
A global model of hourly space heating and cooling demand at multiple spatial scales

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Supplementary Notes

Supplementary Note 1: Physical models

Physical models are based on theories of heat transfer and thermal diffusion and use energy balance equations to simulate a building's energy demand. They vary in complexity from simplified resistance-capacitance models [1,2] to highly detailed models implemented in a variety of purpose-built software (e.g. EnergyPlus [3]). The sheer variation in the built environment and users' interactions with it means that many inputs must be specified (10s to 100s) to simulate heating and cooling loads using physical models [4]. These inputs include physical parameters (e.g. envelope characteristics and HVAC equipment), user behaviours (e.g. occupancy patterns) and local meteorological conditions (e.g. air temperature and solar irradiance) [4–6].

Physical models are ubiquitous in the building industry, particularly in the conceptual design stages where building design is most flexible, because their detailed parametric approach allows the user to customise a very wide range of input parameters to create bespoke estimates of the energy consumption of different building designs. However, such a detailed approach limits the sphere of application of physical models. Where a detailed description of an entire stock of buildings is non-existent, the distribution of building characteristics must be assumed based on the available data [7]. While these generic inputs may effectively describe the building stock in a single neighbourhood or city, they could not be used to describe the stock of another city. As parameters are manually defined and simulation run-times are long, each simulation is also very time-consuming [4]. Consequently, physical models are typically applied only to individual buildings, neighbourhoods or (if sufficiently generalised) cities [4,5,8]. While there are many studies that validate the outputs of physical models against measured energy consumption, there is growing body of evidence that shows significant discrepancies between simulated and measured energy consumption due to mis-calibration [9–14]. The causes of such deviations include inaccurate assumptions regarding building design, user behaviours and occupancy patterns [12,15–17].

Supplementary Note 2: Statistical models

Statistical models extract mathematical relationships between measurements of energy consumption and other variables, which are then applied to predict energy consumption in the unknown future or in new types of building. A wide variety of statistical methods are available which can be broadly categorised as regression models [18,19] and machine learning models [20,21]. The variables or 'features' that are used to predict demand in the model are selected based on their predictive power for energy consumption, although feature selection is ultimately limited by availability of data and processing time [22–24]. The number of features included varies substantially between models, but is typically less than 10 [24]. While some use only temperature to predict energy consumption, others include additional meteorological variables (e.g. solar irradiance, wind speed and humidity) and physical building characteristics (e.g. insulation, glazed area, type of roofing) [24,25]. A key advantage of statistical models is that, where suitable data exist, models can give fast predictions of energy consumption in known buildings, and because the models are derived from measured energy data, they are effectively self-validating – at least within their sample data.

The drawback with statistical models is that it is hard to use their results to inform modelling in new contexts. The high cost of data collection means statistical models are often derived from small underlying datasets, which has two important implications: 1) models based on small samples are often less accurate when predicting out-of-sample (i.e. in new buildings), and 2) in models with many predictors there is a risk of overfitting and producing misleading results [23]. As is manifested in physical models, building energy consumption is influenced by tens or even hundreds of possible features and interactions, which vary by region, culture and so on [5]. As a result, it is difficult to generalise any one statistical model to fit another geographical location or customise it to understand a new context. Even if it were appropriate to generalise or customise statistical models, the model could only be applied to contexts where corresponding data exist.

Supplementary Note 3: Surrogate models

Surrogate models are used to emulate building simulation software (e.g. EnergyPlus) by training a statistical model on simulation input (i.e. weather files and building descriptors) and output data (e.g. heating and cooling demand) [26]. Once trained, evaluating the surrogate model is many orders of magnitude faster than running detailed physical simulations, thereby reducing the computational barrier to building energy simulation [26,27]. Because their training sample is derived using building simulation software, they do not require measured data to derive a statistical model – this is particularly useful when comparing conceptual building designs and for optimising design features [26]. Most surrogates have been trained for specific building projects [28–30] or specific climate zones [31–33], but some surrogates have been trained to cater for a variety of building types across multiple climate zones (e.g. for all climate zones in Morocco [34], Brazil [35] and Canada [36]). The later study [36] is of particular interest as it demonstrates that surrogates can be used to simulate hourly energy demand – as opposed to annual energy demand – albeit with greater error.

With a sufficiently large and generalised training set, a single surrogate model could in theory (though not yet in practice) be used to simulate temporally-resolved energy demand across an exhaustive array of building designs and climate zones [26,36]. Such a model would be both generalisable and customisable. Depending on the setup (i.e. whether it requires a comprehensive or more generic description of the building design), the model could also be applied with widely available (or entirely conceptual) data. The key problem with surrogate models is that they are trained using building simulations, so they are only accurate within the limitations of the simulation program and the input data that are used [26]. While surrogate models often show a high-degree of accuracy in emulating physical models, evidence suggests that the outputs of physical models can deviate significantly from measured data [9–14]. For example, Catalina et al. [31] find that their surrogate model's predictions are within 1% of simulated demand, but are nearly 40% higher than measured demand (before applying a building specific adjustment factor).

Supplementary Note 4: Degree-day models

In contrast to other approaches, degree-day methods are designed to spatially and temporally resolve widely-available but highly aggregated measurements of energy demand in buildings, such as annual or monthly measurements of national energy demand [37]. Space heating and cooling demand represent a major share of total energy demand in buildings and are strongly correlated with outdoor temperatures, which are measured at high spatiotemporal resolution (e.g. 0.5° grid cells and hourly recordings). Temperature data can be used to calculate heating and cooling degree days (HDDs and CDDs), which measure how much (in °C) and for how long (in days) the outdoor air temperature was higher or lower than a given threshold temperature. HDDs and CDDs can then be used to derive a synthetic load profile for each location at any given time (e.g. all grid cells in the UK for each day of the year). These synthetic load profiles can then be weighted according to the population contained in each cell, to account for the higher demand experienced in more populous regions, and scaled according to aggregate energy demand (e.g. annual UK building energy demand).

The advantage of the degree-day method, compared with other methods, is that it can be applied in almost any region using only widely available data, thus satisfying our first and second criteria. Berger and Worlitschek [38] derive daily residential heating profiles for Switzerland using 30-year average temperature data. Sachs *et al.* [39] derive hourly heating and cooling profiles for four seasonally-representative days (i.e. 96 time-slices) across 165 countries using hourly temperature data. The Hot Maps Project [40] estimate daily heating and cooling profiles for residential and tertiary consumers in all NUTS2 regions of the European Union using daily temperature data. When2Heat [41] estimate daily heating profiles for 16 European countries using temperature data and wind speeds. Despite several advances, a recent study shows that the model in [41] performs only marginally better than basic degree-day models when validated against UK gas demand [42]. In both [40] and [41], daily profiles are resolved further to hourly profiles using hourly demand factors derived from the German standard load profile [43]. Degree-day models are also used by industry. For example, the National Grid use this approach to forecast gas demand in the UK [44]. As with [41], their composite weather variable is derived from outdoor temperatures and wind speeds.

Despite their broad applications, degree-day models generally fall short on our third and fourth criteria, as their results can only be customised in limited ways (e.g. by varying threshold temperatures) and they are not extensively validated. Both physical and statistical models show that the physical properties of buildings, occupant dynamics and other meteorological variables can have a significant impact on energy consumption, yet these factors are rarely considered when deriving synthetic load profiles [5,24]. As a result, simulated load profiles typically show low geographical variation, which is compounded by the smoothing effect incurred when aggregating large numbers of buildings [40,45,46]. In

[40] and [41] the authors apply different parameters to differentiate between building types, but they do not account for country-specific building dynamics or activity patterns as all hourly profiles are derived from German standard load profiles. In [41] and [44] the authors incorporate the effects of wind speeds into their profiles, but exclude other potentially influential meteorological variables (i.e. humidity and solar irradiance). The exclusion of these physical, behavioural, and meteorological factors precludes a customisable approach to modelling heating and cooling loads, in which a user can change input parameters to reflect the dynamics of an individual building or occupant. More importantly, existing studies make little attempt to validate their results against measured data relative to the physical and statistical models described previously. In [38] and [39] profiles are not validated against any temporally-resolved measurements. In [40] simulated profiles are validated only for several of the 16 countries, though results of this validation and the countries included are not documented. In [41] outputs are validated for the UK and Germany and, given its scope and application, outputs from [44] are validated extensively, but only for the UK.

Supplementary Note 5: Previous works

Supplementary Table 1 summarises the advantages and disadvantages of each class of model discussed above. We present the Demand.ninja model which builds upon degree-day modelling, incorporating elements of physical and statistical modelling. Degree-day modelling is used as the foundation as it meets the two most important criteria for a universal model of heating and cooling demand: 1) it requires only limited and widely available data, and 2) it can be generalised to any geographical location. We incorporate aspects of physical and statistical modelling to allow the user to customise or optimise simulations without ballooning the number of inputs. We then put extensive effort into validating our profiles against real-world data at the national, regional, and individual-building level; and develop representative parameters to allow for generalised use in any context. In the following paragraphs, we discuss the ways in which our approach builds on existing degree-day studies.

HDDs and CDDs are the foundation of degree-day models. They have been estimated in many different studies, with resources range from academic studies [47–50] and databases [51–53] to online calculators [54,55], with varied spatial and temporal resolution and coverage. One commonality among resources is that HDDs and CDDs are typically calculated using raw temperature data and fixed (often arbitrary) threshold temperatures. This simplistic approach runs contrary to evidence from statistical models that suggests that the inclusion of a range of meteorological variables can improve the accuracy of predictions, and that the heating and cooling requirements of occupants vary depending on geographical, cultural, economic and personal contexts, alongside the physical properties of buildings [5,19,23,24].

In a recent study, Atalla, Gualdi and Lanza [51] produced a global database of HDDs and CDDs using three thermal indices (the Environmental Stress Index [56], Heat Index [57] and Humidex [58]) and three threshold temperatures (15.6, 18.3 and 21.1°C). While their work represents a notable step forward, the database has three key limitations: 1) the indices used do not capture the effect of wind chill (only humidity and/or solar irradiance), 2) the threshold temperatures chosen are not tailored to specific contexts, and 3) their calculations do not account for the thermal inertia of buildings by smoothing temperatures such as in [41,44,59].

Thermal indices are used by meteorological agencies to better reflect the temperature that it ‘feels like’ to people. These indices can be applied as a proxy for the effects of solar irradiance, wind speed and/or humidity on heating and cooling demand. For example, a building will require more heating on days with lower solar radiation (due to reduced solar gains) or higher wind speeds (due to more air changes per hour). These cases would be represented by a lower value in the temperature index, if all else is held constant [44,51]. While there are many thermal indices, few include all potentially influential meteorological variables. For example, the Environmental Stress Index [56] accounts for just humidity and

solar irradiance, while the Heat Index [57] and Humidex [58] account only for humidity. National Grid ESO developed the composite weather variable [44], used to forecast gas demand, which accounts for the effects of temperature and wind speed. This is a better predictor of gas demand than raw temperature, but the omission of solar irradiance means that bespoke correction factors are required for spring and autumn. In a recent study, Copernicus [60] produced a state-of-the-art bioclimatology database (ERA5-HEAT), which includes the effects of solar irradiance, humidity and wind speeds. Their Universal Thermal Climate Index is defined as *“the air temperature of a reference outdoor environment that would elicit in the human body the same physiological model’s response ... as the actual environment”*. We derive a similar index – the Building-Adjusted Internal Temperature (BAIT) – which accounts for the same factors but is optimised to the response of buildings (in terms of energy consumption), rather than human bodies (in terms of perception). This optimisation is pivotal in tailoring our index to the built environment, as meteorological conditions modify the perceived temperature differently indoors (e.g. through solar gains, insulation and ventilation) than they do outdoors.

Dynamic temperature smoothing and threshold temperatures can be used as proxies for the physical and behavioural factors that influence heating and cooling demand. Temperature smoothing (i.e. taking a weighted average over previous days) is designed to capture the thermal inertia of buildings, with smoother temperatures representing buildings with better insulation (i.e. slower heat transfer between the indoor and outdoor environment). This approach is widely employed in the gas industry as it was found to improve the correlation between degree days and measured gas consumption [44,61], and has more recently been applied in academic studies [41,59]. Similarly, threshold temperatures can be used to capture highly individual preferences in users’ demand for heating and cooling. For example, a higher threshold temperature for heating would be used to represent occupants with reduced tolerance to feeling cold, which may occur for economic reasons (greater affluence or lower energy costs), health reasons (e.g. a hospital or care home) and so on. A recent study [62] found that the average threshold temperature varies substantially across European countries. Allowing smoothing factors and threshold temperatures to be customised or optimised to fit a building or occupant helps to address the smoothing effect inherent when aggregating the heating and cooling profiles of many buildings.

Supplementary Note 6: Model simplifications

The approach described in ‘*Calculating degree days*’ relies on four simplifications. First, outdoor temperatures vary throughout the day, but diurnal variations are not explicitly accounted for because HDDs and CDDs are calculated using daily average, rather than hourly temperatures. For example, in temperate climates the daily average outdoor temperature may be higher than the threshold temperature, hence the model computes zero HDDs for that day, even though outdoor temperature falls below the threshold temperature for at least some portion of the night. The thermal inertia of buildings (represented in Equation 3 of the *Methods*) tends to an average of around 0.50, implying that past meteorological conditions are influential with a half-life of 24 hours. Small, short excursions below the heating threshold temperature overnight would therefore not reduce internal temperatures sufficiently to require heating. Hence despite this simplification, we find that the Demand.ninja performs comparably across all climates and seasons (see Figure 4, Supplementary Figures 46–99).

Second, with the metered energy demand data that are available it is not possible to isolate the energy consumed for space heating and cooling demand from other end uses. For example, domestic refrigerators will consume more electricity in summer in regions without air conditioning as internal room temperatures are higher, and this will be captured within our estimates of demand for space cooling. Isolating such effects would require more disaggregated smart-metering data than is currently available; however, from the datasets which do give appliance- or circuit-level granularity, we conclude that space heating and cooling are by far the largest sources of temperature-dependent demand in buildings.

Third, when creating national and regional aggregated profiles, weighting the grid cells within a region based on population density implies that people only demand heating and cooling where they live and does not account for non-residential buildings, or people’s movements throughout the day. For example, facilities such as supermarkets and data centres have substantial cooling demand concentrated in specific areas that may not be highly populated, but will be attributed to the location of households in this approach. Similarly, the number of people in suburbs may decrease during working hours and the number in city centres may increase. This could be improved upon if granular data on industry locations with global scope, and time-varying global gridded data on human locations became openly available.

Finally, the approach to aggregation assumes that all people within a country or region have the same desire for heating and cooling (and so if they experienced the same weather conditions, they would demand the same amount of energy). To improve upon this, the population density in each grid cell was raised to the power of 0.8 to account for households typically having a smaller floor area in high-density cities [39].

The approach described in '*Resolving profiles to hourly resolution*' relies on two simplifications. First, we assume that the diurnal profile for heating and cooling remain constant throughout the year, unlike the profile for baseline demand which is specific to the season and working vs. non-working days. For example, in New South Wales (Supplementary Figure 170) it can be seen that heating demand takes a similar shape during weekdays and weekends in winter and shoulder months, but takes a different shape during summer months. However, this is reasonably inconsequential as the coldest days in the Australian summer require little heating.

Secondly, we assume that the diurnal profiles for heating and cooling are consistent around the world. This is not a perfect approximation, but it holds for countries with a materially-significant demand for heating and/or cooling. For example, the diurnal profiles for cooling across the Australian states, Japan and regions of the US (Supplementary Figure 207) follow a characteristic shape, with a peak around 3 PM and a nadir between 4-6 AM. Cooling profiles in southern European countries (Spain, Italy and Greece) are similar, but with less pronounced variation, as these countries are not as hot; but profiles in northern European countries (Germany, Britain) take a flatter shape. As their demand for cooling is an order of magnitude lower, this different shape has limited impact on the global weighted average. The heating demand profiles are elevated during daytime hours with a small evening peak across many European nations and Australian states, but in Japan and the US regions they take a stronger diurnal profile that is flattened during peak sunlight hours (inverse to cooling).

Supplementary Note 7: Validation for other models

In Figure 4, the Demand.ninja model is compared to three other models from the literature, as shown in Supplementary Figures 100–153. The estimates for space heating and cooling demand from these models were substituted into Equation 11 from *Methods* in place of *HDD* and *CDD*, and a linear regression against metered demand was used to find the intercept (baseline of temperature independent demand), scale factors for heating and cooling demand (analogous to the power coefficients), and time-varying terms for non-working days and long-term trends. The coefficients for scaling each dataset are given in Supplementary Tables 5–7.

For When2Heat [63], demand was estimated from the *'heat_demand_total'* variable. As this model only provides heat demand, the validation was limited to those countries in Europe with limited demand for cooling (fewer than 5% as many CDD as HDD), and individual days with more than 1 CDD were removed from the comparison.

For HotMaps [40], demand was estimated from the *'load profile residential shw and heating yearlong 2010'* and *'load profile residential cooling yearlong 2010'* datasets.

NREL's ResStock and ComStock models [64] provide estimates of total electricity demand, including thermal and non-thermal components. These demand estimates were still run through the regression described above for the sake of fairness, as this could only improve the potential goodness of fit. For each model, energy demand is simulated using specific weather years rather than Typical Meteorological Years, ensuring a fair comparison across models.

Supplementary Note 8: Model calibration

In total we calibrate the model in 43 regions and 4,773 individual buildings across the world using daily energy demand data, and 78 regions using monthly energy demand data. The spread of results (summarised in Supplementary Table 4 and Supplementary Figures 43–44) reflects the diversity of building types, living standards and occupant behaviours.

Averaged across the sample of regions and years that we consider, 7.5% of electricity demand is attributed to heating and 6.3% to cooling. Daily electricity demand increases by 2.6% for every degree that temperature falls below a country's heating threshold, and by 3.7% for every degree above the cooling threshold. Japan is reasonably central among countries; its average electricity demand is 69 GW, and this increases by 2.0 GW for each degree that the BAIT falls below 11.5°C, and increases by 2.5 GW for every degree above 20.1°C. After accounting for differences in population and climate, the US consumes the greatest amounts of electricity for both heating and cooling, while European countries consume considerably less. On average, US states also consume considerably more gas for heating than European countries. Across regions, heating thresholds range from 9.7 to 15.2°C, which is similar to the average thresholds derived for Europe in [62] (i.e. 13.4 and 15.0°C for electric and gas heating respectively). Cooling thresholds derived in this study vary by just 1.6°C (from 18.8 to 20.4°C), which is similar to that reported in [19] (i.e. $19.1 \pm 3.9^\circ\text{C}$).

Across individual buildings we find an optimal smoothing factor of around 0.50. This is the same as the smoothing factor used in [41], except that temperatures are smoothed over the three previous days rather than the two days considered here. Elexon (a British electricity market operator) use a smoothing factor of 0.57, with temperatures smoothed over the previous two days [61]. The smoothing factor does, however, vary considerably across building datasets. For example, buildings in New Zealand have a low smoothing factor, suggesting they are less-well insulated or more frequently ventilated. Many houses in New Zealand are built from wood which has poor insulating properties thereby supporting this inference. In Great Britain, the smoothing factor is many times higher owing to brick-built construction being ubiquitous, and highest in electrically-heated buildings, which are more likely to be flats (where apartments that are adjacent, above or beneath will provide additional thermal moderation) and built according to more recent and stringent building standards (due to changes in construction demographics).

The solar, wind and humidity coefficients all vary considerably both within and across building datasets. Buildings with higher solar coefficients experience greater solar gains. Solar gains increase with the amount of sunlight that reaches the inside of the building, which in turn depends on the proportion of the building that is covered in windows, the orientation of the house and the shading of the house (e.g. by trees or other buildings). The wind coefficient becomes more negative as buildings become draughtier and more

ventilated, which in turn depends on the exposure of the building, the airtightness of the envelope and occupant behaviour (keeping windows open during cold weather). The humidity coefficient increases as buildings are more exposed to humid air outside of the building, which again depends on the airtightness of the building envelope. Buildings are heterogenous, in terms of their age, style, orientation, fabric efficiency, heating system, users, and so forth, and so it is not possible to characterise the right parameters for a given 'type' of dwelling (e.g. brick-built terraces in the UK or timber detached houses in the US). Even for individual buildings it is not possible to concretely determine the key driver of variation in solar, wind and humidity coefficients, because the building datasets that are available to us provide insufficient metadata (in most cases nothing beyond the building's approximate location) due to the costs and confidentiality issues of gathering more detailed data. In the absence of more detailed datasets for calibration, users can use the generic parameters of the model, which have been shown to accurately simulate out-of-sample demand, or subjectively consider the range of parameters we found across large populations of diverse buildings to select the parameters that best fit the building they seek to simulate. For example, a higher solar coefficient could be used to model a building with a larger glazed area and a lower smoothing coefficient could be used to model a poorly insulated building.

Supplementary Tables

Supplementary Table 1: Classes of building heating and cooling models, compared against four criteria that we believe are desirable for the energy modelling community. While other models meet only one or two of these criteria, the Demand.ninja model meets all four.

Model class	Uses widely available data	Can be generalised geographically	Can be customised by users	Validated against real-world data
Physical	No	No	Yes, but very time consuming	Yes but can perform poorly
Statistical	No	No	No	Self-validating but limited to sample
Surrogate	No	Yes (with very broad training data)	Yes	Rarely and can perform poorly
Degree-day	Yes	Yes	No	Limited to a few countries
Demand.ninja	Yes	Yes	Yes	Yes

Supplementary Table 2: Details of the seven national and regional scale data sets used for calibrating and validating national and regional demand.

Location	Years covered	Time resolution	Gas / Electricity	No. of countries or regions	Spatial resolution	Ref.
UK	2015-19	Hourly/daily	Gas	1	National	[65]
Europe	Various ^a	Hourly/daily	Electricity	25	National	[66]
US	2016-19 ^b	Hourly/daily	Electricity	13	ISO regions	[67]
Australia	2017-19	Hourly/daily	Electricity	4	States	[68]
Japan	2016-19	Hourly/daily	Electricity	1	National	[66]
Europe	2013-19	Monthly	Gas	29	National	[69]
US	2010-19	Monthly	Gas	51	States	[70]

^a 2012-19 for DE GB, 2015-19 for BE FI FR LV PT AT DK EE GR LT NL NO RO ES SE IE, 2016-19 for IT CH, 2017-19 for BG SK CZ HU, 2018-19 for PL

^b 2012-19 for ERCOT, 2017-19 for MISO

Supplementary Table 3: Details of the ten smart metering data sets used for validating building level demand. Metered demand in all datasets is aggregated from hourly/sub-hourly to daily resolution.

Name	Location	Years covered	Domestic / Commercial	Gas / Electricity	No. buildings included	Ref.
BRE	UK	1988-91	Domestic	Both	46	[71]
Energy Demand Research Project	UK	2007-10	Domestic	Both	2,314	[72]
Customer Led Network Revolution	UK	2014-18	Both	Electricity	90	[73]
New Zealand Green Grid	NZ	2014-16	Domestic	Electricity	43	[74]
Elergone Energia	PT	2011-14	Domestic	Electricity	103	[75]
Home Energy Metering Study	US	2018-22	Domestic	Electricity	93	[76]
Residential Building Stock Assessment	US	2011-13	Domestic	Electricity	41	[77]
Pecan Street	US	2014-19	Domestic	Electricity	88	[78]
Building Data Genome Project 2	US/EU	2016-17	Commercial	Electricity	448	[79]
Smart-Grid Smart-City	AUS	2010-14	Domestic	Electricity	1,507	[80]

Supplementary Table 4: Optimal parameters and measures of model fit across all regional and building-level datasets. For each dataset, the table gives the number of profiles modelled, n , the eight input parameters used by the Demand.ninja model (heating and cooling thresholds, heating and cooling power coefficients and BAIT coefficients), the normalised root mean square error (NRMSE) relative to maximum demand, and R^2 value of the fit between modelled and actual demand. For national and regional datasets, the heating and cooling power coefficients are measured in $W/(^{\circ}C \cdot \text{capita})$ and for building datasets they are measured in $W/(^{\circ}C \cdot \text{building})$. BAIT parameters are not calculated for datasets with monthly resolution, as these were modelled using the generic parameters (given in *Modelling global heating and cooling demand*) which are the average across all other datasets. The central value and spread for each type of dataset is given as the demand-weighted mean and standard deviation across all datasets within a given type/fuel/region grouping. The standard deviation can be greater than the mean even for parameters that only take positive values due to the non-normality of distributions.

Type	Fuel	Regions	n	Heating threshold [$^{\circ}C$]	Cooling threshold [$^{\circ}C$]	Heating power [$W/(^{\circ}C \cdot p)$]	Cooling power [$W/(^{\circ}C \cdot p)$]	Smooth coef. [day^{-1}]	Solar coef. [$^{\circ}C/(Wm^{-2})$]	Wind coef. [$^{\circ}C/(ms^{-1})$]	Humidity coef. [$^{\circ}C/(gkg^{-1})$]	NRMSE	R^2
Regional/national	Daily electricity	APAC	5	11.9 ± 1.0	20.4 ± 0.9	29 ± 13	52 ± 30	0.73 ± 0.06	0.014 ± 0.003	-0.12 ± 0.05	0.036 ± 0.006	$3.4 \pm 0.5\%$	$91.2 \pm 1.1\%$
		Europe	24	12.7 ± 1.1	20.4 ± 1.0	18 ± 28	16 ± 6	0.62 ± 0.20	0.019 ± 0.010	-0.13 ± 0.25	0.032 ± 0.027	$3.3 \pm 0.8\%$	$93.6 \pm 4.8\%$
		US	13	9.7 ± 1.4	18.8 ± 1.3	31 ± 16	59 ± 18	0.35 ± 0.22	0.011 ± 0.007	-0.10 ± 0.11	0.022 ± 0.025	$2.9 \pm 0.6\%$	$95.0 \pm 2.1\%$
	Daily gas	GB	1	13.3	—	98	—	0.42	0.010	-0.18	0.051	2.1%	99.0%
	Monthly gas	Europe	28	14.7 ± 1.4	—	89 ± 37	—	—	—	—	—	$3.6 \pm 1.4\%$	$95.6 \pm 4.2\%$
		US	50	15.2 ± 1.5	—	126 ± 35	—	—	—	—	—	$3.1 \pm 0.9\%$	$97.2 \pm 2.9\%$
Residential buildings	Daily gas	GB (BRE)	46	13.8 ± 1.7	—	192 ± 95	—	0.43 ± 0.17	0.005 ± 0.005	-0.46 ± 0.13	0.150 ± 0.108	$8.0 \pm 1.1\%$	$87.9 \pm 3.7\%$
		GB (EDRP)	2,062	13.1 ± 1.8	—	288 ± 116	—	0.44 ± 0.20	0.013 ± 0.006	-0.18 ± 0.10	0.071 ± 0.084	$6.2 \pm 2.6\%$	$89.9 \pm 3.9\%$
	Daily electricity	GB (EDRP)	252	12.1 ± 2.2	—	100 ± 60	—	0.69 ± 0.31	0.013 ± 0.011	-0.16 ± 0.13	0.105 ± 0.116	$8.1 \pm 1.7\%$	$86.7 \pm 6.4\%$
		GB (CLNR)	90	11.8 ± 2.7	—	31 ± 24	—	0.60 ± 0.25	0.014 ± 0.012	-0.23 ± 0.14	0.046 ± 0.128	$8.7 \pm 1.7\%$	$79.5 \pm 8.1\%$
		Australia	1,507	16.7 ± 1.6	21.2 ± 1.8	80 ± 50	107 ± 96	0.51 ± 0.23	0.014 ± 0.007	-0.09 ± 0.14	0.028 ± 0.034	$8.9 \pm 1.7\%$	$73.4 \pm 9.2\%$
		New Zealand	43	12.3 ± 1.4	20.1 ± 2.5	74 ± 42	183 ± 127	0.09 ± 0.12	0.017 ± 0.007	-0.09 ± 0.11	0.031 ± 0.068	$9.5 \pm 1.5\%$	$70.8 \pm 9.5\%$
		US (RBSA)	41	12.0 ± 3.7	20.0 ± 2.5	49 ± 26	100 ± 70	0.32 ± 0.26	0.007 ± 0.008	-0.39 ± 0.28	0.033 ± 0.046	$7.4 \pm 1.3\%$	$83.8 \pm 9.1\%$
		US (Pecan)	88	14.6 ± 3.2	20.6 ± 2.6	33 ± 31	99 ± 65	0.46 ± 0.27	0.010 ± 0.010	-0.34 ± 0.32	0.038 ± 0.026	$8.5 \pm 2.5\%$	$87.4 \pm 6.1\%$
		US (HEMS)	93	13.2 ± 2.9	18.2 ± 3.2	146 ± 80	290 ± 91	0.63 ± 0.26	0.005 ± 0.008	-0.19 ± 0.31	0.014 ± 0.035	$8.0 \pm 1.3\%$	$80.9 \pm 8.4\%$
	Daily electricity	Portugal	103	13.8 ± 2.5	18.0 ± 1.3	6884 ± 7480	56129 ± 176977	0.78 ± 0.25	0.012 ± 0.011	-0.12 ± 0.19	0.052 ± 0.065	$4.1 \pm 0.9\%$	$84.4 \pm 7.1\%$
		Global (Genome)	448	13.0 ± 3.3	18.2 ± 3.6	1937 ± 2083	3927 ± 6145	0.37 ± 0.31	0.007 ± 0.012	-0.49 ± 0.18	0.042 ± 0.055	$6.8 \pm 3.2\%$	$76.5 \pm 13.3\%$

Supplementary Table 5: Comparison of model quality between Demand.ninja and the Hotmaps model [40] when simulating daily electricity demand during 2010. The normalised root mean squared error (NRMSE) is given relative to maximum demand in each region (as plotted in the main paper Figure 4e) and the adjusted-R² of modelled demand compared to measured demand on working days from the sources listed in Supplementary Table 2. Weekends and national holidays are excluded due to non-weather influences. The bottom rows give a summary of the mean and standard deviation across all countries, weighted by the mean demand in each country. For each country, the equation used to scale the Hotmaps data to national demand is given, where P_{total} is total demand, H and C is the model's variable for total heating and cooling demand (as detailed in 'Translating degree days into energy demand' within Methods), and the error term gives the standard deviation of residuals. European countries are represented by their ISO2 code.

		Demand.ninja		HotMaps		Equation for scaling HotMaps variables to national demand
		NRMSE	R ²	NRMSE	R ²	
European Electricity	FR	1.54%	98.7%	3.42%	93.6%	$P_{total} = 46.897 + 5.514 \cdot H + 0.111 \cdot C \pm 3.003 \text{ GW}$
	DE	1.85%	89.0%	2.29%	83.3%	$P_{total} = 54.783 + 1.132 \cdot H + 0.025 \cdot C \pm 1.626 \text{ GW}$
	GB	1.51%	97.7%	3.05%	90.7%	$P_{total} = 32.950 + 1.388 \cdot H + 0.009 \cdot C \pm 1.502 \text{ GW}$
	IT	1.61%	89.3%	2.20%	79.9%	$P_{total} = 36.748 + 0.904 \cdot H + 0.547 \cdot C \pm 1.053 \text{ GW}$
	ES	1.85%	90.8%	2.75%	79.6%	$P_{total} = 27.939 + 1.435 \cdot H + 0.442 \cdot C \pm 1.026 \text{ GW}$
	SE	1.64%	98.6%	2.88%	95.6%	$P_{total} = 12.743 + 5.080 \cdot H + 0.020 \cdot C \pm 0.702 \text{ GW}$
	PL	1.53%	94.9%	2.26%	88.7%	$P_{total} = 15.523 + 0.874 \cdot H + 0.012 \cdot C \pm 0.463 \text{ GW}$
	NL	1.35%	92.0%	2.24%	77.9%	$P_{total} = 12.433 + 0.599 \cdot H + 0.028 \cdot C \pm 0.337 \text{ GW}$
	BE	1.58%	93.5%	2.13%	88.2%	$P_{total} = 9.990 + 0.709 \cdot H + 0.007 \cdot C \pm 0.270 \text{ GW}$
	FI	1.93%	97.3%	2.99%	93.5%	$P_{total} = 8.246 + 3.606 \cdot H + 0.000 \cdot C \pm 0.412 \text{ GW}$
	CZ	1.61%	96.9%	2.50%	92.2%	$P_{total} = 6.629 + 1.120 \cdot H + 0.005 \cdot C \pm 0.241 \text{ GW}$
	AT	1.44%	95.8%	2.19%	90.3%	$P_{total} = 6.287 + 0.805 \cdot H + 0.019 \cdot C \pm 0.188 \text{ GW}$
	PT	2.16%	88.4%	3.55%	68.4%	$P_{total} = 5.728 + 0.850 \cdot H + 0.138 \cdot C \pm 0.270 \text{ GW}$
	CH	1.44%	95.8%	2.62%	86.0%	$P_{total} = 5.699 + 0.653 \cdot H + 0.023 \cdot C \pm 0.312 \text{ GW}$
	RO	1.79%	92.5%	2.45%	85.8%	$P_{total} = 5.693 + 0.524 \cdot H + 0.035 \cdot C \pm 0.270 \text{ GW}$
	GR	2.19%	94.0%	3.98%	80.2%	$P_{total} = 5.407 + 0.354 \cdot H + 0.489 \cdot C \pm 0.324 \text{ GW}$
	HU	1.71%	87.6%	2.33%	77.0%	$P_{total} = 4.332 + 0.332 \cdot H + 0.044 \cdot C \pm 0.120 \text{ GW}$
	DK	1.84%	95.0%	2.62%	89.8%	$P_{total} = 3.730 + 1.001 \cdot H + 0.017 \cdot C \pm 0.136 \text{ GW}$
	BG	1.74%	97.4%	3.16%	91.5%	$P_{total} = 3.532 + 0.989 \cdot H + 0.067 \cdot C \pm 0.201 \text{ GW}$
	SK	1.22%	96.8%	2.07%	90.9%	$P_{total} = 2.985 + 0.685 \cdot H + 0.013 \cdot C \pm 0.082 \text{ GW}$
	IE	1.79%	95.6%	3.20%	86.1%	$P_{total} = 2.681 + 1.944 \cdot H + 0.000 \cdot C \pm 0.127 \text{ GW}$
	LT	1.99%	93.6%	2.73%	88.0%	$P_{total} = 1.014 + 1.118 \cdot H + 0.039 \cdot C \pm 0.040 \text{ GW}$
	EE	1.65%	98.4%	3.34%	93.5%	$P_{total} = 0.753 + 1.900 \cdot H + 0.000 \cdot C \pm 0.047 \text{ GW}$
	LV	1.48%	97.9%	2.64%	93.4%	$P_{total} = 0.694 + 1.195 \cdot H + 0.029 \cdot C \pm 0.030 \text{ GW}$
	Mean	1.66%	93.9%	2.72%	86.6%	
	S.D.	0.19%	4.1%	0.51%	6.4%	

Supplementary Table 6: Comparison of model quality between Demand.ninja and the When2Heat model [63] when simulating daily electricity demand during 2016-19. The normalised root mean squared error (NRMSE) is given relative to maximum demand in each region (as plotted in the main paper Figure 4e) and the adjusted-R² of modelled demand compared to measured demand on working days from the sources listed in Supplementary Table 2. Weekends and national holidays are excluded due to non-weather influences. The bottom rows give a summary of the mean and standard deviation across all countries, weighted by the mean demand in each country. For each country, the equation used to scale the When2Heat to national demand are given, where P_{total} is total demand, H is the model's variable for total heating demand (as detailed in 'Translating degree days into energy demand' within Methods), and the error term gives the standard deviation of residuals. European countries are represented by their ISO2 code. The When2Heat dataset only covers heating demand, so five countries which had more than 5% as many CDD as HDD were excluded from the comparison (RO 6%, PT 13%, IT 37%, ES 44%, GR 66%). For all remaining countries, any days with more than 1 CDD were removed, to give the fairest comparison.

		Demand.ninja		When2Heat		Equation for scaling When2Heat
		NRMSE	R ²	NRMSE	R ²	variable to national demand
Gas	GB	2.00%	99.1%	4.33%	95.6%	$P_{total} = 1.306 + 1.22 \cdot H \pm 6.207 \text{ GW}$
European Electricity	FR	1.29%	98.8%	3.07%	93.0%	$P_{total} = 41.145 + 0.349 \cdot H \pm 2.709 \text{ GW}$
	DE	2.13%	81.1%	2.80%	67.4%	$P_{total} = 55.988 + 0.060 \cdot H \pm 2.235 \text{ GW}$
	GB	1.54%	96.5%	2.68%	89.4%	$P_{total} = 28.882 + 0.143 \cdot H \pm 1.183 \text{ GW}$
	PL	1.53%	91.0%	2.03%	84.5%	$P_{total} = 18.993 + 0.082 \cdot H \pm 0.476 \text{ GW}$
	BE	1.69%	91.0%	2.48%	80.7%	$P_{total} = 9.361 + 0.105 \cdot H \pm 0.305 \text{ GW}$
	CZ	1.74%	94.0%	1.84%	93.2%	$P_{total} = 7.048 + 0.143 \cdot H \pm 0.190 \text{ GW}$
	AT	1.79%	93.9%	2.59%	87.1%	$P_{total} = 6.726 + 0.148 \cdot H \pm 0.246 \text{ GW}$
	HU	1.96%	87.3%	2.44%	81.7%	$P_{total} = 4.671 + 0.068 \cdot H \pm 0.145 \text{ GW}$
	SK	1.74%	92.6%	1.76%	92.5%	$P_{total} = 3.206 + 0.129 \cdot H \pm 0.074 \text{ GW}$
	IE	1.50%	94.7%	2.84%	80.3%	$P_{total} = 2.939 + 0.145 \cdot H \pm 0.113 \text{ GW}$
	SE	1.41%	98.6%	2.40%	95.7%	$P_{total} = 11.786 + 0.498 \cdot H \pm 0.581 \text{ GW}$
	NL	1.92%	83.6%	3.15%	58.2%	$P_{total} = 12.728 + 0.075 \cdot H \pm 0.495 \text{ GW}$
	CH	2.76%	86.3%	3.60%	74.6%	$P_{total} = 6.147 + 0.067 \cdot H \pm 0.325 \text{ GW}$
	DK	1.96%	91.0%	2.95%	79.7%	$P_{total} = 3.507 + 0.097 \cdot H \pm 0.143 \text{ GW}$
	FI	1.68%	97.2%	2.51%	93.4%	$P_{total} = 7.596 + 0.307 \cdot H \pm 0.360 \text{ GW}$
	LV	1.66%	94.5%	2.59%	85.5%	$P_{total} = 0.754 + 0.079 \cdot H \pm 0.029 \text{ GW}$
	EE	1.82%	96.6%	3.25%	85.9%	$P_{total} = 0.824 + 0.178 \cdot H \pm 0.044 \text{ GW}$
	LT	1.89%	92.3%	2.64%	85.5%	$P_{total} = 1.237 + 0.118 \cdot H \pm 0.045 \text{ GW}$
Mean		1.75%	92.7%	2.98%	84.7%	
S.D.		0.35%	7.15%	0.70%	12.0%	

Supplementary Table 7: Comparison of model quality between Demand.ninja and the NREL ResStock/ComStock model [64] when simulating daily electricity demand during 2018. The normalised root mean squared error (NRMSE) is given relative to maximum demand in each region (as plotted in the main paper Figure 4e) and the adjusted-R² of modelled demand compared to measured demand on working days from the sources listed in Supplementary Table 2. Weekends and national holidays are excluded due to non-weather influences. The bottom rows give a summary of the mean and standard deviation across all regions, weighted by the mean demand in each region. For each region, the equation used to scale the NREL demand values to national demand are given, where P_{total} is total demand, R and C are the total demand variables from ResStock and ComStock respectively. The US is divided into power markets represented by their names or acronyms.

		Demand.ninja		NREL		Equation for scaling NREL variables to national demand
		NRMSE	R ²	NRMSE	R ²	
American Electricity	CAISO	2.66%	92.6%	4.05%	82.9%	$P_{total} = 4.547 + 5.529 \cdot R + 12.032 \cdot C \pm 1.830 \text{ GW}$
	Carolinas	1.90%	96.4%	4.48%	80.1%	$P_{total} = 0.960 + 2.368 \cdot R + 3.933 \cdot C \pm 3.003 \text{ GW}$
	Central	1.67%	97.2%	4.07%	83.4%	$P_{total} = 2.871 + 1.946 \cdot R + 22.416 \cdot C \pm 1.686 \text{ GW}$
	ERCOT	1.61%	98.3%	1.82%	97.8%	$P_{total} = 1.324 + 0.787 \cdot R + 3.064 \cdot C \pm 0.266 \text{ GW}$
	Florida	2.05%	96.9%	2.20%	96.4%	$P_{total} = 1.310 + 3.544 \cdot R + 9.200 \cdot C \pm 0.779 \text{ GW}$
	ISONE	1.74%	96.7%	3.51%	86.6%	$P_{total} = 2.647 + 1.746 \cdot R + 14.027 \cdot C \pm 0.758 \text{ GW}$
	MISO	2.16%	92.6%	2.68%	88.7%	$P_{total} = 2.004 + 1.972 \cdot R + 19.452 \cdot C \pm 2.586 \text{ GW}$
	NYISO	1.18%	98.5%	2.50%	93.1%	$P_{total} = 0.349 + 2.832 \cdot R + 8.868 \cdot C \pm 0.678 \text{ GW}$
	PJM	1.21%	98.0%	2.17%	93.5%	$P_{total} = 4.052 + 2.528 \cdot R + 15.145 \cdot C \pm 2.771 \text{ GW}$
	Tennessee	1.58%	97.0%	2.99%	89.4%	$P_{total} = 0.236 + 2.545 \cdot R + 30.490 \cdot C \pm 0.870 \text{ GW}$
Mean		1.76%	96.0%	2.91%	89.4%	
S.D.		0.50%	2.40%	0.88%	5.3%	

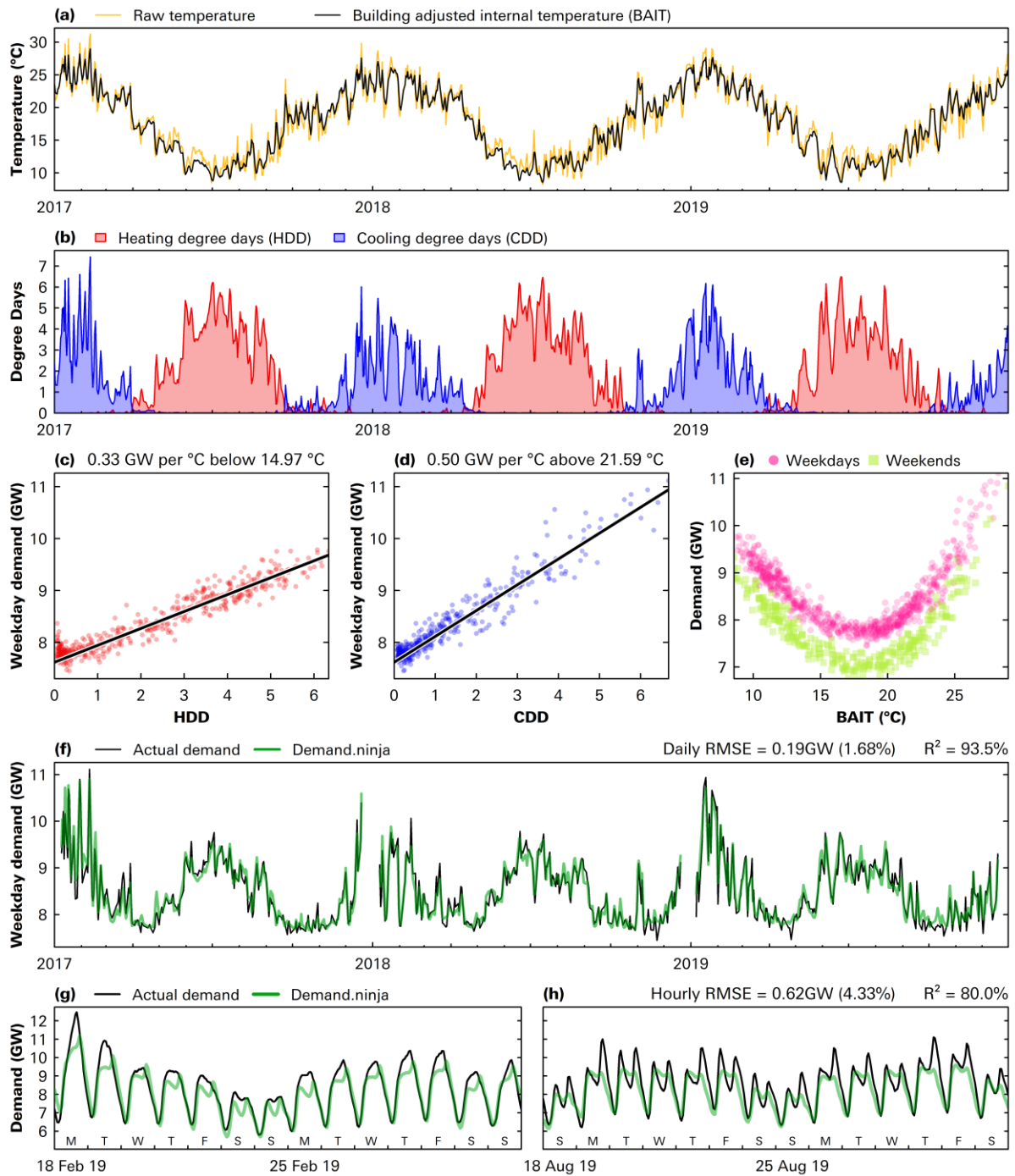
Supplementary Table 8: Model quality of the Demand.ninja when simulating daily electricity demand in countries and regions not considered by the other models shown in Supplementary Tables 5–7. The normalised root mean squared error (NRMSE) is given relative to maximum demand in each region (as plotted in the main paper Figure 4e) and the adjusted- R^2 of modelled demand compared to measured demand on working days from the sources listed in Supplementary Table 2. Weekends and national holidays are excluded due to non-weather influences. The US is divided into power markets and Australia into states, with each group ordered from highest to lowest annual energy demand.

		Demand.ninja	
		NRMSE	R^2
US Elec	Northwest	1.65%	94.2%
	Southeast	1.91%	96.5%
	Southwest	2.43%	96.7%
Elec	Japan	1.80%	94.5%
Australian Electricity	NSW	1.94%	89.4%
	QLD	1.60%	92.7%
	VIC	2.29%	86.5%
	SA	3.22%	84.5%

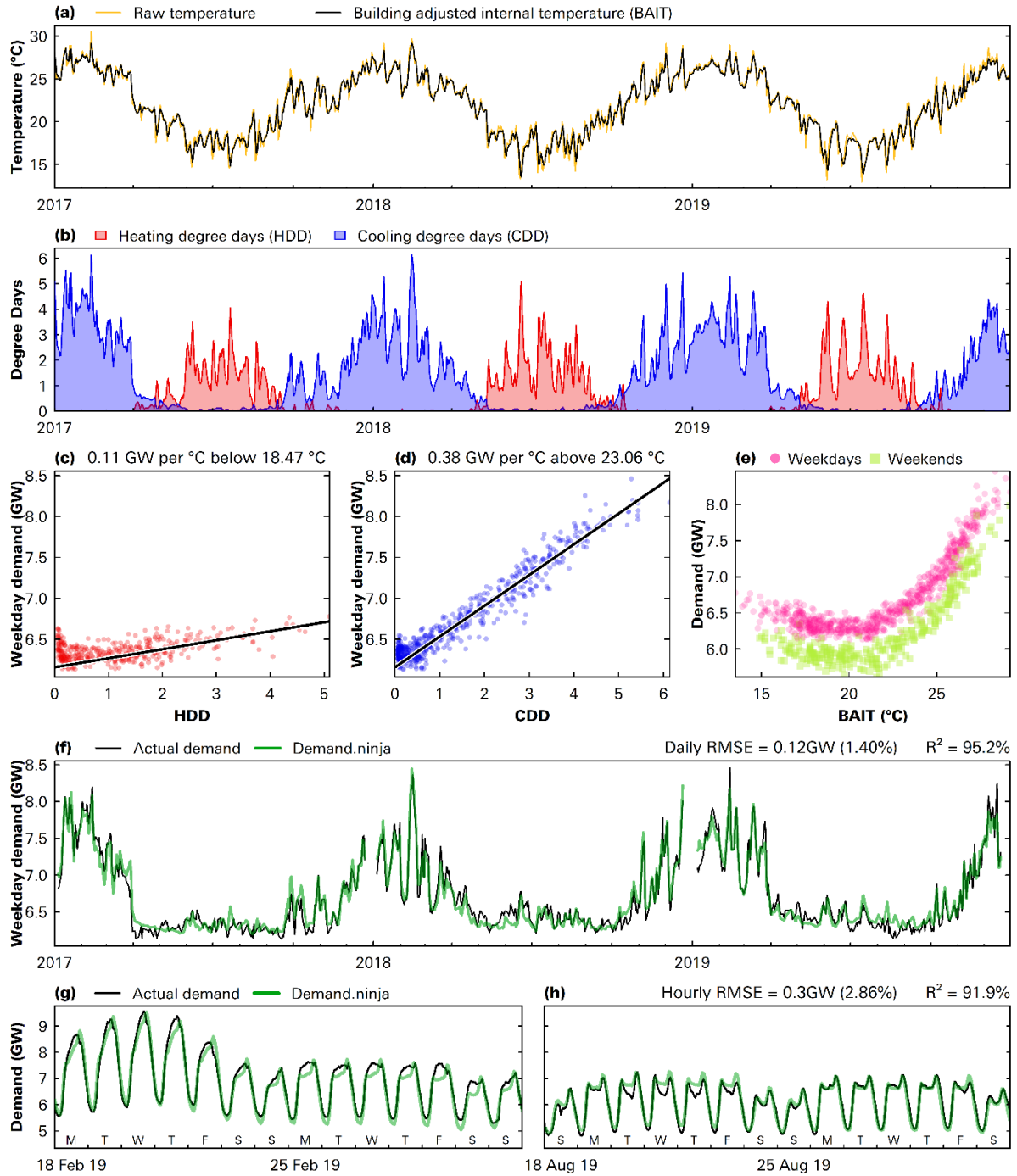
Supplementary Table 9: Cooling degree days, model coefficients, and electricity required for cooling across all studied regions. Current average CDDs refers to the estimated value for 2022 based on linear regression of annual CDDs from 1980–2022. This represents the average expectation, free from inter-annual weather variability. Increase per decade is based on the slope of this regression. Cooling threshold and power coefficients are those reported in Supplementary Figures 1–41. Annual cooling demand is calculated from the combination of CDDs and P_{cool} .

Region	Cooling Degree Days		Cooling threshold (T_{cool} , °C)	Cooling power (P_{cool} , GW/°C)	Annual cooling demand (TWh)	
	Current average	Increase per decade			Current average	Increase per decade
Australia NSW	393	22.1	21.6	0.5	4.69	0.26
Australia QLD	1020	35.5	23.1	0.38	9.19	0.32
Australia SA	301	22.2	21.5	0.1	0.7	0.05
Australia VIC	159	11.4	20.4	0.34	1.3	0.09
Austria	107	16.2	24.8	0.30	0.78	0.12
Belgium	49	7.4	24.6	0.43	0.51	0.08
Bulgaria	312	39.1	21.6	0.10	0.79	0.10
Czechia	104	19.1	25.9	0	0	0
Denmark	17	2.8	22.7	0.21	0.09	0.01
Estonia	41	9.7	25.1	0	0	0
Finland	27	6.3	24.4	0	0	0
France	138	16.1	22.7	1.59	5.25	0.61
Great Britain	11	2.1	20.9	1.36	0.36	0.07
Germany	83	14.3	23.1	0.55	1.09	0.19
Greece	655	50.9	22.6	0.35	5.58	0.43
Hungary	305	40.9	24.6	0.35	2.58	0.35
Ireland	1	0.1	21.5	0.16	0	0
Italy	451	39.9	20.6	1.46	15.85	1.40
Japan	553	32.3	20.9	3.00	39.84	2.32
Latvia	46	10.4	23.8	0.11	0.12	0.03
Lithuania	56	11.6	25.0	0.18	0.25	0.05
Netherlands	41	6.8	25.0	0.24	0.24	0.04
Norway	7	1	22.7	0	0	0
Poland	112	20.0	23.9	0.83	2.22	0.40
Portugal	197	2.3	21.7	0.34	1.59	0.02
Romania	366	43.1	22.2	0.20	1.76	0.21
Slovakia	153	24.4	24.9	0.08	0.28	0.05
Spain	414	26.8	19.8	0.88	8.74	0.57
Sweden	26	5.1	21.8	0	0	0
Switzerland	65	10.7	25.8	0.16	0.25	0.04
US CAISO	373	17.0	17.7	1.36	12.20	0.56
US ERCOT	1239	45.0	20.7	0.55	16.32	0.59
US MISO	449	23.3	19.3	4.66	50.24	2.61
US NYISO	298	31.6	17.6	1.07	7.61	0.81
US PJM	453	33.1	18.5	4.93	53.62	3.91
US Carolinas	786	36.1	19.6	1.27	23.94	1.10
US Central	678	28.1	19.1	1.56	25.39	1.05
US Florida	1584	63.5	21.1	1.65	62.86	2.52
US New England	245	28.3	17.9	0.90	5.32	0.61
US Northwest	213	18.9	15.2	1.38	7.09	0.63
US Southeast	904	36.1	19.5	1.35	29.26	1.17
US Southwest	831	33.2	19.1	0.69	13.77	0.55
US Tennessee	677	25.7	18.9	0.83	13.43	0.51

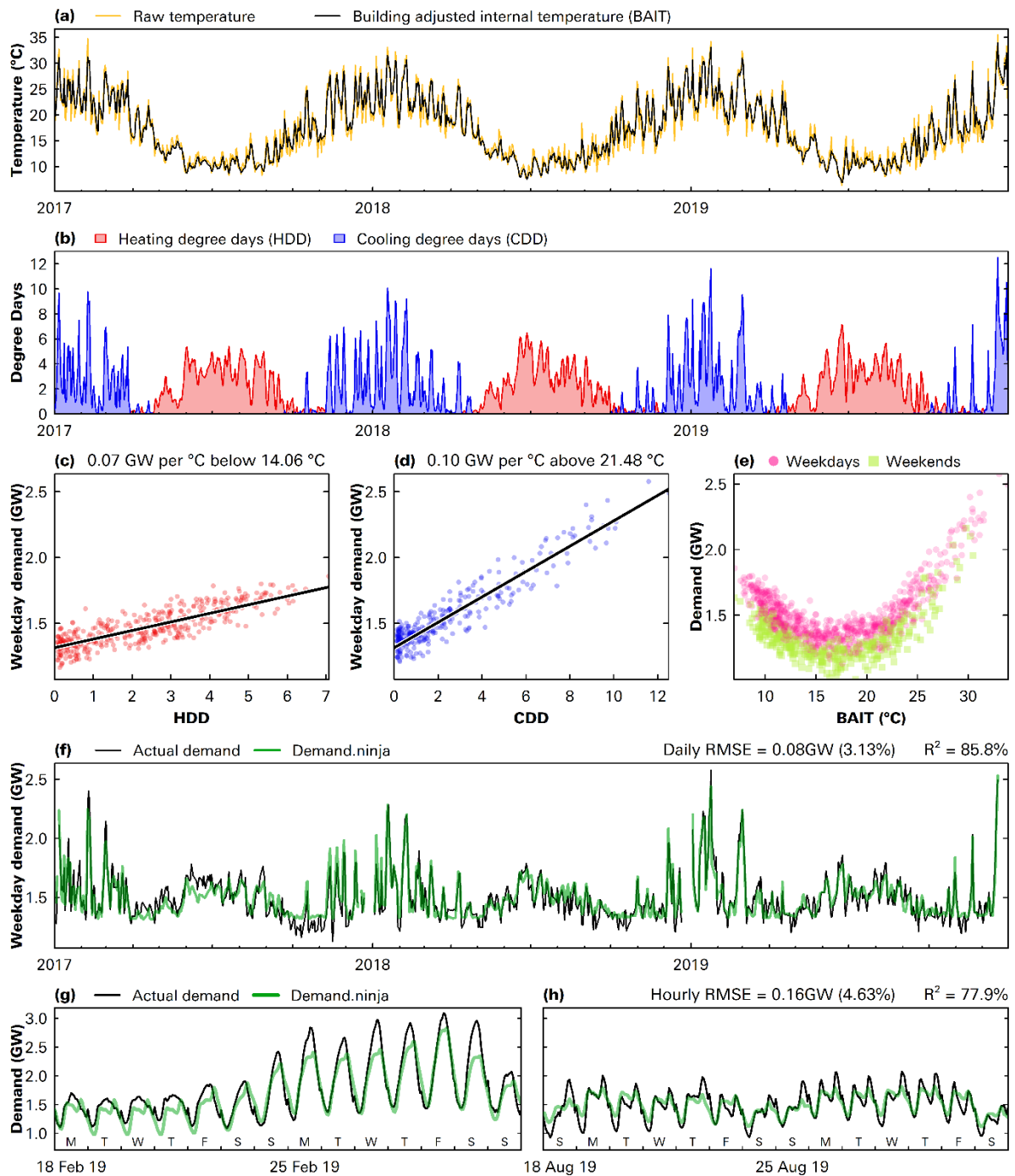
Supplementary Figures



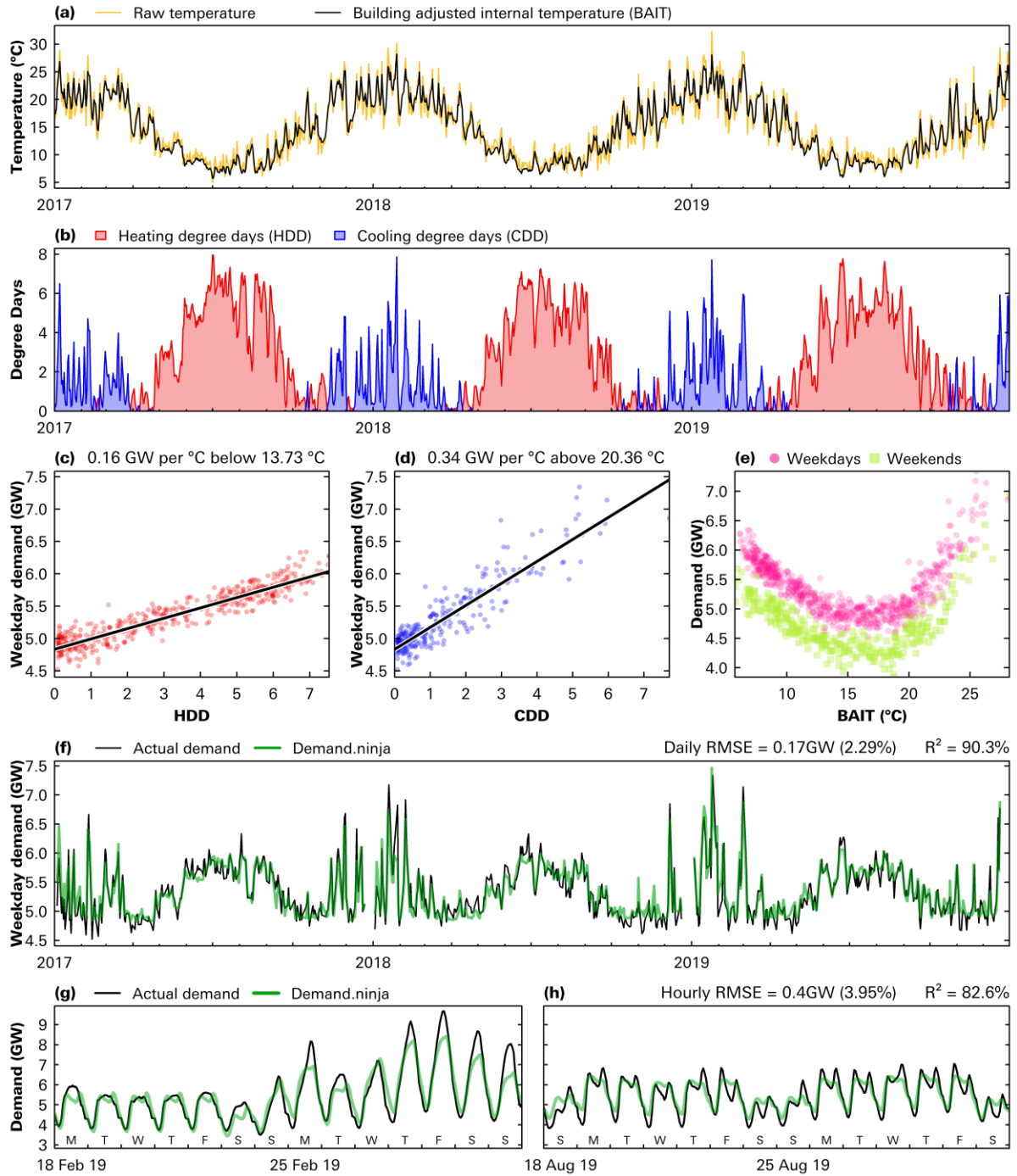
Supplementary Figure 1: Visualisation of the process of converting from temperature to BAIT to HDD and CDD to energy consumption in New South Wales, Australia. Figure follows the same design as Figure 2 in the main manuscript and see the caption there for more detail.



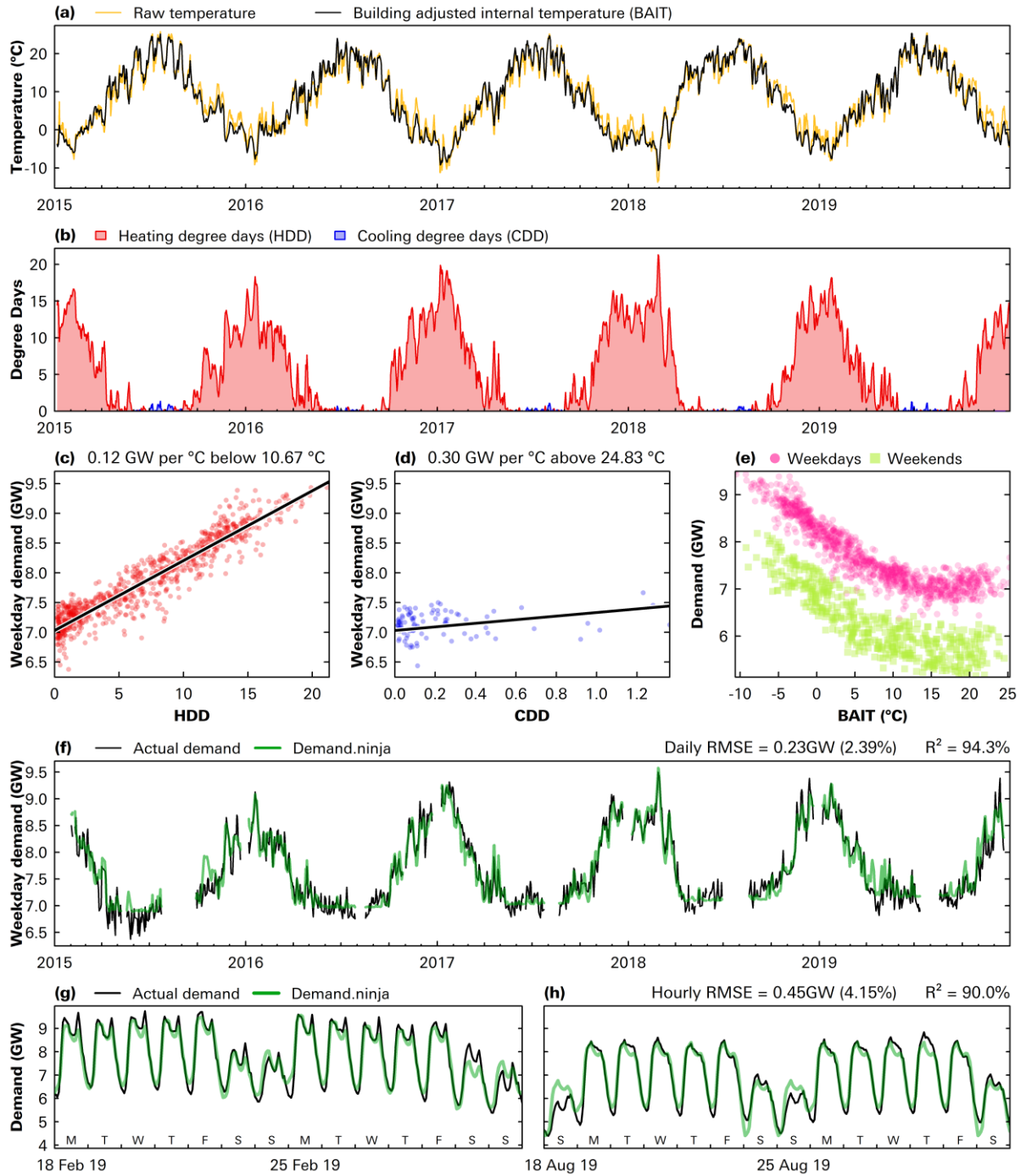
Supplementary Figure 2: Visualisation of the process of converting from temperature to BAIT to HDD and CDD to energy consumption in Queensland, Australia. Figure follows the same design as Figure 2 in the main manuscript; see the caption there for more detail.



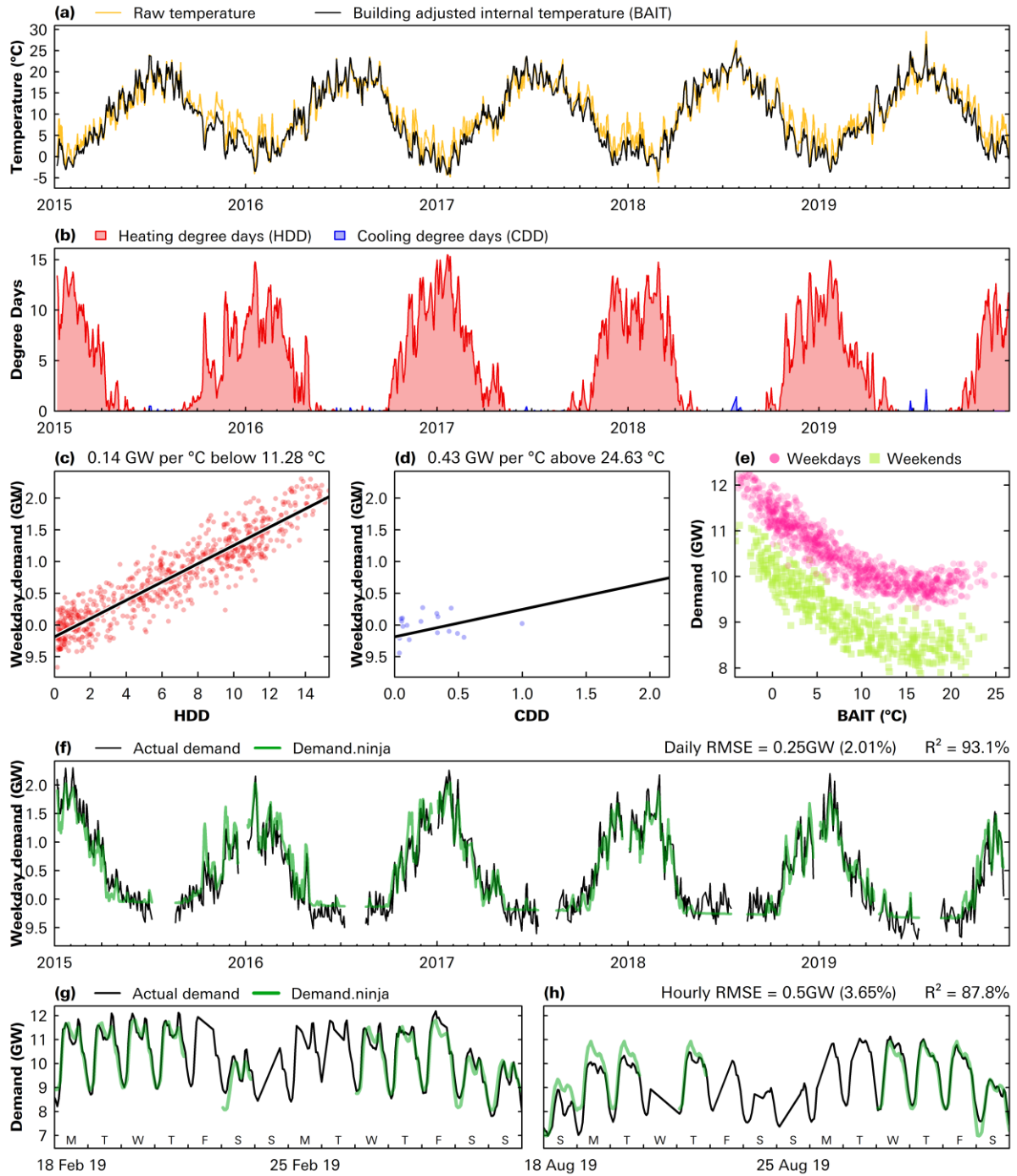
Supplementary Figure 3: Visualisation of the process of converting from temperature to BAIT to HDD and CDD to energy consumption in Southern Australia. Figure follows the same design as Figure 2 in the main manuscript; see the caption there for more detail.



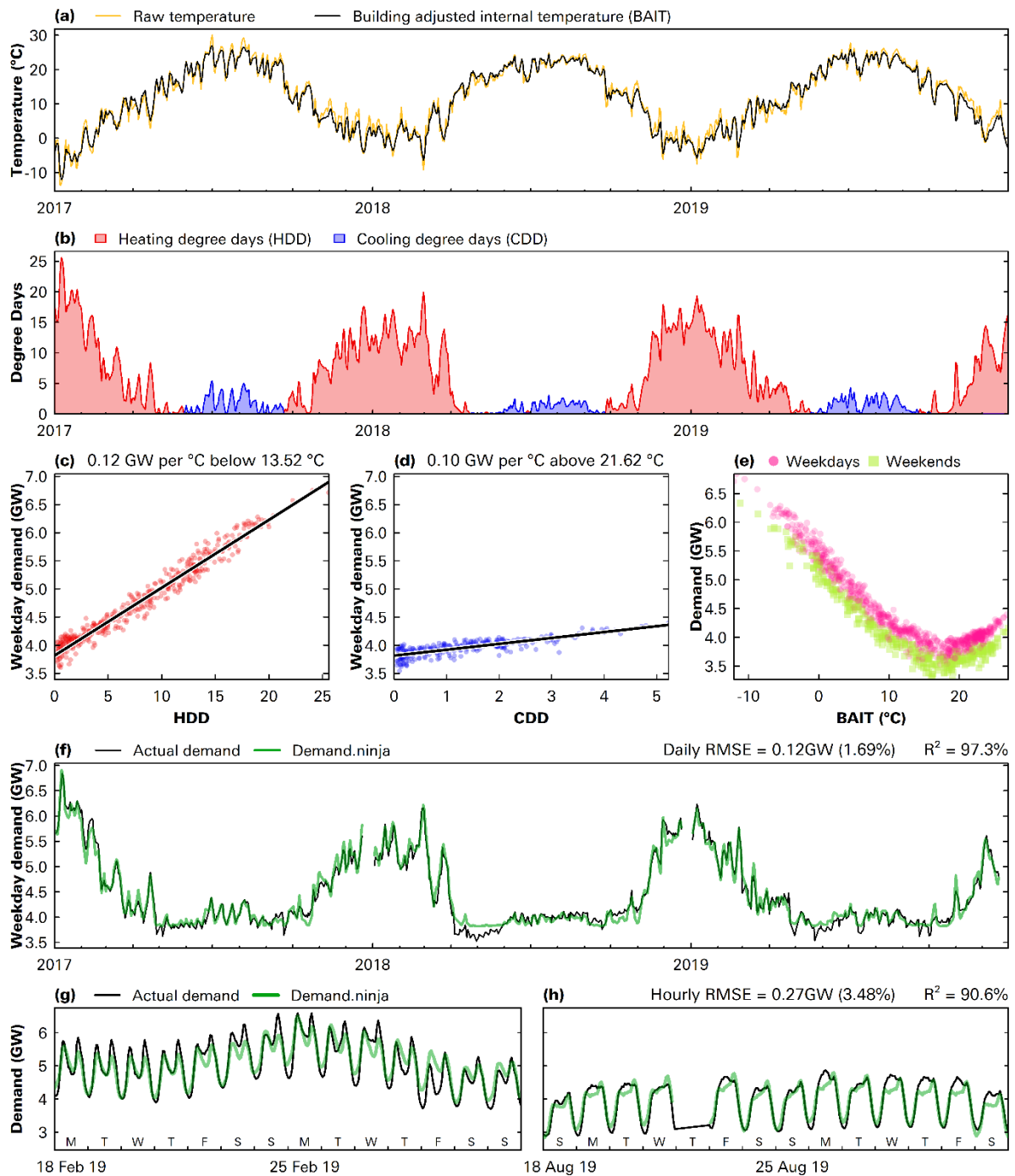
Supplementary Figure 4: Visualisation of the process of converting from temperature to BAIT to HDD and CDD to energy consumption in Victoria, Australia. Figure follows the same design as Figure 2 in the main manuscript; see the caption there for more detail.



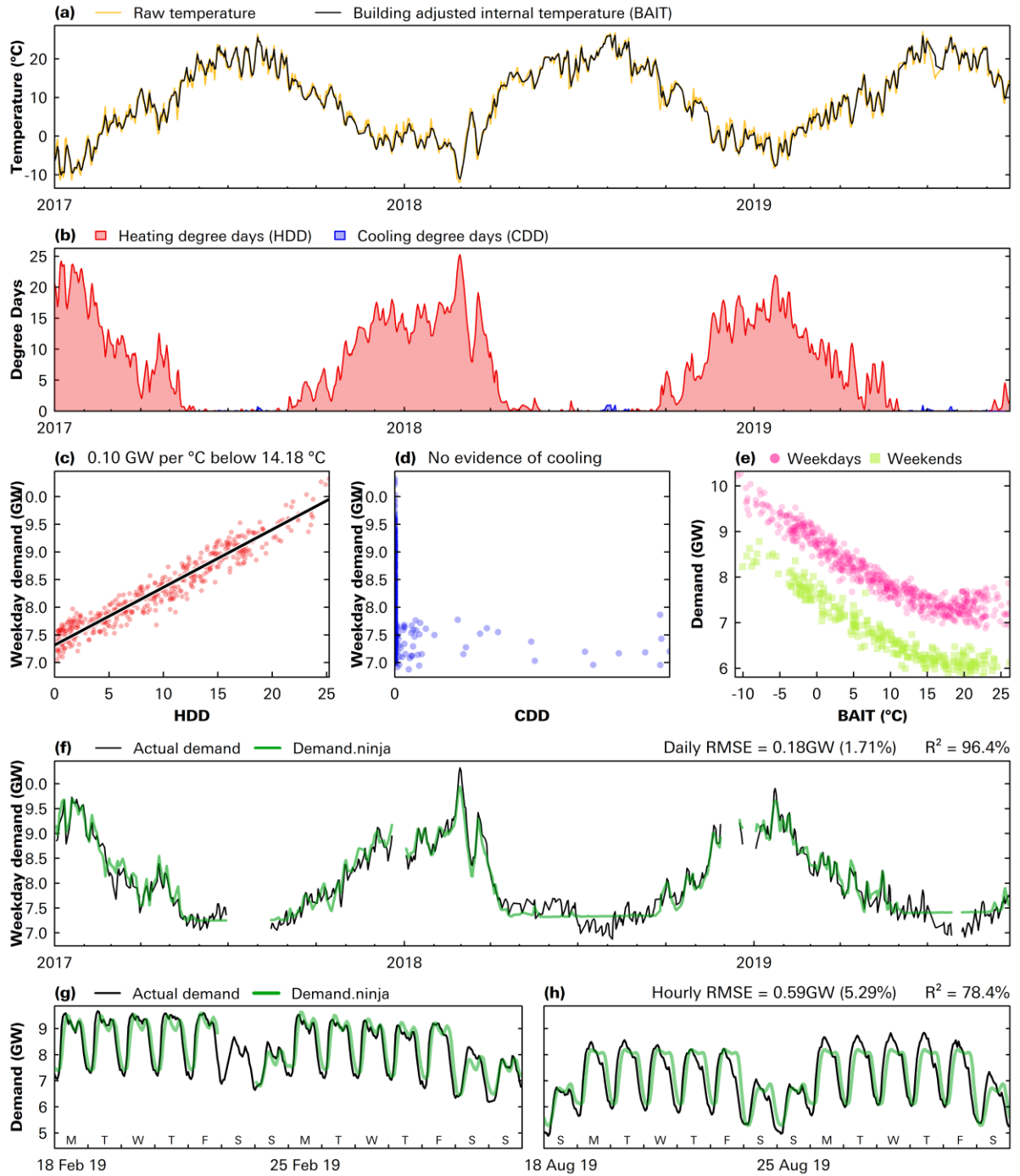
Supplementary Figure 5: Visualisation of the process of converting from temperature to BAIT to HDD and CDD to energy consumption in Austria. Figure follows the same design as Figure 2 in the main manuscript; see the caption there for more detail.



