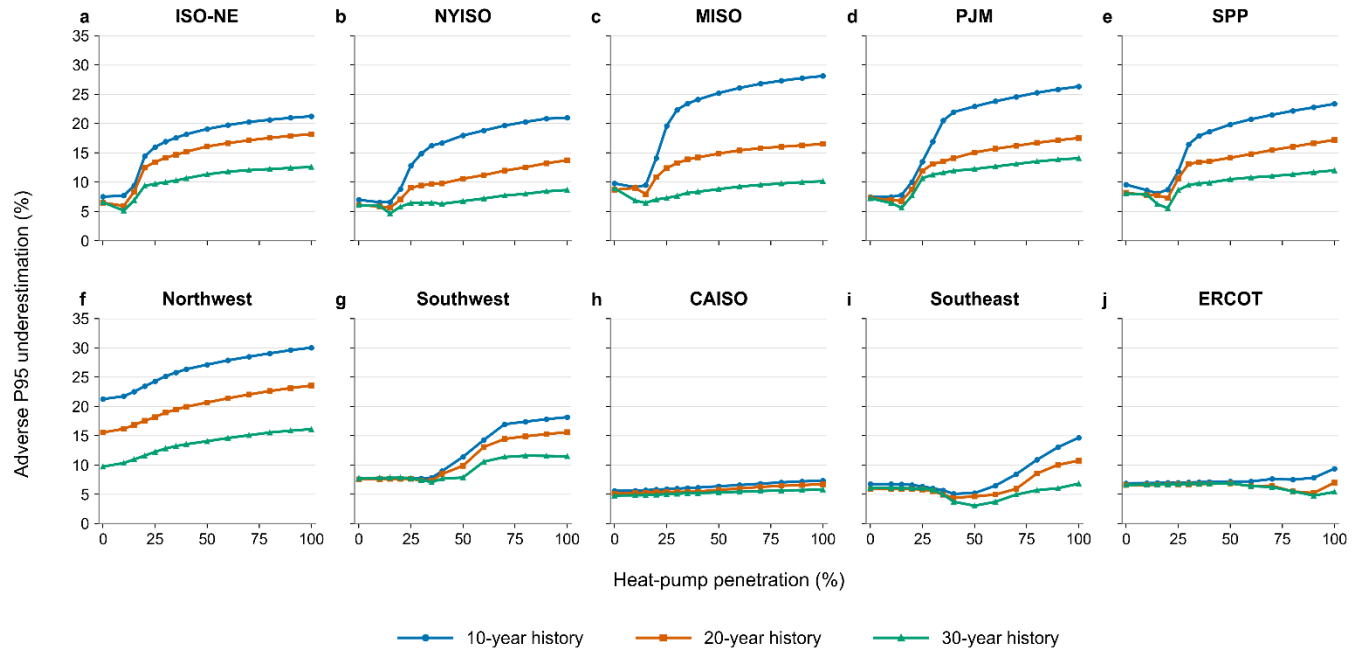


Figure S20. Sensitivity of historic record length on the extreme case of future extreme peak demand underestimation. Supplementary figure for Figure 4

