

A global base temperature dataset for **residential** building energy demand modelling

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Abstract. Accurate building energy demand modelling is critical to decarbonizing regional energy systems. The cooling and heating degree-day models are widely used due to their simplicity and low data requirements; however, the lack of accurate base temperature data limits their performance. In particular, the scarcity of high temporal resolution building energy demand data constrains regional-scale base temperature estimation through conventional methods such as the energy signature method and the performance line method. To address this limitation, this study develops a global regional-scale base temperature dataset based on the BiLSTM neural network framework with an attention mechanism. The dataset includes both cooling base temperature (*Tcool*) and heating base temperature (*Theat*) for each region, defined at a spatial scale equivalent to a U.S. state or a Chinese province. The BiLSTM framework demonstrates strong performance, with RMSE values of 1.39°C for training and 1.33°C for testing, and Pearson correlation coefficients of 0.84 for *Tcool* and 0.70 for *Theat*. Predicted results show that global *Tcool* ranges from 19-25°C and *Theat* from 14-18°C, consistent with physical principles. External validations using 16 independent datasets demonstrate that the predicted base temperatures **consistently** improve the accuracy of building energy demand modelling, reducing RMSE by **approximately 10% for both cooling and heating**, compared to official or empirical base temperatures. This dataset supplements sparse observational base temperature data and enhances the accuracy of building energy demand modelling, contributing to low-carbon energy system planning and broader climate impact assessment. The proposed global *Tbase* dataset can be acquired from <https://doi.org/10.6084/m9.figshare.30646376.v2> (He et al., 2025a).

1 Introduction

Reductions in energy demand and carbon emissions in the building sector play a crucial role in achieving the low-carbon energy system transition and the Paris Agreement climate goals (Camarasa et al., 2022). **Buildings accounted for 36% of global end-use energy and contributed approximately 39% of energy and process-related CO₂ emissions in 2018, with space heating and cooling representing a major component of total building energy use (UN, 2019). However, building energy demand varies substantially across regions because it is strongly shaped by local climate, ambient temperature, occupant behaviour, and socioeconomic conditions (Deroubaix et al., 2021; Wenz et al., 2017; Staffell et al., 2023).** An increase in ambient temperature will reduce heating demand

but increase cooling demand across different regions (Abajian et al., 2025; Wang et al., 2023; Filahi et al., 2025; Clarke et al., 2018; Zhou et al., 2013), and identical building configurations exhibit distinct energy demand patterns across different climate zones (Mahdavinejad et al., 2024; Yu et al., 2014). Beyond climate zones, terrain and topography further modulate local microclimate, ventilation, and solar exposure, thereby shaping heating and cooling energy demand and occupant responses (Papada & Kaliampakos, 2016; Zhang et al., 2024a). Occupant responses to temperature changes, such as adjusting clothing, using air-conditioning, or changing activity patterns, further contribute to this spatial heterogeneity (Bae et al., 2025; Gupta et al., 2024; IEA, 2024). Accurate characterization of building energy demand therefore requires approaches that account for regional differences rather than assuming uniform responses across locations.

The degree-day method is one of the most commonly used approaches for modelling heating and cooling energy demand in buildings. Degree-day models exhibit substantial advantages in terms of data availability and geographic generalization when compared to physical and statistical models (Prataviera et al., 2021; Ahmad et al., 2018). The base temperatures define thresholds for heating (below the heating base temperature) or cooling (above the cooling base temperature) in buildings (De Rosa et al., 2015; Martinopoulos et al., 2019). Degree days are calculated as the difference between the average daily temperature and this base temperature, with values below the threshold being the heating degree day (HDD) and those above the threshold being the cooling degree day (CDD). Base temperature values are influenced by local climatic conditions, occupant behaviour, building types, and thermal properties (Ramon et al., 2020; Hao et al., 2022), which suggests significant spatial heterogeneity in base temperature selection. Moreover, base temperature has been linked to indoor thermal comfort, which differs across populations, so the temperature thresholds for initiating heating or cooling vary between regions (Staffell et al., 2023). In the United States, 18.3°C is the most common base temperature, above which cooling demand is considered to increase and below which heating demand increases (Petri & Caldeira, 2015). In the UK, the HDD and CDD are calculated using 15.5°C and 22°C as the base temperatures, respectively (UK Climate Projections, 2014). In China, 18°C and 24°C are widely used as the base temperatures for the degree-day model (Yang et al., 2024; Li et al., 2018). Conventionally, recommended base temperatures have served as key parameters in modelling heating and cooling energy demand across buildings, regions, and countries (Camarasa et al., 2022; Deroubaix et al., 2021). However, the application of uniform base temperatures across broad geographical areas inadequately represents the sensitivity of building energy demand to local climatic variations, raising concerns about the accuracy and uncertainty of degree-day modelling. To illustrate, a 1°C change in the base temperature can result in approximately 20 additional or fewer CDDs per month in San Luis Obispo (Woods & Fuller, 2014). Inaccurate base temperatures also trigger a nonlinear relationship between building energy demand and degree days (Day et al., 2003).

Accurate base temperature selection is essential for reliable degree-day modelling. The energy signature approach and performance line analysis are commonly used to determine optimal base temperatures at regional scales by integrating building energy consumption data and local meteorological data (Bhatnagar et al., 2018; Staffell et al., 2023; Anjomshoaa & Salmanzadeh, 2017; Woods & Fuller, 2014). In the energy signature method, energy consumption is correlated with outdoor temperature to identify a non-linear relationship, and the inflection point of the resulting curve is taken as the base temperature (Anjomshoaa & Salmanzadeh, 2017; Meng et al., 2018). The performance line method estimates the base temperature by plotting the best-fit straight line of energy consumption relative to the HDD or CDD (Bhatnagar et al., 2018). A major strength of both approaches is that

they use observed energy use that integrates local weather conditions and occupancy behaviour, providing empirically grounded base temperatures for specific regions. For example, Bhatnagar et al. (2018) applied both the energy signature method and the performance line method to determine base temperatures across 60 Indian cities, reporting median base temperatures of 18.3°C for cooling and 17.4°C for heating. In Kerman, Iran, the L-curve relationship between average daily temperature and natural gas consumption is derived using the energy signature method, revealing base temperatures of 15.42 and 21.18°C for the region (Anjomshoaa & Salmanzadeh, 2017). Furthermore, Staffell et al. (2023) evaluated indoor temperature thresholds for heating and cooling across several countries and regions based on the energy signature method. However, these benchmark methods also have important limitations. They typically require building energy consumption data at high temporal resolution together with matched meteorological records, which restricts their application to data-rich regions and makes large scale or global benchmarking costly and impractical. Consequently, although these methods are valuable for local and regional calibration, they cannot be readily extended to produce consistent base temperature estimates across data scarce regions worldwide.

When empirical base temperature calibration is unavailable, regional and global assessments of temperature-dependent building energy demand often rely on harmonized base temperatures rather than locally derived values (e.g., Deroubaix et al., 2021; Scoccimarro et al., 2023; Falchetta et al., 2024). This reliance may obscure spatial heterogeneity in building climate responses and reduce the reliability of degree-day-based energy modelling at broader scales. These challenges highlight the critical need for a practical methodology that can predict base temperatures at a global scale using limited data—a prerequisite for accurate global energy demand modelling. To address this gap, this research develops a global regional-scale base temperature dataset by combining energy demand derived labels from segmented linear regression with a BiLSTM framework incorporating an attention mechanism. Using limited building energy observations together with regional weather and socioeconomic data, cooling base temperature (T_{cool}) and heating base temperature (T_{heat}) are mapped at provincial resolution and upscaled to continuous global maps. An integrated validation framework is further established to assess the reliability of the predicted base temperatures for building energy demand modelling. The resulting dataset provides spatially explicit base temperature information to support regional energy demand modelling and low-carbon energy system planning.

2 Data and methods

2.1 Data

Energy demand data

The energy demand data encompasses multi-timescale time series electricity or natural gas demand data from 172 regions worldwide (see Table A1). These data are utilized to estimate region-specific base temperatures (T_{base}), which serve as critical input data for subsequent analyses. Two types of energy demand are considered: building-level and region-level. Building-level energy demand data predominantly consists of residential demand across various temporal resolutions (second, minute, and hourly intervals), which are aggregated to a daily scale (kWh d^{-1}) to better reflect seasonal patterns linked to local temperatures and weather conditions. Due to the scarcity of available residential data, a small number of public building energy demand datasets are also included to expand coverage. Region-level energy demand data, available at daily and monthly temporal scales (kWh d^{-1}

or MWh month⁻¹), can also capture seasonal variations when the time series is sufficiently long, as demonstrated by Wenz et al. (2017), Huang & Gurney (2016), and Staffell et al. (2023). All energy demand datasets are spatially matched to the finest available administrative boundaries using location metadata, thereby enabling integrated analysis with local climatic conditions.

Meteorological variables

Meteorological data are primary drivers of temporal variations in building energy demand. This study utilizes five key variables from the ERA5-Land Reanalysis data (monthly averages from 1950 to present): 2-meter air temperature (T2m, K), dew point temperature (Td, K), 10-m u- and v-components of wind (u, v, m s⁻¹), and surface downward solar radiation (SSRD, J m⁻²). The u- and v-components are combined into 10-m wind speed (WS) for analysis. The 2-meter air temperature reflects diurnal variations and seasonal trends across a wide range of environments and is strongly correlated with building energy demand (Li et al., 2018; Mishra et al., 2024). Dew point temperature, in relation to air temperature, captures atmospheric humidity variations. In winter, higher humidity enhances thermal comfort at lower temperatures, while in summer, it intensifies perceived heat stress and elevates cooling energy requirements, as occupants tend to set lower setpoint temperatures to achieve comfort (Pawlak et al., 2021; Choi et al., 2017; Mansouri et al., 2023). Wind speed affects the heat transfer process through the building envelope (Cholewa et al., 2021). Higher wind speeds typically increase heating energy demand during winter through enhanced heat losses and may reduce cooling loads in summer due to improved natural ventilation (Hirth et al., 2024). However, the impact of wind speed varies by region, with some areas showing little sensitivity (e.g., Chambers & Oreszczyn, 2019). Solar radiation provides beneficial passive heat gains during winter, thereby reducing building heating needs, but can exacerbate overheating in summer, increasing cooling demand (Huang & Kang, 2021; Zhao et al., 2024).

The spatiotemporal heterogeneity of meteorological variables, combined with the varying sensitivity of building energy demand to different meteorological conditions, adds complexity to the accurate estimation of *Tbase*. Among these variables, air temperature is the most dominant factor affecting building energy demand, while humidity, wind speed, and solar radiation function as correction terms that modify temperature effects. Their physical interdependence with temperature amplifies the nonlinear dynamics of building energy demand and contributes to the uncertainty in determining *Tbase*.

Static features

Static features include socioeconomic variables, along with the geographic coordinates (longitude and latitude) of each region, as shown in Table 1. Population density (persons km⁻²) is critical in shaping regional microclimate through urban densification, which in turn affects thermal comfort. In densely built urban environments, reduced wind speeds in narrow canyons limit heat circulation and removal, thereby worsening thermal conditions (Perera et al., 2023). This degraded thermal environment forces residents to rely more on mechanical cooling during the summer months. In addition, per capita heating energy demand varies substantially across population density ranges (Zarco-Periñán et al., 2021), which reflects the heterogeneous impact of population density on energy demand. Regional affluence, characterized by economic density (GDP per unit area, 2017 int. \$ km⁻²), also strongly influences residential energy access and consumption patterns (Rode et al., 2021; Abajian et al., 2025; van Ruijven et al., 2019). Typically, in low-income areas, the adoption of air conditioning is often delayed due to financial constraints (Duan et al., 2023), resulting in higher summer base temperatures. Conversely, in high-income areas, cooling systems are typically activated at lower ambient temperatures. This

disparity is particularly pronounced in rural-urban comparisons, where urban populations tend to exhibit lower temperature thresholds for initiating electricity demand (Shi et al., 2025).

Geographic coordinates (longitude and latitude) serve as fundamental determinants of regional climate variability and influence local populations' adaptive behavioural responses to thermal conditions. For instance, residents in high-latitude regions tend to be more acclimated to cold climates and typically initiate heating systems at lower temperatures than those in lower-latitude counterparts (Yilmaz & Canan, 2025).

2.2 Model development

This study developed a novel framework to spatially generate an accurate dataset of base temperatures at the regional scale by integrating a statistical model and a Bidirectional Long Short-Term Memory (BiLSTM)-based neural network framework (Fig.1a). First, the target data for the training set is prepared by a statistical model. The BiLSTM model is then trained to obtain optimal parameters, incorporating both stratified sampling and an attention mechanism. Stratified sampling ensures a more representative division of the dataset into training and test sets, while the attention mechanism enhances prediction accuracy by automatically focusing on the most relevant time steps for T_{base} estimation. The final step is the generation and assessment of T_{base} values at the regional scale.

2.2.1 Target base temperature data preparation

Two types of base temperature, the cooling base temperature (T_{cool}) and the heating base temperature (T_{heat}), are used as training targets. These targets are derived from the nonlinear relationship between actual energy demand and outdoor temperature across different regions. To adequately capture seasonal changes in energy use, the time series of daily energy demand should be at least one year long, while monthly energy demand data should be at least five years long. Furthermore, location metadata is essential for each energy demand dataset, as regional climate-energy relationships are critical for accurately estimating spatial variations in T_{base} . Detailed information on the datasets used in this research is provided in Table A1.

Regression approaches are used to estimate T_{base} values by modelling the relationship between energy demand and outdoor temperature. This relationship can be represented using a variety of specifications, including linear, polynomial, and exponential models (Fung et al., 2006; Ihara et al., 2008; Li, 2018). Although complex nonlinear models can provide precise model fits, they often pose challenges such as overfitting and limited interpretability of parameters, which limits their applicability across diverse regions (Staffell et al., 2023). To address these limitations, this study adopts a segmented linear regression model, grounded in the energy signature method (Bhatnagar et al., 2018), to identify the critical turning points in the energy demand-temperature relationship, namely the cooling and heating base temperatures (T_{cool} and T_{heat}). The segmented linear regression model is expressed as follows:

$$E_{ti} = \begin{cases} a + b_1(Theat - T_{ti}), & T_{ti} < Theat \\ a, & Theat \leq T_{ti} \leq T_{cool} \\ a + b_2(T_{ti} - T_{cool}), & T_{ti} > T_{cool} \end{cases} \quad (1)$$

where E_{ti} represents energy demand at location i on day (or month) t . For daily datasets, E_{ti} is expressed in kWh d⁻¹; for monthly regional datasets, it is expressed in MWh month⁻¹. T_{ti} denotes the corresponding average outdoor temperature (°C). $Theat$ and T_{cool} represent the heating and cooling base temperatures at location i (°C), respectively. Coefficients b_1 and b_2 denote the slopes of heating and cooling segments in the energy-temperature

relationship. Specifically, b_1 indicates that heating demand decreases as outdoor temperature increases, while b_2 indicates that cooling demand increases with rising temperature. When outdoor temperature T_{ti} falls between $Theat$ and $Tcool$, the building does not require active neither heating nor cooling, and the energy demand reflects the baseline load independent of temperature variations. When $T_{ti} < Theat$, heating is required to maintain indoor thermal comfort, and when $T_{ti} > Tcool$, cooling is necessary.

The segmented linear regression model identifies $Tbase$ values through a three-step process. (1) Determining the number of base temperatures: for each energy-temperature dataset, both two-segment linear regression and quadratic regression are performed. The number of $Tbase$ values is determined by comparing their R^2 values. When the quadratic regression yields a higher R^2 , the energy-temperature relationship is likely U- or V-shaped, indicating the presence of both heating and cooling base temperatures. Otherwise, only a single $Tbase$ is identified: a positive slope in the non-horizontal segment corresponds to $Tcool$, while a negative slope indicates $Theat$. (2) Calculating base temperatures: for datasets with a single base temperature, $Tbase$ corresponds to the breakpoint of the fitted line. For datasets with two base temperatures, the minimum temperature point ($Tmin$) from quadratic regression is used as a reference. Intervals of ($Tmin-6\text{ }^{\circ}\text{C}$, $Tmin$) and ($Tmin$, $Tmin+8\text{ }^{\circ}\text{C}$) are examined at $0.05\text{ }^{\circ}\text{C}$ increments to search for two breakpoints maximizing the R^2 of a three-segment linear regression, and the resulting breakpoints are identified as $Theat$ and $Tcool$, respectively. The search intervals were set empirically, with a wider margin on the cooling side to accommodate more diverse active cooling responses. All detected $Theat$ and $Tcool$ values fell within these intervals rather than at their boundaries, indicating that the chosen range is sufficiently wide to capture the true breakpoints without truncation. (3) Producing the target dataset: detected $Tbase$ values are retained only if the segmented regression achieves an R^2 above 0.5, ensuring an adequate model fit, and if the resulting $Theat$ and $Tcool$ values are physically plausible (i.e., $Theat < Tcool$, and both values fall within typical comfort temperature ranges of $10\text{--}30^{\circ}\text{C}$). Ultimately, base temperature values from 131 out of 172 geographical units are included in the final labeled dataset, as shown in Fig.1b-d and Table A2.

Building-level energy demand datasets require careful pre-processing prior to segmented linear regression to ensure reliable analysis. For each dataset, three pre-processing steps are performed: (1) The energy demand time series for each building is visualized to exclude those without cyclical variation patterns, as such buildings typically exhibit temperature-independent demand (e.g., warehouses) (Staffell et al., 2023); (2) Daily energy demand of all buildings within each geographical unit are aggregated and averaged to represent regional building energy demand; (3) Using two-dimensional energy-temperature data, a density-based clustering method is used to eliminate abnormal daily records, which are often the results of data errors or abnormal demand patterns due to holidays. For region-level datasets, only outlier detection is performed, as their monthly temporal resolution naturally smooths out short-term fluctuations such as holiday effects.

2.2.2 Model training

The model has been trained using $Tbase$ values and corresponding feature data from 131 geographic units. Monthly-scale meteorological data are chosen as dynamic features because their temporal smoothing effectively filters out high-frequency noise while retaining medium- and long-term trends. These retained signals are more strongly correlated with energy demand and $Tbase$, enabling the model to capture more stable physical relationships and enhance spatial generalization.

Weather data exhibit complex time-series characteristics, including cyclical patterns, seasonal variations, and long-term trends, which are closely linked to variations in occupant energy demand for cooling and heating across different regions. To address the temporal complexity of meteorological data and their nonlinear relationships with energy demand, this study constructs a neural network framework based on a Bidirectional Long Short-Term Memory (BiLSTM) architecture to model the relationship between time-series weather data and T_{base} (Fig. 1a).

LSTM networks represent an advancement over traditional recurrent neural networks (RNNs), effectively addressing the fundamental challenge of preserving information across extended sequences—also known as long-term memory capacity, which makes them particularly well suited for processing time-series data (Hochreiter & Schmidhuber, 1997). Each LSTM cell integrates three gates (input, forget, and output) and a storage unit (Zhang et al., 2024). The input gate regulates how much new information is added to the memory. The storage unit preserves historical information across time steps, enabling the network to maintain long-term dependencies. The forget gate determines which information is discarded, while the output gate determines which information is passed on to the next hidden state (Kim et al., 2024b; Chen et al., 2023). By controlling whether to retain or discard information, LSTM networks mitigate the vanishing and exploding gradient problems that commonly affect traditional RNNs during training.

The BiLSTM model extends the standard LSTM by processing input sequences in both forward and backward directions (Schuster, M. & Paliwal, K. K, 1997; Palazzoli et al., 2025). This bidirectional architecture captures temporal dependencies more comprehensively, enabling the model to learn complex patterns from both past and future contexts in historical weather data. The forward processing captures the temporal evolution of weather patterns, while the reverse processing identifies important contextual relationships that may be missed in a unidirectional processing. By leveraging this full temporal context, the BiLSTM model yields more accurate estimates of T_{base} values.

In the BiLSTM framework, monthly meteorological data at the regional level and annual socioeconomic data by region from 2000 to 2020, as well as latitude and longitude, are used for model training. For dynamic features, sequence normalization is applied within each geographic unit to preserve the periodicity and seasonality inherent in meteorological variables. For static features, global standardization across all units is performed to highlight absolute differences between geographic units. Furthermore, latitude and longitude are encoded to capture rich location information. A sequence length of 24 months is chosen, which provides a balance between capturing patterns of climate variability and maintaining a sufficient number of training samples. An attention mechanism is applied to the BiLSTM outputs, assigning learnable weights across time steps so that months more relevant to the base temperature contribute more to the aggregated temporal representation; a residual connection is added to stabilize training. To address the issue of sparse and unevenly distributed samples, K-means clustering is applied using geographic coordinates (latitude and longitude) to classify the 131 geographic units into three clusters. Training and test sets are then constructed proportionally within each cluster, ensuring stratified sampling and preserving the geographical representativeness of the training set—thus enhancing the model’s capacity for spatial generalization. The final train-test split follows an 8:2 ratio. To prevent data leakage, all sequences from each geographic unit are assigned exclusively to either the training or test set. Model training adopts an early stopping strategy, halting if no improvement is observed over 20 consecutive epochs, with a maximum of 50 epochs.