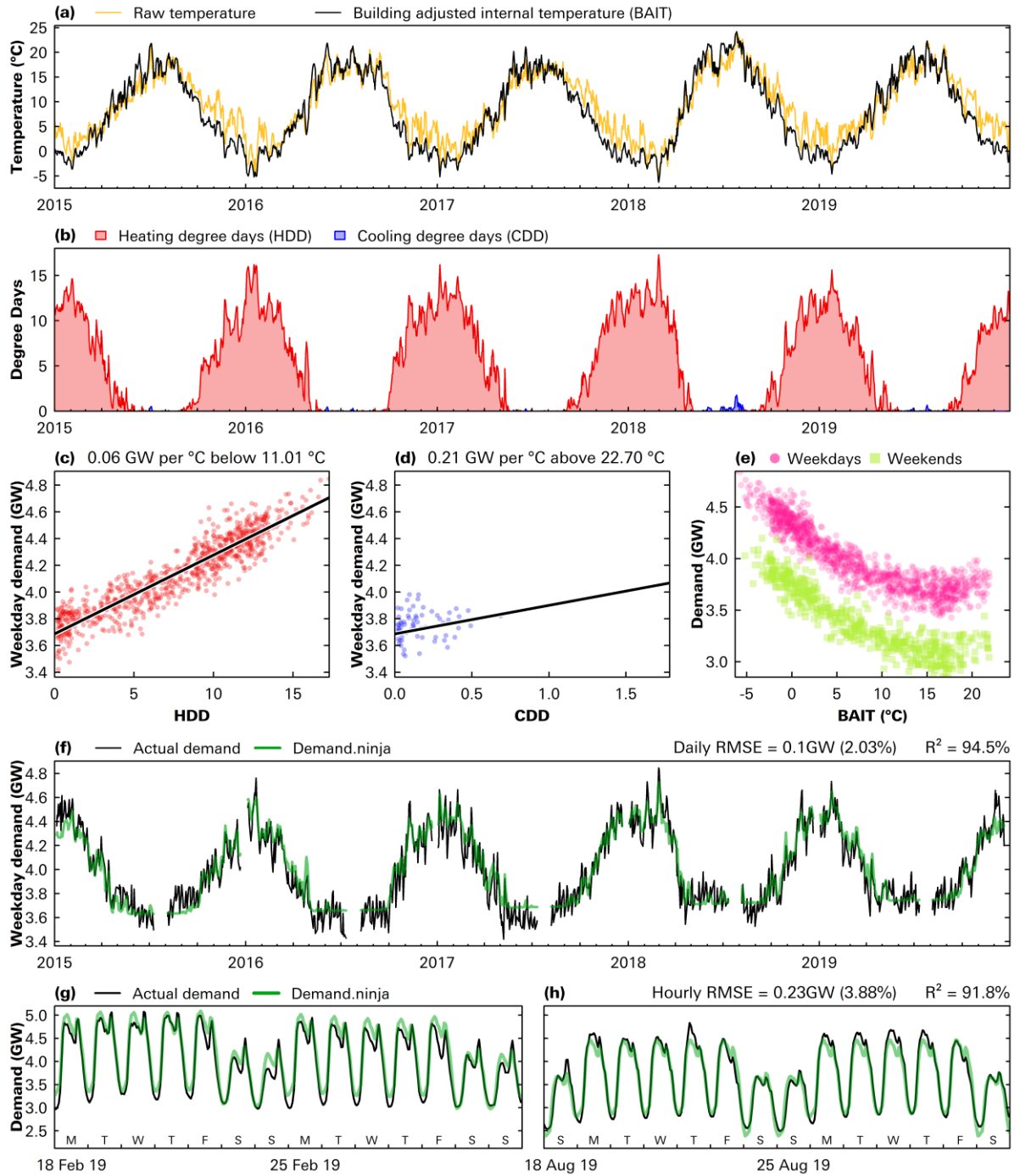
Supplementary Figure 6: Visualisation of the process of converting from temperature to BAIT to HDD and CDD to energy consumption in Belgium. Figure follows the same design as Figure 2 in the main manuscript; see the caption there for more detail.



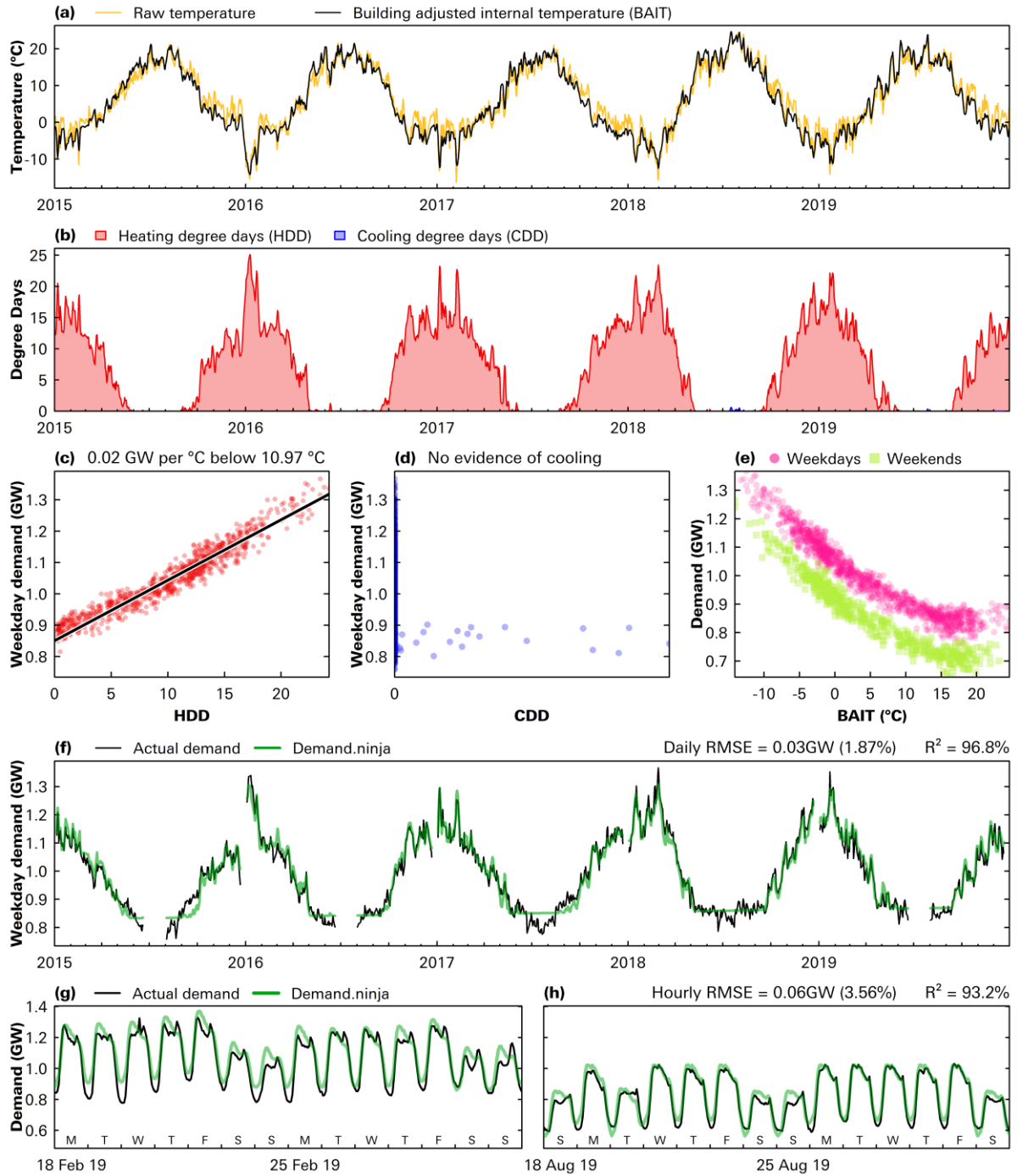
Supplementary Figure 7: Visualisation of the process of converting from temperature to BAIT to HDD and CDD to energy consumption in Bulgaria. Figure follows the same design as Figure 2 in the main manuscript; see the caption there for more detail.



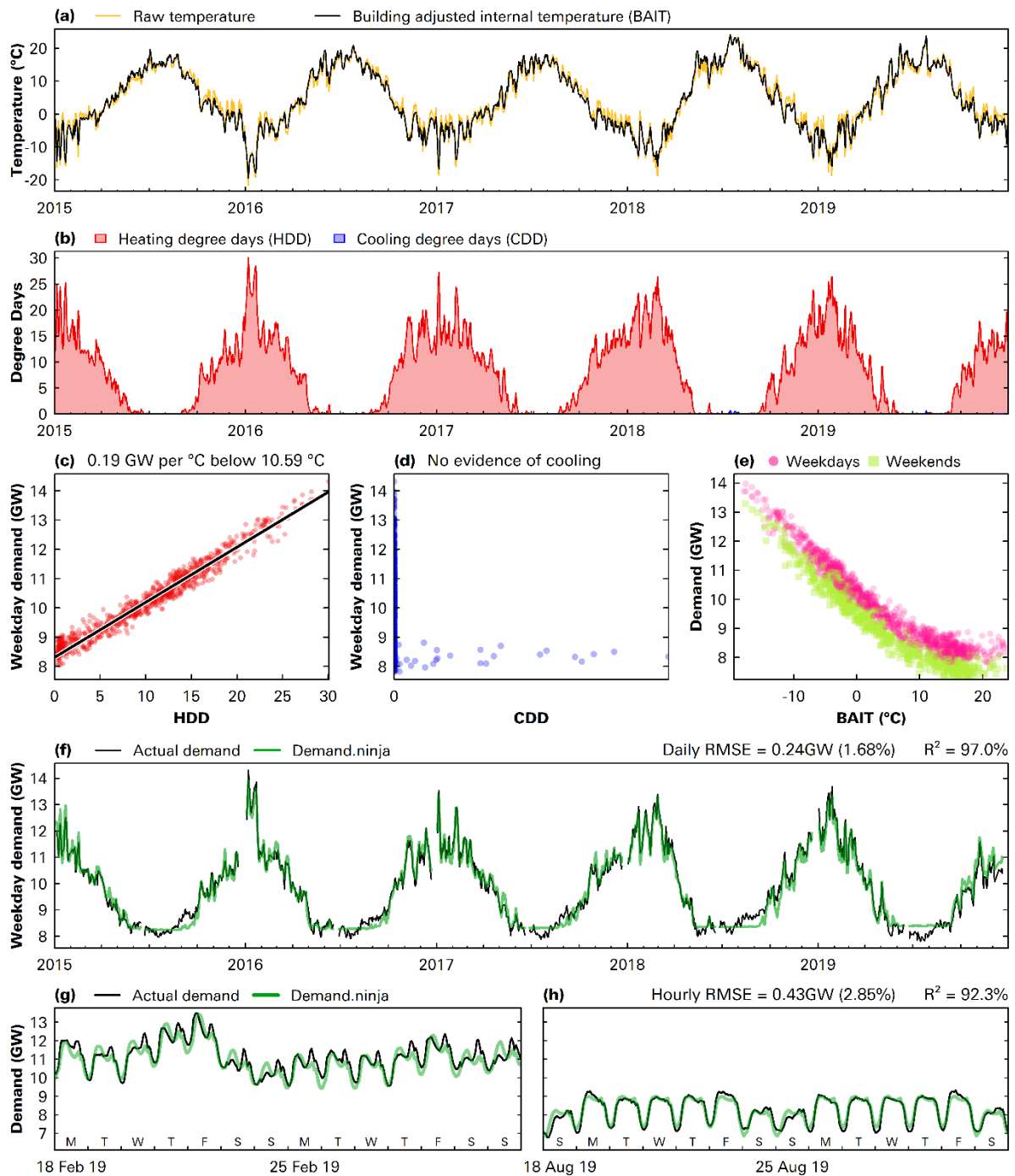
Supplementary Figure 8: Visualisation of the process of converting from temperature to BAIT to HDD and CDD to energy consumption in Czechia. Figure follows the same design as Figure 2 in the main manuscript; see the caption there for more detail.



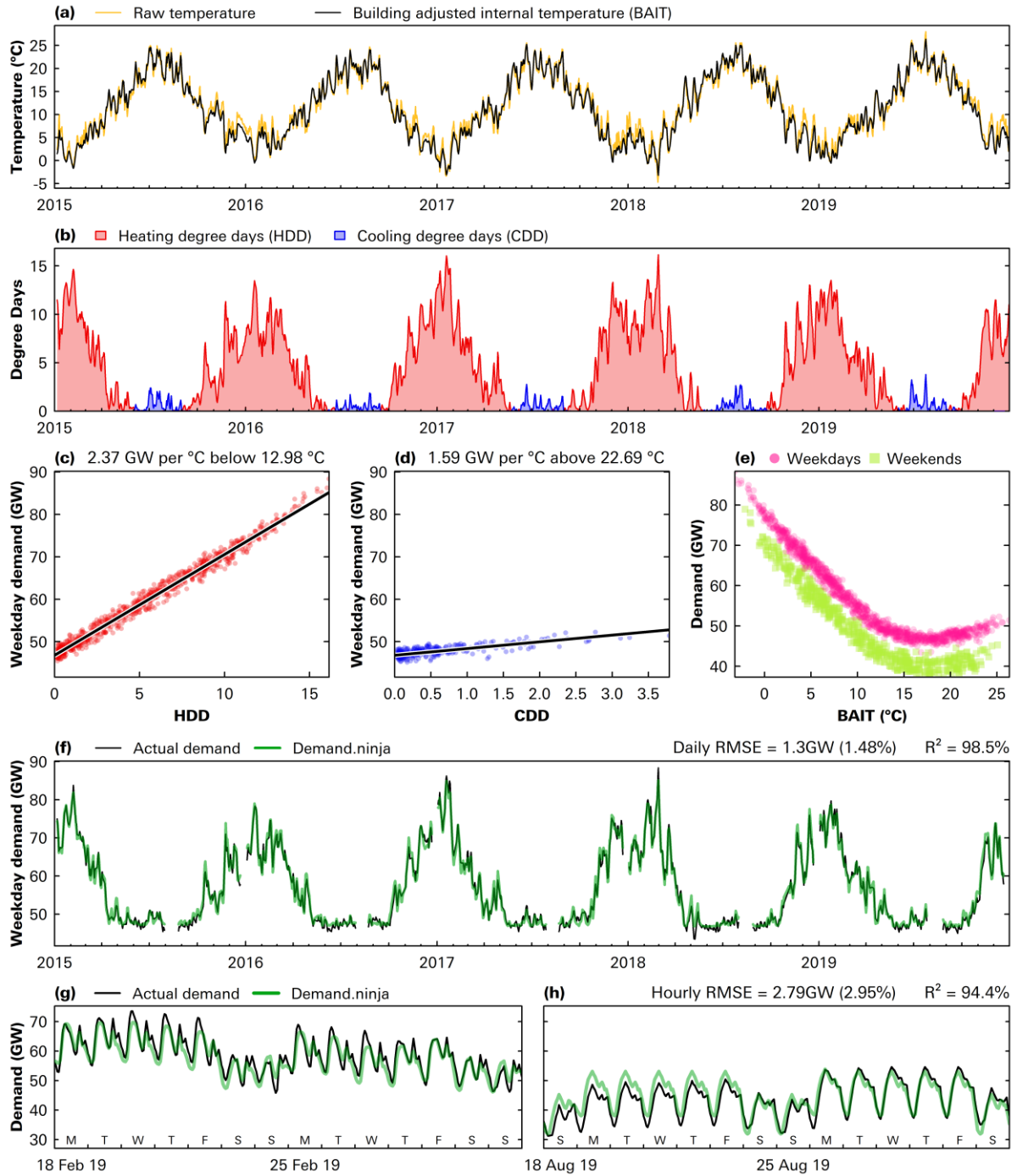
Supplementary Figure 9: Visualisation of the process of converting from temperature to BAIT to HDD and CDD to energy consumption in Denmark. Figure follows the same design as Figure 2 in the main manuscript; see the caption there for more detail.



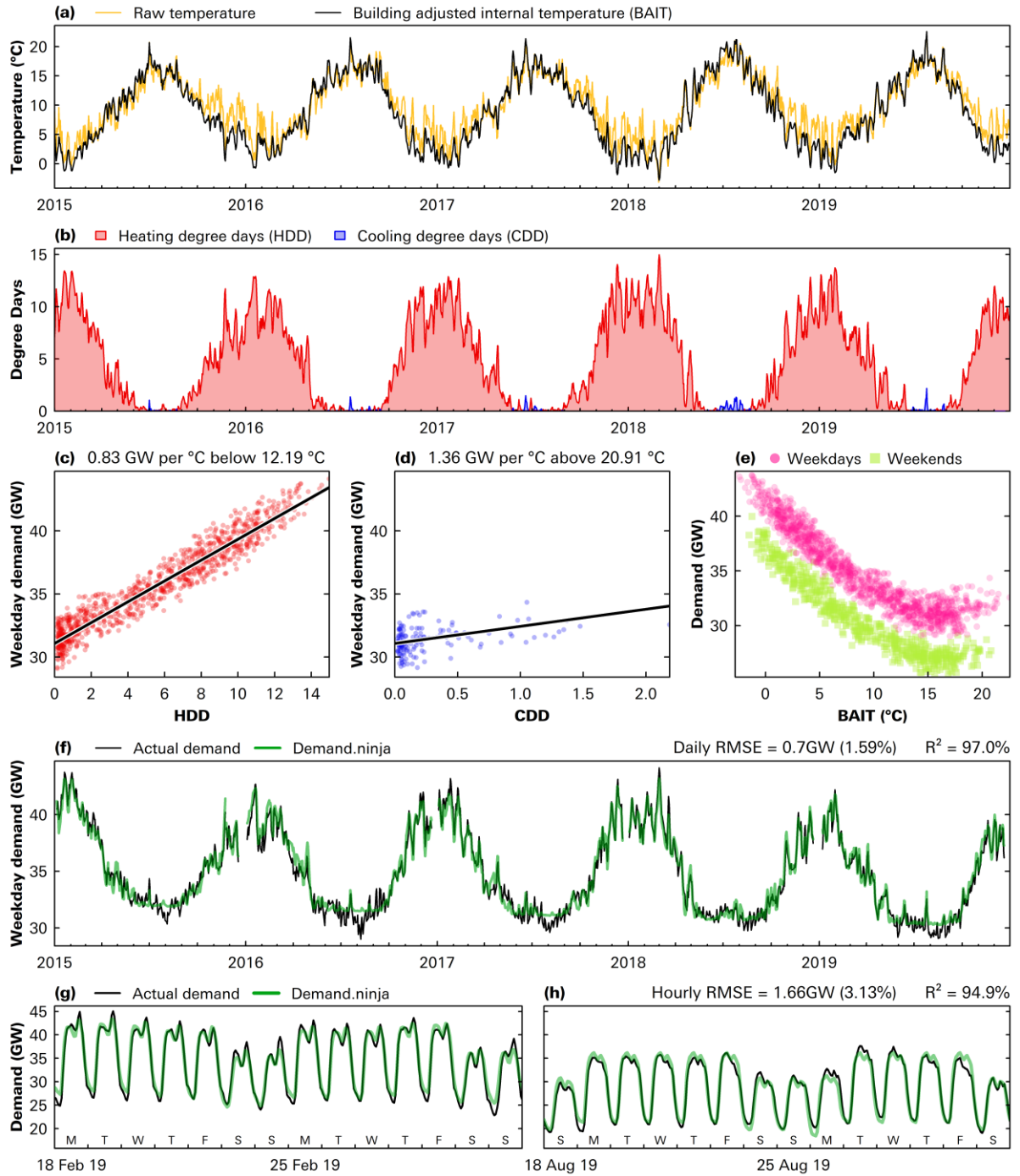
Supplementary Figure 10: Visualisation of the process of converting from temperature to BAIT to HDD and CDD to energy consumption in Estonia. Figure follows the same design as Figure 2 in the main manuscript; see the caption there for more detail.



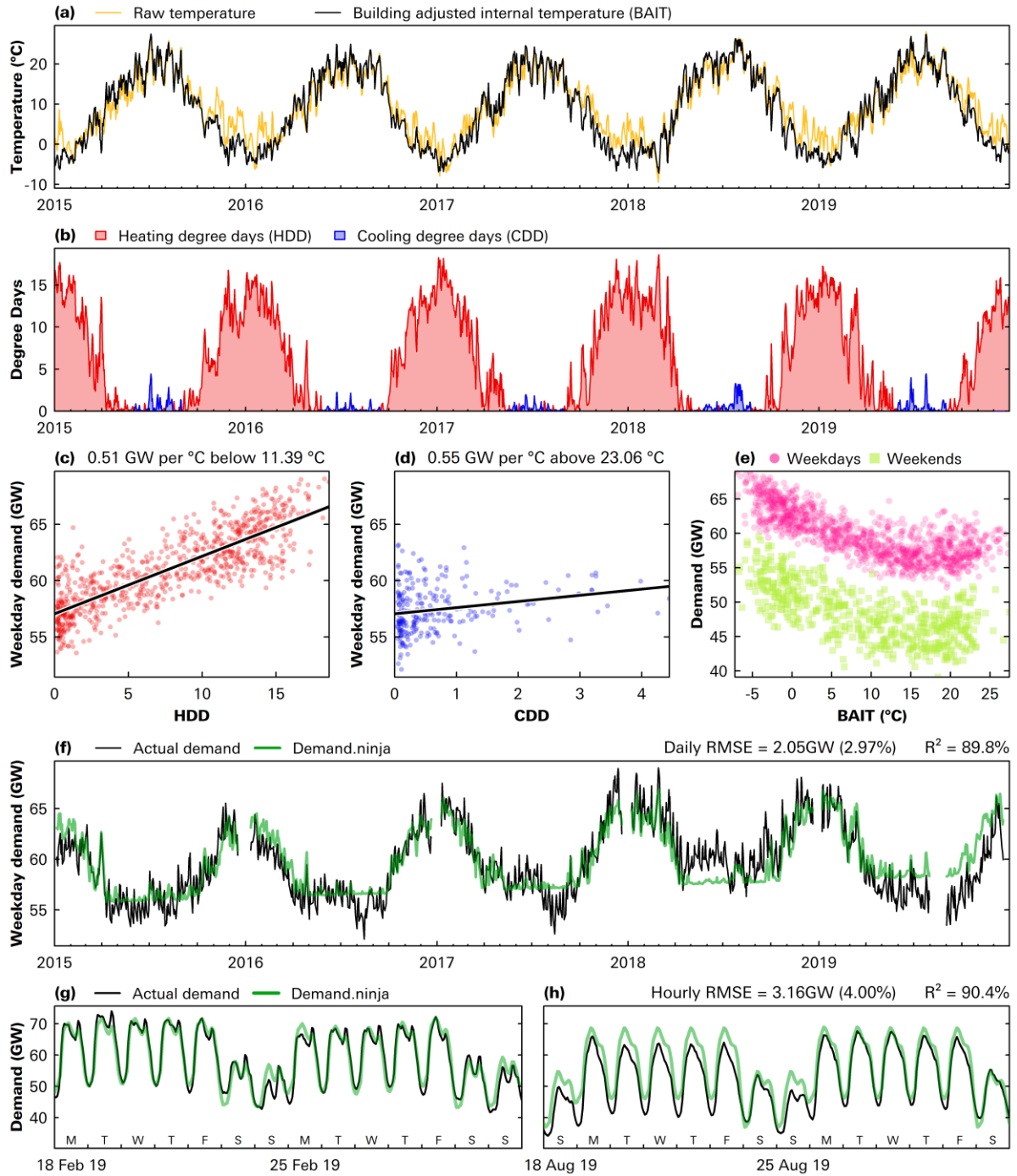
Supplementary Figure 11: Visualisation of the process of converting from temperature to BAIT to HDD and CDD to energy consumption in Finland. Figure follows the same design as Figure 2 in the main manuscript; see the caption there for more detail.



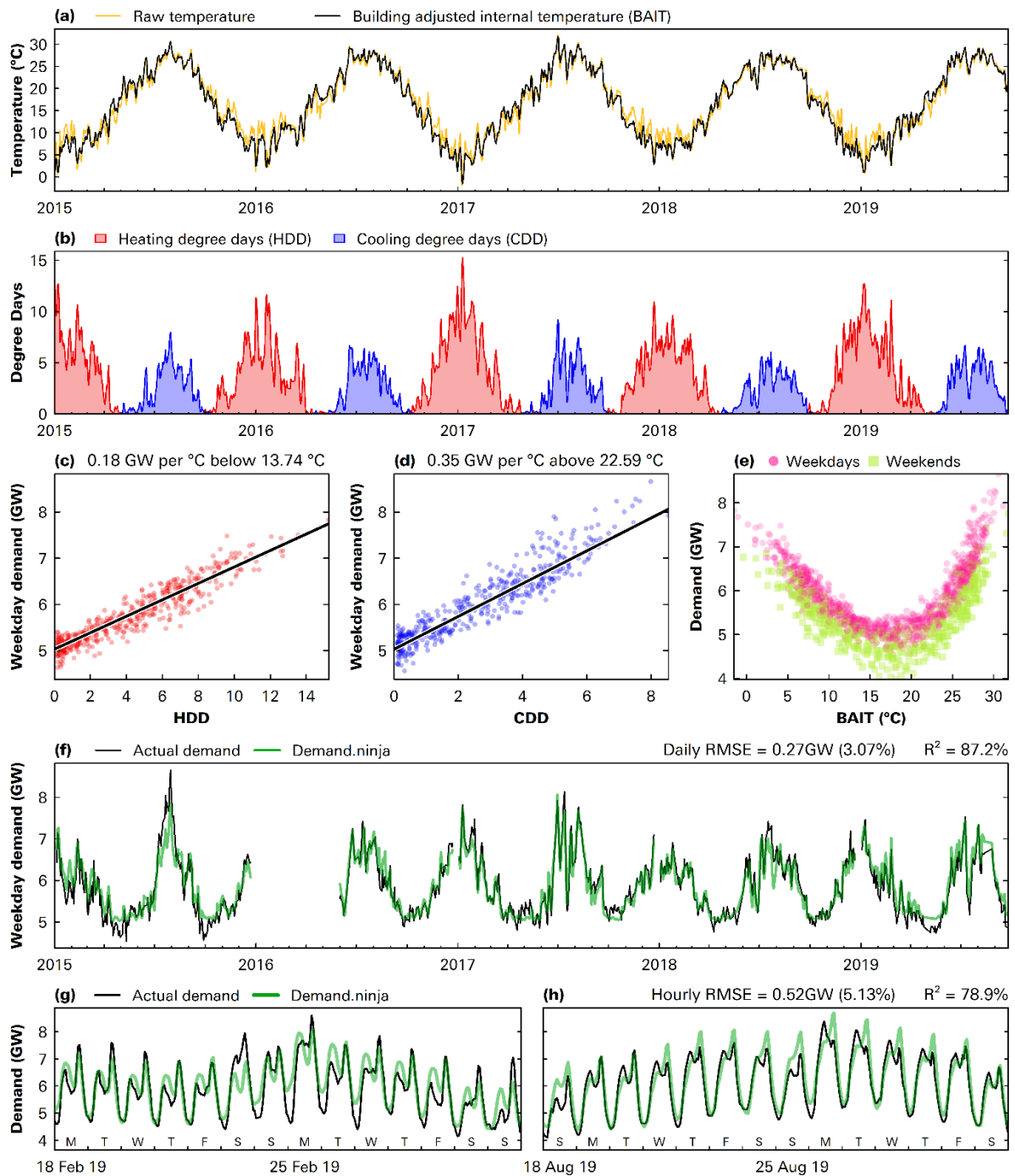
Supplementary Figure 12: Visualisation of the process of converting from temperature to BAIT to HDD and CDD to energy consumption in France. Figure follows the same design as Figure 2 in the main manuscript; see the caption there for more detail.



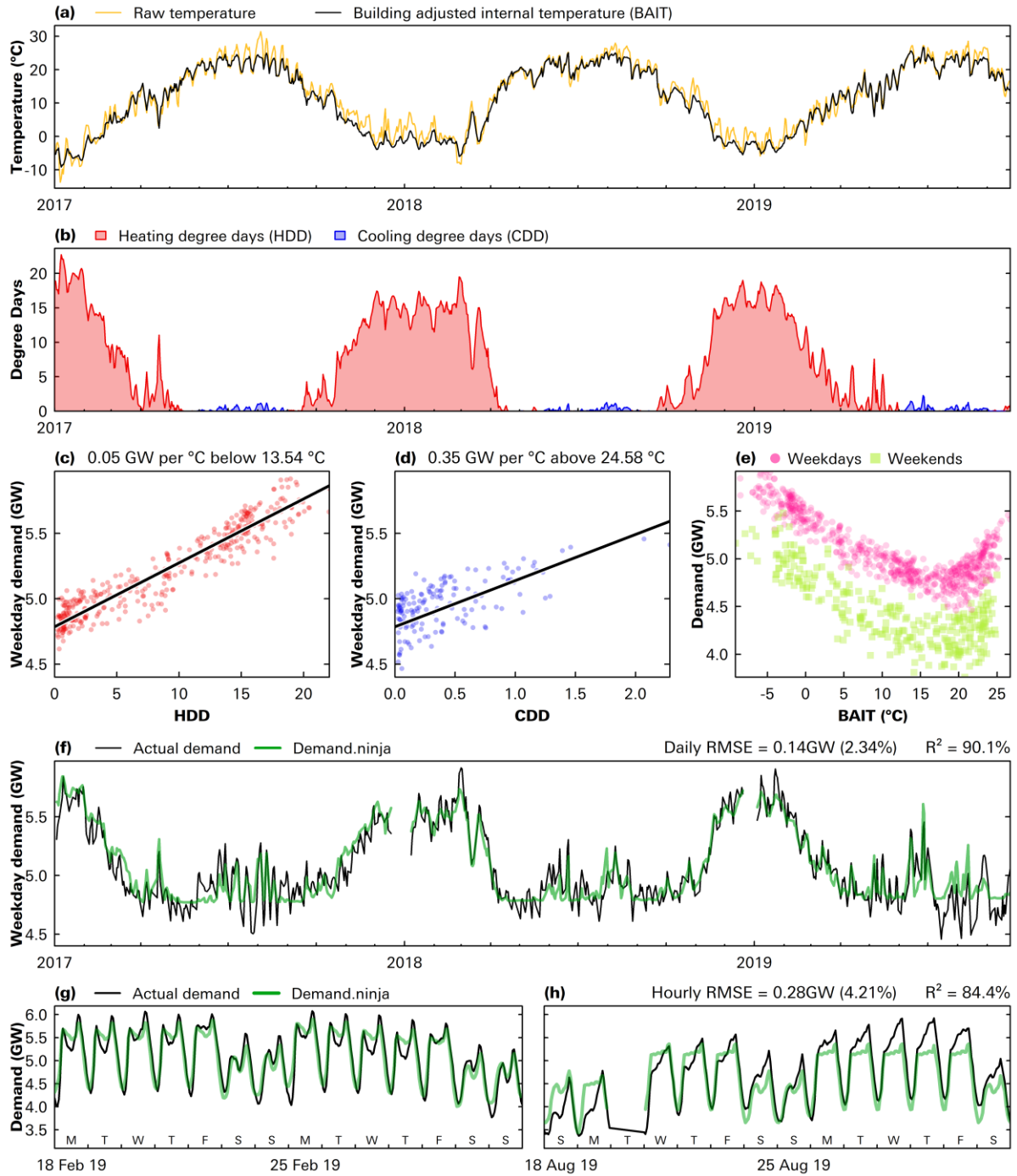
Supplementary Figure 13: Visualisation of the process of converting from temperature to BAIT to HDD and CDD to energy consumption in Great Britain. Figure follows the same design as Figure 2 in the main manuscript; see the caption there for more detail.



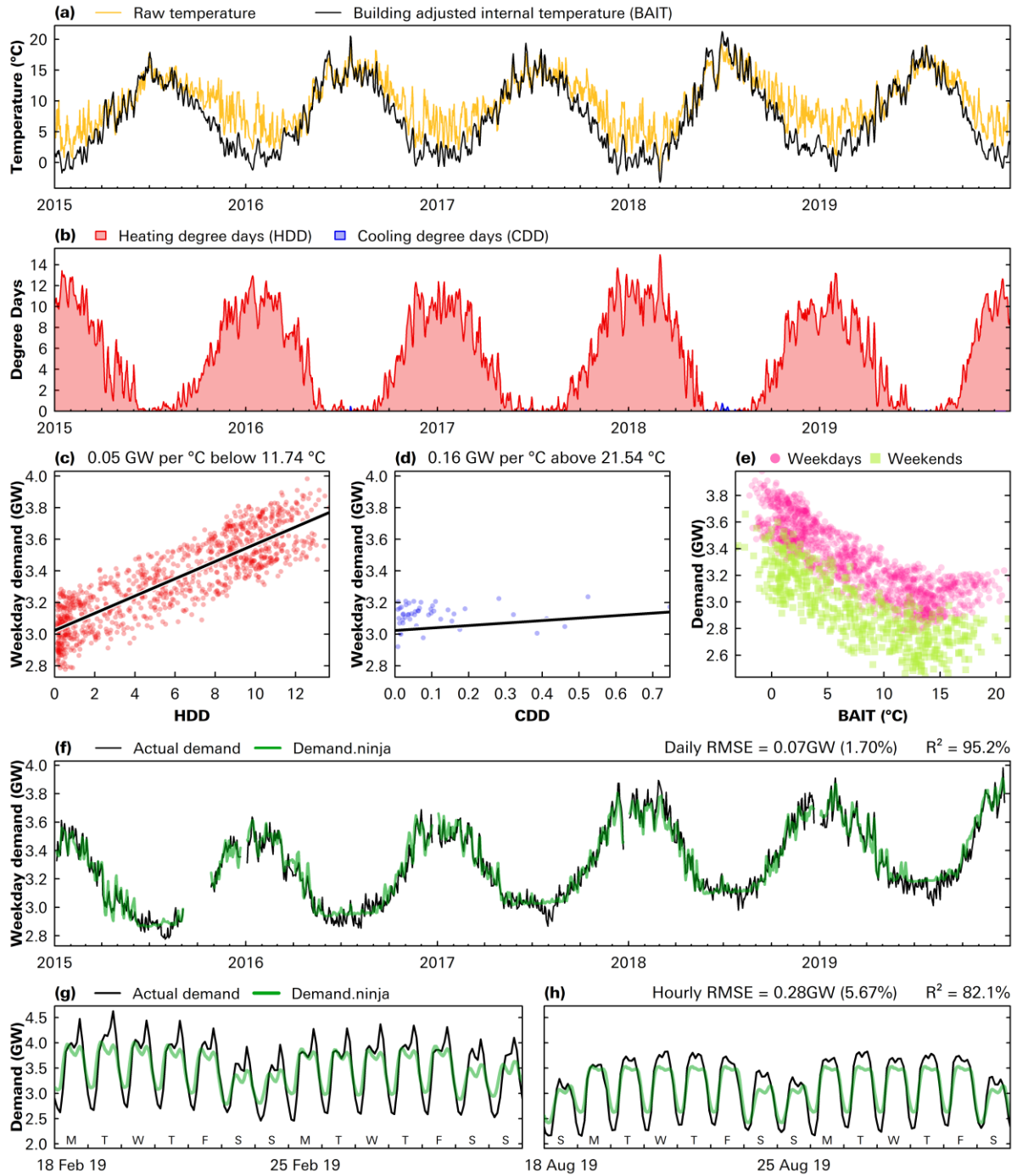
Supplementary Figure 14: Visualisation of the process of converting from temperature to BAIT to HDD and CDD to energy consumption in Germany. Figure follows the same design as Figure 2 in the main manuscript; see the caption there for more detail.



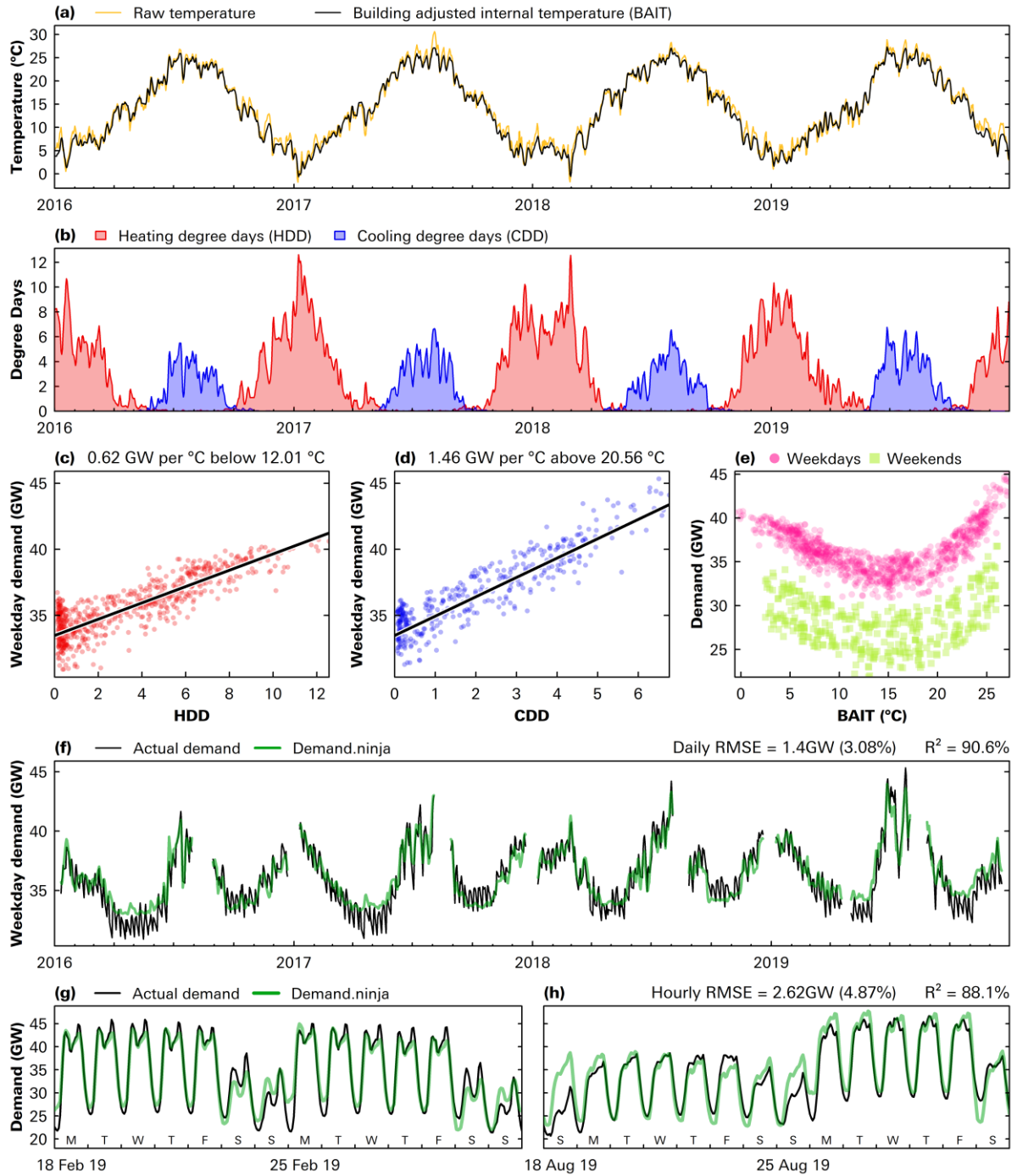
Supplementary Figure 15: Visualisation of the process of converting from temperature to BAIT to HDD and CDD to energy consumption in Greece. Figure follows the same design as Figure 2 in the main manuscript; see the caption there for more detail.



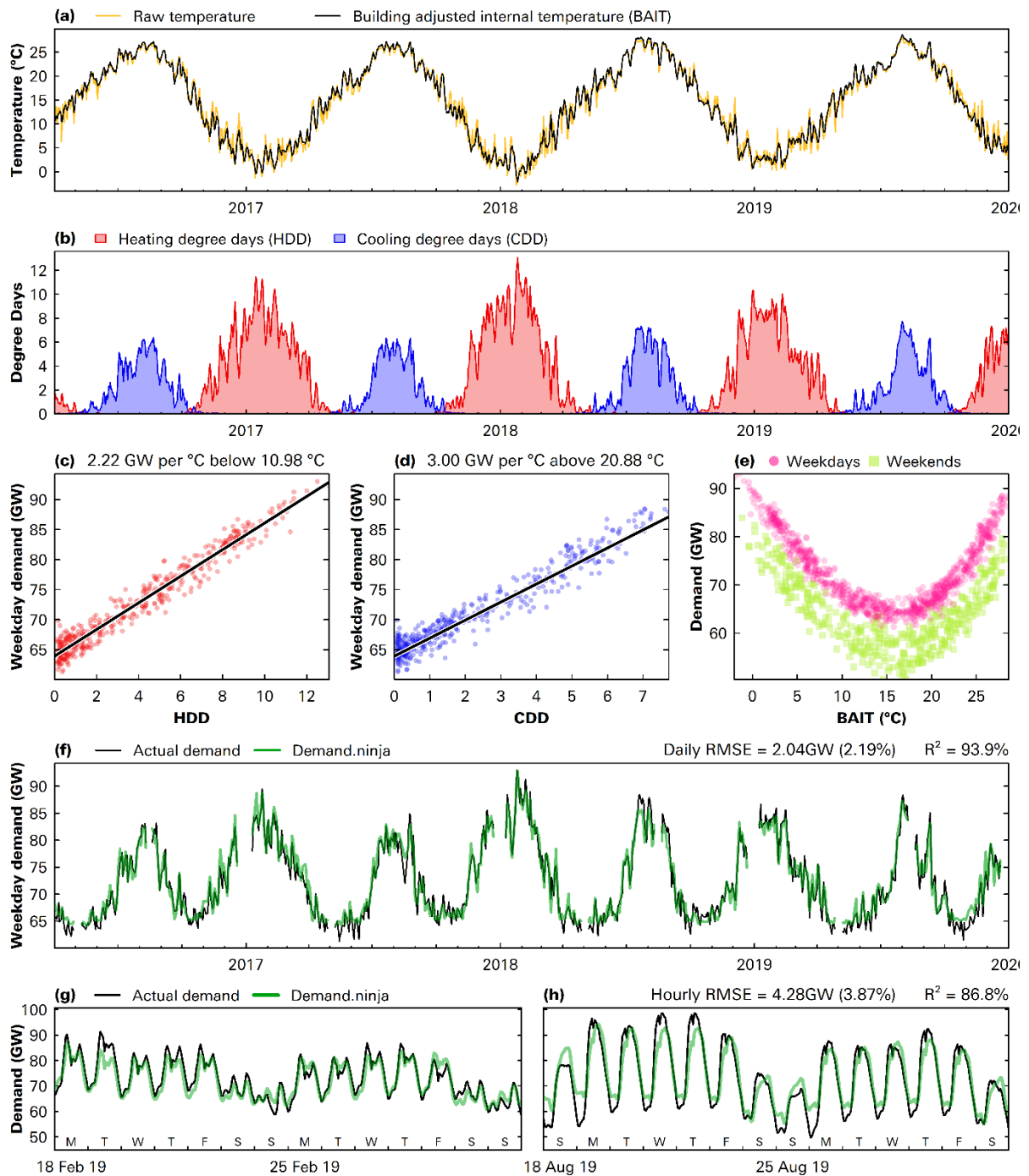
Supplementary Figure 16: Visualisation of the process of converting from temperature to BAIT to HDD and CDD to energy consumption in Hungary. Figure follows the same design as Figure 2 in the main manuscript; see the caption there for more detail.



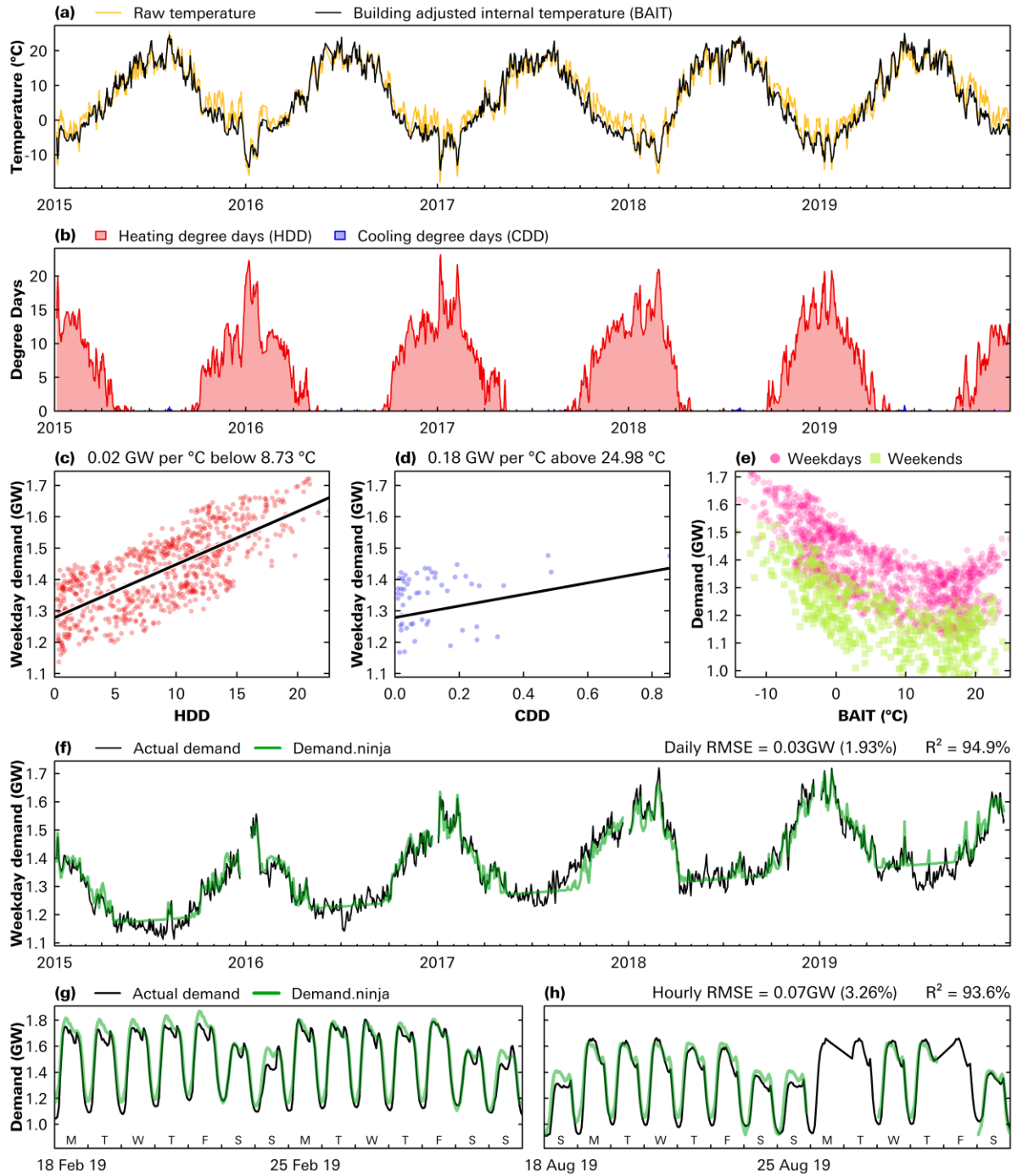
Supplementary Figure 17: Visualisation of the process of converting from temperature to BAIT to HDD and CDD to energy consumption in Ireland. Figure follows the same design as Figure 2 in the main manuscript; see the caption there for more detail.



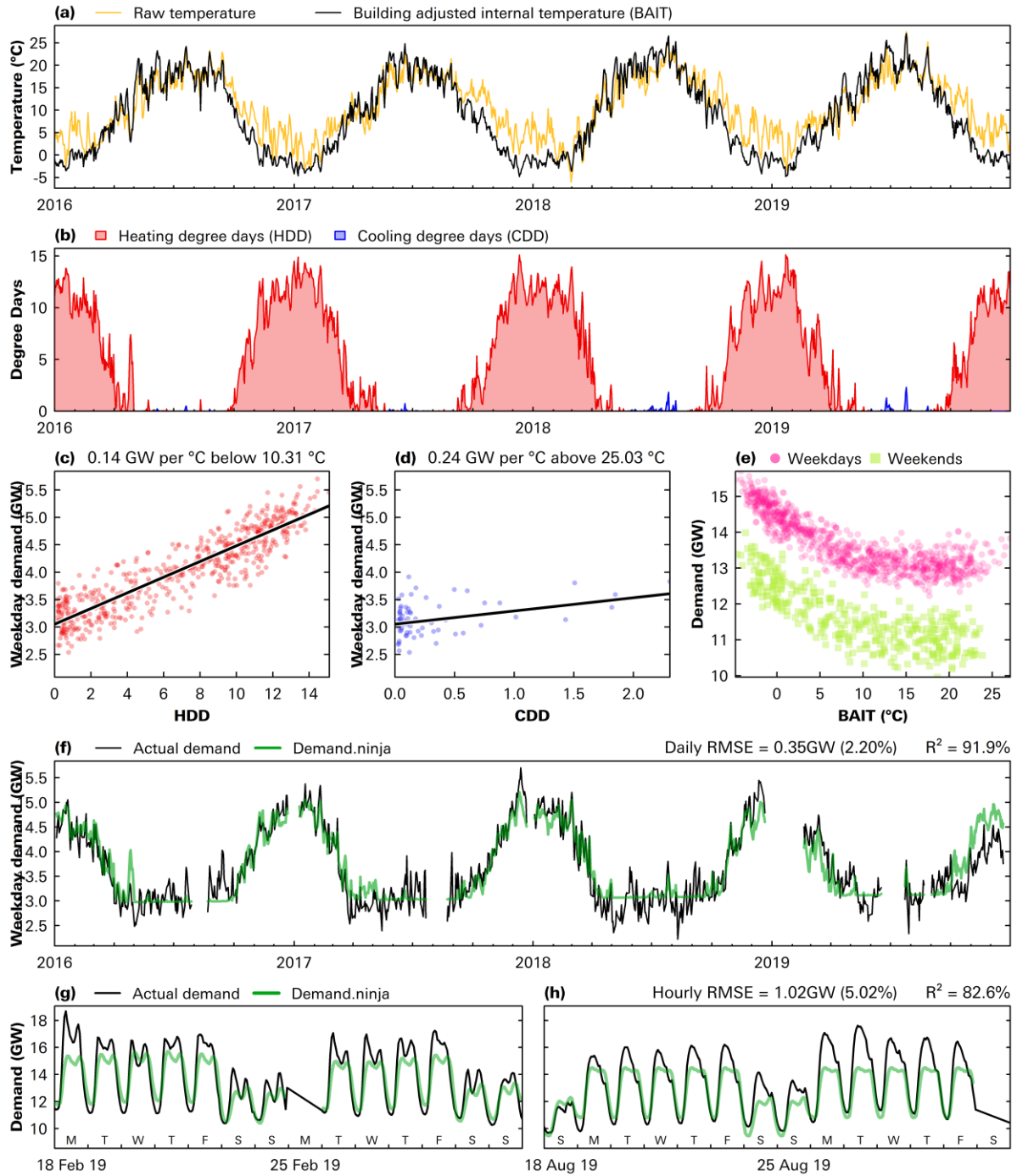
Supplementary Figure 18: Visualisation of the process of converting from temperature to BAIT to HDD and CDD to energy consumption in Italy. Figure follows the same design as Figure 2 in the main manuscript; see the caption there for more detail.



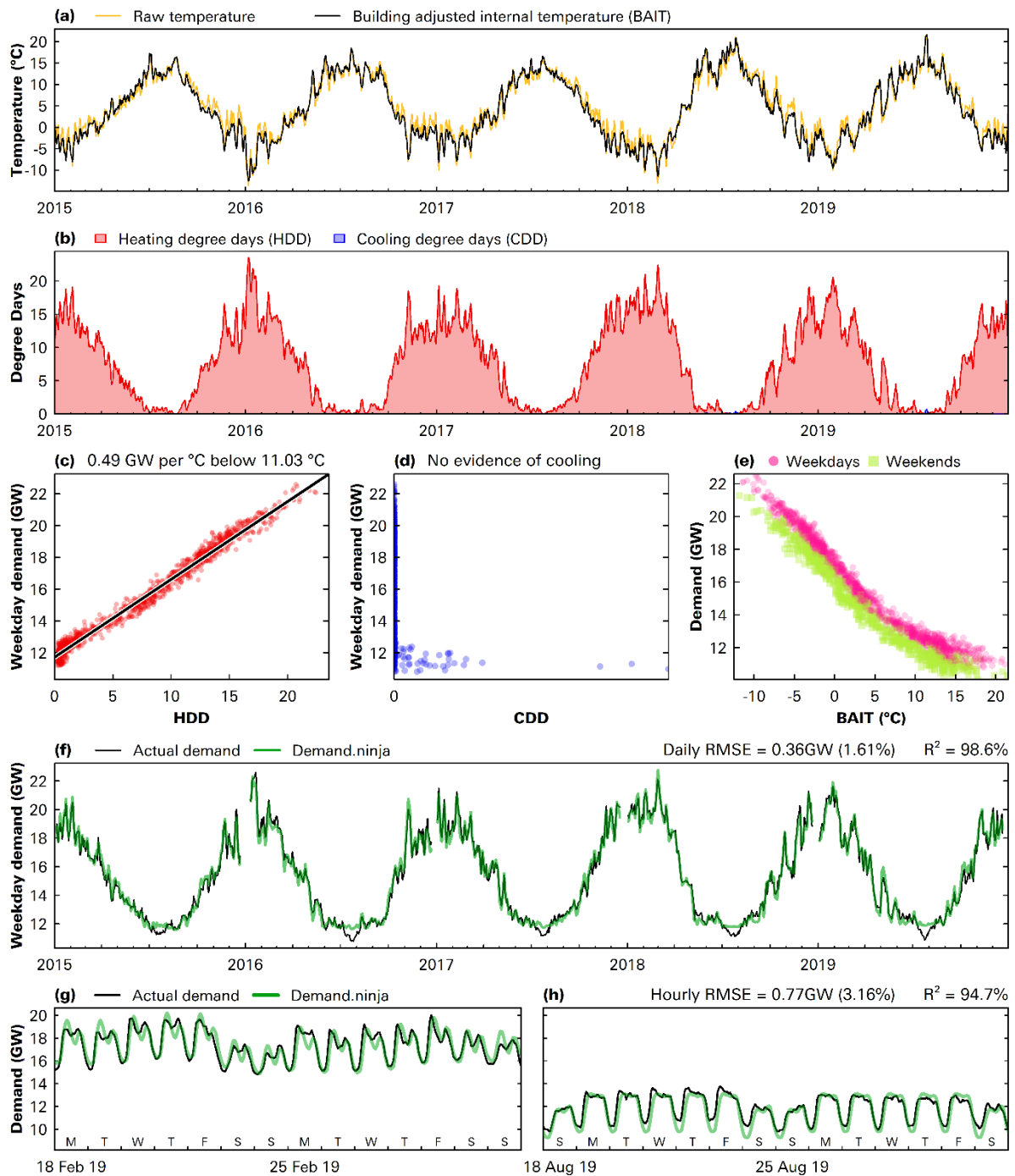
Supplementary Figure 19: Visualisation of the process of converting from temperature to BAIT to HDD and CDD to energy consumption in Japan. Figure follows the same design as Figure 2 in the main manuscript; see the caption there for more detail.



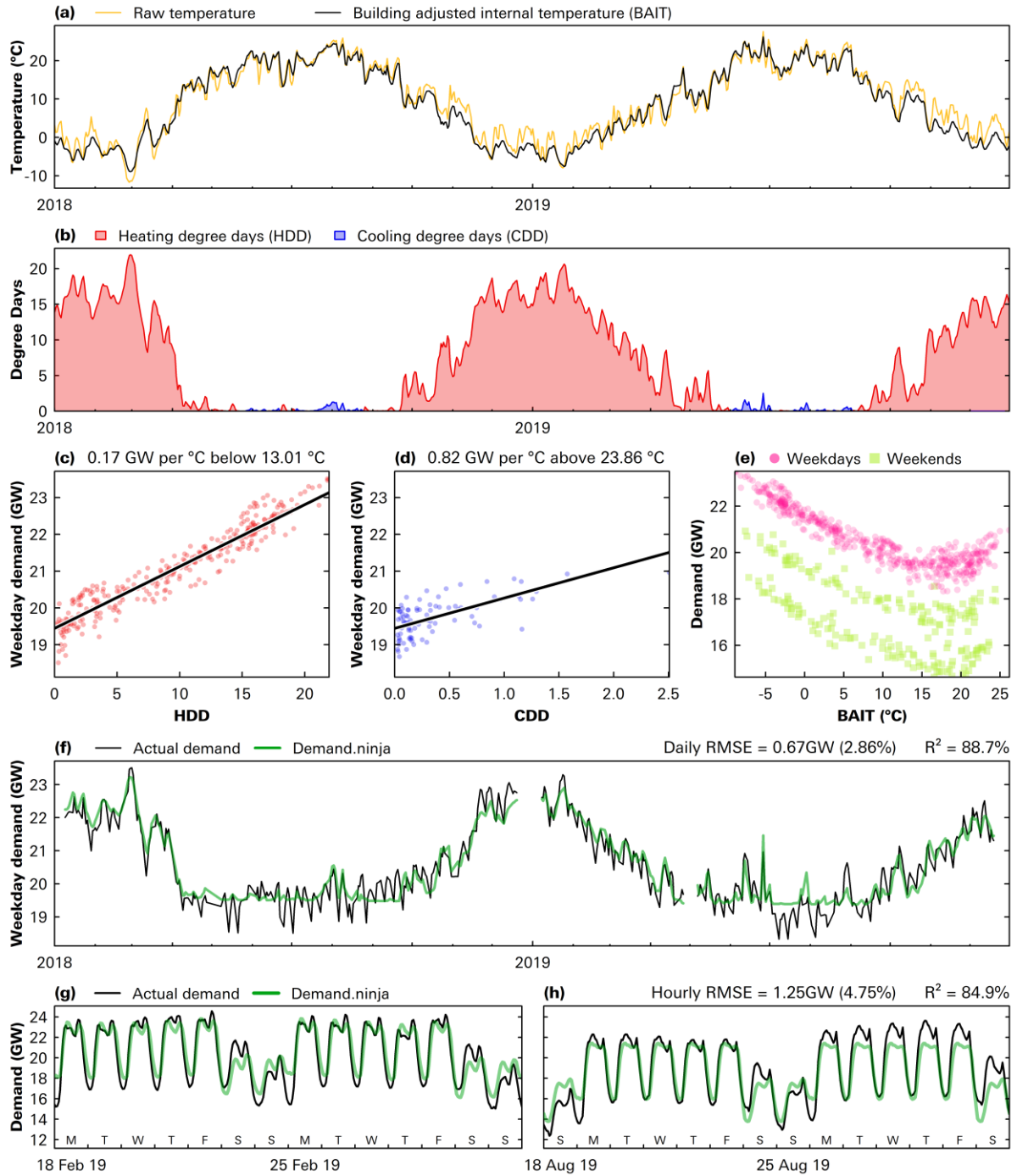
Supplementary Figure 20: Visualisation of the process of converting from temperature to BAIT to HDD and CDD to energy consumption in Lithuania. Figure follows the same design as Figure 2 in the main manuscript; see the caption there for more detail.



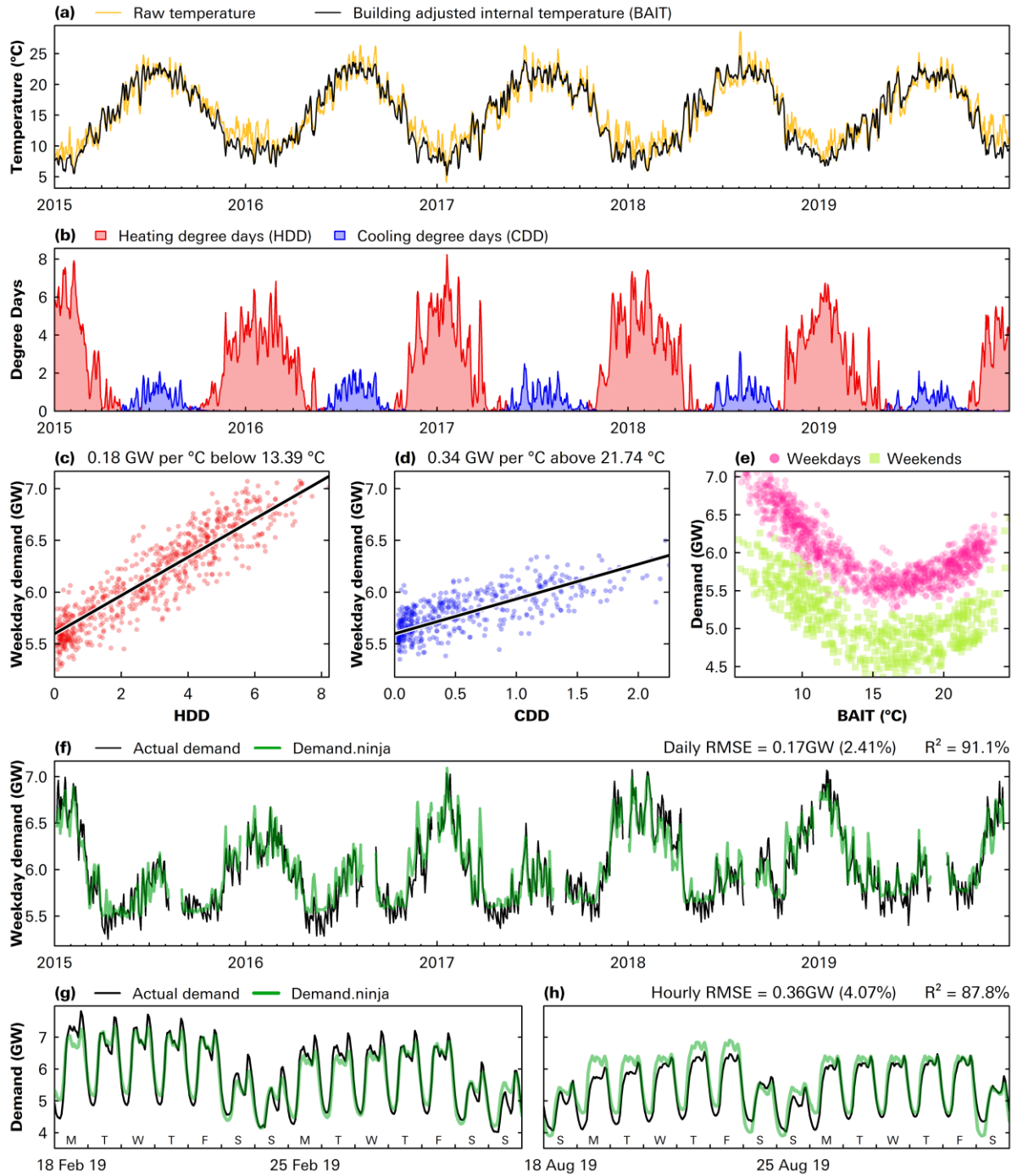
Supplementary Figure 21: Visualisation of the process of converting from temperature to BAIT to HDD and CDD to energy consumption in the Netherlands. Figure follows the same design as Figure 2 in the main manuscript; see the caption there for more detail.



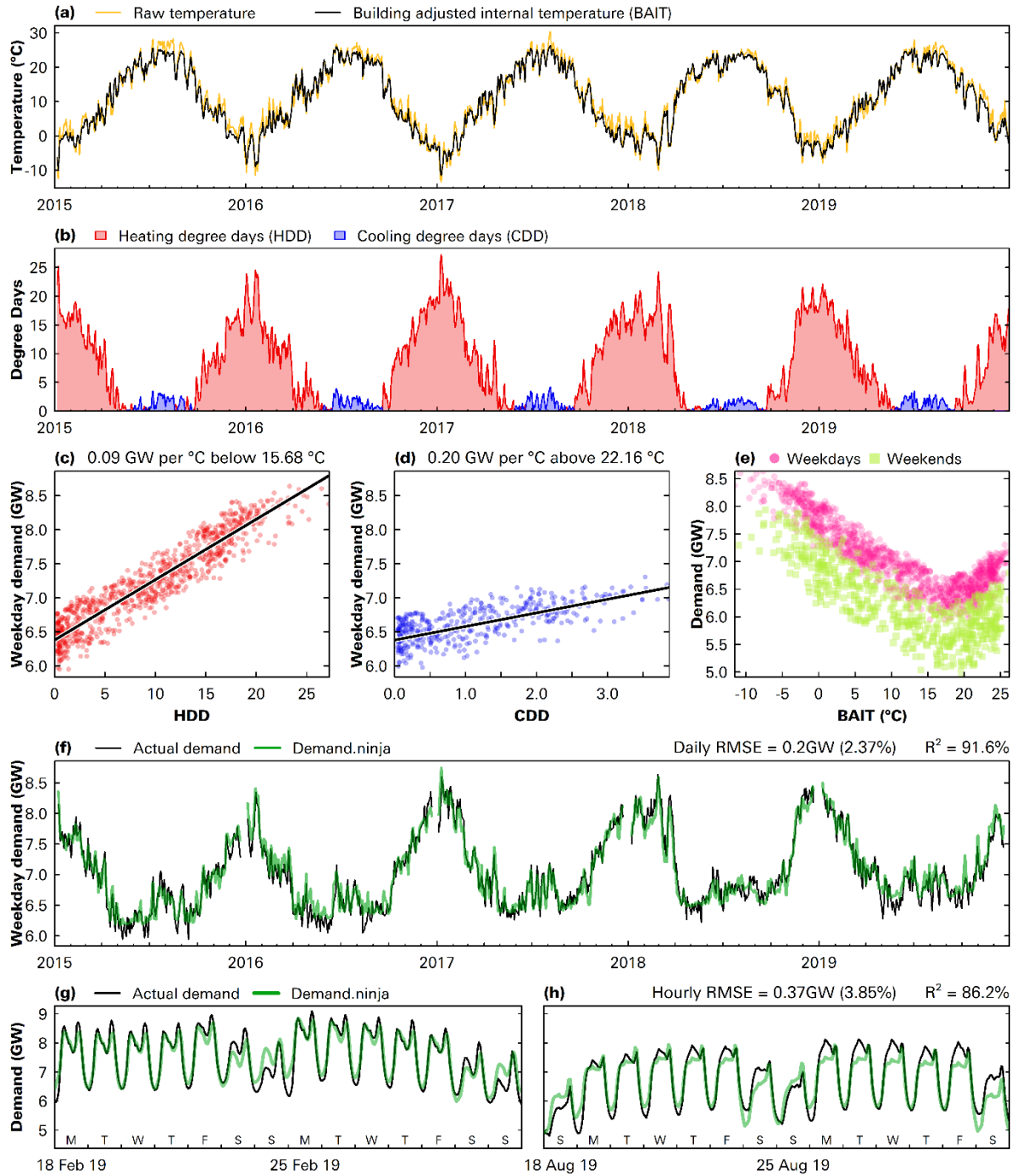
Supplementary Figure 22: Visualisation of the process of converting from temperature to BAIT to HDD and CDD to energy consumption in Norway. Figure follows the same design as Figure 2 in the main manuscript; see the caption there for more detail.



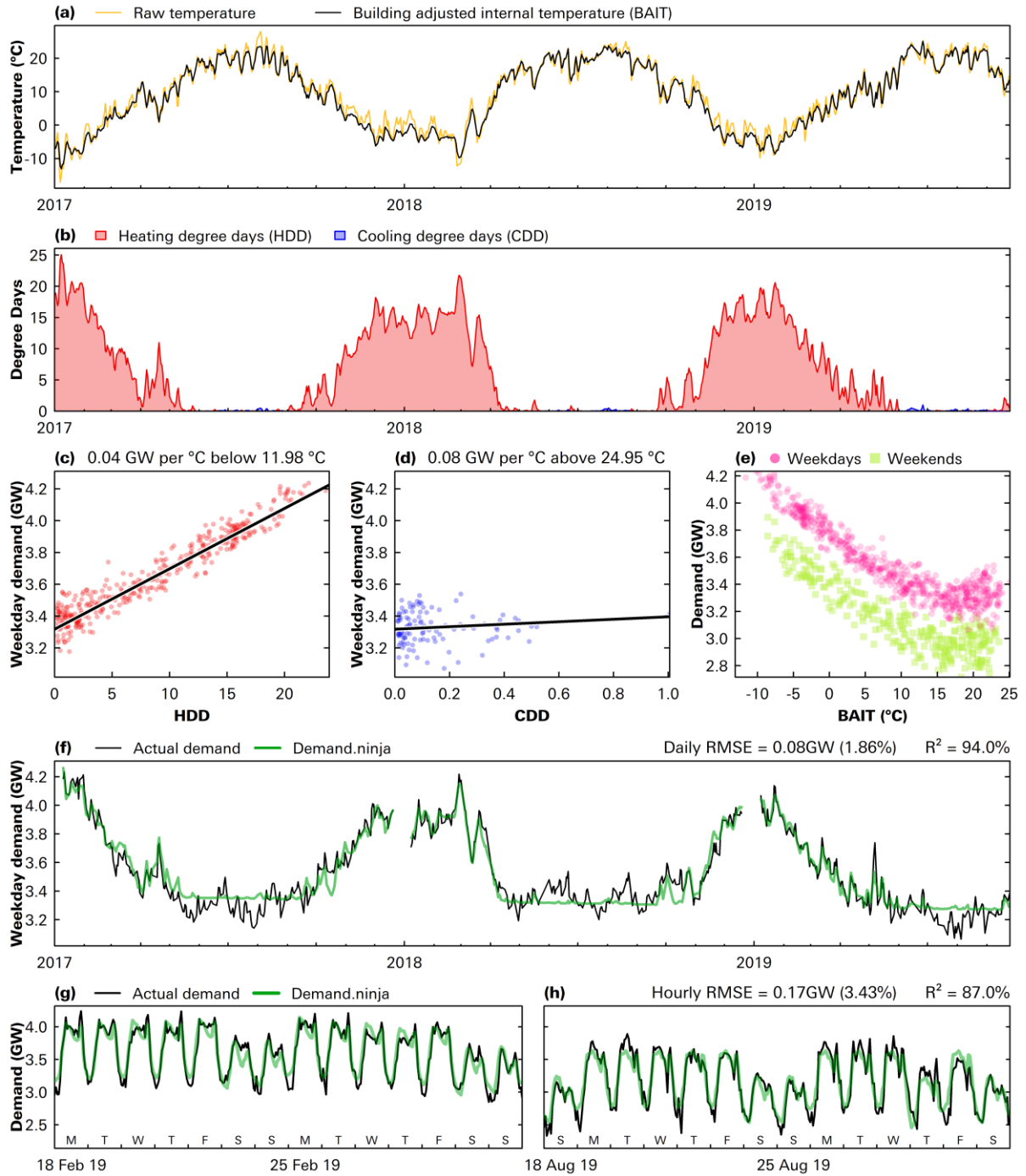
Supplementary Figure 23: Visualisation of the process of converting from temperature to BAIT to HDD and CDD to energy consumption in Poland. Figure follows the same design as Figure 2 in the main manuscript; see the caption there for more detail.



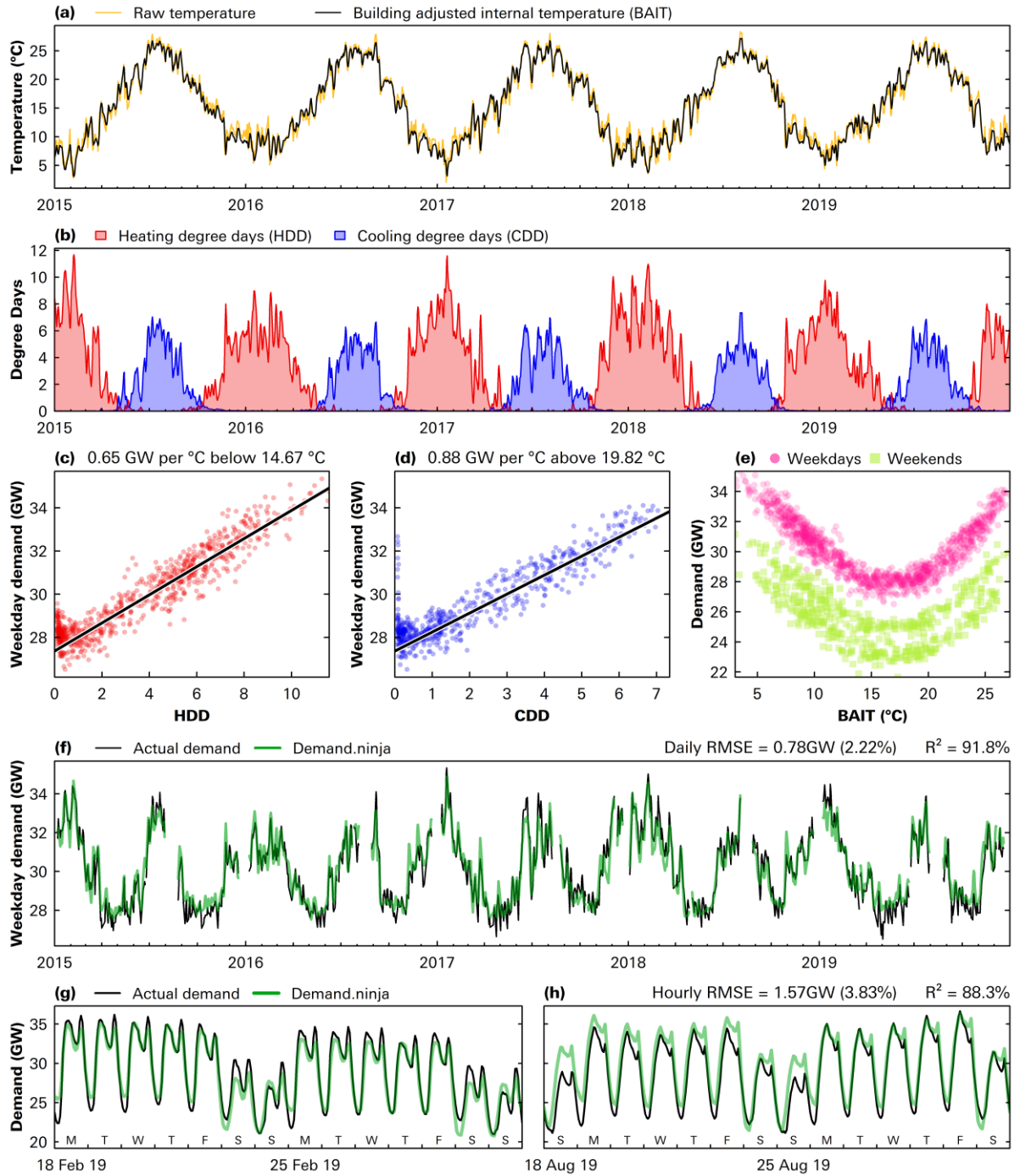
Supplementary Figure 24: Visualisation of the process of converting from temperature to BAIT to HDD and CDD to energy consumption in Portugal. Figure follows the same design as Figure 2 in the main manuscript; see the caption there for more detail.



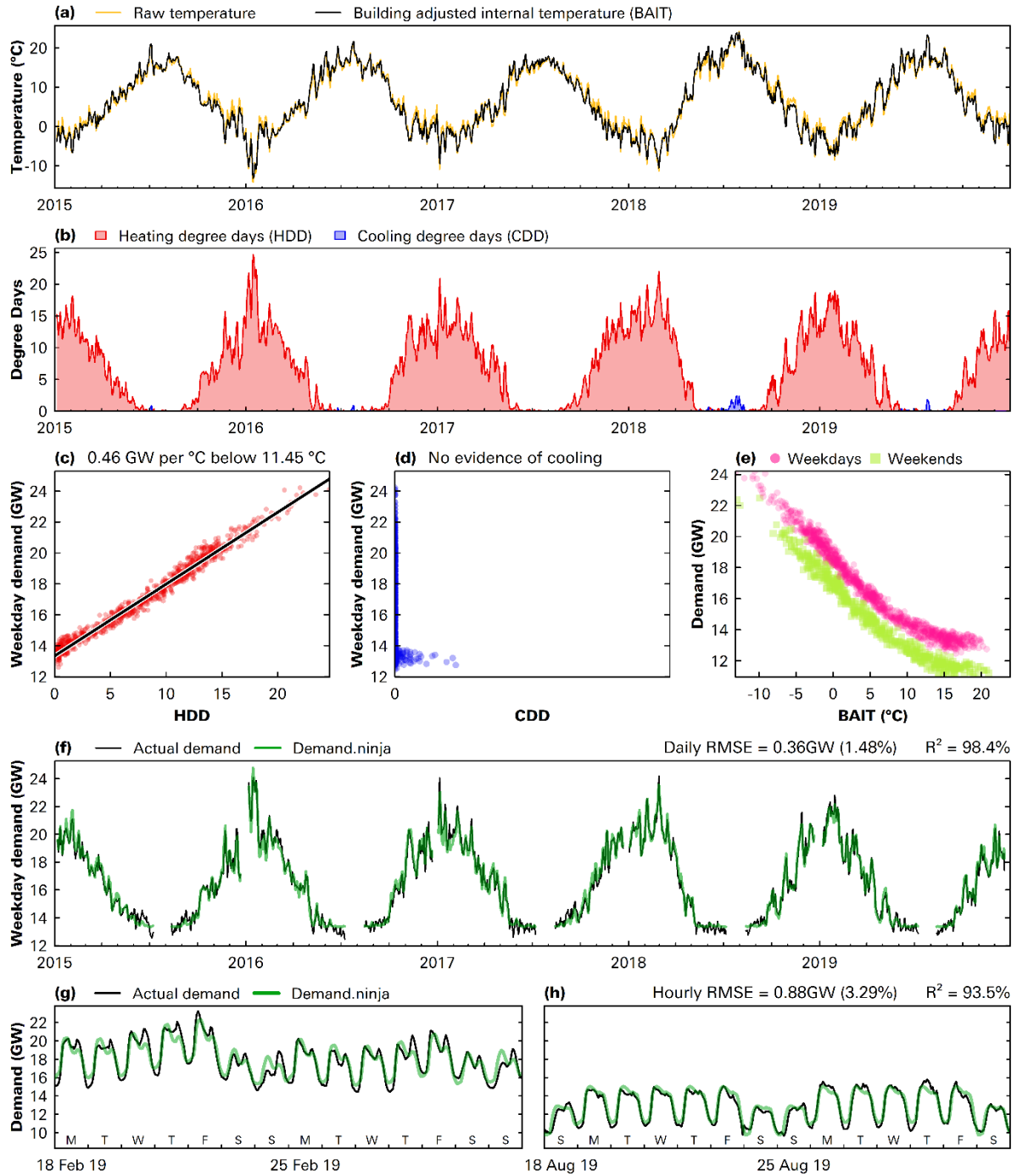
Supplementary Figure 25: Visualisation of the process of converting from temperature to BAIT to HDD and CDD to energy consumption in Romania. Figure follows the same design as Figure 2 in the main manuscript; see the caption there for more detail.