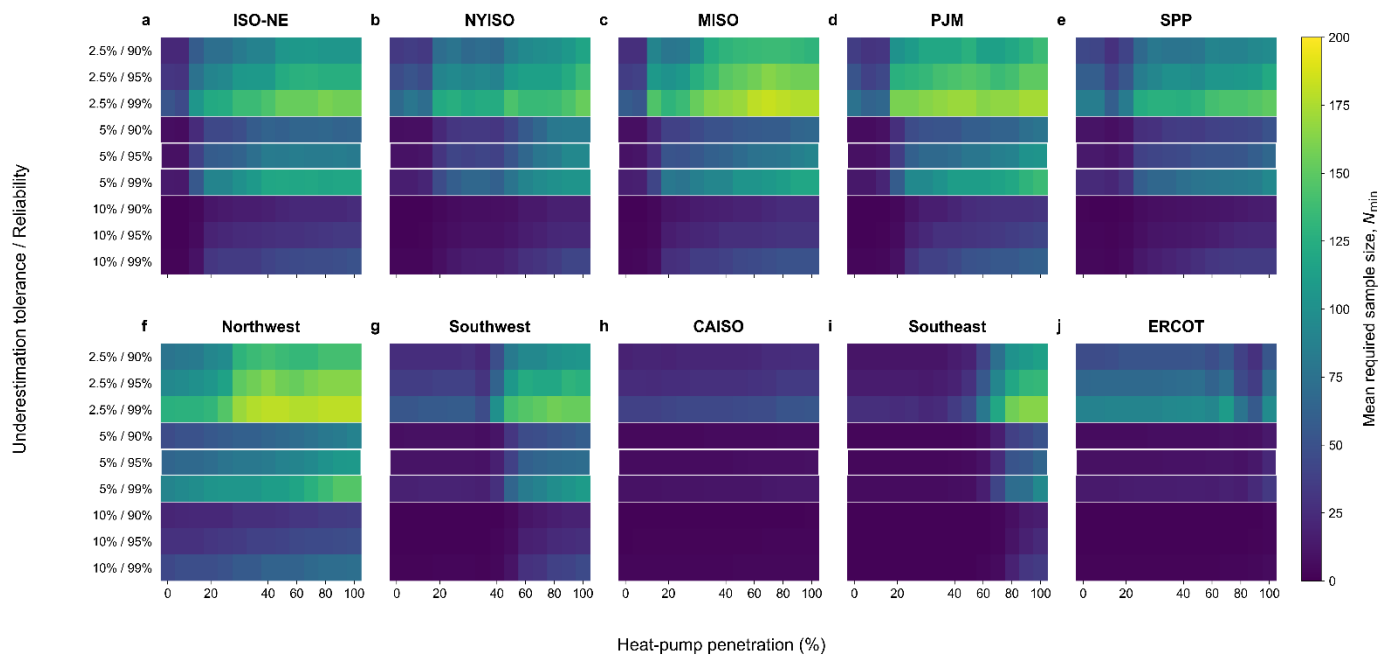


Figure S21. Sensitivity of underestimation tolerance and reliability on minimum weather-ensemble size for extreme peak. Supplementary Figure for Figure 5

Supplementary Note 6 Sensitivity and robustness analysis

Our central finding that peak-demand uncertainty increases rapidly within a distinct penetration range are robust to the heat-pump efficiency. Here, we test the sensitivity of heat-pump efficiency through an alternative residential ultra-high-efficiency heat-pumps with both higher heating/cooling efficiency and extreme-low temperature capacity retention. Compared to our baseline scenario, higher efficiency can increase normalized peak demand uncertainty because it reduces median demand proportionally more than extreme demand. It can also broaden or shift the rapid-growth phase toward higher penetration. For example, the steepest increase in PJM shifts from 20-25% to 30-35% penetration.

We also test the sensitivity of the peak demand uncertainty growth trajectory for different target years (i.e. 2030, 2040 and 2050) and different peak extreme percentiles (P90 and P99). We find that uncertainty growth remains concentrated within a distinct penetration interval across these cases). Changing to more extreme percentile primarily increases peak demand uncertainty and accelerates its uncertainty growth, while the rapid-growth interval remains broadly similar in most transitioning regions.