The mean squared error (MSE) is used as the loss function, which is particularly sensitive to large errors and thus encourages the model to minimize substantial prediction biases. This study designs an adaptive MSE to handle

missing target variables in certain regions, such as T_{cool} being absent in cold regions or T_{heat} being unavailable in hot regions. The loss function automatically identifies and skips missing values through a dynamic masking mechanism, ensuring that only valid labels are used for error calculation. This design enables the model to fully utilize the label data, improving the efficiency of data utilization and the stability of model training. For each sample in an epoch, the loss function is defined as:

$$L_i = \frac{1}{|M_i|} \sum_{j \in M_i} (Tbase_{i,j} - \widehat{Tbase}_{i,j})^2 \quad (2)$$

where $Tbase_{i,j}$ is the target value j of sample i , where $j \in \{0,1\}$ corresponding to T_{cool} and T_{heat} , respectively. The $\widehat{Tbase}_{i,j}$ is the predictive value of $Tbase_{i,j}$. M_i represents the set of indices of non-missing labels in sample i , and $|M_i|$ indicates the number of non-missing labels. Given that each region contains at least one valid label, $|M_i| \in \{1,2\}$. The total loss per epoch is:

$$L_{batch} = \frac{1}{N} \sum_{i=1}^N L_i \quad (3)$$

where N is the number of samples.

In addition, the correlation coefficient r is further considered to evaluate the overall performance of the prediction model. The formula for r is as follows:

$$r = \frac{\sum_{m=1}^K (Tbase_{obse,m} - \overline{Tbase})(Tbase_{pred,m} - \widehat{\overline{Tbase}})}{\sqrt{\sum_{m=1}^K (Tbase_{obse,m} - \overline{Tbase})^2} \sqrt{\sum_{m=1}^K (Tbase_{pred,m} - \widehat{\overline{Tbase}})^2}} \quad (4)$$

where K represents the number of geographical units, $\overline{Tbase}$ represents the mean of the observations. $Tbase_{obse,m}$ is the observation value of the m^{th} geographic unit; $Tbase_{pred,m}$ is the predicted value of the m^{th} geographic unit; $\widehat{\overline{Tbase}}$ is the mean of the predicted values.

The hyperparameters for the BiLSTM model are determined through combinatorial optimization, with model performance evaluated using the MSE as the selection criterion. The hyperparameter search space included hidden state dimensions (128, 256), dropout rates (0.2, 0.3), and learning rates (0.001, 0.002, 0.0005). Based on experimental comparisons, the optimal configuration was selected as a dropout rate of 0.2, a learning rate of 0.002, and a hidden layer size of 256.

2.2.3 Global data generation

By utilizing provincial-level monthly meteorological data, annual socioeconomic data aligned with the training set, and geographic coordinates (Table 1), the above estimation procedure for $Tbase$ can be extended to the global scale. Global regional administrative boundaries are obtained from GADM (<https://gadm.org/data.html>), with first-level boundaries selected to correspond to the U.S. state or Chinese province scales. Considering the validity of the population mask, a total of 3385 spatial units with valid feature data are obtained globally. Theoretically, each provincial unit corresponds to two base temperatures: T_{cool} and T_{heat} . This study adopts a unified modelling strategy that does not predefine the ranges or distribution patterns of $Tbase$ based on traditional climate zoning. This approach allows the model to learn the distribution pattern of dynamic features from the data, avoiding fixed climate zoning that might obscure climate change evolution, thus revealing $Tbase$ in a more objective way.

3 Results and discussion

3.1 Model performance

The performance of the BiLSTM model is assessed using *MSE* and *r* by comparing actual values with predicted values. The results showed that the *MSE* of the training set is 1.94 °C², while the test set achieved an *MSE* of 1.78 °C², with corresponding *RMSE* values of 1.39 °C and 1.33 °C, respectively, indicating good model generalization without significant overfitting. Target-specific analysis revealed differences in predictive performance: *Tcool* achieved a strong correlation ($r = 0.84$) while *Theat* showed a moderate correlation ($r = 0.70$). The lower performance in predicting *Theat* compared to *Tcool* reflects the greater complexity of heating demand patterns, as evidenced by Kim et al. (2024a), who found that *Theat* showed significantly higher variability than *Tcool* when differentiating buildings by construction year and floor area in South Korea.

To justify the choice of the BiLSTM architecture, we compared it with three baseline models (Ridge regression, Random Forest, and a unidirectional LSTM) using three-fold cross-validation. This approach provides a robust performance estimate by ensuring every sample serves as part of a held-out validation set across folds. Once the architecture was selected, the final BiLSTM model was retrained on the full training dataset following standard machine learning practice. Therefore, the cross-validation results presented in Table 2 are intended for model comparison and are not directly comparable to the final model performance reported above. In this comparison, BiLSTM achieved the highest Pearson correlation on the more challenging heating base temperature ($r = 0.63$, versus ≤ 0.52 for the other benchmarks) and outperformed the unidirectional LSTM, confirming the benefit of the bidirectional architecture. For the cooling base temperature, which all models predicted well ($r \geq 0.70$), simpler models performed comparably. The advantage of BiLSTM is thus most pronounced where the temperature–demand relationship is harder to capture. This strength, together with its ability to model temporal sequences end-to-end and to jointly predict both base temperatures under missing labels, supports its selection.

3.2 Global *Tbase* analysis

Global *Tbase* mapping reveals regionally differentiated temperature-dependent energy demand responses. Globally, *Tcool* ranges from 19 to 25 °C, with a mean of 22 °C and a median of 21.94 °C, while *Theat* ranges from 14 to 18 °C, with a mean of 16 °C and a median of 15.87 °C, which is consistent with physical logic (Fig. 2a, b).

The *Tcool* and *Theat* present a generally consistent distribution pattern, characterized by lower *Tbase* values in high-latitude regions and higher values in low-latitude regions (Fig. 2c). North America and Europe, which are predominantly composed of developed countries, have the lowest median *Tcool* and *Theat*. These patterns are consistent with prior findings that higher-income populations may use cooling at lower outdoor temperatures (Cong et al., 2022), and that well-insulated building stocks are associated with lower heating thresholds. However, Libya, Gabon, Algeria, Botswana, and South Africa in the African region have relatively low *Theat*, indicating within-continent heterogeneity that the dataset is able to capture. Asia spans the longest latitudinal range and exhibits the largest inter-regional economic disparities, resulting in the widest distribution of *Tbase* values (*Tcool*: 19.57 - 24.99°C, *Theat*: 14.18 - 18.05°C). Southern China and India have higher *Tbase* values. A base temperature test for India based on the energy signature method showed that the median *Theat* in many regions is 17.4°C (Bhatnagar et al., 2018), which closely aligns with the median *Theat* of 17.05°C found in this study. Oceania's *Tbase* is more dispersed, which is due to the smallest number of regions included. Differentiated *Tbase* can support energy-saving planning, building renovation, and climate-adaptive design.

3.3 Technical validation

To further demonstrate the effectiveness of the predicted *Tbase*, a comprehensive validation framework is employed, as shown in Fig. 3. In this framework, energy demand datasets from 16 regions are employed to perform external validations of *Tbase* (Table A3). These datasets cover major continents globally, with relatively uniform distribution to ensure the comprehensiveness and representativeness of the validation results.

Three validation approaches are employed to assess whether predicted *Tbase* improves the accuracy of temperature-dependent energy demand modelling, including direct validation, indirect validation and sensitivity analysis (Fig. 3). Direct validation applies the segmented linear regression method described earlier to determine *Tbase* for each dataset, and then compares these results with the predicted values to validate the accuracy and reliability of the prediction results in practical applications. Indirect validation uses both the predicted *Tbase* and reference values from literature or official sources to forecast building energy demand through degree-day modelling. For each energy dataset, the following indirect validation procedure is adopted to evaluate the accuracy of the predicted *Tbase*. First, based on the corresponding temperature data, two sets of degree days are calculated: (1) HDD and CDD calculated using the predicted *Tbase* from this study; (2) HDD and CDD calculated using reference *Tbase* values from literature or official sources. Subsequently, statistical analyses are performed on the above two sets of degree days with actual energy consumption data, including: (1) correlation analysis, calculating the time-series correlation coefficient (TCC) to quantify the linear relationship between degree days and energy consumption. The TCC is computed as the cross-correlation between the two series; at zero time lag it is equivalent to the Pearson correlation coefficient, and the zero-lag value is adopted here. (2) regression analysis, establishing degree day-energy consumption regression models and calculating root mean square error (RMSE) to evaluate prediction accuracy. Finally, the modelling performance of the predicted *Tbase* is evaluated through comparative analysis. If the HDD and CDD calculated based on the predicted *Tbase* exhibit higher correlation coefficients with actual energy consumption and the corresponding regression models have lower RMSE, this indicates superior accuracy. For sensitivity analysis, the TCC is used to analyse how changes in *Tbase* affect the correlation between energy demand and HDD or CDD, thereby evaluating the performance of the predicted *Tbase*.

For the 16 energy demand datasets at the regional and building levels, the validation results are summarized in Table 3. Both direct and indirect validation results show that the predicted *Tbase* performs well across most datasets. Direct validation yields average errors of 0.68°C for *Tcool* and 1.08°C for *Theat* across the 16 datasets. Indirect validation demonstrates that the predicted *Tbase* substantially improves the accuracy of building energy demand modelling in two key aspects. First, the TCC between energy demand and HDD/CDD calculated using the predicted *Tbase* is greater than or equal to that obtained using reference *Tbase* values. This indicates that predicted *Tbase* maintains or enhances the explanatory power of temperature-dependent energy demand variations. On average, the predicted *Tbase* improves TCC across the validation datasets from 0.67 to 0.81. Second, the predicted *Tbase* substantially reduces the RMSE of both cooling and heating energy demand modelling. Specifically, the RMSE of cooling and heating energy demand modelling decreases by comparable margins, averaging approximately 10% in both cases.

The sensitivity analysis evaluates the proximity of the TCC value derived from the predicted *Tbase* to the maximum achievable TCC value. A TCC value approaching the maximum indicates higher accuracy of the predicted *Tbase* and enhanced performance in temperature-dependent energy demand modelling. Fig. A2-A15 demonstrate that across all datasets, the TCC values calculated using the predicted *Tbase* approximate their

respective maxima, confirming the effectiveness of the predicted *Tbase* parameters in HDD/CDD-based modelling. Although three datasets show prediction errors greater than 2°C, the indirect validation results indicate that predicted *Tbase* still contributes to enhanced energy demand modelling accuracy, as evidenced by consistent RMSE reductions in all instances. Overall, the predicted *Tbase* improves the ability to explain and model temperature-dependent energy demand variations.

3.3.1 Building-level validation

In order to present the validation process more clearly, the detailed results of a building-level dataset and a regional-level dataset are presented below. Fig. 4 shows the validation results of a residential building in South Australia, Australia (Sharma et al., 2019). Direct validation shows absolute prediction errors of 0.3°C between the predicted *Tcool* (21.4°C) and the actual value (21.10°C), and 0.6°C between the predicted *Theat* (15.5°C) and the actual value (16.10°C) (Fig. 4a). Fig. 4b demonstrates that the TCCs corresponding to *Tcool* and *Theat* approach their respective maximum values across the tested base temperature range, implying that the predicted *Tbase* effectively captures temperature-dependent energy demand variations. Following previous studies, 14°C and 24°C are adopted as reference base temperatures for this dataset (Livada et al., 2021), and indirect validation is performed to compare the reliability of predicted versus reference *Tbase* values in residential energy demand modelling. The TCC calculated using predicted *Tbase* (15.5°C/21.4°C) reaches 0.91, exceeding the TCC based on the reference *Tbase* (14°C/24°C) of 0.88, representing a modest improvement of 0.03 (Fig. 4c). For heating energy demand modelling, RMSE decreases from 1.82 kWh to 1.69 kWh, achieving a relative improvement of 7.14% (Fig. 4d, f). For cooling energy modelling, RMSE is reduced from 1.84 kWh to 1.45 kWh, corresponding to a relative improvement of 21.20% (Fig. 4e, g). These results indicate that energy demand modelling based on predicted *Tbase* is more reliable.

3.3.2 Region-level validation

For the regional-level energy demand dataset, Fig. 5 presents the validation results of daily energy demand modelling in Tacoma, USA. To extract residential energy demand from the raw dataset, the residential sector's share of annual end-use energy demand from the U.S. Energy Information Administration (EIA) (<https://www.eia.gov/>) has been applied to daily total energy consumption data to derive daily residential energy demand. The direct validation results suggest that this area has significant heating demand, with an error of only 0.1°C between the predicted *Theat* (14.5°C) and the actual value (14.4°C) (Fig. 5a). Fig. 5b shows that the TCC corresponding to *Theat* is very close to its maximum value, demonstrating that the predicted *Tbase* effectively captures residential energy demand variations. The official value of 18°C is adopted as the reference *Tbase* for residential energy demand modelling in this dataset. The TCC calculated using the predicted *Tbase* (14.5 °C) reaches 0.94, exceeding the TCC based on the reference *Tbase* (18 °C) of 0.91 (Fig. 5c) (ASHRAE, 2009). The RMSE is reduced from 172.65 MWh to 150.46 MWh, corresponding to a relative improvement of 12.85% (Fig. 5d, e). These results demonstrate that the predicted base temperatures have good applicability in regional-scale energy demand modelling.

3.4 Potential application of the *Tbase* dataset

Efforts to enhance degree-day models persist in order to improve efficiency and accuracy in building energy modelling. Numerous studies have calculated region-specific *Tbase* across Europe, Africa, India, and globally (Wenz et al., 2017; Bhatnagar et al., 2018; Staffell et al., 2023), significantly improving the accuracy of regional building energy demand modelling. However, the heavy reliance on actual building energy demand datasets constrains the extension of *Tbase* estimation to broader detailed spatial scales. This study addresses this limitation through a machine learning approach.

The *Tbase* dataset developed in this study has significant potential for use in a wide range of areas related to degree-day modelling. Firstly, applying *Tbase* to heating and cooling energy demand modelling on a consistent global scope can provide scientific support for differentiated energy system planning and climate adaptation strategies in building design. Secondly, *Tbase* can be used for a wide range of heat exposure assessments, contributing to studies on the health dimensions of climate change impacts and providing data to support strategies for heatwave warning and the protection of vulnerable populations (Broomandi et al., 2025; Hu et al., 2025). Finally, *Tbase* holds significant value in large-scale model coupling. Integration of the *Tbase* datasets into various Earth System Models (e.g., CESM) and Integrated Assessment Models (e.g., GCAM, IMAGE) could help reduce long-term modelling uncertainties. In turn, incorporating these more accurate representations of energy demand modelling results into energy-economic models (e.g., TIMES, MARKAL) can provide a reliable modelling framework for designing decarbonization pathways.

3.5 Limitations and uncertainties of the *Tbase* dataset

Limitations and uncertainties related to the research design and model are discussed below. Firstly, the dataset's reliance on electricity and natural gas consumption statistics inadequately captures heating demand from alternative energy sources. Especially in energy-poor regions, the decentralized nature of heating makes it difficult to account for the use of polluting sources, such as coal and diesel (Burguillo & Juez-Martel, 2024; Kozarcenin et al., 2019). This limitation in data acquisition makes it difficult to accurately characterize heating demand patterns across time and temperature. Secondly, given the unavailability of extensive data, building characteristics such as type, age, floor area, insulation performance, number of floors, and other attributes are not differentiated in this study. The *Tbase* dataset, therefore, provides generalized energy demand estimates rather than building-type-specific predictions. In addition, the dynamic changes in *Tbase* were not taken into account due to the limitations of acquiring extensive long-term energy consumption data.

To assess how choices in the label-generation process affect the dataset, we tested the sensitivity to the goodness-of-fit threshold of the segmented regression. Relaxing the inclusion criterion from $R^2 > 0.5$ to 0.4 and tightening it to 0.6 changed the number of retained units between 123 and 149, while the overall label distribution remained essentially unchanged: mean *Theat* ranged over 14.47–14.67 °C (range 0.2 °C) and mean *Tcool* over 20.66–21.49 °C (range 0.83 °C), both smaller than the model uncertainty interval. This indicates that the dataset is insensitive to the fitting threshold. In addition, *Theat* estimated with a UKMO-based alternative breakpoint method over 20 UK regions differs from that from Eq. (1) by only 0.83 °C on average (Text A1), further suggesting limited dependence on the breakpoint-selection approach.

Beyond the label-generation process examined above, uncertainty in the *Tbase* results also arises from the model itself. This can be decomposed into aleatoric (data noise) and epistemic (model knowledge) uncertainty (Xu et al., 2025; He et al., 2025). The epistemic uncertainty of the *Tbase* dataset was estimated by 30 data sampling

analyses using MC Dropout for meteorological, socioeconomic, and geographic background data collected for 3,385 spatial units. The MC Dropout employs a neural disconnection mechanism based on randomness to evaluate network sensitivity to model variations (Xu et al., 2025). This approach is widely used for uncertainty quantification due to its computational simplicity and efficiency. Uncertainty was quantified by calculating the standard deviation (std) across the results of multiple analyses, where larger values indicate greater uncertainty in *Tbase* estimates due to model variability or limited data. The results are shown in Fig. 6. The uncertainty ranges for *Theat* and *Tcool* are [0.56, 1.61] and [0.82, 2.26] °C, respectively. Although *Theat* shows lower model accuracy, its target distribution is more concentrated (the interquartile range, IQR, is narrower, see Fig. 1d), resulting in a smaller uncertainty interval. By focusing on the maximum uncertainty and normalizing by their respective mean values (22°C for *Tcool*, 16°C for *Theat*), both variables exhibit comparable relative uncertainties of approximately 10%, indicating consistent uncertainty quantification across different targets. The spatial distribution of std shows that the uncertainty is at a medium-low level in most regions, such as North America, Europe, northern Asia, and Oceania. The training samples in Africa, South America, and western Asia are sparse, and the std is relatively high. In the future, further increasing the sample size in sparsely sampled regions will reduce the epistemic uncertainty of the model.

The representativeness of the training sample also affects the reliability of the global extrapolation. The 131 training units span 24 countries and are mainly concentrated in temperate, mid-to-high-latitude regions. This distribution covers the climatic and socioeconomic conditions of most inhabited areas reasonably well, while tropical, arid, and Southern-Hemisphere regions are covered more sparsely. The MC Dropout analysis above quantifies model uncertainty, whereas limited spatial coverage introduces an additional, extrapolation-related uncertainty; the two compound in sparsely trained regions, consistent with the higher standard deviations found over Africa, South America, and western Asia in the MC Dropout results. Therefore, users are encouraged to consult the accompanying uncertainty layer when interpreting results for these regions, and expanding the training sample there in the future would further improve representativeness.

4 Data availability

The proposed global *Tbase* dataset can be acquired from <https://doi.org/10.6084/m9.figshare.30646376.v2> (He et al., 2025a).

5 Conclusion

This study developed a global regional-scale *Tbase* dataset, including both *Tcool* and *Theat*, by integrating comprehensive energy demand, meteorological, and socioeconomic data using a BiLSTM framework with an attention mechanism. The *Tbase* values varied across regions worldwide, with *Tcool* ranging from 19 to 25°C (mean: 22°C; median: 21.94°C), and *Theat* ranging from 14 to 18°C (mean: 16°C; median: 15.87°C). Compared to the use of a fixed *Tbase*, these heterogeneous values better capture local climate characteristics, socioeconomic conditions, and energy use behaviours. The *Tbase* is primarily applicable to general building energy demand modelling for assessing energy requirements to achieve universal thermal comfort.

The model construction incorporates several strategies to minimize the impact of small samples. First, stratified sampling based on geographic clustering ensures representative distribution between the training and

test sets. Second, joint training of *Tcool* and *Theat* using an adaptive MSE-based loss function maximizes data utilization. Third, the attention mechanism captures critical temporal patterns to enhance training efficiency. Based on 131 regions (with 80% used for training and 20% for testing), internal validation shows RMSE values of 1.39°C (training) and 1.33°C (testing), with correlation coefficients of 0.84 for *Tcool* and 0.70 for *Theat*, demonstrating good generalization performance.