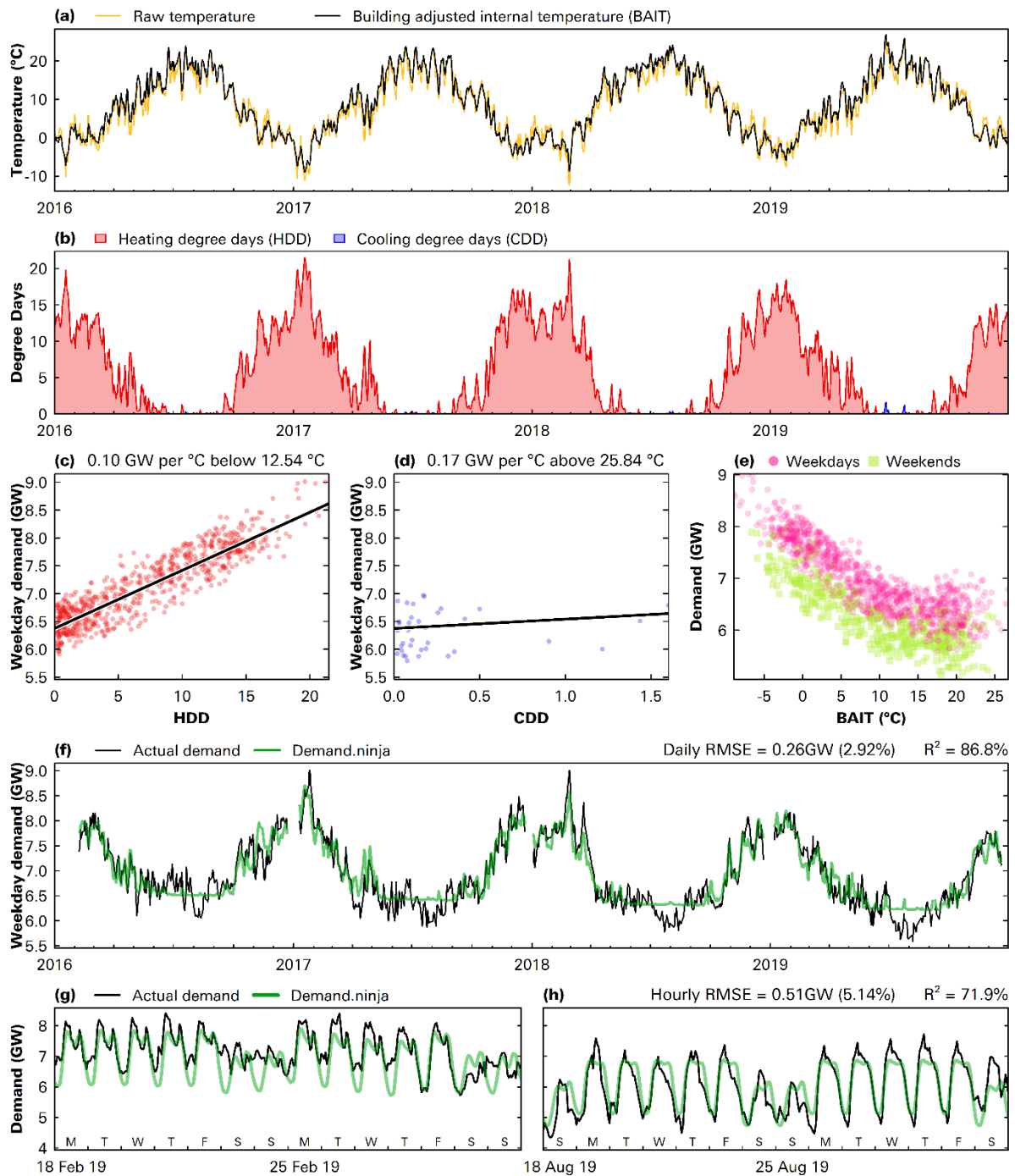
Supplementary Figure 26: Visualisation of the process of converting from temperature to BAIT to HDD and CDD to energy consumption in Slovakia. Figure follows the same design as Figure 2 in the main manuscript; see the caption there for more detail.



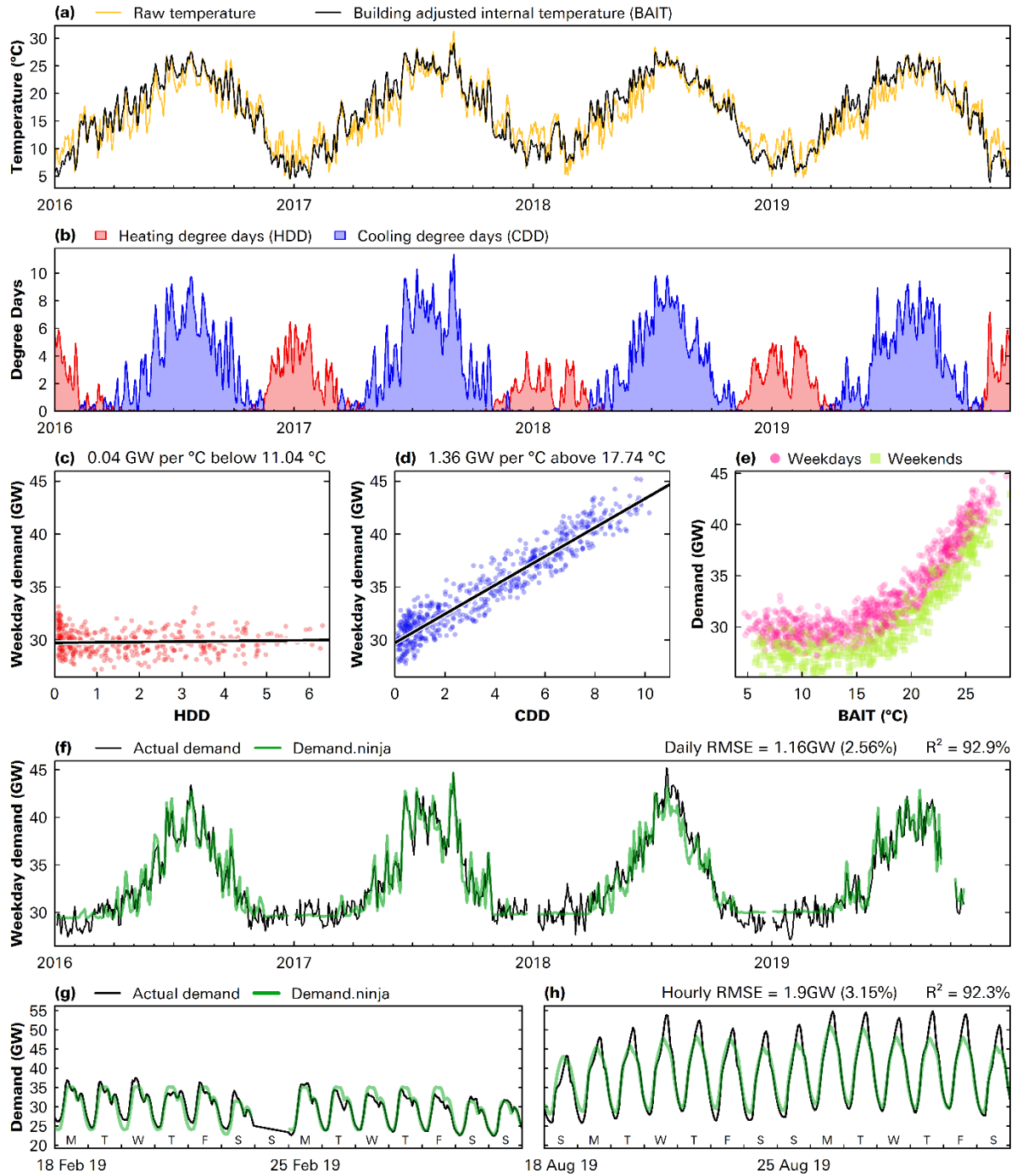
Supplementary Figure 27: Visualisation of the process of converting from temperature to BAIT to HDD and CDD to energy consumption in Spain. Figure follows the same design as Figure 2 in the main manuscript; see the caption there for more detail.



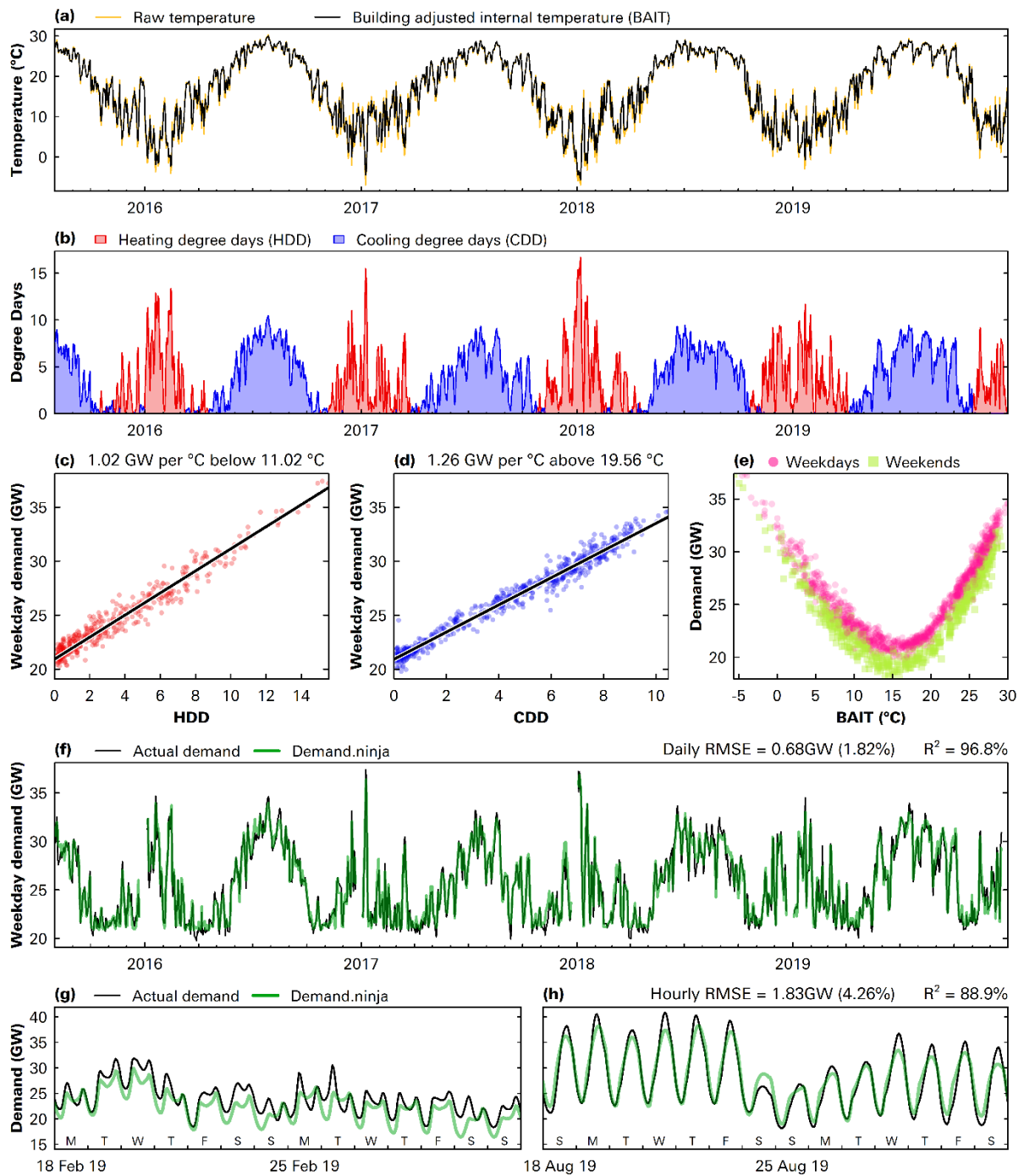
Supplementary Figure 28: Visualisation of the process of converting from temperature to BAIT to HDD and CDD to energy consumption in Sweden. Figure follows the same design as Figure 2 in the main manuscript; see the caption there for more detail.



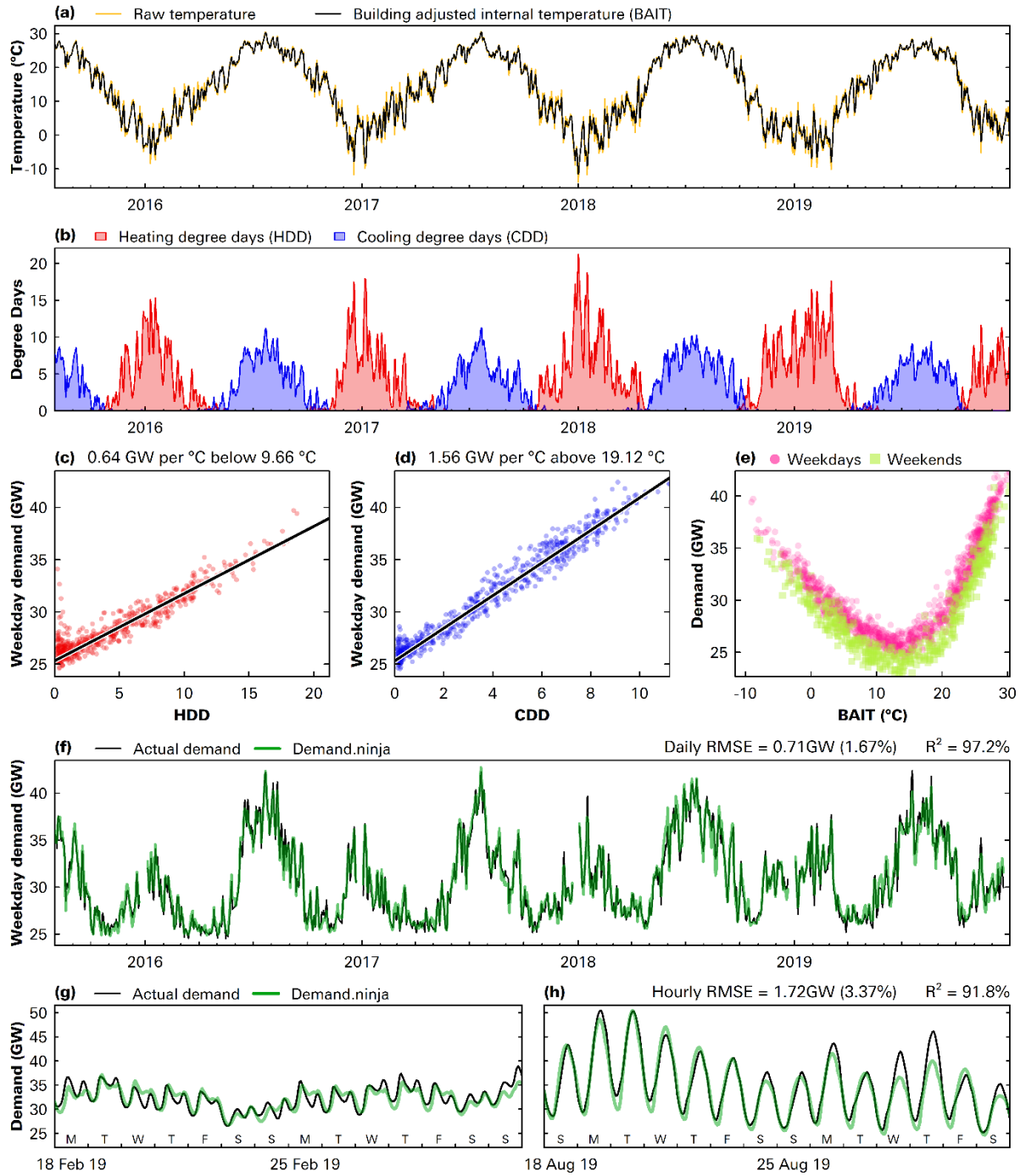
Supplementary Figure 29: Visualisation of the process of converting from temperature to BAIT to HDD and CDD to energy consumption in Switzerland. Figure follows the same design as Figure 2 in the main manuscript; see the caption there for more detail.



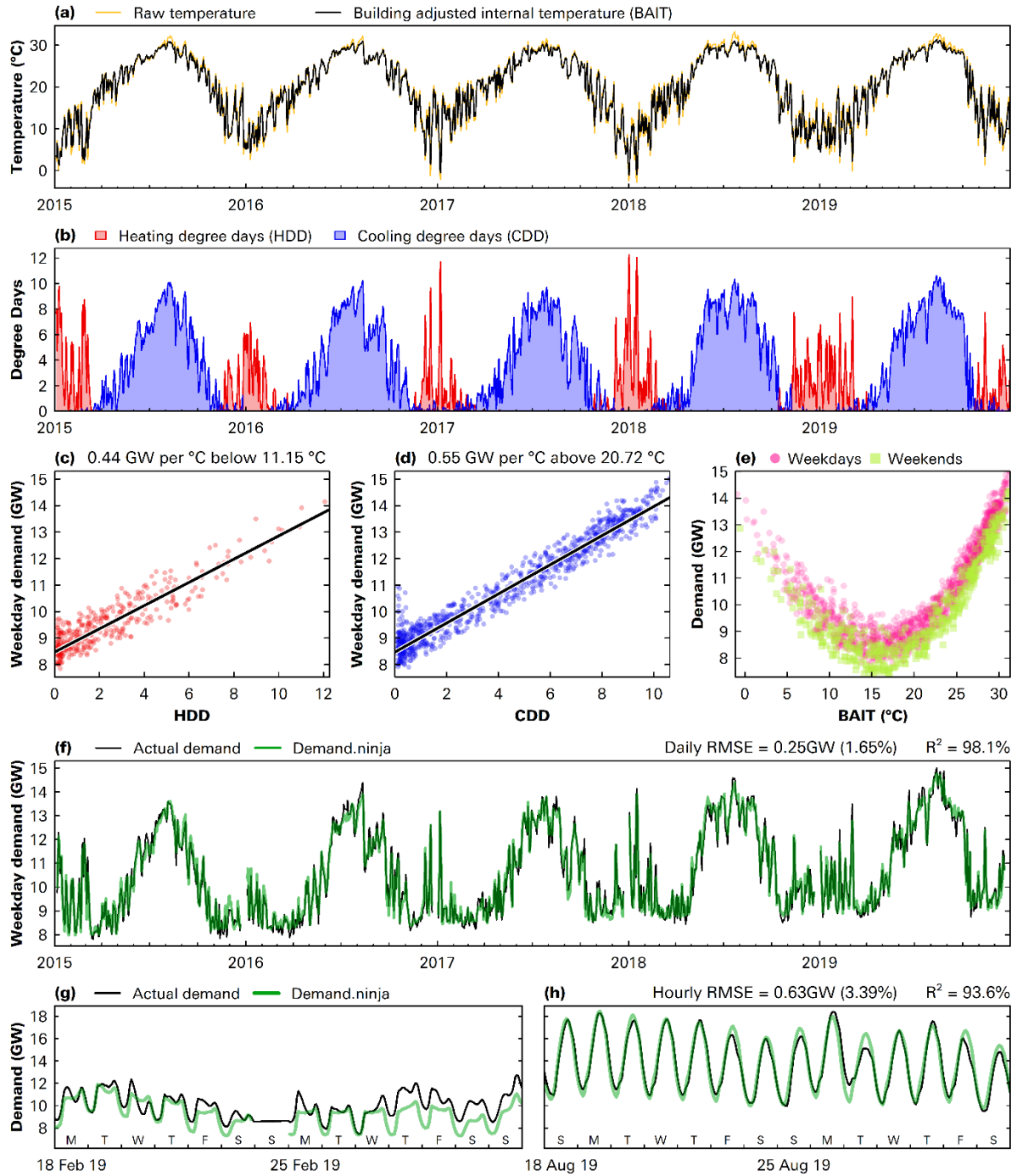
Supplementary Figure 30: Visualisation of the process of converting from temperature to BAIT to HDD and CDD to energy consumption in the CAISO power market, US. Figure follows the same design as Figure 2 in the main manuscript; see the caption there for more detail.



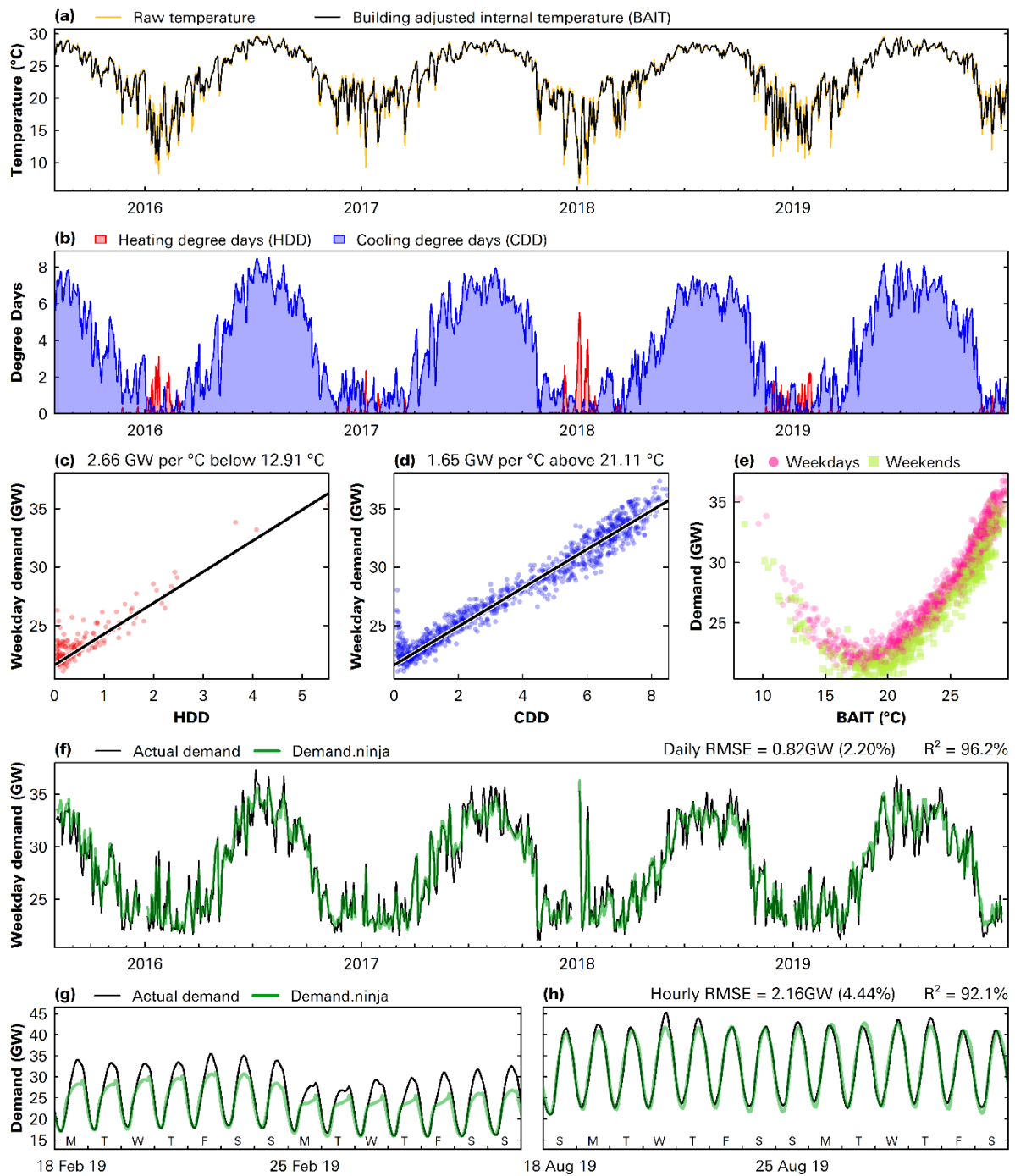
Supplementary Figure 31: Visualisation of the process of converting from temperature to BAIT to HDD and CDD to energy consumption in the Carolinas power market, US. Figure follows the same design as Figure 2 in the main manuscript; see the caption there for more detail.



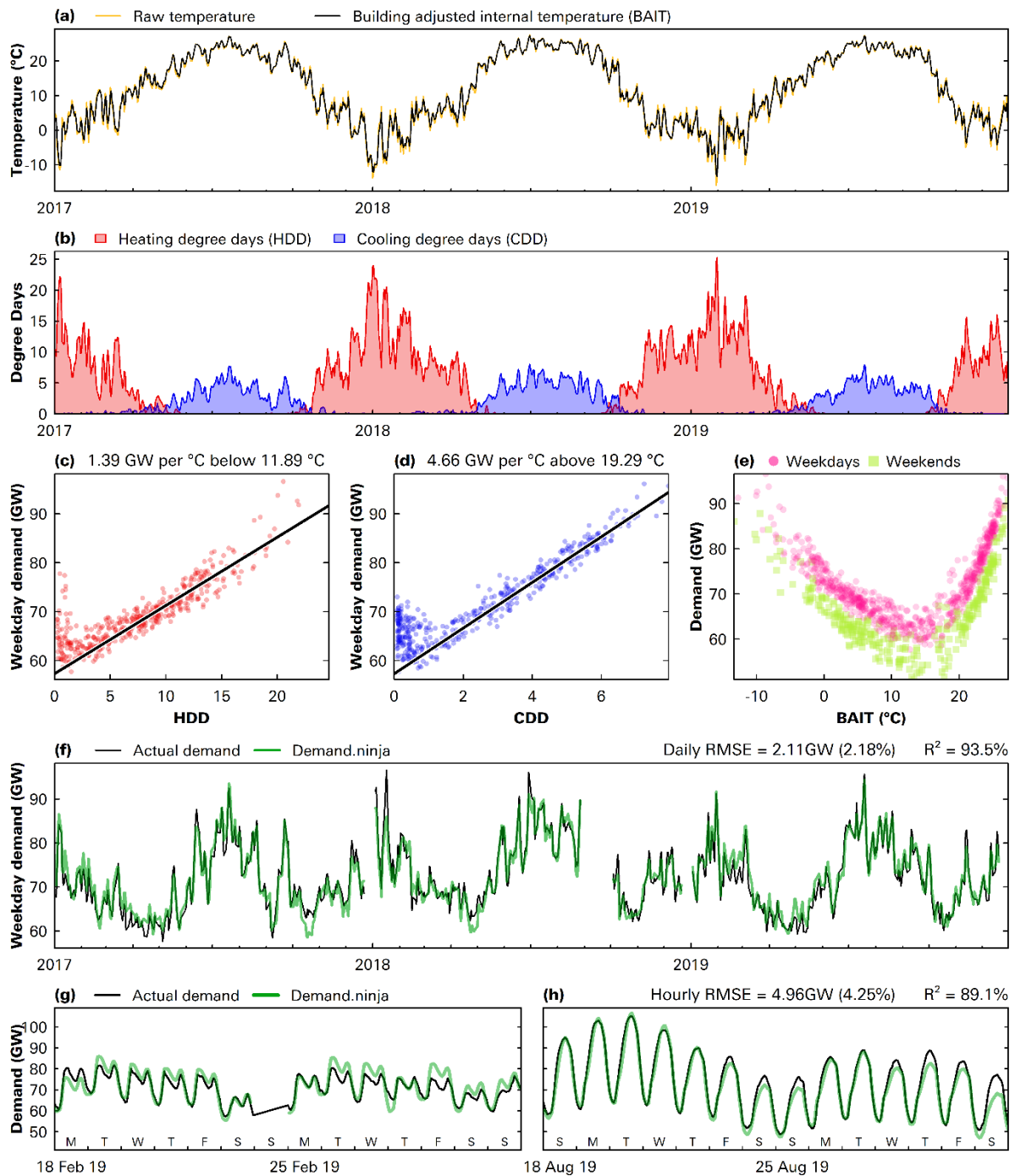
Supplementary Figure 32: Visualisation of the process of converting from temperature to BAIT to HDD and CDD to energy consumption in the Central power market, US. Figure follows the same design as Figure 2 in the main manuscript; see the caption there for more detail.



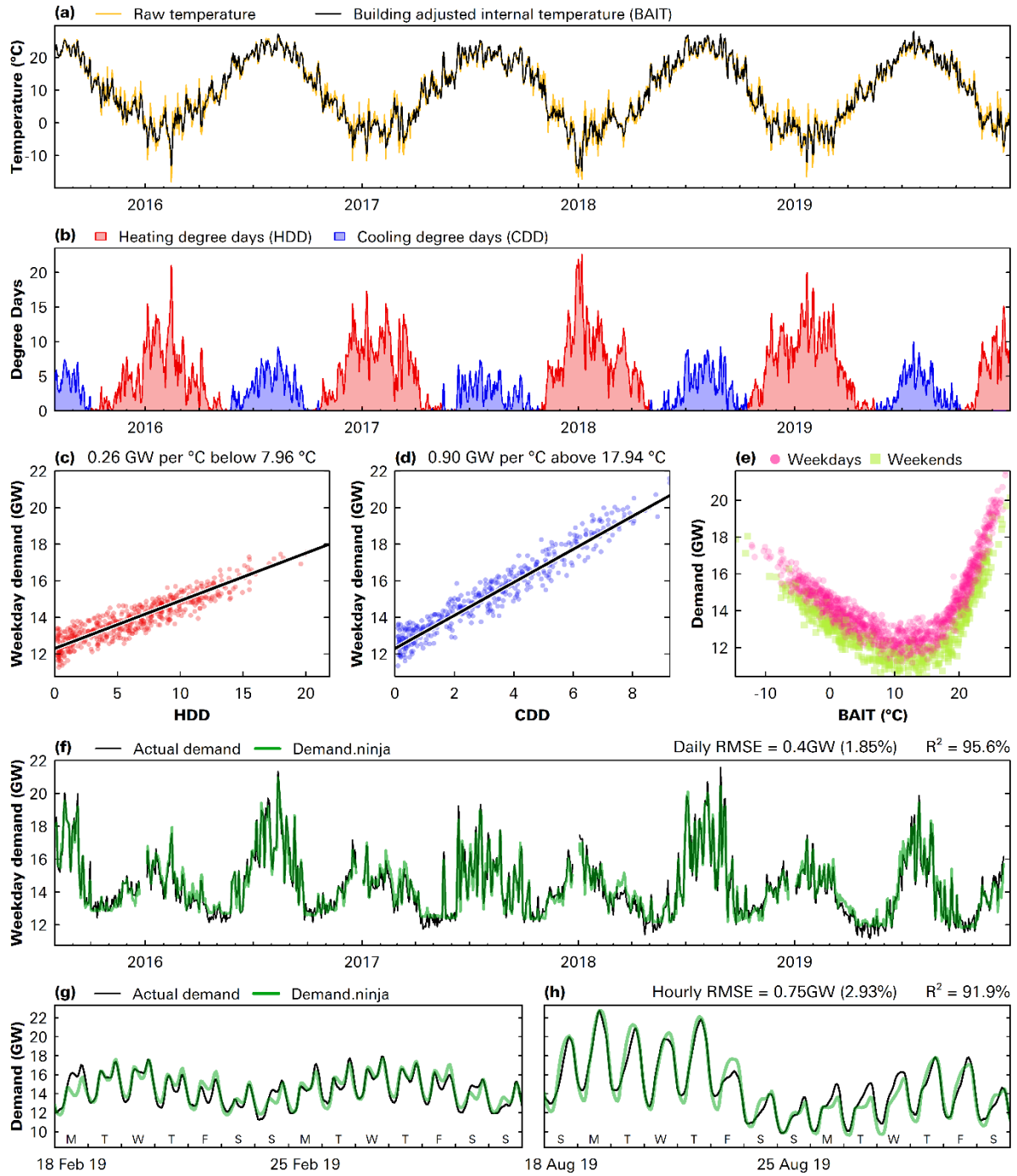
Supplementary Figure 33: Visualisation of the process of converting from temperature to BAIT to HDD and CDD to energy consumption in the ERCOT power market, US. Figure follows the same design as Figure 2 in the main manuscript; see the caption there for more detail.



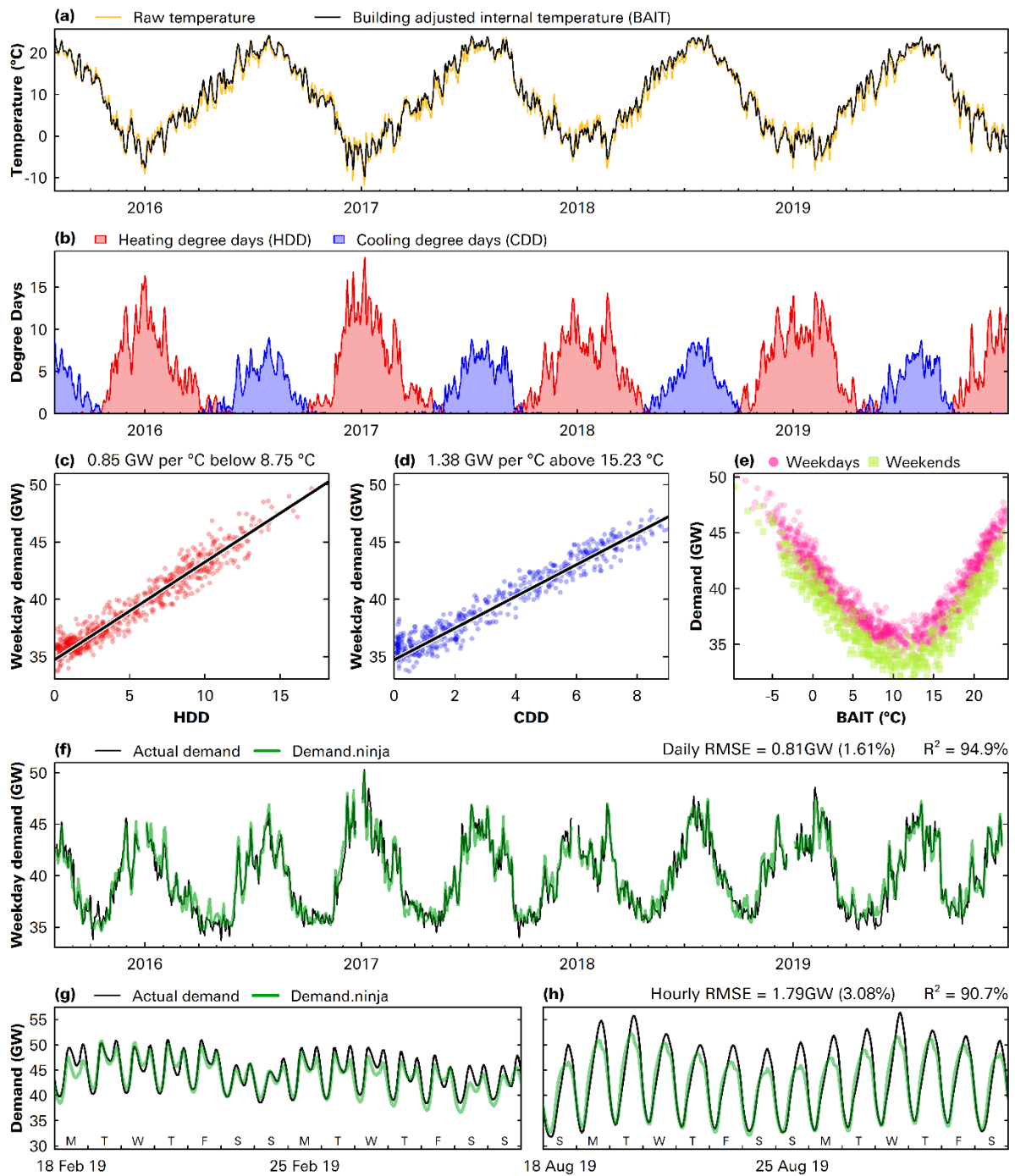
Supplementary Figure 34: Visualisation of the process of converting from temperature to BAIT to HDD and CDD to energy consumption in the Florida power market, US. Figure follows the same design as Figure 2 in the main manuscript; see the caption there for more detail.



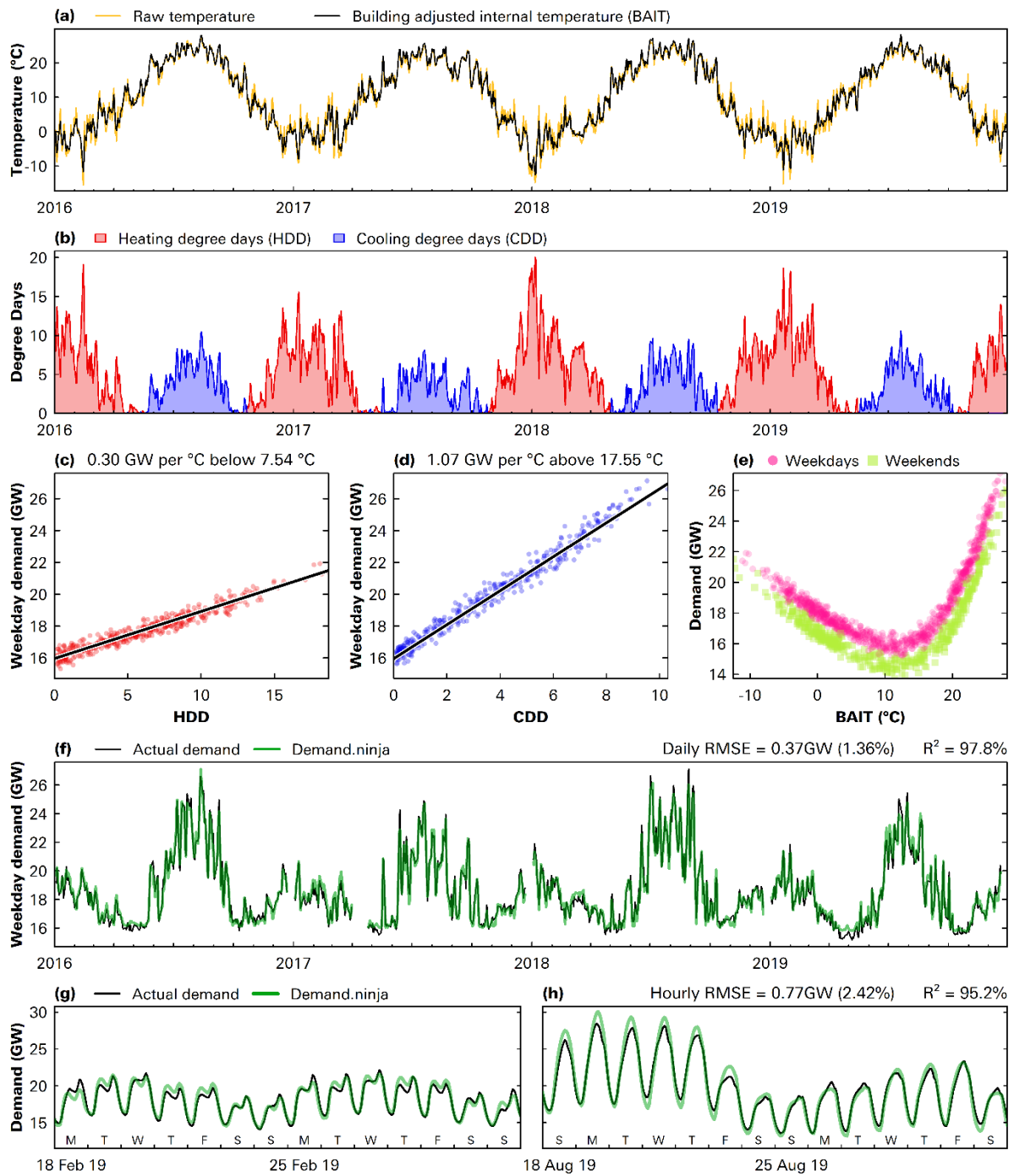
Supplementary Figure 35: Visualisation of the process of converting from temperature to BAIT to HDD and CDD to energy consumption in the MISO power market, US. Figure follows the same design as Figure 2 in the main manuscript; see the caption there for more detail.



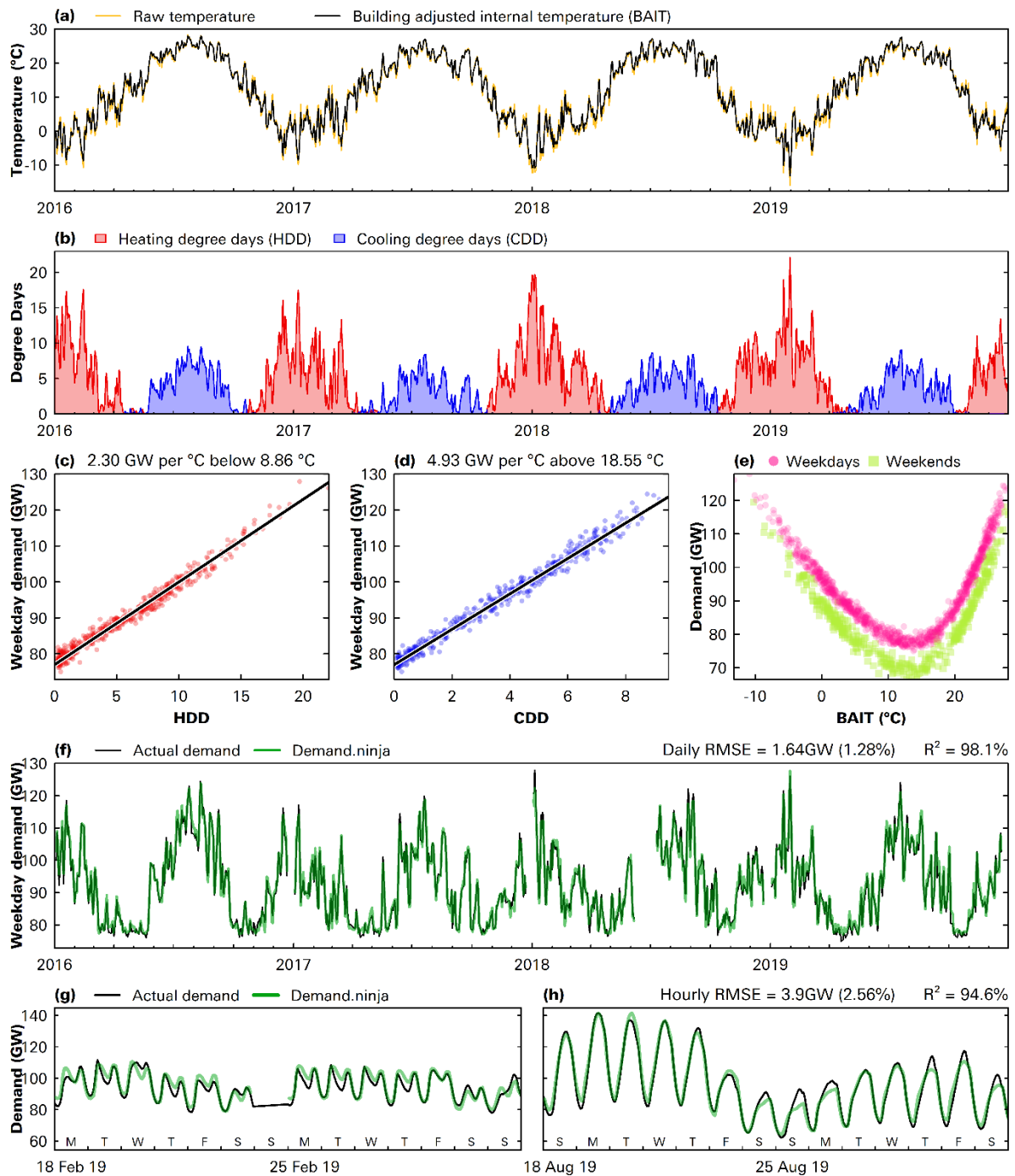
Supplementary Figure 36: Visualisation of the process of converting from temperature to BAIT to HDD and CDD to energy consumption in the ISONE power market, US. Figure follows the same design as Figure 2 in the main manuscript; see the caption there for more detail.



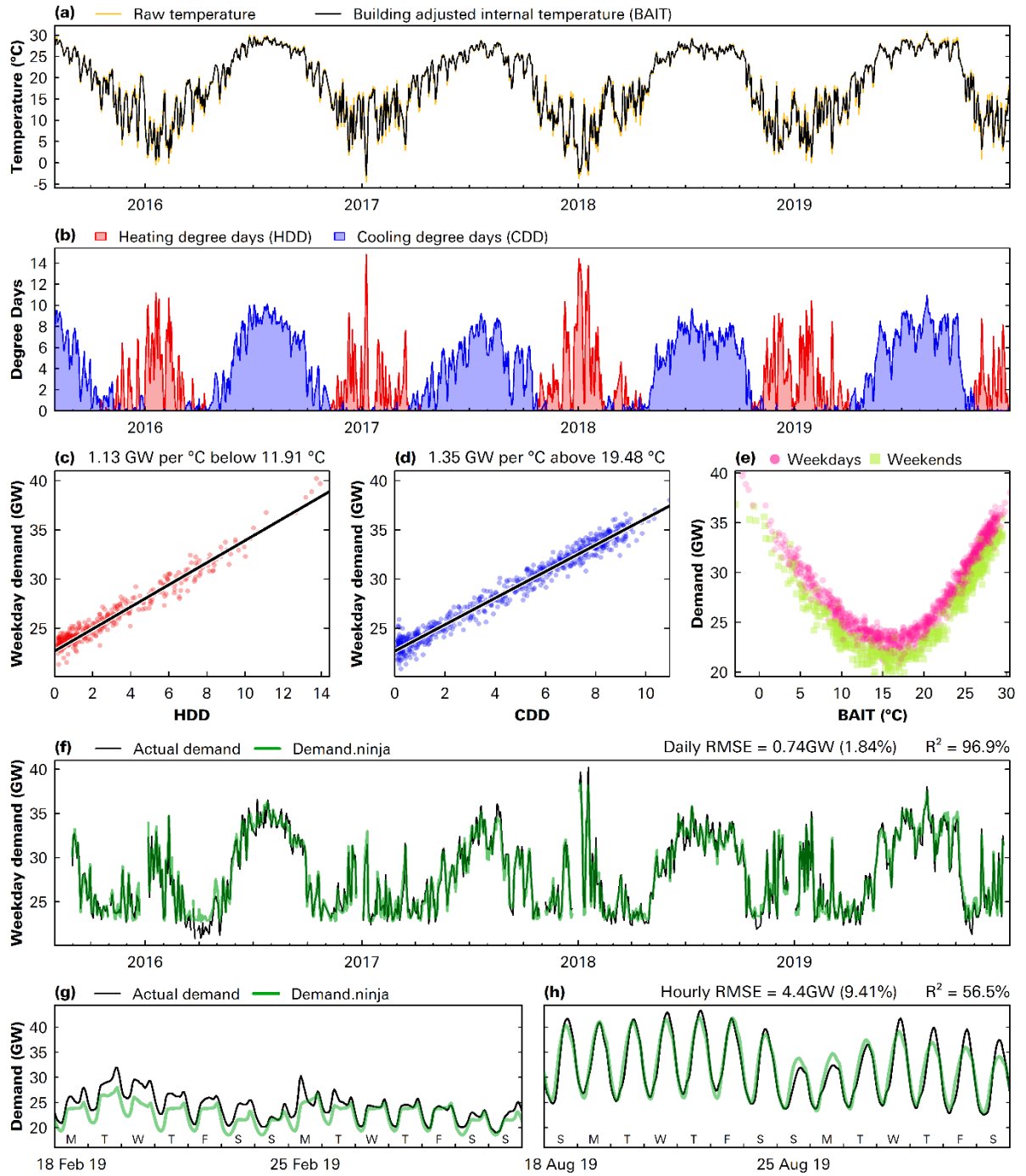
Supplementary Figure 37: Visualisation of the process of converting from temperature to BAIT to HDD and CDD to energy consumption in the Northwest power market, US. Figure follows the same design as Figure 2 in the main manuscript; see the caption there for more detail.



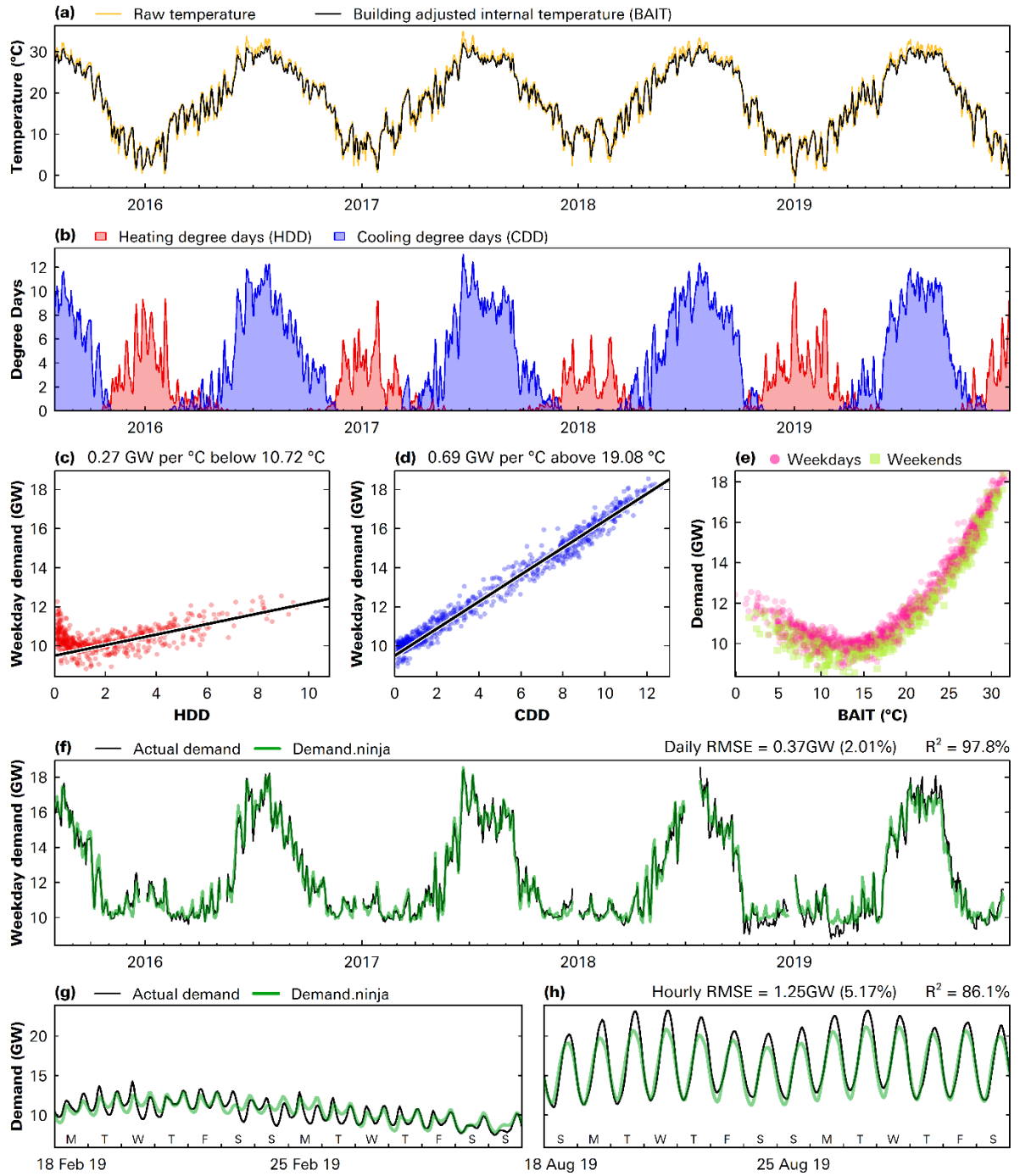
Supplementary Figure 38: Visualisation of the process of converting from temperature to BAIT to HDD and CDD to energy consumption in the NYISO power market, US. Figure follows the same design as Figure 2 in the main manuscript; see the caption there for more detail.



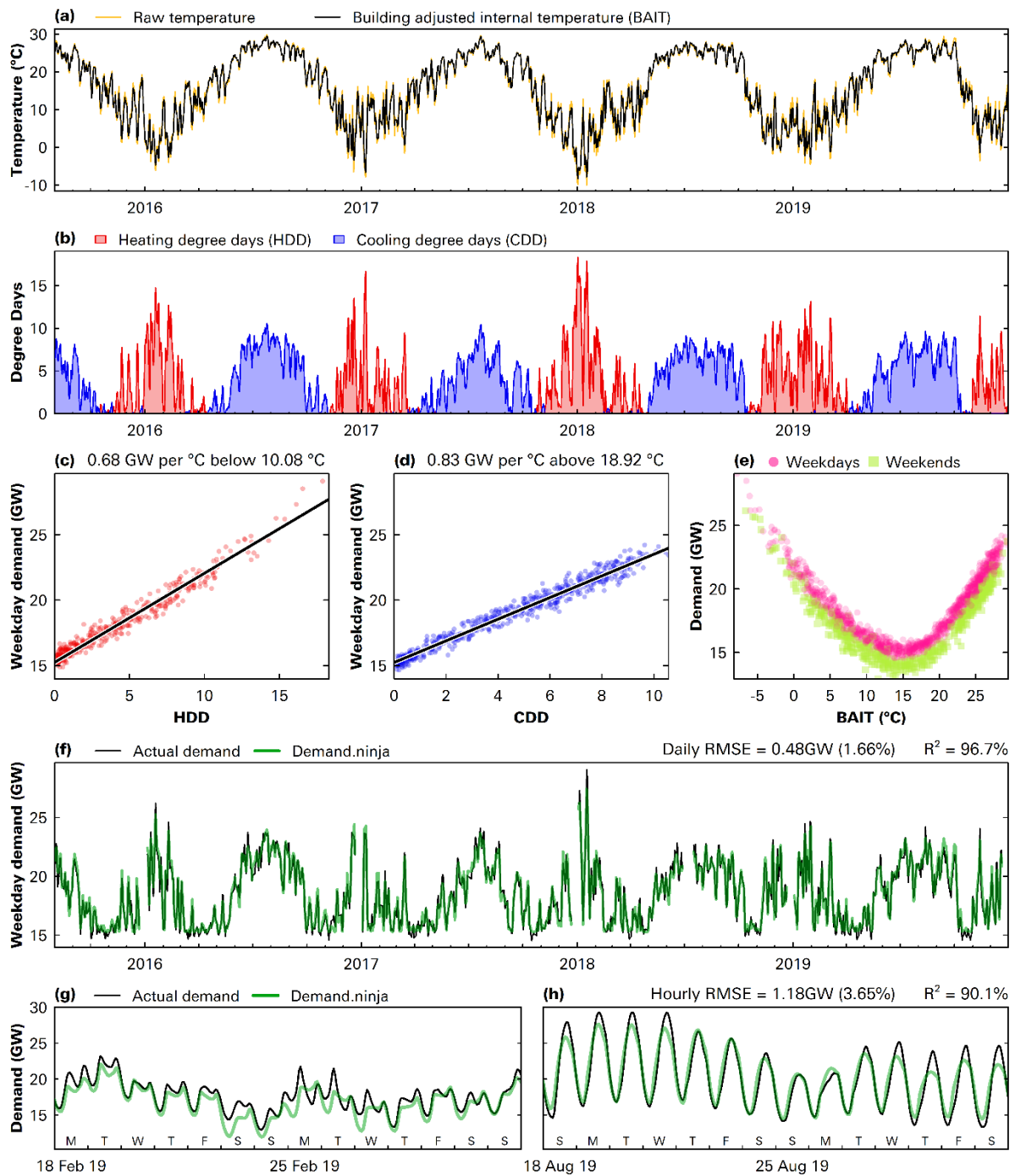
Supplementary Figure 39: Visualisation of the process of converting from temperature to BAIT to HDD and CDD to energy consumption in the PJM power market, US. Figure follows the same design as Figure 2 in the main manuscript; see the caption there for more detail.



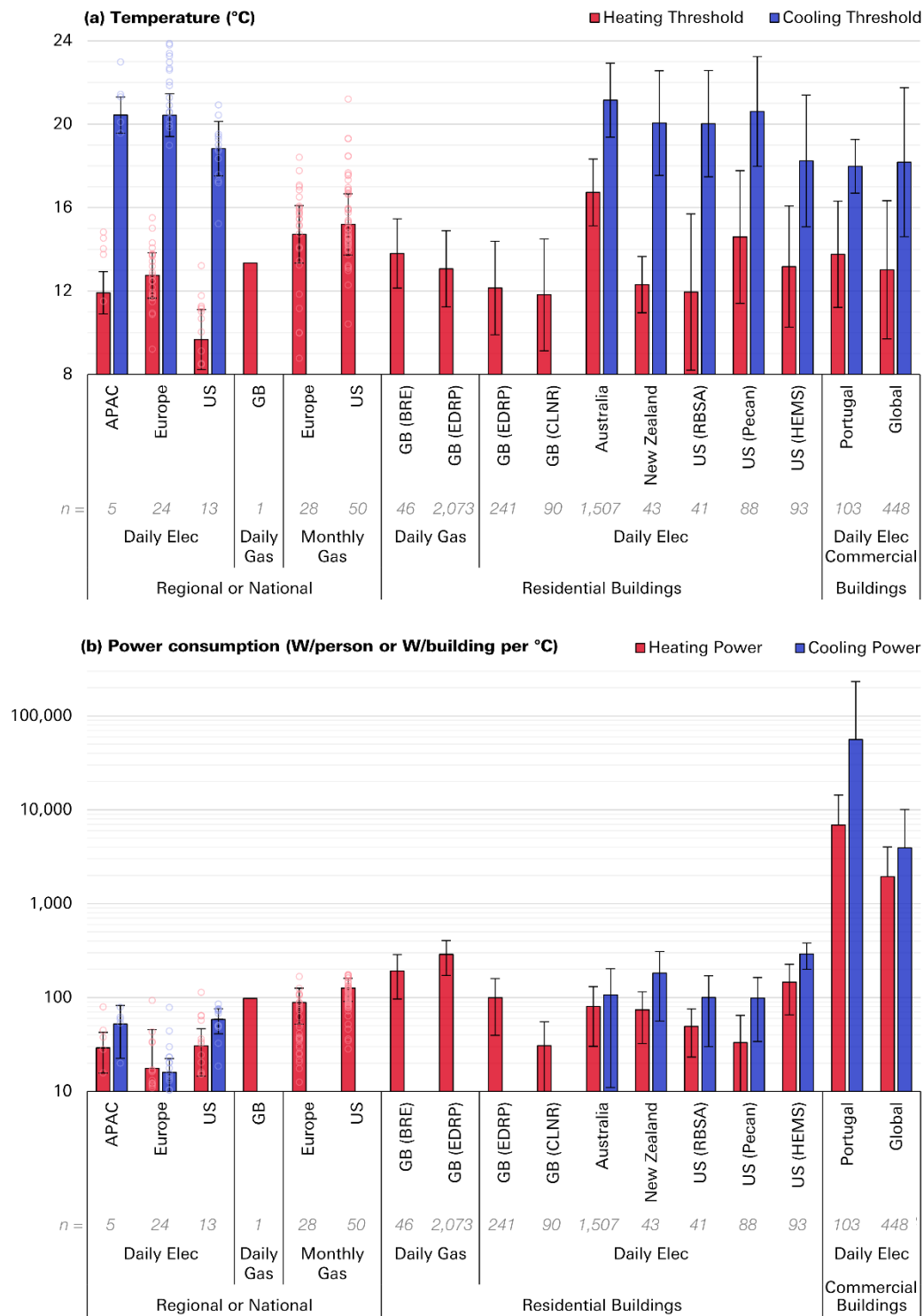
Supplementary Figure 40: Visualisation of the process of converting from temperature to BAIT to HDD and CDD to energy consumption in the Southeast power market, US. Figure follows the same design as Figure 2 in the main manuscript; see the caption there for more detail.



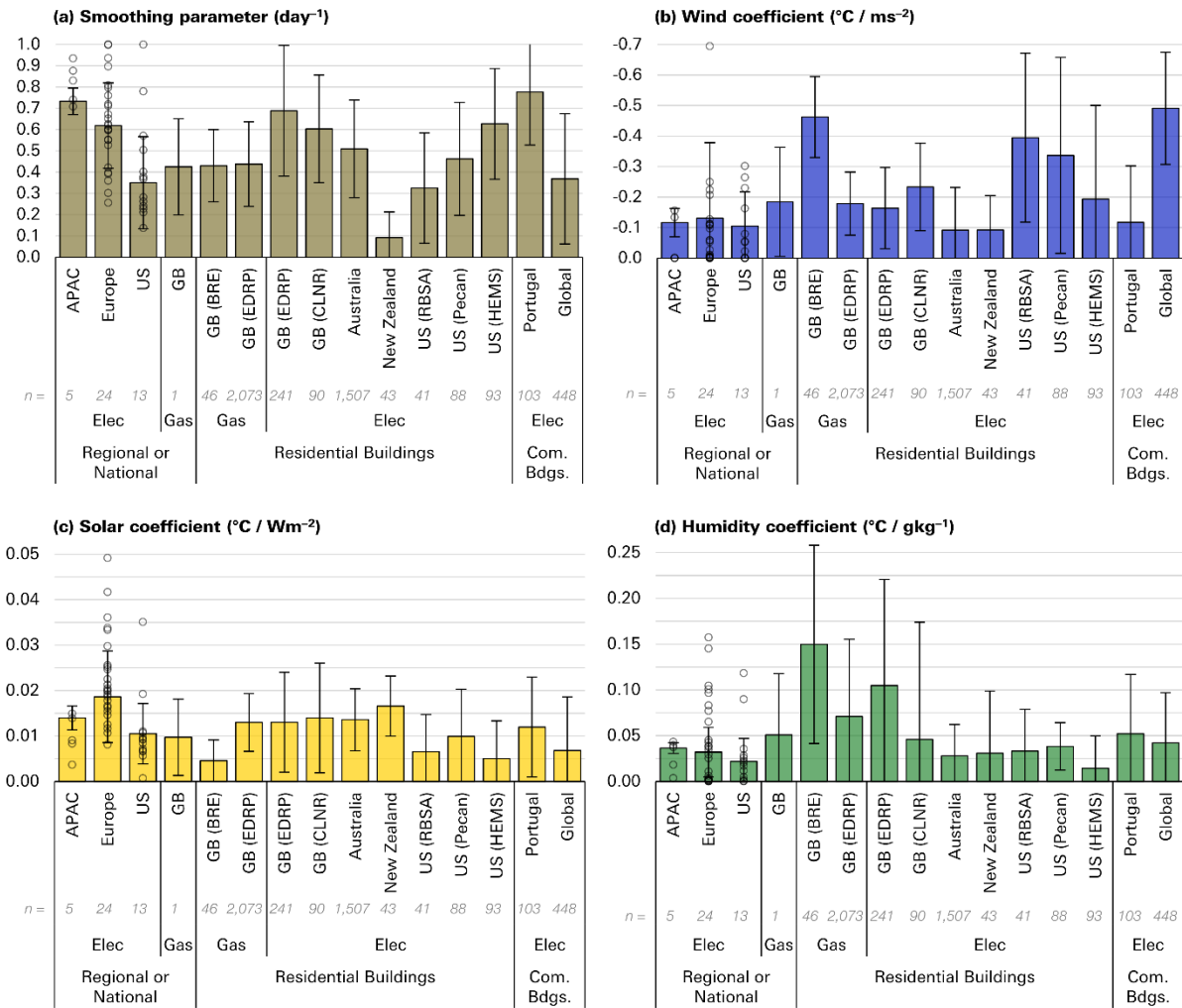
Supplementary Figure 41: Visualisation of the process of converting from temperature to BAIT to HDD and CDD to energy consumption in the Southwest power market, US. Figure follows the same design as Figure 2 in the main manuscript; see the caption there for more detail.



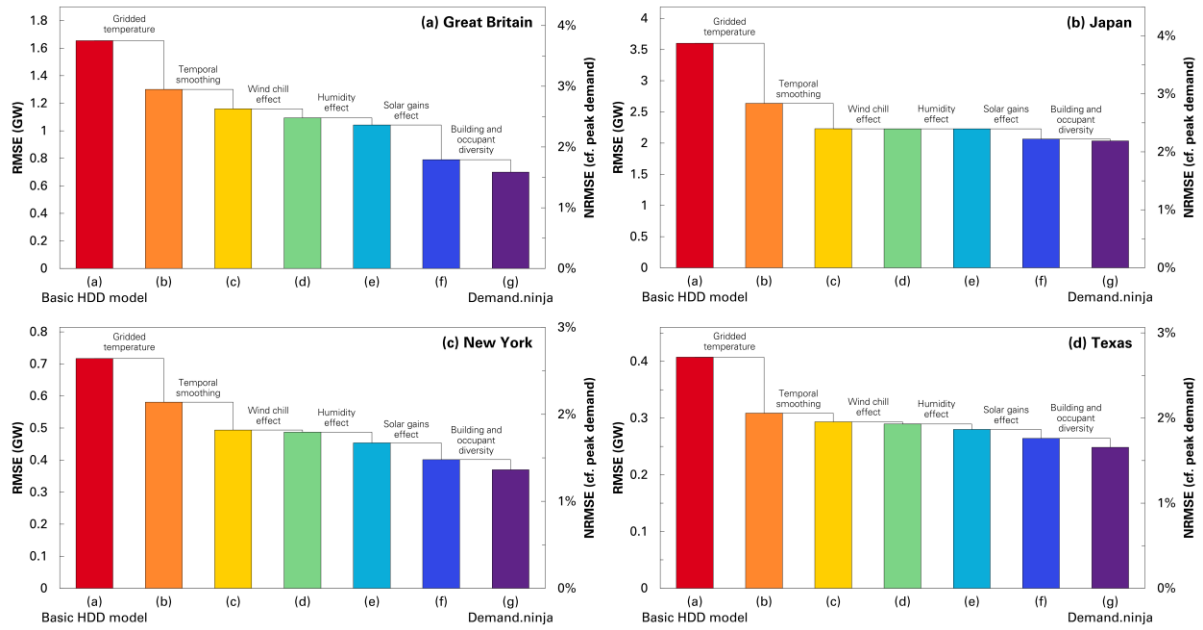
Supplementary Figure 42: Visualisation of the process of converting from temperature to BAIT to HDD and CDD to energy consumption in the Tennessee power market, US. Figure follows the same design as Figure 2 in the main manuscript; see the caption there for more detail.



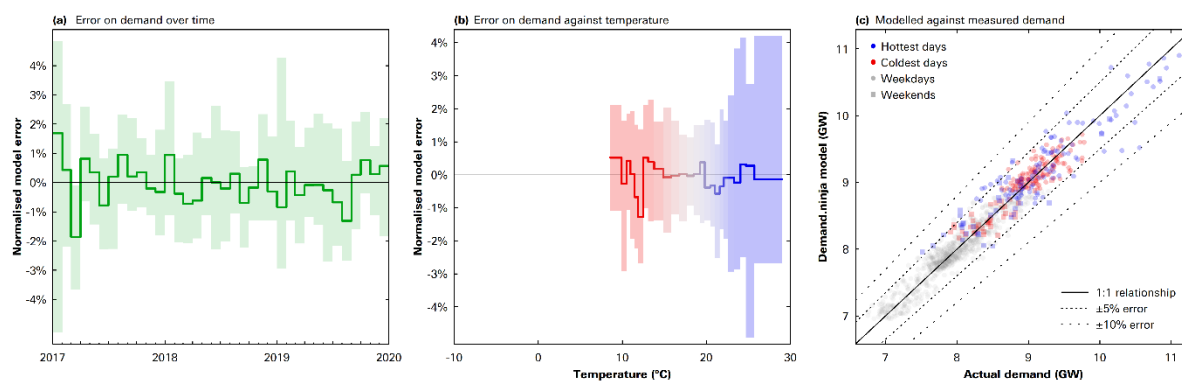
Supplementary Figure 43: Bar charts of the optimal model parameters. Panel (a) shows heating and cooling thresholds and panel (b) shows power coefficients across all regional and building level datasets. For national and regional datasets, the heating and cooling power coefficients are measured in $W/(^{\circ}C \cdot \text{capita})$ and for building datasets they are measured in $W/(^{\circ}C \cdot \text{building})$. In all cases, the central bar and error bars depict the demand-weighted mean and standard deviation across all regions or buildings within the dataset. For regional and national datasets, all individual values are shown as overlaid datapoints. See Supplementary Table 4 for more details.



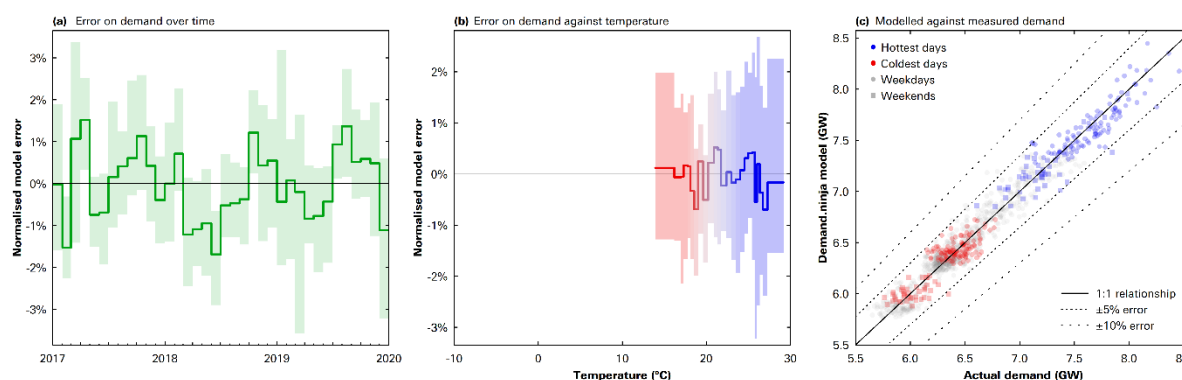
Supplementary Figure 44: Bar charts showing the optimal BAIT coefficients across all regional and building level datasets. Panels show (a) optimal smoothing parameter, (b) wind coefficient, (c) solar coefficient, and (d) humidity coefficient. In all cases, the central bar and error bars depict the demand-weighted mean and standard deviation across all regions or buildings within the dataset. For regional and national datasets, all individual values are shown as overlaid datapoints. The non-normality of the data mean that standard deviations can exceed the feasible range for each parameter (i.e. [0–1] for smoothing, <0 for wind, >0 for solar and humidity). Chart axes are capped at these feasible ranges, but otherwise all data values are shown. See Supplementary Table 4 for more details.



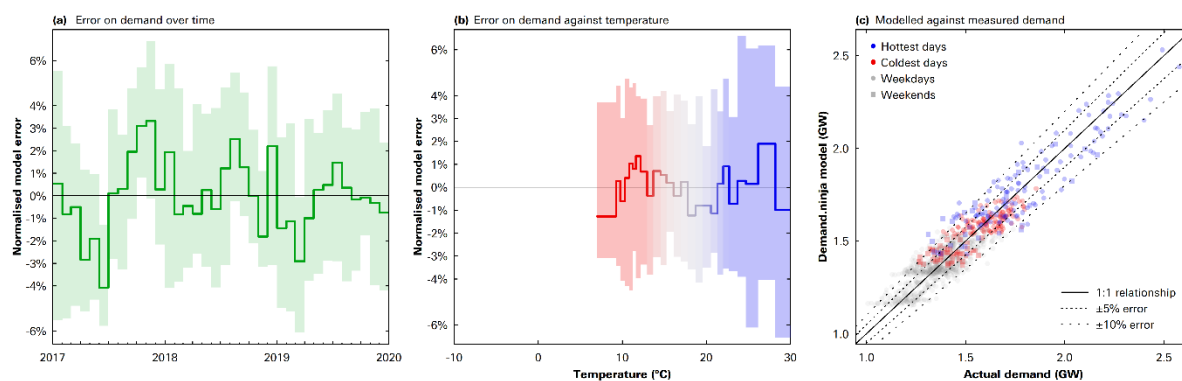
Supplementary Figure 45: Summary of the improvement in the quality of modelling electricity demand in four regional and national markets when adding each element of the Demand.ninja process. Panels (a) to (d) show the change in RMSE (both absolute and normalised against peak demand) for the four regions. The format of each panel is the same as in panel (h) of Figure 3 in the main manuscript. The letters labelling each bar correspond to the following: (a) shows a basic heating degree day model using the national average temperature; (b) shows basic heating degree days calculated using gridded temperatures that have been population-weighted; (c) shows the addition of smoothing temperatures over the preceding two days; (d) shows the addition of wind chill (higher wind speeds reducing the temperature index); (e) shows the addition of humidity effect (greater humidity reducing the temperature index when it is cold or increasing it when it is hot – note that this has a more influential impact in hotter climates); (f) shows the addition of solar gains (greater irradiance increasing the temperature index); and (g) shows the superposition of multiple simulations with stochastically varied parameters to reflect the diversity of building construction and occupant behaviour.



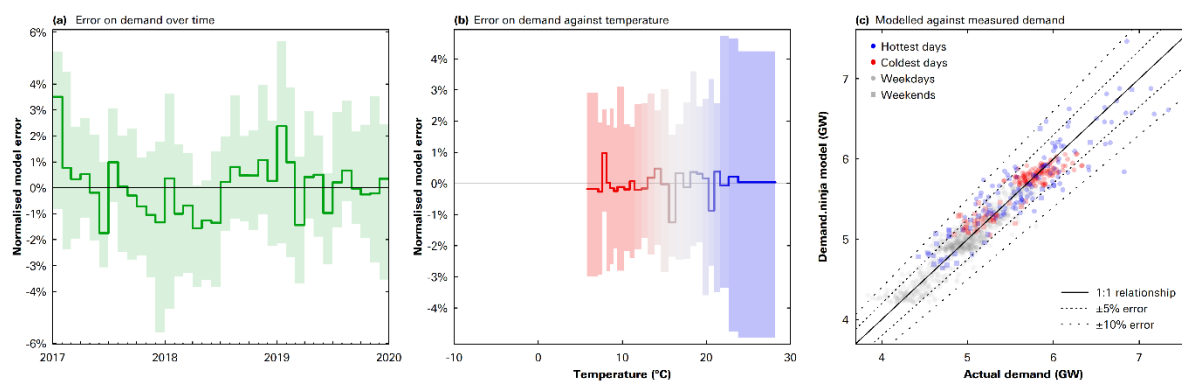
Supplementary Figure 46: Quality of modelling daily energy demand in New South Wales, Australia. Panels (a) and (b) summarise the error (Demand.ninja minus metered demand, normalised by maximum demand within each region). Panel (a) gives the error over time, the central line shows the median (P_{50}) of all days in each month, the shaded area shows the 5th and 95th percentile (P_5 – P_{95}). Panel (b) summarises the error as a function of outdoor air temperature, showing the same percentiles as in panel (a). Observations are grouped into 50 bins with an equal number of observations, hence they have variable widths. Bins are coloured according to the average number of heating (red) and cooling (blue) degree days in the observations they contain, giving an indication of balance point temperatures. Panel (c) shows observed against modelled daily demand, highlighting the 10% of hottest and coldest days.



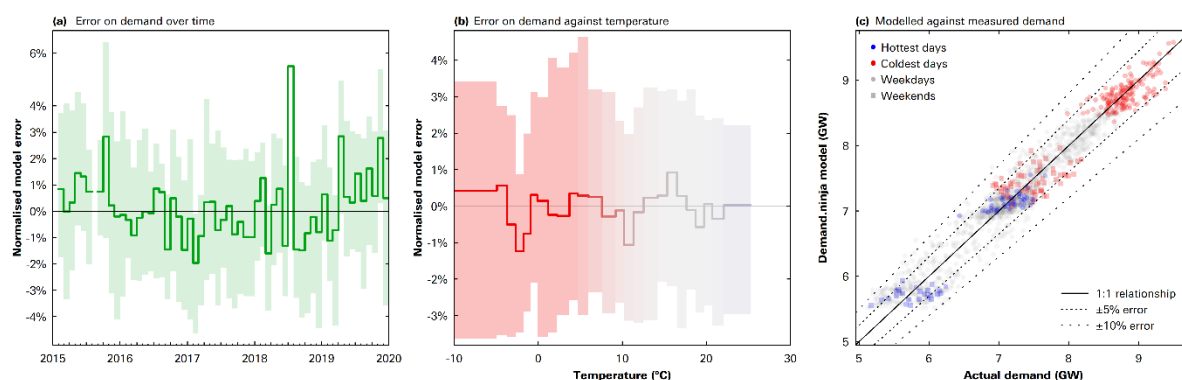
Supplementary Figure 47: Quality of modelling daily energy demand in Queensland, Australia. Figure follows the same design as Supplementary Figure 46; see the caption there for more detail.



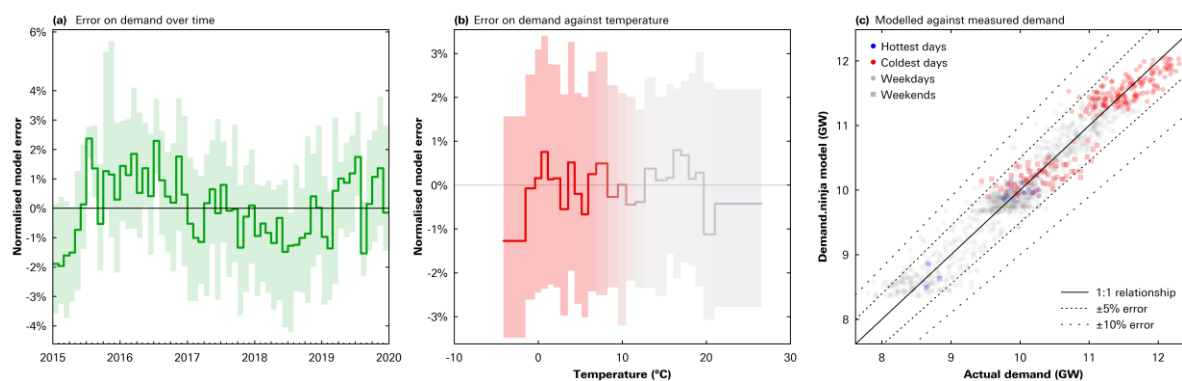
Supplementary Figure 48: Quality of modelling daily energy demand in Southern Australia. Figure follows the same design as Supplementary Figure 46; see the caption there for more detail.