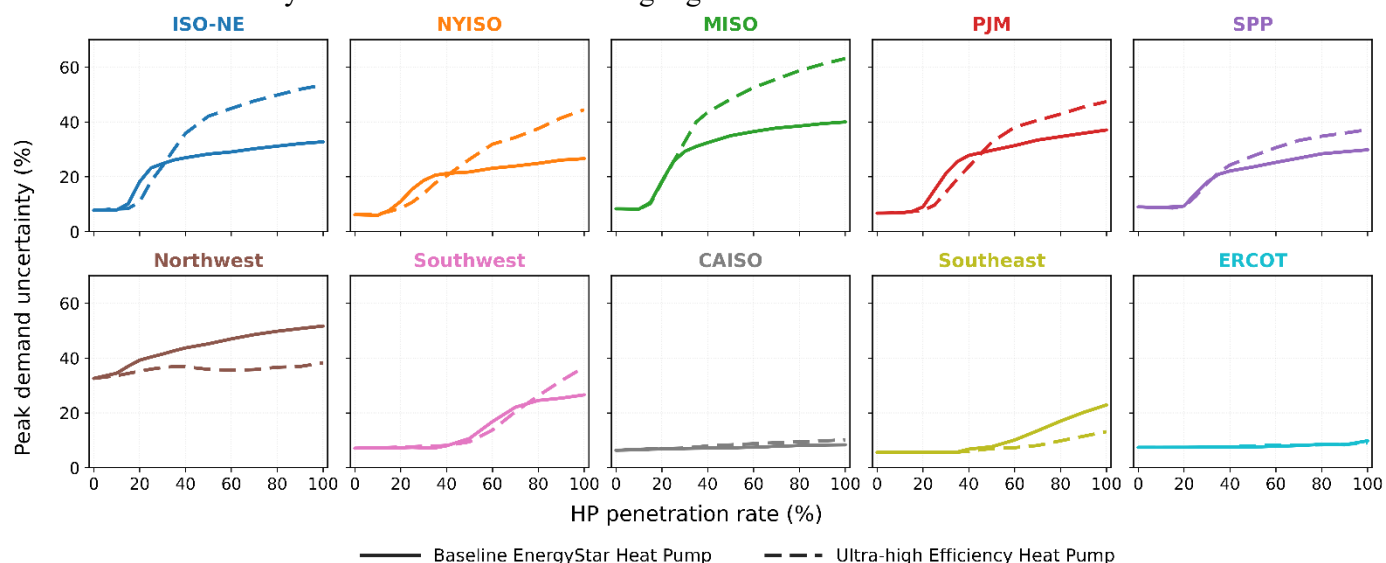


Fig S22 Sensitivity of annual peak-demand uncertainty to residential heat-pump efficiency.