External validation using 16 independent building energy demand datasets from various global regions (completely separate from the 131 regions used in the model construction phase) demonstrates that predicted *Tbase* consistently improves the accuracy of energy demand modelling. The average prediction errors for *Tcool* and *Theat* are 0.68°C and 1.08°C, respectively. Compared with official or empirical *Tbase* values, the predicted *Tbase* increases the average TCC between energy demand and CDD/HDD from 0.67 to 0.81 and reduces RMSE by comparable margins of approximately 10% for cooling and heating. Uncertainty analysis revealed epistemic uncertainties of 0.56-2.26°C, with the highest values confined to sparsely sampled regions, indicating that most regions are reliable while sparsely trained areas carry higher uncertainty. These results underscore the model's ability to effectively capture regional heterogeneity in temperature-dependent energy demand responses.

The resulting dataset supports a wide range of regional-scale applications and increases research productivity across multiple domains. Most significantly, it improves the accuracy of degree-day energy demand models, enabling the exploration of how adjustments to temperature thresholds affect energy requirements. Additionally, the dataset facilitates climate change impact assessments, such as accurate heat exposure analysis. Finally, coupling the *Tbase* dataset with Earth system models and integrated assessment models has the potential to reduce uncertainty in climate-energy interactions, thereby enhancing long-term energy modelling performance. Overall, this spatially continuous *Tbase* dataset helps address key limitations in building energy modelling and opens new research opportunities in climate-responsive energy planning.

Author contributions

Y. Zhou contributed to the conceptualization, project supervision and administration, funding acquisition, and review. X. He contributed to the data analysis, methodology, writing and dataset submission. J. Eom contributed to the data analysis, review and editing. S. Yu contributed to investigation, supervision, review and editing. S. Liu contributed to the data curation and methodology. W. Xu contributed to review and editing.

Competing interests

The contact author has declared that none of the authors has any competing interests.

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Table 1 Description of meteorological variables and static features

types	variables	unit	temporal resolution	source	description
dynamic	2m temperature	K	daily/ monthly	ERA5-Land (Muñoz-Sabater et al., 2021)	Calculated temperature and its lag features and rolling average
	2m dewpoint temperature	K			Calculated relative humidity
	surface solar radiation downwards	J m ⁻²			Calculated total energy received per unit area of surface
	10m u-component of wind	m s ⁻¹			Calculated wind speed
	10m v-component of wind	m s ⁻¹			
static	population density	persons/km ²	yearly	Lebakula et al., 2024	Population per unit area
	GDP	Int. \$ 2017		Kummu et al., 2025	GDP per unit area
	latitude	°	-	GADM (https://gadm.org/data.html)	Latitude and longitude of the centre point
	longitude	°			

Note: Int. \$ 2017: 2017 international dollars (purchasing power parity).

Table 2 Benchmark comparison of model architectures

Model	RMSE _{T_{cool}} (°C)	RMSE _{T_{heat}} (°C)	r _{T_{cool}}	r _{T_{heat}}
Ridge regression	1.08	1.12	0.81	0.49
Random forest	1.16	1.15	0.79	0.50
Uni-LSTM	1.33	1.10	0.71	0.52
BiLSTM	1.24	1.00	0.75	0.63

Note: Values are pooled out-of-fold predictions from three-fold cross-validation and are not directly comparable to the final-model performance in Section 3.1. RMSE_{T_{cool}} and RMSE_{T_{heat}} are the root mean squared errors (°C) of the out-of-fold predictions of the cooling and heating base temperatures, respectively. r_{T_{cool}} and r_{T_{heat}} are Pearson correlations between the predicted and labeled cooling and heating base temperatures, respectively.

630 **Table 3** Summaries of validation

Location	predicted value		direct validation				indirect validation					
	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII
Austin, USA	20.4	14.8	19.8	0.6	14.1	0.7	-0.29	0.81	6.83%	29.98%	23.8	23.8 ^①
Kitakyushu, Japan	20	14.4	19.12	0.88	13.97	0.43	0.04	0.76	12.27%	20.41%	26	18 ^②
Lower Saxony, Germany	-	14.5	-	-	15.3	0.8	0.93	0.93	-	1.87%	-	15.5 ^③
Trondheim, Norway	-	14.8	-	-	12.3	2.5	0.97	0.97	-	1.27%	-	15.5 ^③
Agder, Norway	-	14.8	-	-	12.6	2.2	0.95	0.95	-	1.12%	-	15.5 ^③
Northeastern Mexico	20.1	-	19.8	0.3	-	-	0.73	0.75	2.41%	-	18 ^④	-
South Australia, Australia	21.4	15.5	21.1	0.3	16.1	0.6	0.88	0.91	21.20%	7.14%	24	14 ^⑤
Hawkes Bay, New Zealand	-	16.2	-	-	-	-	0.8	0.81	-	1.62%	-	14 ^⑤
Itakyry, Paraguay	22.1	-	21.4	0.7	-	-	0.63	0.66	3.98%	-	24 ^⑥	-
Presidente Franco, Paraguay	22.1	-	20.6	1.5	-	-	0.81	0.87	18.19%	-	24 ^⑥	-
Acaray, Paraguay	22.1	-	20.7	1.4	-	-	0.69	0.75	8.91%	-	24 ^⑥	-
Philadelphia, USA	20.2	14.7	20.1	0.1	12.8	1.9	0.62	0.66	15.89%	5.00%	18	18 ^⑦
Tacoma, USA	-	14.5	-	-	14.4	0.1	0.91	0.94	-	12.85%	-	18 ^⑦
Victoria, Australia	21	15.2	20.8	0.2	15.7	0.5	0.58	0.6	0.75%	2.46%	24	14 ^⑦
Delhi, India	23.1	16.7	22.3	0.8	-	-	0.75	0.86	17.67%	26.51%	26	16 ^⑧
Abidjan, Côte d'Ivoire	22.8	-	-	-	-	-	0.73	0.74	1.89%	-	25 ^⑨	-
Mean	-	-	-	0.68	-	1.08	0.67	0.81	10.00%	10.02%	-	-

Note 1: I: predicted *Tcool* from BiLSTM framework; II: predicted *Theat* from BiLSTM framework; III: *Tcool* from segmented linear regression method; IV: Absolute error of *Tcool*; V: *Theat* from segmented linear regression method; VI: Absolute error of *Theat*; VII: TCC based on reference *Tbase*; VIII: TCC based on predicted *Tbase*; IX: decreased RMSE for CDD-energy demand modelling by predicted *Tcool*; X: decreased RMSE for HDD-energy demand modelling by predicted *Theat*; XI: reference *Tcool*; XII: reference *Theat*.

635 Note 2: ①: Feng et al., 2021; ②: Yuan et al., 2024; ③: Filahi et al., 2024; ④: Corrales-Suastegui et al., 2021; ⑤: Livada et al., 2021; ⑥: Kennard et al., 2022; ⑦: ASHRAE, 2009; ⑧: Borah et al., 2015. ⑨: Dicko et al., 2024.

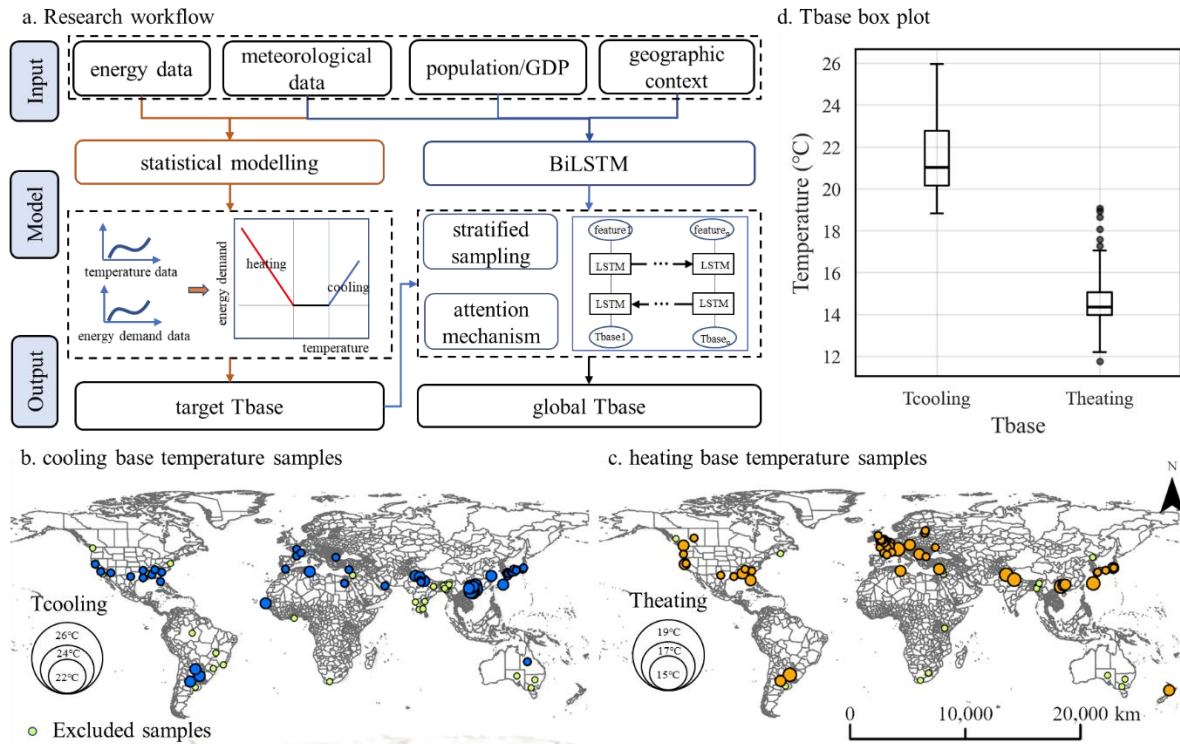


Figure 1: Workflow and Data Preparation. a, Research workflow based on a segmented linear regression model and BiLSTM; b, cooling base temperature samples; c, heating base temperature samples; d, Box plot of base temperature samples.

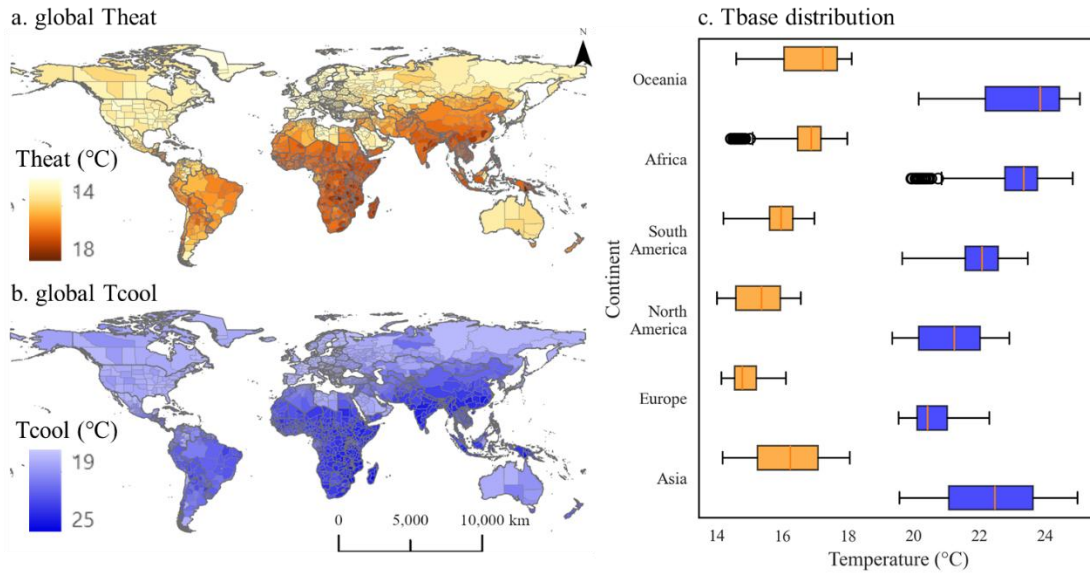


Figure 2: Global mapping of predicted base temperatures (*Tcool* and *Theat*) from the BiLSTM framework. **a**, Geographic distribution of predicted cooling and heating base temperatures. **b**, Box plots of the same predictions grouped by continent. Box plots show the median, interquartile range, and whiskers ($1.5 \times \text{IQR}$); points beyond the whiskers are outliers. Values are provided for all regions, including those where local temperatures currently do not cross a threshold and thus have no present-day cooling or heating demand; whether such demand occurs depends on local temperature evolution and population distribution, and may change under future climate warming.

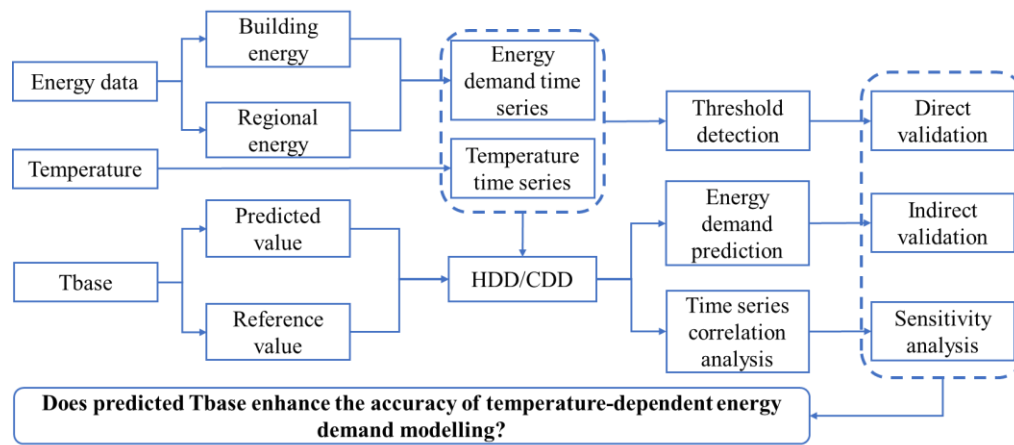


Figure 3: Workflow for technical validation.

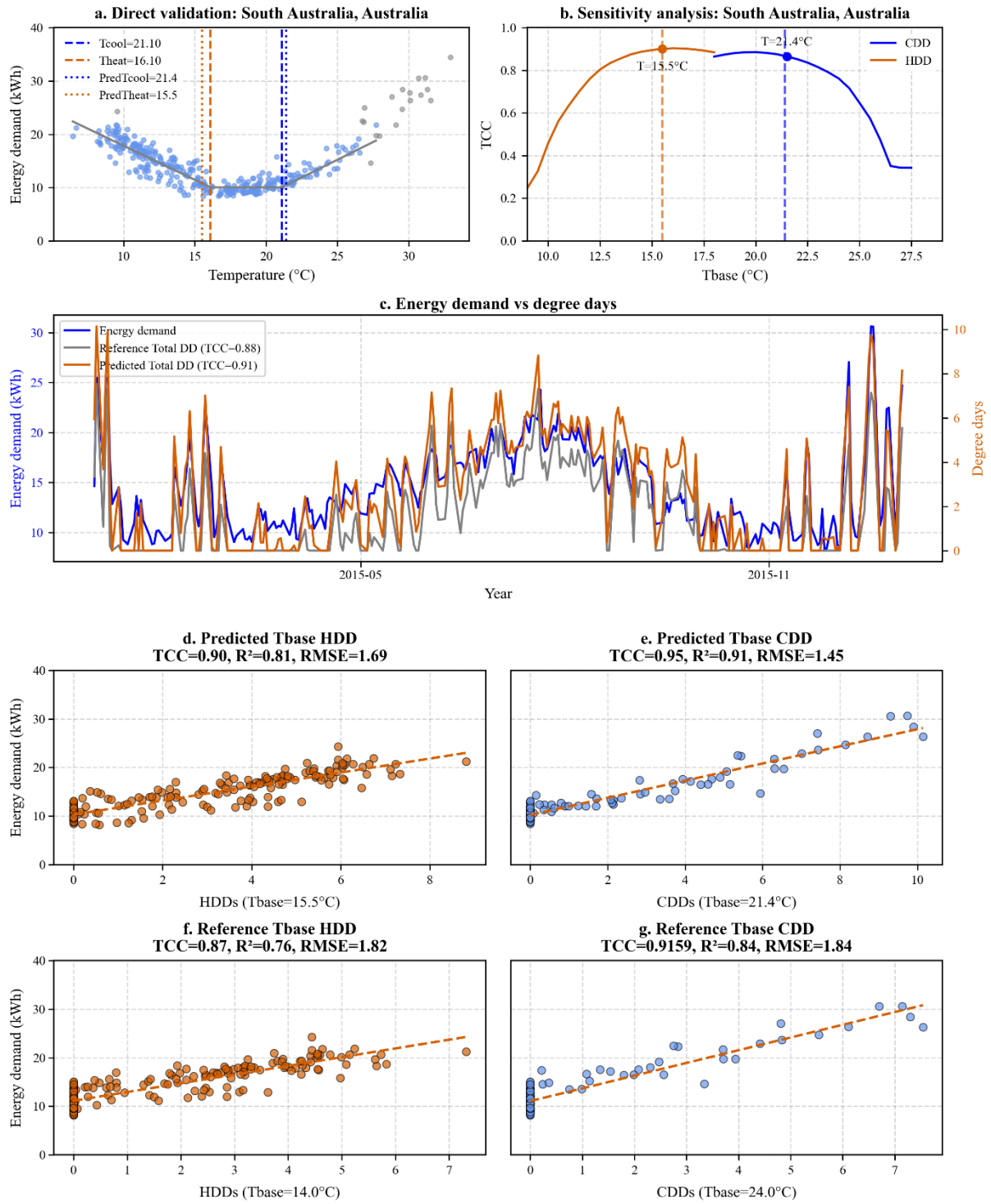


Figure 4: Visualization of CDD and HDD versus energy consumption at different base temperatures of a building in South Australia, Australia. **a**, direct validation of T_{cool} and T_{heat} ; **b**, TCC versus base temperature; **c**, indirect validation (TCC, predicted vs reference T_{base}); **d–g**, heating and cooling energy demand modelling and RMSE using predicted versus reference base temperatures.

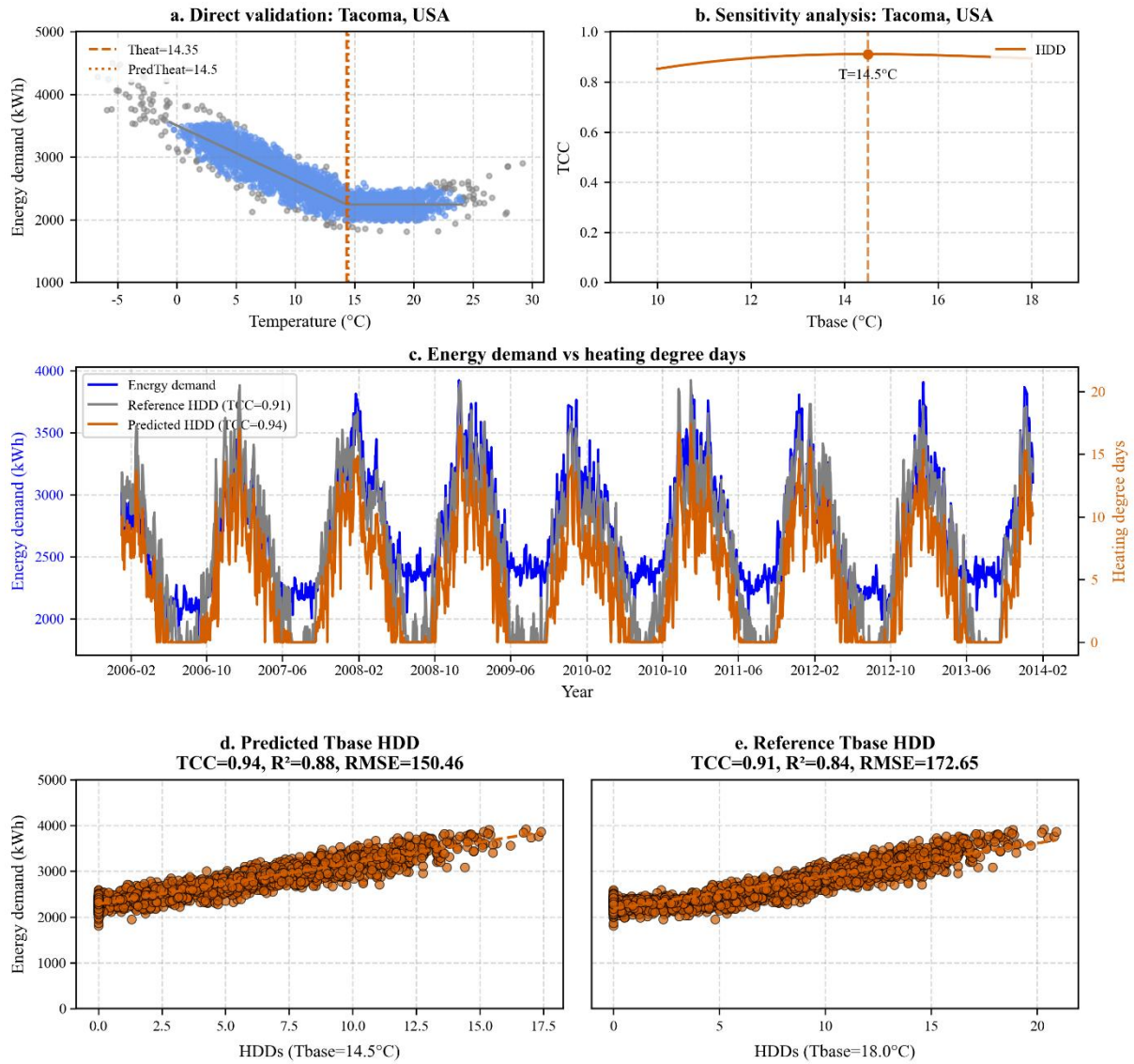


Figure 5: Visualization of HDD versus energy consumption at different base temperatures in Tacoma, USA. **a**, direct validation of *Theat*; **b**, TCC versus base temperature; **c**, indirect validation (TCC, predicted vs reference *Tbase*); **d–e**, heating energy demand modelling and RMSE using predicted versus reference base temperatures.