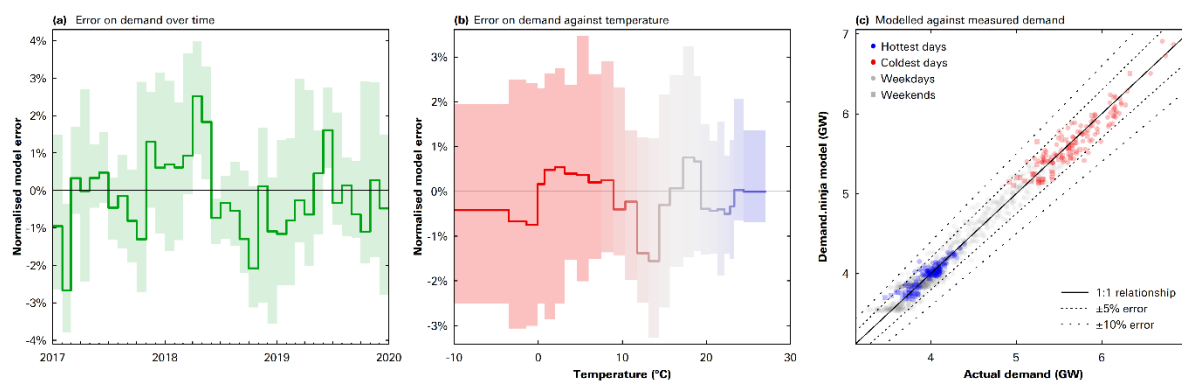
Supplementary Figure 49: Quality of modelling daily energy demand in Victoria, Australia. Figure follows the same design as Supplementary Figure 46; see the caption there for more detail.



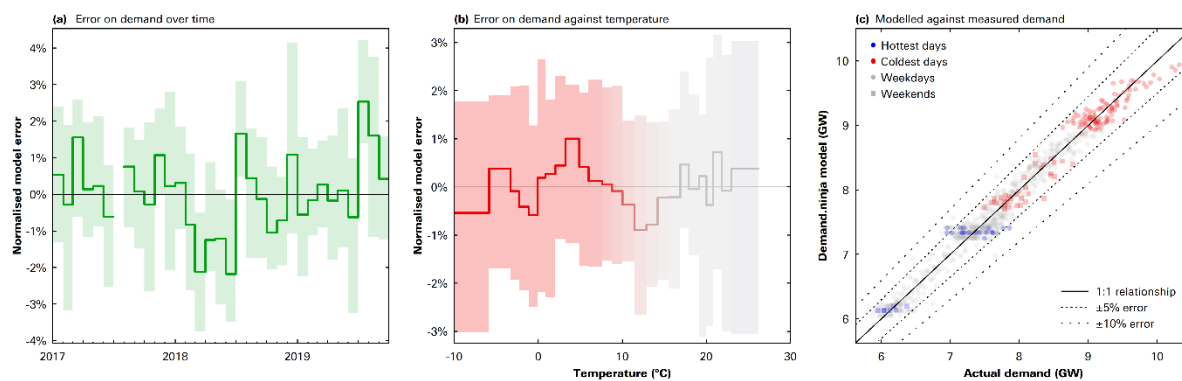
Supplementary Figure 50: Quality of modelling daily energy demand in Austria. Figure follows the same design as Supplementary Figure 46; see the caption there for more detail.



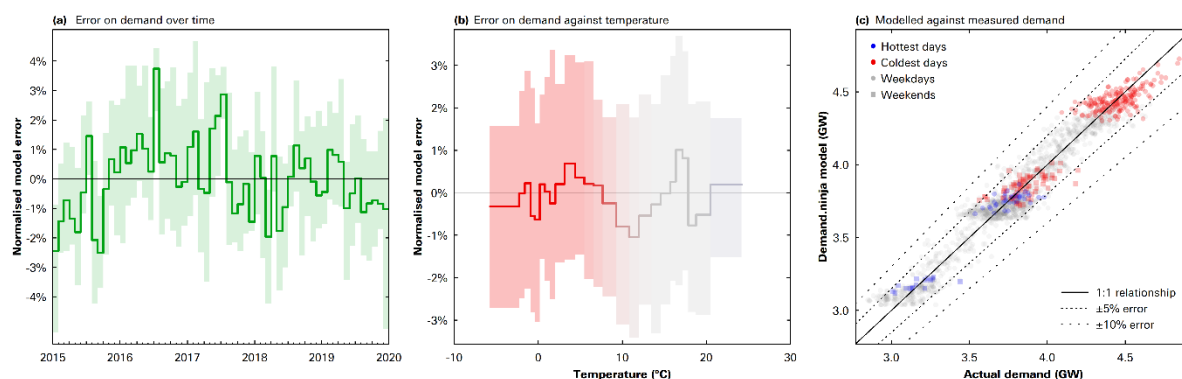
Supplementary Figure 51: Quality of modelling daily energy demand in Belgium. Figure follows the same design as Supplementary Figure 46; see the caption there for more detail.



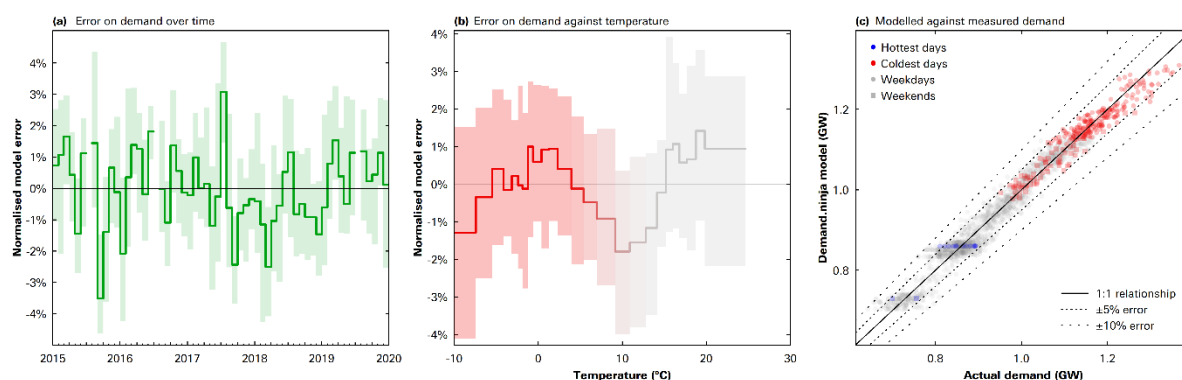
Supplementary Figure 52: Quality of modelling daily energy demand in Bulgaria. Figure follows the same design as Supplementary Figure 46; see the caption there for more detail.



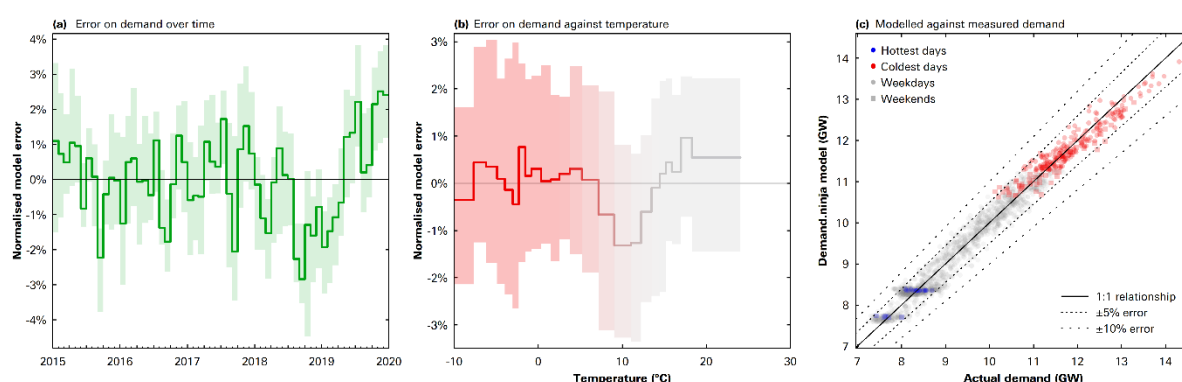
Supplementary Figure 53: Quality of modelling daily energy demand in Czechia. Figure follows the same design as Supplementary Figure 46; see the caption there for more detail.



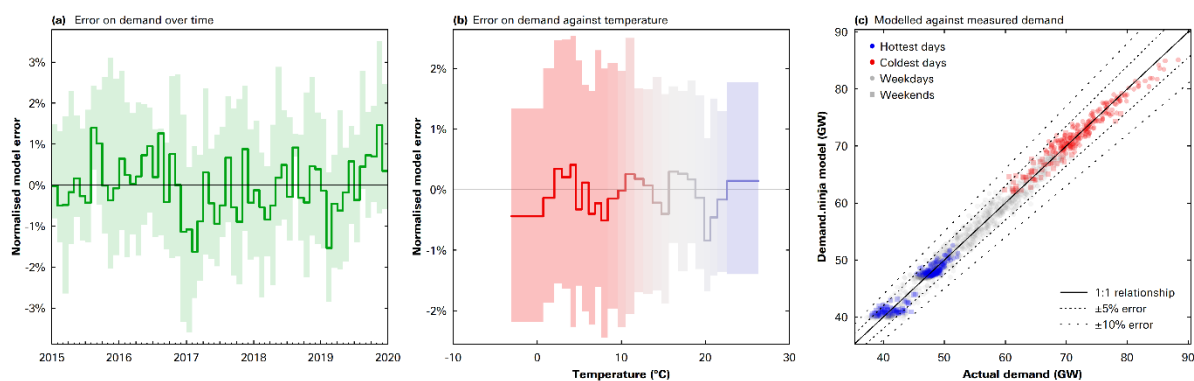
Supplementary Figure 54: Quality of modelling daily energy demand in Denmark. Figure follows the same design as Supplementary Figure 46; see the caption there for more detail.



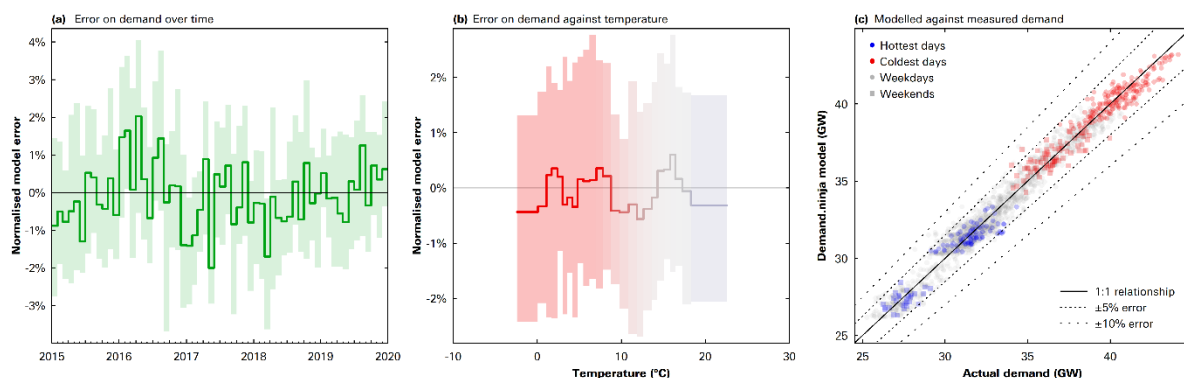
Supplementary Figure 55: Quality of modelling daily energy demand in Estonia. Figure follows the same design as Supplementary Figure 46; see the caption there for more detail.



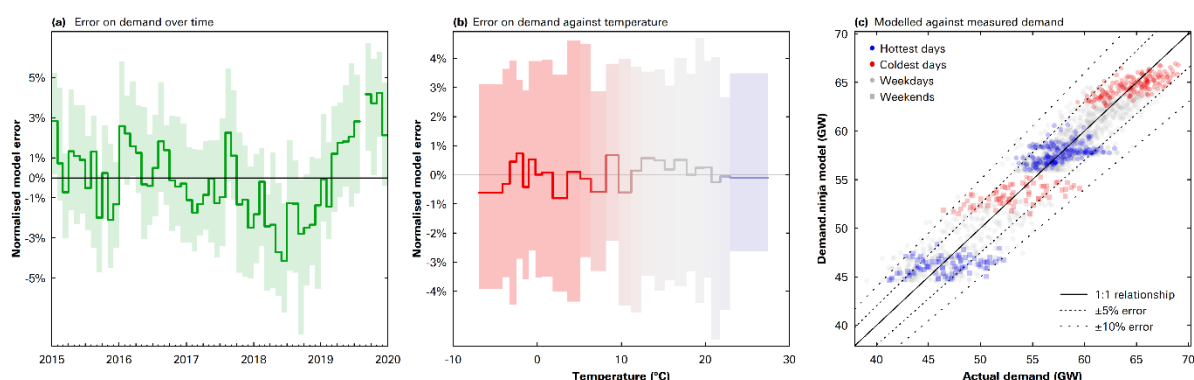
Supplementary Figure 56: Quality of modelling daily energy demand in Finland. Figure follows the same design as Supplementary Figure 46; see the caption there for more detail.



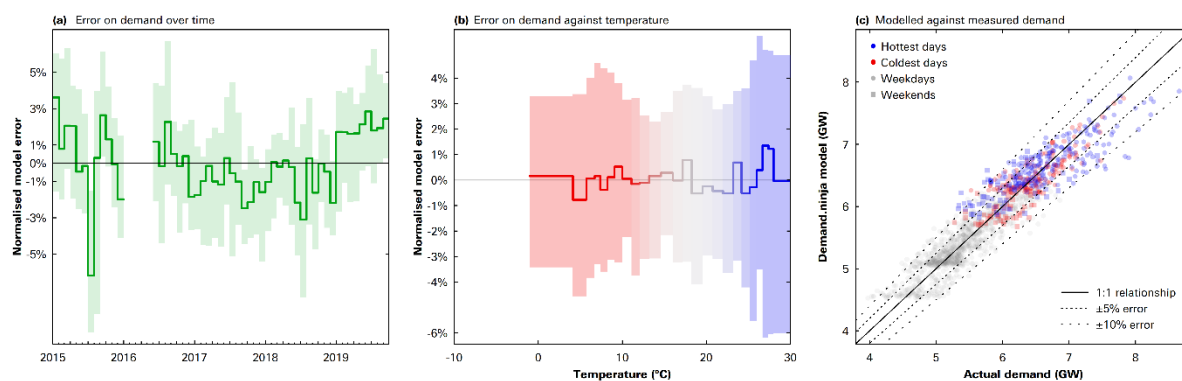
Supplementary Figure 57: Quality of modelling daily energy demand in France. Figure follows the same design as Supplementary Figure 46; see the caption there for more detail.



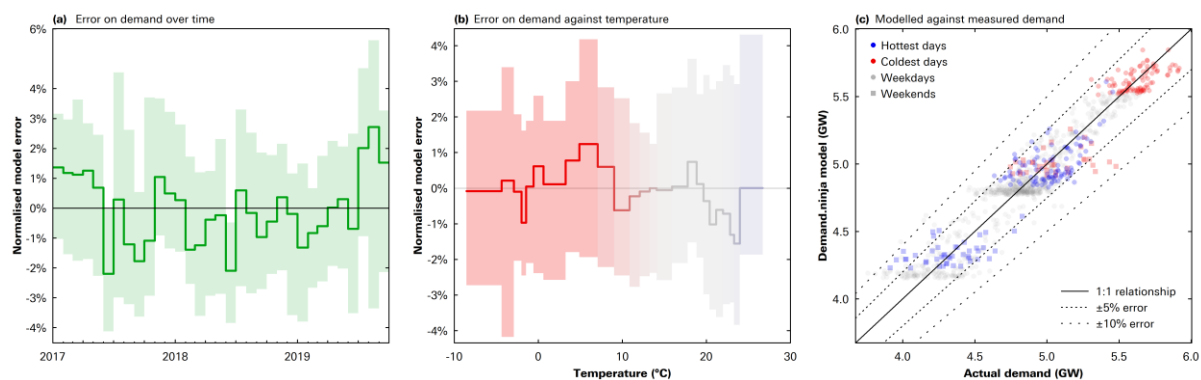
Supplementary Figure 58: Quality of modelling daily energy demand in Great Britain. Figure follows the same design as Supplementary Figure 46; see the caption there for more detail.



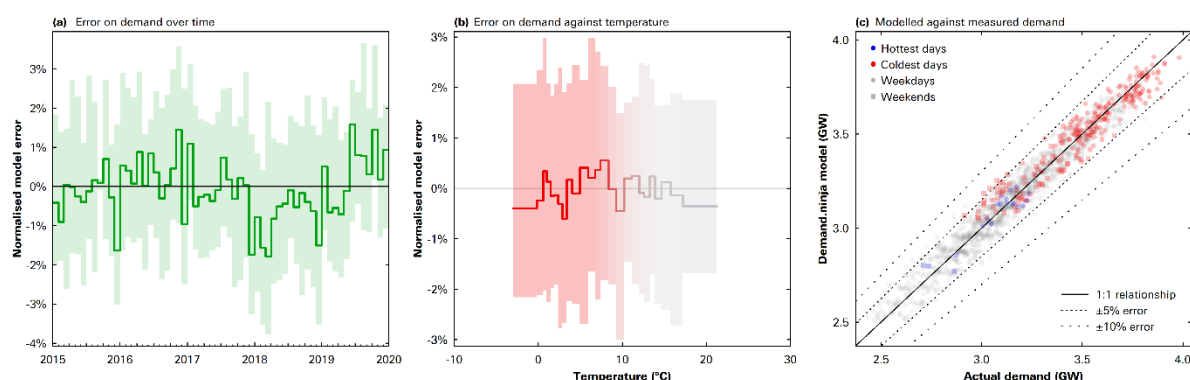
Supplementary Figure 59: Quality of modelling daily energy demand in Germany. Figure follows the same design as Supplementary Figure 46; see the caption there for more detail.



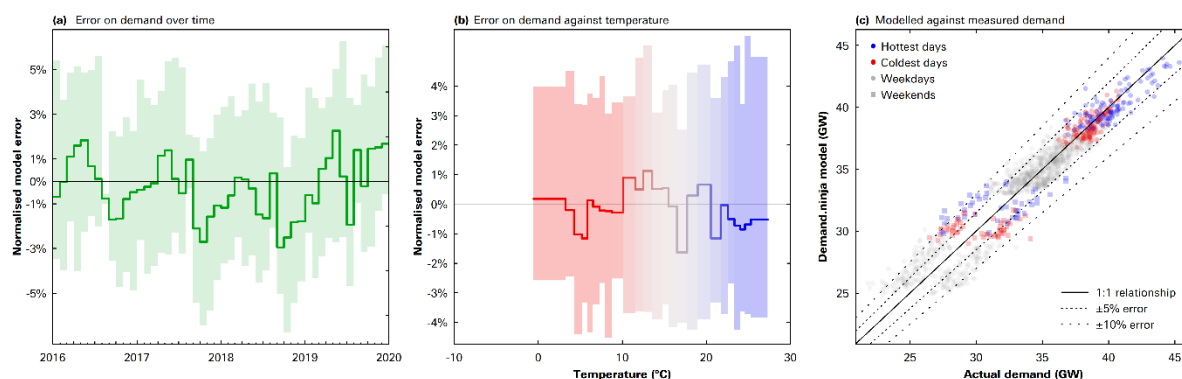
Supplementary Figure 60: Quality of modelling daily energy demand in Greece. Figure follows the same design as Supplementary Figure 46; see the caption there for more detail.



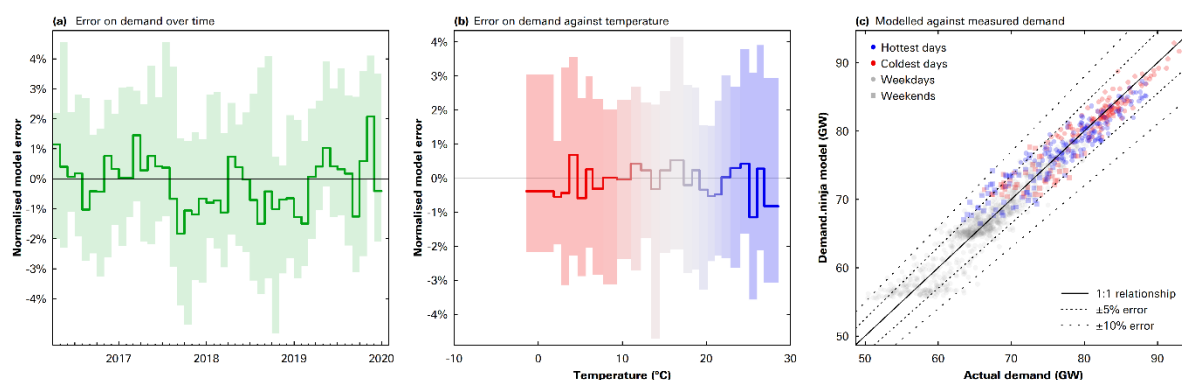
Supplementary Figure 61: Quality of modelling daily energy demand in Hungary. Figure follows the same design as Supplementary Figure 46; see the caption there for more detail.



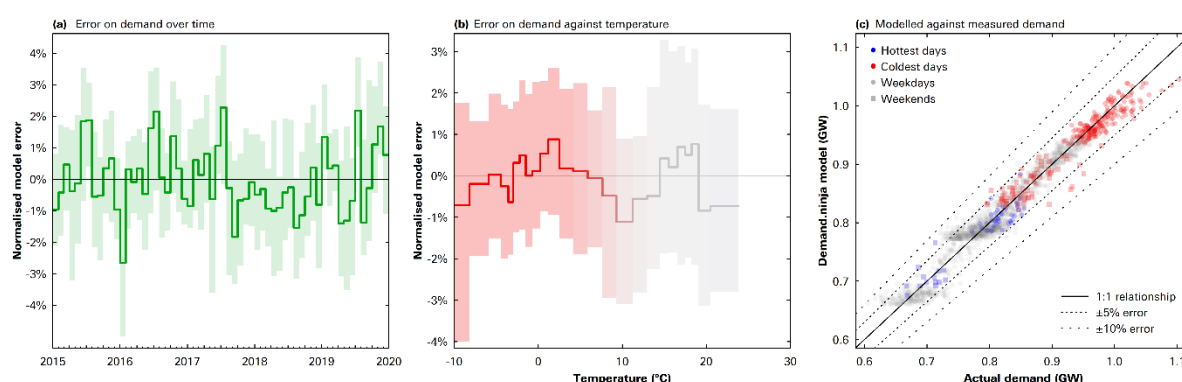
Supplementary Figure 62: Quality of modelling daily energy demand in Ireland. Figure follows the same design as Supplementary Figure 46; see the caption there for more detail.



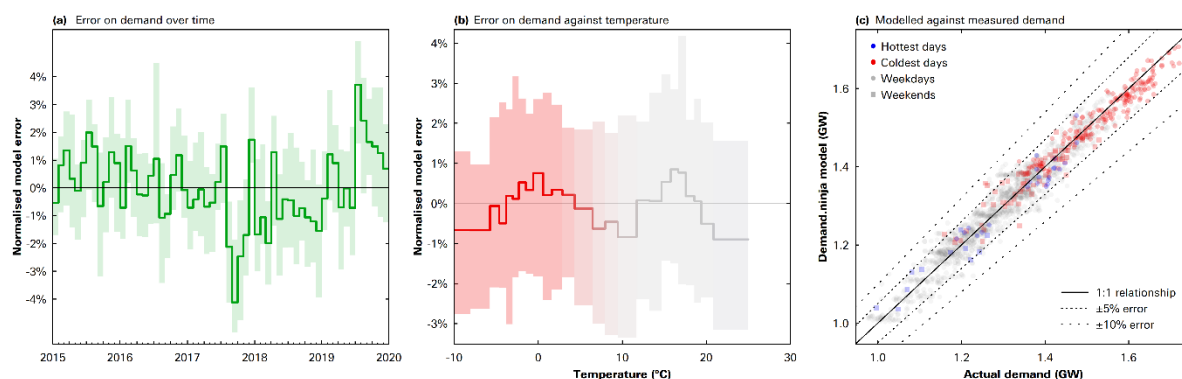
Supplementary Figure 63: Quality of modelling daily energy demand in Italy. Figure follows the same design as Supplementary Figure 46; see the caption there for more detail.



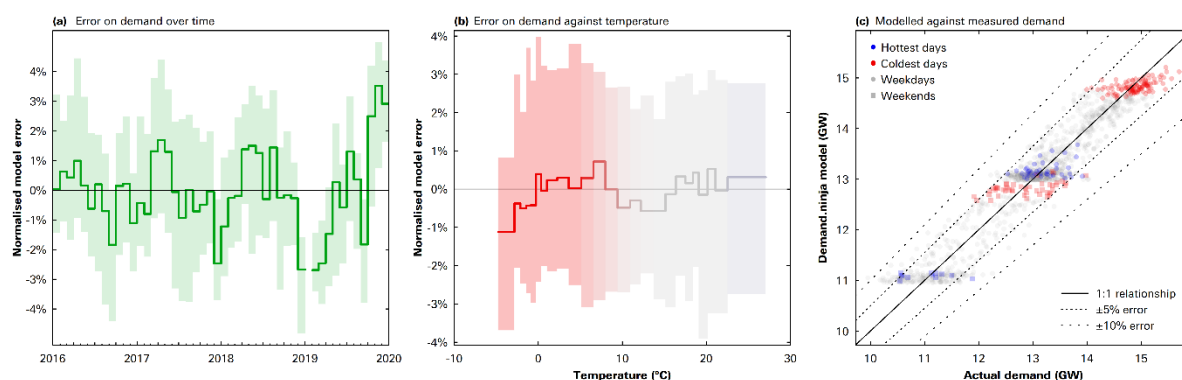
Supplementary Figure 64: Quality of modelling daily energy demand in Japan. Figure follows the same design as Supplementary Figure 46; see the caption there for more detail.



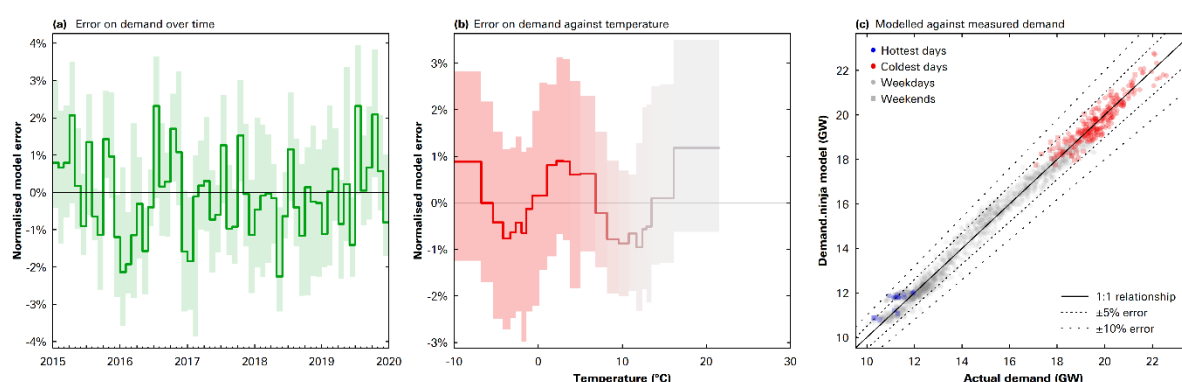
Supplementary Figure 65: Quality of modelling daily energy demand in Latvia. Figure follows the same design as Supplementary Figure 46; see the caption there for more detail.



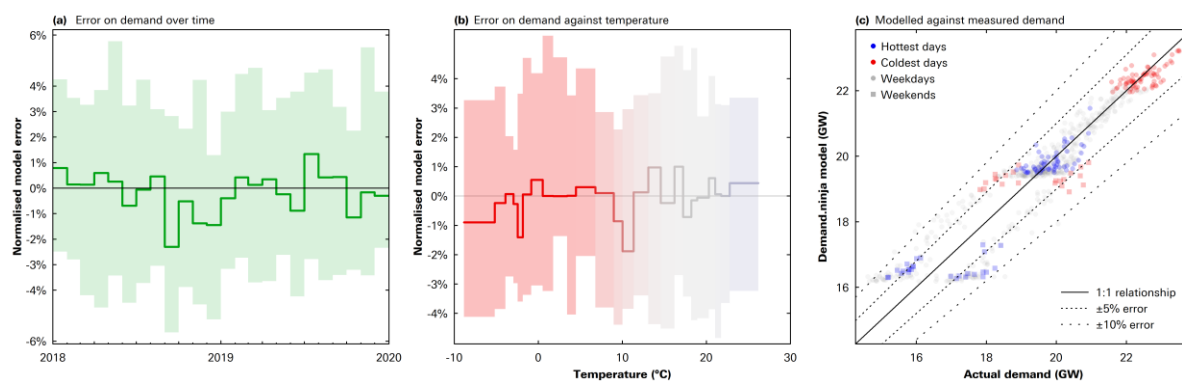
Supplementary Figure 66: Quality of modelling daily energy demand in Lithuania. Figure follows the same design as Supplementary Figure 46; see the caption there for more detail.



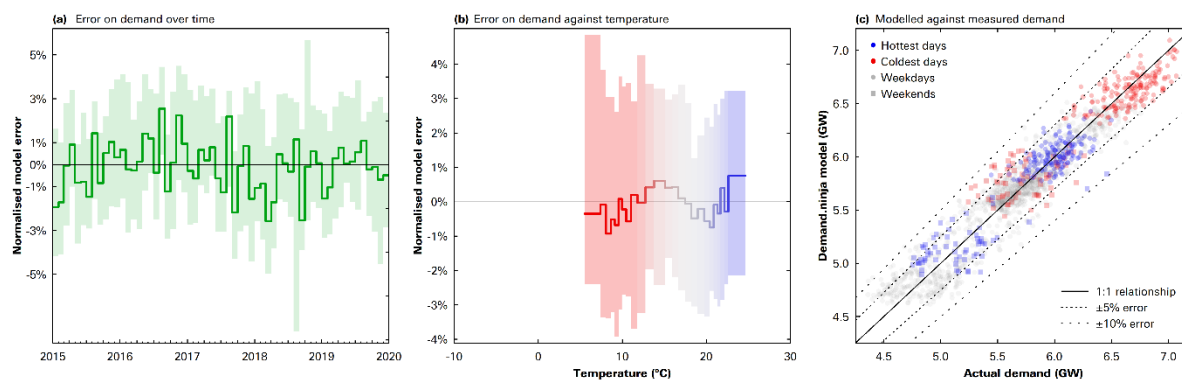
Supplementary Figure 67: Quality of modelling daily energy demand in the Netherlands. Figure follows the same design as Supplementary Figure 46; see the caption there for more detail.



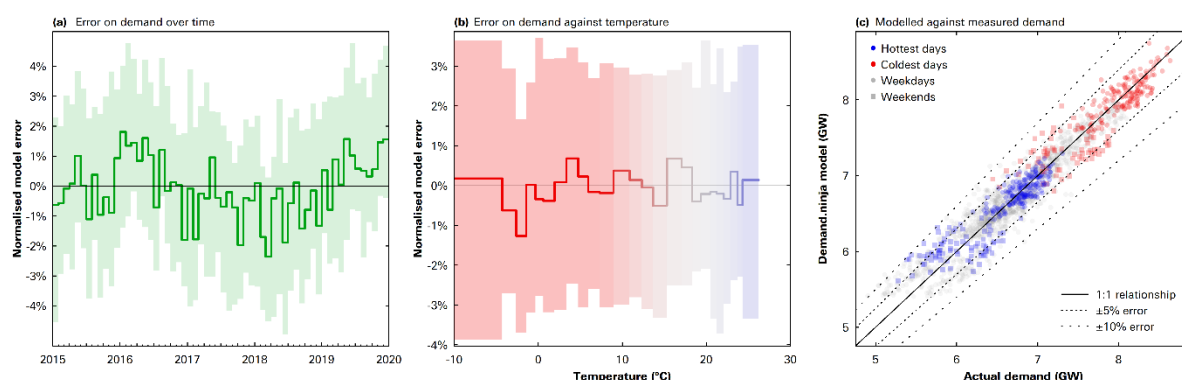
Supplementary Figure 68: Quality of modelling daily energy demand in Norway. Figure follows the same design as Supplementary Figure 46; see the caption there for more detail.



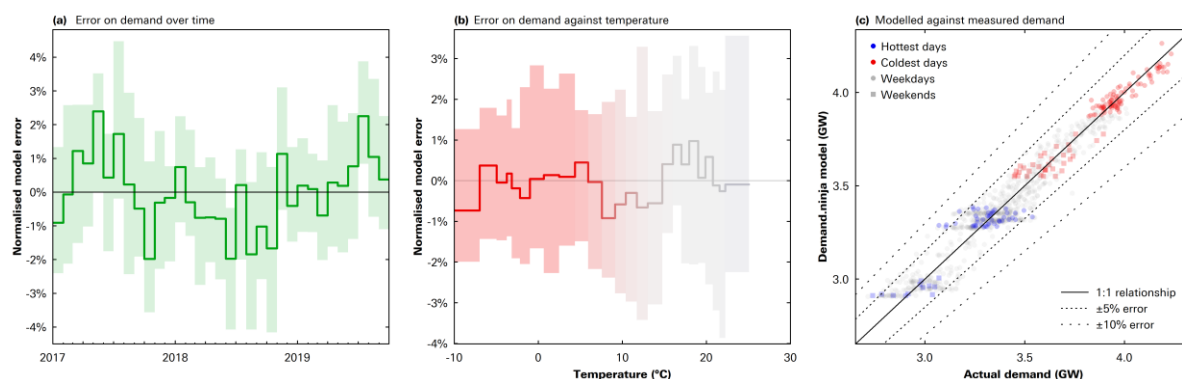
Supplementary Figure 69: Quality of modelling daily energy demand in Poland. Figure follows the same design as Supplementary Figure 46; see the caption there for more detail.



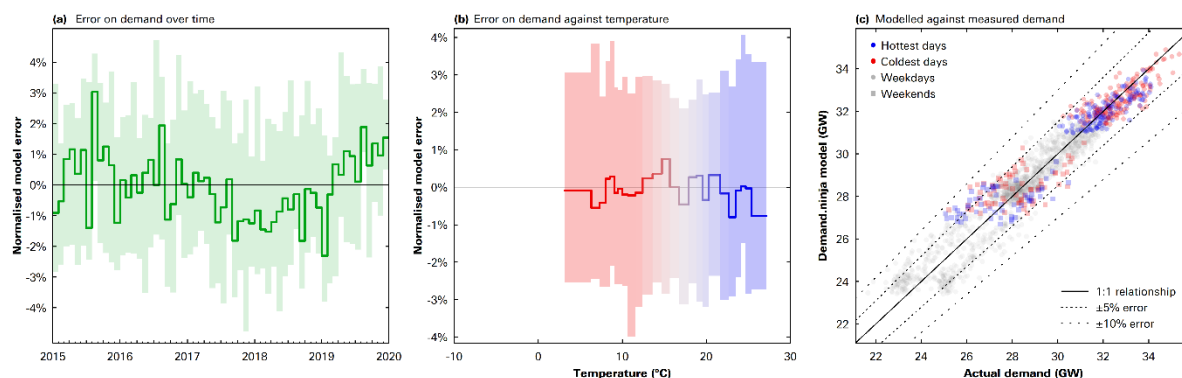
Supplementary Figure 70: Quality of modelling daily energy demand in Portugal. Figure follows the same design as Supplementary Figure 46; see the caption there for more detail.



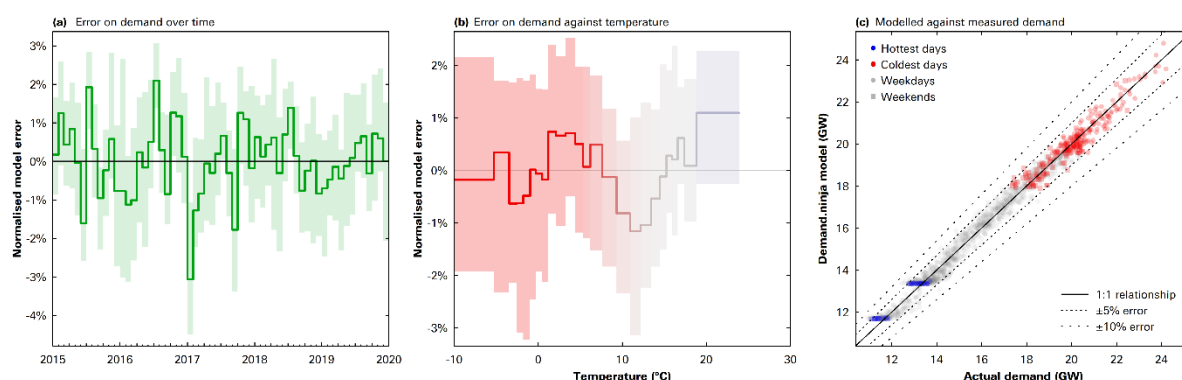
Supplementary Figure 71: Quality of modelling daily energy demand in Romania. Figure follows the same design as Supplementary Figure 46; see the caption there for more detail.



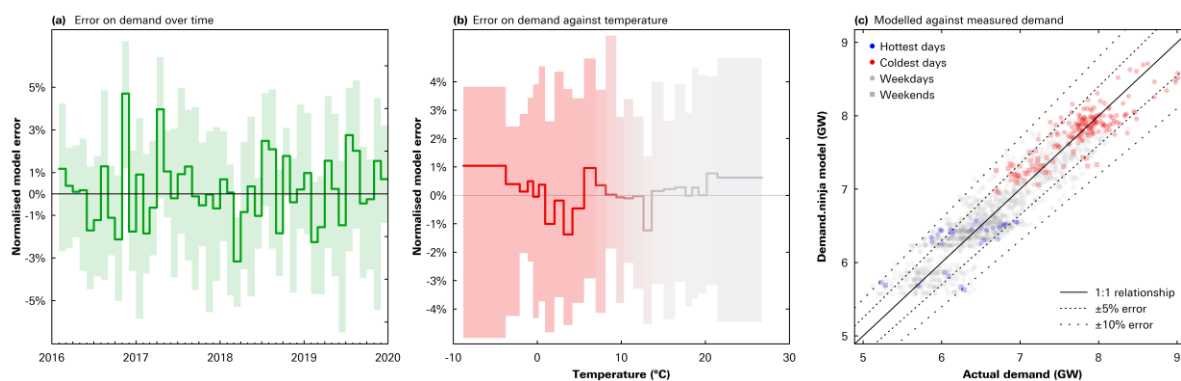
Supplementary Figure 72: Quality of modelling daily energy demand in Slovakia. Figure follows the same design as Supplementary Figure 46; see the caption there for more detail.



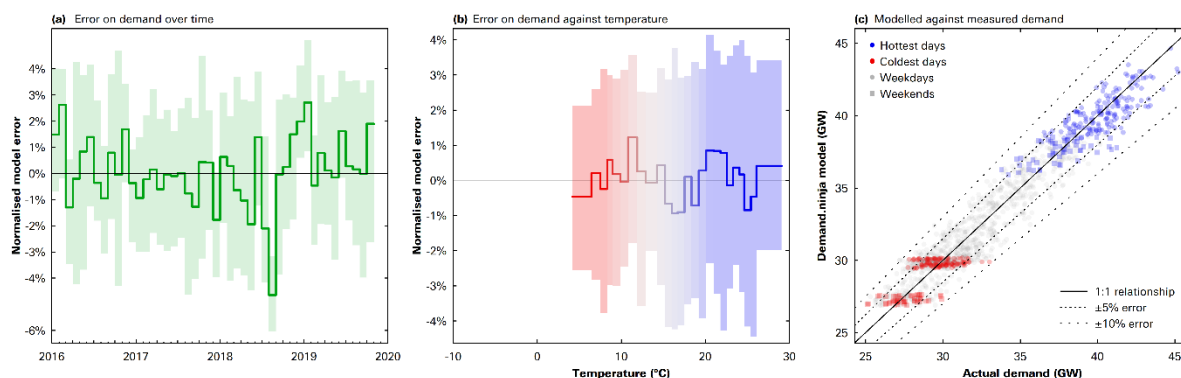
Supplementary Figure 73: Quality of modelling daily energy demand in Spain. Figure follows the same design as Supplementary Figure 46; see the caption there for more detail.



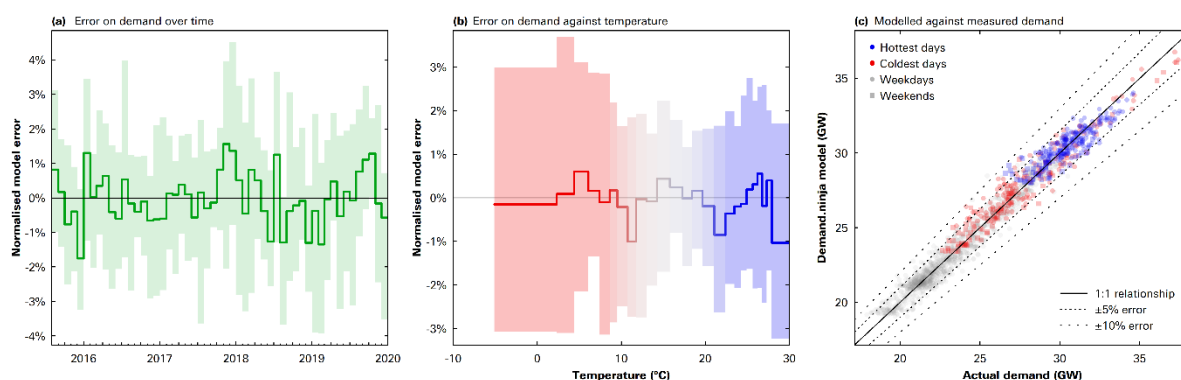
Supplementary Figure 74: Quality of modelling daily energy demand in Sweden. Figure follows the same design as Supplementary Figure 46; see the caption there for more detail.



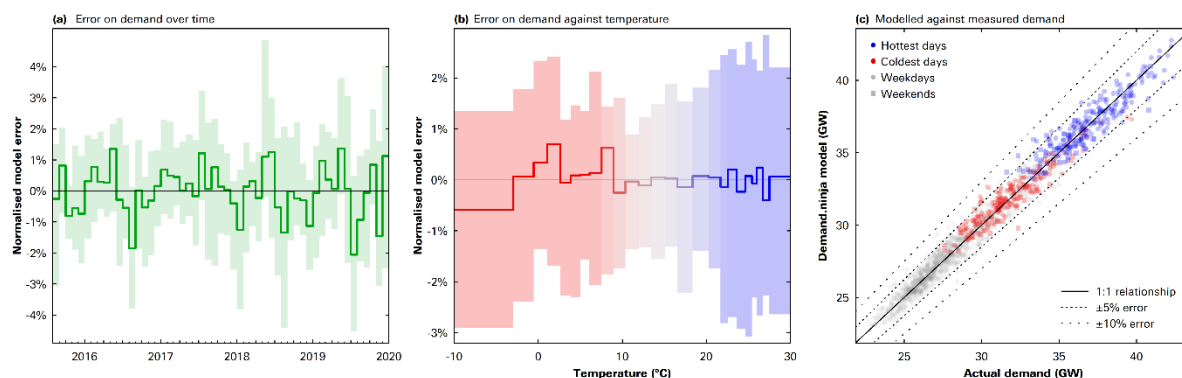
Supplementary Figure 75: Quality of modelling daily energy demand in Switzerland. Figure follows the same design as Supplementary Figure 46; see the caption there for more detail.



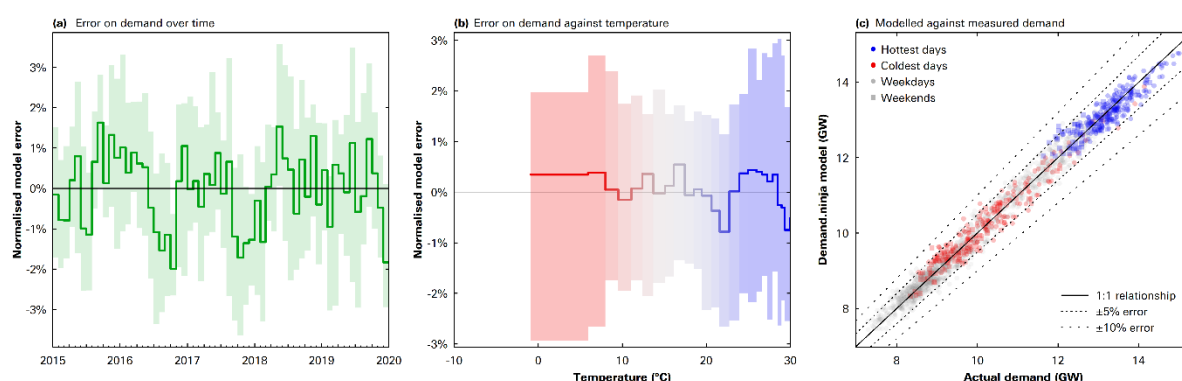
Supplementary Figure 76: Quality of modelling daily energy demand in the CAISO power market, US. Figure follows the same design as Supplementary Figure 46; see the caption there for more detail.



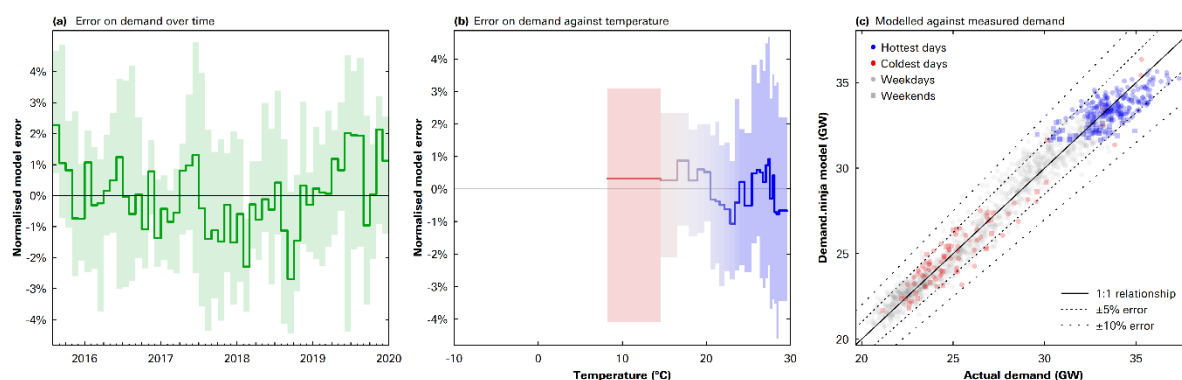
Supplementary Figure 77: Quality of modelling daily energy demand in the Carolinas power market, US. Figure follows the same design as Supplementary Figure 46; see the caption there for more detail.



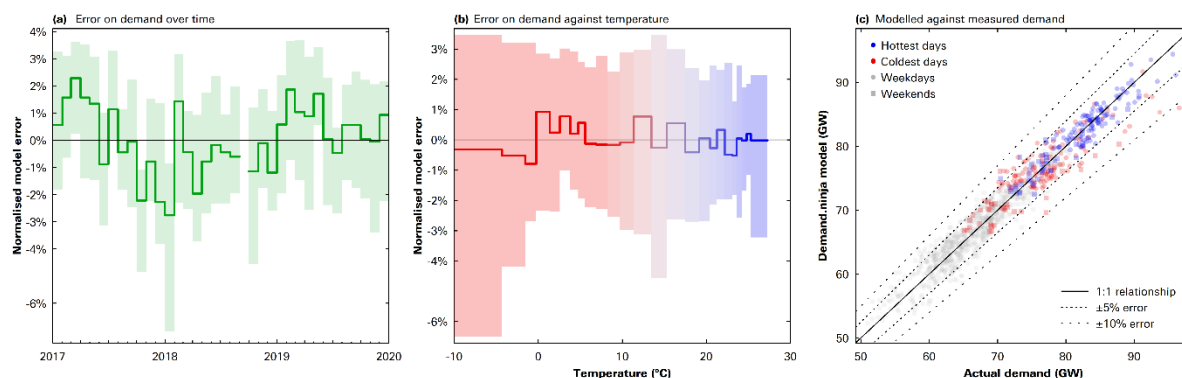
Supplementary Figure 78: Quality of modelling daily energy demand in the Central power market, US. Figure follows the same design as Supplementary Figure 46; see the caption there for more detail.



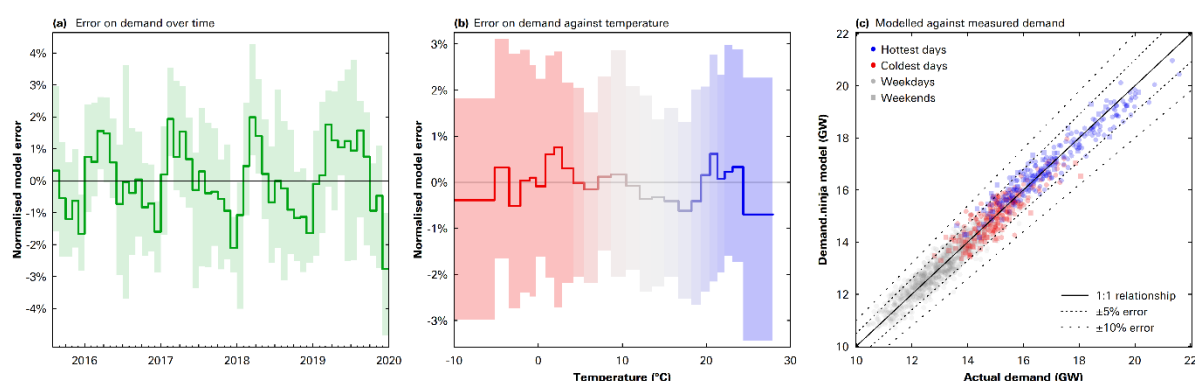
Supplementary Figure 79: Quality of modelling daily energy demand in the ERCOT power market, US. Figure follows the same design as Supplementary Figure 46; see the caption there for more detail.



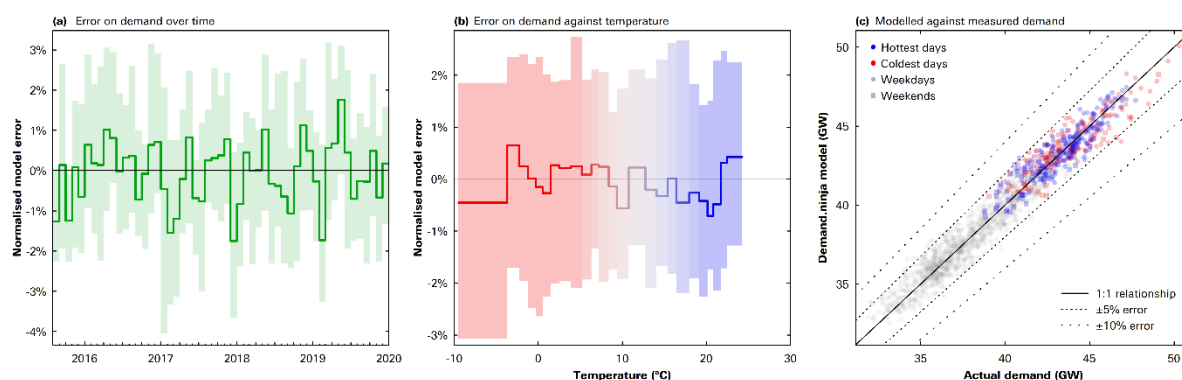
Supplementary Figure 80: Quality of modelling daily energy demand in the Florida power market, US. Figure follows the same design as Supplementary Figure 46; see the caption there for more detail.



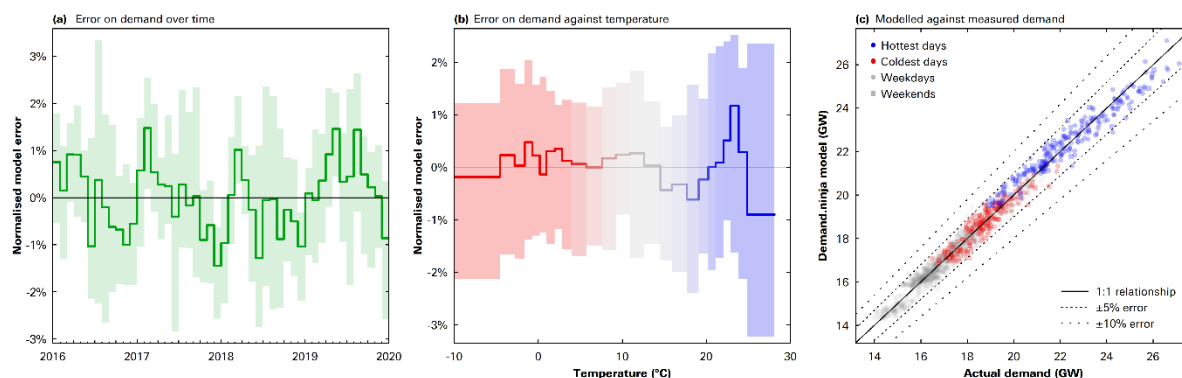
Supplementary Figure 81: Quality of modelling daily energy demand in the MISO power market, US. Figure follows the same design as Supplementary Figure 46; see the caption there for more detail.



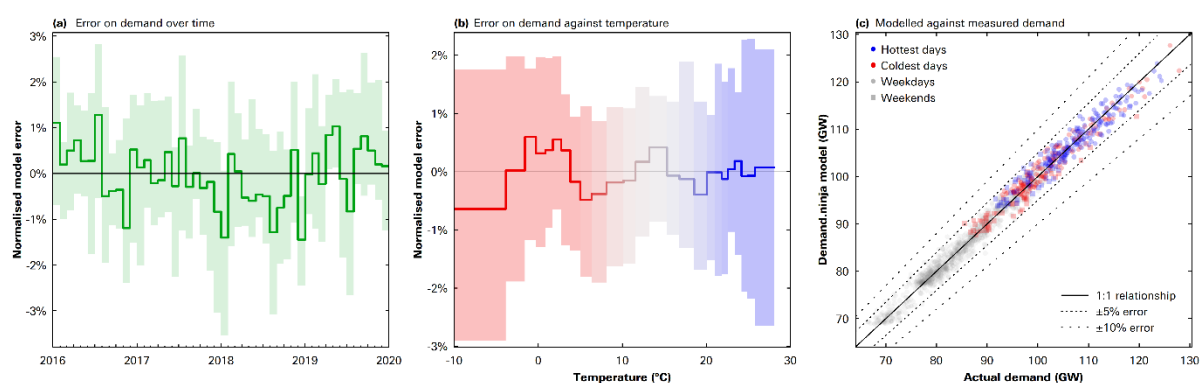
Supplementary Figure 82: Quality of modelling daily energy demand in the ISONE power market, US. Figure follows the same design as Supplementary Figure 46; see the caption there for more detail.



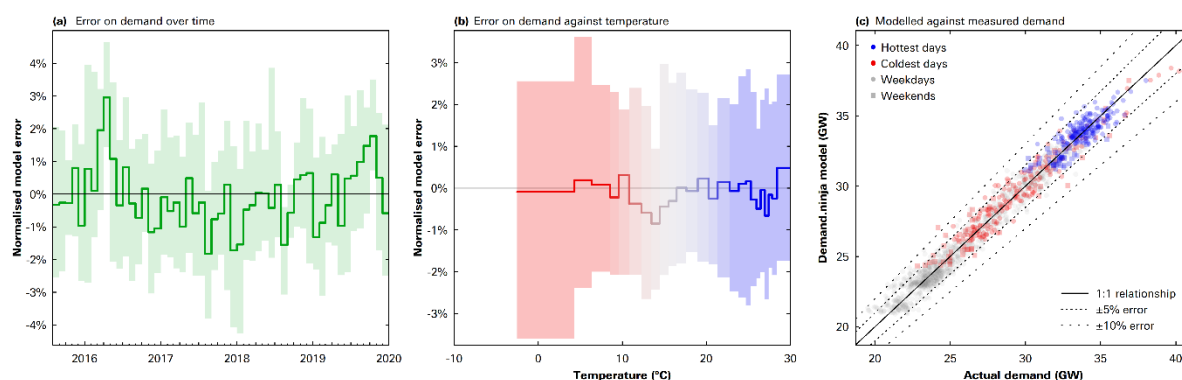
Supplementary Figure 83: Quality of modelling daily energy demand in the Northwest power market, US. Figure follows the same design as Supplementary Figure 46; see the caption there for more detail.



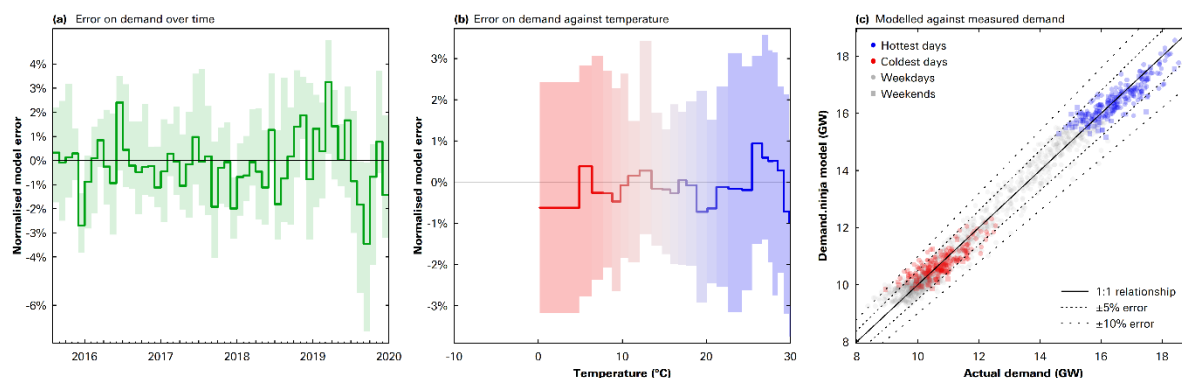
Supplementary Figure 84: Quality of modelling daily energy demand in the NYISO power market, US. Figure follows the same design as Supplementary Figure 46; see the caption there for more detail.



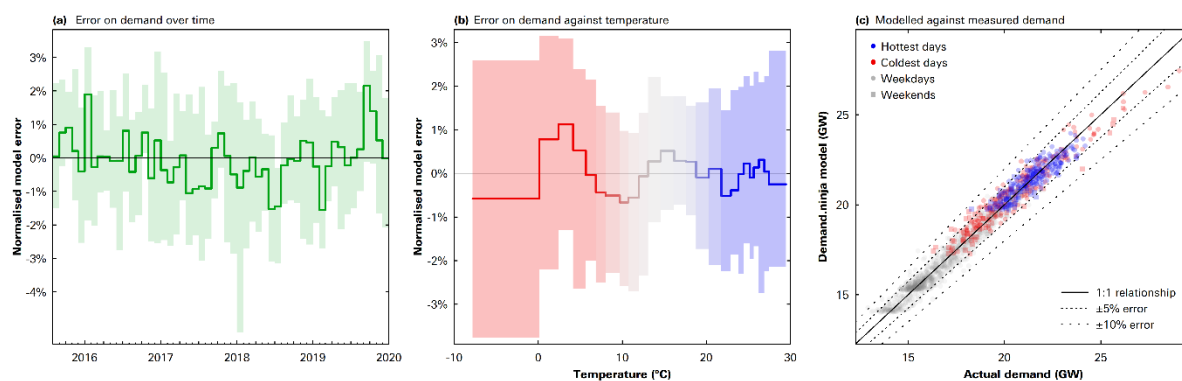
Supplementary Figure 85: Quality of modelling daily energy demand in the PJM power market, US. Figure follows the same design as Supplementary Figure 46; see the caption there for more detail.



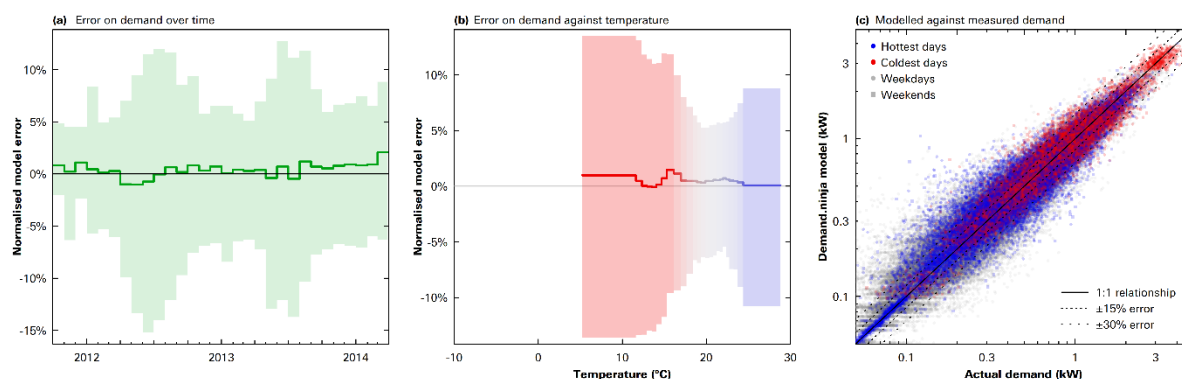
Supplementary Figure 86: Quality of modelling daily energy demand in the Southeast power market, US. Figure follows the same design as Supplementary Figure 46; see the caption there for more detail.



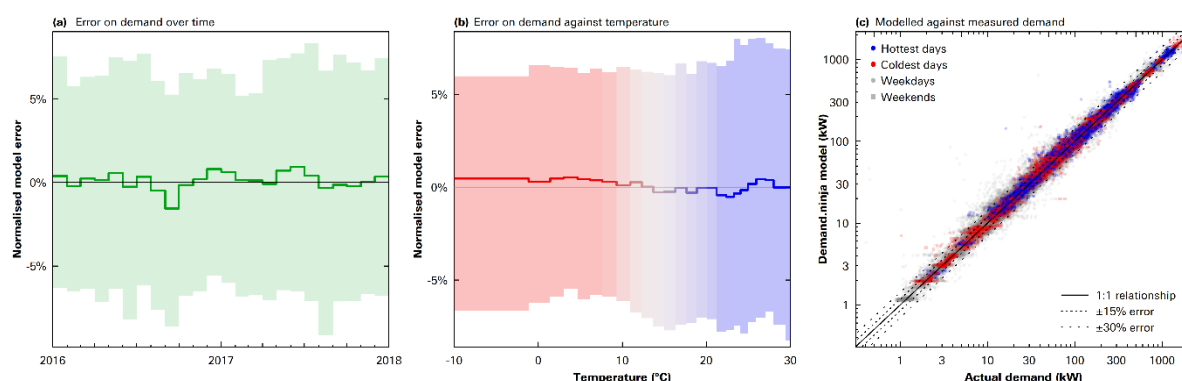
Supplementary Figure 87: Quality of modelling daily energy demand in the Southwest power market, US. Figure follows the same design as Supplementary Figure 46; see the caption there for more detail.



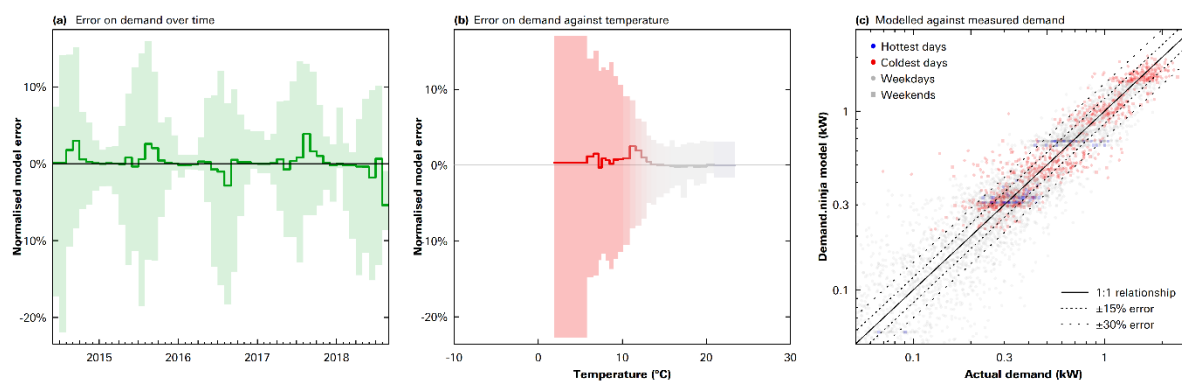
Supplementary Figure 88: Quality of modelling daily energy demand in the Tennessee power market, US. Figure follows the same design as Supplementary Figure 46; see the caption there for more detail.



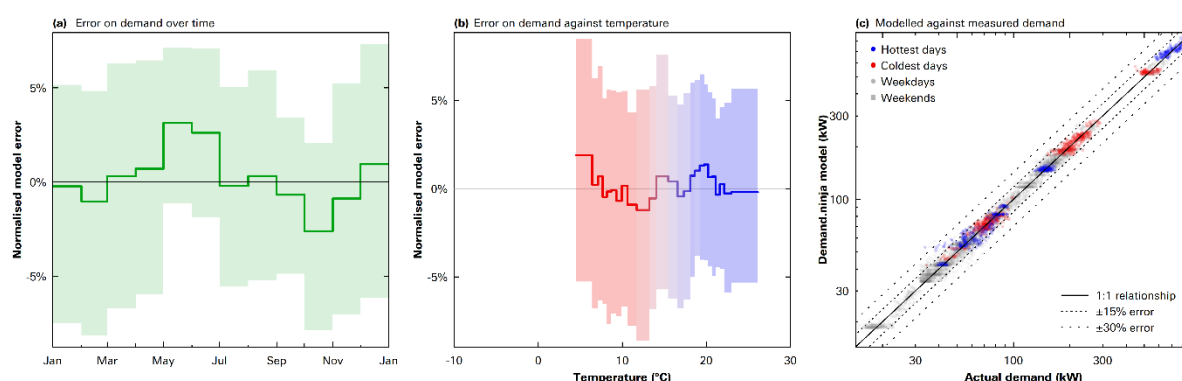
Supplementary Figure 89: Quality of modelling daily electricity demand from 1,507 individual residential buildings in the Smart-Grid Smart-City dataset (Australia). Panels (a) and (b) summarise the error (Demand.ninja minus metered demand, normalised by maximum demand within each building) across all buildings within the dataset. Panel (a) gives the error over time, the central line shows the median (P₅₀) of all days in each month across all buildings, the shaded area shows the 5th and 95th percentile (P₅–P₉₅). Panel (b) summarises the error as a function of outdoor air temperature, showing the same percentiles as in panel (a). Observations are grouped into 50 bins with an equal number of observations, hence they have variable widths. Bins are coloured according to the average number of heating (red) and cooling (blue) degree days in the observations they contain, giving an indication of balance point temperatures. Panel (c) shows observed against modelled daily demand across all buildings, highlighting the 10% of hottest and coldest days.



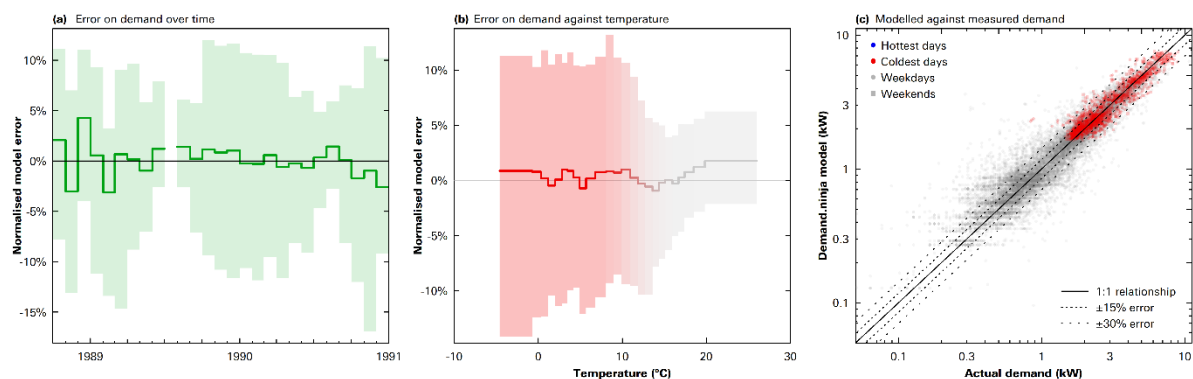
Supplementary Figure 90: Quality of modelling daily electricity demand from 448 individual commercial buildings in the Building Data Genome Project 2 dataset (global). Figure follows the same design as Supplementary Figure 89; see the caption there for more detail.



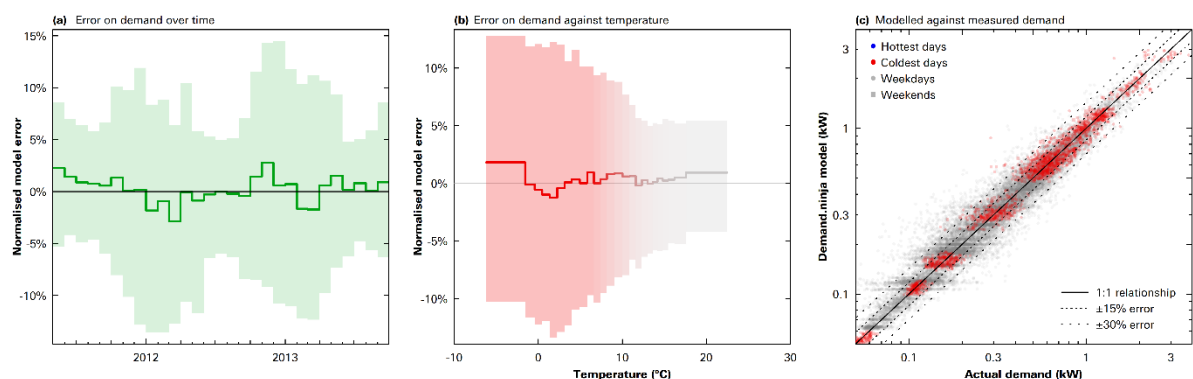
Supplementary Figure 91: Quality of modelling daily electricity demand from 43 individual residential buildings in the Green Grid dataset (New Zealand). Figure follows the same design as Supplementary Figure 89; see the caption there for more detail.



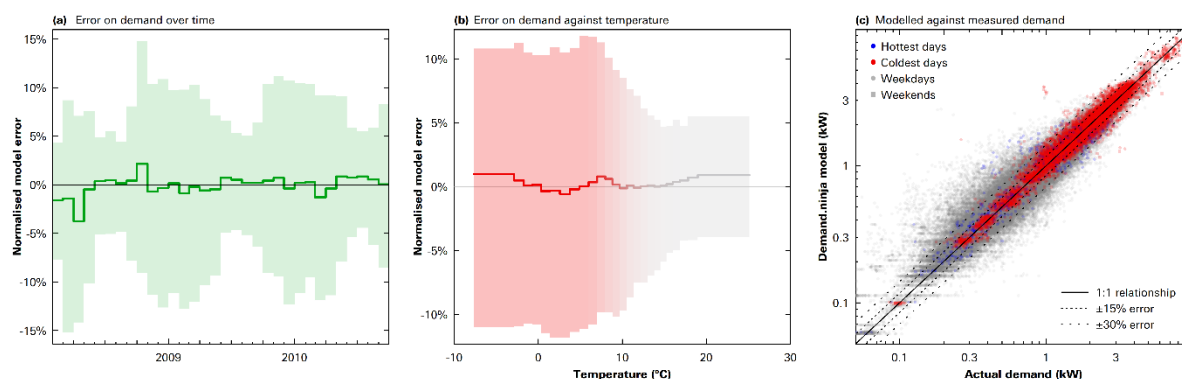
Supplementary Figure 92: Quality of modelling daily electricity demand from 103 individual commercial buildings in the Elergone Energia dataset (Portugal). Figure follows the same design as Supplementary Figure 89; see the caption there for more detail.



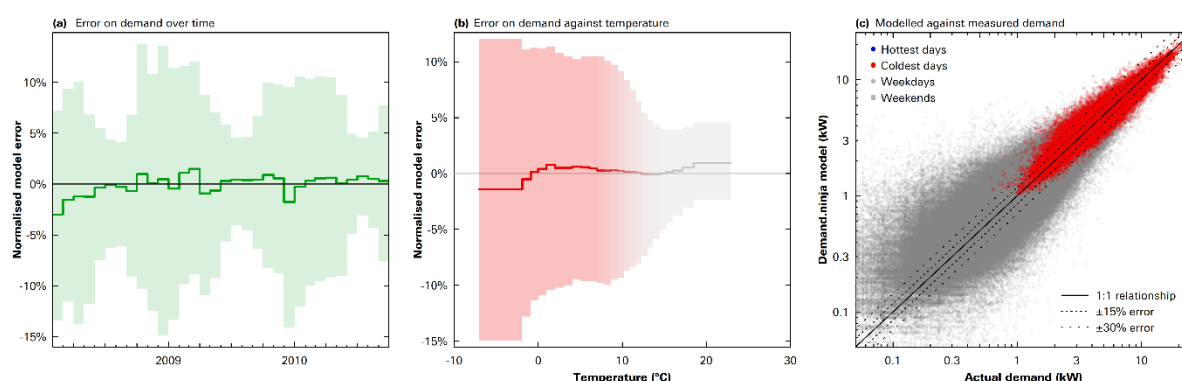
Supplementary Figure 93: Quality of modelling daily natural gas demand from 46 individual residential buildings in the BRE dataset (UK). Figure follows the same design as Supplementary Figure 89; see the caption there for more detail.



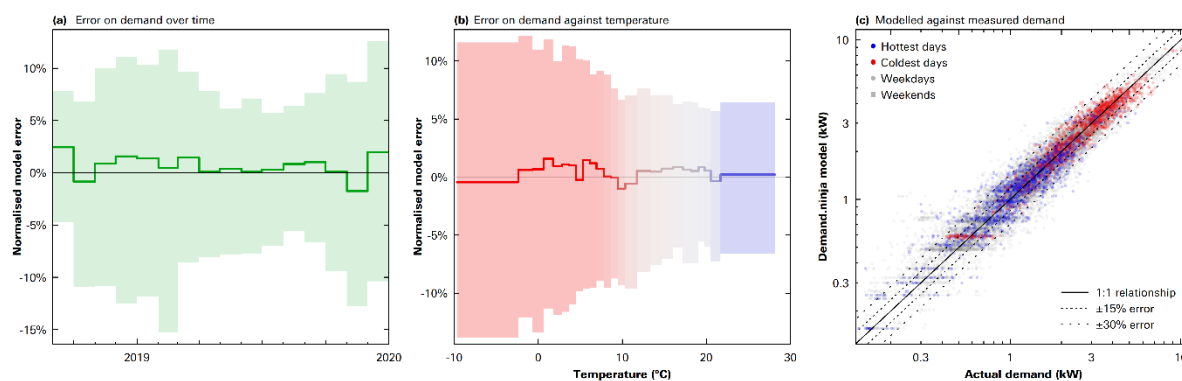
Supplementary Figure 94: Quality of modelling daily electricity demand from 90 individual residential buildings in the Customer Led Network Revolution dataset (UK). Figure follows the same design as Supplementary Figure 89; see the caption there for more detail.



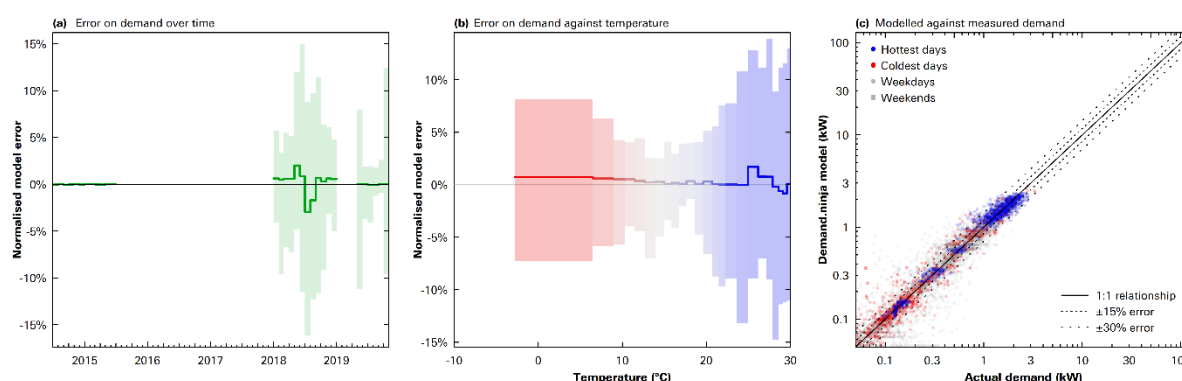
Supplementary Figure 95: Quality of modelling daily natural gas demand from 252 individual residential buildings in the Customer Led Network Revolution dataset (UK). Figure follows the same design as Supplementary Figure 89; see the caption there for more detail.



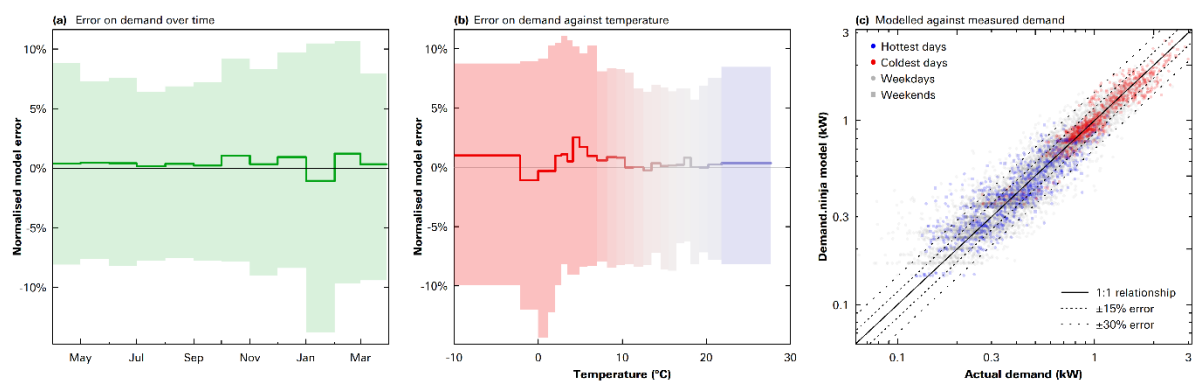
Supplementary Figure 96: Quality of modelling daily natural gas demand from 2,062 individual residential buildings in the Energy Demand Research Project dataset (UK). Figure follows the same design as Supplementary Figure 89; see the caption there for more detail.