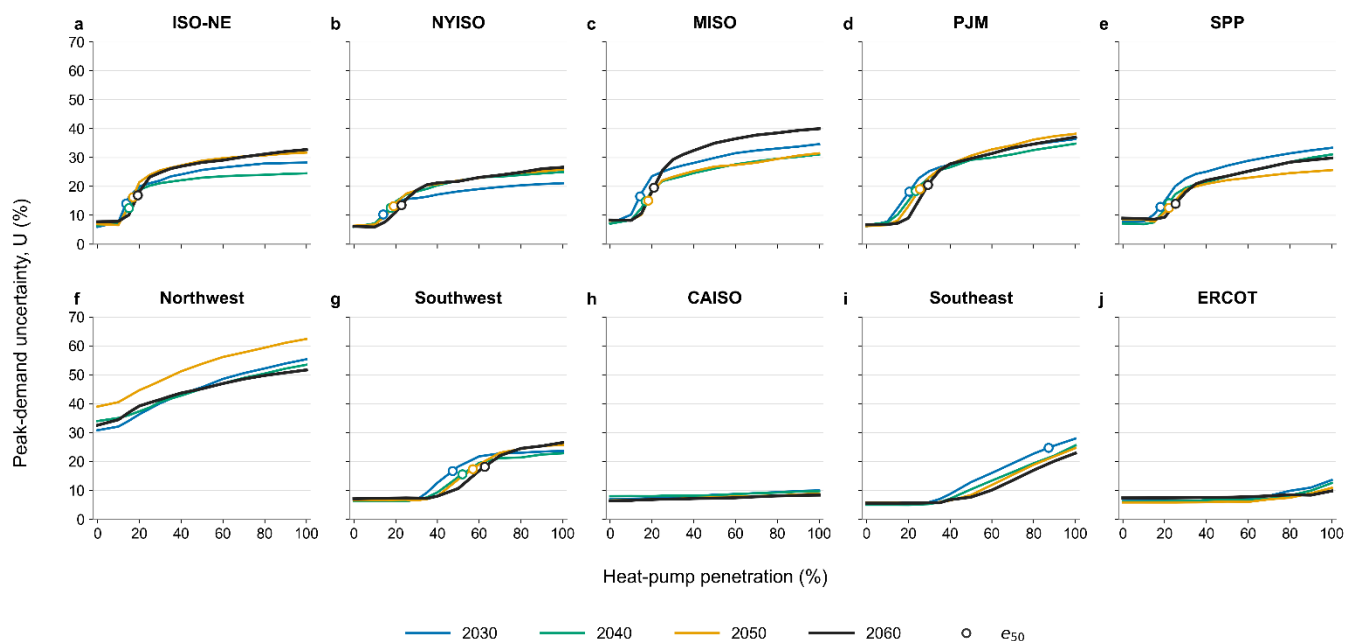


Figure S23. Sensitivity of peak-demand uncertainty and seasonal-transition position to target climate period

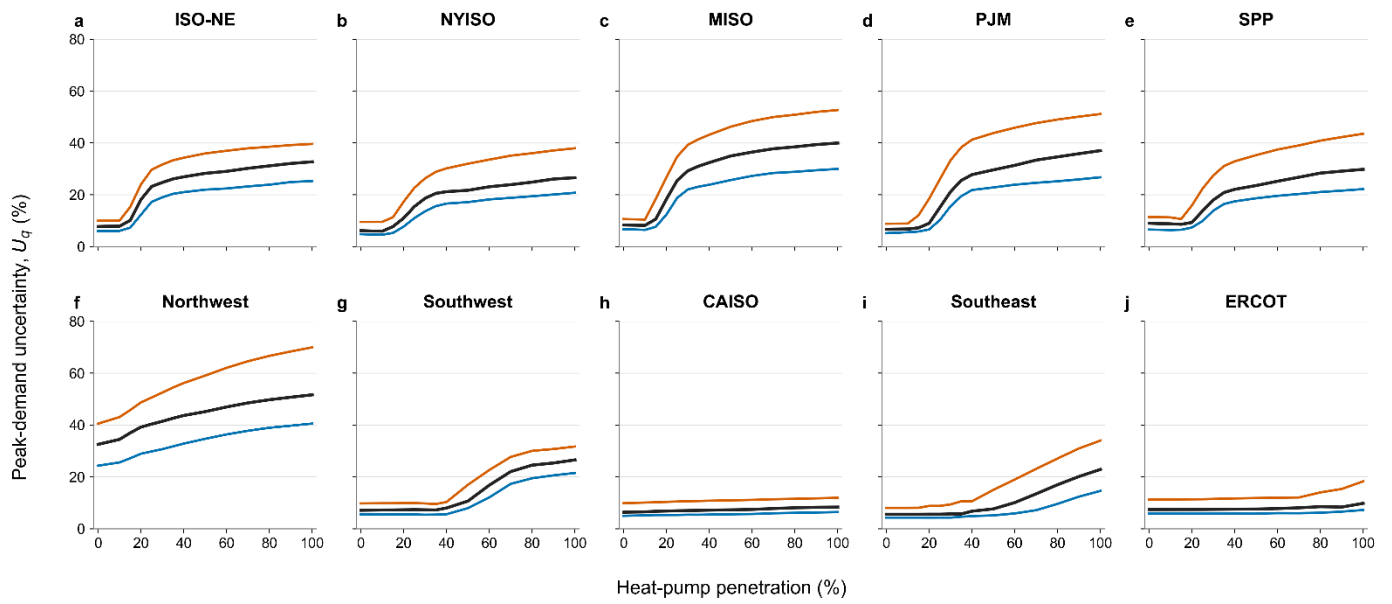


Figure S24. Sensitivity of peak-demand uncertainty to the extreme-percentile definition.