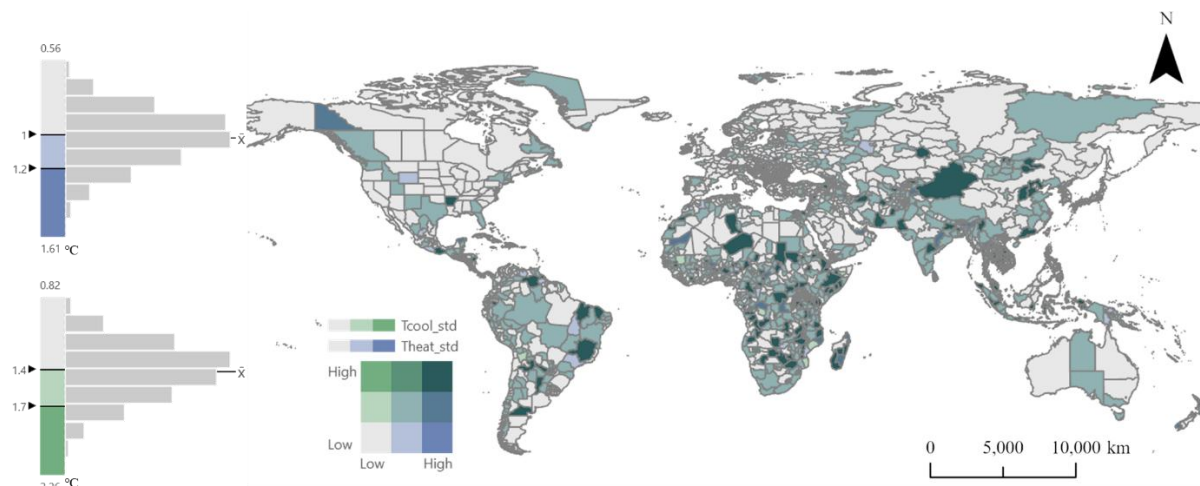


Figure 6: *Tbase* uncertainty analysis based on the limitations in the model.

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Appendix

Text A1: Cross-method validation of base temperatures against a UKMO-based approach

To assess our base-temperature estimates against an independent, max/min-based method in a European context, we compared the heating base temperature from Eq. (1) with that obtained from a UK Met Office (UKMO) degree-day formulation combined with a performance-line fit (Deroubaix et al., 2021; CIBSE, 2006; Spinoni et al., 2018). The HDD under the UKMO method is computed from the daily minimum, mean, and maximum temperatures (T_{min} , T_{mean} , T_{max}) relative to a $Theat$:

$$HDD = \begin{cases} 0, & T_{heat} \leq T_{min} \\ \frac{T_{heat} - T_{min}}{4}, & T_{min} < T_{heat} < T_{mean} \\ \frac{T_{heat} - T_{min}}{2} - \frac{T_{max} - T_{heat}}{4}, & T_{mean} < T_{heat} < T_{max} \\ T_{heat} - T_{mean}, & T_{heat} > T_{max} \end{cases} \quad (a1)$$

The base temperatures from Eq. (1) agree closely with those from an independent UKMO-based method, indicating that our estimates are robust to the choice of estimation formulation. For each region we scanned candidate base temperatures from 10 to 18 °C in 0.25 °C steps. At each candidate $Theat$ we computed the daily HDD series and regressed daily energy demand on HDD; candidates yielding a non-positive slope were discarded. The $Theat$ giving the highest R^2 was taken as the UKMO-based heating base temperature ($Theat$, UKMO). To keep the comparison fair, energy demand was cleaned using the same procedure applied to Eq. (1). The comparison used the 20 UK regions with the most complete daily energy records. Across these regions, the two methods agree closely (mean absolute difference 0.83 °C, RMSE 0.87 °C, Pearson $r = 0.83$), with Eq. (1) giving slightly lower values. As shown in Fig. A1, the R^2 profiles are broadly flat near their maxima, so this offset corresponds to a negligible difference in goodness-of-fit; the two methods are therefore effectively equivalent in how well they explain the observed energy–temperature relationship.

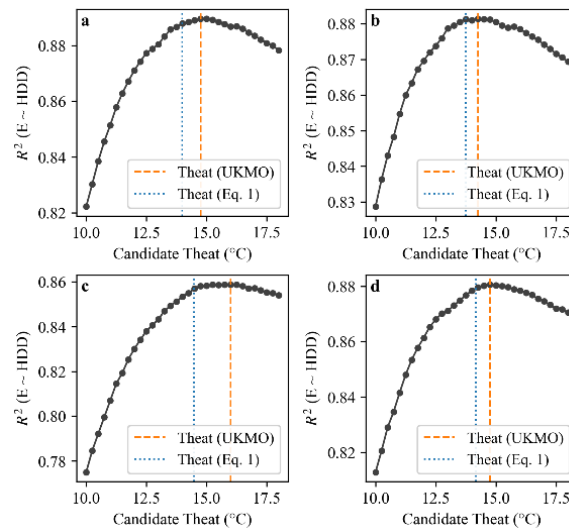


Figure A1: $R^2(E \sim HDD)$ as a function of candidate heating base temperature for four representative UK regions, selected by the median **a**, minimum **b**, maximum **c**, and near-mean **d** difference between the two methods. Dashed line: $Theat$ from the UKMO performance line (R^2 maximum); dotted line: $Theat$ from Eq. (1).

Table A1 Details of the energy datasets used for calculating the target *Tbase*.

Country	Datasets	Year period	Time resolution	Gas / Electricity	Spatial units	Type	Source
Argentina	Base Demanda Diaria	2017-2025	monthly	Electricity	3	energy	CAMMESA, 2025
Australia	AEMO	2012-2020	daily	Electricity	4	energy	AEMO, 2025
Brazil	Empresa de Pesquisa Energética - EPE	2004-2024	monthly	Electricity	4	energy	EPE, 2024
Bulgaria	EMBER	2015-2025	monthly	Electricity	1	energy	Ember, 2025
Canada	HUE	2012-2020	hourly	Electricity	1	building energy	Makonin, 2019
Canada	-	2000-2007	hourly	Electricity	1	energy	Canadian Centre for Energy Information, n.d.
Canada	-	2008-2024	monthly	Electricity	3	energy	Canadian Centre for Energy Information, n.d.
China	residential electricity load data	2022-2023	hourly	Electricity	10	building energy	Li et al., 2025
China	High-resolution electric power load data	2016-2021	hourly	Electricity	1	building energy	Zhou et al., 2023
Cyprus	EMBER	2017-2024	monthly	Electricity	1	energy	Ember, 2025
Czech Republic	EMBER	2015-2025	monthly	Electricity	1	energy	Ember, 2025
Egypt	EMBER	2016-2024	monthly	Electricity	1	energy	Ember, 2025
Estonia	EMBER	2015-2025	monthly	Electricity	1	energy	Ember, 2025
France	Rte-France	2014-2024	monthly	Electricity	10	energy	RTE, n.d.
Germany	DEKN	2015-2019	minute	Electricity	1	building energy	Open Power System Data, 2020
India	Monthly energy demand dataset	2007-2011	monthly	Electricity	13	energy	Central Electricity Authority, 2024
India	Ecohen4/Energy	2011-2013	hourly	Electricity	2	energy	Cohen et al., 2015
India	Smart Meter Data: Mathura & Bareilly	2019-2021	minute	Electricity	2	building energy	Agrawal et al., 2021
Japan	Statistics-METI	2016-2024	monthly	Electricity	21	energy	Agency for Natural Resources and Energy, n.d.
Japan	Ecohen4/Energy	2006-2014	hourly	Electricity	1	energy	Cohen et al., 2015
Latvia	EMBER	2015-2025	monthly	Electricity	1	energy	Ember, 2025
Morocco	Power Consumption Prediction project	2017	minute	Electricity	1	energy	Salam et al., 2018
New Zealand	New Zealand Green Grid	2014-2016	minute	Electricity	2	building energy	B. Anderson et al., 2018
Pakistan	PRECON	2018-2019	minute	Electricity	1	building energy	Nadeem & Arshad, 2019
Senegal	Ecohen4/Energy	2011-2014	hourly	Electricity	1	energy	Cohen et al., 2015
Serbia	EMBER	2016-2025	monthly	Electricity	1	energy	Ember, 2025
Switzerland	Swiss Smart Meter Data	2019-2020	minute	Electricity	1	building energy	Afroz, 2023
the United Arab Emirates	SEWA Energy Demand data	2020-2021	daily	Electricity	1	energy	Rastogi, 2024
Tunisia	EMBER	2020-2024	monthly	Electricity	1	energy	Ember, 2025
UK	Energy Demand Research Project	2007-2010	minute	both	64	building energy	AECOM Ltd., 2014
Ukraine	EMBER	2014-2022	monthly	Electricity	1	energy	Ember, 2025
USA	Ecohen4/Energy	2003-2018	hourly	Electricity	5	energy	Cohen et al., 2015
USA	EMBER	2001-2024	monthly	Electricity	7	energy	Ember, 2025
USA	Building Data Genome Project 2	2016-2017	hourly	Electricity	2	building energy	C. Miller, 2020
USA	Residential power usage-Houston	2016-2020	hourly	Electricity	1	building energy	Srinuti, 2020

780 **Table A2** *Tcool* and *Theat* values used for model training.

RegionID	Region	<i>Tcool</i>	<i>Theat</i>	RegionID	Region	<i>Tcool</i>	<i>Theat</i>
1	Chattanooga, USA	19.15	11.75	45	Melton, UK	-	14.19
2	Eugene, USA	-	13.55	46	North West Leicestershire, UK	-	14.48
3	Los Angeles, USA	20.06	-	47	Oadby and Wigston, UK	-	14.65
4	Sacramento, USA	19.85	13.85	48	North Kesteven, UK	-	14.25
5	Maricopa, USA	21.02	-	49	South Kesteven, UK	-	14.44
6	Alameda, USA	-	16.43	50	Daventry, UK	-	14.09
7	Alabama, USA	20.46	15.46	51	East Northamptonshire, UK	-	14.32
8	Arkansas, USA	21.08	-	52	Kettering, UK	-	14.17
9	Florida, USA	21.21	16.21	53	Northampton, UK	-	14.07
10	Louisiana, USA	20.18	14.73	54	South Northamptonshire, UK	-	14.46
11	South Carolina, USA	21.14	13.34	55	Wellingborough, UK	-	14.33
12	Texas, USA	20.28	14.45	56	Ashfield, UK	-	14.63
13	Vancouver, Canada	-	15.60	57	Bassetlaw, UK	-	14.78
14	Alberta, Canada	-	12.20	58	Broxtowe, UK	-	14.70
15	Auvergne-Rhône-Alpes, France	19.09	13.14	59	Gedling, UK	-	14.45
16	Bretagne, France	-	14.41	60	Mansfield, UK	-	14.02
17	Centre-Val de Loire, France	19.77	14.72	61	Newark and Sherwood, UK	-	14.37
18	Hauts-de-France, France	-	15.42	62	Rushcliffe, UK	-	14.20
19	Normandie, France	-	14.85	63	East Staffordshire, UK	-	13.77
20	Nouvelle-Aquitaine, France	-	13.95	64	Lichfield, UK	-	14.29
21	Occitanie, France	19.53	12.78	65	Staffordshire Moorlands, UK	-	13.99
22	Pays de la Loire, France	-	14.96	66	Elmbridge, UK	-	14.33
23	Île-de-France, France	-	15.21	67	Guildford, UK	-	14.46
24	Lucerne, Switzerland	-	17.05	68	Reigate and Banstead, UK	-	15.12
25	Tetouan, Morocco	20.31	-	69	Nuneaton and Bedworth, UK	-	14.17
26	Dakar, Senegal	22.25	-	70	Rugby, UK	-	13.88
27	Sharjah, United Arab Emirates	20.15	-	71	Warwick, UK	-	14.07
28	Chandigarh, India	22.08	-	72	Arun, UK	-	15.47
29	Delhi, India	21.40	-	73	Mid Sussex, UK	-	13.80
30	Lahore, Pakistan	23.22	18.07	74	Redditch, UK	-	14.35
31	Bareilly, India	22.42	17.27	75	Wyre Forest, UK	-	13.66
32	Mathura, India	19.45	-	76	Birmingham, UK	-	14.14
33	Tokyo, Japan	21.42	15.97	77	Coventry, UK	-	14.25
34	Kyoto, Japan	20.20	-	78	Dudley, UK	-	14.22
35	Saga, Japan	20.86	13.01	79	Sandwell, UK	-	13.90
36	Chiba, Japan	21.02	13.47	80	Solihull, UK	-	14.48
37	Wakayama, Japan	20.28	13.28	81	Walsall, UK	-	13.86
38	Osaka, Japan	20.79	-	82	Wolverhampton, UK	-	15.01
39	Nara, Japan	19.28	-	83	Bromley, UK	-	14.77
40	Tokushima, Japan	20.21	-	84	Croydon, UK	-	14.96
41	Ehime, Japan	20.11	-	85	South Lanarkshire, UK	-	13.62
42	Okinawa, Japan	23.64	18.64	86	Suzhou, China	23.82	-
43	Shiga, Japan	19.91	-	87	Guilin, China	25.18	16.68
44	Kumamoto, Japan	20.14	-	88	Liuzhou, China	23.84	16.79
89	Fukuoka, Japan	20.95	-	111	Hechi, China	24.03	18.93
90	Ibaraki, Japan	19.21	13.81	112	Baise, China	22.91	-

91	Nagasaki, Japan	21.41	13.41	113	Wuzhou, China	24.86	-
92	Kagawa, Japan	20.69	-	114	Guigang, China	25.12	-
93	Kochi, Japan	20.02	-	115	Nanning, China	24.76	-
94	Tottori, Japan	19.33	-	116	Qinzhou, China	24.77	-
95	Kagoshima, Japan	21.85	-	117	Fangchengang, China	24.22	19.07
96	Derby, UK	-	14.02	118	Beihai, China	25.96	-
97	Rutland, UK	-	13.99	119	CENTRO, Argentina	22.87	15.02
98	Nottingham, UK	-	14.27	120	LITORAL, Argentina	23.28	17.58
99	Stoke-on-Trent, UK	-	13.65	121	NORESTE, Argentina	22.66	-
100	Medway, UK	-	15.28	122	Queensland, Australia	21.16	-
101	Amber Valley, UK	-	14.09	123	Bulgaria	18.82	13.62
102	Bolsover, UK	-	13.74	124	Cyprus	20.38	15.38
103	Erewash, UK	-	13.98	125	Czechia	-	15.58
104	South Derbyshire, UK	-	14.55	126	Egypt	21.69	-
105	Wealden, UK	-	15.43	127	Estonia	-	14.24
106	Blaby, UK	-	13.74	128	Latvia	-	14.76
107	Charnwood, UK	-	14.16	129	Serbia	-	15.56
108	Harborough, UK	-	14.44	130	Tunisia	22.23	16.68
109	Hinckley and Bosworth, UK	-	14.06	131	Ukraine	-	13.88
110	New Plymouth, New Zealand	-	15.24				

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Table A3 Details of 16 energy demand datasets used for external validation.

Location	Year period	Time resolution	Gas / Electricity	Type	Source
Austin, USA	2000-2020	monthly	Electricity	building energy	U.S. EIA, 2020
Northeastern Mexico	2022	daily	Gas / Electricity	building energy	Aguirre-Fraire et al., 2024
Trondheim, Norway	2019-2021	hourly	Electricity	building energy	Hofmann et al., 2023
Agder, Norway	2019-2022	hourly	Electricity	building energy	Hofmann et al., 2023
Estación Itakyry, Paraguay	2017-2020	hourly	Electricity	energy	Velázquez et al., 2022
Presidente Franco, Paraguay	2017-2020	hourly	Electricity	energy	Velázquez et al., 2022
Acaray, Paraguay	2017-2020	hourly	Electricity	energy	Velázquez et al., 2022
South Australia, Australia	2015	hourly	Electricity	building energy	Sharma et al., 2019
Kitakyushu, Japan	2015-2018	hourly	Gas/Electricity	building energy	Liao et al., 2024
Lower Saxony, Germany	2018-2021	hourly	Electricity	building energy	Schlemminger et al., 2022
Hawkes Bay, New Zealand	2014-2016	minute	Electricity	building energy	B. Anderson et al., 2018
Philadelphia, USA	2009-2011	daily	Electricity	energy	Cohen et al., 2015
Tacoma, USA	2006-2013	daily	Electricity	energy	Cohen et al., 2015
Victoria, Australia	2000-2007	daily	Electricity	energy	AEMO, 2025
Delhi, India	2011-2013	daily	Electricity	energy	Cohen et al., 2015
Abidjan, Côte d'Ivoire	2012-2013	daily	Electricity	energy	Cohen et al., 2015

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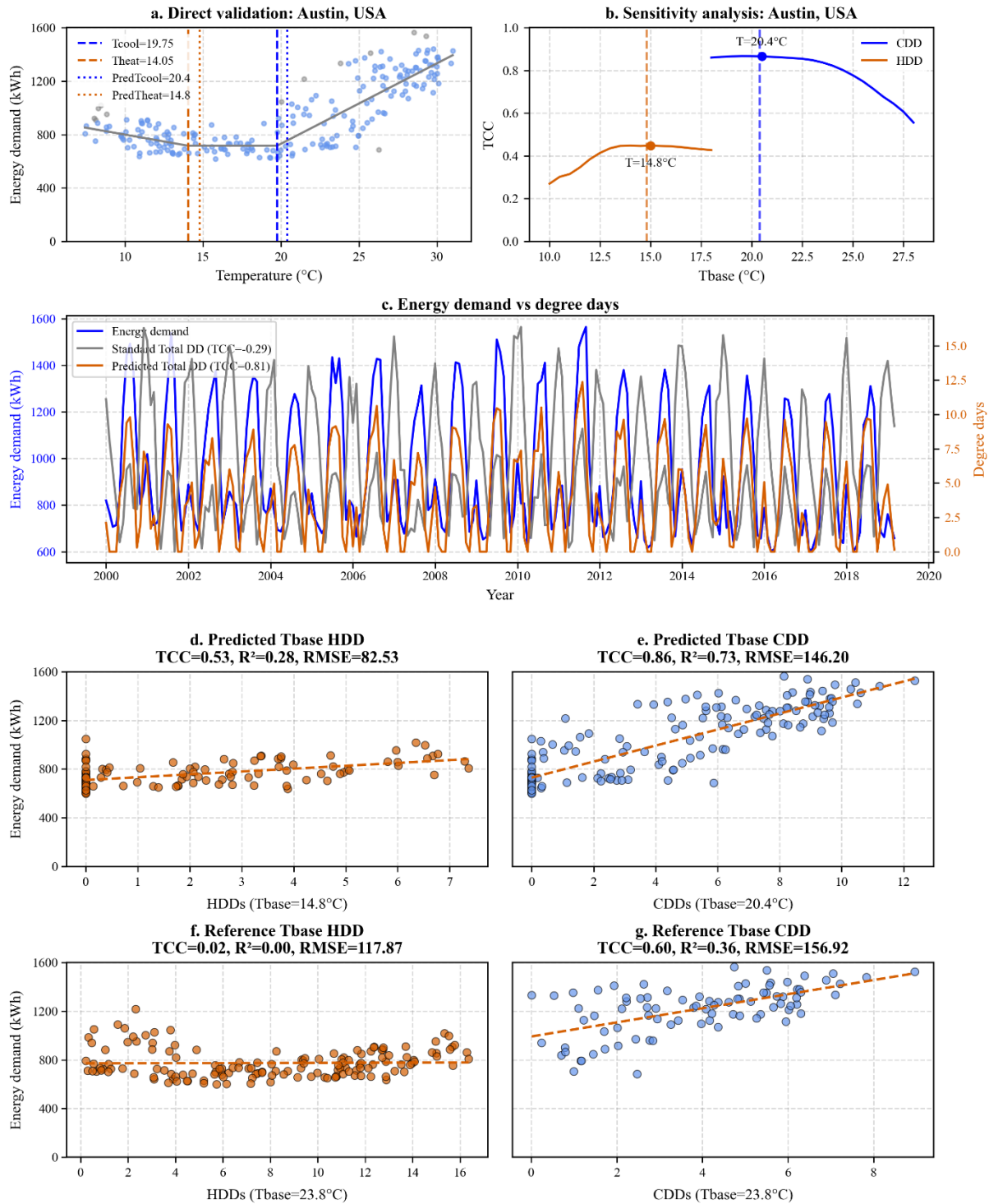


Figure A2: Visualization of HDD and CDD versus energy consumption at different base temperatures in Austin, USA. **a**, direct validation of T_{cool} and T_{heat} ; **b**, TCC versus base temperature; **c**, indirect validation (TCC, predicted vs reference T_{base}); **d–g**, heating and cooling energy demand modelling and RMSE using predicted versus reference base temperatures.