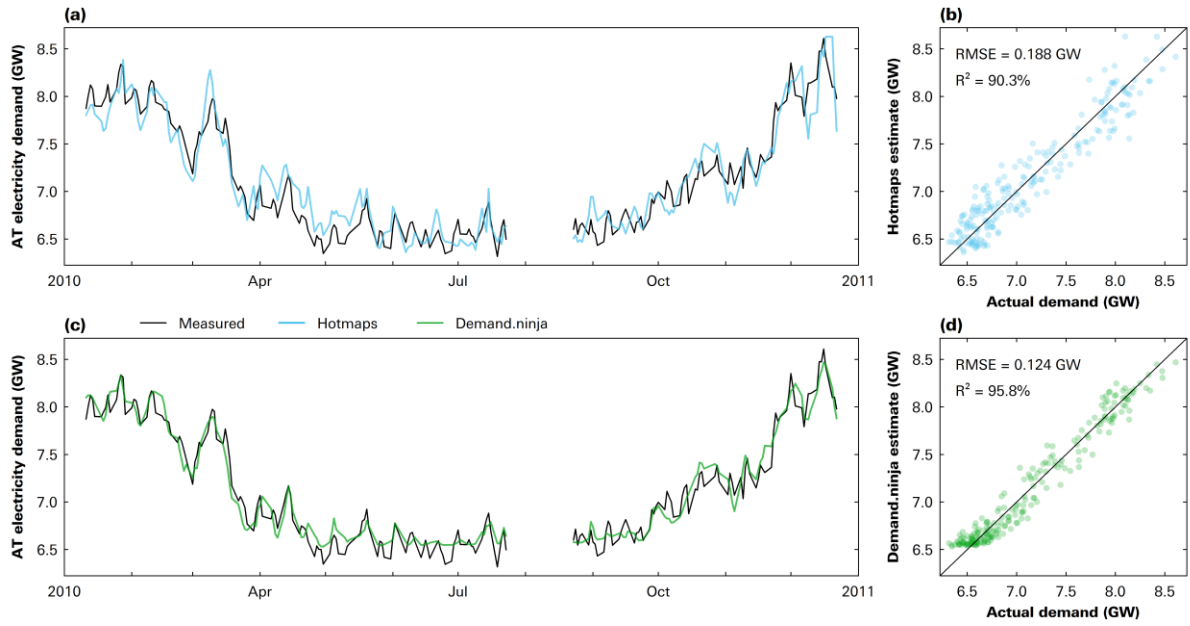
Supplementary Figure 97: Quality of modelling daily electricity demand from 93 individual residential buildings in Home Energy Metering Study dataset (US). Figure follows the same design as Supplementary Figure 89; see the caption there for more detail.



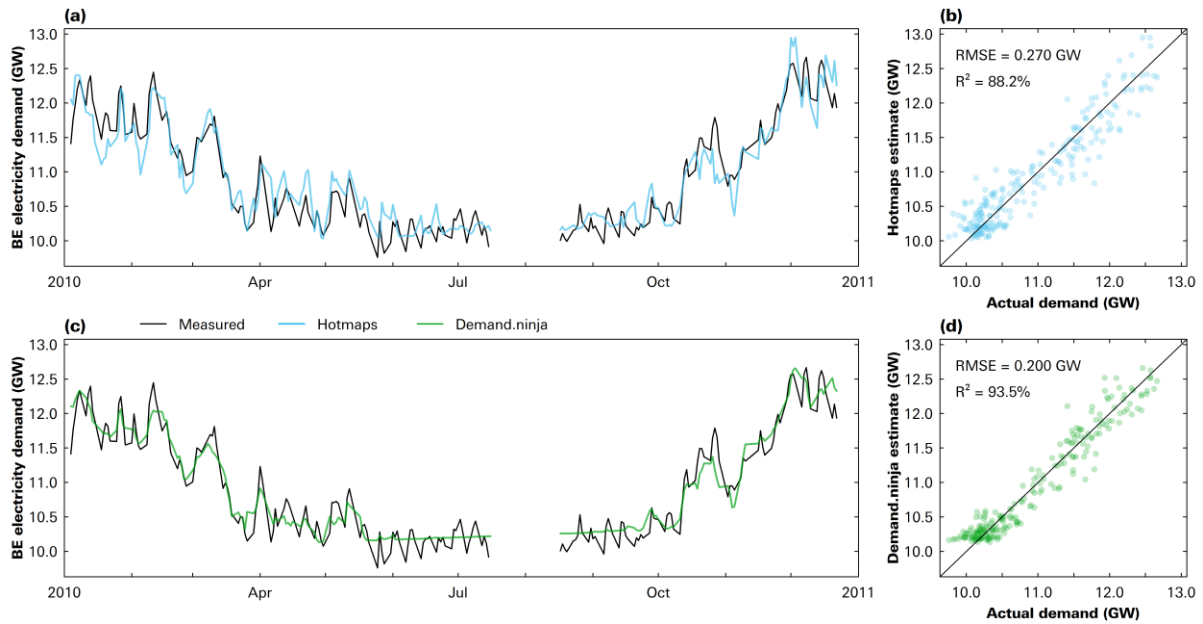
Supplementary Figure 98: Quality of modelling daily electricity demand from 88 individual residential buildings in Pecan Street dataset (US). Figure follows the same design as Supplementary Figure 89; see the caption there for more detail.



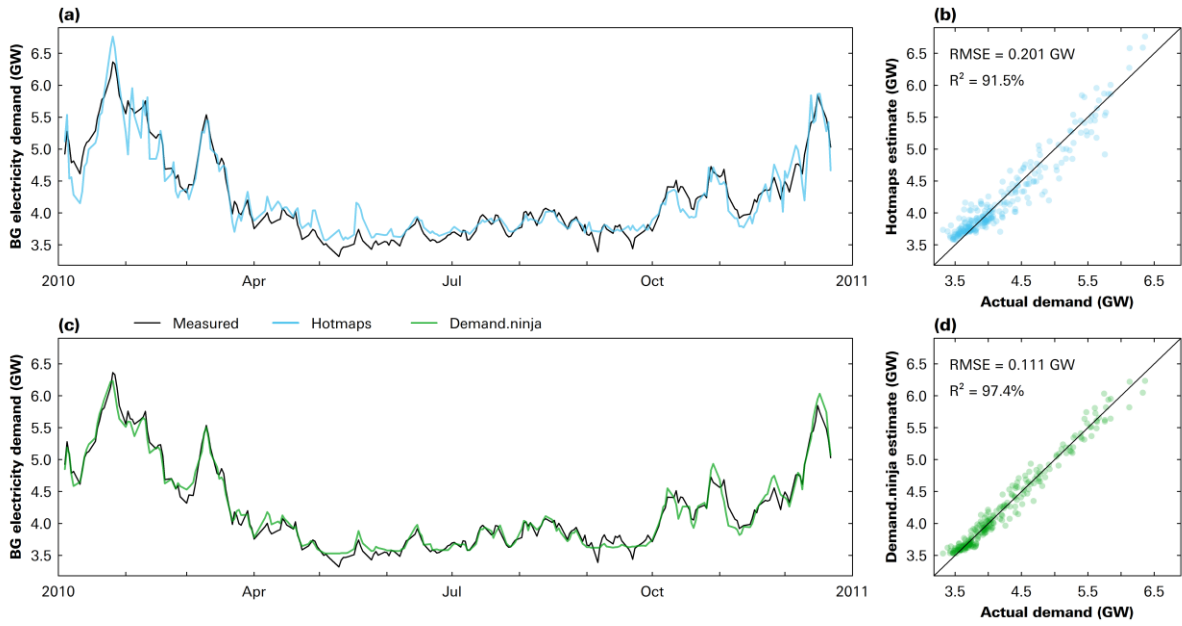
Supplementary Figure 99: Quality of modelling daily electricity demand from 41 individual residential buildings in Residential Building Stock Assessment dataset (US). Figure follows the same design as Supplementary Figure 89; see the caption there for more detail.



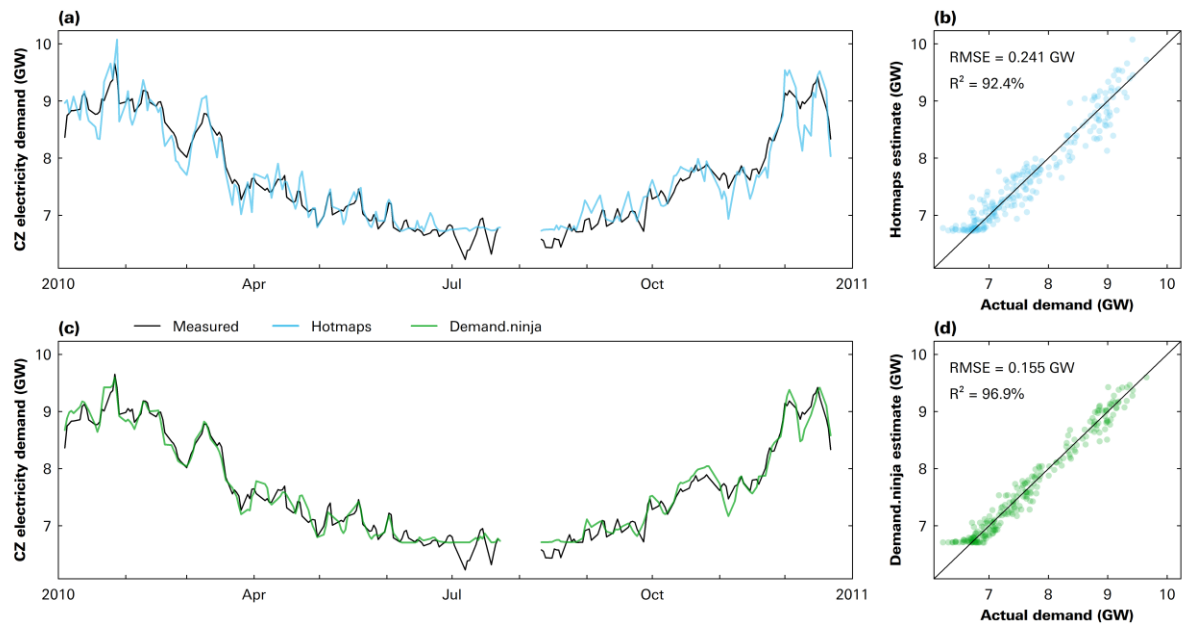
Supplementary Figure 100: Time-series plots of daily electricity demand in Austria. Panels (a) and (b) show the Hotmaps model [40], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences.



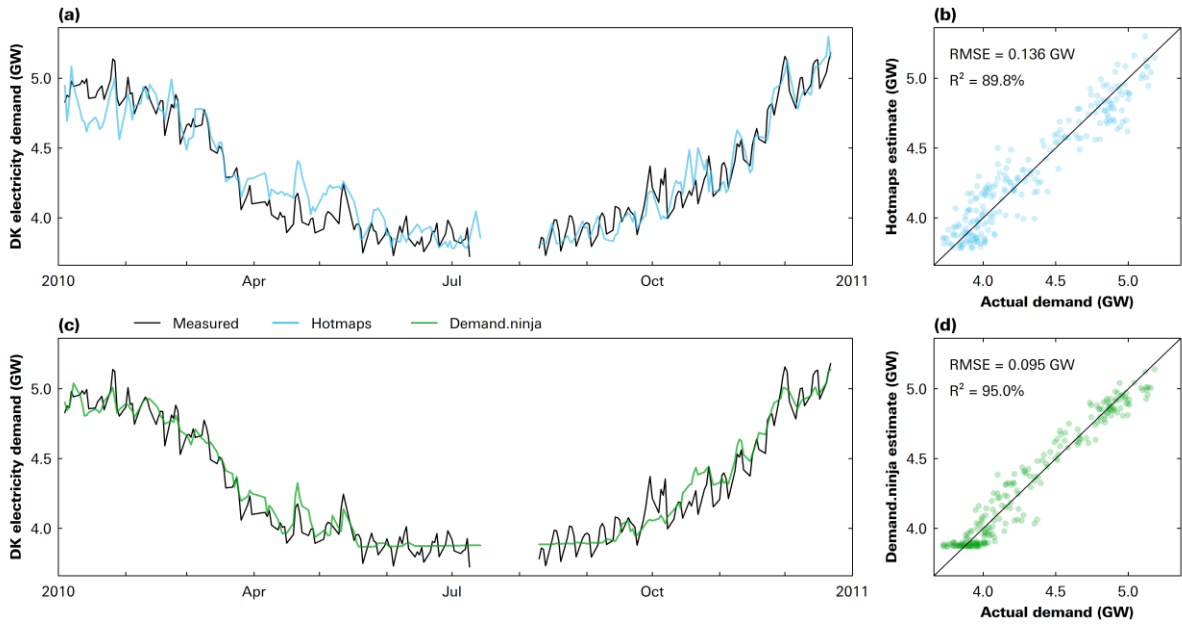
Supplementary Figure 101: Time-series plots of daily electricity demand in Belgium. Panels (a) and (b) show the Hotmaps model [40], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences.



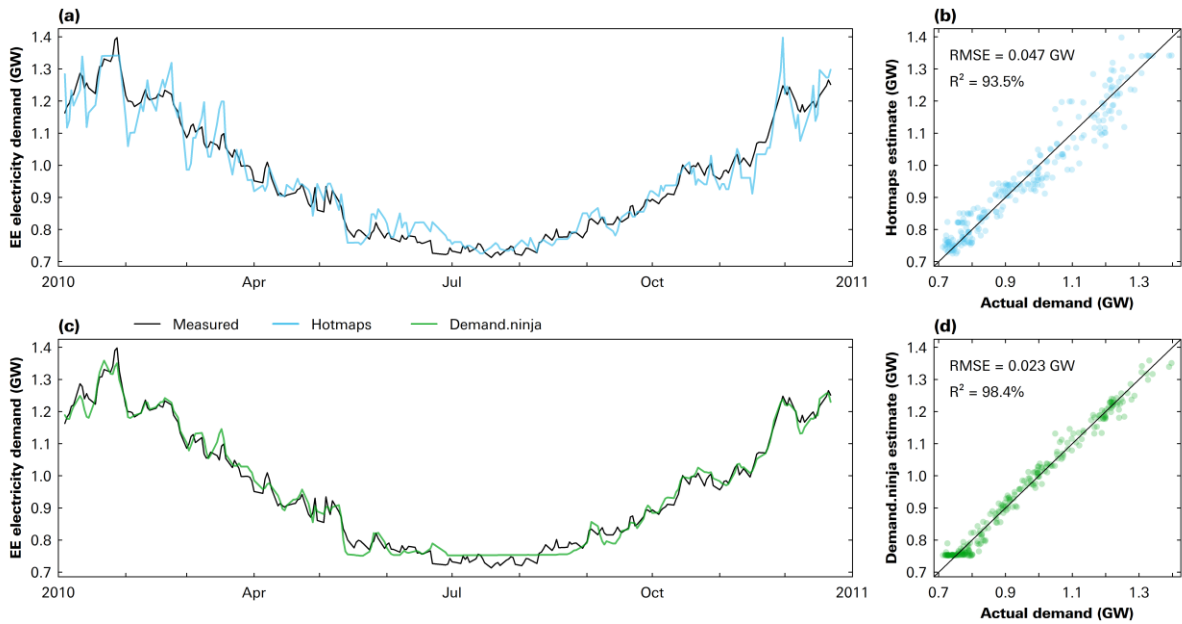
Supplementary Figure 102: Time-series plots of daily electricity demand in Bulgaria. Panels (a) and (b) show the Hotmaps model [40], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences.



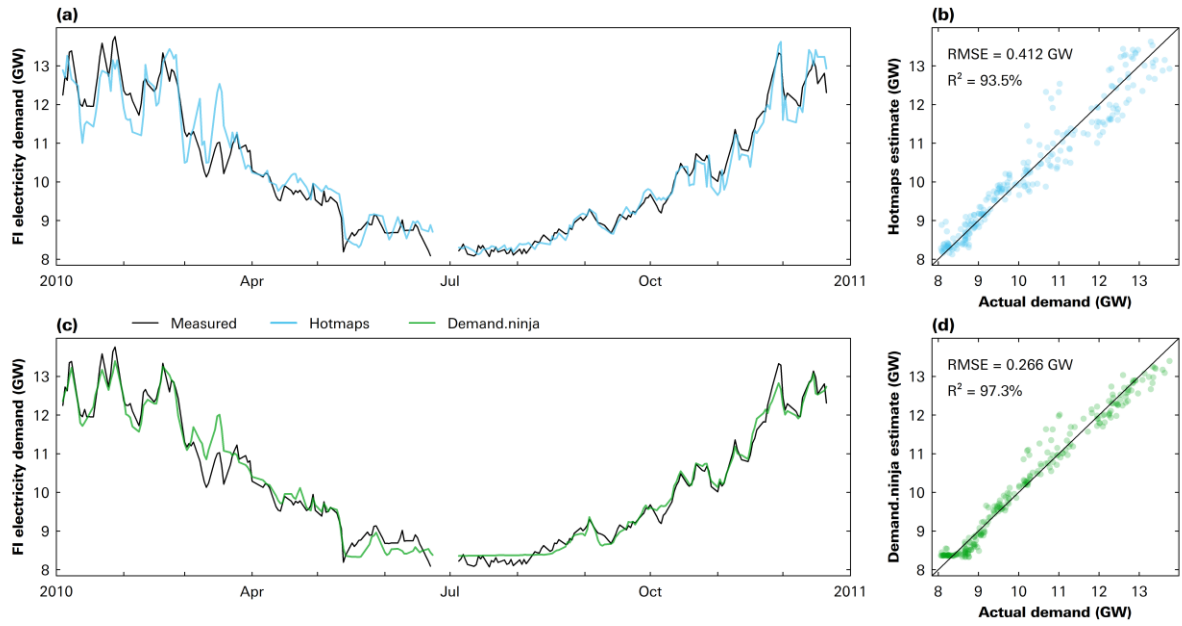
Supplementary Figure 103: Time-series plots of daily electricity demand in Czechia. Panels (a) and (b) show the Hotmaps model [40], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences.



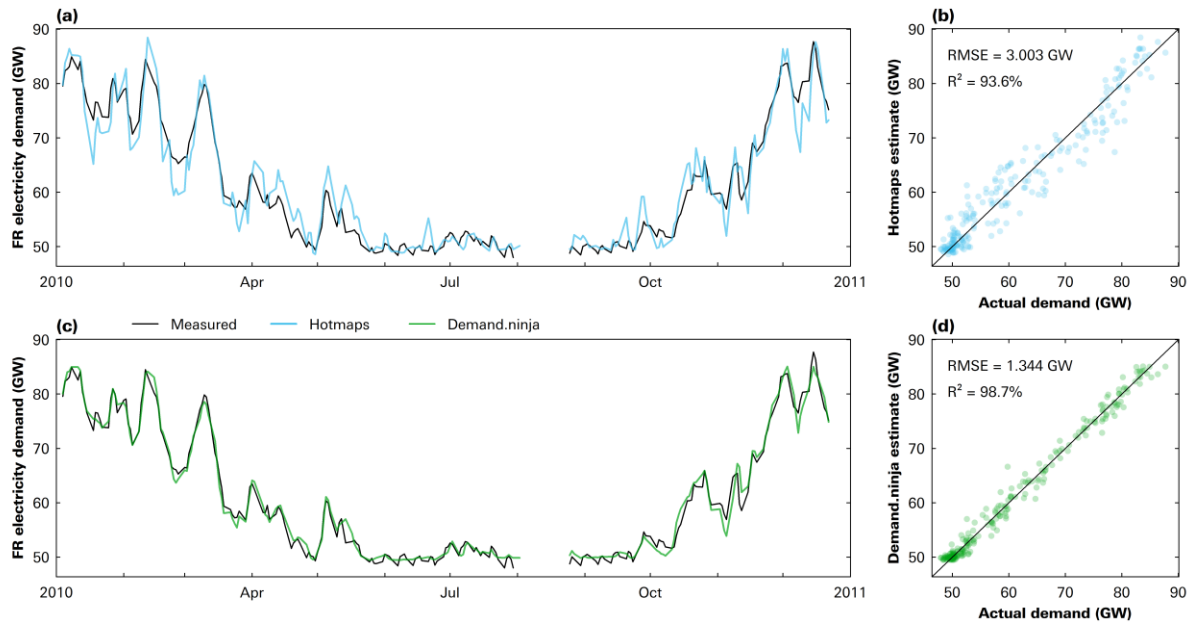
Supplementary Figure 104: Time-series plots of daily electricity demand in Denmark. Panels (a) and (b) show the Hotmaps model [40], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences.



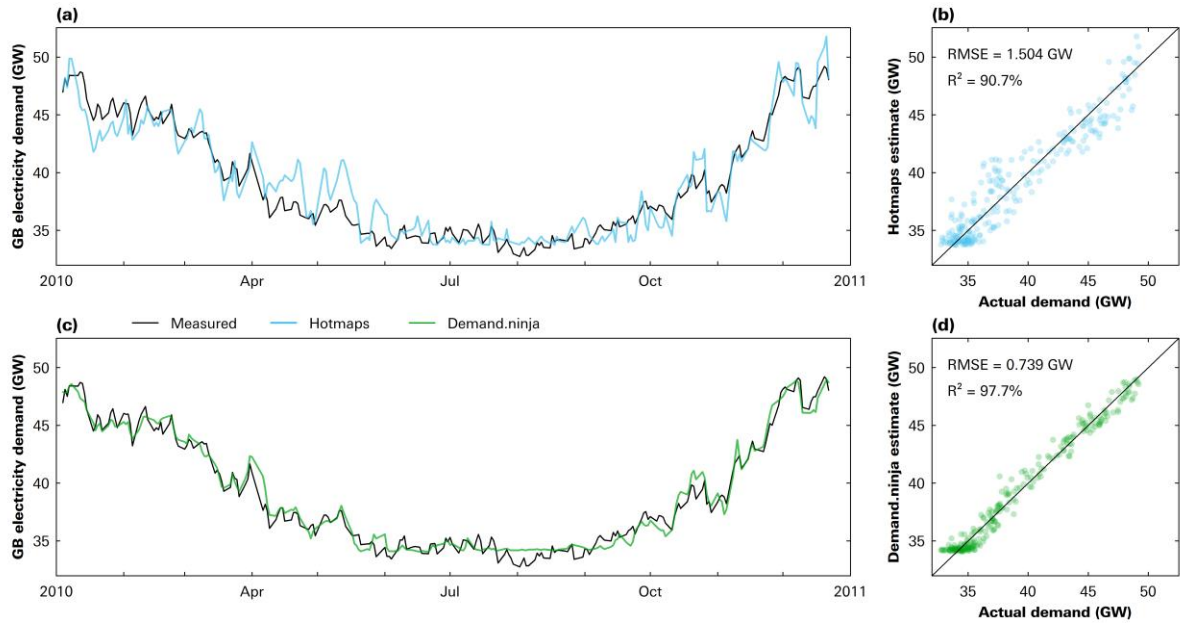
Supplementary Figure 105: Time-series plots of daily electricity demand in Estonia. Panels (a) and (b) show the Hotmaps model [40], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences.



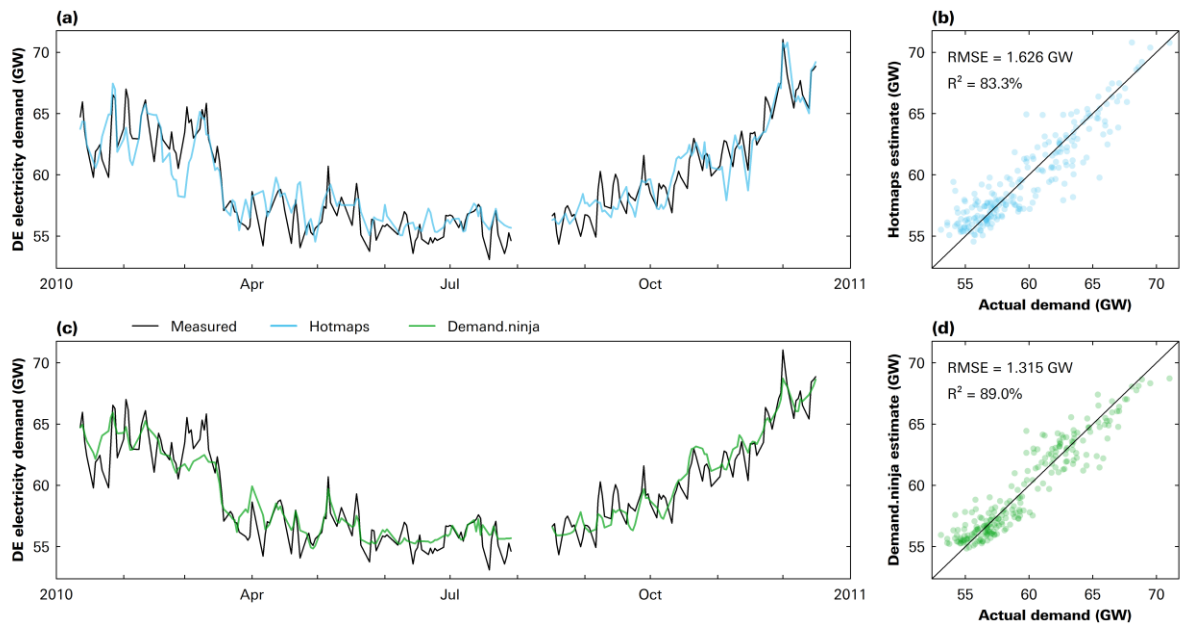
Supplementary Figure 106: Time-series plots of daily electricity demand in Finland. Panels (a) and (b) show the Hotmaps model [40], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences.



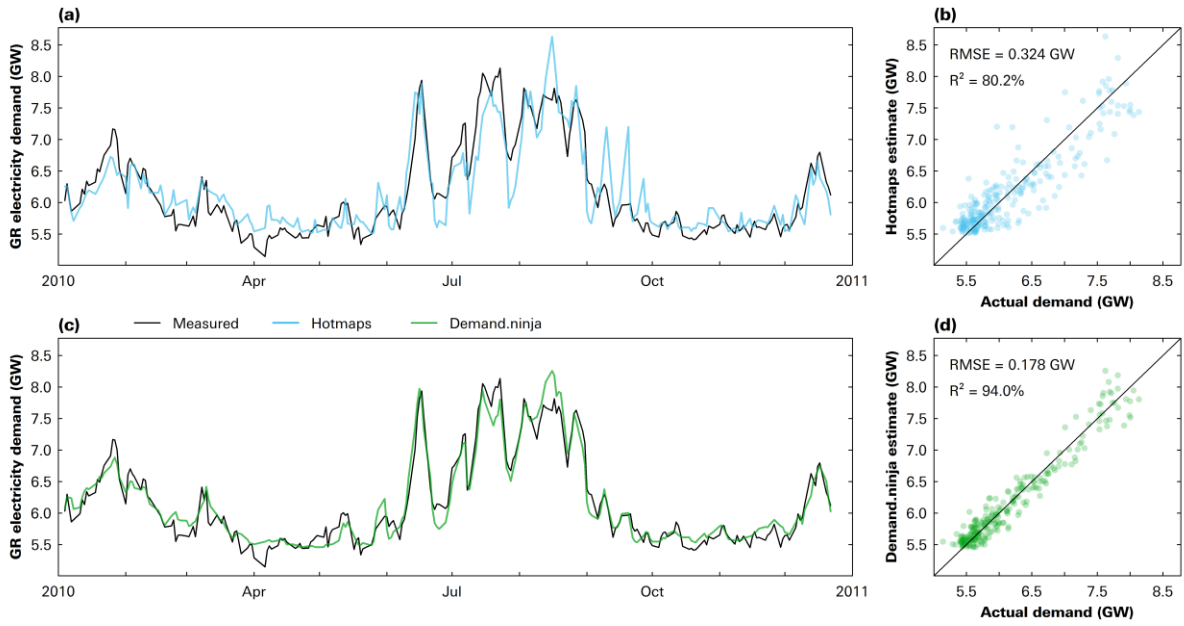
Supplementary Figure 107: Time-series plots of daily electricity demand in France. Panels (a) and (b) show the Hotmaps model [40], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences.



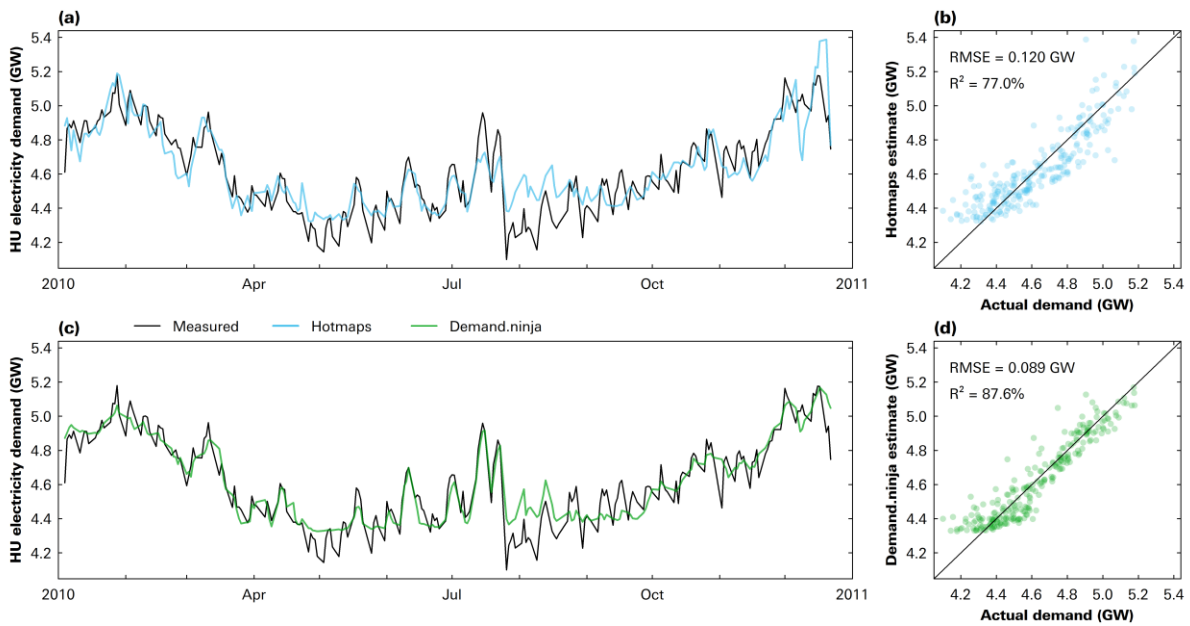
Supplementary Figure 108: Time-series plots of daily electricity demand in Great Britain. Panels (a) and (b) show the Hotmaps model [40], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences.



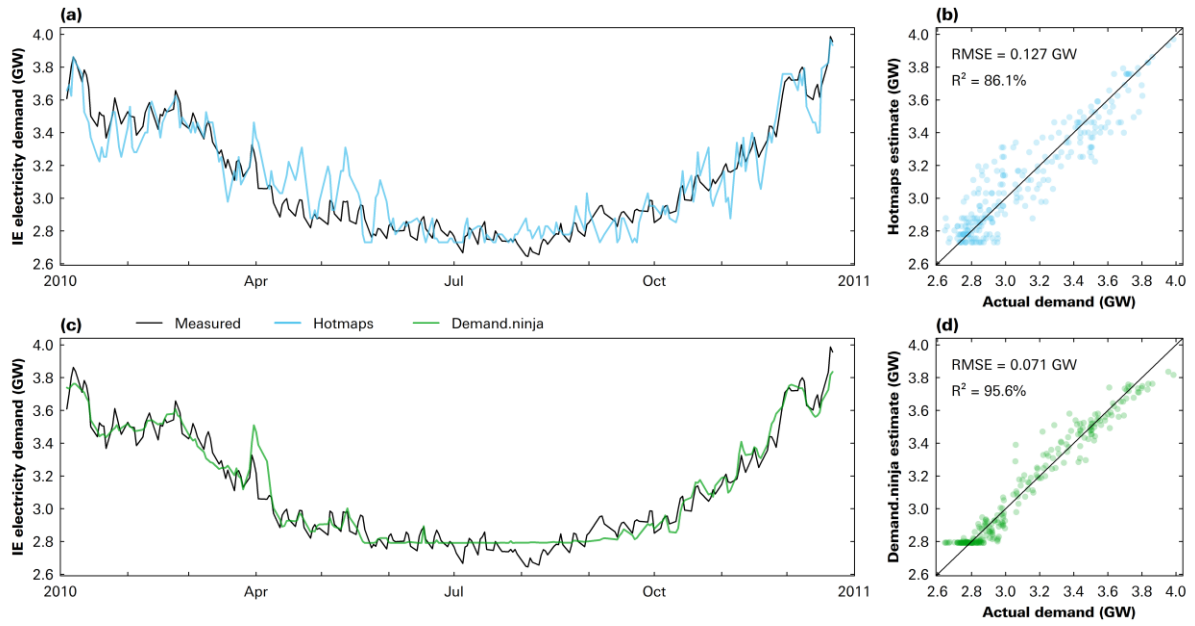
Supplementary Figure 109: Time-series plots of daily electricity demand in Germany. Panels (a) and (b) show the Hotmaps model [40], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences.



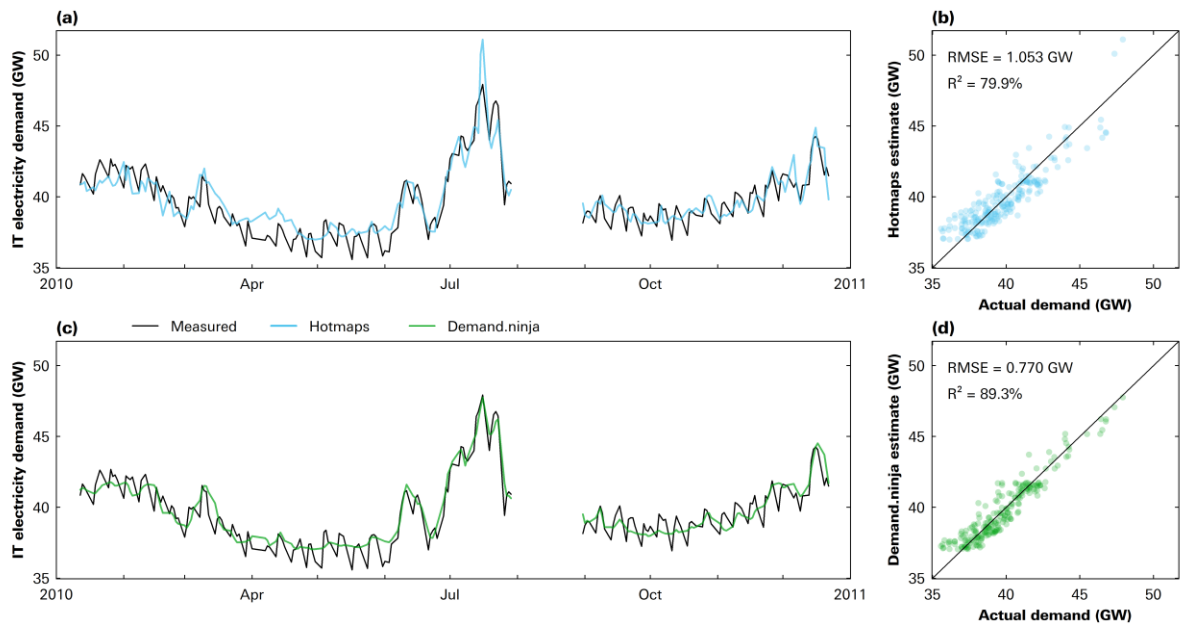
Supplementary Figure 110: Time-series plots of daily electricity demand in Greece. Panels (a) and (b) show the Hotmaps model [40], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences.



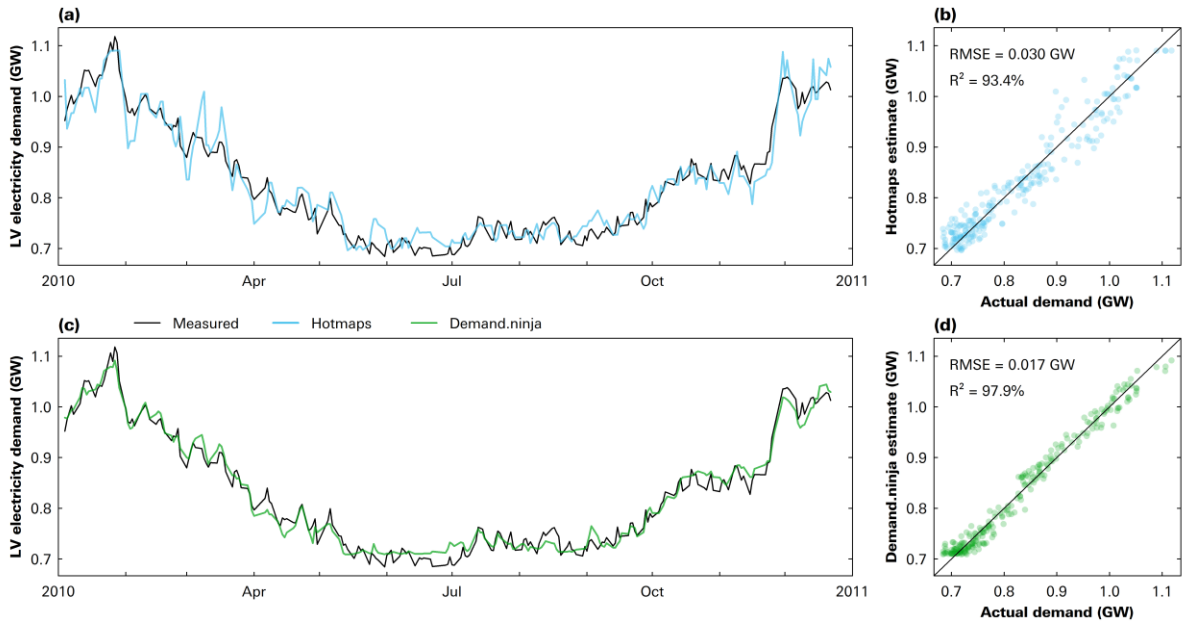
Supplementary Figure 111: Time-series plots of daily electricity demand in Hungary. Panels (a) and (b) show the Hotmaps model [40], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences.



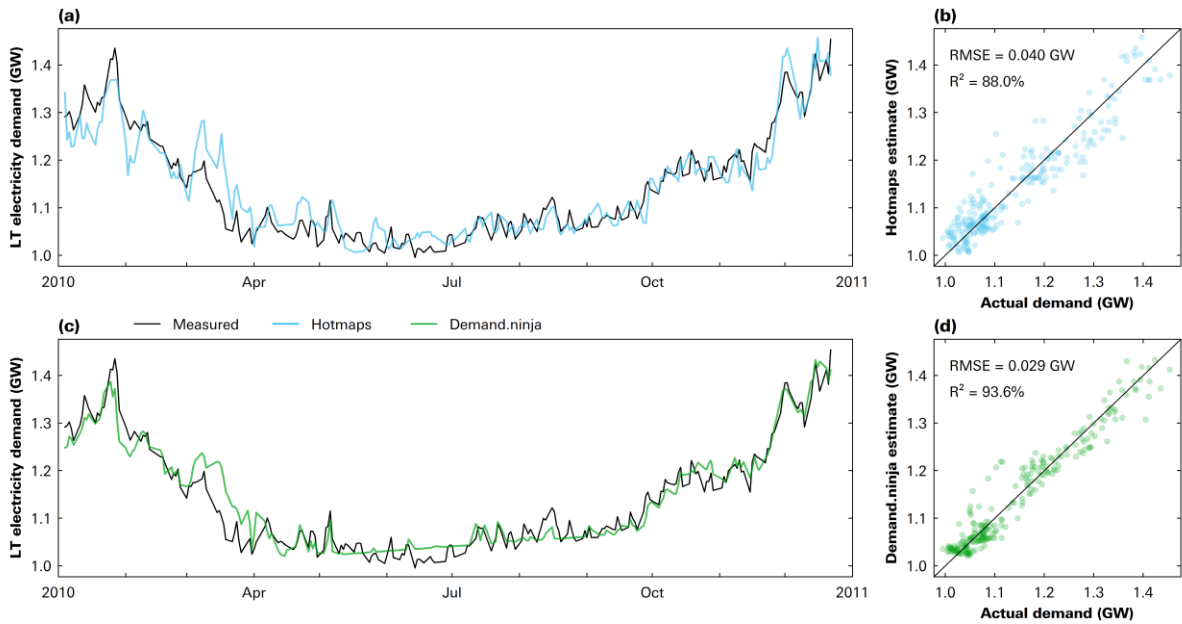
Supplementary Figure 112: Time-series plots of daily electricity demand in Ireland. Panels (a) and (b) show the Hotmaps model [40], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences.



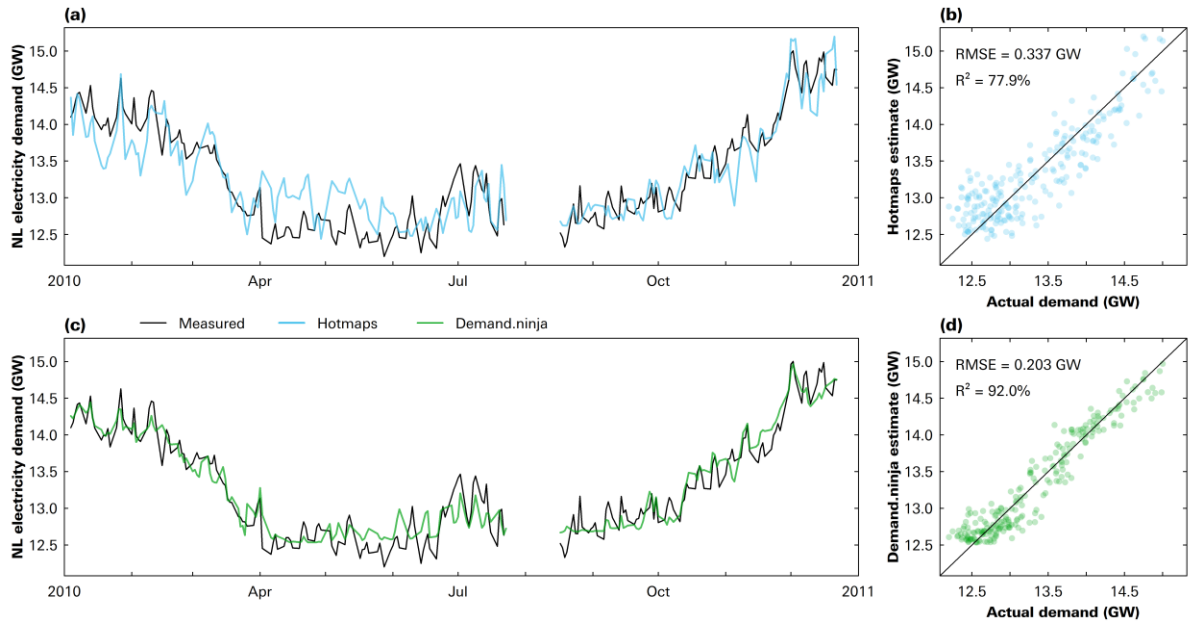
Supplementary Figure 113: Time-series plots of daily electricity demand in Italy. Panels (a) and (b) show the Hotmaps model [40], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences.



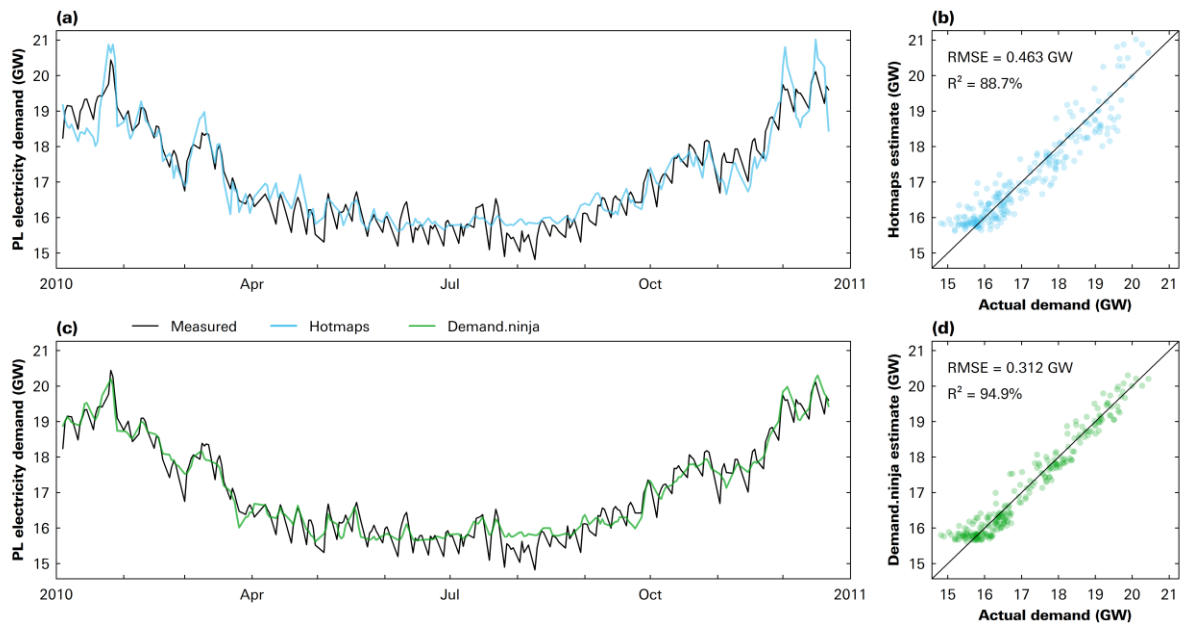
Supplementary Figure 114: Time-series plots of daily electricity demand in Latvia. Panels (a) and (b) show the Hotmaps model [40], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences.



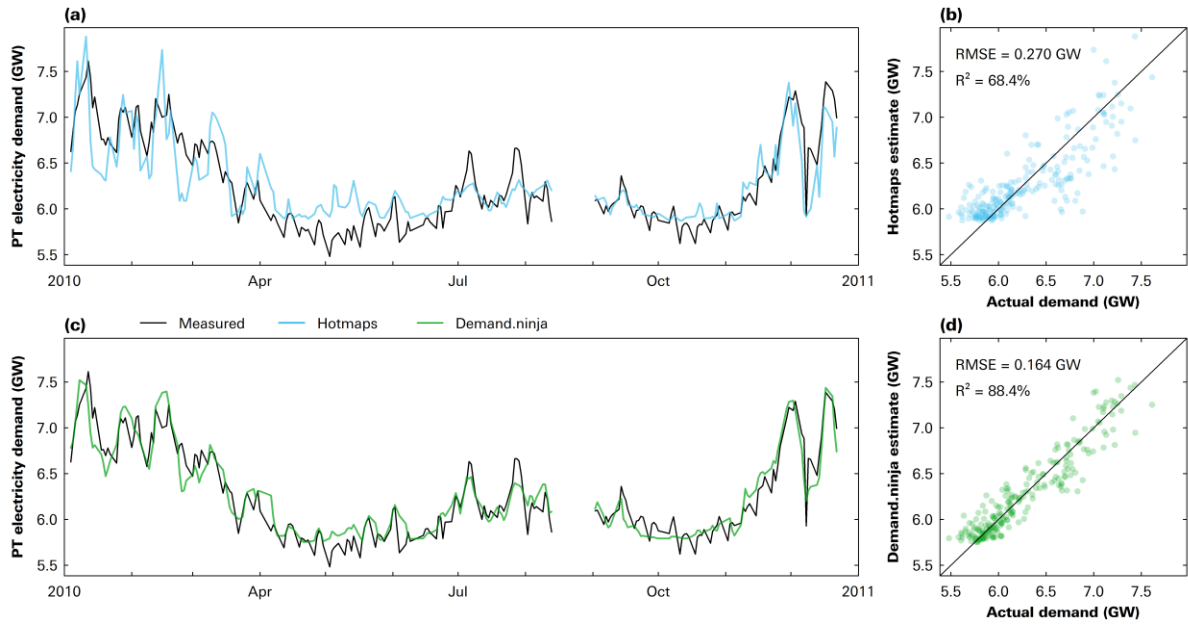
Supplementary Figure 115: Time-series plots of daily electricity demand in Lithuania. Panels (a) and (b) show the Hotmaps model [40], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences.



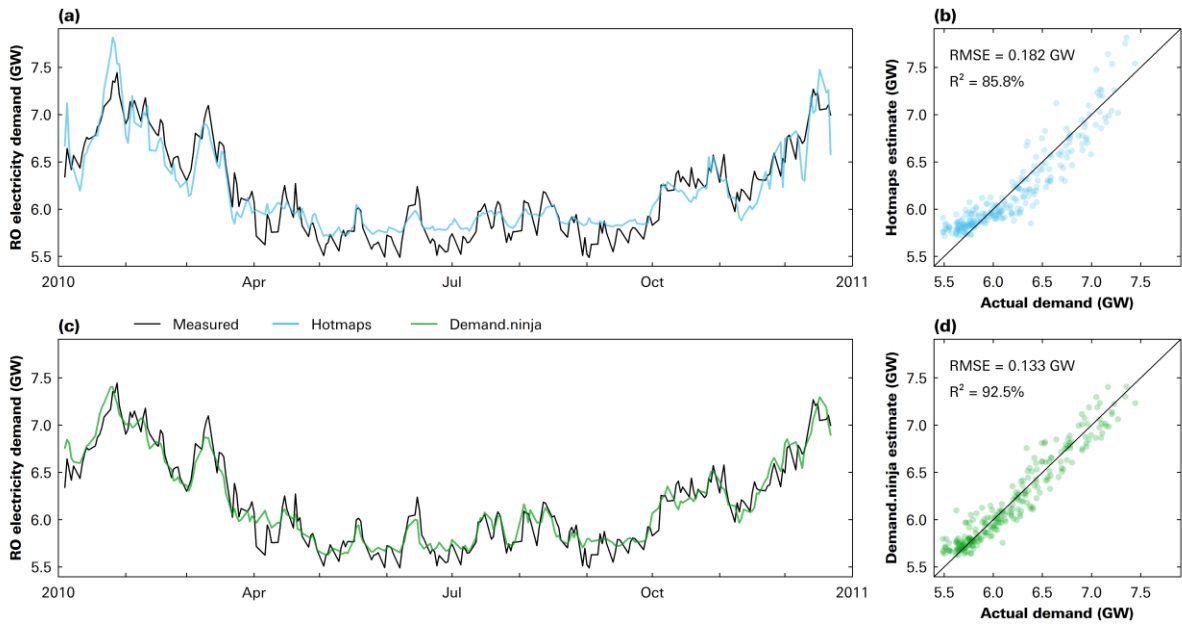
Supplementary Figure 116: Time-series plots of daily electricity demand in the Netherlands. Panels (a) and (b) show the Hotmaps model [40], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences.



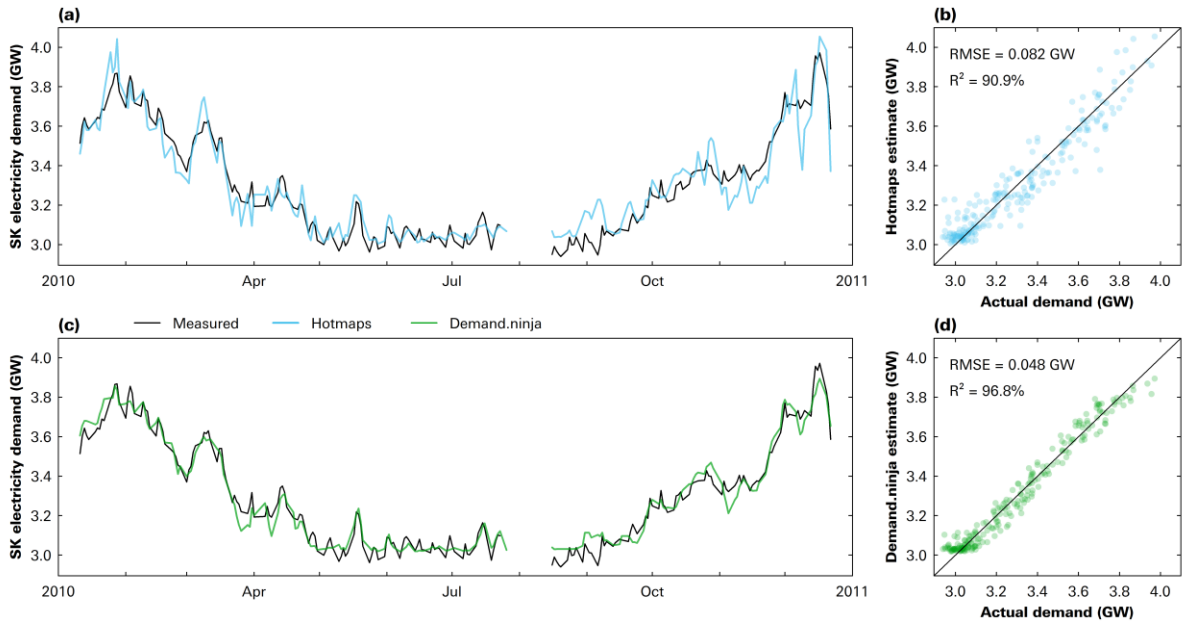
Supplementary Figure 117: Time-series plots of daily electricity demand in Poland. Panels (a) and (b) show the Hotmaps model [40], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences.



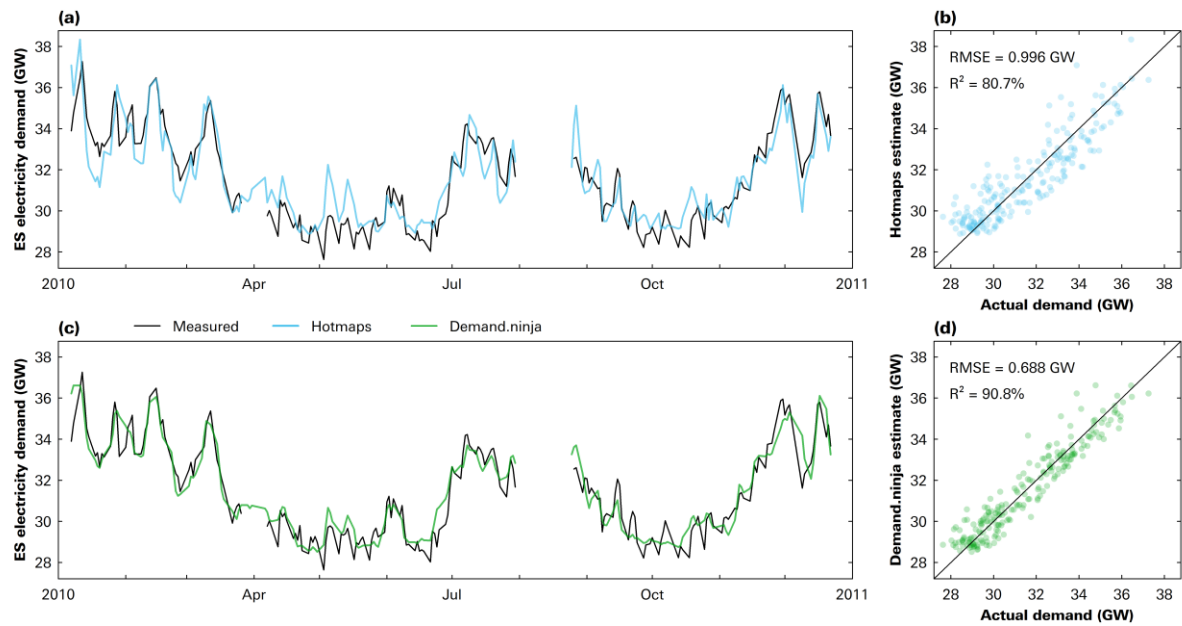
Supplementary Figure 118: Time-series plots of daily electricity demand in Portugal. Panels (a) and (b) show the Hotmaps model [40], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences.



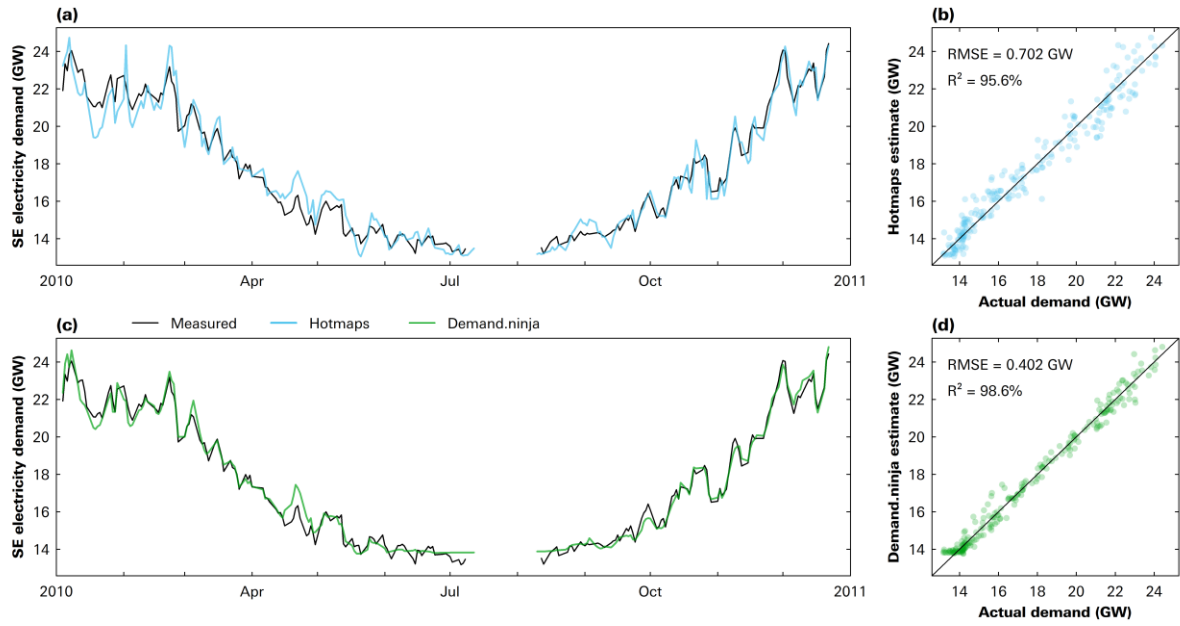
Supplementary Figure 119: Time-series plots of daily electricity demand in Romania. Panels (a) and (b) show the Hotmaps model [40], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences.



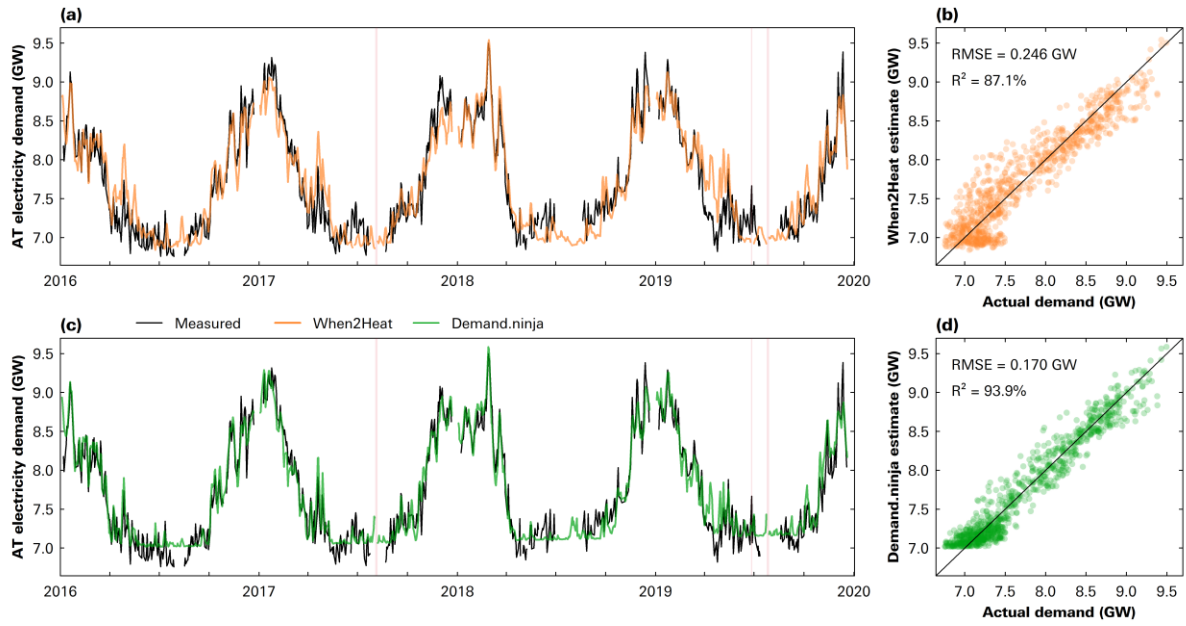
Supplementary Figure 120: Time-series plots of daily electricity demand in Slovakia. Panels (a) and (b) show the Hotmaps model [40], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences.



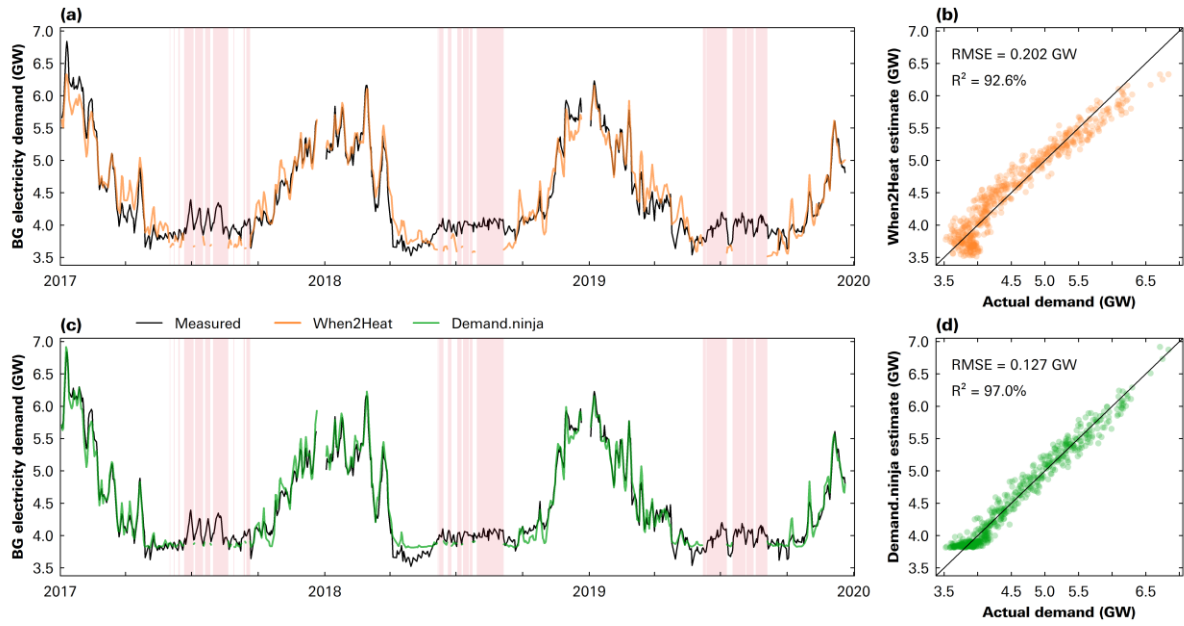
Supplementary Figure 121: Time-series plots of daily electricity demand in Spain. Panels (a) and (b) show the Hotmaps model [40], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences.



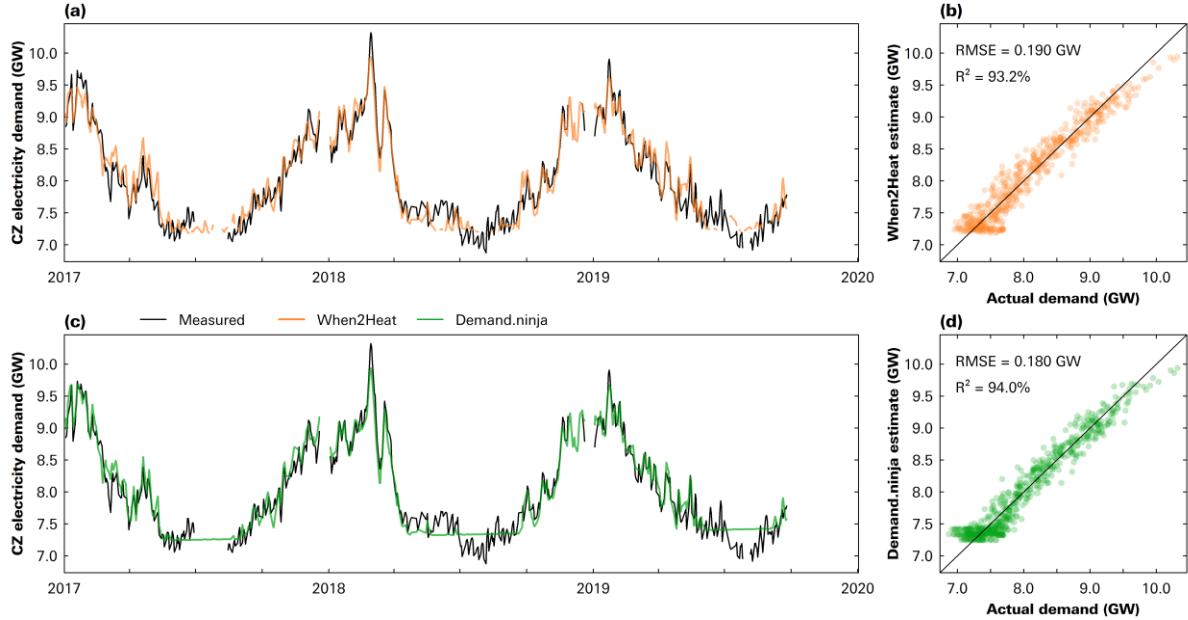
Supplementary Figure 122: Time-series plots of daily electricity demand in Sweden. Panels (a) and (b) show the Hotmaps model [40], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences.



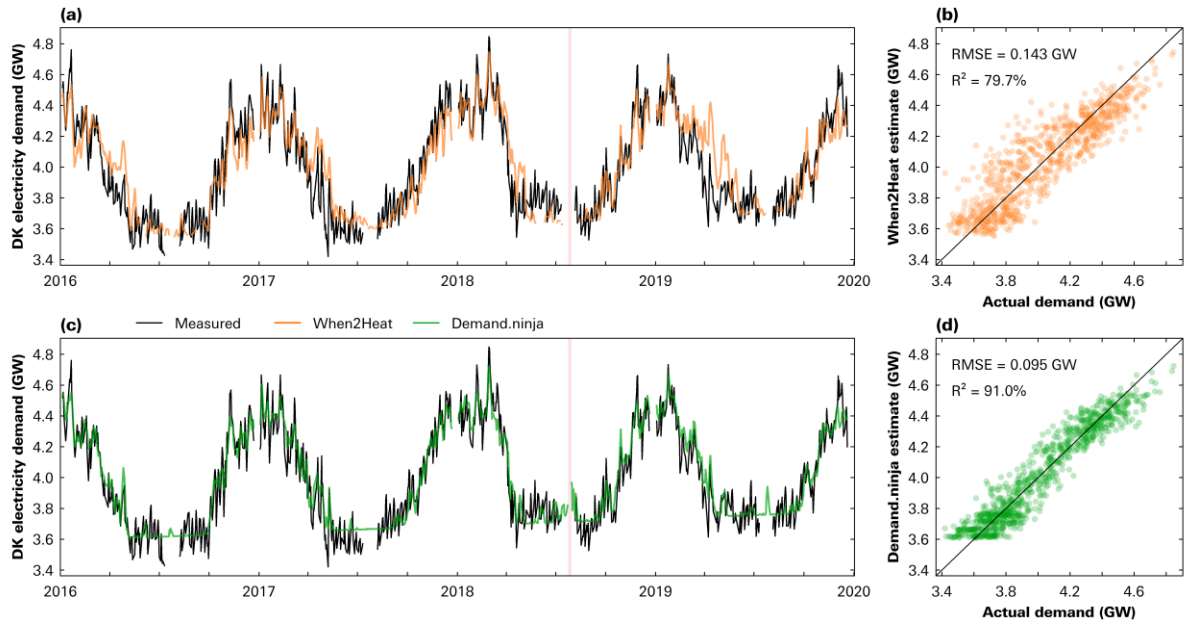
Supplementary Figure 123: Time-series plots of daily electricity demand in Austria. Panels (a) and (b) show the When2Heat model [63], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences. Pink shading indicates the 0.4% of days that had >1 CDD and so were also removed, as the When2Heat model does not provide estimates for cooling demand. Countries with large cooling demands are shown here for completeness, but are excluded from the main comparisons (Figure 4e in the main text).



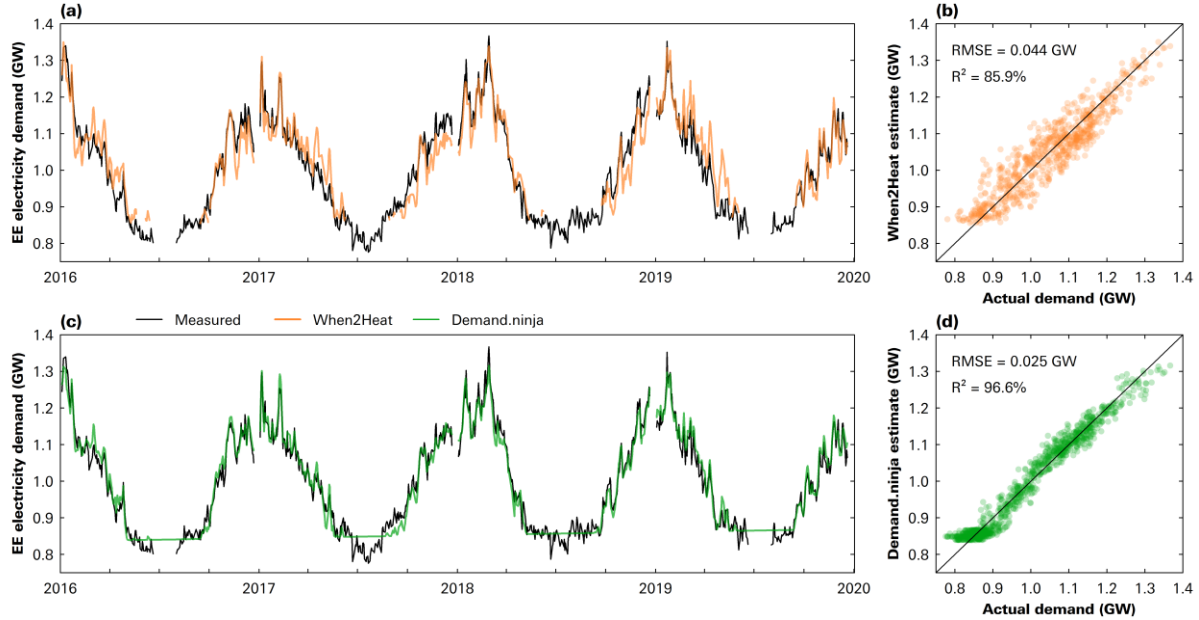
Supplementary Figure 124: Time-series plots of daily electricity demand in Bulgaria. Panels (a) and (b) show the When2Heat model [63], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences. Pink shading indicates the 19.3% of days that had >1 CDD and so were also removed; see Supplementary Figure 123 for further detail.



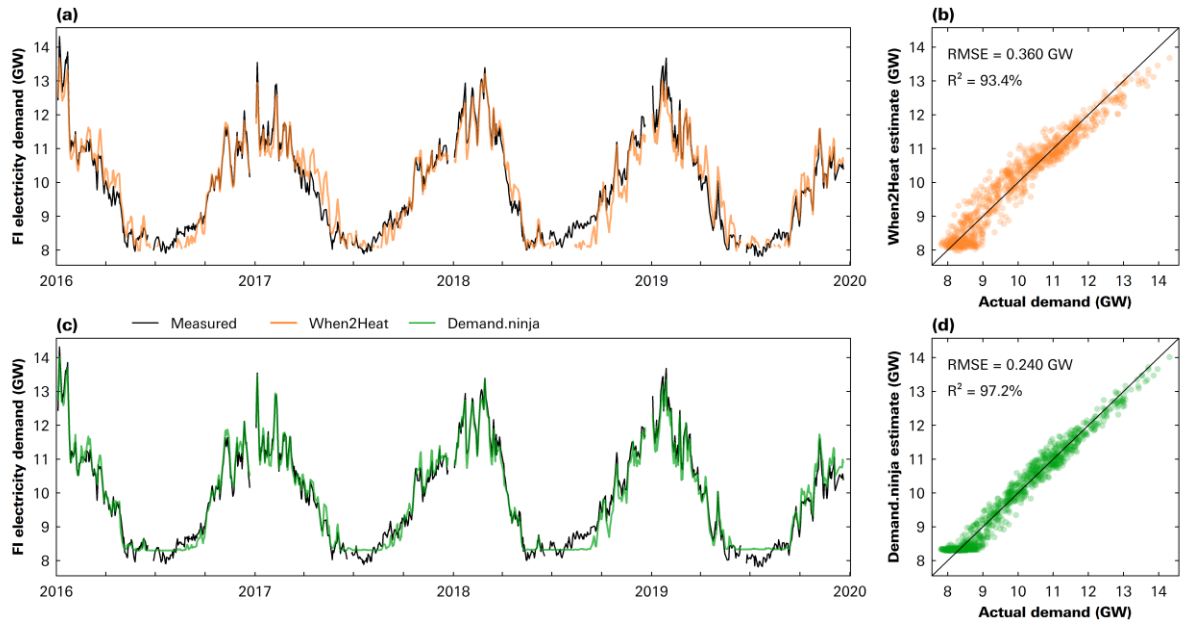
Supplementary Figure 125: Time-series plots of daily electricity demand in Czechia. Panels (a) and (b) show the When2Heat model [63], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences. No additional days were removed for having >1 CDD; see Supplementary Figure 123 for further detail.



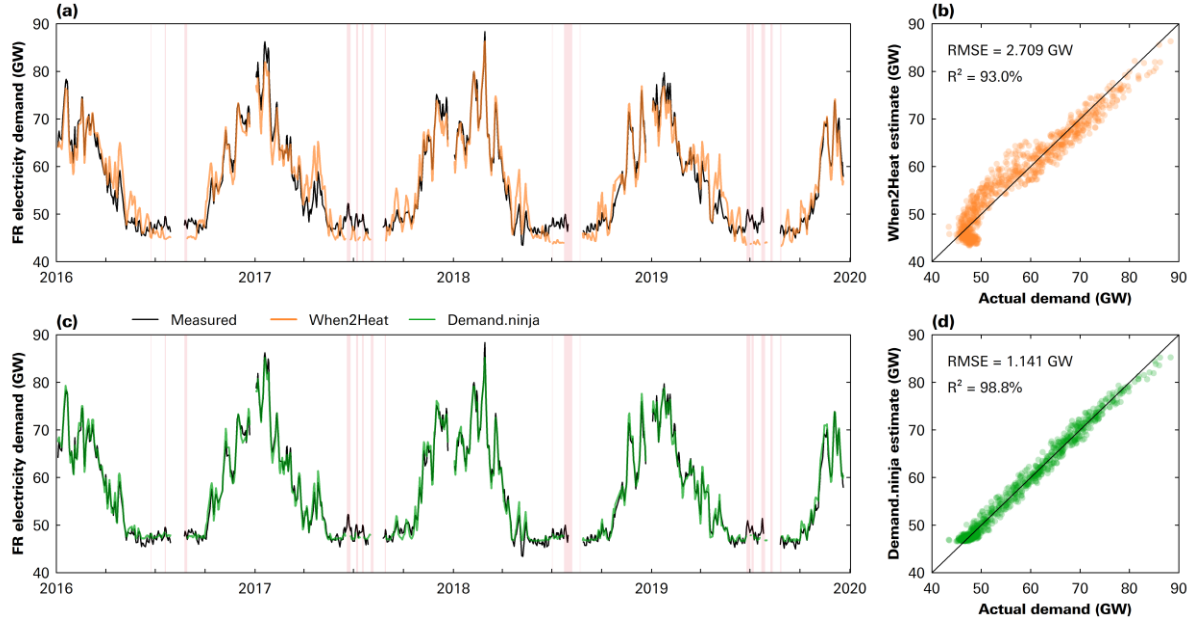
Supplementary Figure 126: Time-series plots of daily electricity demand in Denmark. Panels (a) and (b) show the When2Heat model [63], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences. Pink shading indicates the 0.3% of days that had >1 CDD and so were also removed; see Supplementary Figure 123 for further detail.



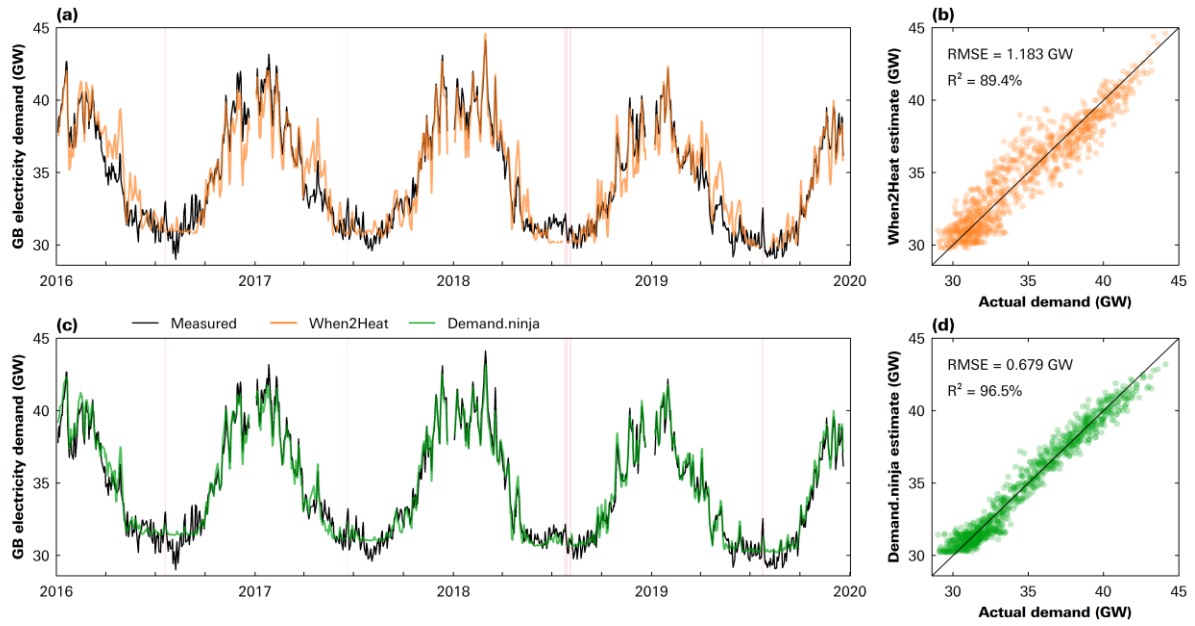
Supplementary Figure 127: Time-series plots of daily electricity demand in Estonia. Panels (a) and (b) show the When2Heat model [63], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences. No additional days were removed for having >1 CDD; see Supplementary Figure 123 for further detail.



