

Article

Assessment of Regional Residential Energy Performance Using Degree Days

Akio Tanaka ^{1,*}, Yutaka Tonooka ² and Yujiro Hirano ³ ¹ Faculty of Human Environmental Studies, Hiroshima Shudo University, Hiroshima 731-3195, Japan² Saitama University, Saitama 338-8570, Japan; ytonooka@nifty.com³ Social Systems Division, National Institute for Environmental Studies (NIES), Tsukuba 305-8506, Japan; yhirano@nies.go.jp

* Correspondence: aktanaka@shudo-u.ac.jp

Abstract

This study proposes a climate-adjusted framework for evaluating regional residential energy performance by introducing Energy Consumption per Degree-Day (ECDD), an indicator that normalizes end-use energy consumption by climatic demand. This study belongs to the second category of research. Using microdata from Japan's Statistical Survey on Household CO₂ Emissions (SSH), we constructed a bias-reduced Household Micro-Resampled Population (HMRP) through stratified resampling that controls for climatic zone, urban scale, household size, dwelling type, and construction year, enabling consistent regional comparison. Results indicate that newer dwellings exhibit lower energy intensity. Heating and hot water ECDD show a positive nonlinear relationship with degree-days, converging under high thermal loads. In contrast, cooling-related ECDD shows a negative correlation with cooling degree-days, suggesting relatively efficient operation in warmer regions. These findings demonstrate that climate-adjusted efficiency is jointly shaped by structural characteristics and occupant behavior. The proposed ECDD–HMRP framework provides a practical and internationally relevant approach for climate-normalized residential energy assessment.

Keywords: climate-adjusted energy efficiency; energy consumption per degree-day; residential energy performance; heating and cooling demand; building thermal behavior

1. Introduction

Improving residential energy efficiency is a central pillar of global decarbonization strategies. Residential buildings account for approximately 20–30% of final energy consumption worldwide, and their performance is strongly influenced by climatic conditions, demographic change, and evolving living standards. As climate change accelerates and temperature variability intensifies, the need for robust climate-normalized indicators of residential energy performance has become increasingly urgent.

Conventional assessments of residential energy efficiency often rely on total energy consumption or energy use intensity (EUI) per floor area or per household. However, such indicators do not adequately adjust for climatic variability. Because more than 60% of residential energy demand arises from temperature-sensitive end uses—including space heating, cooling, and water heating—regional comparisons based solely on total consumption may confound structural efficiency with climatic exposure.

Degree-day normalization, using Heating Degree Days (HDDs) and Cooling Degree Days (CDDs), has been widely adopted to adjust for climatic differences. While these



Academic Editor: Apple L.S. Chan

Received: 31 January 2026

Revised: 21 February 2026

Accepted: 24 February 2026

Published: 27 February 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and

conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

methods provide a first-order correction, they are typically applied at aggregated regional or utility scales and rarely integrate household-level demographic heterogeneity. Moreover, existing climate-adjusted metrics often treat efficiency as the inverse of energy intensity without distinguishing between thermodynamic performance and operational behavior.

Three methodological gaps therefore remain in the international literature:

Climate normalization is frequently applied to aggregated data, limiting insight into household-level heterogeneity.

Sampling biases in large-scale surveys are seldom corrected through stratified micro-resampling.

End-use-specific climate-adjusted efficiency indicators that integrate structural and behavioral dimensions remain underdeveloped.

To address these gaps, this study introduces Energy Consumption per Degree-Day (ECDD), a climate-adjusted operational efficiency indicator defined at the end-use level. Unlike conventional HDD-adjusted total consumption metrics, ECDD normalizes energy use by climatic demand while integrating demographic stratification through a bias-reduced Household Micro-Resampled Population (HMRP).

Using microdata from Japan's Statistical Survey on Household CO₂ Emissions (SSH) [1], we construct a nationally representative micro-resampled dataset that corrects for climatic zone, urban scale, household size, dwelling type, and construction year. Japan serves as a valuable case study due to its pronounced climatic diversity, aging population, and mixture of detached and apartment housing stocks, making it well suited for evaluating climate-adjusted operational efficiency.

The contribution of this study is methodological rather than geographic. By integrating degree-day normalization with micro-level bias correction and end-use differentiation, the proposed ECDD–HMRP framework advances climate-adjusted residential energy assessment beyond aggregated normalization approaches. This framework provides an empirically grounded operational efficiency metric suitable for cross-regional and potentially cross-national comparison.

The following sections review the international literature, present the microdata-based methodological framework, and demonstrate how the ECDD indicator captures the integrated response of residential energy consumption to climatic and demographic conditions.