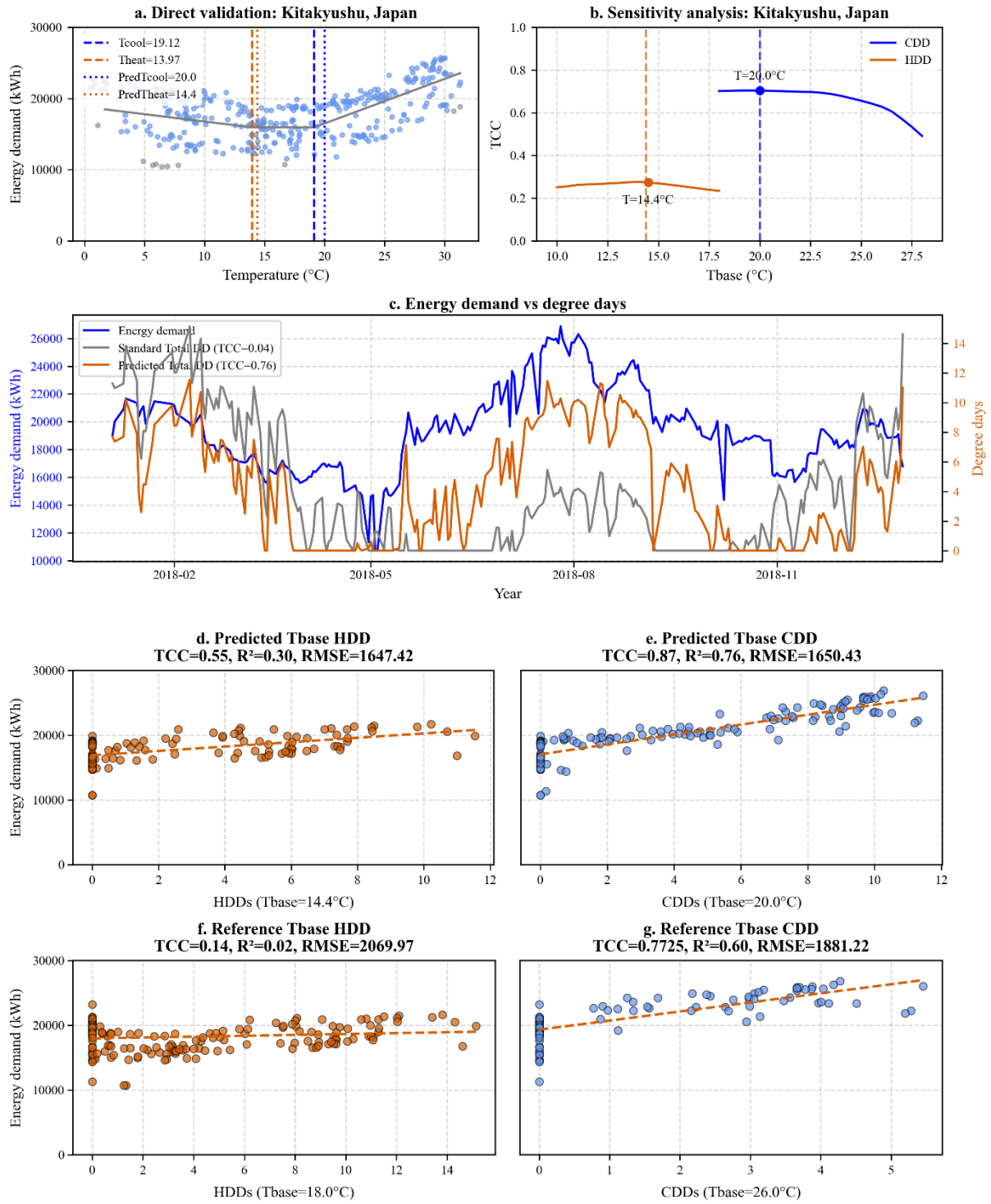


Figure A3: Visualization of HDD and CDD versus energy consumption at different base temperatures in Kitakyushu, Japan. **a**, direct validation of T_{cool} and T_{heat} ; **b**, TCC versus base temperature; **c**, indirect validation (TCC, predicted vs reference T_{base}); **d–g**, heating and cooling energy demand modelling and RMSE using predicted versus reference base temperatures.

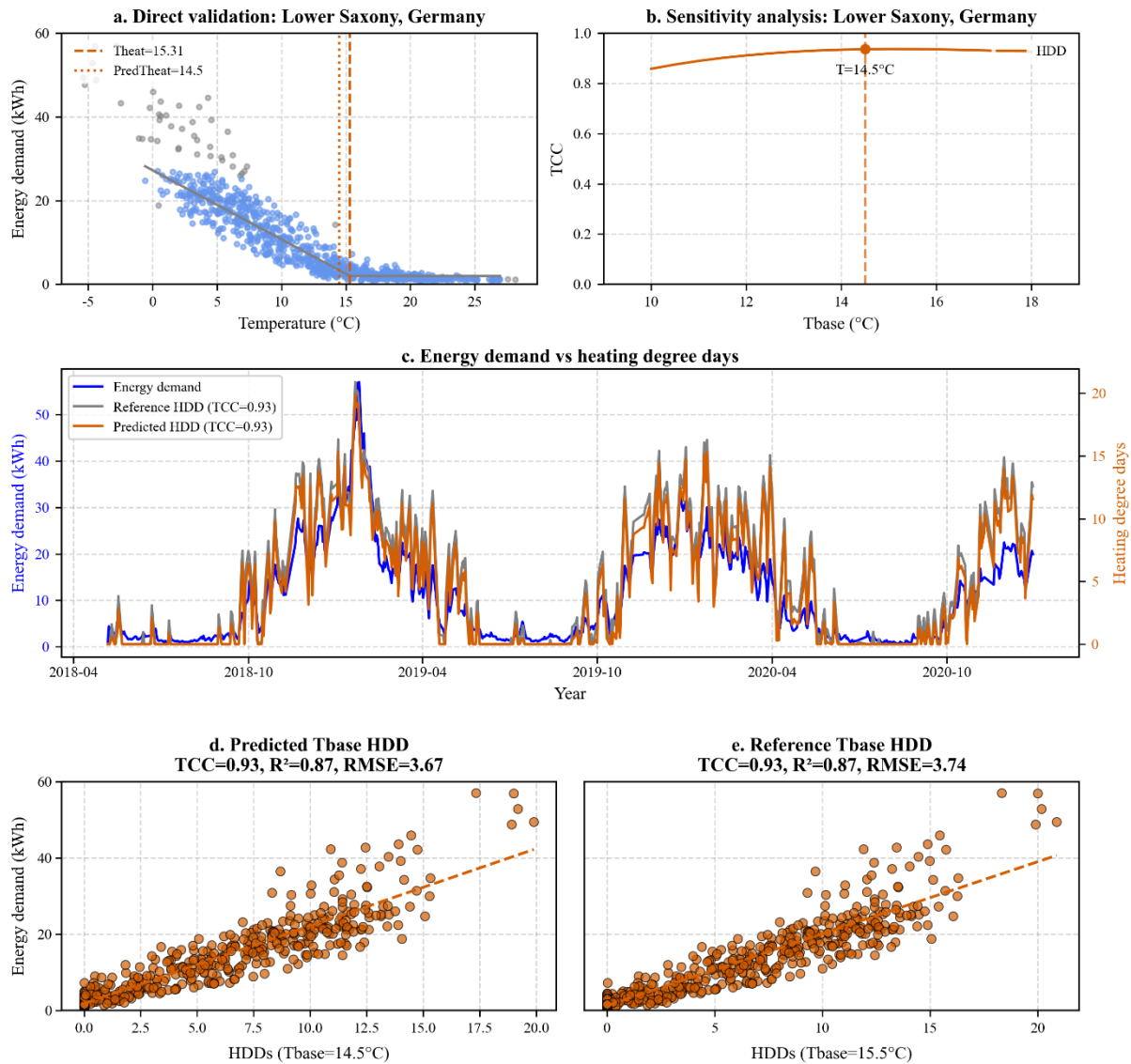


Figure A4: Visualization of HDD versus energy consumption at different base temperatures in Lower Saxony, Germany. **a**, direct validation of *Theat*; **b**, TCC versus base temperature; **c**, indirect validation (TCC, predicted vs reference *Tbase*); **d**, **e**, heating energy demand modelling and RMSE using predicted versus reference base temperatures.

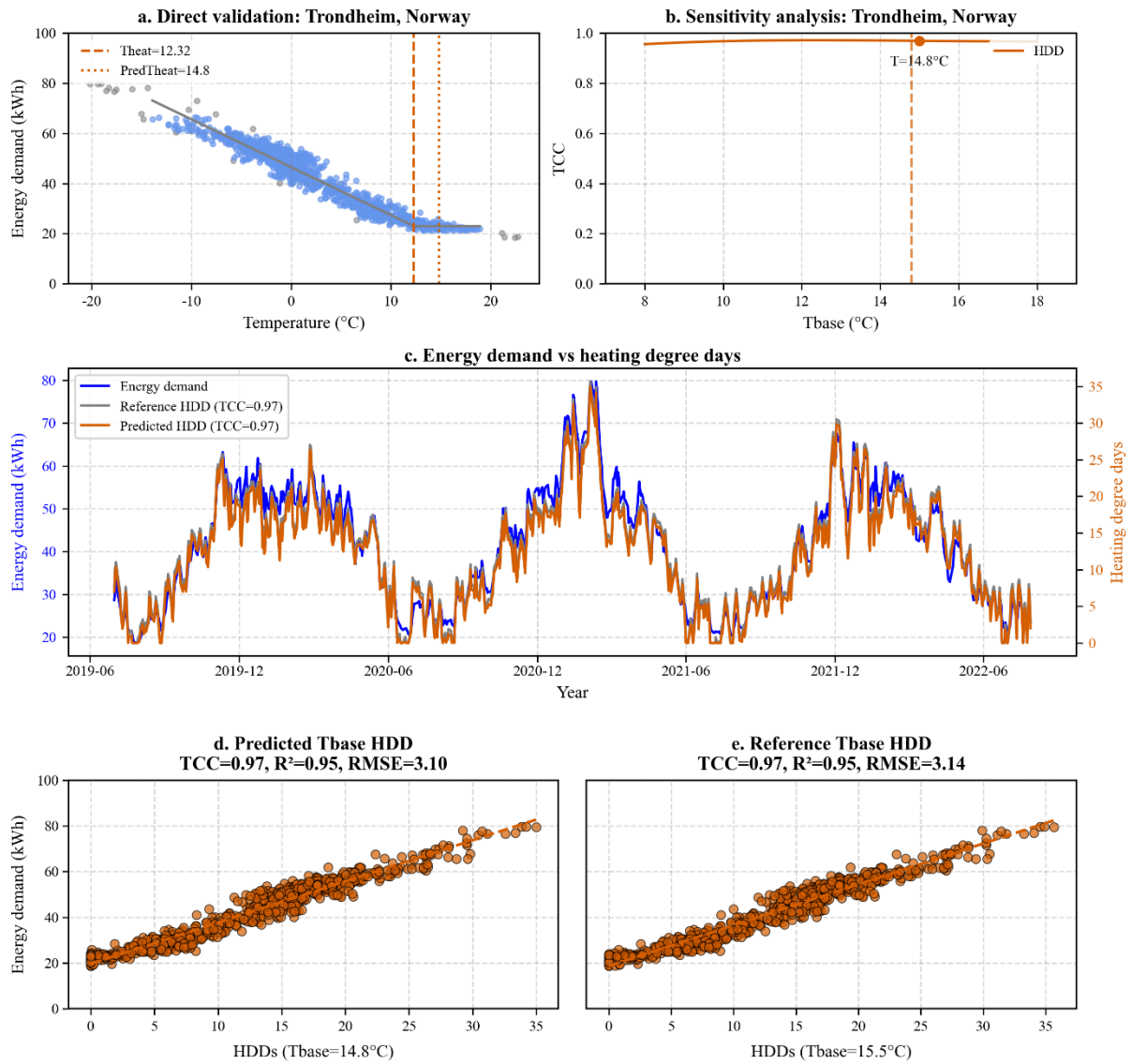


Figure A5: Visualization of HDD versus energy consumption at different base temperatures in Trondheim, Norway. **a**, direct validation of *Theat*; **b**, TCC versus base temperature; **c**, indirect validation (TCC, predicted vs reference *Tbase*); **d**, **e**, heating energy demand modelling and RMSE using predicted versus reference base temperatures.

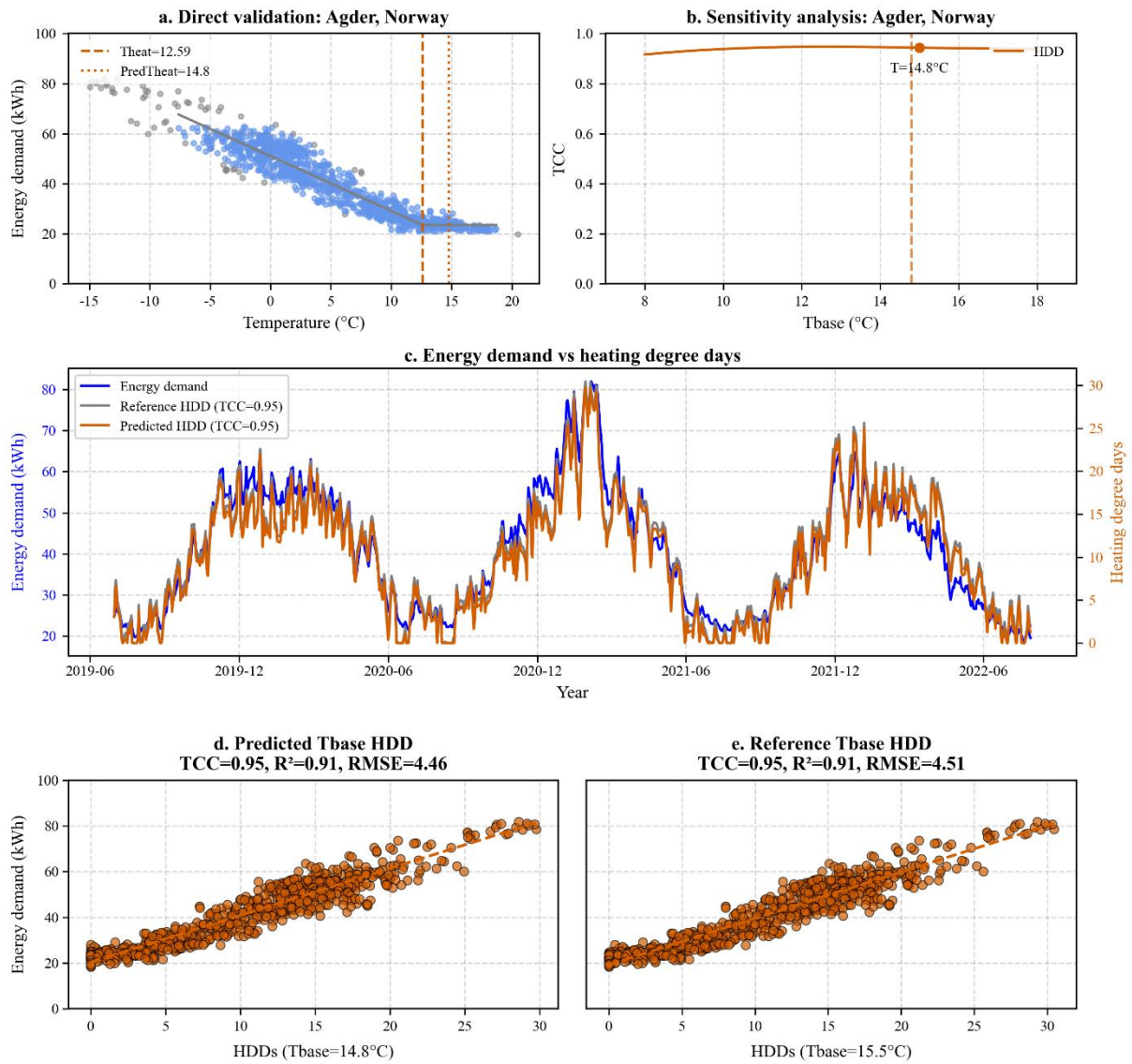


Figure A6: Visualization of HDD versus energy consumption at different base temperatures in Agder, Norway. **a**, direct validation of *Theat*; **b**, TCC versus base temperature; **c**, indirect validation (TCC, predicted vs reference *Tbase*); **d**, **e**, heating energy demand modelling and RMSE using predicted versus reference base temperatures.

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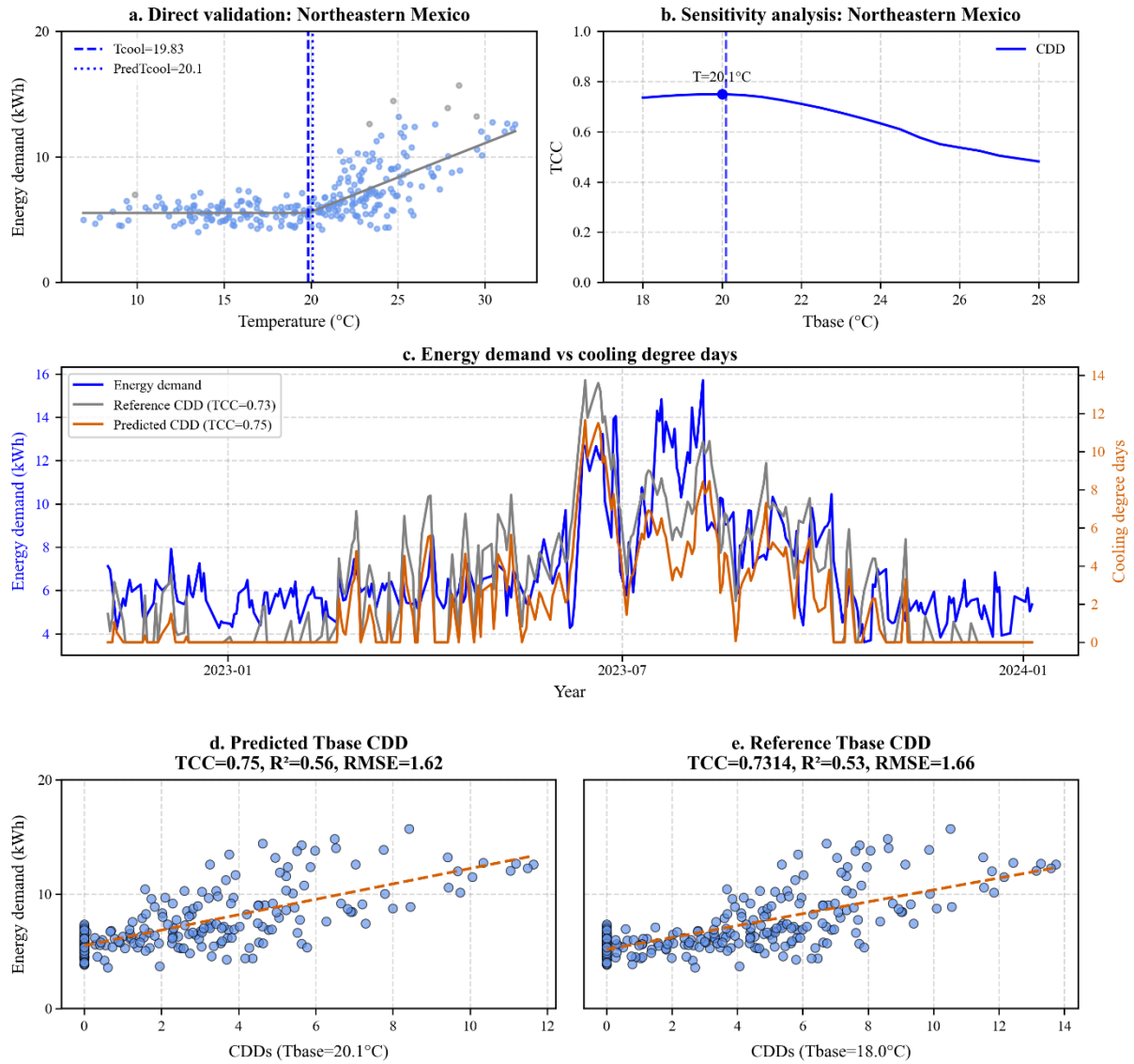


Figure A7: Visualization of CDD versus energy consumption at different base temperatures in Northeastern Mexico. **a**, direct validation of T_{cool} ; **b**, TCC versus base temperature; **c**, indirect validation (TCC, predicted vs reference T_{base}); **d**, **e**, cooling energy demand modelling and RMSE using predicted versus reference base temperatures.