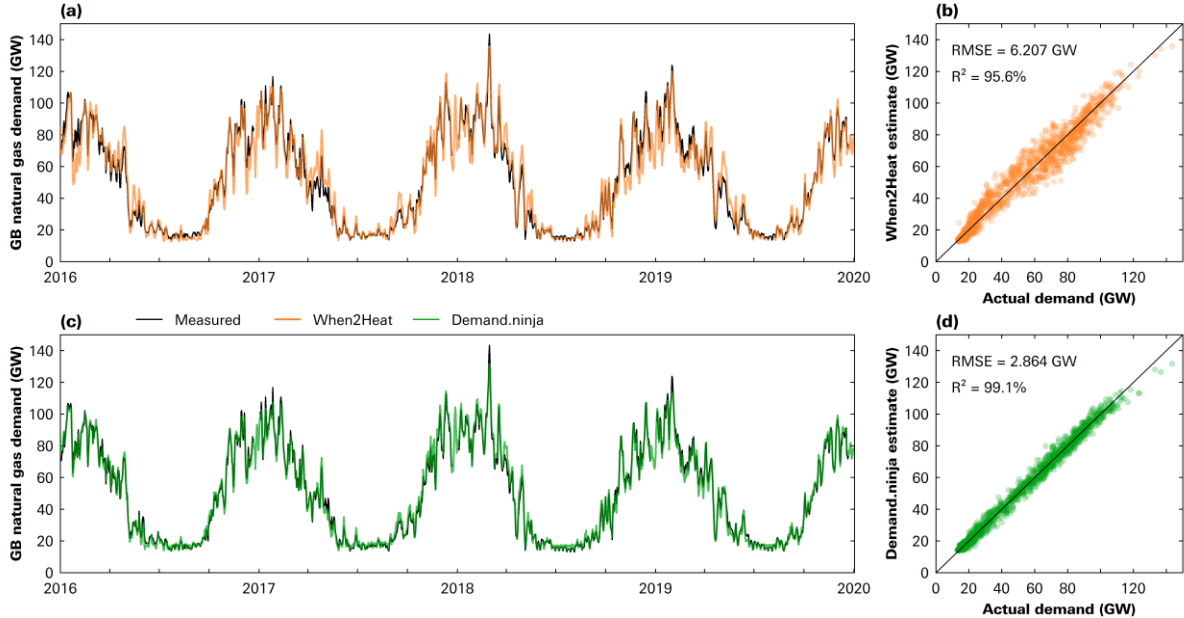
Supplementary Figure 128: Time-series plots of daily electricity demand in Finland. Panels (a) and (b) show the When2Heat model [63], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences. Pink shading indicates the 0.1% of days that had >1 CDD and so were also removed; see Supplementary Figure 123 for further detail.



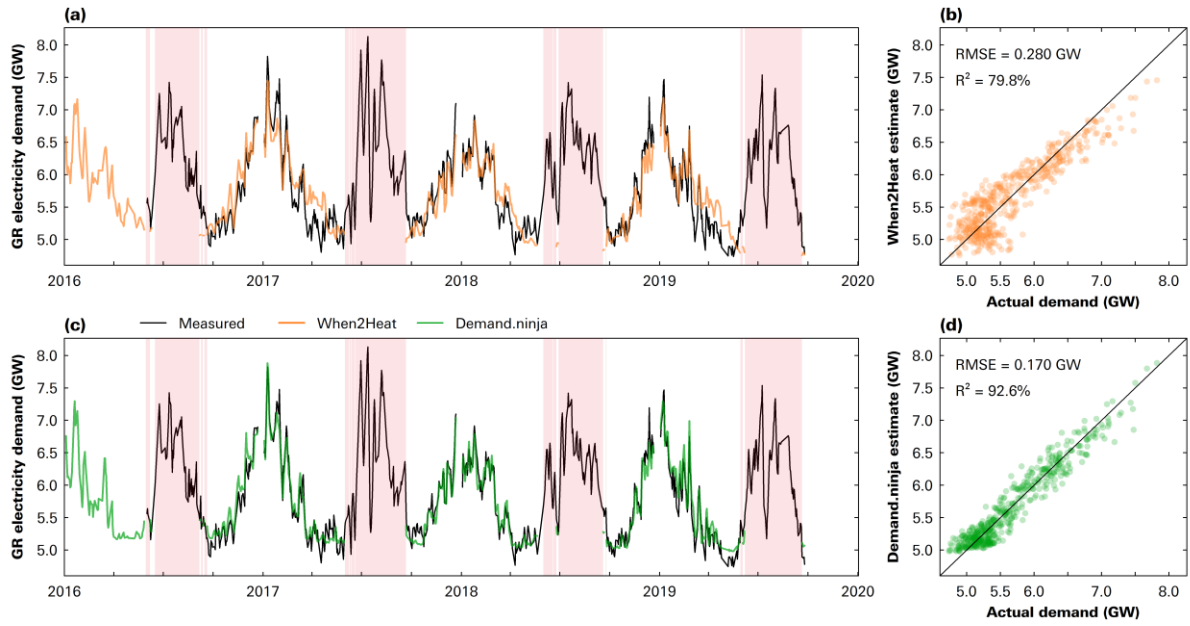
Supplementary Figure 129: Time-series plots of daily electricity demand in France. Panels (a) and (b) show the When2Heat model [63], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences. Pink shading indicates the 4.3% of days that had >1 CDD and so were also removed; see Supplementary Figure 123 for further detail.



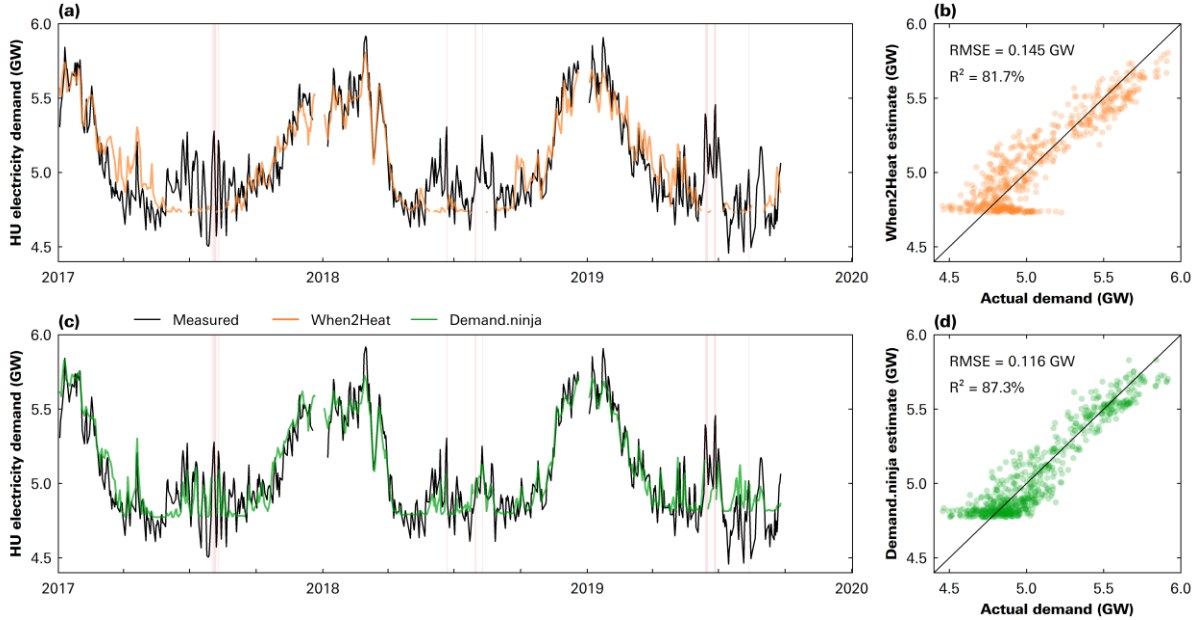
Supplementary Figure 130: Time-series plots of daily electricity demand in Great Britain. Panels (a) and (b) show the When2Heat model [63], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences. Pink shading indicates the 0.8% of days that had >1 CDD and so were also removed; see Supplementary Figure 123 for further detail.



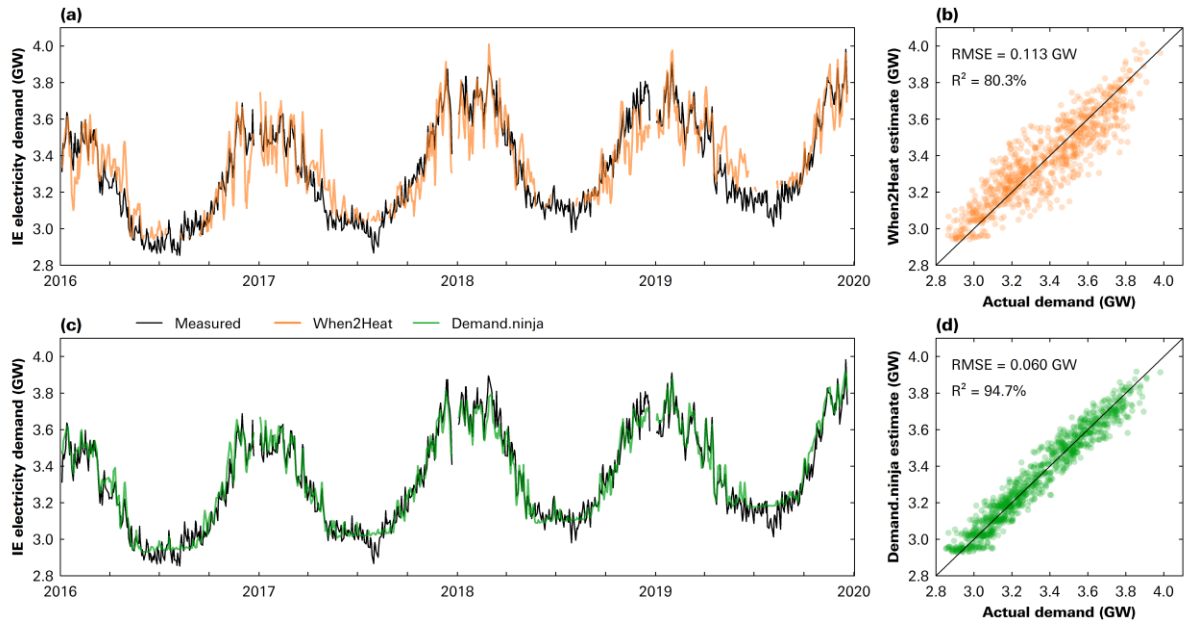
Supplementary Figure 131: Time-series plots of daily natural gas demand in Great Britain. Panels (a) and (b) show the When2Heat model [63], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences. No additional days were removed as gas is not used for cooling; see Supplementary Figure 123 for further detail.



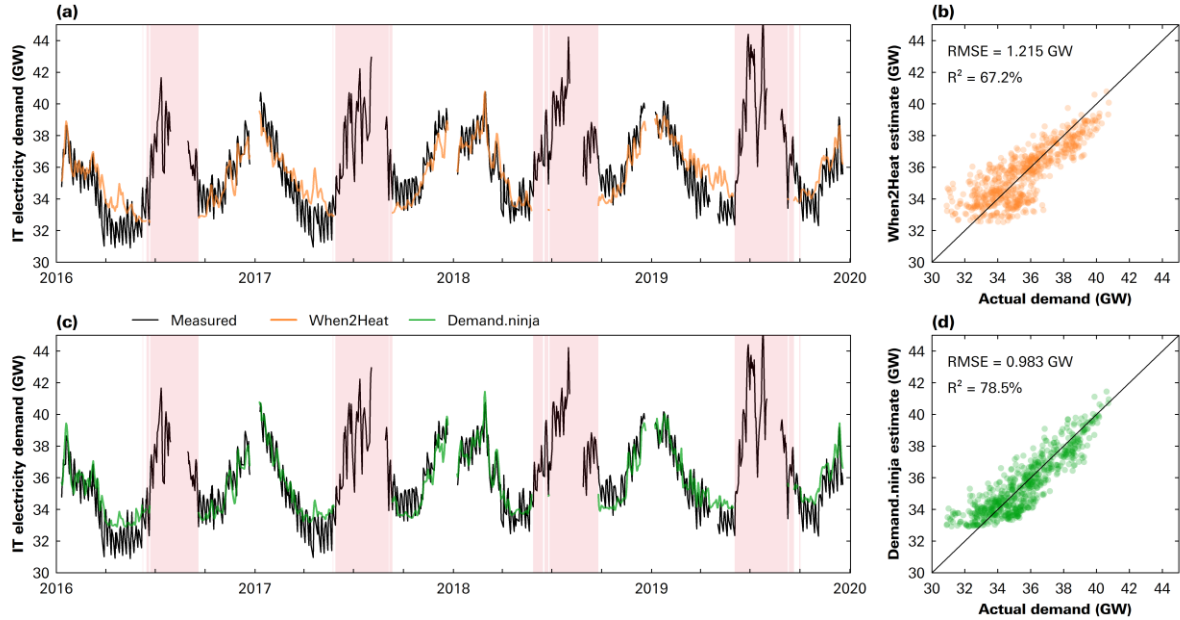
Supplementary Figure 132: Time-series plots of daily electricity demand in Greece. Panels (a) and (b) show the When2Heat model [63], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences. Pink shading indicates the 31.4% of days that had >1 CDD and so were also removed; see Supplementary Figure 123 for further detail.



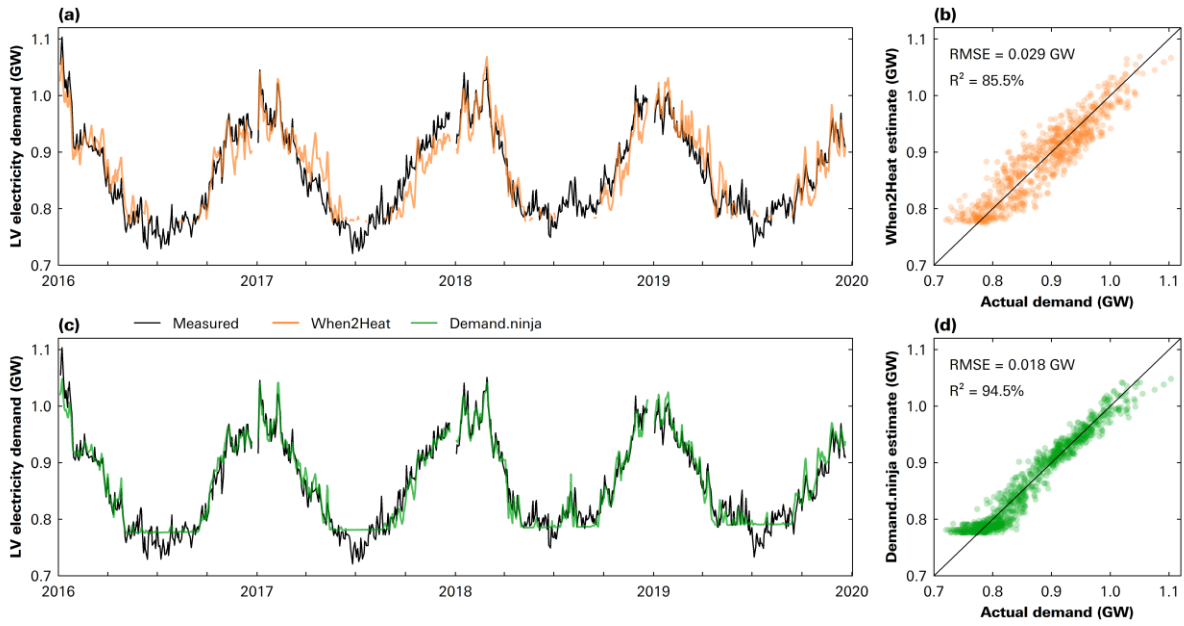
Supplementary Figure 133: Time-series plots of daily electricity demand in Hungary. Panels (a) and (b) show the When2Heat model [63], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences. Pink shading indicates the 1.5% of days that had >1 CDD and so were also removed; see Supplementary Figure 123 for further detail.



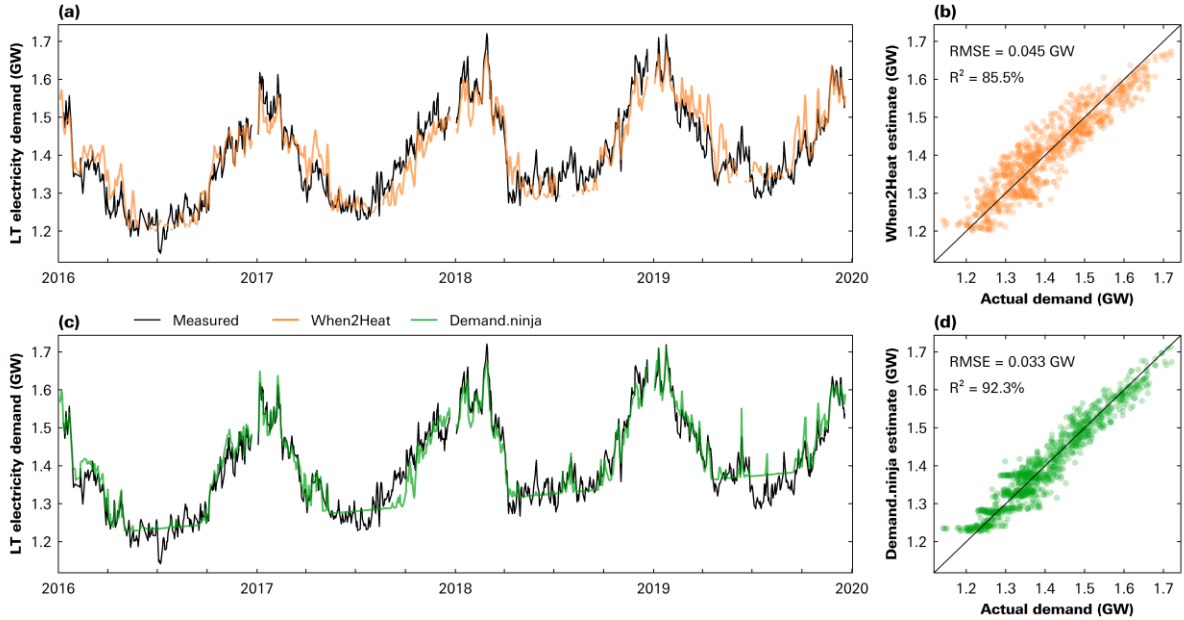
Supplementary Figure 134: Time-series plots of daily electricity demand in Ireland. Panels (a) and (b) show the When2Heat model [63], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences. No additional days were removed for having >1 CDD; see Supplementary Figure 123 for further detail.



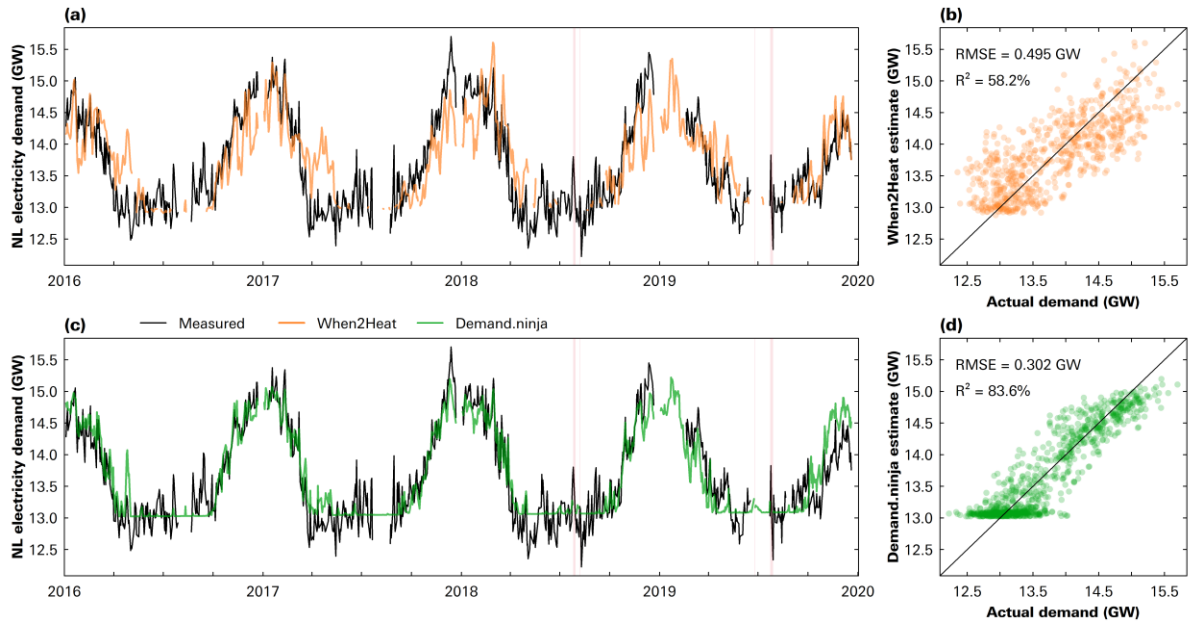
Supplementary Figure 135: Time-series plots of daily electricity demand in Italy. Panels (a) and (b) show the When2Heat model [63], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences. Pink shading indicates the 29.8% of days that had >1 CDD and so were also removed; see Supplementary Figure 123 for further detail.



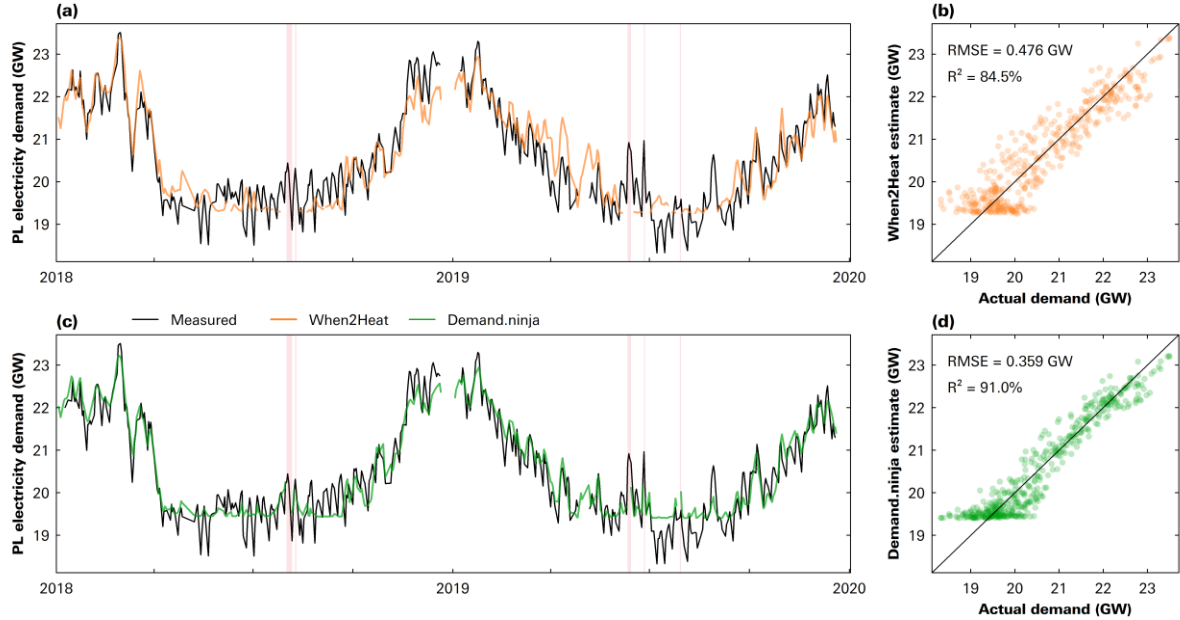
Supplementary Figure 136: Time-series plots of daily electricity demand in Latvia. Panels (a) and (b) show the When2Heat model [63], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences. No additional days were removed for having >1 CDD; see Supplementary Figure 123 for further detail.



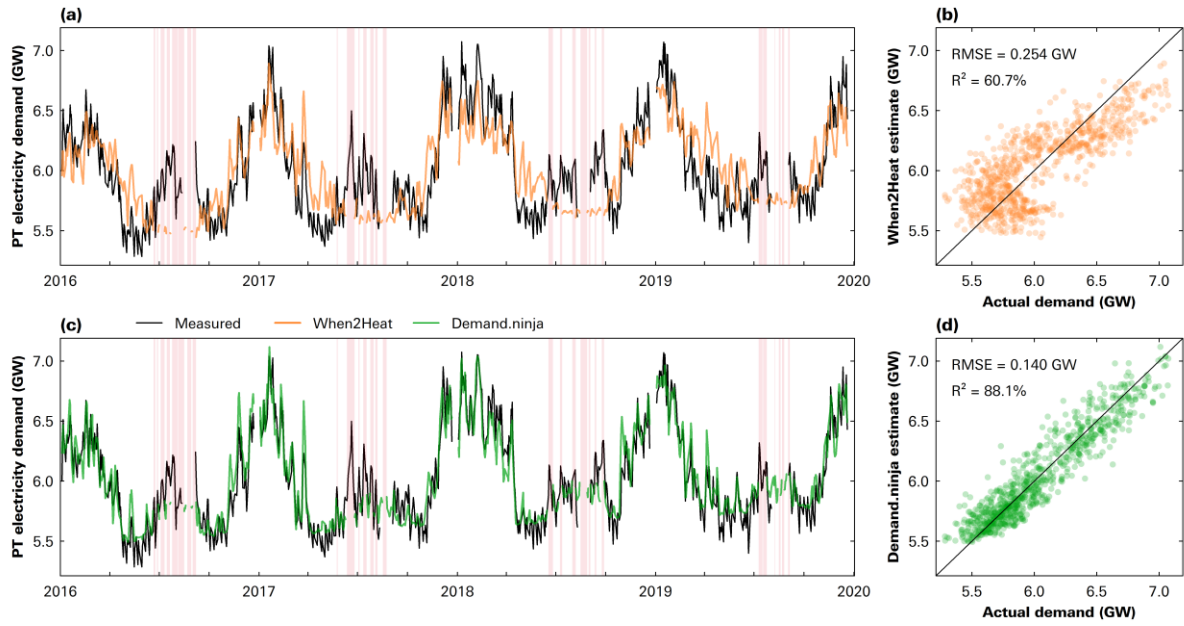
Supplementary Figure 137: Time-series plots of daily electricity demand in Lithuania. Panels (a) and (b) show the When2Heat model [63], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences. No additional days were removed for having >1 CDD; see Supplementary Figure 123 for further detail.



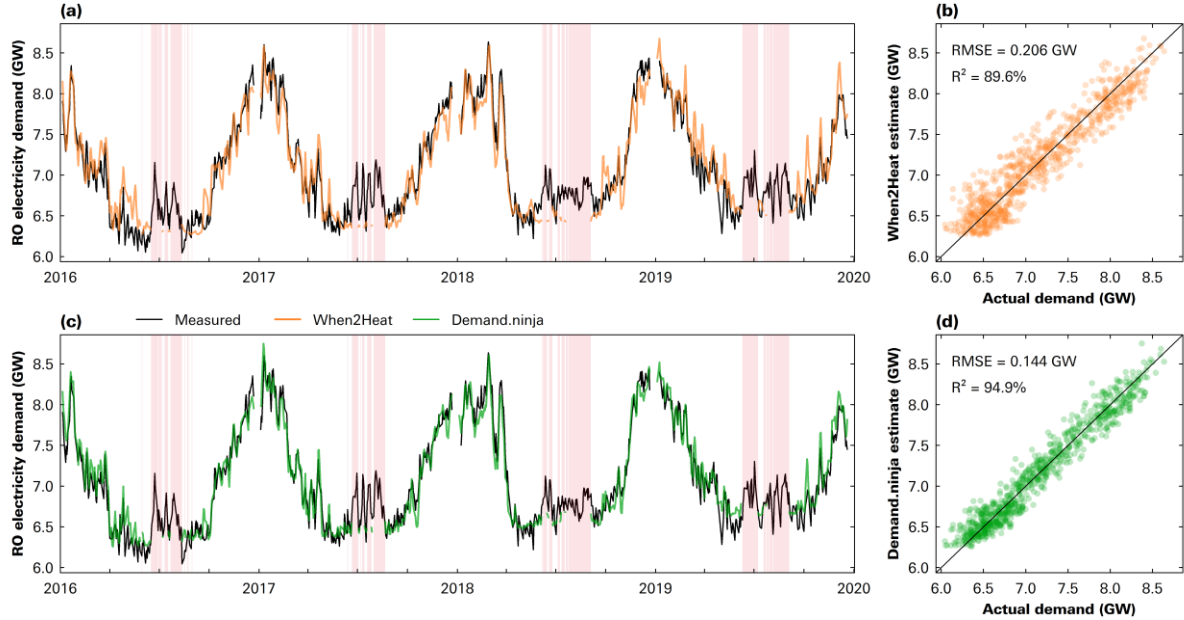
Supplementary Figure 138: Time-series plots of daily electricity demand in the Netherlands. Panels (a) and (b) show the When2Heat model [63], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences. Pink shading indicates the 0.5% of days that had >1 CDD and so were also removed; see Supplementary Figure 123 for further detail.



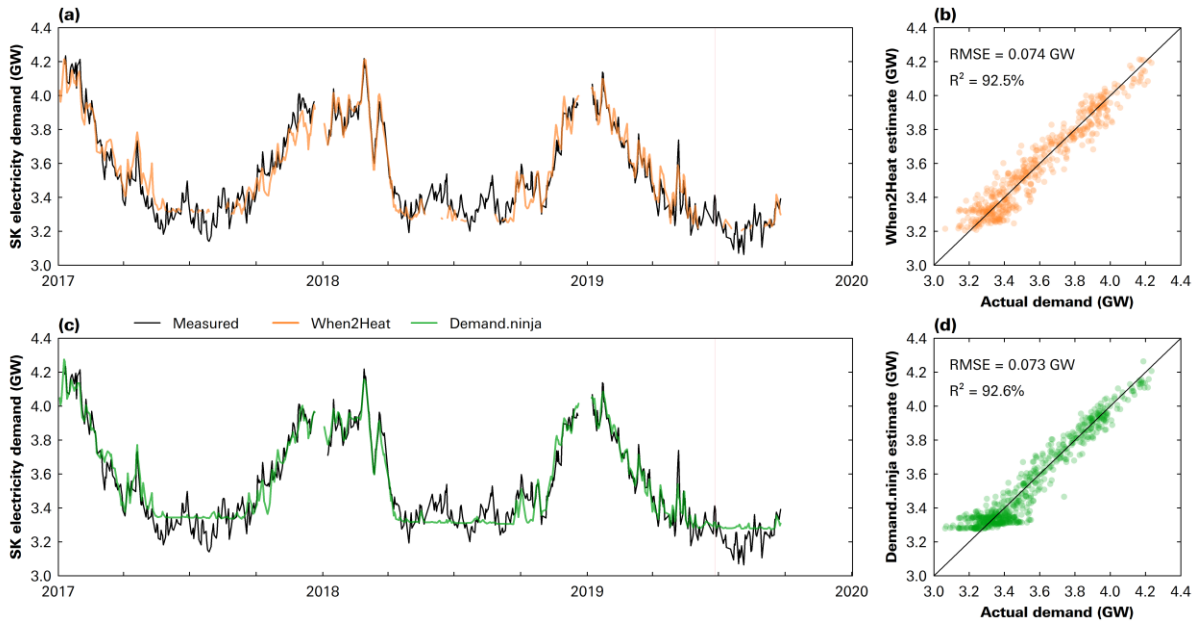
Supplementary Figure 139: Time-series plots of daily electricity demand in Poland. Panels (a) and (b) show the When2Heat model [63], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences. Pink shading indicates the 1.5% of days that had >1 CDD and so were also removed; see Supplementary Figure 123 for further detail.



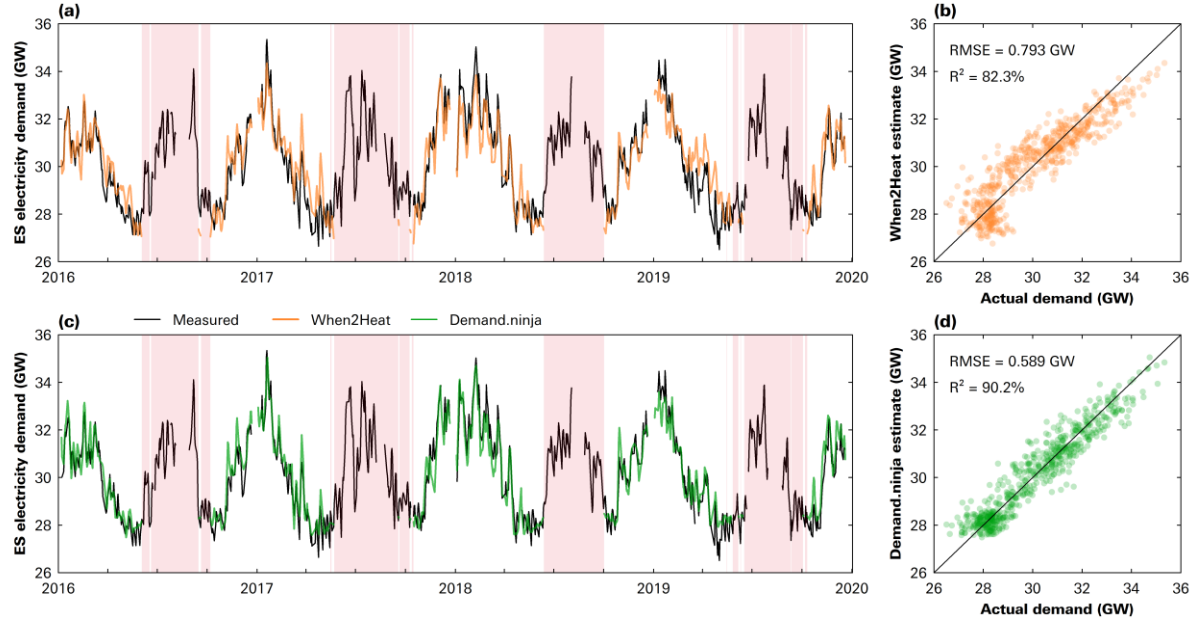
Supplementary Figure 140: Time-series plots of daily electricity demand in Portugal. Panels (a) and (b) show the When2Heat model [63], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences. Pink shading indicates the 10.7% of days that had >1 CDD and so were also removed; see Supplementary Figure 123 for further detail.



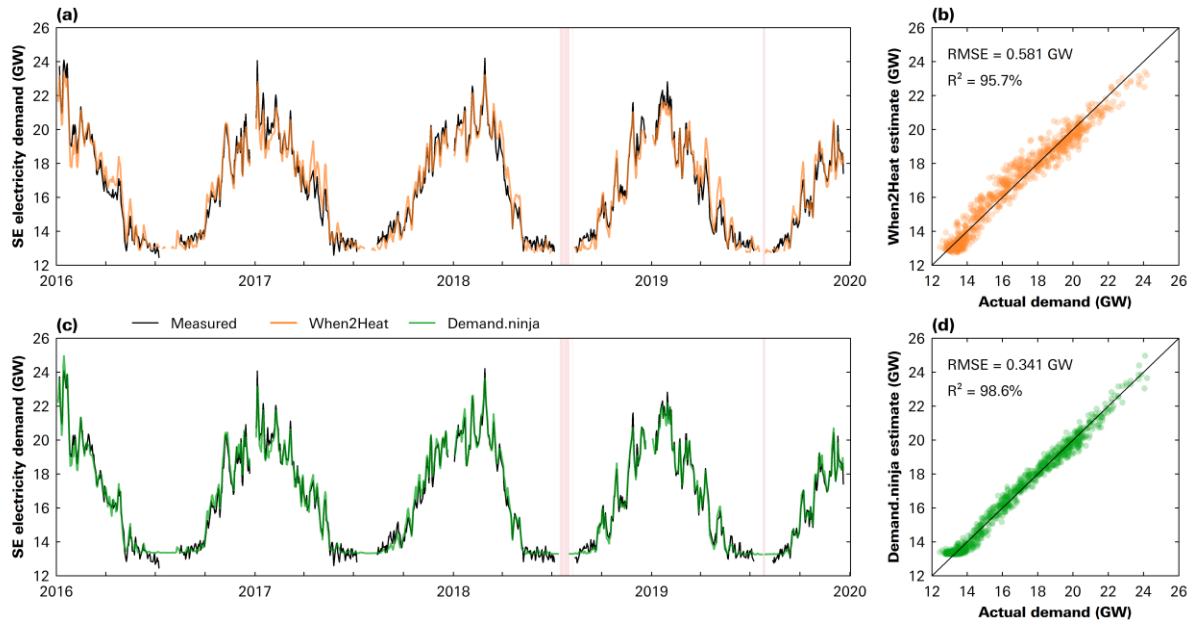
Supplementary Figure 141: Time-series plots of daily electricity demand in Romania. Panels (a) and (b) show the When2Heat model [63], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences. Pink shading indicates the 16.1% of days that had >1 CDD and so were also removed; see Supplementary Figure 123 for further detail.



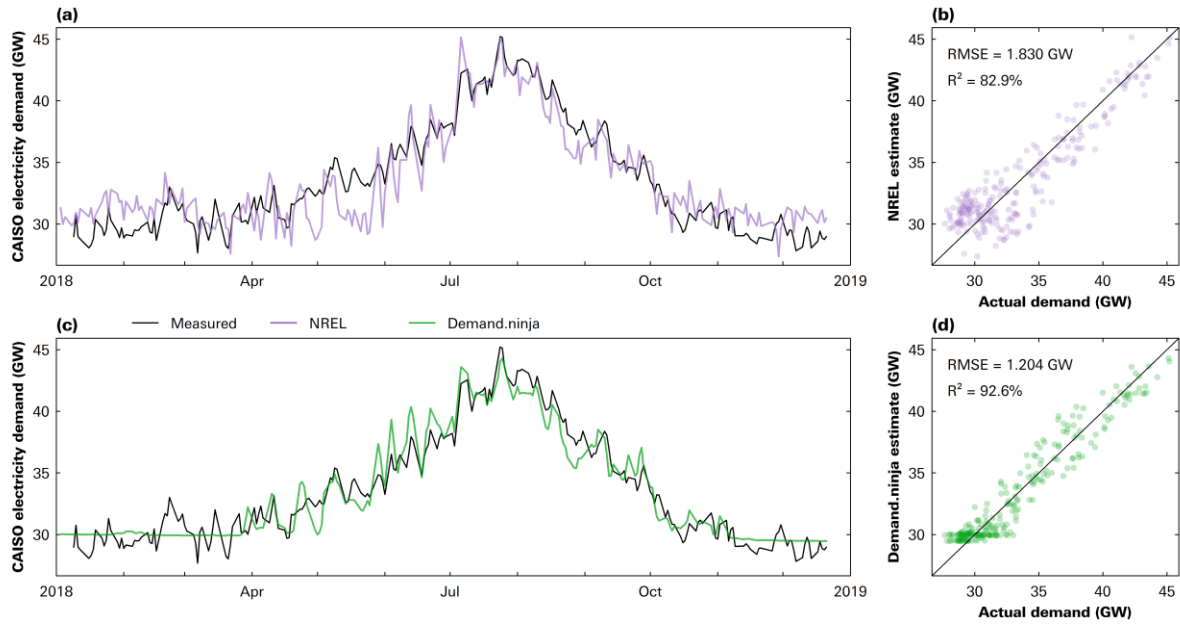
Supplementary Figure 142: Time-series plots of daily electricity demand in Slovakia. Panels (a) and (b) show the When2Heat model [63], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences. Pink shading indicates the 0.1% of days that had >1 CDD and so were also removed; see Supplementary Figure 123 for further detail.



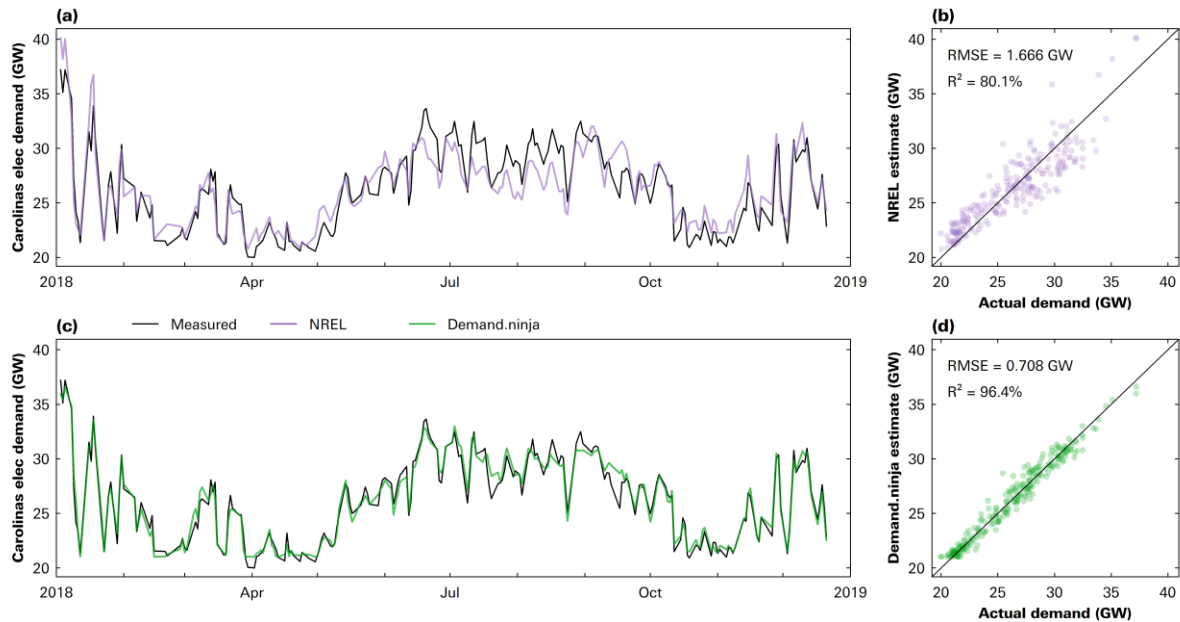
Supplementary Figure 143: Time-series plots of daily electricity demand in Spain. Panels (a) and (b) show the When2Heat model [63], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences. Pink shading indicates the 34.2% of days that had >1 CDD and so were also removed; see Supplementary Figure 123 for further detail.



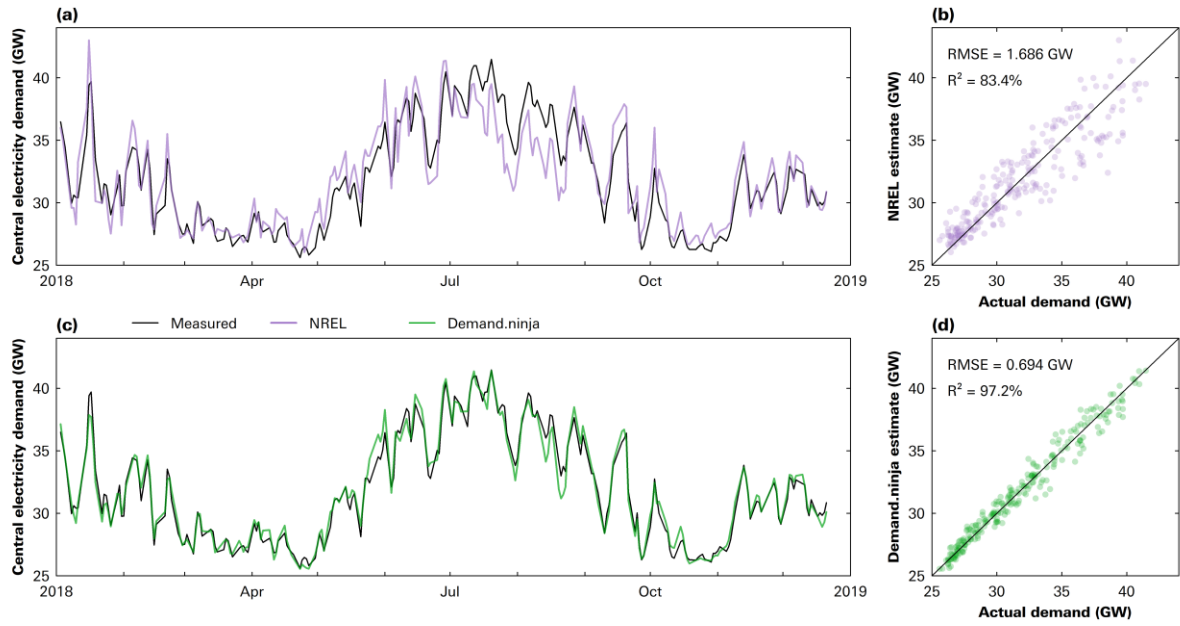
Supplementary Figure 144: Time-series plots of daily electricity demand in Sweden. Panels (a) and (b) show the When2Heat model [63], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences. Pink shading indicates the 1.4% of days that had >1 CDD and so were also removed; see Supplementary Figure 123 for further detail.



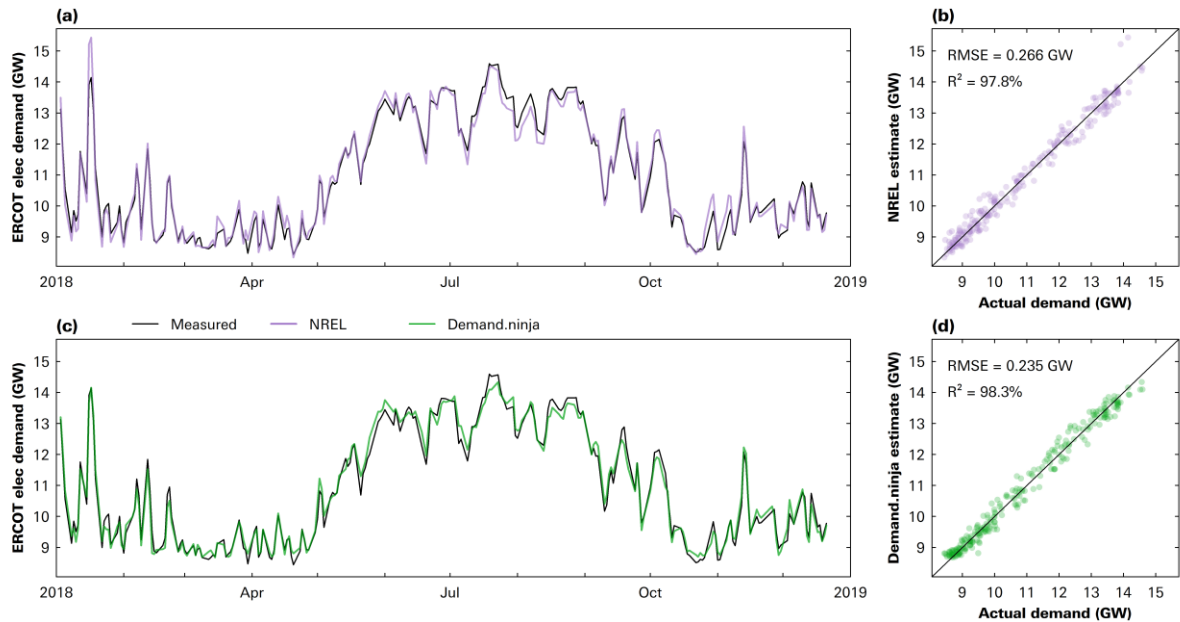
Supplementary Figure 145: Time-series plots of daily electricity demand in the CAISO power market (US). Panels (a) and (b) show the ResStock and Comstock models [64], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences.



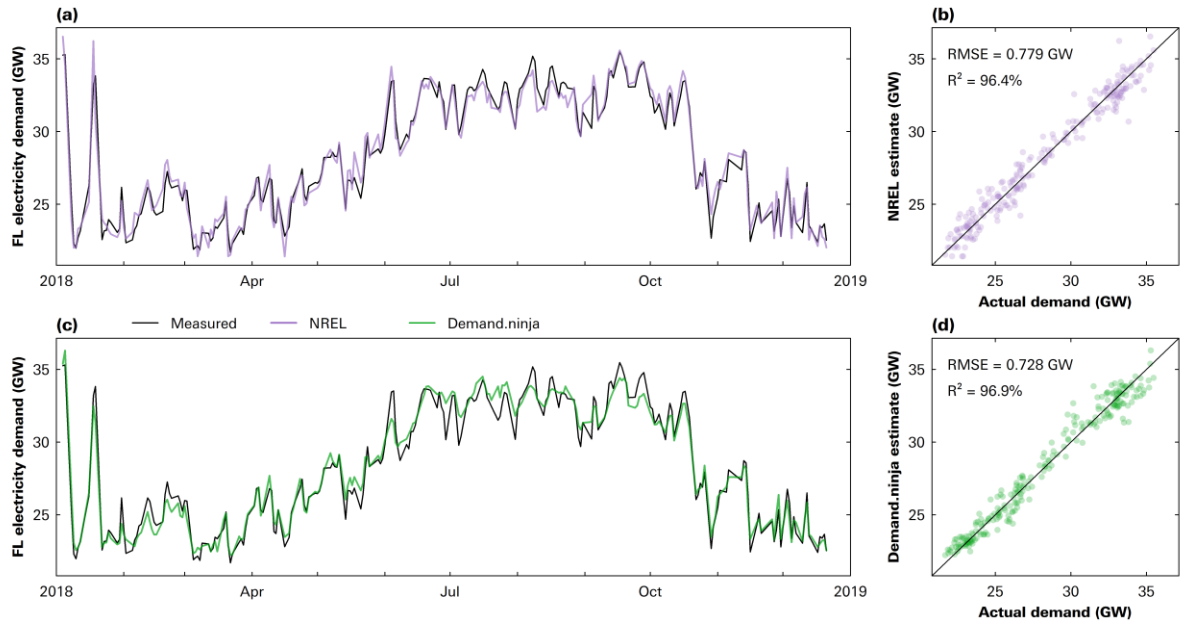
Supplementary Figure 146: Time-series plots of daily electricity demand in the Carolinas power market (US). Panels (a) and (b) show the ResStock and Comstock models [64], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences.



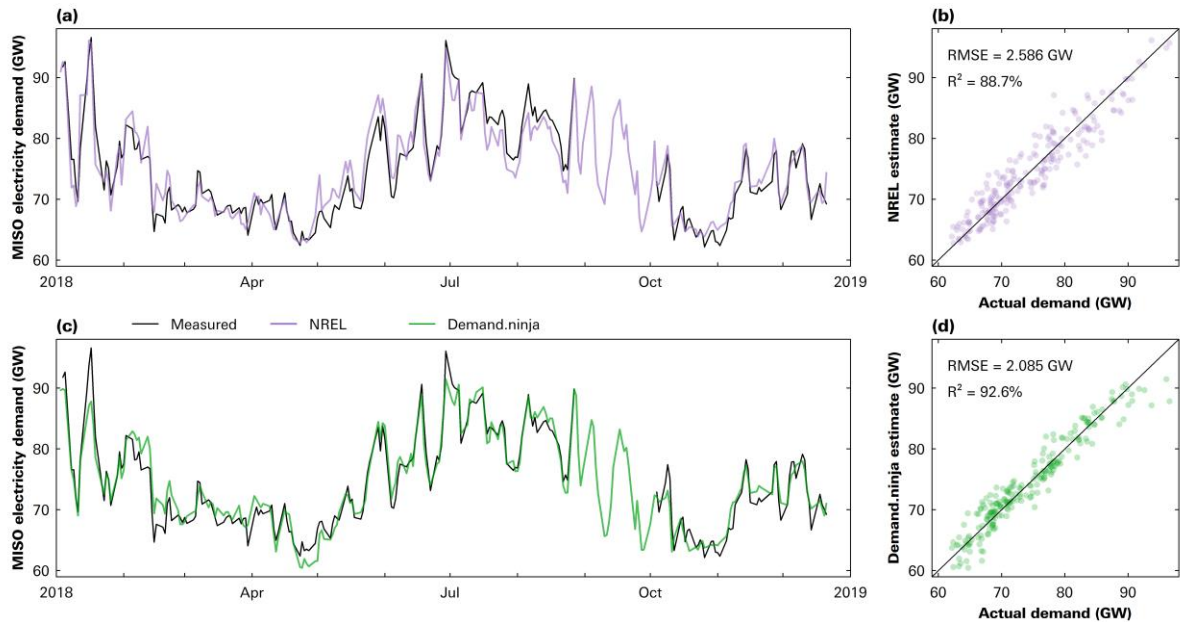
Supplementary Figure 147: Time-series plots of daily electricity demand in the Central power market (US). Panels (a) and (b) show the ResStock and Comstock models [64], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences.



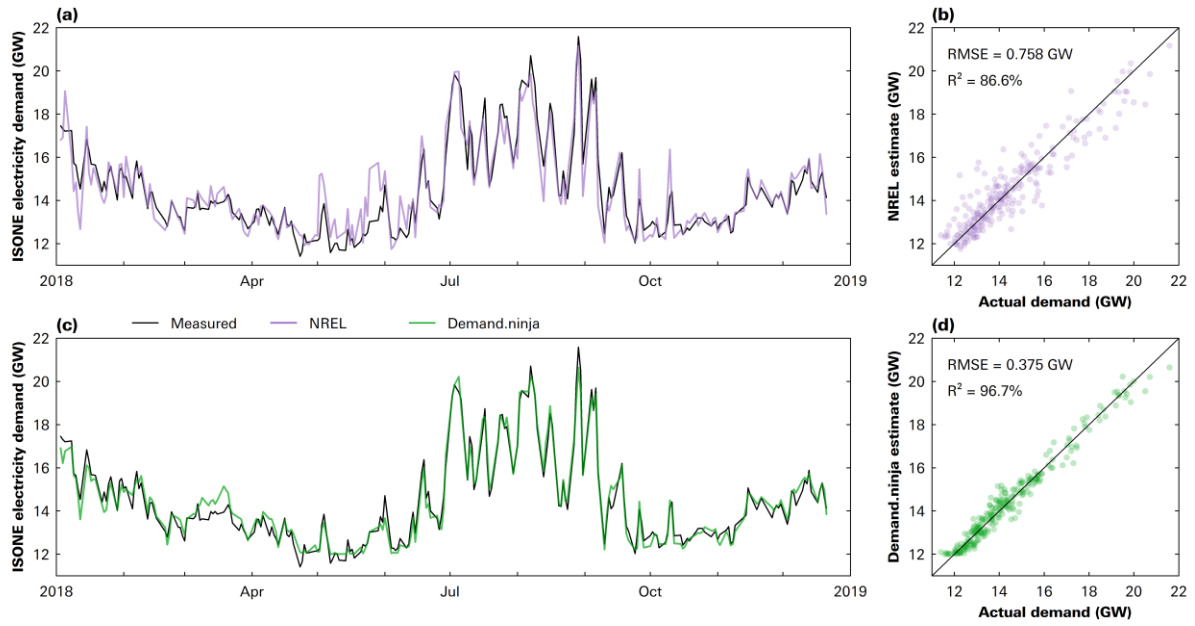
Supplementary Figure 148: Time-series plots of daily electricity demand in the ERCOT power market (US). Panels (a) and (b) show the ResStock and Comstock models [64], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences.



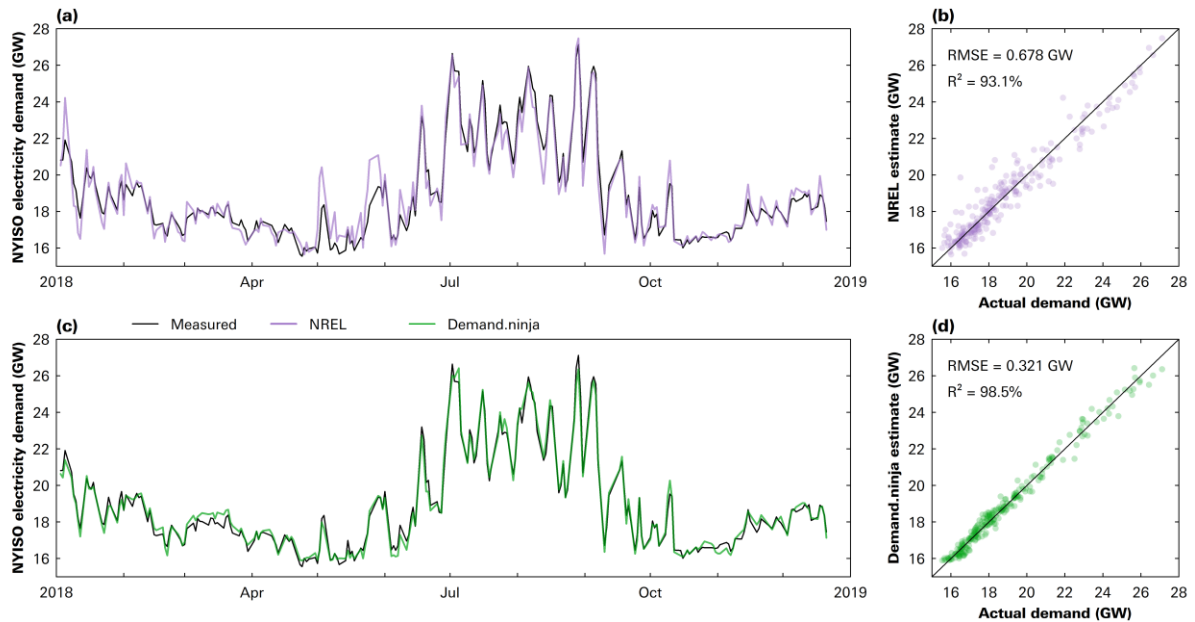
Supplementary Figure 149: Time-series plots of daily electricity demand in the Florida power market (US). Panels (a) and (b) show the ResStock and Comstock models [64], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences.



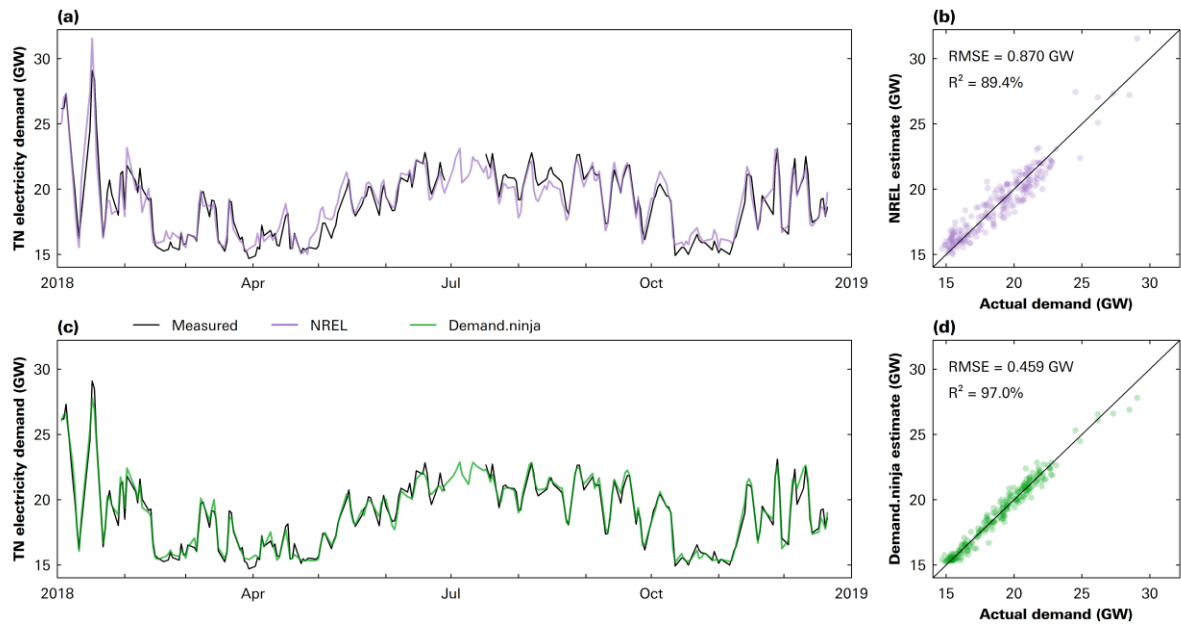
Supplementary Figure 150: Time-series plots of daily electricity demand in the MISO power market (US). Panels (a) and (b) show the ResStock and Comstock models [64], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences.



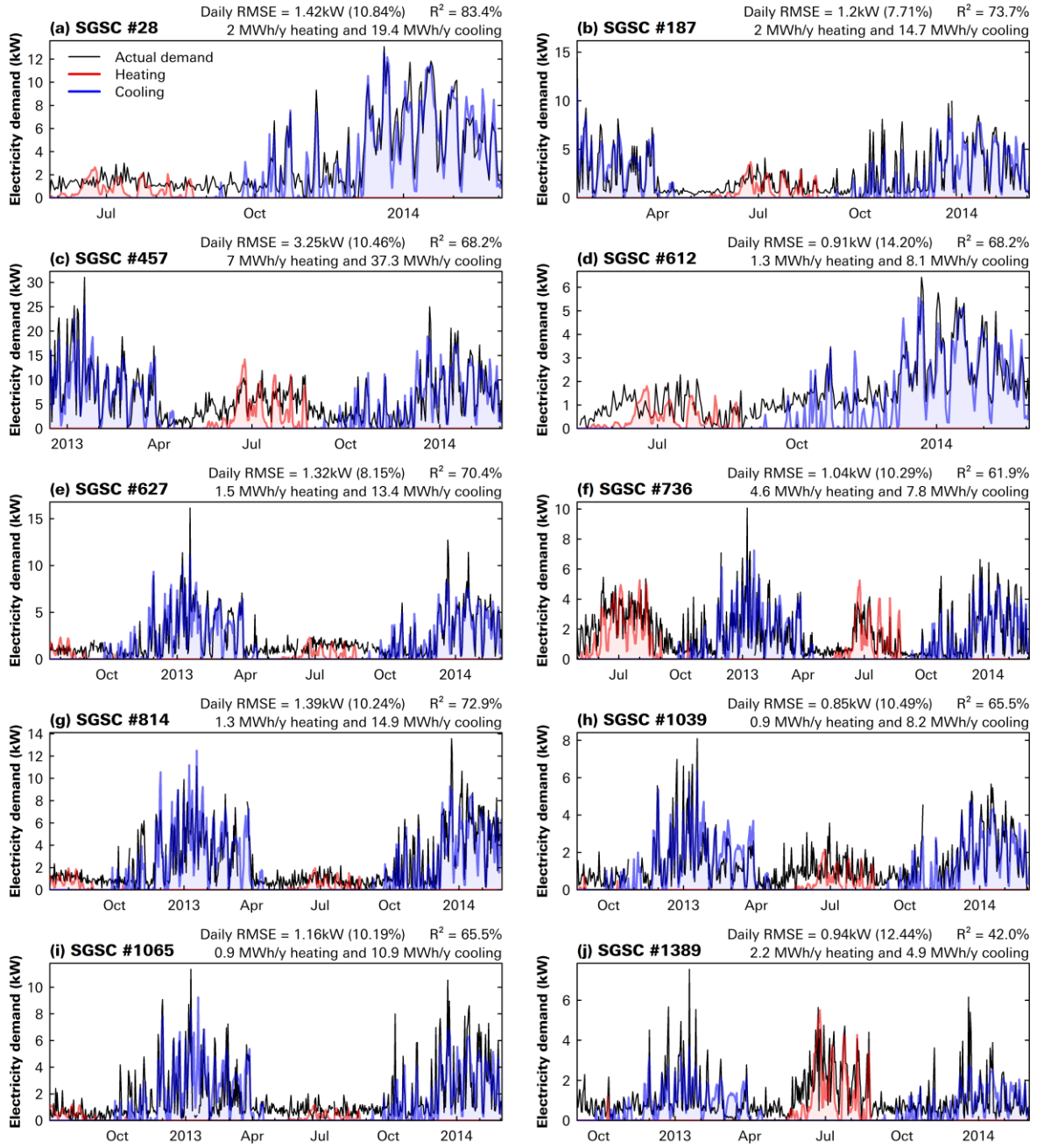
Supplementary Figure 151: Time-series plots of daily electricity demand in the ISONE power market (US). Panels (a) and (b) show the ResStock and Comstock models [64], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences.



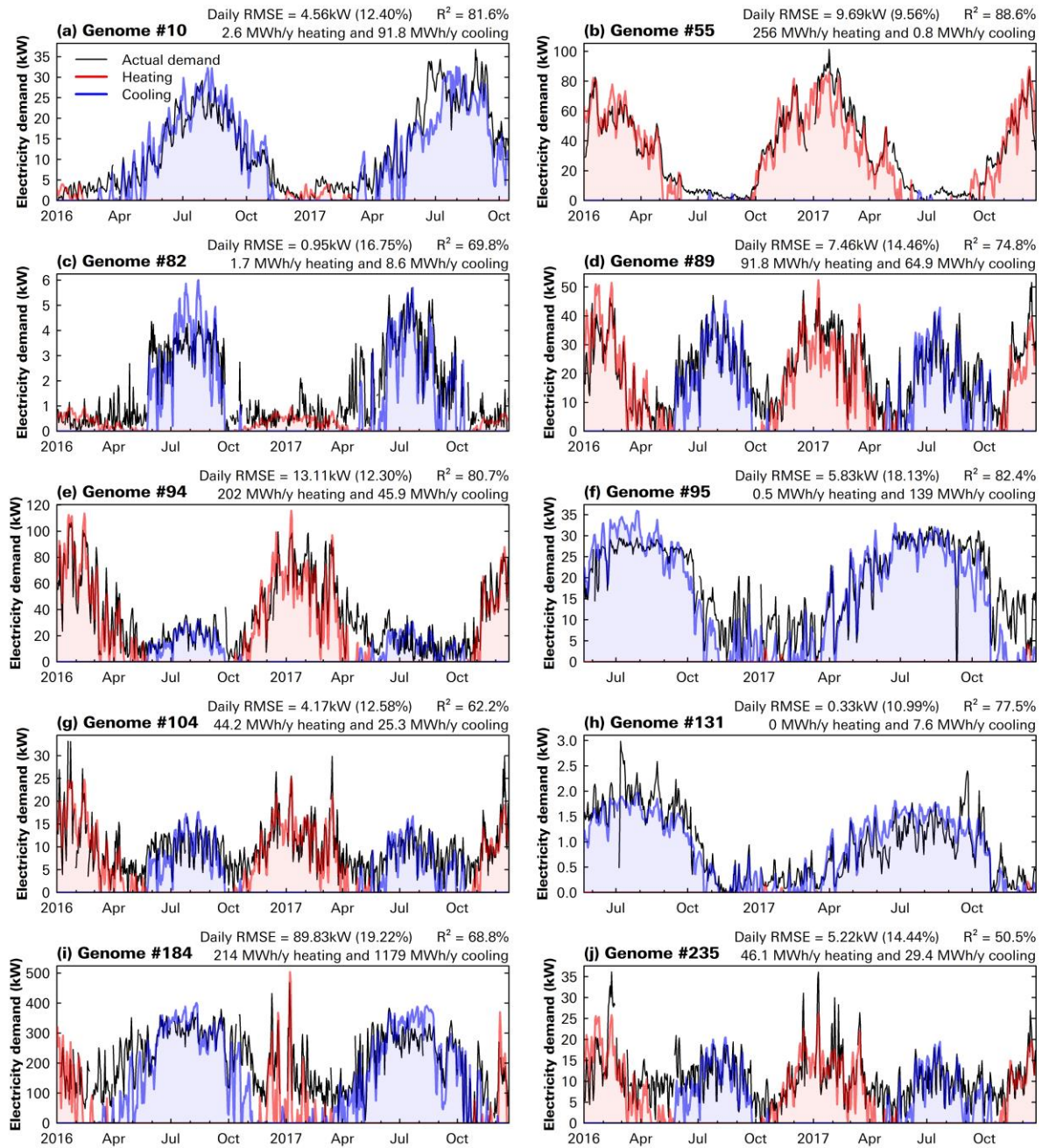
Supplementary Figure 152: Time-series plots of daily electricity demand in the NYISO power market (US). Panels (a) and (b) show the ResStock and Comstock models [64], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences.



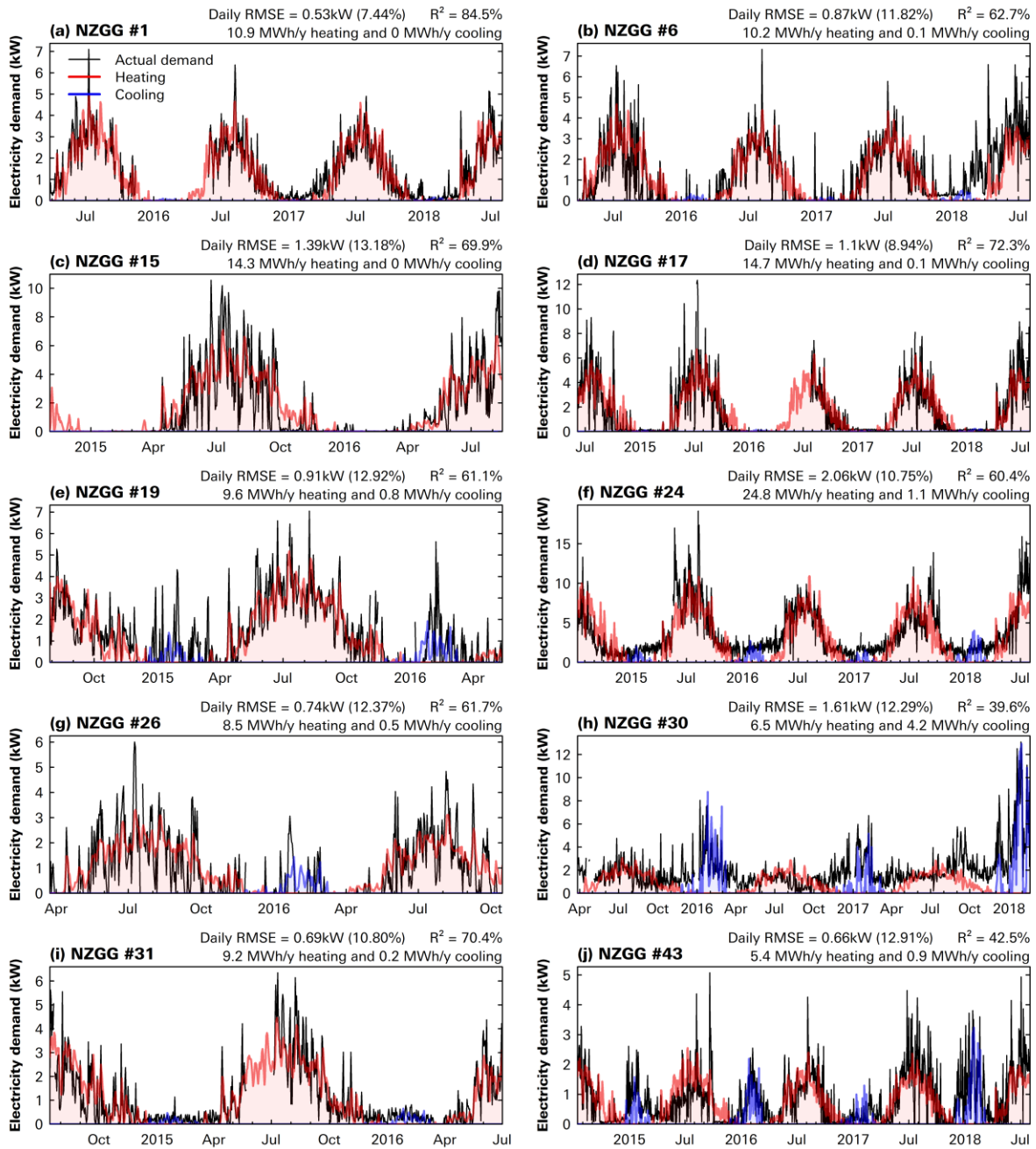
Supplementary Figure 153: Time-series plots of daily electricity demand in the Tennessee power market (US). Panels (a) and (b) show the ResStock and Comstock models [64], panels (c) and (d) show the Demand.ninja model. Weekends and national holidays are excluded due to non-weather-related influences.



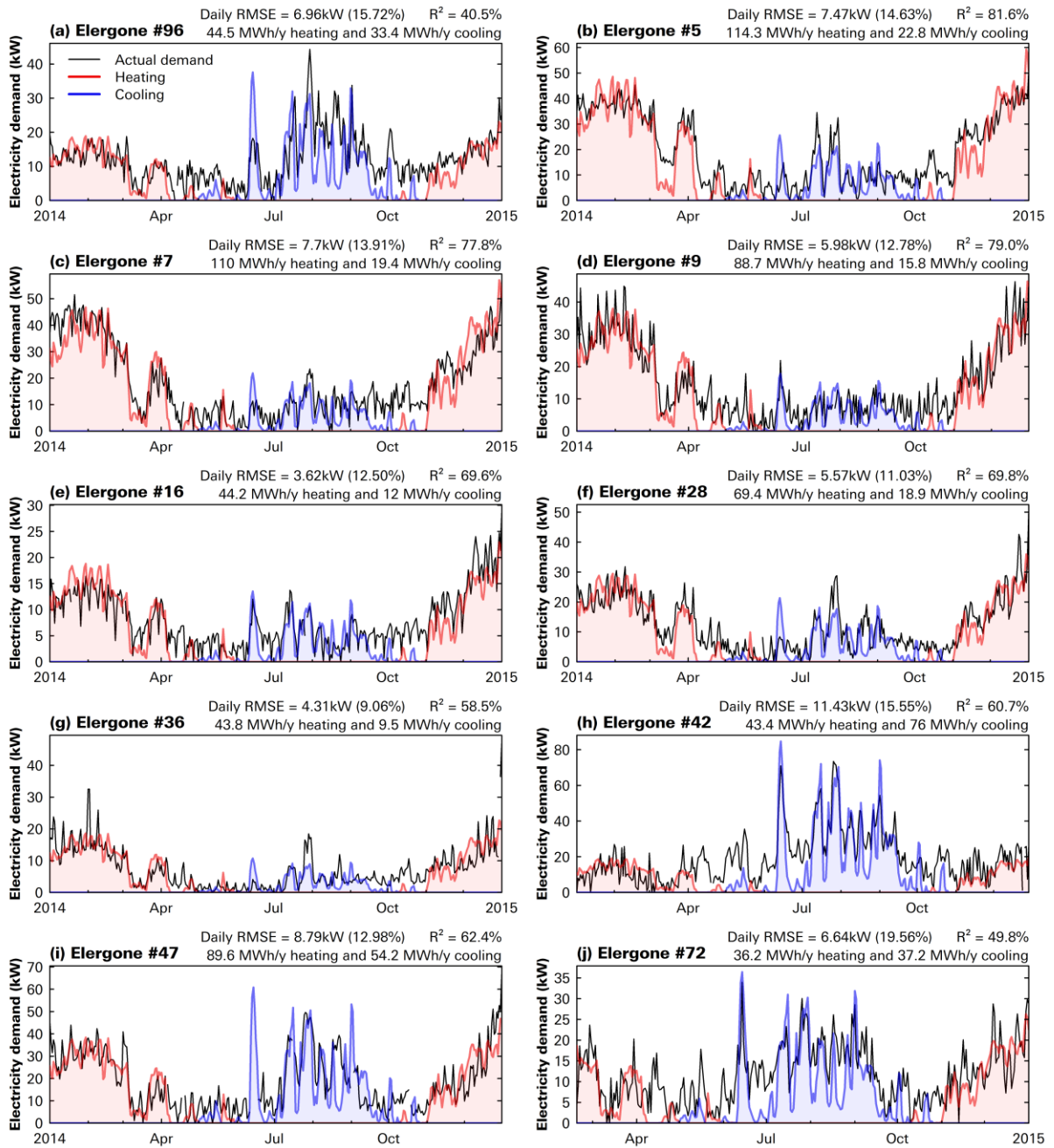
Supplementary Figure 154: Simulations of individual building demand from 10 randomly selected buildings from the Smart-Grid Smart-City dataset (Australia). In all cases, the default BAIT parameters and temperature thresholds were used, and the baseline power coefficient (P_{base}) was fixed at zero, giving an indication of how the model performs when given only the location of a building and its annual energy demand. Estimates of heating and cooling energy demand estimates could be improved if bespoke temperature thresholds were used.