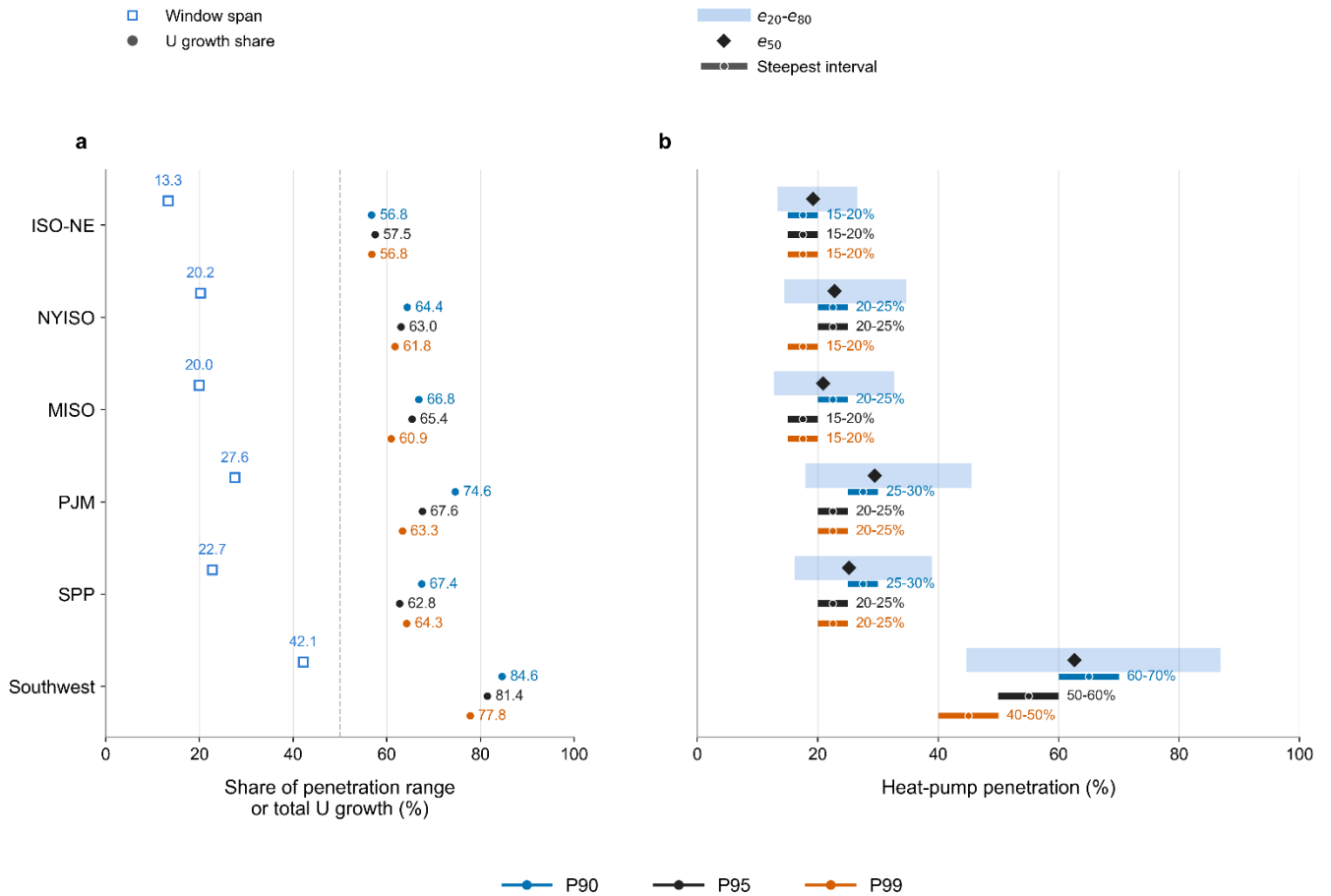


Figure S25 Sensitivity of uncertainty-concentration and location to the extreme-percentile definition

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