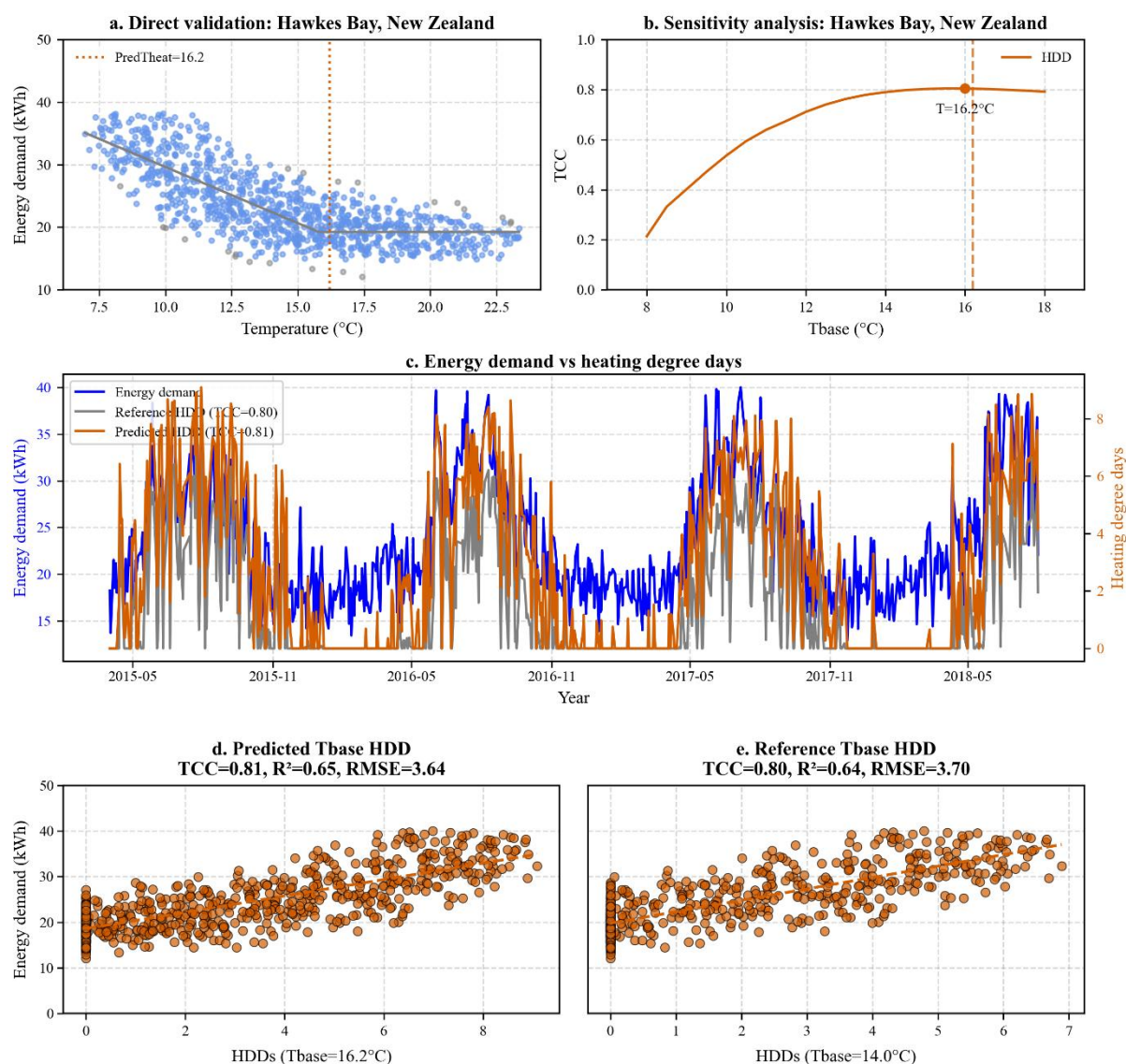


Figure A8: Visualization of HDD versus energy consumption at different base temperatures in Hawkes Bay, New Zealand. **a**, direct validation of *Theat*; **b**, TCC versus base temperature; **c**, indirect validation (TCC, predicted vs reference *Tbase*); **d**, **e**, heating energy demand modelling and RMSE using predicted versus reference base temperatures.

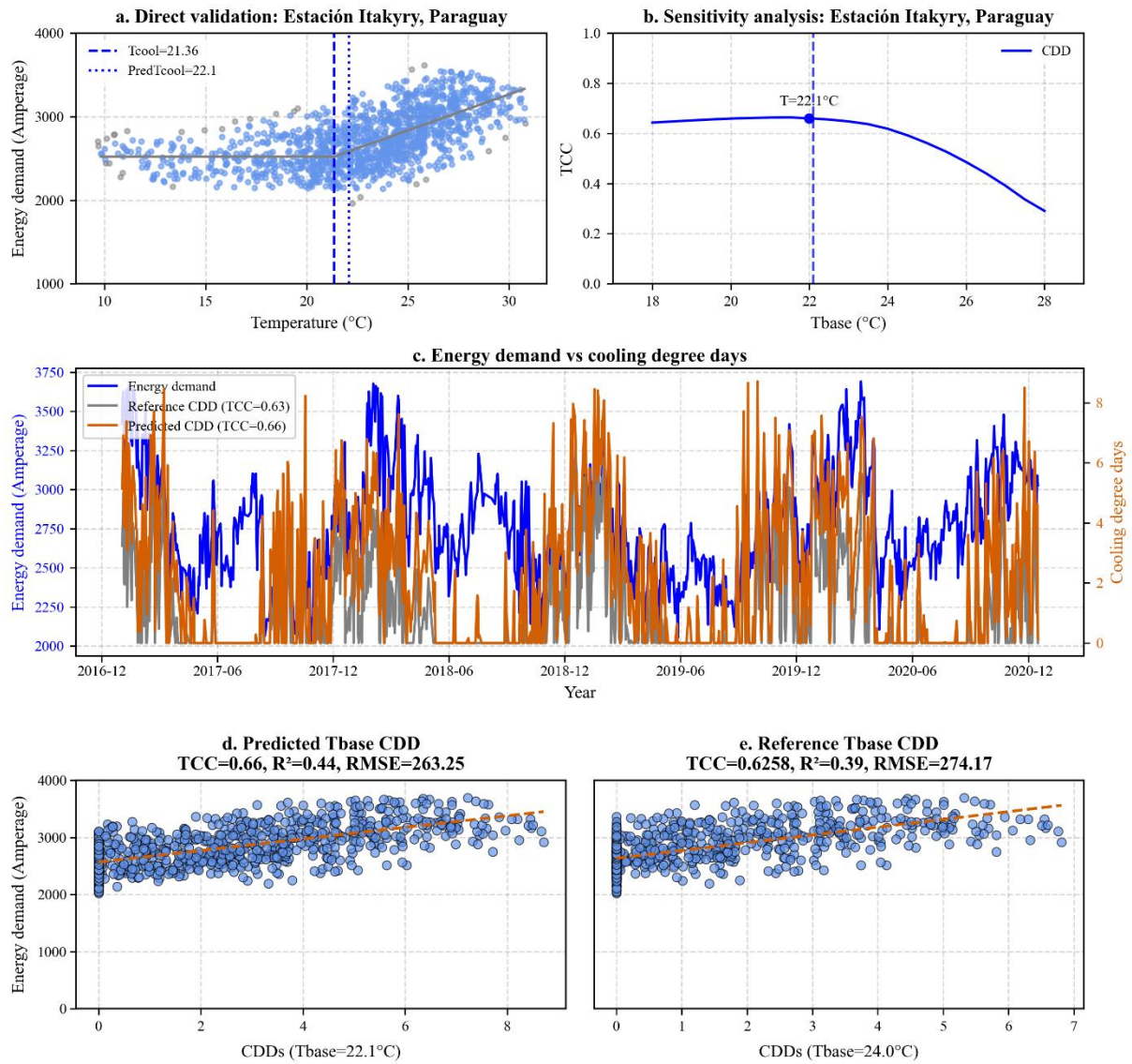


Figure A9: Visualization of CDD versus energy consumption at different base temperatures in Itakyry, Paraguay. **a**, direct validation of T_{cool} ; **b**, TCC versus base temperature; **c**, indirect validation (TCC, predicted vs reference T_{base}); **d**, **e**, cooling energy demand modelling and RMSE using predicted versus reference base temperatures.

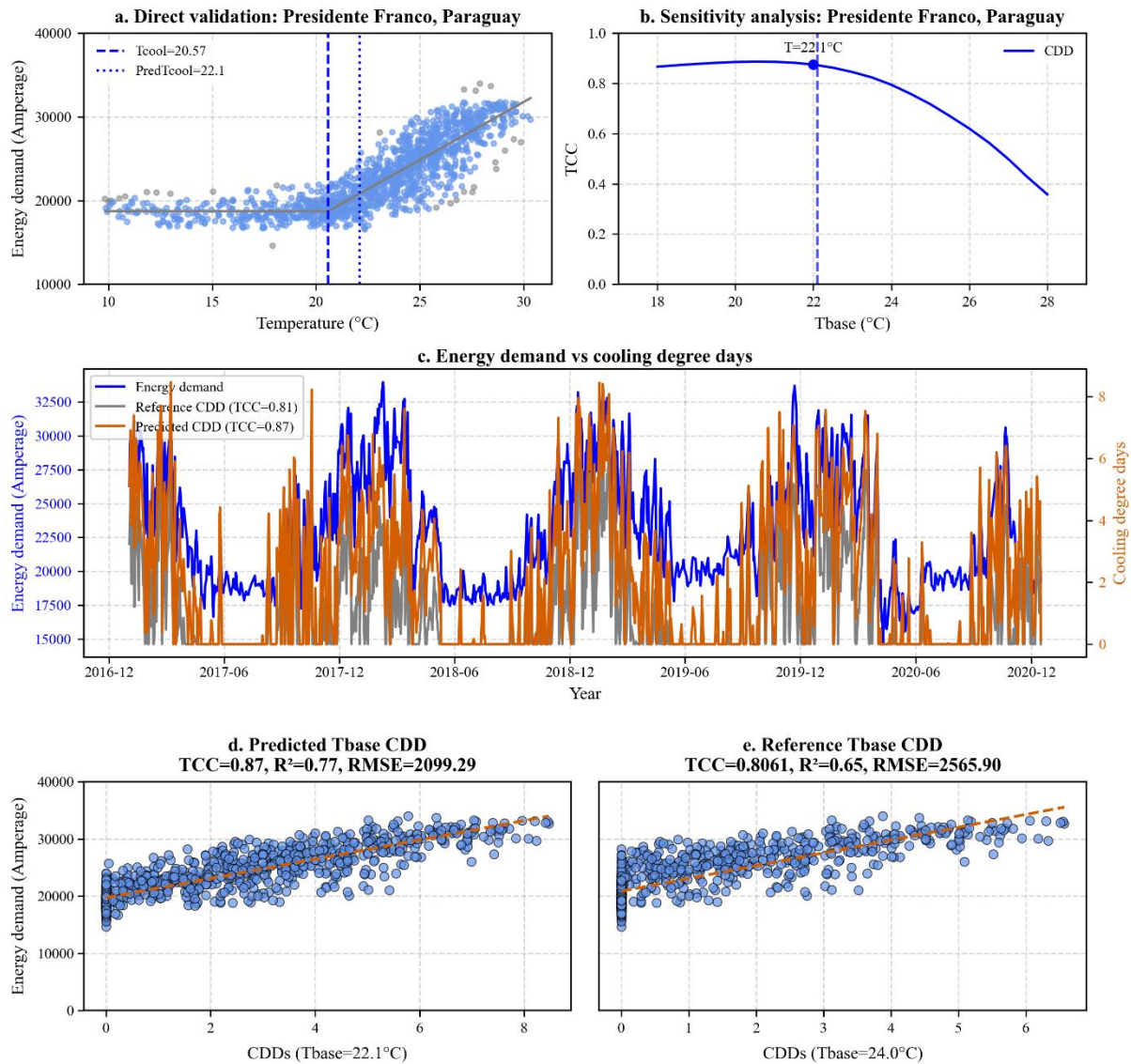


Figure A10: Visualization of CDD versus energy consumption at different base temperatures in Presidente Franco, Paraguay. **a**, direct validation of T_{cool} ; **b**, TCC versus base temperature; **c**, indirect validation (TCC, predicted vs reference T_{base}); **d**, **e**, cooling energy demand modelling and RMSE using predicted versus reference base temperatures.

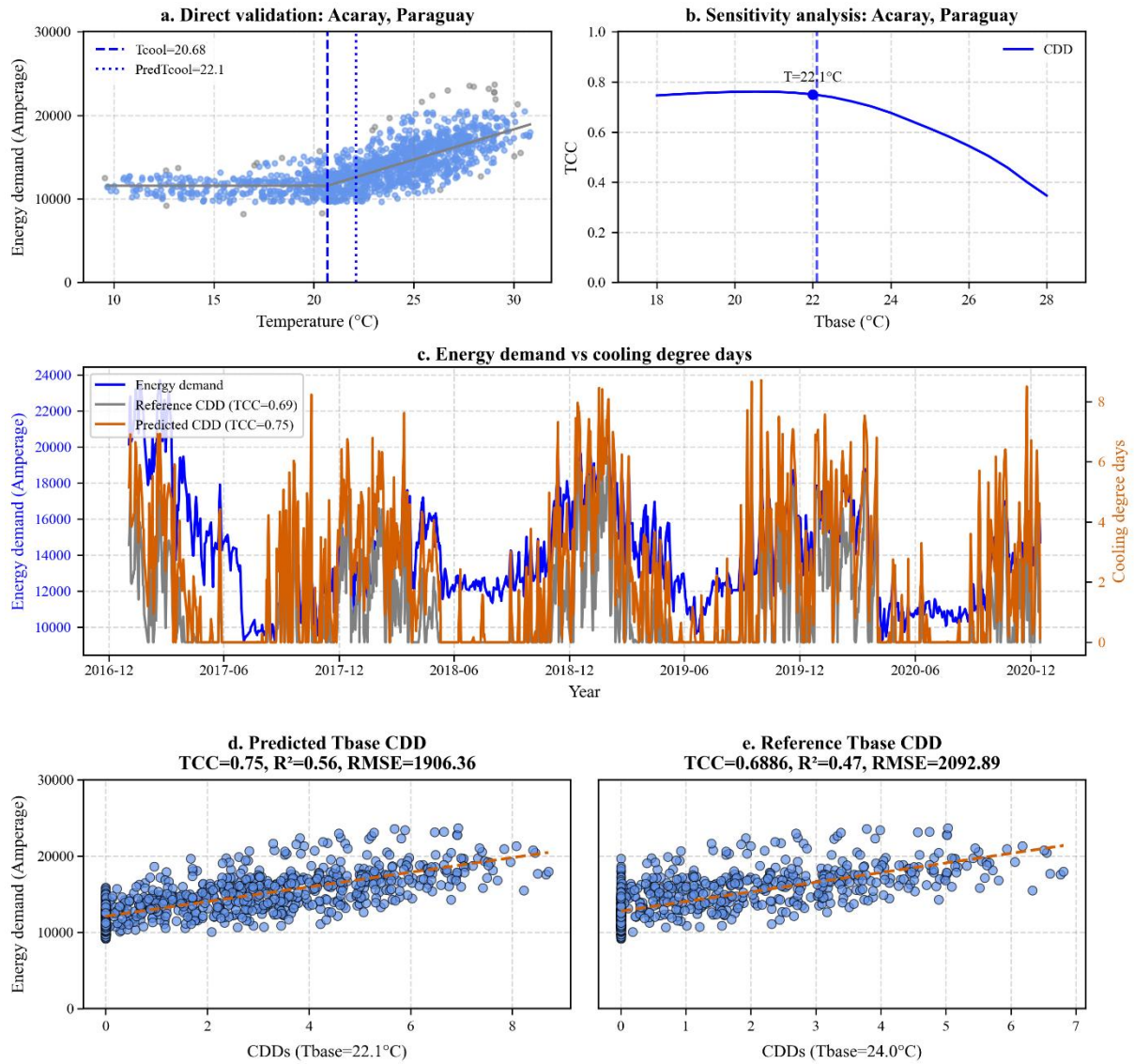


Figure A11: Visualization of CDD versus energy consumption at different base temperatures in Acaray, Paraguay. **a**, direct validation of T_{cool} ; **b**, TCC versus base temperature; **c**, indirect validation (TCC, predicted vs reference T_{base}); **d**, **e**, cooling energy demand modelling and RMSE using predicted versus reference base temperatures.

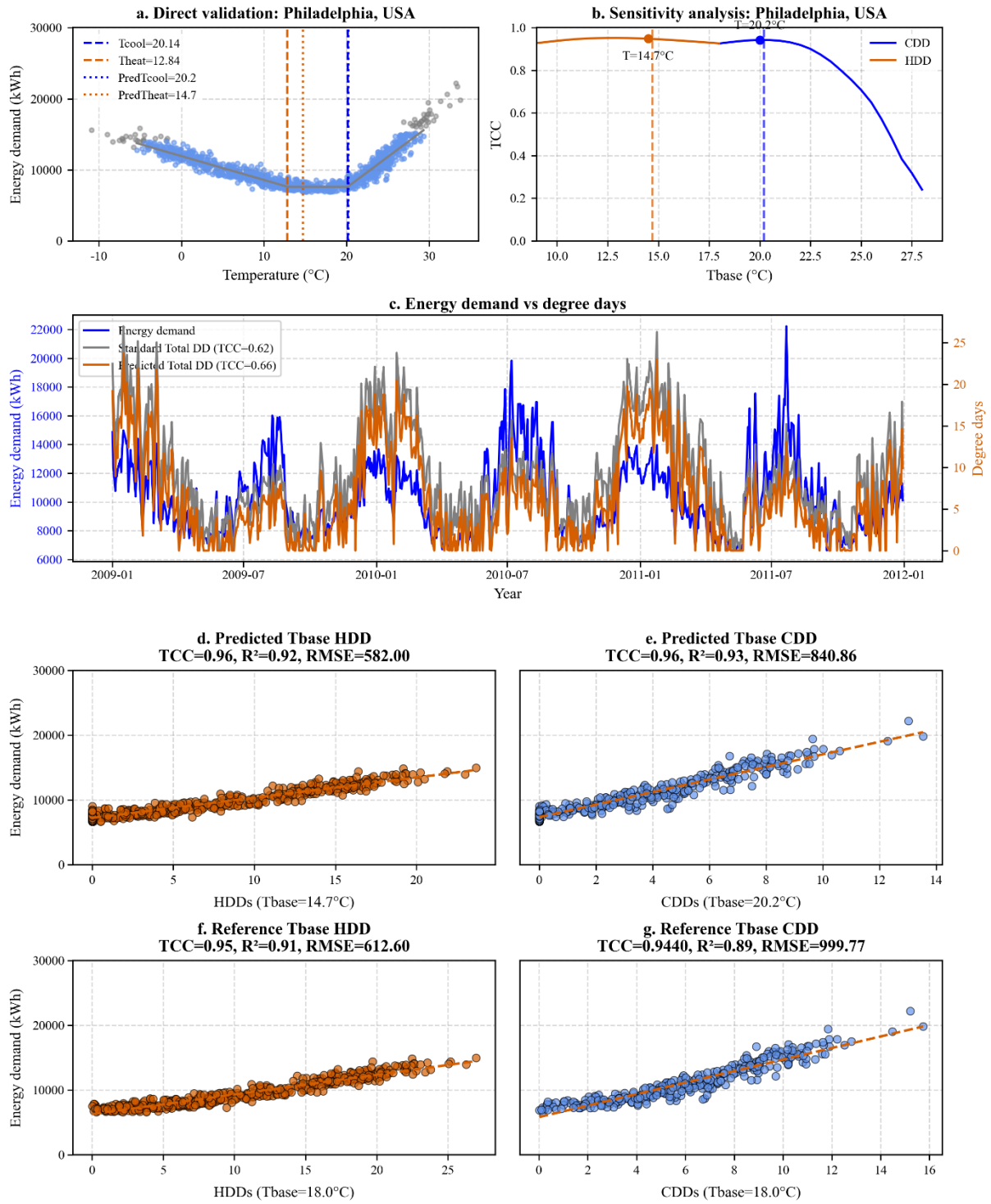


Figure A12: Visualization of HDD and CDD versus energy consumption at different base temperatures in Philadelphia, USA. **a**, direct validation of T_{cool} and T_{heat} ; **b**, TCC versus base temperature; **c**, indirect validation (TCC, predicted vs reference T_{base}); **d–g**, heating and cooling energy demand modelling and RMSE using predicted versus reference base temperatures.