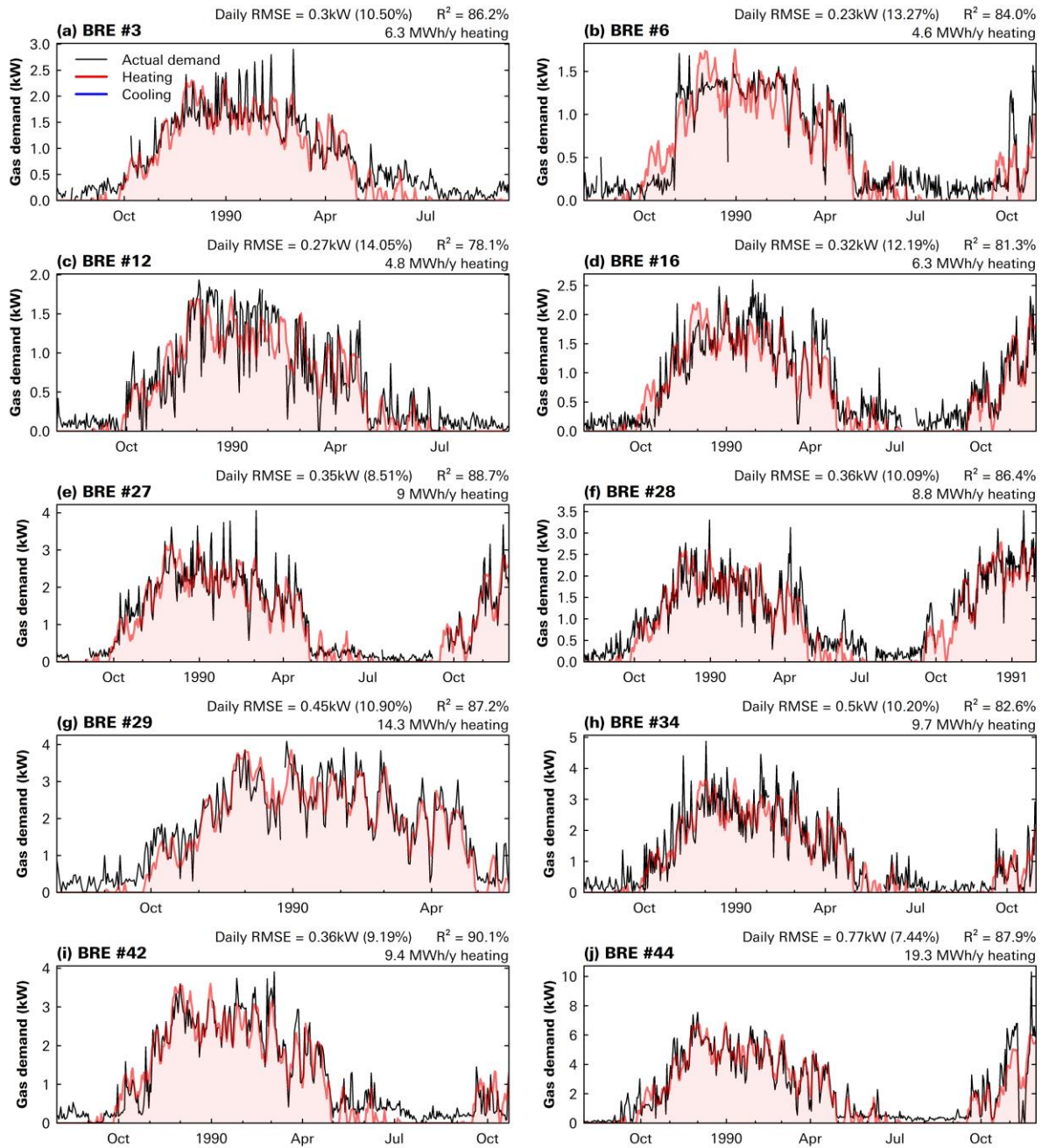
Supplementary Figure 155: Simulations of individual building demand from 10 randomly selected buildings from the Building Data Genome Project 2 dataset (global). In all cases, the default BAIT parameters and temperature thresholds were used, and the baseline power coefficient (P_{base}) was fixed at zero, giving an indication of how the model performs when given only the location of a building and its annual energy demand. Estimates of heating and cooling energy demand estimates could be improved if bespoke temperature thresholds were used.



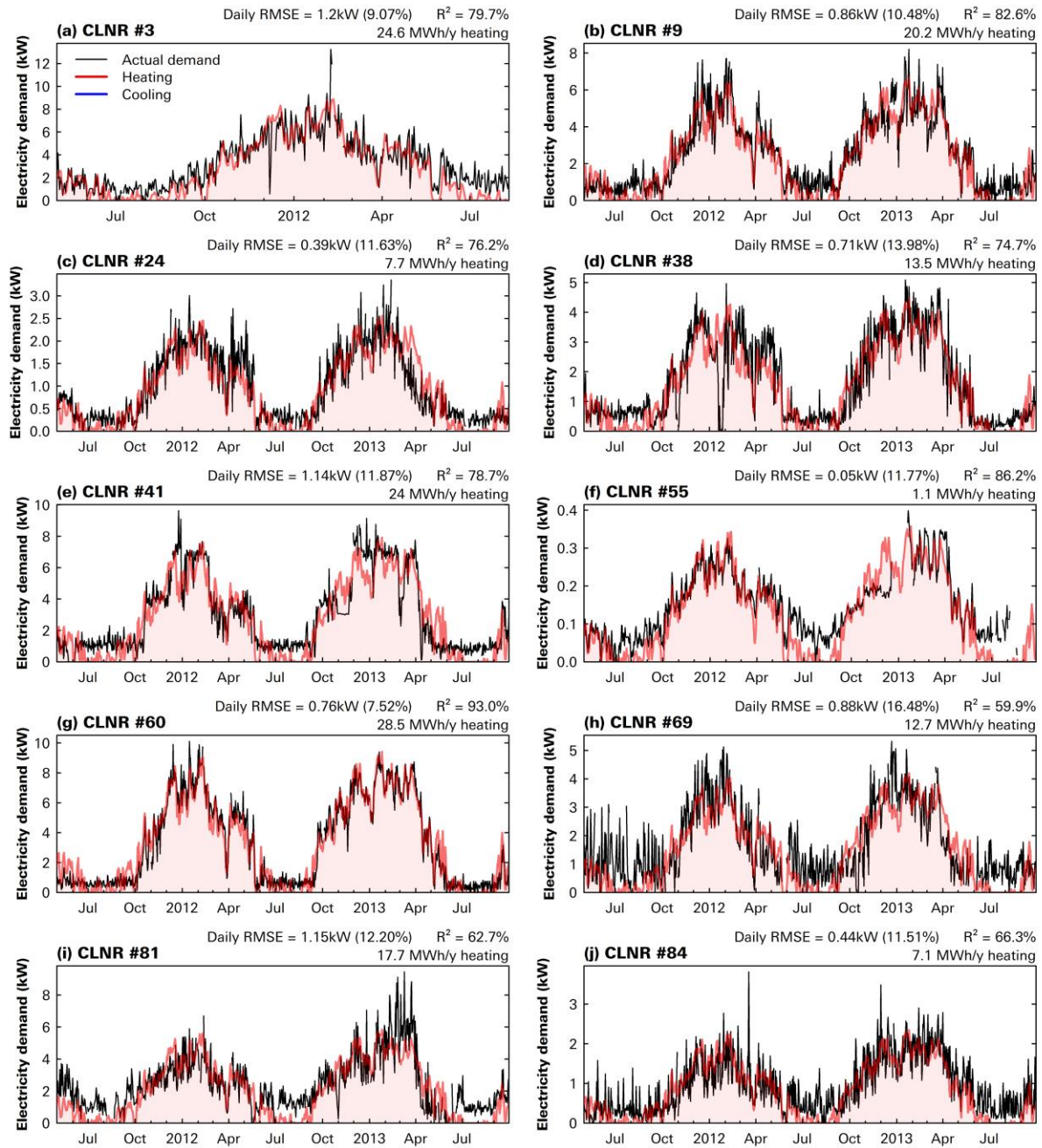
Supplementary Figure 156: Simulations of individual building demand from 10 randomly selected buildings from the Green Grid dataset (New Zealand). In all cases, the default BAIT parameters and temperature thresholds were used, and the baseline power coefficient (P_{base}) was fixed at zero, giving an indication of how the model performs when given only the location of a building and its annual energy demand. Estimates of heating and cooling energy demand estimates could be improved if bespoke temperature thresholds were used.



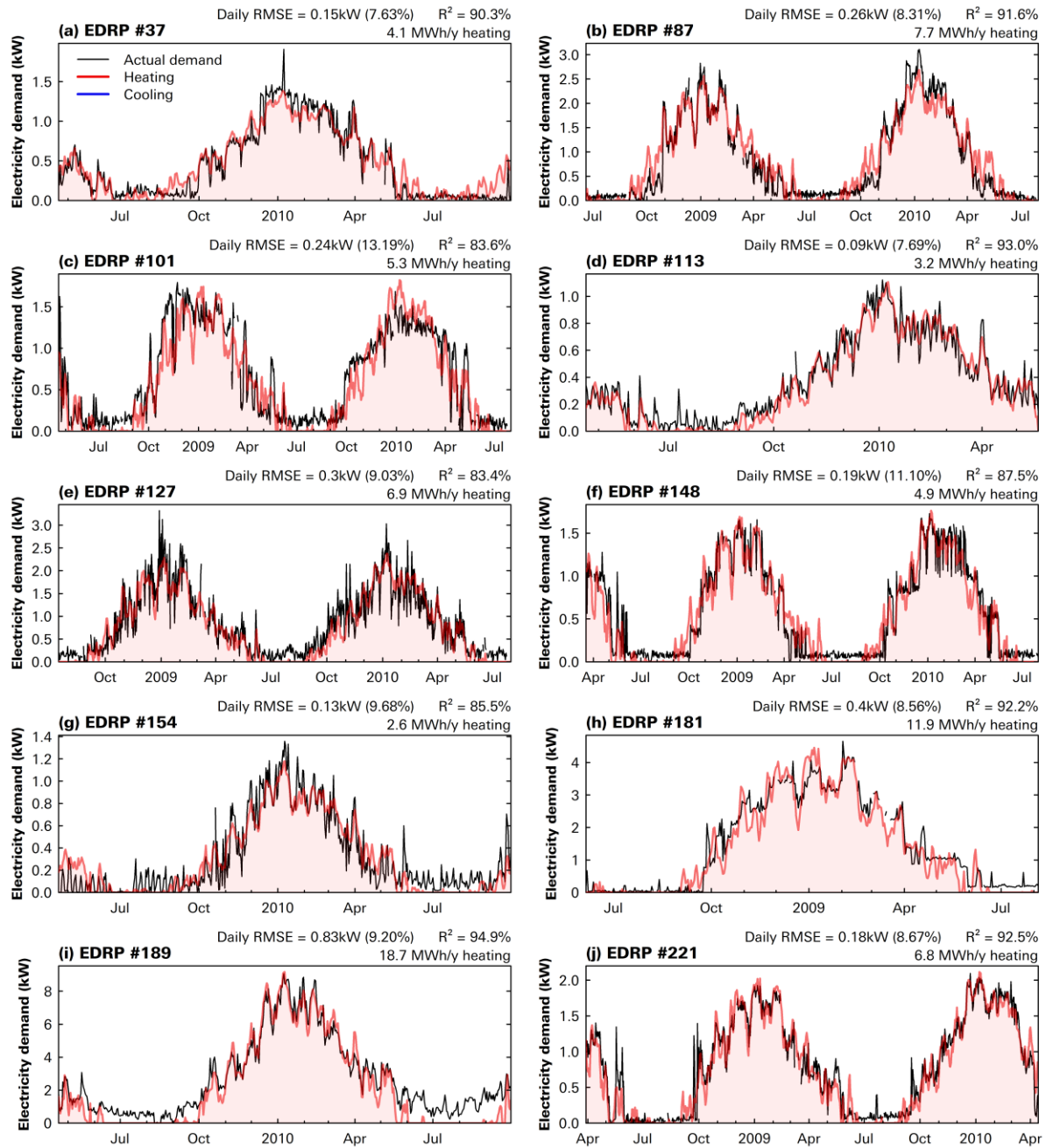
Supplementary Figure 157: Simulations of individual building demand from 10 randomly selected buildings from the Elergone Energia dataset (Portugal). In all cases, the default BAIT parameters and temperature thresholds were used, and the baseline power coefficient (P_{base}) was fixed at zero, giving an indication of how the model performs when given only the location of a building and its annual energy demand. Estimates of heating and cooling energy demand estimates could be improved if bespoke temperature thresholds were used.



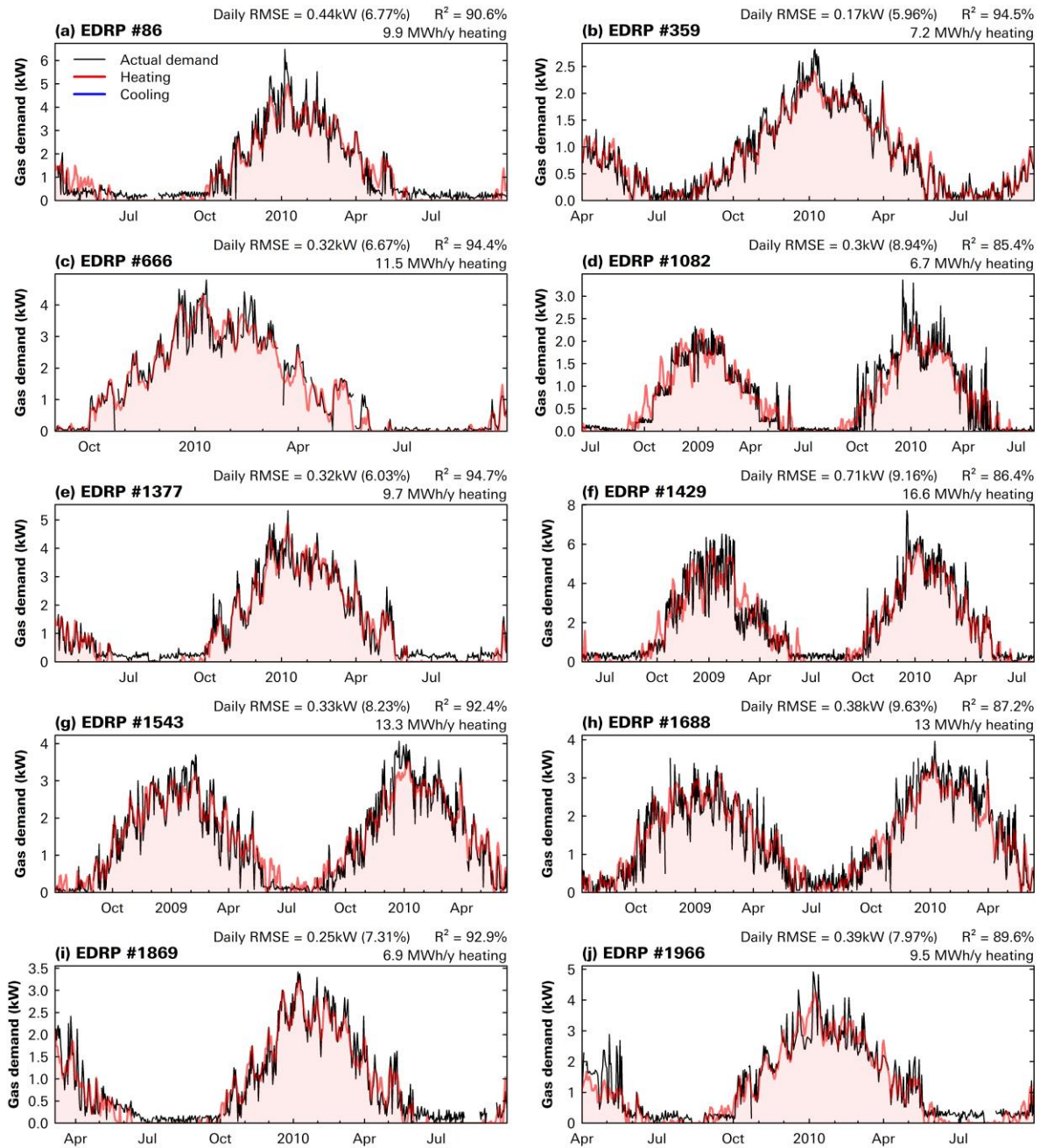
Supplementary Figure 158: Simulations of individual building demand from 10 randomly selected buildings from the BRE dataset (UK). In all cases, the default BAIT parameters and temperature thresholds were used, and the baseline power coefficient (P_{base}) was fixed at zero, giving an indication of how the model performs when given only the location of a building and its annual energy demand. Estimates of heating and cooling energy demand estimates could be improved if bespoke temperature thresholds were used.



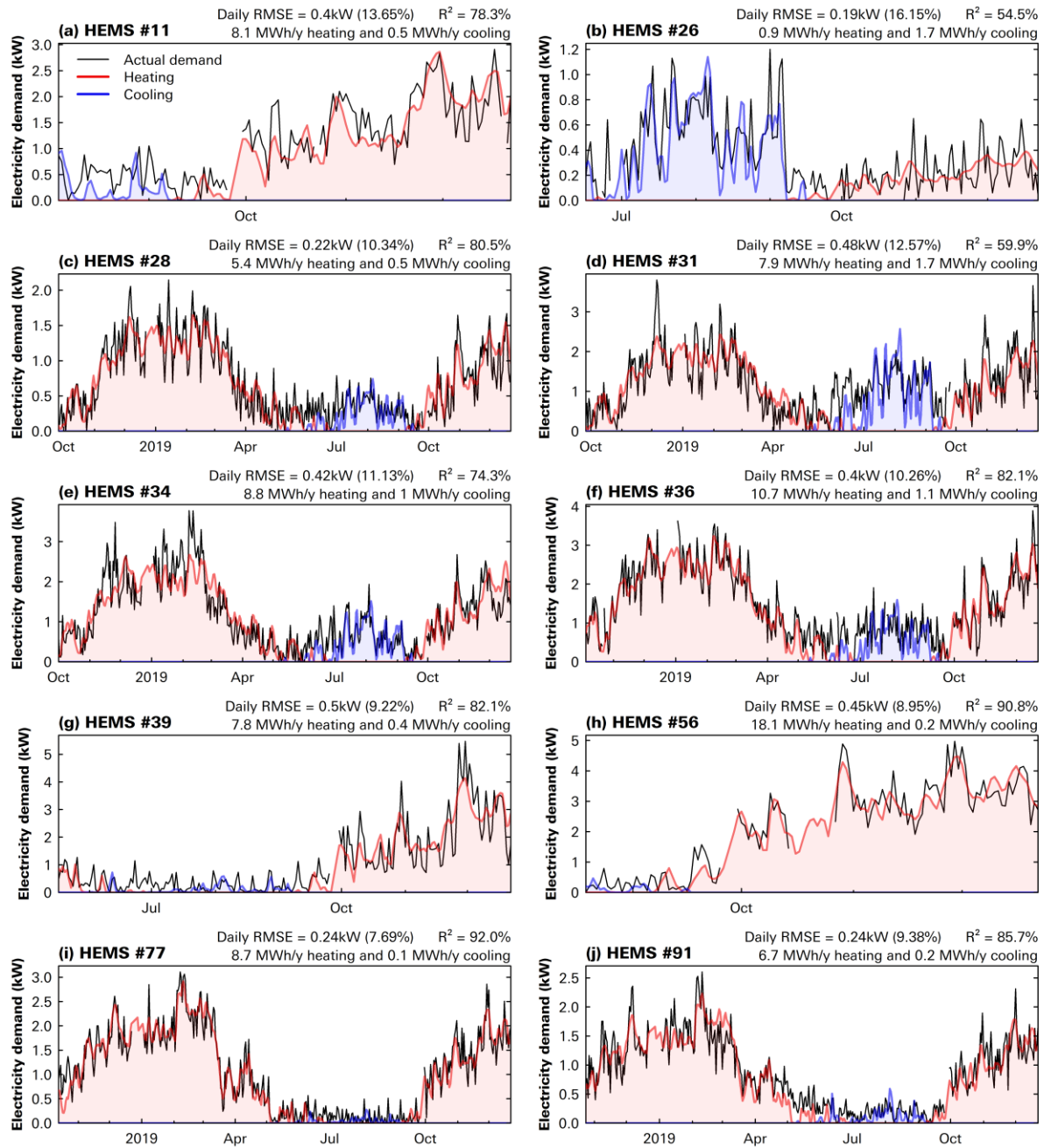
Supplementary Figure 159: Simulations of individual building demand from 10 randomly selected buildings from the Customer Led Network Revolution dataset (UK). In all cases, the default BAIT parameters and temperature thresholds were used, and the baseline power coefficient (P_{base}) was fixed at zero, giving an indication of how the model performs when given only the location of a building and its annual energy demand. Estimates of heating and cooling energy demand estimates could be improved if bespoke temperature thresholds were used.



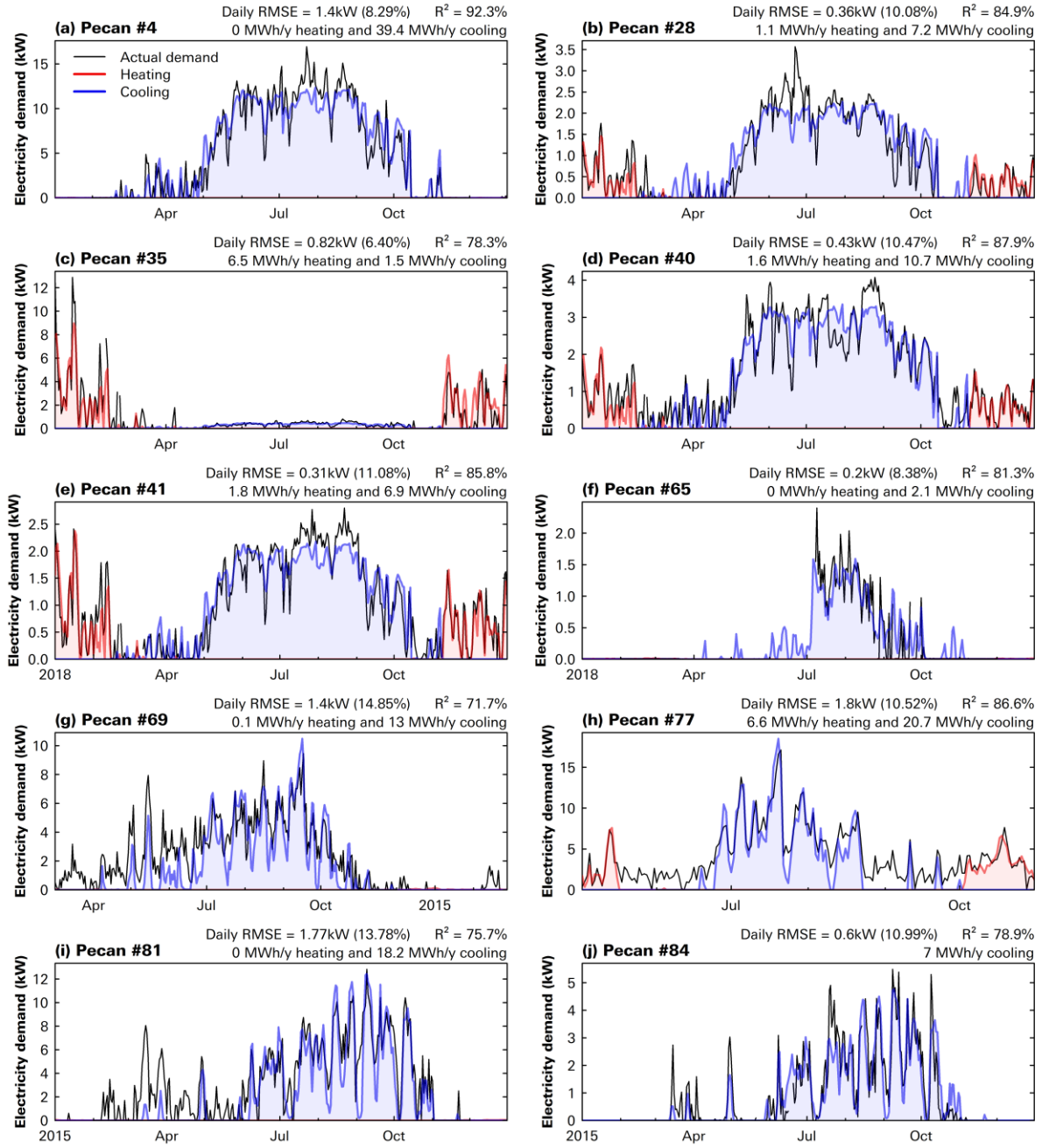
Supplementary Figure 160: Simulations of individual building demand from 10 randomly selected buildings from the Energy Demand Research Project electricity dataset (UK). In all cases, the default BAIT parameters and temperature thresholds were used, and the baseline power coefficient (P_{base}) was fixed at zero, giving an indication of how the model performs when given only the location of a building and its annual energy demand. Estimates of heating and cooling energy demand estimates could be improved if bespoke temperature thresholds were used.



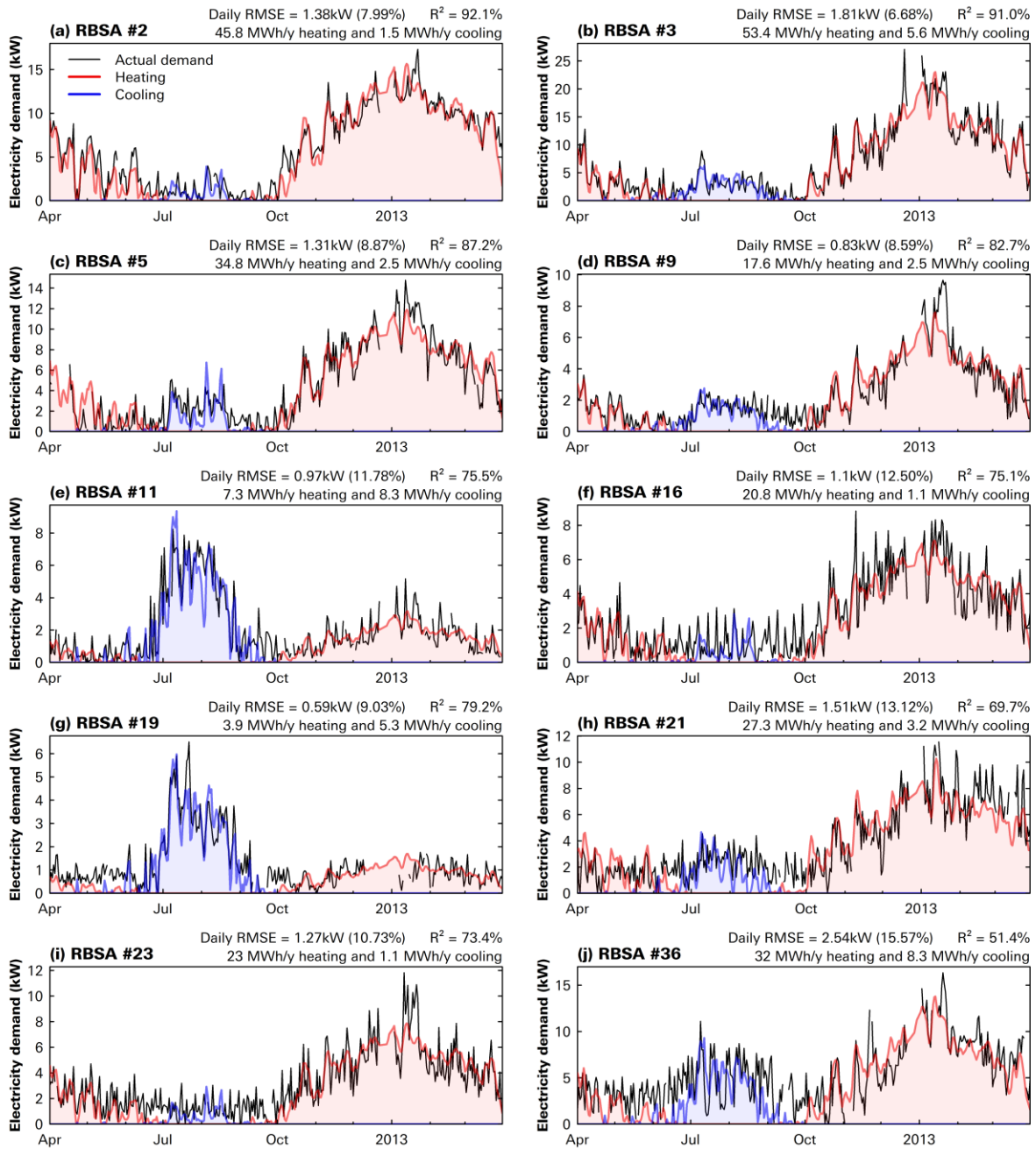
Supplementary Figure 161: Simulations of individual building demand from 10 randomly selected buildings from the Energy Demand Research Project natural gas dataset (UK). In all cases, the default BAIT parameters and temperature thresholds were used, and the baseline power coefficient (P_{base}) was fixed at zero, giving an indication of how the model performs when given only the location of a building and its annual energy demand. Estimates of heating and cooling energy demand estimates could be improved if bespoke temperature thresholds were used.



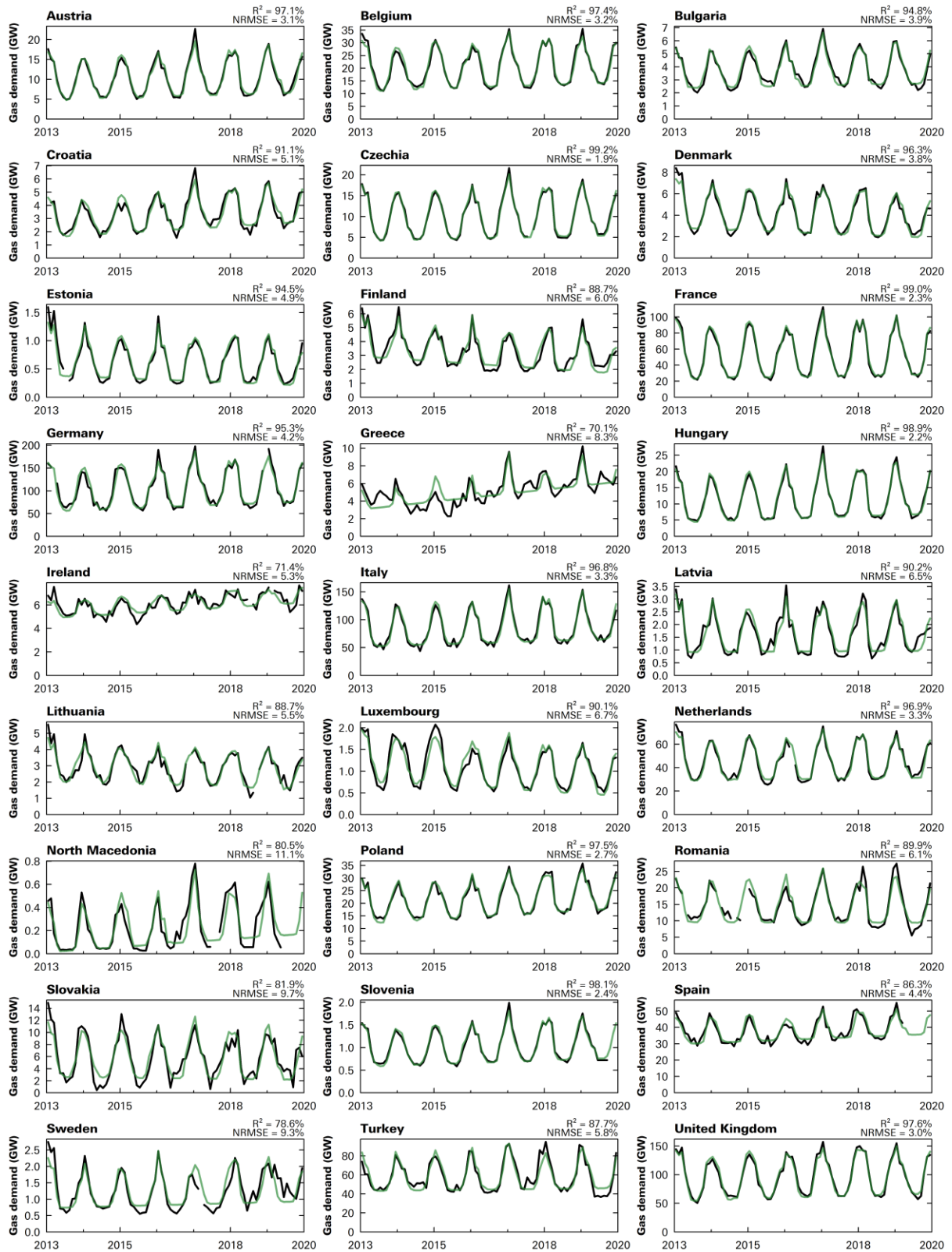
Supplementary Figure 162: Simulations of individual building demand from 10 randomly selected buildings from the Home Energy Metering Study dataset (US). In all cases, the default BAIT parameters and temperature thresholds were used, and the baseline power coefficient (P_{base}) was fixed at zero, giving an indication of how the model performs when given only the location of a building and its annual energy demand. Estimates of heating and cooling energy demand estimates could be improved if bespoke temperature thresholds were used.



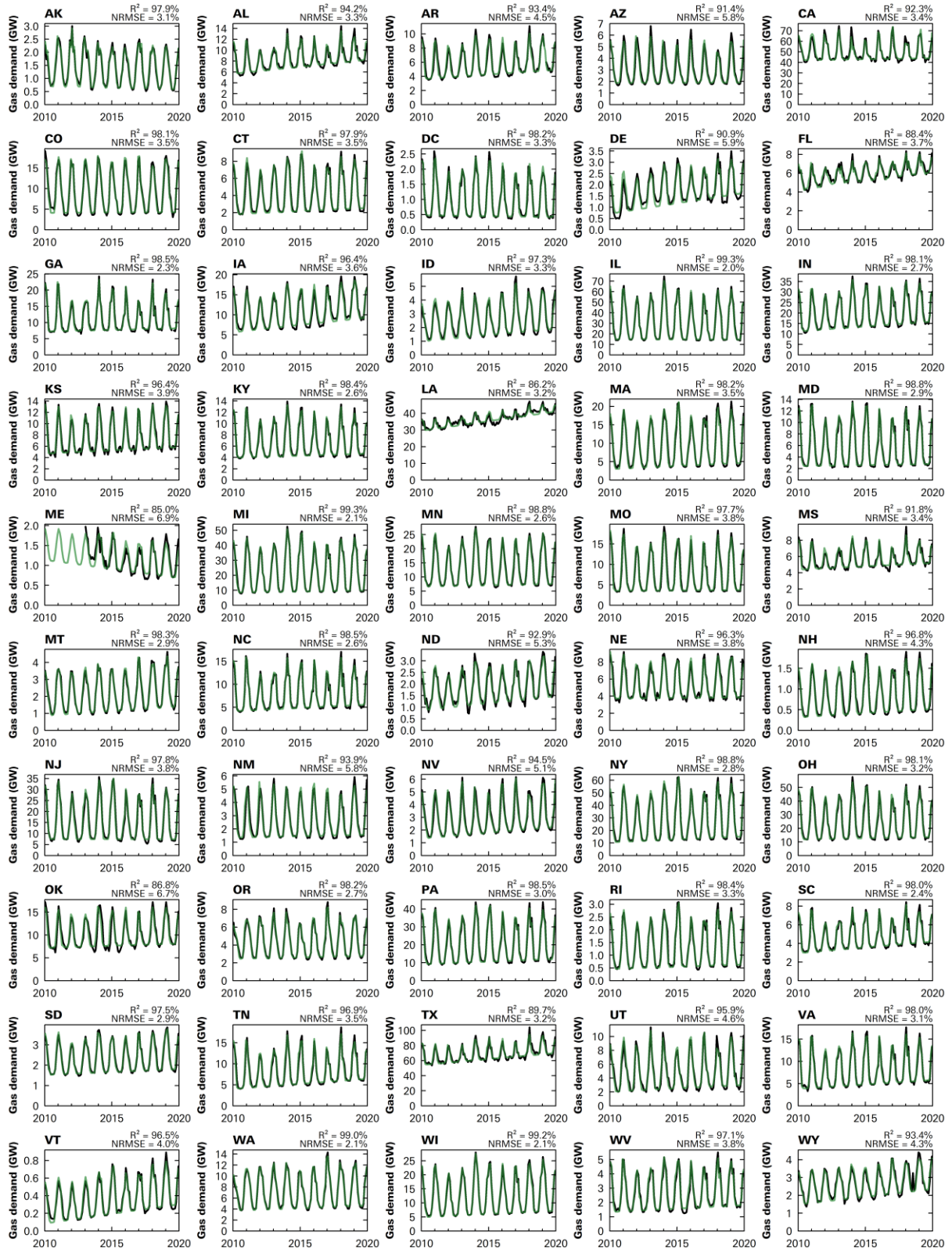
Supplementary Figure 163: Simulations of individual building demand from 10 randomly selected buildings from the Pecan Street dataset (US). In all cases, the default BAIT parameters and temperature thresholds were used, and the baseline power coefficient (P_{base}) was fixed at zero, giving an indication of how the model performs when given only the location of a building and its annual energy demand. Estimates of heating and cooling energy demand estimates could be improved if bespoke temperature thresholds were used.



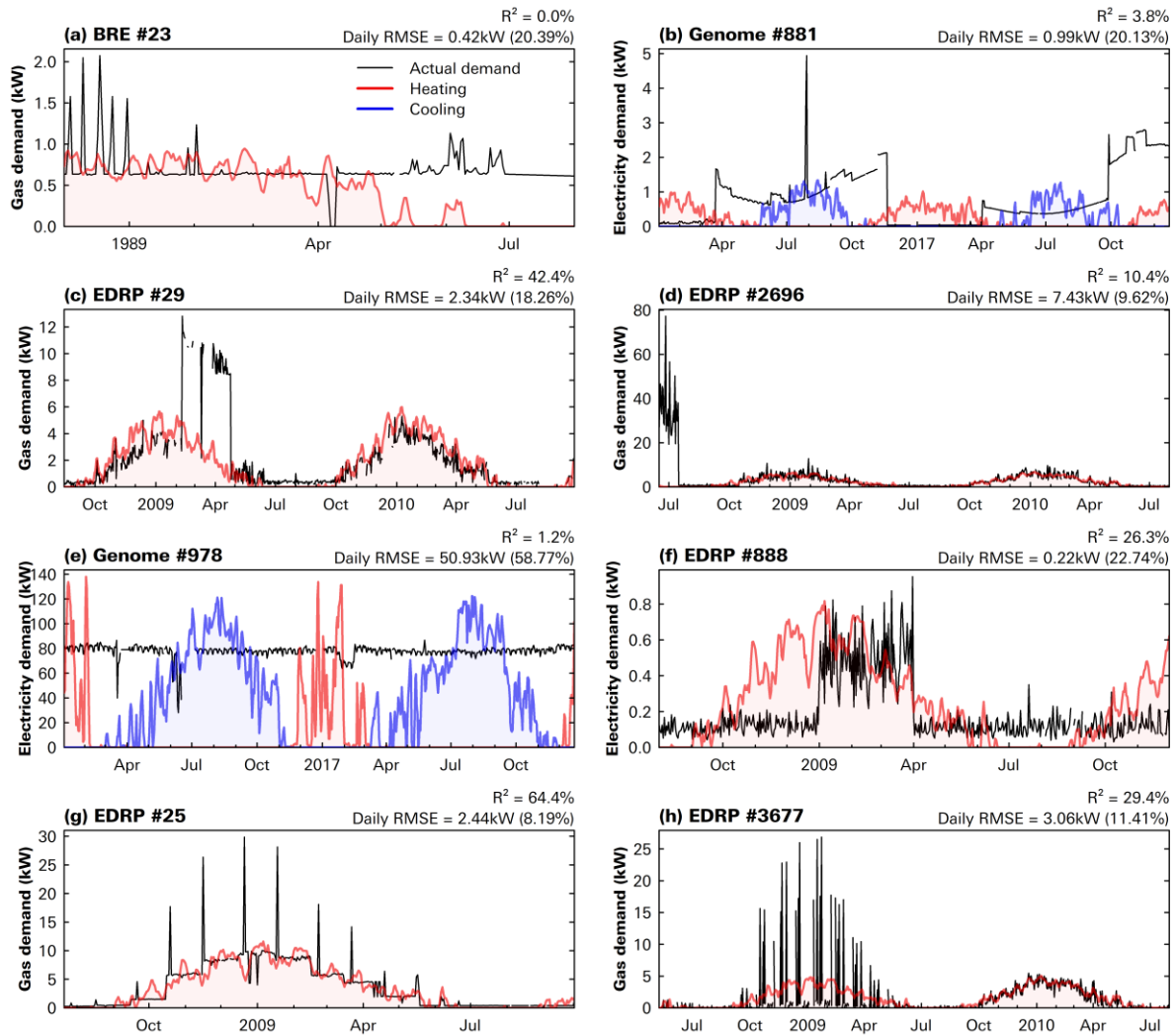
Supplementary Figure 164: Simulations of individual building demand from 10 randomly selected buildings from the Residential Building Stock Assessment dataset (US). In all cases, the default BAIT parameters and temperature thresholds were used, and the baseline power coefficient (P_{base}) was fixed at zero, giving an indication of how the model performs when given only the location of a building and its annual energy demand. Estimates of heating and cooling energy demand estimates could be improved if bespoke temperature thresholds were used.



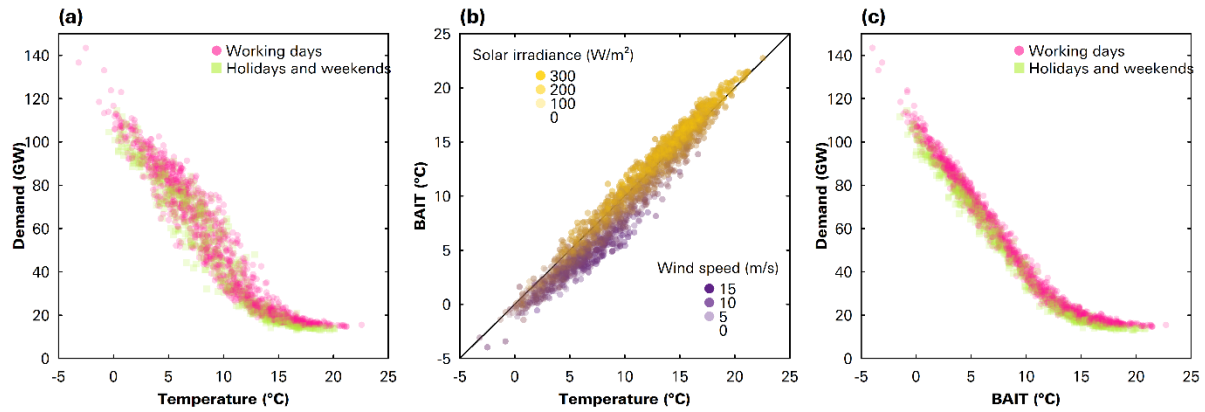
Supplementary Figure 165: Quality of the Demand.ninja at representing daily natural gas demand in European countries (2013-2019). In each panel, the black line represents metered demand, the green line represents the Demand.ninja estimate.



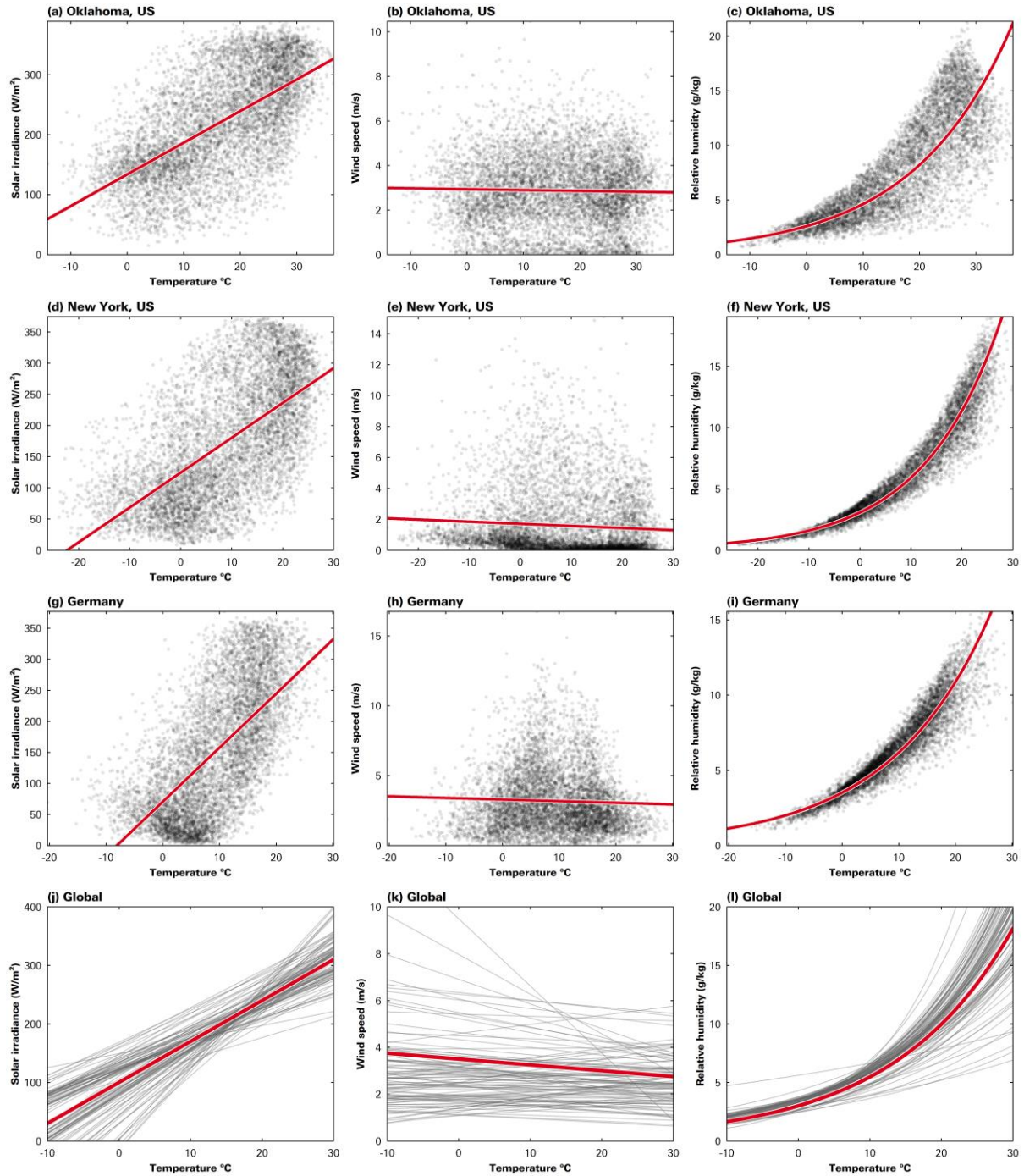
Supplementary Figure 166: Quality of the Demand.ninja at representing daily natural gas demand in US states (2010-2019). In each panel, the black line represents metered demand, the green line represents the Demand.ninja estimate.



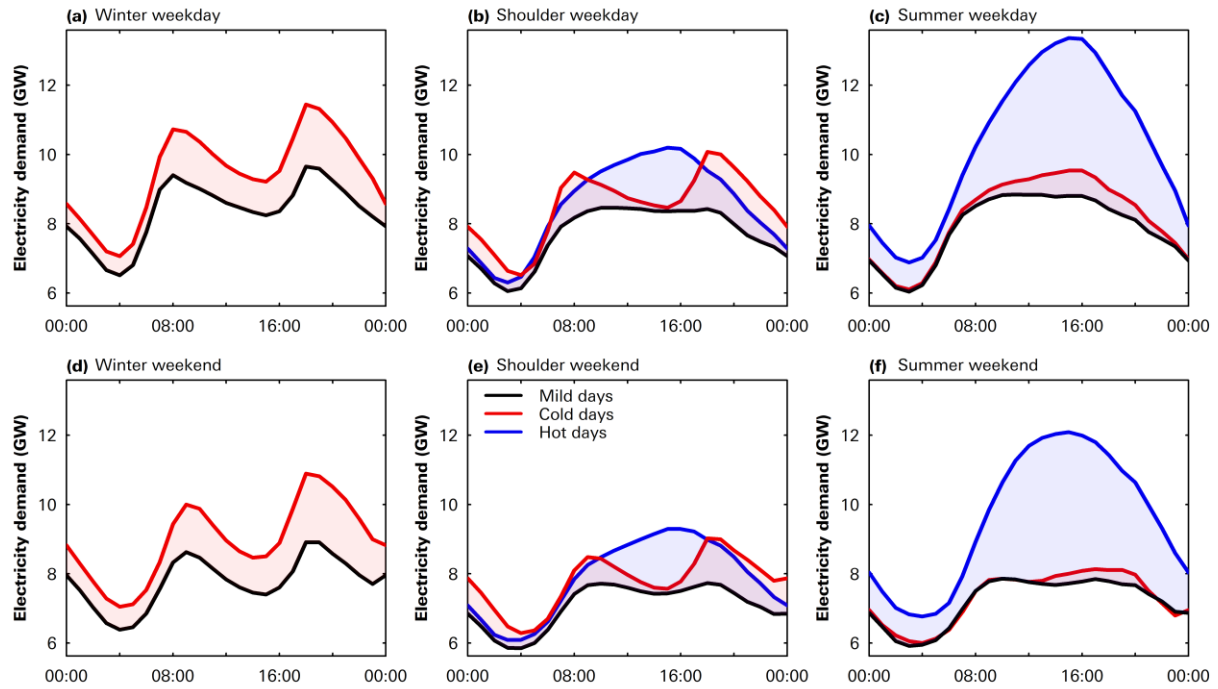
Supplementary Figure 167: Eight energy demand profiles from exemplary buildings that were discarded from the datasets reported in Supplementary Table 3. Building energy demand profiles were typically discarded if they had an R^2 coefficient below 0.6 in smaller datasets, or below 0.8 in datasets with over 10,000 buildings, but profiles were added back into the dataset if they were below these thresholds and displayed none of the erroneous traits shown below. The common erroneous traits we experienced were: buildings that were simply not conditioned using the metered fuel (panel a and e), that had non-standard occupancy patterns such as holiday homes (panel f, occupied from January to March), or which use heating timers (panel g shown as a small number of discrete consumption levels), or suspected monitoring or data entry errors (panels b, c, d, and h).



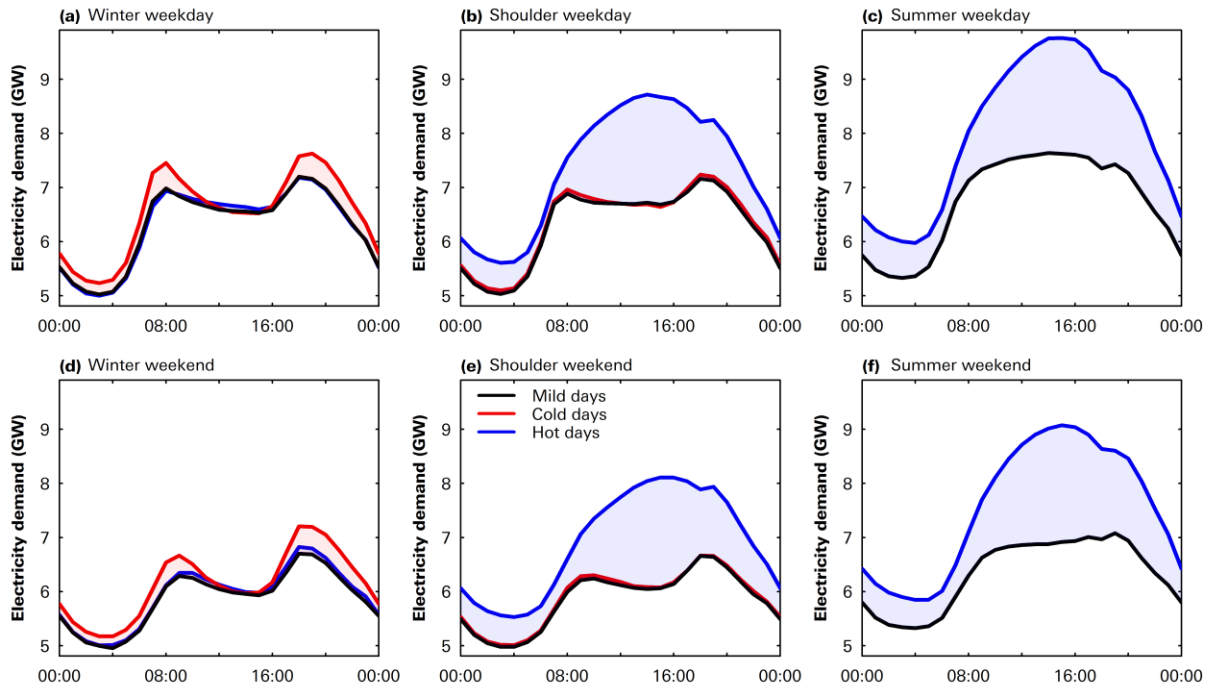
Supplementary Figure 168: Demonstration of the relationships between temperature, BAIT and energy demand, using national gas consumption in Great Britain from 2015–19 as an example. Comparing panel (a) and panel (c) shows how moving from raw temperature to BAIT greatly improves the fit with gas demand. Panel (b) shows that BAIT generally corresponds with air temperature and is not systematically higher or lower.



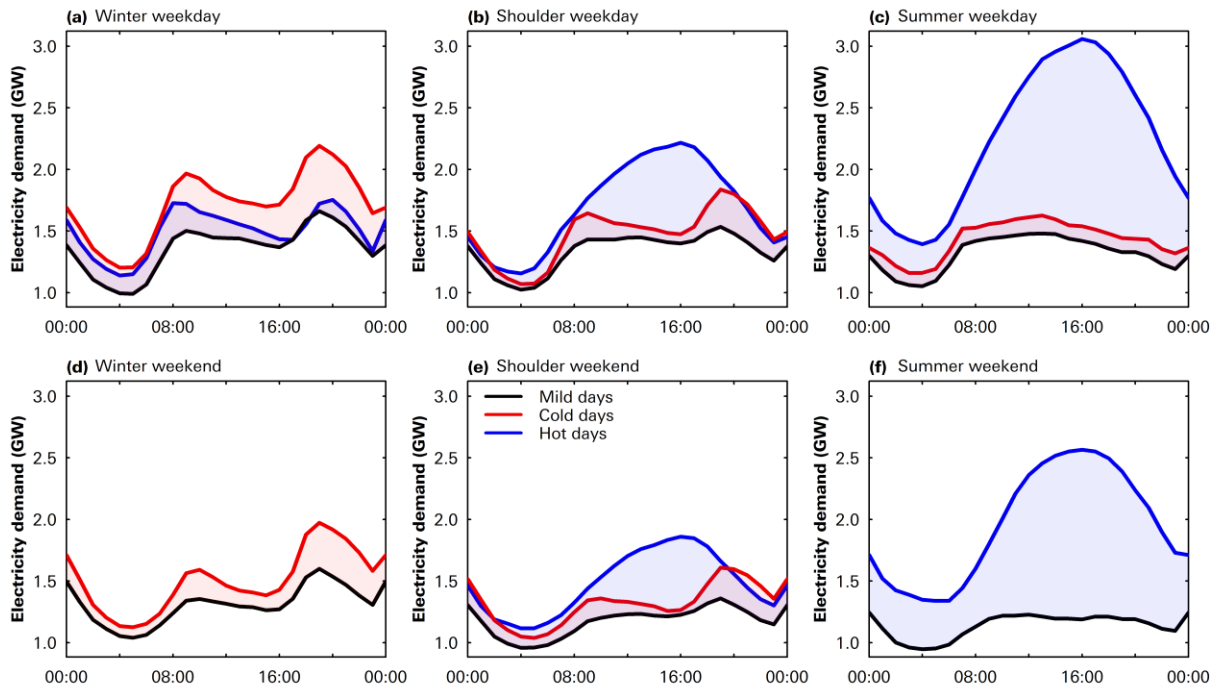
Supplementary Figure 169: Regressions correlating temperature to other weather variables in three example regions, and a summary of the regressions from all locations considered in this study. Panels (a, d, g) consider solar irradiance and panels (b, e, h) consider wind speed, with red lines showing the linear regressions. Panels (c, f, j) consider relative humidity, with red lines showing log-linear regressions. The regression lines from all regions are summarised in panels (h, i, j) as grey lines, with thick red lines representing the demand-weighted mean across all regions, which defined the relationships for the weather counterfactuals in this study.



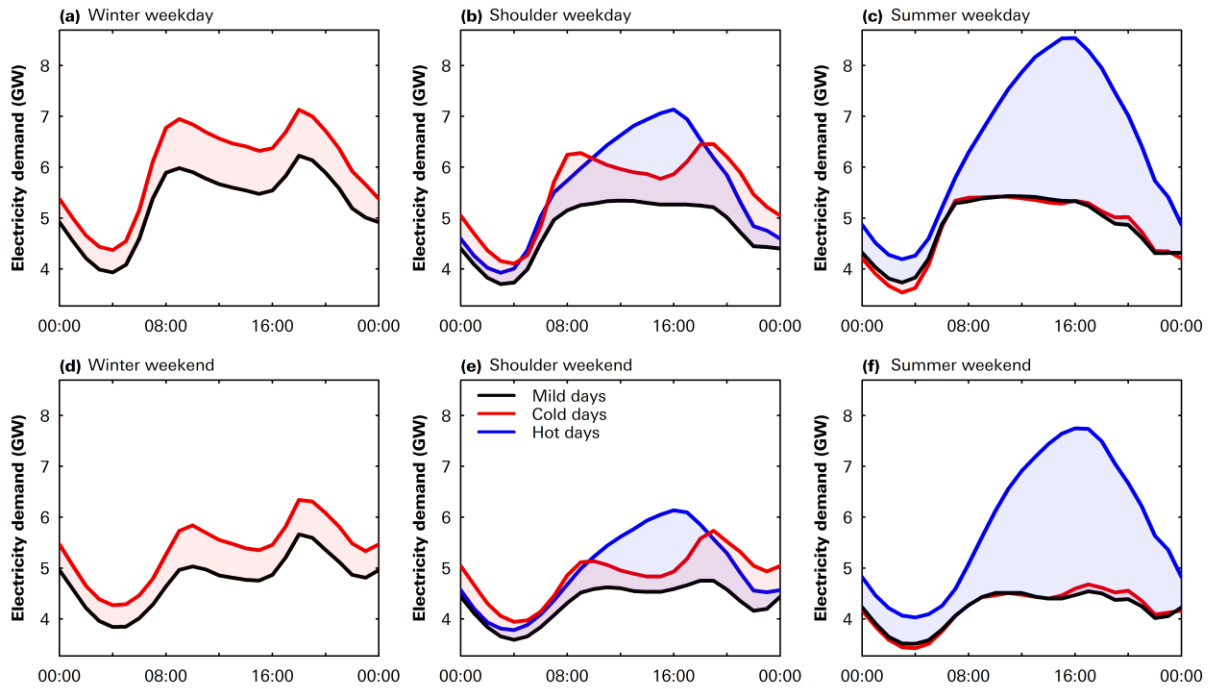
Supplementary Figure 170: Hourly diurnal profiles of electricity demand in New South Wales, Australia. Panels show weekdays (a to c) and weekends (d to f), during the winter (a and d), shoulder (b and e), and summer (c and f) months. Lines show the mean diurnal profile during each group of days, and the shaded areas represent the additional demand experienced during hot and cold days, which we ascribe to cooling and heating respectively. Days that are above the 90th percentile for HDDs or CDDs are classified as cold or hot days, respectively. Days that fall below the 10th percentile for both HDDs and CDDs are classified as mild days.



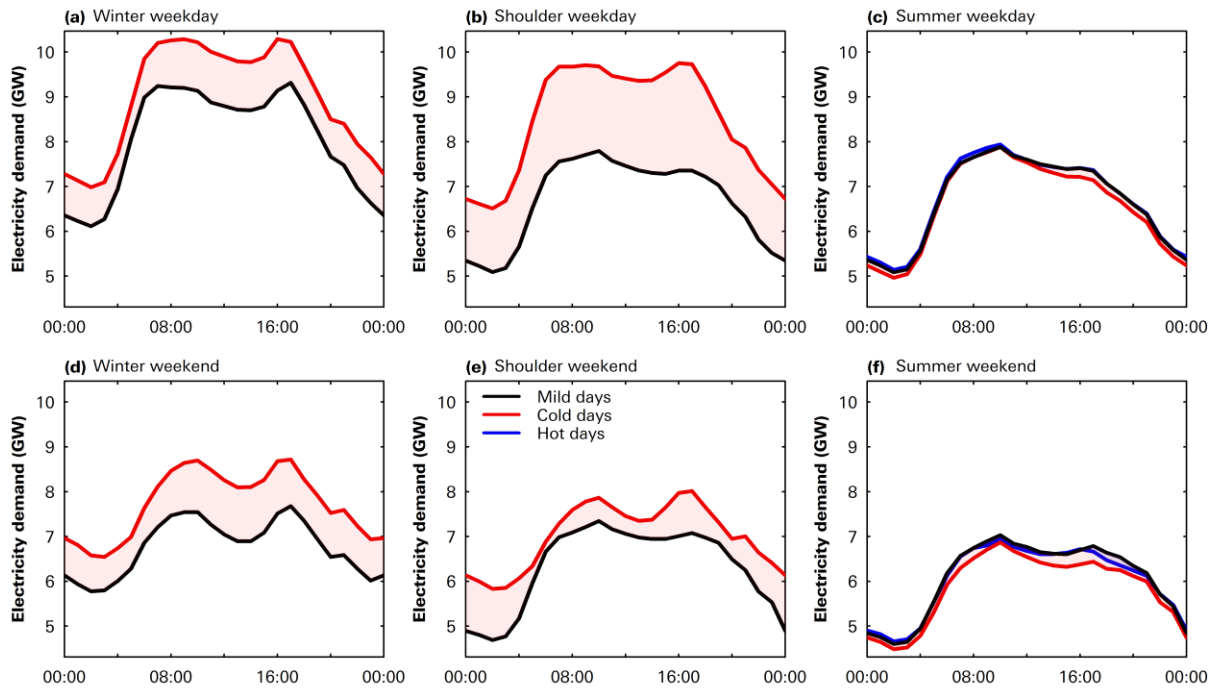
Supplementary Figure 171: Hourly diurnal profiles of electricity demand in Queensland, Australia. Figure follows the same design as Supplementary Figure 170; see the caption there for more detail.



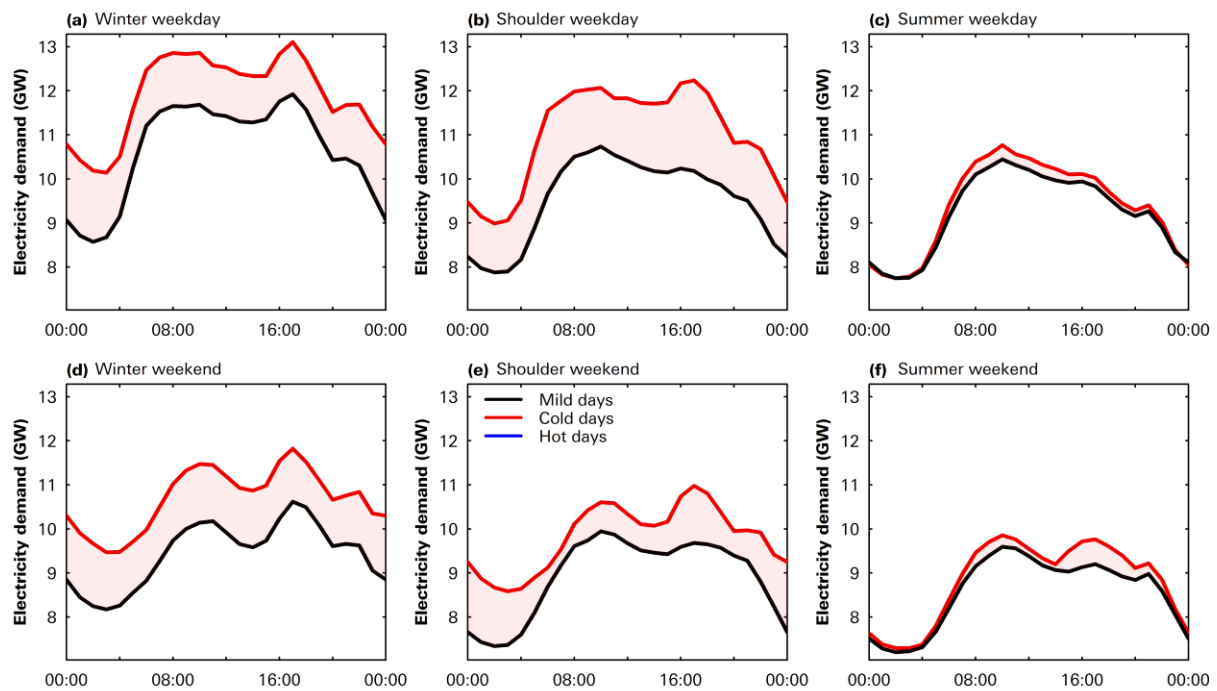
Supplementary Figure 172: Hourly diurnal profiles of electricity demand in Southern Australia. Figure follows the same design as Supplementary Figure 170; see the caption there for more detail.



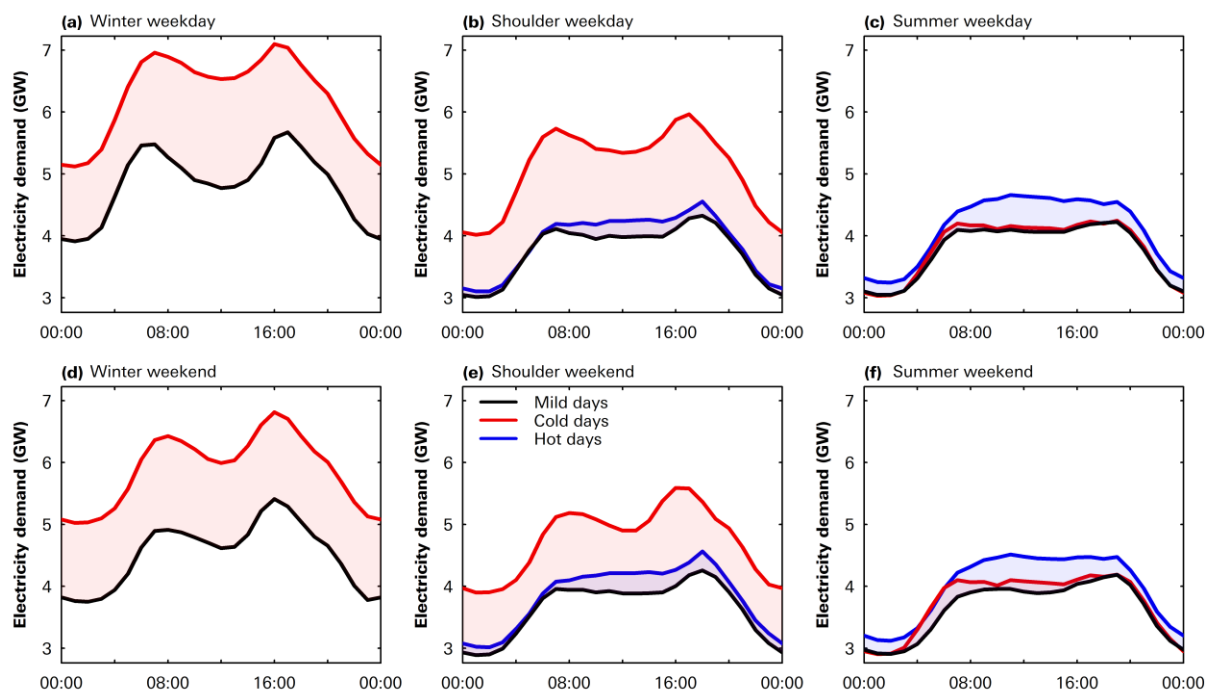
Supplementary Figure 173: Hourly diurnal profiles of electricity demand in Victoria Australia. Figure follows the same design as Supplementary Figure 170; see the caption there for more detail.



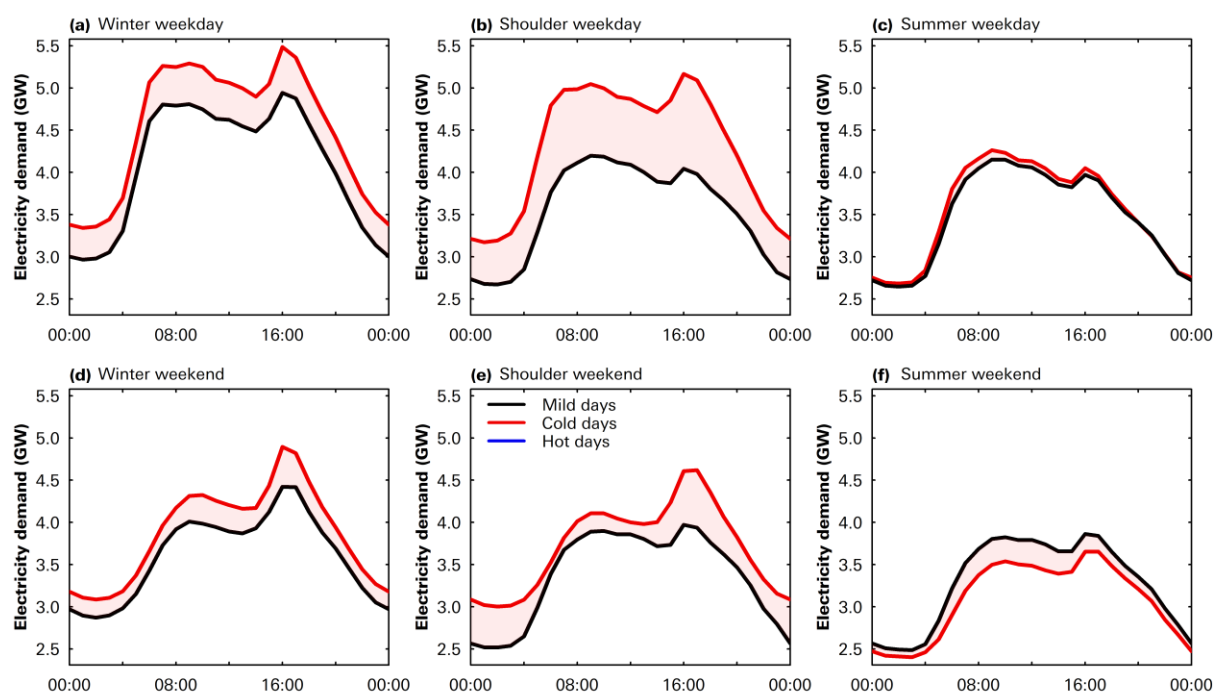
Supplementary Figure 174: Hourly diurnal profiles of electricity demand in Austria. Figure follows the same design as Supplementary Figure 170; see the caption there for more detail.



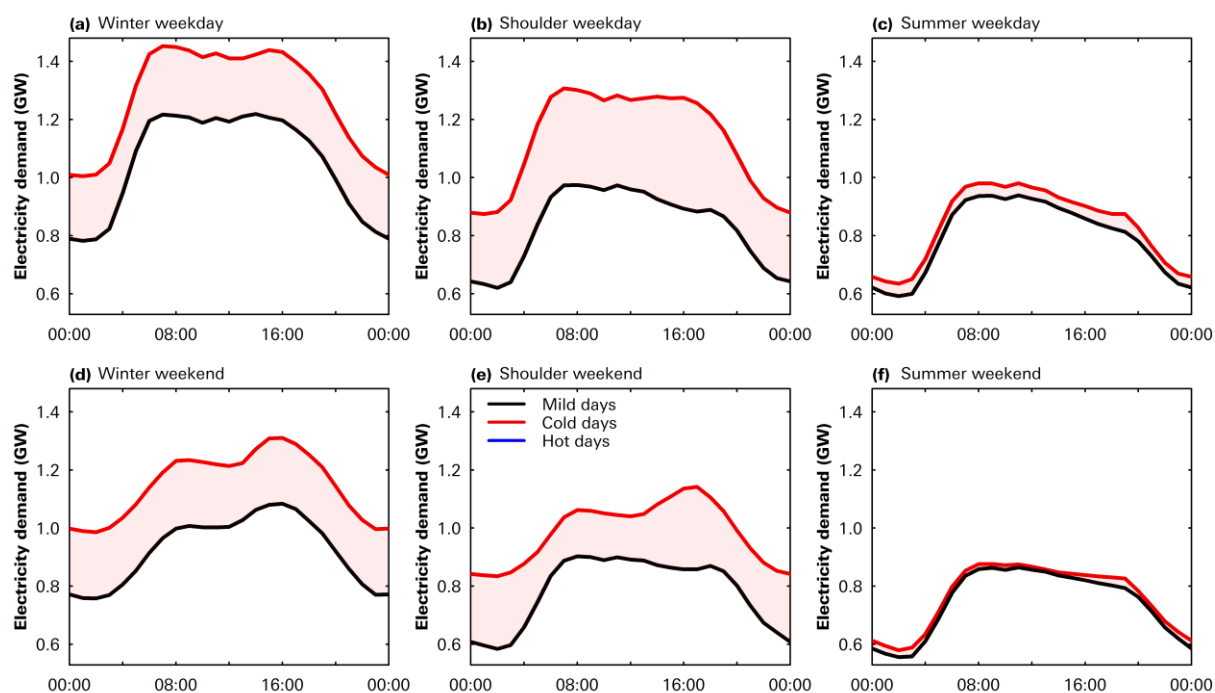
Supplementary Figure 175: Hourly diurnal profiles of electricity demand in Belgium. Figure follows the same design as Supplementary Figure 170; see the caption there for more detail.



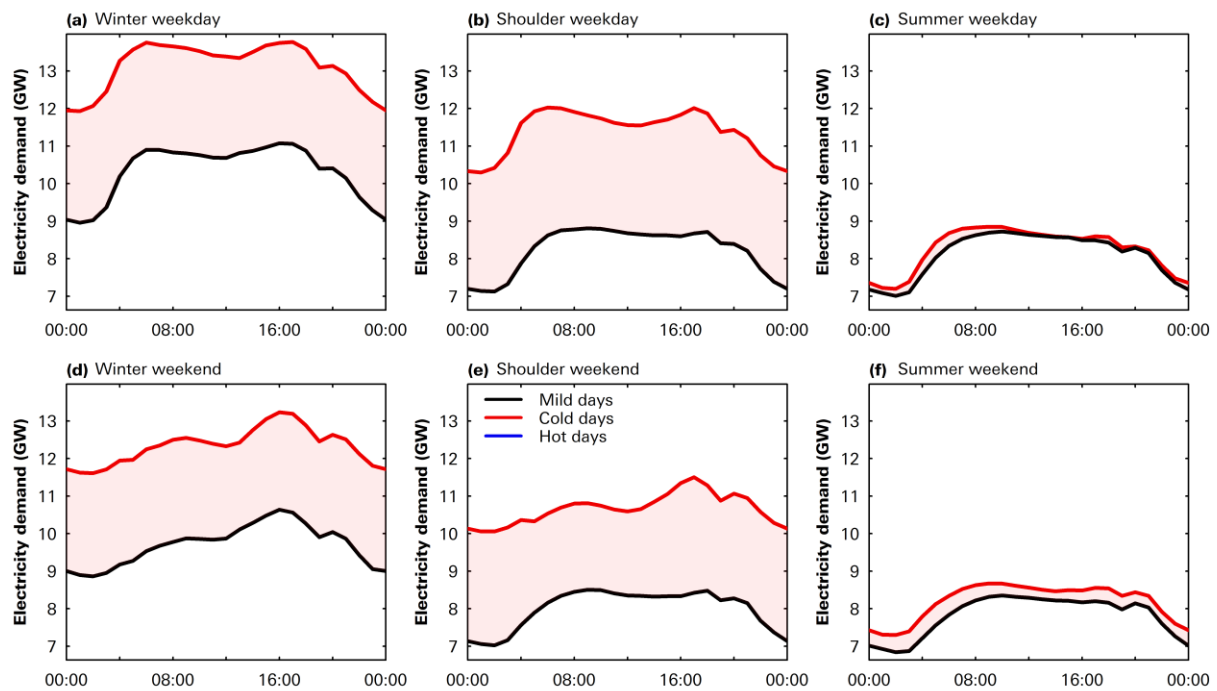
Supplementary Figure 176: Hourly diurnal profiles of electricity demand in Bulgaria. Figure follows the same design as Supplementary Figure 170; see the caption there for more detail.



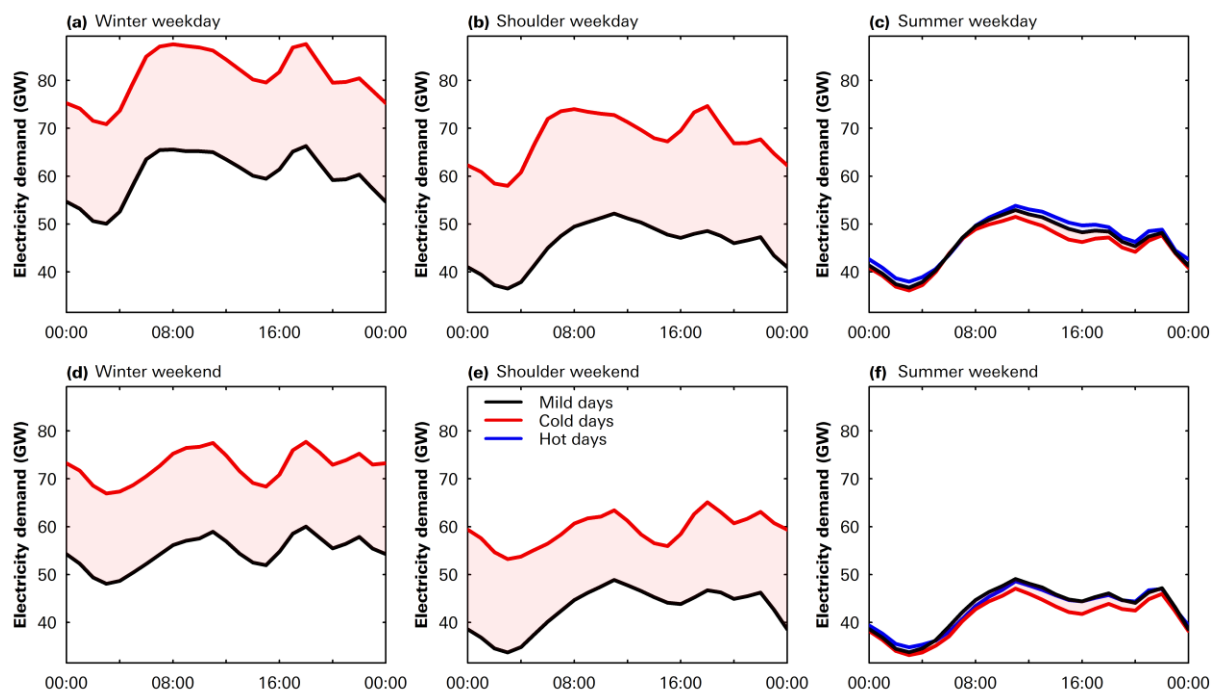
Supplementary Figure 177: Hourly diurnal profiles of electricity demand in Denmark. Figure follows the same design as Supplementary Figure 170; see the caption there for more detail.