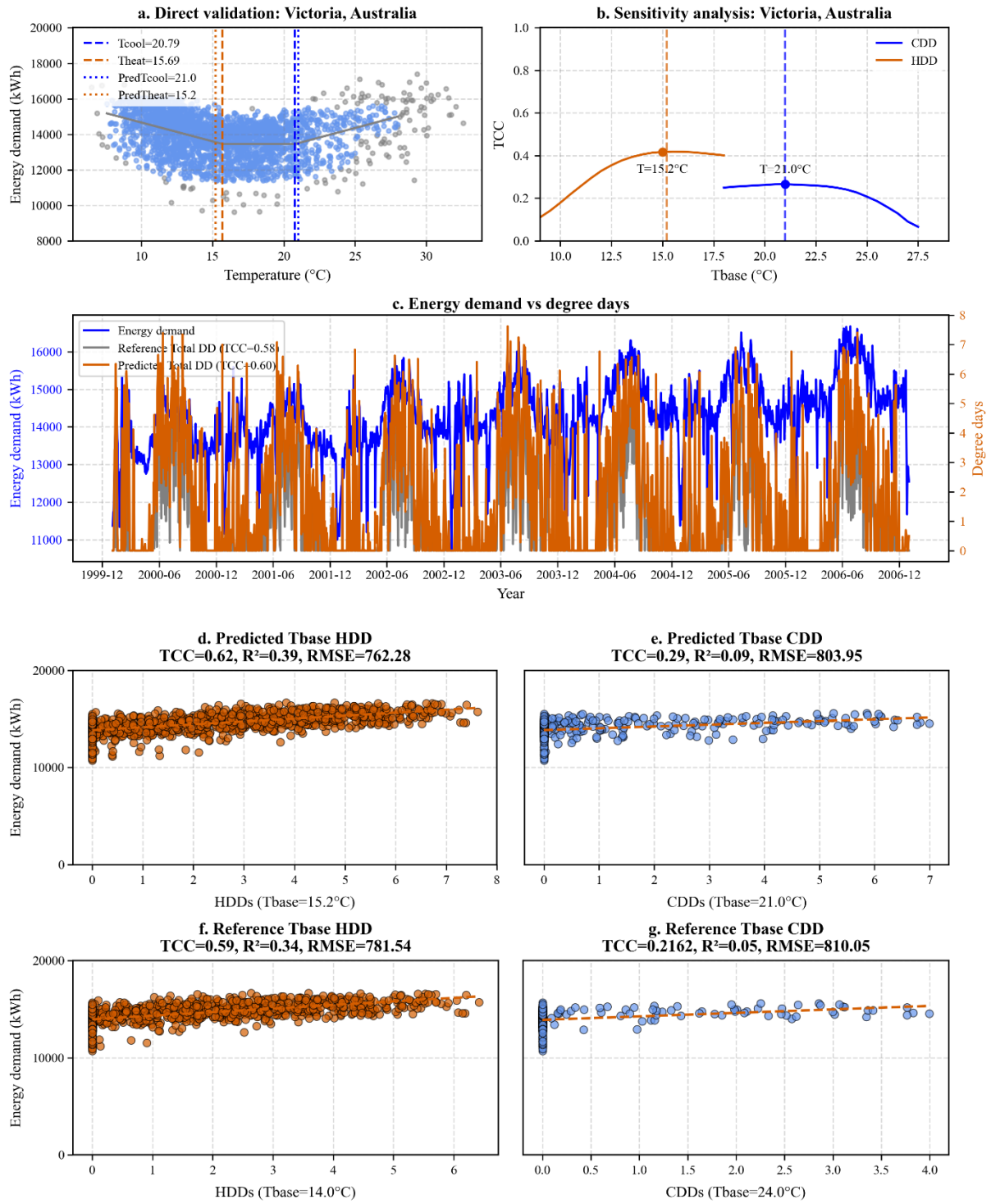


Figure A13: Visualization of HDD and CDD versus energy consumption at different base temperatures in Victoria, Australia. **a**, direct validation of T_{cool} and T_{heat} ; **b**, TCC versus base temperature; **c**, indirect validation (TCC, predicted vs reference T_{base}); **d–g**, heating and cooling energy demand modelling and RMSE using predicted versus reference base temperatures.

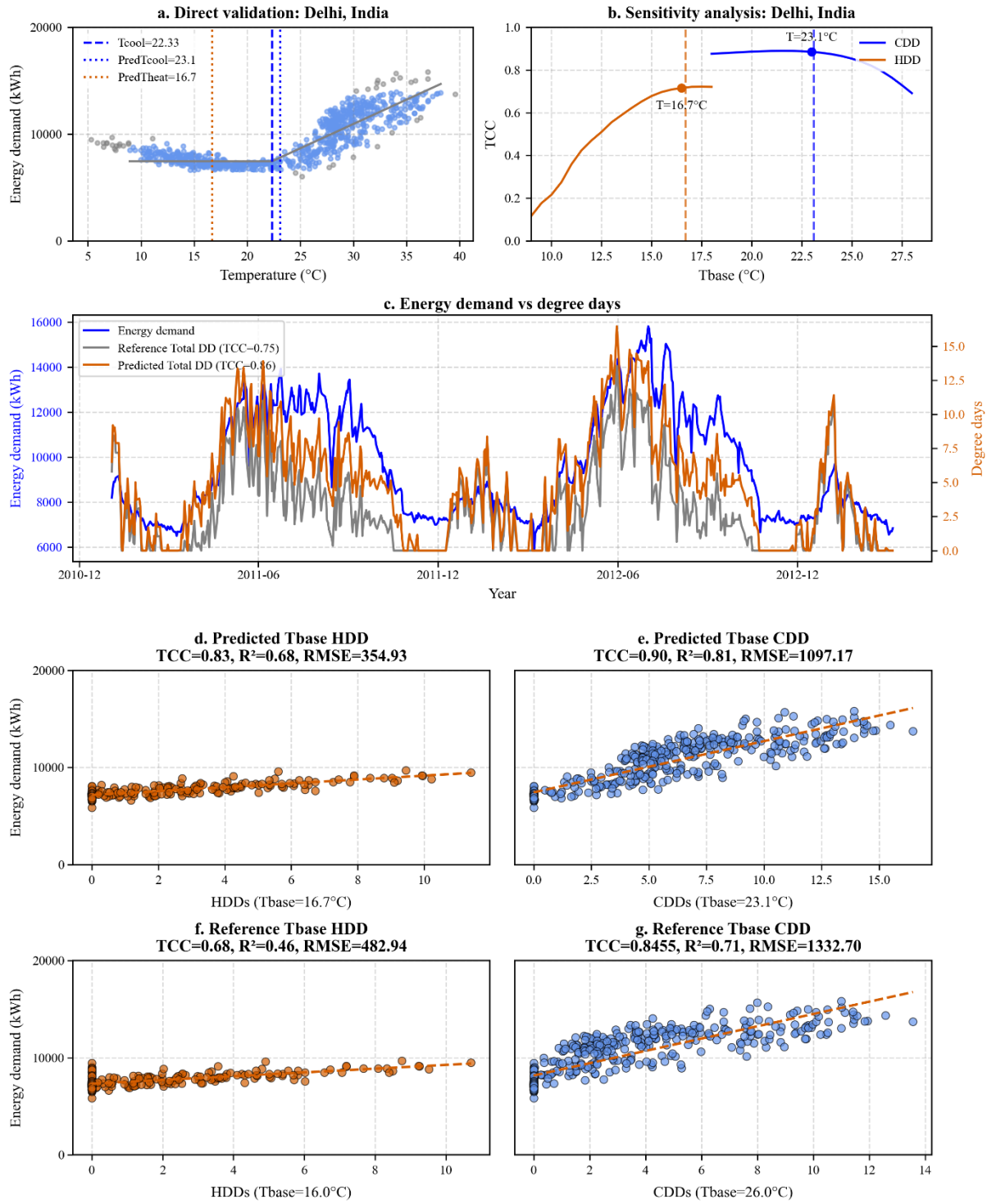


Figure A14: Visualization of HDD and CDD versus energy consumption at different base temperatures in Delhi, India. **a**, direct validation of T_{cool} and T_{heat} ; **b**, TCC versus base temperature; **c**, indirect validation (TCC, predicted vs reference T_{base}); **d–g**, heating and cooling energy demand modelling and RMSE using predicted versus reference base temperatures.

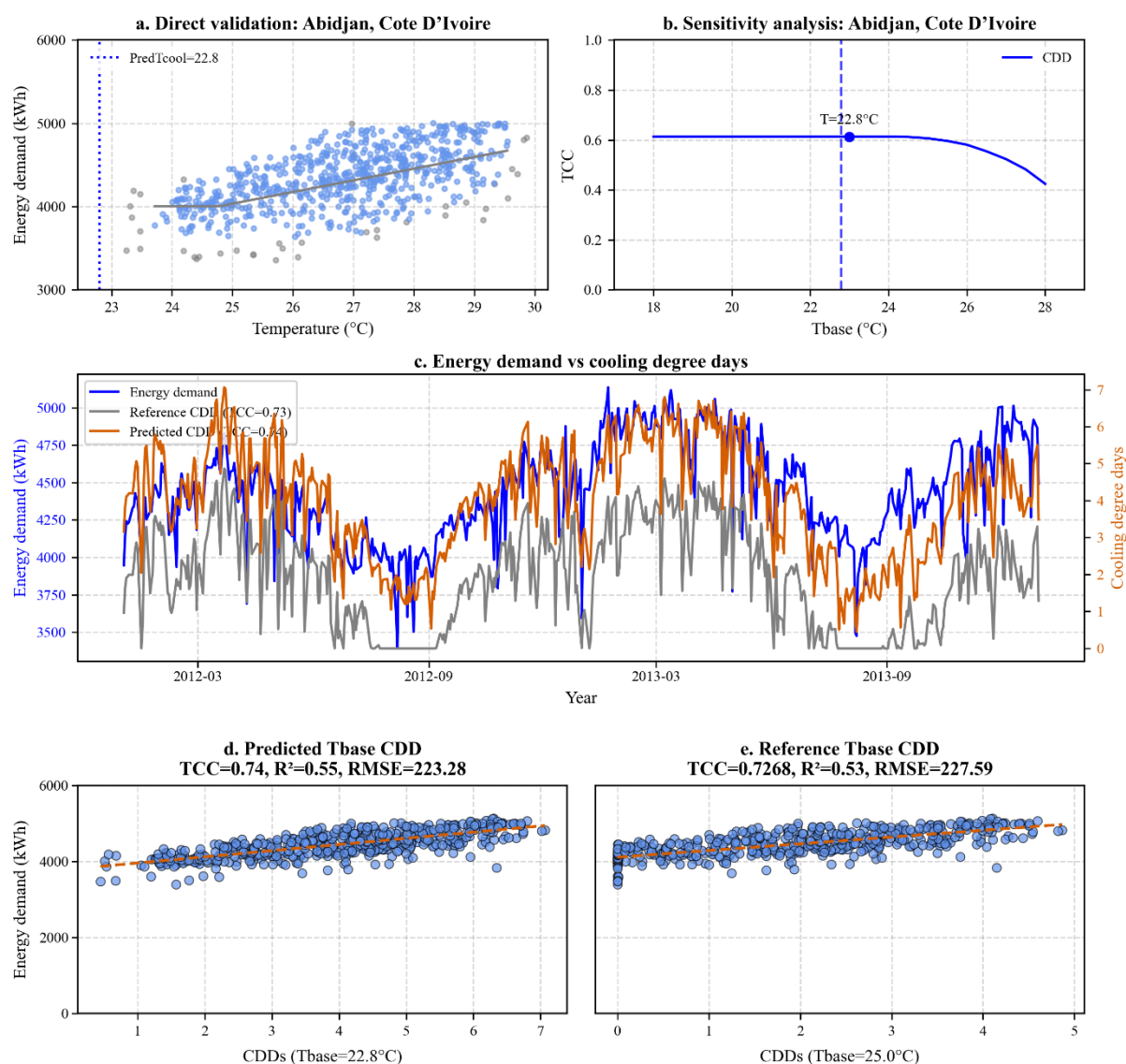


Figure A15: Visualization of CDD versus energy consumption at different base temperatures in Abidjan, Cote D'Ivoire. **a**, direct validation of T_{cool} ; **b**, TCC versus base temperature; **c**, indirect validation (TCC, predicted vs reference T_{base}); **d**, **e**, cooling energy demand modelling and RMSE using predicted versus reference base temperatures.

Reference

- Abajian, A. C., Carleton, T., Meng, K. C., & Deschênes, O. (2025). Quantifying the global climate feedback from energy-based adaptation. *Nature Communications*, 16(1). <https://doi.org/10.1038/s41467-025-59201-7>
- 990 AECOM Building Engineering, Energy Demand Research Project: Early Smart Meter Trials, 2007-2010, (2014).
- Afroz. (2023). Swiss Smart Meter Data [Data set]. Kaggle. <https://www.kaggle.com/datasets/pythonafroz/swiss-smart-meter-data>
- Agency for Natural Resources and Energy. (n.d.). Electric power survey statistics: Historical data [Data set]. Ministry of Economy, Trade and Industry. Retrieved November 12, 2025, from https://www.enecho.meti.go.jp/statistics/electric_power/ep002/results_archive.html
- 995 Agrawal, S., Mani, S., Ganesan, K., & Jain, A. (2021). High frequency smart meter data from two districts in India (Mathura and Bareilly) (Version 2) [Data set]. Harvard Dataverse. <https://doi.org/10.7910/DVN/GOCHJH>
- Aguirre-Fraire, B., Beltrán, J., & Soto-Mendoza, V. (2024). A comprehensive dataset integrating household energy consumption and weather conditions in a north-eastern Mexican urban city. *Data in Brief*, 54, 110452.
- 1000 Ahmad, T., Chen, H., Guo, Y., & Wang, J. (2018). A comprehensive overview on the data driven and large scale based approaches for forecasting of building energy demand: A review. In *Energy and Buildings* (Vol. 165, pp. 301–320). Elsevier Ltd. <https://doi.org/10.1016/j.enbuild.2018.01.017>
- Anjomshoaa, A., & Salmanzadeh, M. (2017). Estimation of the changeover times and degree-days balance point temperatures of a city using energy signatures. *Sustainable Cities and Society*, 35, 538–543.
- 1005 <https://doi.org/10.1016/j.scs.2017.08.028>
- ASHRAE. (2009). *Handbook of Fundamentals*. American Society of Heating, Refrigerating and Air-Conditioning Engineers, Atlanta, Georgia.
- Australian Energy Market Operator (AEMO). (2025). Electricity price & demand [dataset]. Retrieved from <https://aemo.com.au/>
- 1010 B. Anderson, D. Evers, R. Ford, D. Giraldo Ocampo, R. Peniamina, J. Stephenson, K. Suomalainen, L. Wilcocks, M. Jack, New Zealand GREEN Grid Household Electricity Demand Study 2014-2018, (2018). <https://doi.org/http://doi.org/10.5255/UKDA-SN 853334>.
- Bae, C., Lee, H., & Chun, C. (2025). Beyond the thermostat: A behavioral study of residential cooling practices. *Building and Environment*, 282. <https://doi.org/10.1016/j.buildenv.2025.113250>
- 1015 Bhatnagar, M., Mathur, J., & Garg, V. (2018). Determining base temperature for heating and cooling degree-days for India. *Journal of Building Engineering*, 18, 270–280. <https://doi.org/10.1016/j.job.2018.03.020>
- Borah, P., Singh, M. K., & Mahapatra, S. (2015). Estimation of degree-days for different climatic zones of North-East India. *Sustainable Cities and Society*, 14(1), 70–81. <https://doi.org/10.1016/j.scs.2014.08.001>
- Broomandi, P., Satyanaga, A., Bagheri, M., Hadei, M., Galán-Madruga, D., Fard, A. M., ... & Kim, J. R. (2025). Extreme temperature events in Kazakhstan and their impacts on public health and energy demand. *Global challenges*, 9(2), 2400207.
- 1020 Burguillo, M., & Juez-Martel, P. (2024). Just energy heating transitions: lessons from characteristics of households using different heating sources. *Energy Efficiency*, 17(6). <https://doi.org/10.1007/s12053-024-10241-w>

- 1025 C. Miller, A. Kathirgamanathan, B. Picchetti, P. Arjunan, J.Y. Park, Z. Nagy, P. Raftery, B.W. Hobson, Z. Shi, F. Meggers, The Building Data Genome Project 2, energy meter data from the ASHRAE Great Energy Predictor III competition, (2020).
- Camarasa, C., Mata, É., Navarro, J. P. J., Reyna, J., Bezerra, P., Angelkorte, G. B., Feng, W., Filippidou, F., Forthuber, S., Harris, C., Sandberg, N. H., Ignatiadou, S., Kranzl, L., Langevin, J., Liu, X., Müller, A., Soria, R., Villamar, D., Dias, G. P., ... Yaramenka, K. (2022). A global comparison of building decarbonization scenarios by 2050 towards 1.5–2 °C targets. *Nature Communications*, 13(1). <https://doi.org/10.1038/s41467-022-29890-5>
- 1030 CAMMESA. (2025). Base Demanda Diaria 2017-2025 [Dataset]. Compañía Administradora del Mercado Mayorista Eléctrico. <https://cammesaweb.cammesa.com/2025/11/07/covid-19-comportamiento-de-la-demanda-de-energia-electrica-en-el-mem>
- 1035 Canadian Centre for Energy Information. (n.d.). High-Frequency Electricity Data: Visualization Tool (Beta) [Data set]. Canadian Centre for Energy Information, in collaboration with Natural Resources Canada and the Canada Energy Regulator. <https://energy-information.canada.ca/en/resources/high-frequency-electricity-data>
- 1040 Central Electricity Authority. (2024). Power supply position [Data set]. Open Government Data Platform India. Retrieved November 12, 2025, from <https://www.data.gov.in/catalog/power-supply-position>
- Chambers, J. D., & Oreszczyn, T. (2019). Deconstruct: A scalable method of as-built heat power loss coefficient inference for UK dwellings using smart meter data. *Energy and Buildings*, 183, 443–453. <https://doi.org/10.1016/j.enbuild.2018.11.016>
- 1045 Chen, J., Chen, J., Zhang, X. J., Peng, P., & Risi, C. (2023). A century and a half precipitation oxygen isoscape for China generated using data fusion and bias correction. *Scientific Data*, 10(1). <https://doi.org/10.1038/s41597-023-02095-1>
- Choi, S., Pellen, A., & Masson, V. (2017). How does daylight saving time affect electricity demand? An answer using aggregate data from a natural experiment in Western Australia. *Energy Economics*, 66, 247–260. <https://doi.org/10.1016/j.eneco.2017.06.018>
- 1050 Cholewa, T., Siuta-Olcha, A., Smolarz, A., Muryjas, P., Wolszczak, P., Anasiewicz, R., & Balaras, C. A. (2021). A simple building energy model in form of an equivalent outdoor temperature. *Energy and Buildings*, 236. <https://doi.org/10.1016/j.enbuild.2021.110766>
- CIBSE, T. (2006). *Degree-days: theory and application*. The Chartered Institution of Building Services Engineers, 222.
- 1055 Clarke, L., Eom, J., Marten, E. H., Horowitz, R., Kyle, P., Link, R., ... & Zhou, Y. (2018). Effects of long-term climate change on global building energy expenditures. *Energy Economics*, 72, 667–677.
- Cohen, E., Modi, V., Torbey, H., Piccirelli, M. & Yu-Tian. Global trends in urban energy use. GitHub Repository (2015). <https://github.com/Ecohen4/Energy>
- 1060 Cong, S., Nock, D., Qiu, Y. L., & Xing, B. (2022). Unveiling hidden energy poverty using the energy equity gap. *Nature Communications*, 13(1). <https://doi.org/10.1038/s41467-022-30146-5>
- Corrales-Suastegui, A., Ruiz-Alvarez, O., Torres-Alavez, J. A., & Pavia, E. G. (2021). Analysis of cooling and heating degree days over mexico in present and future climate. *Atmosphere*, 12(9). <https://doi.org/10.3390/atmos12091131>

- 1065 Day, A. R., Knight, I., Dunn, G., & Gaddas, R. (2003). Improved methods for evaluating base temperature for use in building energy performance lines. *Building Services Engineering Research and Technology*, 24(4), 221-228.
- De Rosa, M., Bianco, V., Scarpa, F., & Tagliafico, L. A. (2015). Historical trends and current state of heating and cooling degree days in Italy. *Energy Conversion and Management*, 90, 323–335.
- 1070 <https://doi.org/10.1016/j.enconman.2014.11.022>
- Deroubaix, A., Labuhn, I., Camredon, M., Gaubert, B., Monerie, P. A., Popp, M., Ramarohetra, J., Ruprich-Robert, Y., Silvers, L. G., & Siour, G. (2021). Large uncertainties in trends of energy demand for heating and cooling under climate change. *Nature Communications*, 12(1). <https://doi.org/10.1038/s41467-021-25504-8>
- Dicko, K., Umaru, E. T., Sanogo, S., Okhimamhe, A. A., & Loewner, R. (2024). A Trend Analysis of Changes in Cooling Degree Days in West Africa Under Global Warming. *Atmosphere*, 15(11).
- 1075 <https://doi.org/10.3390/atmos15111376>
- Duan, H., Ming, X., Zhang, X. B., Sterner, T., & Wang, S. (2023). China’s adaptive response to climate change through air-conditioning. *IScience*, 26(3). <https://doi.org/10.1016/j.isci.2023.106178>
- Ember. (n.d.). Monthly electricity data [Data set]. Retrieved November 12, 2025, from <https://ember-energy.org/data/monthly-electricity-data/>
- 1080 Empresa de Pesquisa Energética (EPE). Monthly Electricity Consumption by Class (regions and subsystems). Rio de Janeiro: EPE, [2024]. <https://www.epe.gov.br/en/open-data/publications/monthly-electricity-consumption>
- Falchetta, G., Cian, E. De, Pavanello, F., & Wing, I. S. (2024). Inequalities in global residential cooling energy use to 2050. *Nature Communications*, 15(1). <https://doi.org/10.1038/s41467-024-52028-8>
- 1085 Feng, Y., Duan, Q., Chen, X., Yakkali, S. S., & Wang, J. (2021). Space cooling energy usage prediction based on utility data for residential buildings using machine learning methods. *Applied Energy*, 291. <https://doi.org/10.1016/j.apenergy.2021.116814>
- Filahi, H., Drobinski, P., Oueslati, B., Claudel, S., & Laurent, M. H. (2025). Rising power system strains despite decreasing heating demand in a warming climate. *Scientific Reports*, 15(1). <https://doi.org/10.1038/s41598-025-96174-5>
- 1090 Filahi, H., Omrani, H., Claudel, S., & Drobinski, P. (2024). Temporal fragmentation of the energy demand in Europe: Impact of climate change on the maneuverability of energy system. *Climate Services*, 34. <https://doi.org/10.1016/j.cliser.2024.100469>
- 1095 Fung, W. Y., Lam, K. S., Hung, W. T., Pang, S. W., & Lee, Y. L. (2006). Impact of urban temperature on energy consumption of Hong Kong. In *Energy* (Vol. 31, Issue 14, pp. 2623–2637). Elsevier Ltd. <https://doi.org/10.1016/j.energy.2005.12.009>
- Gupta, V., Sarkar, A., Saxena, A., Jana, A., & Bandyopadhyay, S. (2024). Appliance utility in low-income housing: On the relation between socio-economic characteristics, thermal comfort and appliance usage pattern. *Energy and Buildings*, 323. <https://doi.org/10.1016/j.enbuild.2024.114849>
- 1100 Hao, Z., Zhang, X., Xie, J., Yin, K., & Liu, J. (2022). Balance point temperature and heating degree-days in different climate conditions for building energy efficiency applications. *Building and Environment*, 216. <https://doi.org/10.1016/j.buildenv.2022.109013>

- He, J., Zhang, S., Yu, M., Liang, Q., Cao, M., Xu, H., ... & Liu, J. (2025). Predicting indoor PM2. 5 levels in
1105 shared office using LSTM method. *Journal of Building Engineering*, 104, 112407.
- He, X., Eom, J., Yu, S., Liu, S., Xu, W., Zhou, Y. (2025a). A global base temperature dataset for building energy
demand modeling. figshare. Dataset. <https://doi.org/10.6084/m9.figshare.30646376.v2>
- Hirth, L., Khanna, T. M., & Ruhnau, O. (2024). How aggregate electricity demand responds to hourly wholesale
price fluctuations. *Energy Economics*, 135. <https://doi.org/10.1016/j.eneco.2024.107652>
- 1110 Hochreiter, S., & Unger Schmidhuber, J. ". (n.d.). Long Short-Term Memory. <http://direct.mit.edu/neco/article-pdf/9/8/1735/813796/neco.1997.9.8.1735.pdf>
- Hofmann, M., Bjarghov, S., & Nessa, S. (2023). Norwegian hourly residential electricity demand data with
consumer characteristics during the European energy crisis. *Data in Brief*, 51, 109687.
- 1115 **Hu, J. X., Zhuo, Y. L., He, G. H., Liu, J. M., Guo, Y. F., Li, T. T., ... & Liu, T. (2025). National mortality burden
attributable to the unprecedented heatwave in 2022 in China. *Military Medical Research*, 12(1), 92.**
- Huang, J., & Gurney, K. R. (2016). The variation of climate change impact on building energy consumption to
building type and spatiotemporal scale. *Energy*, 111, 137–153. <https://doi.org/10.1016/j.energy.2016.05.118>
- Huang, L., & Kang, J. (2021). Thermal comfort in winter incorporating solar radiation effects at high altitudes
and performance of improved passive solar design—Case of Lhasa. *Building Simulation*, 14(6), 1633–1650.
1120 <https://doi.org/10.1007/s12273-020-0743-x>
- Ihara, T., Genchi, Y., Sato, T., Yamaguchi, K., & Endo, Y. (2008). City-block-scale sensitivity of electricity
consumption to air temperature and air humidity in business districts of Tokyo, Japan. *Energy*, 33(11), 1634–
1645. <https://doi.org/10.1016/j.energy.2008.06.005>
- International Energy Agency (IEA). (2024). World energy outlook 2024. [https://www.iea.org/reports/world-](https://www.iea.org/reports/world-energy-outlook-2024)
1125 [energy-outlook-2024](https://www.iea.org/reports/world-energy-outlook-2024)
- Kennard, H., Oreszczyn, T., Mistry, M., & Hamilton, I. (2022). Population-weighted degree-days: The global
shift between heating and cooling. *Energy and Buildings*, 271.
<https://doi.org/10.1016/j.enbuild.2022.112315>
- Kim, H. G., Kim, S. S., & Ahn, H. (2024a). Data-driven analysis of heating and cooling base temperatures for
buildings: Case studies in South Korea. *Energy and Buildings*, 322, 114709.
- 1130 Kim, S., Nathaniel, J., Hou, Z., Zheng, T., & Gentine, P. (2024b). Spatiotemporal upscaling of sparse air-sea
pCO2 data via physics-informed transfer learning. *Scientific Data* , 11(1). [https://doi.org/10.1038/s41597-](https://doi.org/10.1038/s41597-024-03959-w)
[024-03959-w](https://doi.org/10.1038/s41597-024-03959-w)
- Kozarcenin, S., Andresen, G. B., & Staffell, I. (2019). Estimating country-specific space heating threshold
temperatures from national gas and electricity consumption data. *Energy and Buildings*, 199, 368–380.
1135 <https://doi.org/10.1016/j.enbuild.2019.07.013>
- Kummu, M., Kosonen, M., & Masoumzadeh Sayyar, S. (2025). Downscaled gridded global dataset for gross
domestic product (GDP) per capita PPP over 1990–2022. *Scientific Data*, 12(1), 178.
- Lebakula, V., Epting, J., Moehl, J., Stipek, C., Adams, D., Reith, A., Kaufman, J., Gonzales, J., Reynolds, B.,
1140 Basford, S., Martin, A., Buck, W., Faxon, A., Cunningham, A., Roy, A., Barbose, Z., Massaro, J., Walters,
S., Woody, C., ... Urban, M. (2024). LandScan Silver Edition [Data set]. Oak Ridge National Laboratory.
<https://doi.org/10.48690/1531770>

- Li, B., Yu, R., Gan, K., Ruan, G., Liu, S., Yang, M., ... & Zhong, H. (2025). A Large-Scale Residential Load Dataset in a Southern Province of China. *Scientific Data*, 12(1), 1-14.
- 1145 Li, J., Yang, L., & Long, H. (2018). Climatic impacts on energy consumption: Intensive and extensive margins. *Energy Economics*, 71, 332–343. <https://doi.org/10.1016/j.eneco.2018.03.010>
- Li, X. X. (2018). Linking residential electricity consumption and outdoor climate in a tropical city. *Energy*, 157, 734–743. <https://doi.org/10.1016/j.energy.2018.05.192>
- Liao, W., Jin, X., Ran, Y., Xiao, F., Gao, W., & Li, Y. (2024). A twenty-year dataset of hourly energy generation and consumption from district campus building energy systems. *Scientific data*, 11(1), 1400.
- 1150 Livada, I., Pyrgou, A., Haddad, S., Sadeghi, M., & Santamouris, M. (2021). Recent climatic trends and analysis of monthly heating and cooling degree hours in Sydney. *Climate*, 9(7). <https://doi.org/10.3390/cli9070114>
- Mahdavinejad, M., Bazazzadeh, H., Mehrvarz, F., Berardi, U., Nasr, T., Pourbagher, S., & Hoseinzadeh, S. (2024). The impact of facade geometry on visual comfort and energy consumption in an office building in different climates. *Energy Reports*, 11, 1–17. <https://doi.org/10.1016/j.egyr.2023.11.021>
- 1155 Makonin, S. (2019). HUE: The hourly usage of energy dataset for buildings in British Columbia. *Data in brief*, 23, 103744.
- Mansouri, A., Abolmasoumi, A. H., & Ghadimi, A. A. (2023). Weather sensitive short term load forecasting using dynamic mode decomposition with control. *Electric Power Systems Research*, 221. <https://doi.org/10.1016/j.epsr.2023.109387>
- 1160 Martinopoulos, G., Alexandru, A., & Papakostas, K. T. (2019). Mapping temperature variation and degree-days in metropolitan areas with publicly available sensors. *Urban Climate*, 28. <https://doi.org/10.1016/j.uclim.2019.100464>
- Meng, Q., Mourshed, M., & Wei, S. (2018). Going beyond the Mean: Distributional Degree-Day Base Temperatures for Building Energy Analytics Using Change Point Quantile Regression. *IEEE Access*, 6, 39532–39540. <https://doi.org/10.1109/ACCESS.2018.2852478>
- 1165 Mishra, A., Lone, H. R., & Mishra, A. (2024). DECODE: Data-driven energy consumption prediction leveraging historical data and environmental factors in buildings. *Energy and Buildings*, 307. <https://doi.org/10.1016/j.enbuild.2024.113950>
- 1170 Muñoz-Sabater, J., Dutra, E., Agustí-Panareda, A., Albergel, C., Arduini, G., Balsamo, G., ... & Thépaut, J. N. (2021). ERA5-Land: A state-of-the-art global reanalysis dataset for land applications. *Earth system science data*, 13(9), 4349-4383.
- Nadeem, A. & Arshad, N. Precon: Pakistan residential electricity consumption dataset. 52–57, <https://doi-org.eproxy.lib.hku.hk/10.1145/3307772.3328317> (2019).
- 1175 Open Power System Data. Data package household data. https://data.open-power-system-data.org/household_data/2020-04-15/ (2020).
- Palazzoli, I., Ceola, S., & Gentine, P. (2025). GRAiCE: reconstructing terrestrial water storage anomalies with recurrent neural networks. *Scientific Data*, 12(1). <https://doi.org/10.1038/s41597-025-04403-3>
- Papada, L., & Kaliampakos, D. (2016). Developing the energy profile of mountainous areas. *Energy*, 107, 205-214.
- 1180

- Pawlak, J., Faghih Imani, A., & Sivakumar, A. (2021). How do household activities drive electricity demand? Applying activity-based modelling in the context of the United Kingdom. *Energy Research and Social Science*, 82. <https://doi.org/10.1016/j.erss.2021.102318>
- Perera, A. T. D., Javanroodi, K., Mauree, D., Nik, V. M., Florio, P., Hong, T., & Chen, D. (2023). Challenges resulting from urban density and climate change for the EU energy transition. *Nature Energy*, 8(4), 397–412. <https://doi.org/10.1038/s41560-023-01232-9>
- Petri, Y., & Caldeira, K. (2015). Impacts of global warming on residential heating and cooling degree-days in the United States. *Scientific reports*, 5(1), 12427.
- Prataviera, E., Romano, P., Carneletto, L., Pirotti, F., Vivian, J., & Zarrella, A. (2021). EURECA: An open-source urban building energy modelling tool for the efficient evaluation of cities energy demand. *Renewable Energy*, 173, 544–560. <https://doi.org/10.1016/j.renene.2021.03.144>
- Ramon, D., Allacker, K., De Troyer, F., Wouters, H., & van Lipzig, N. P. M. (2020). Future heating and cooling degree days for Belgium under a high-end climate change scenario. *Energy and Buildings*, 216. <https://doi.org/10.1016/j.enbuild.2020.109935>
- Rastogi, K. (2024). SEWA Energy Demand Forecasting [Data set]. Kaggle. <https://www.kaggle.com/datasets/kaustubhrastogi17/sewa-energy-demand-forecasting>
- Rode, A., Carleton, T., Delgado, M., Greenstone, M., Houser, T., Hsiang, S., Hultgren, A., Jina, A., Kopp, R. E., McCusker, K. E., Nath, I., Rising, J., & Yuan, J. (2021). Estimating a social cost of carbon for global energy consumption. *Nature*, 598(7880), 308–314. <https://doi.org/10.1038/s41586-021-03883-8>
- RTE. (n.d.). Regional electricity data [Data set]. Retrieved November 12, 2025, from <https://analyseseetdonnees.rte-france.com/en/regions/overview-region>
- Salam, A. R., & El Hibaoui, A. (2018). Comparison of machine learning algorithms for the power consumption prediction: Case study of Tetouan city. In 2018 6th International Renewable and Sustainable Energy Conference (IRSEC) (pp. 1–5). IEEE.
- Salehin, I., Noman, S. M., & Hasan, M. M. (2024). Electricity energy dataset “BanE-16”: Analysis of peak energy demand with environmental variables for machine learning forecasting. *Data in Brief*, 52, 109967.
- Schlemminger, M., Ohrdes, T., Schneider, E., & Knoop, M. (2022). Dataset on electrical single-family house and heat pump load profiles in Germany. *Scientific data*, 9(1), 56.
- Schuster, M., & Paliwal, K. K. (1997). Bidirectional recurrent neural networks. *IEEE transactions on Signal Processing*, 45(11), 2673–2681.
- Scoccimarro, E., Cattaneo, O., Gualdi, S., Mattion, F., Bizeul, A., Risquez, A. M., & Quadrelli, R. (2023). Country-level energy demand for cooling has increased over the past two decades. *Communications Earth and Environment*, 4(1). <https://doi.org/10.1038/s43247-023-00878-3>
- Sharma, V., Haque, M. H., & Aziz, S. M. (2019). PV generation and load profile data of net zero energy homes in South Australia. *Data in brief*, 25, 104235.
- Shi, H., Wang, B., Deng, N., Xu, S., & Wang, Z. (2025). Examining energy poverty under high temperatures in China. *Renewable and Sustainable Energy Reviews*, 215. <https://doi.org/10.1016/j.rser.2025.115575>
- Spinoni, J., Vogt, J. V., Barbosa, P., Dosio, A., McCormick, N., Bigano, A., & Füssel, H. M. (2018). Changes of heating and cooling degree-days in Europe from 1981 to 2100. *International Journal of Climatology*, 38, e191–e208.

- Srinuti. (2020). Residential power usage 3years data - Timeseries [Data set]. Kaggle. <https://www.kaggle.com/datasets/srinuti/residential-power-usage-3years-data-timeseries>
- Staffell, I., Pfenninger, S., & Johnson, N. (2023). A global model of hourly space heating and cooling demand at multiple spatial scales. *Nature Energy*, 8(12), 1328–1344. <https://doi.org/10.1038/s41560-023-01341-5>
- 1225 UK Climate Projections Projections. (2014). How have cooling degree days (CDD) and heating degree days (HDD) been calculated in UKCP09? (<http://ukclimateprojections.metoffice.gov.uk/22715>)
- United Nations (UN). (2019). Environment Programme & Global Alliance for Buildings and Construction: 2019 Global Status Report for Buildings and Construction.
- U.S. Energy Information Administration. (2020). Residential Average Monthly kWh and Bills [Data set]. Data.gov. <https://catalog.data.gov/dataset/residential-average-monthly-kwh-and-bills>
- 1230 van Ruijven, B. J., De Cian, E., & Sue Wing, I. (2019). Amplification of future energy demand growth due to climate change. *Nature Communications*, 10(1). <https://doi.org/10.1038/s41467-019-10399-3>
- Velázquez, G., Morales, F., García-Torres, M., Gómez-Vela, F., Divina, F., Noguera, J. L. V., ... & Román, J. C. M. (2022). Distribution level electric current consumption and meteorological data set of the east region of Paraguay. *Data in Brief*, 40, 107699.
- 1235 Wang, C., Song, J., Shi, D., Reyna, J. L., Horsey, H., Feron, S., Zhou, Y., Ouyang, Z., Li, Y., & Jackson, R. B. (2023). Impacts of climate change, population growth, and power sector decarbonization on urban building energy use. *Nature Communications*, 14(1). <https://doi.org/10.1038/s41467-023-41458-5>
- Wenz, L., Levermann, A., & Auffhammer, M. (2017). North–south polarization of european electricity consumption under future warming. *Proceedings of the National Academy of Sciences*, 114(38), 201704339.
- 1240 Woods, J., & Fuller, C. (2014). Estimating base temperatures in econometric models that include degree days. *Energy Economics*, 45, 166–171. <https://doi.org/10.1016/j.eneco.2014.06.006>
- Xu, X., Hu, Y., Atamturktur, S., Chen, L., & Wang, J. (2025). Systematic review on uncertainty quantification in machine learning-based building energy modeling. *Renewable and Sustainable Energy Reviews*, 218, 115817.
- 1245 Yang, S., Jahanger, A., & Awan, A. (2024). Temperature variation and urban electricity consumption in China: Implications for demand management and planning. *Utilities Policy*, 90. <https://doi.org/10.1016/j.jup.2024.101782>
- Yilmaz, S., & Canan, F. (2025). Establishing the thresholds for outdoor thermal comfort in cold climate urban areas. *Energy and Buildings*, 342. <https://doi.org/10.1016/j.enbuild.2025.115861>
- 1250 Yu, S., Eom, J., Zhou, Y., Evans, M., & Clarke, L. (2014). Scenarios of building energy demand for China with a detailed regional representation. *Energy*, 67, 284–297.
- Yuan, J., Jiao, Z., Xiao, X., Emura, K., & Farnham, C. (2024). Impact of future climate change on energy consumption in residential buildings: A case study for representative cities in Japan. *Energy Reports*, 11, 1675–1692. <https://doi.org/10.1016/j.egyr.2024.01.042>
- 1255 Zarco-Periñán, P. J., Zarco-Soto, I. M., & Zarco-Soto, F. J. (2021). Influence of the population density of cities on energy consumption of their households. *Sustainability (Switzerland)*, 13(14). <https://doi.org/10.3390/su13147542>

- 1260 Zhang, T., Li, M., Wang, Y., Zhou, J., Li, Y., Zhang, F., ... & He, B. J. (2024a). Refined building thermal climate zoning scheme in regions with mountainous terrain for accurate building energy-saving potential estimation. *Energy and Buildings*, 313, 114228.
- Zhang, W., Liu, D., Tian, H., Pan, N., Yang, R., Tang, W., Yang, J., Lu, F., Dayananda, B., Mei, H., Wang, S., & Shi, H. (2024). Parsimonious estimation of hourly surface ozone concentration across China during 2015–2020. *Scientific Data*, 11(1). <https://doi.org/10.1038/s41597-024-03302-3>
- 1265 Zhao, Y., Ding, X., Wu, Z., Yin, S., Fan, Y., & Ge, J. (2024). Impact of urban form on building energy consumption in different climate zones of China. *Energy and Buildings*, 320. <https://doi.org/10.1016/j.enbuild.2024.114579>
- Zhou, K., Hu, D., Hu, R., & Zhou, J. (2023). High-resolution electric power load data of an industrial park with multiple types of buildings in China. *Scientific Data*, 10(1), 870.
- 1270 Zhou, Y., Eom, J., & Clarke, L. (2013). The effect of global climate change, population distribution, and climate mitigation on building energy use in the US and China. *Climatic Change*, 119(3), 979-992.