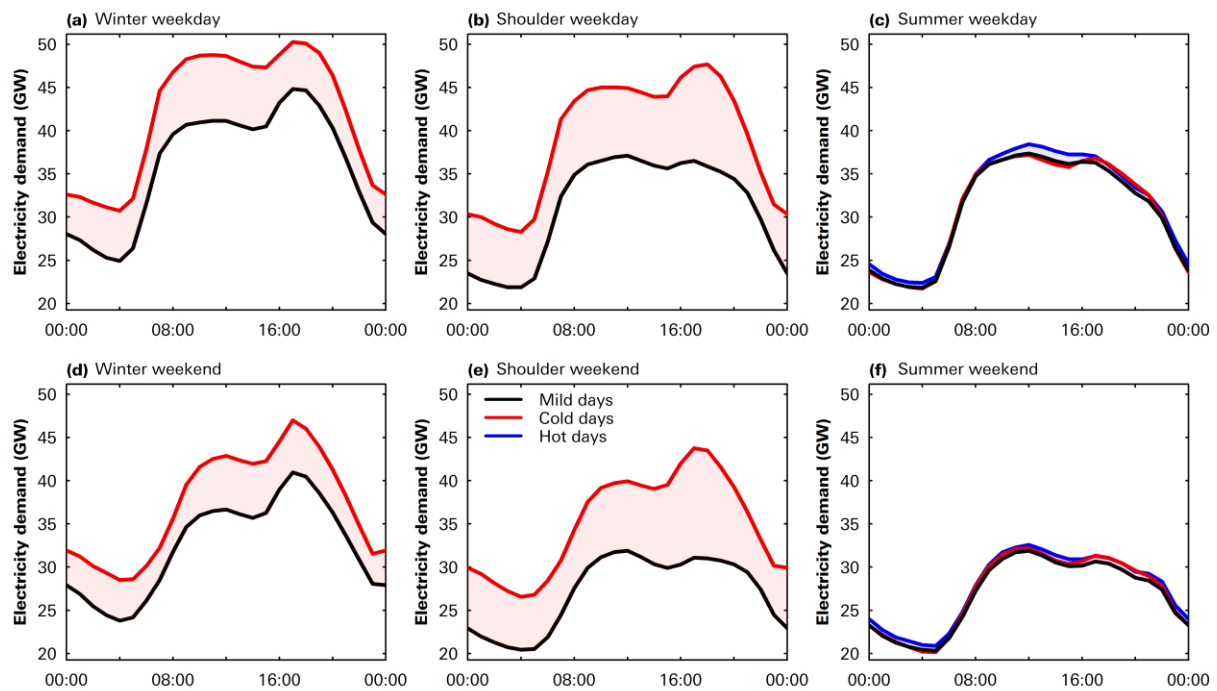
Supplementary Figure 178: Hourly diurnal profiles of electricity demand in Estonia. Figure follows the same design as Supplementary Figure 170; see the caption there for more detail.



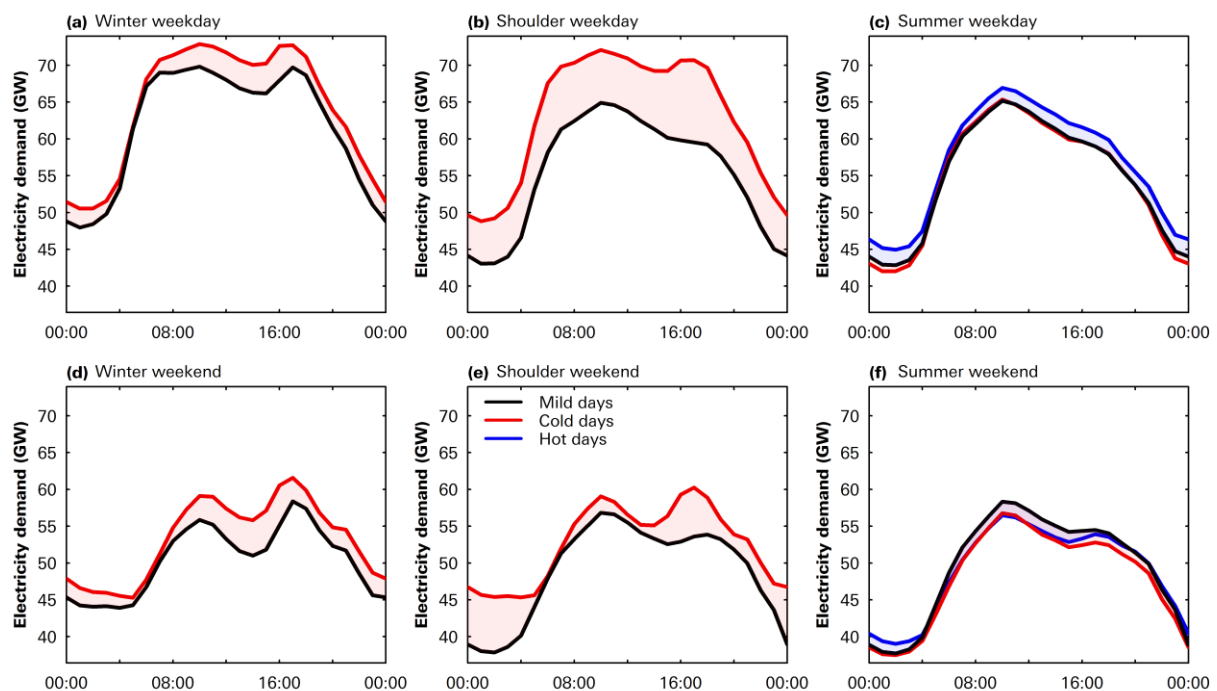
Supplementary Figure 179: Hourly diurnal profiles of electricity demand in Finland. Figure follows the same design as Supplementary Figure 170; see the caption there for more detail.



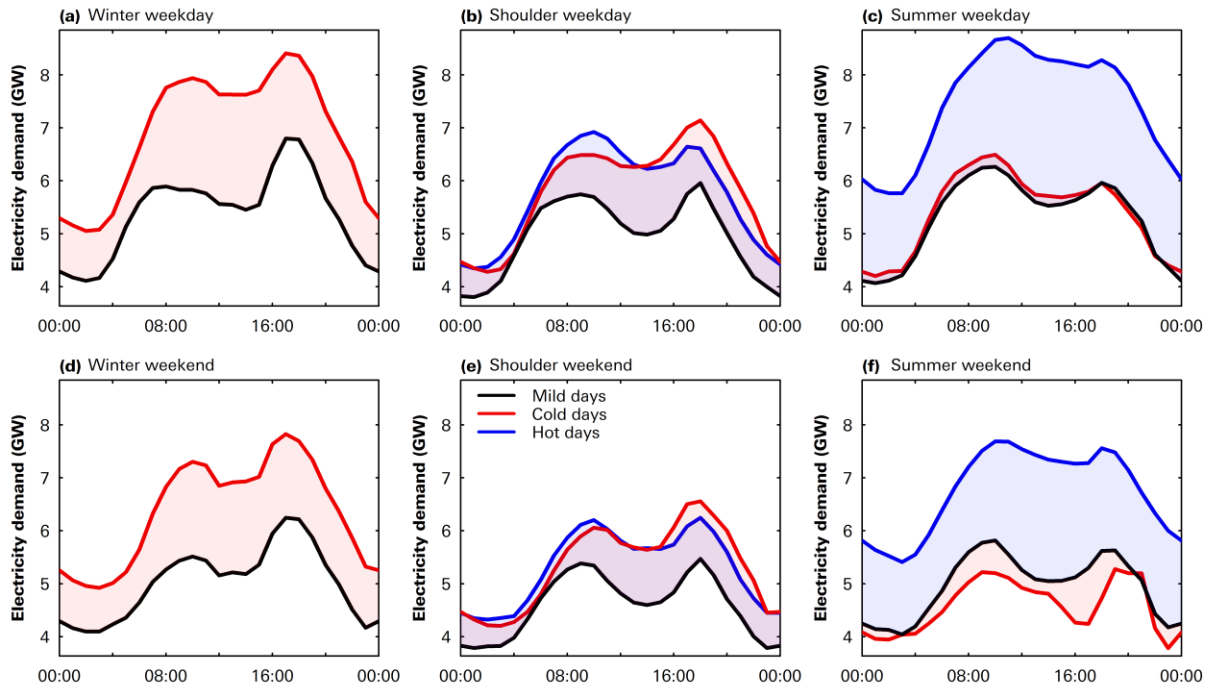
Supplementary Figure 180: Hourly diurnal profiles of electricity demand in France. Figure follows the same design as Supplementary Figure 170; see the caption there for more detail.



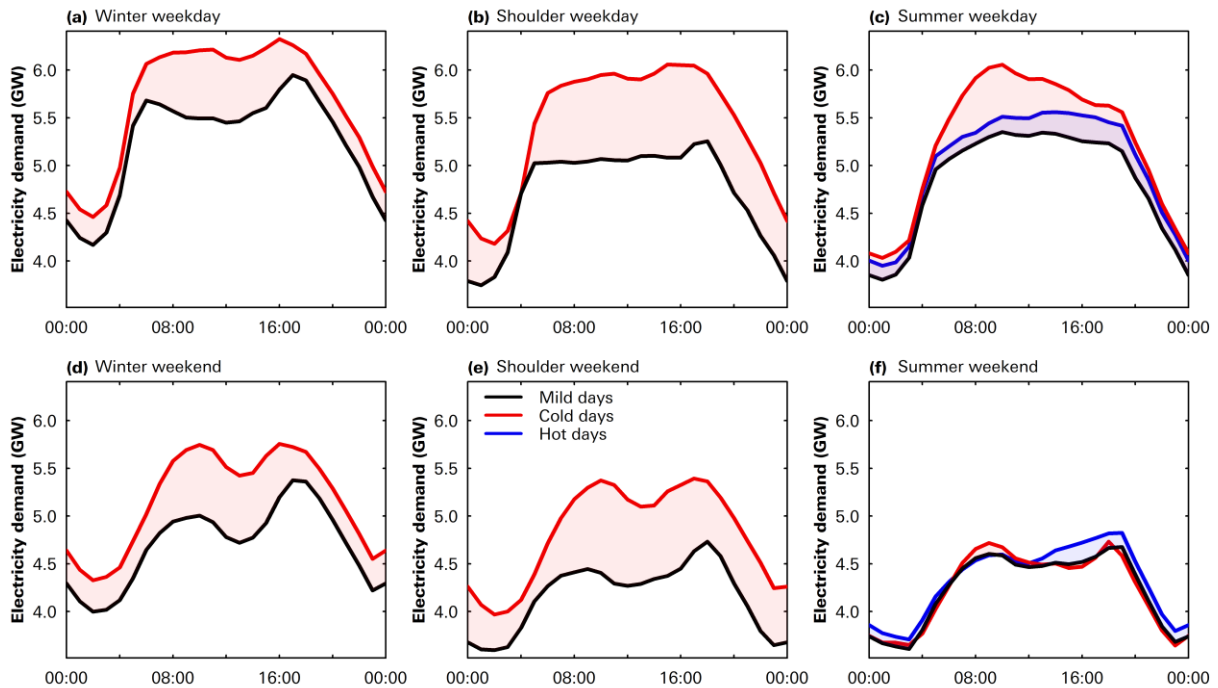
Supplementary Figure 181: Hourly diurnal profiles of electricity demand in Great Britain. Figure follows the same design as Supplementary Figure 170; see the caption there for more detail.



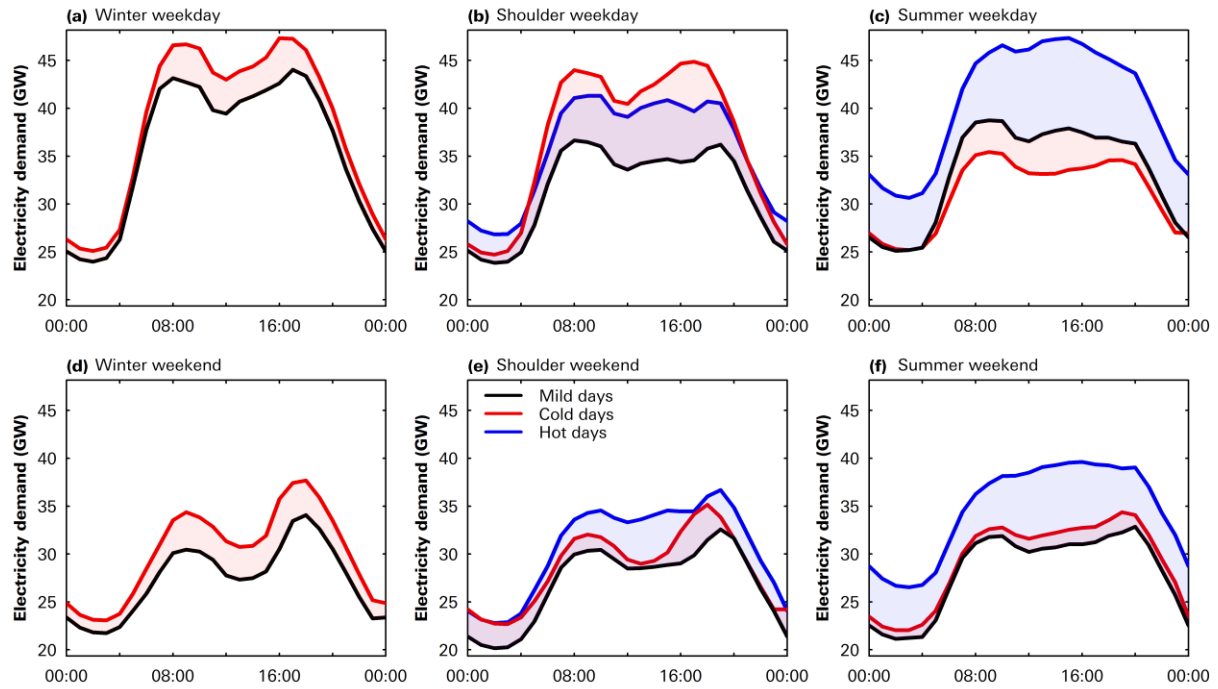
Supplementary Figure 182: Hourly diurnal profiles of electricity demand in Germany. Figure follows the same design as Supplementary Figure 170; see the caption there for more detail.



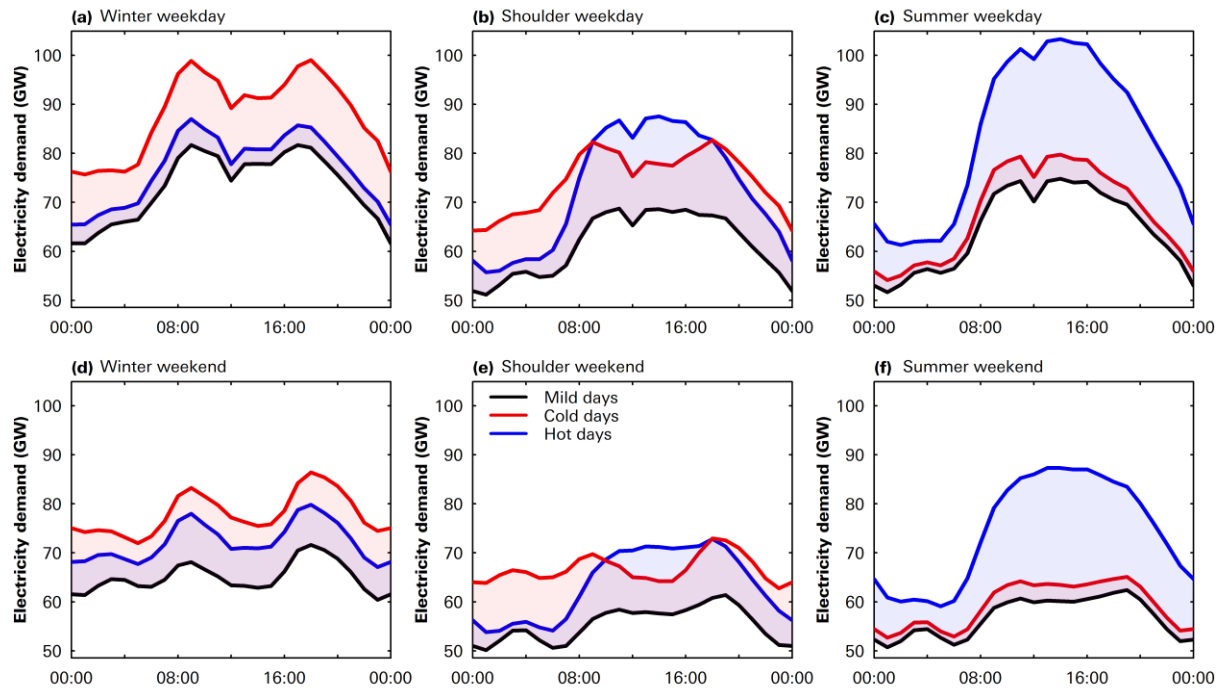
Supplementary Figure 183: Hourly diurnal profiles of electricity demand in Greece. Figure follows the same design as Supplementary Figure 170; see the caption there for more detail.



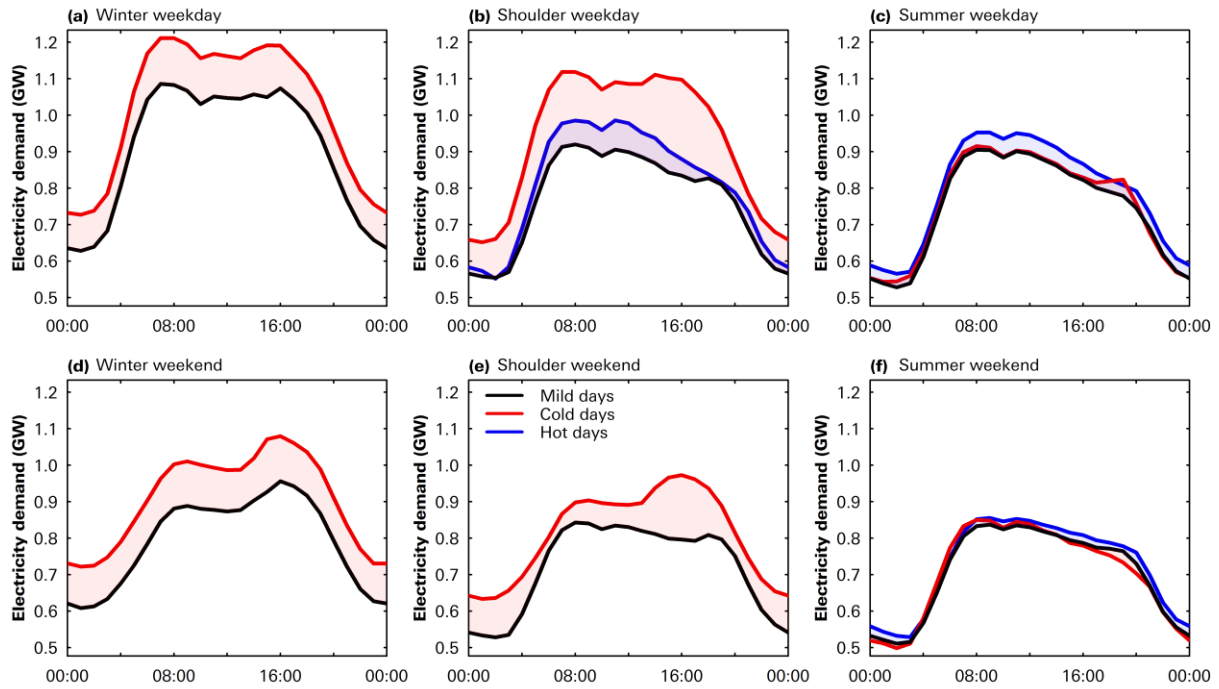
Supplementary Figure 184: Hourly diurnal profiles of electricity demand in Hungary. Figure follows the same design as Supplementary Figure 170; see the caption there for more detail.



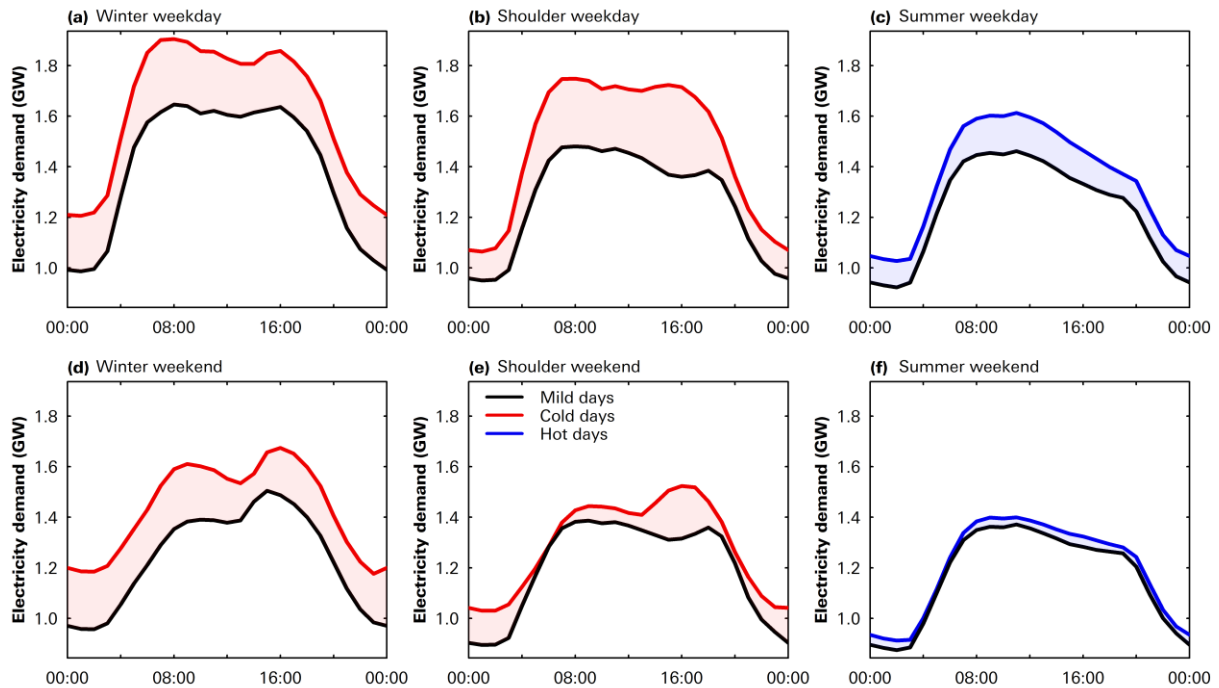
Supplementary Figure 185: Hourly diurnal profiles of electricity demand in Italy. Figure follows the same design as Supplementary Figure 170; see the caption there for more detail.



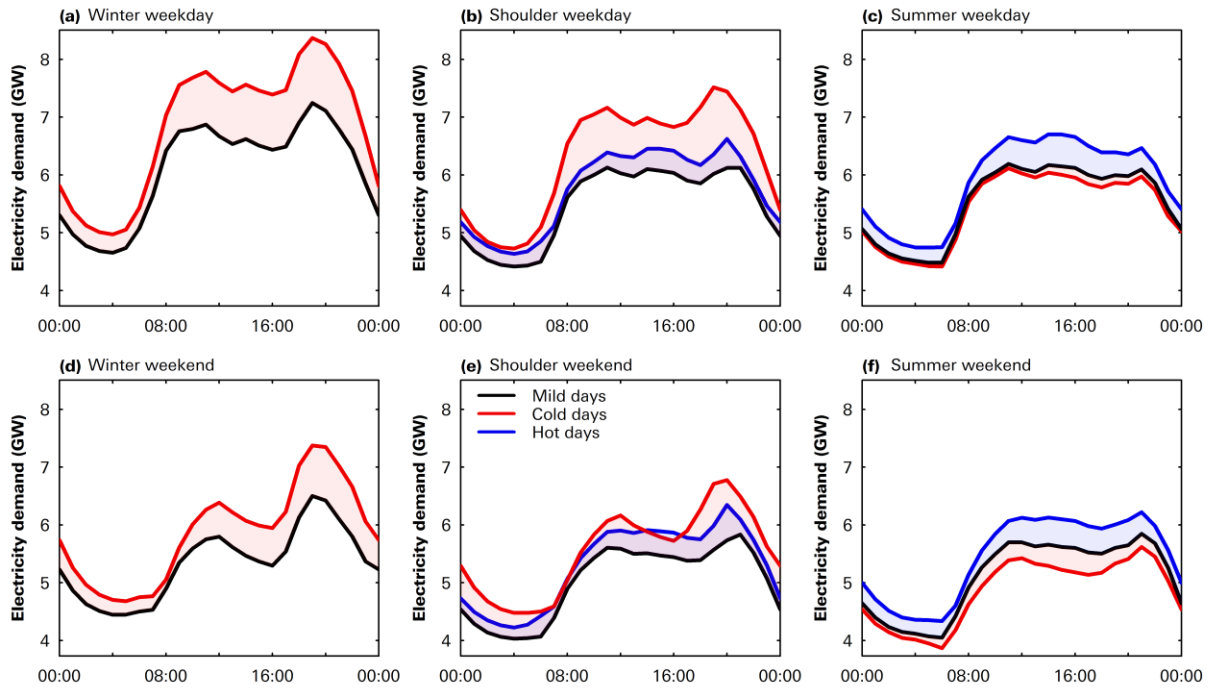
Supplementary Figure 186: Hourly diurnal profiles of electricity demand in Japan. Figure follows the same design as Supplementary Figure 170; see the caption there for more detail.



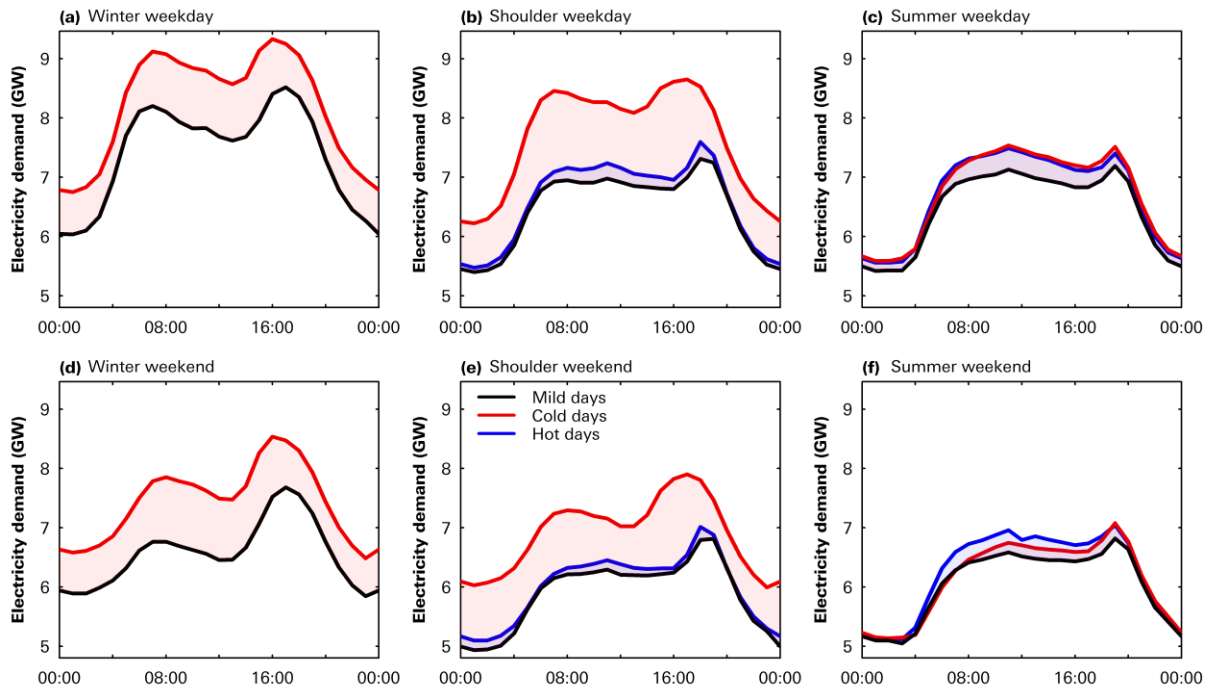
Supplementary Figure 187: Hourly diurnal profiles of electricity demand in Latvia. Figure follows the same design as Supplementary Figure 170; see the caption there for more detail.



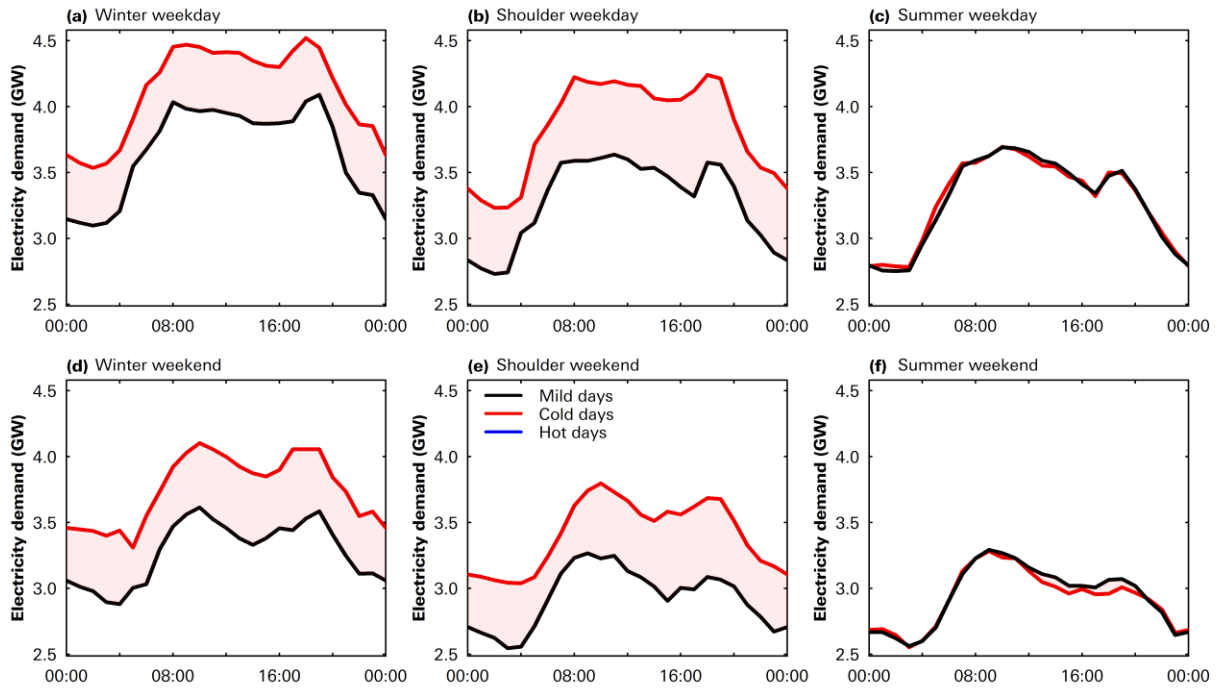
Supplementary Figure 188: Hourly diurnal profiles of electricity demand in Lithuania. Figure follows the same design as Supplementary Figure 170; see the caption there for more detail.



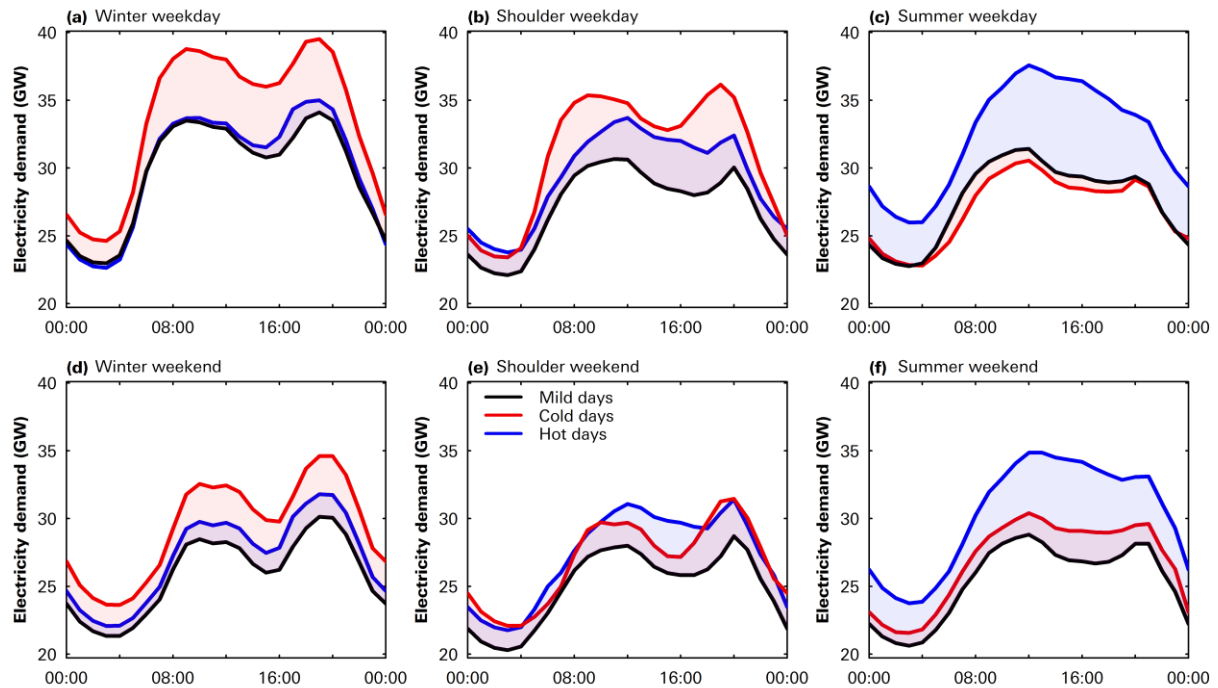
Supplementary Figure 189: Hourly diurnal profiles of electricity demand in Portugal. Figure follows the same design as Supplementary Figure 170; see the caption there for more detail.



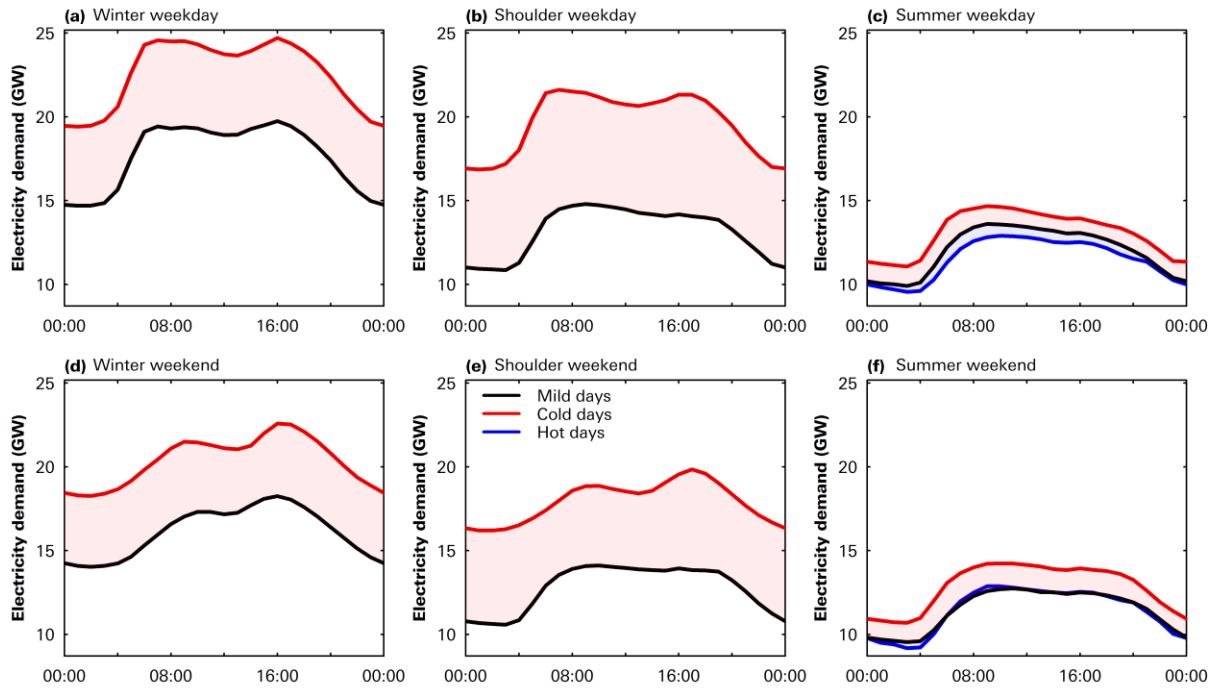
Supplementary Figure 190: Hourly diurnal profiles of electricity demand in Romania. Figure follows the same design as Supplementary Figure 170; see the caption there for more detail.



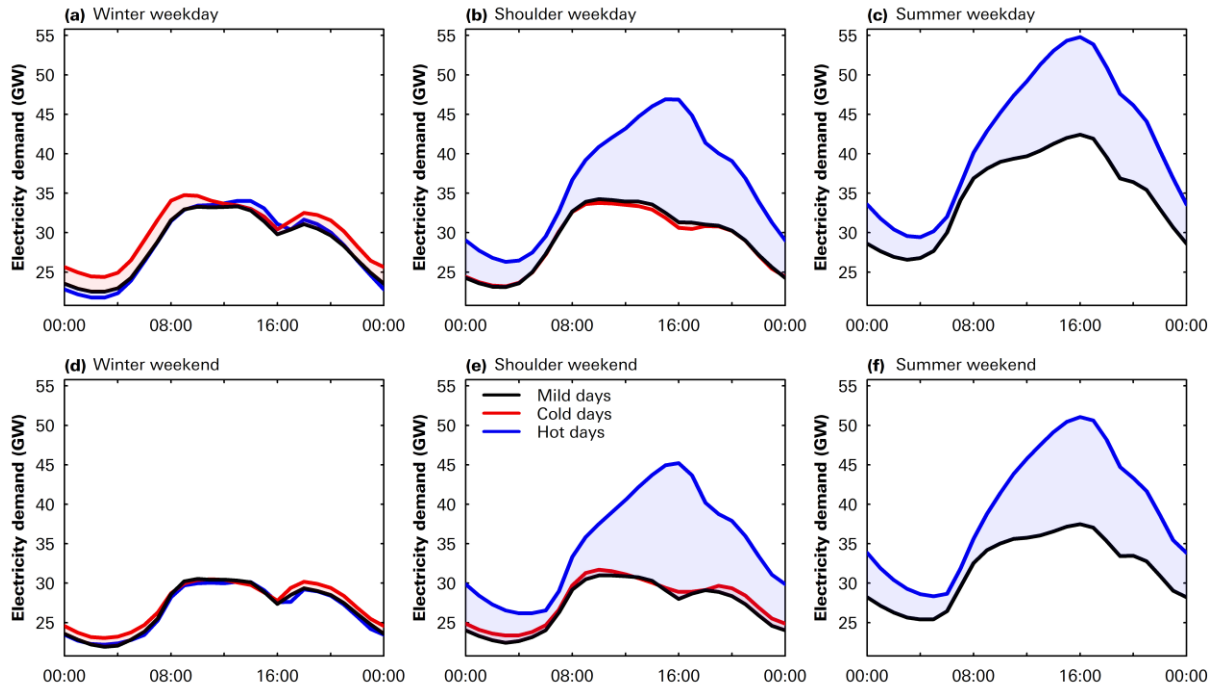
Supplementary Figure 191: Hourly diurnal profiles of electricity demand in Slovakia. Figure follows the same design as Supplementary Figure 170; see the caption there for more detail.



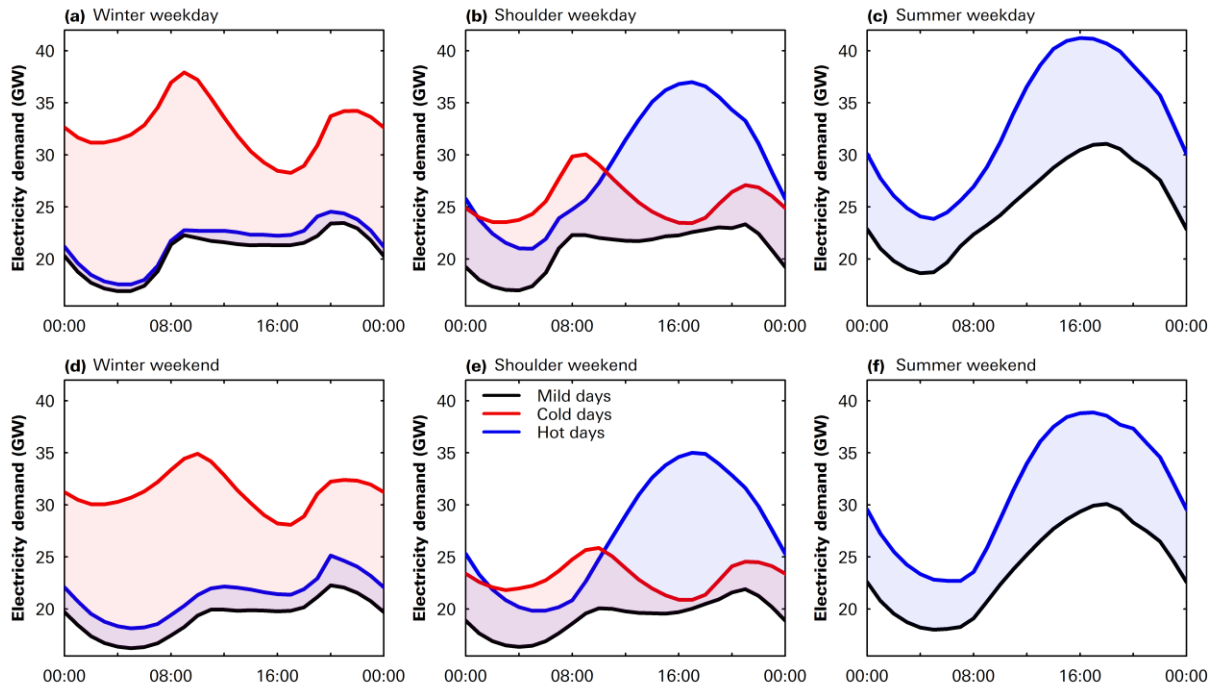
Supplementary Figure 192: Hourly diurnal profiles of electricity demand in Spain. Figure follows the same design as Supplementary Figure 170; see the caption there for more detail.



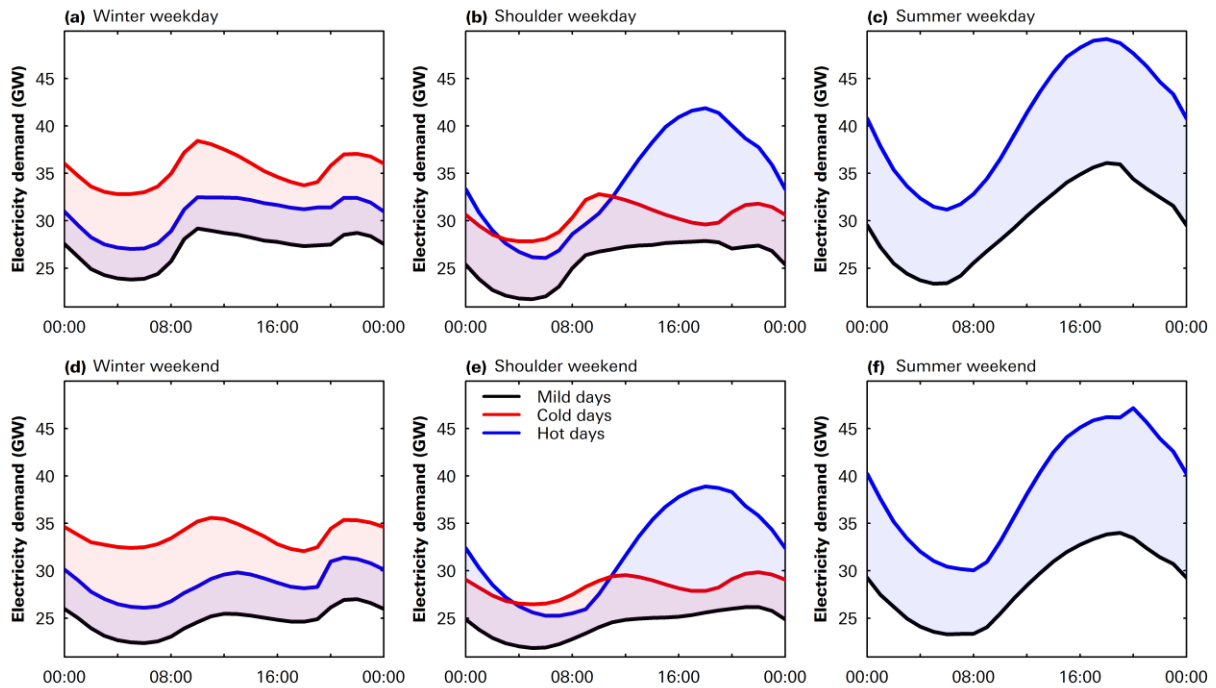
Supplementary Figure 193: Hourly diurnal profiles of electricity demand in Sweden. Figure follows the same design as Supplementary Figure 170; see the caption there for more detail.



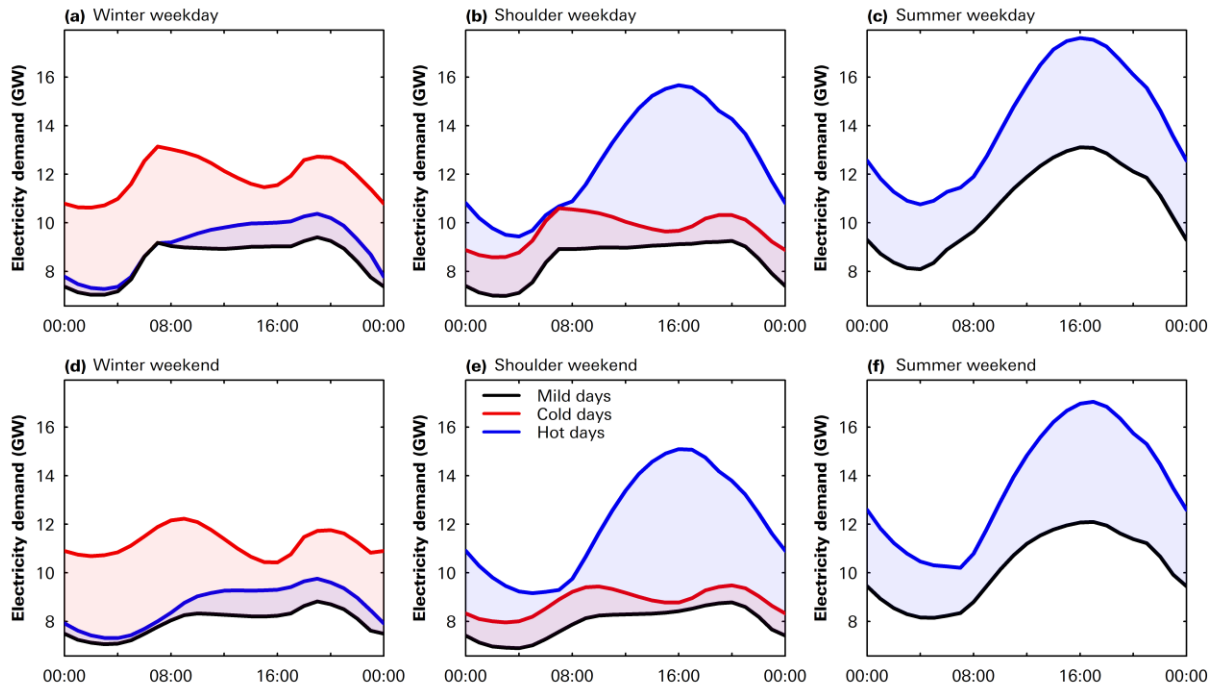
Supplementary Figure 194: Hourly diurnal profiles of electricity demand in the CAISO electricity market (US). Figure follows the same design as Supplementary Figure 170; see the caption there for more detail.



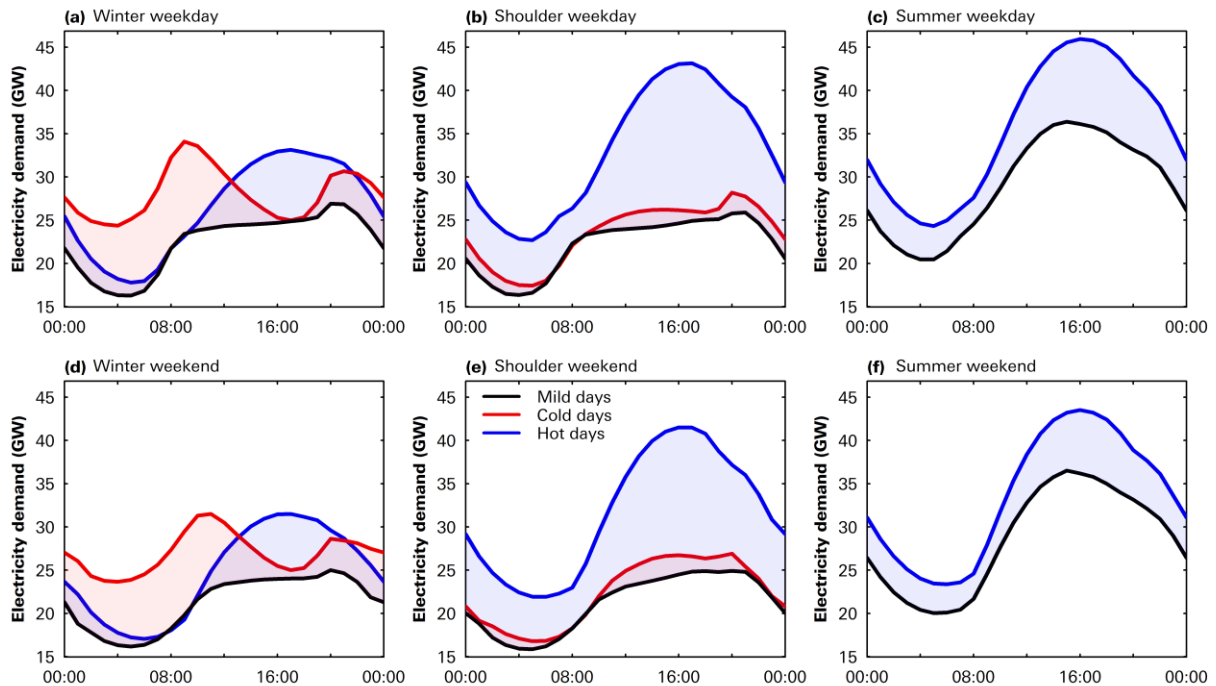
Supplementary Figure 195: Hourly diurnal profiles of electricity demand in the Carolinas electricity market (US). Figure follows the same design as Supplementary Figure 170; see the caption there for more detail.



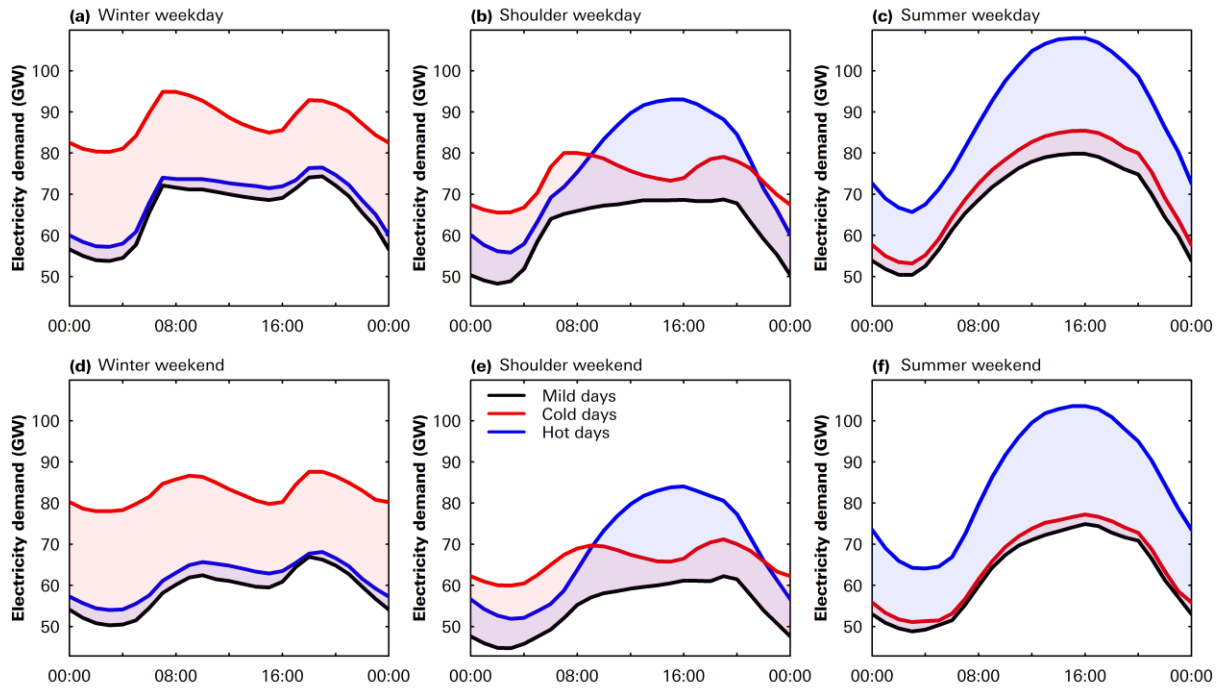
Supplementary Figure 196: Hourly diurnal profiles of electricity demand in the Central electricity market (US). Figure follows the same design as Supplementary Figure 170; see the caption there for more detail.



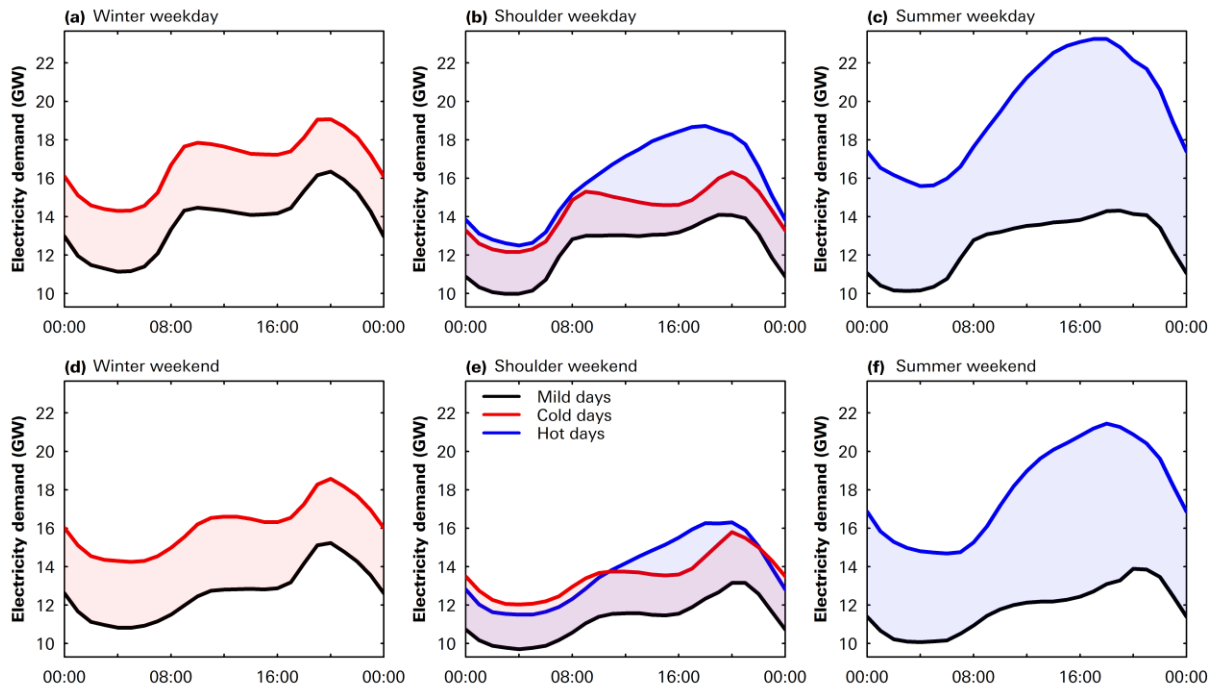
Supplementary Figure 197: Hourly diurnal profiles of electricity demand in the ERCOT electricity market (US). Figure follows the same design as Supplementary Figure 170; see the caption there for more detail.



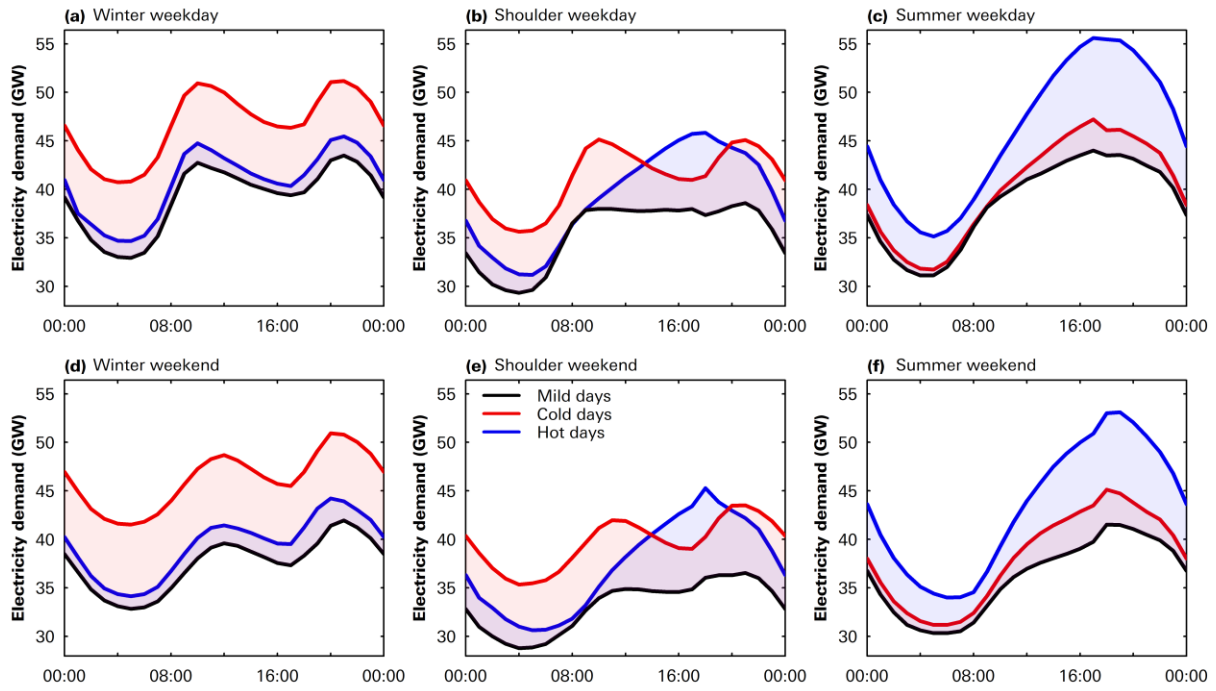
Supplementary Figure 198: Hourly diurnal profiles of electricity demand in the Florida electricity market (US). Figure follows the same design as Supplementary Figure 170; see the caption there for more detail.



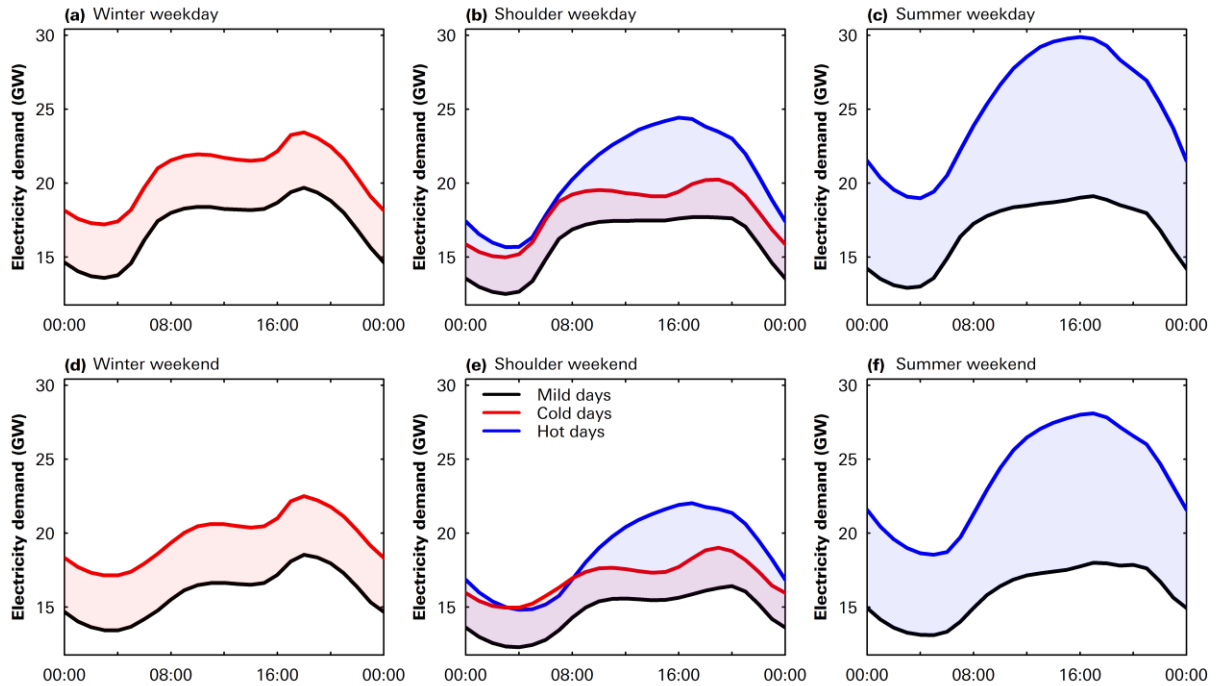
Supplementary Figure 199: Hourly diurnal profiles of electricity demand in the MISO electricity market (US). Figure follows the same design as Supplementary Figure 170; see the caption there for more detail.



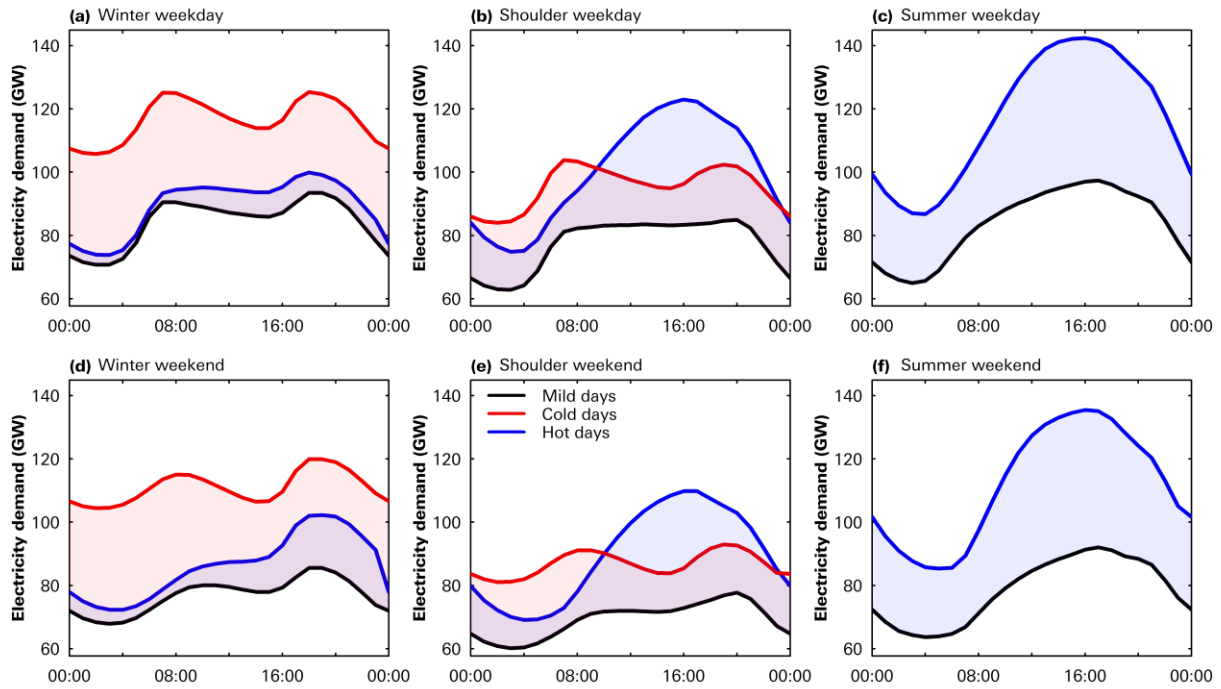
Supplementary Figure 200: Hourly diurnal profiles of electricity demand in the ISONE electricity market (US). Figure follows the same design as Supplementary Figure 170; see the caption there for more detail.



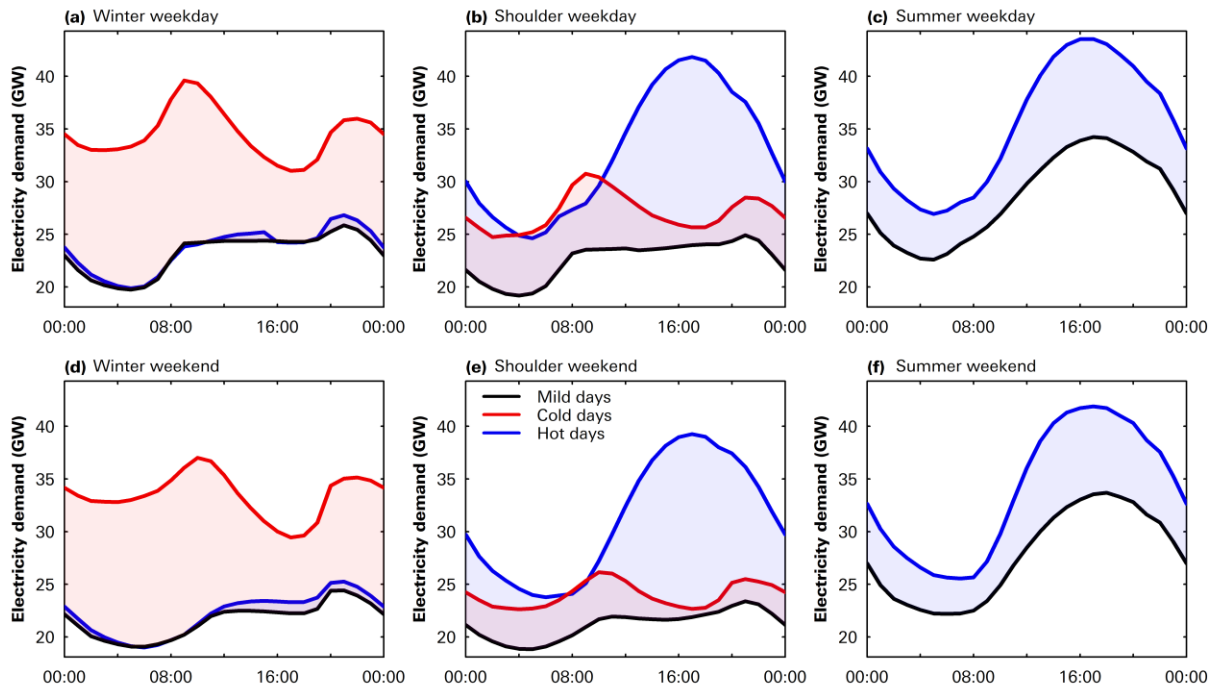
Supplementary Figure 201: Hourly diurnal profiles of electricity demand in the Northwest electricity market (US). Figure follows the same design as Supplementary Figure 170; see the caption there for more detail.



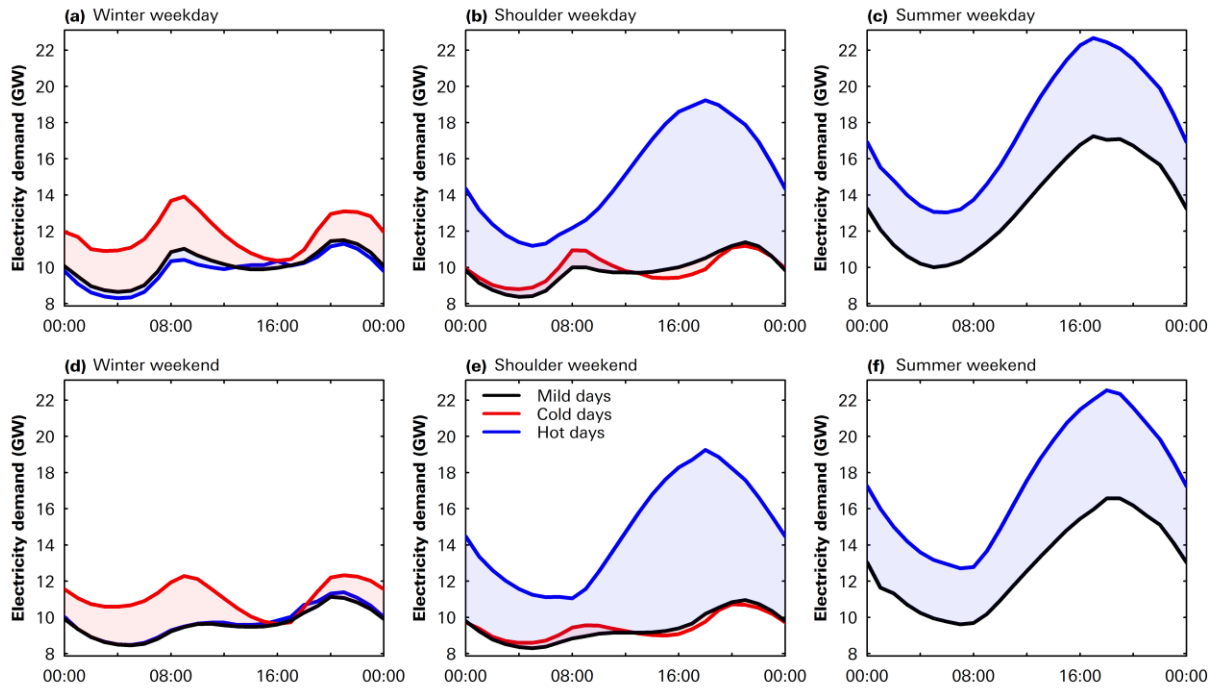
Supplementary Figure 202: Hourly diurnal profiles of electricity demand in the NYISO electricity market (US). Figure follows the same design as Supplementary Figure 170; see the caption there for more detail.



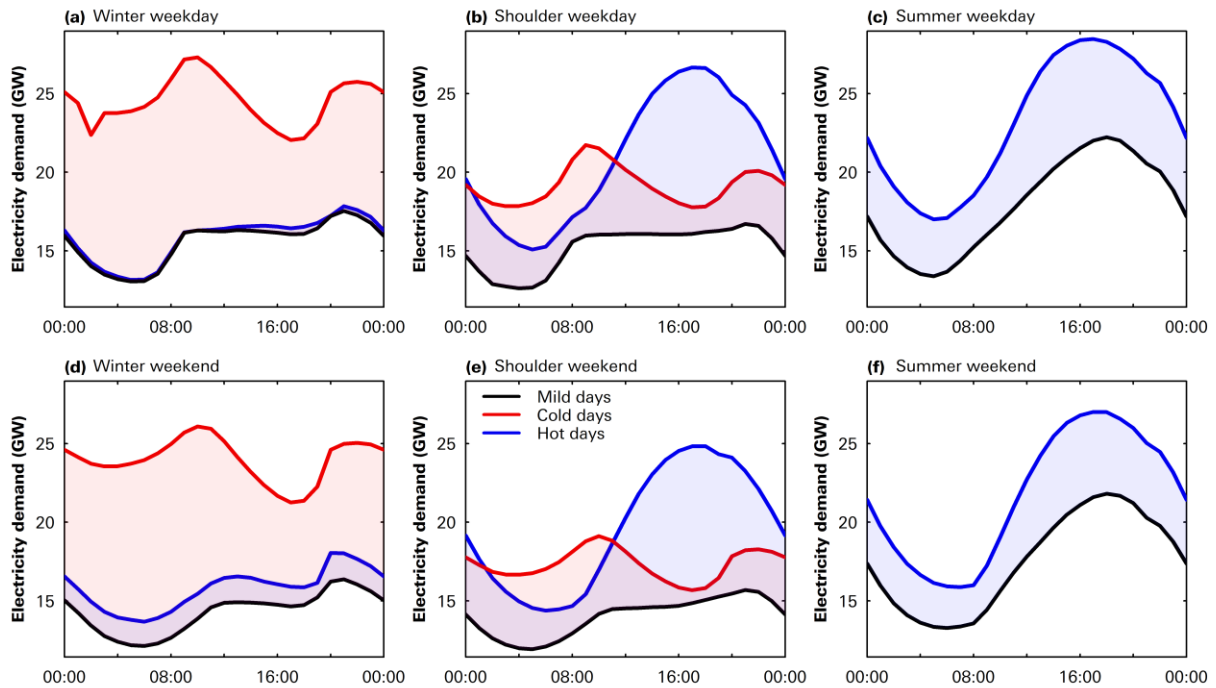
Supplementary Figure 203: Hourly diurnal profiles of electricity demand in the PJM electricity market (US). Figure follows the same design as Supplementary Figure 170; see the caption there for more detail.



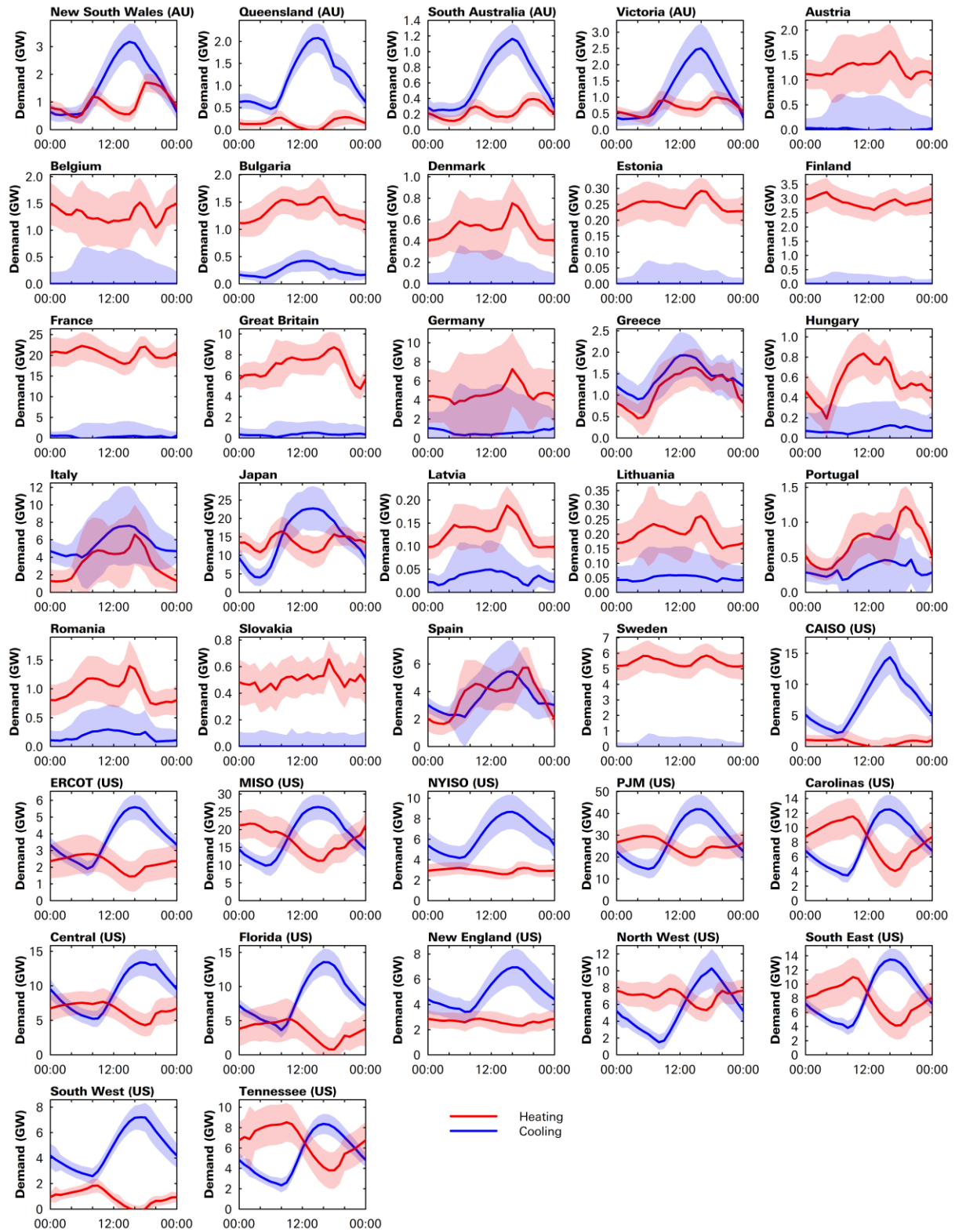
Supplementary Figure 204: Hourly diurnal profiles of electricity demand in the Southeast electricity market (US). Figure follows the same design as Supplementary Figure 170; see the caption there for more detail.



Supplementary Figure 205: Hourly diurnal profiles of electricity demand in the Southwest electricity market (US). Figure follows the same design as Supplementary Figure 170; see the caption there for more detail.



Supplementary Figure 206: Hourly diurnal profiles of electricity demand in the Tennessee electricity market (US). Figure follows the same design as Supplementary Figure 170; see the caption there for more detail.



Supplementary Figure 207: Hourly diurnal profiles of electricity demand for heating and cooling across all countries and regions for which we have data. Profiles are generated by subtracting diurnal demand during mild days from demand during hot / cold days. Lines show the mean profile and shaded areas show the standard deviation across all days.

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