This study makes three distinct contributions to the international literature on residential energy performance assessment. First, it advances climate normalization by defining Energy Consumption per Degree-Day (ECDD) at the end-use level, thereby separating thermal demand from operational response more explicitly than aggregated HDD-adjusted metrics. Second, it integrates demographic and structural heterogeneity through a bias-reduced Household Micro-Resampled Population (HMRP), addressing compositional distortions that are rarely corrected in large-scale survey analyses. Third, it reframes residential efficiency as climate-adjusted operational efficiency rather than pure thermodynamic performance, thereby bridging the gap between engineering-based building standards and empirically observed energy use. Taken together, the ECDD–HMRP framework provides a statistically controlled and behaviorally inclusive approach to climate-adjusted residential efficiency evaluation that is applicable beyond the Japanese context.

2. Literature Review and Conceptual Framework

2.1. Climate-Normalized Residential Energy Indicators

Weather normalization is widely recognized as a necessary procedure in evaluating building and residential energy performance across different climatic contexts. Among the most commonly applied methods are Heating Degree Days (HDDs) and Cooling Degree Days (CDDs), which relate energy demand to deviations from a base temper-

ature. Degree-Day indicators have been extensively applied in both empirical and simulation-based research to assess heating and cooling energy requirements under varying climatic conditions [2,3].

Recent studies have further expanded the application of degree-day approaches. For instance, Andrade et al. [4] analyzed projected changes in HDD and CDD under climate change scenarios to estimate future heating and cooling demands across European regions. Their findings highlight the robustness of degree-day-based normalization in long-term climate impact assessments. Similarly, Song et al. [5] employed HDD-based normalization to evaluate central heating energy consumption in northern China, demonstrating that degree-day methods can effectively isolate climatic effects from structural and socio-economic factors.

In building performance modeling, HDD–CDD normalization has also been used to validate energy models and estimate base temperatures more accurately [6]. These studies confirm that degree-day methods remain a fundamental tool in climate-adjusted energy analysis. However, conventional degree-day normalization typically adjusts total energy consumption without explicitly integrating household characteristics or end-use differentiation.

2.2. International Residential Energy Modeling and Climate Adjustment

Beyond simple normalization, residential energy modeling has increasingly incorporated socio-demographic variables, dwelling characteristics, and behavioral factors. Decomposition analyses in the European Union, for example, have demonstrated that climatic factors interact with household size, income, and dwelling type in shaping residential energy demand [7]. These findings indicate that purely climatic indicators may underestimate the role of demographic and structural determinants.

More recent studies have adopted hybrid statistical models to evaluate the influence of temperature variability on electricity consumption [8]. These analyses show that deviations from seasonal norms significantly affect household energy use, particularly in regions experiencing rapid climate warming. However, most international studies focus either on macro-level aggregated data or on utility-level electricity consumption, often lacking detailed microdata that allow for stratified household-level modeling.

Systematic reviews of residential energy research [9] further indicate that while climate adjustment is common, there remains limited consensus on how to integrate behavioral, structural, and climatic factors within a unified efficiency indicator. This methodological fragmentation suggests the need for indicators capable of capturing both climatic normalization and household-level heterogeneity.

2.3. Comparison of Climate-Adjusted Efficiency Indicators

Existing indicators for evaluating residential energy performance can be broadly classified into three categories:

- (1) Energy Use Intensity (EUI)—typically expressed per floor area or per household, without explicit climate normalization.
- (2) Weather-Normalized Energy Use—adjusted using HDD/CDD, but usually applied to aggregated data.
- (3) Model-Based Efficiency Indicators—derived from simulation or regression-based estimation.

While HDD/CDD normalization effectively accounts for climatic variability, it often assumes homogeneous behavioral patterns and building characteristics. Conversely, engineering-based efficiency metrics emphasize thermodynamic performance but may neglect actual operational behavior.

The ECDD (Energy Consumption per Degree-Day) indicator introduced in this study differs from conventional HDD/CDD normalization in two important ways. First, it integrates household microdata stratified by demographic and dwelling characteristics, thereby accounting for heterogeneity in occupancy and building type. Second, by normalizing energy use at the end-use level (heating, cooling, hot water), it allows for differentiated efficiency assessment across thermal services rather than relying on total household consumption.

Unlike conventional thermodynamic efficiency metrics, the inverse of ECDD does not represent pure equipment or envelope efficiency. Instead, it reflects an integrated behavioral and operational response to climatic demand. This conceptual distinction aligns with the broader international literature on the performance gap between modeled and actual building energy use, where occupant behavior plays a decisive role.

2.4. International Context and Research Gap

Despite extensive international research on climate-adjusted residential energy consumption, several gaps remain:

- Most degree-day analyses are applied at aggregated regional or national scales.
- Few studies incorporate bias-reduced micro-resampled populations to correct sampling distortions.
- End-use-specific climate normalization at the household level remains limited.

In addition, the majority of global studies focus on Europe, North America, or China, while detailed microdata-based climate-adjusted efficiency analysis in East Asian contexts remains underrepresented in international journals.

The present study addresses these gaps by combining:

- Climate normalization through degree-days;
- Stratified microdata modeling using a bias-reduced household population (HMRP);
- End-use-specific efficiency assessment across climatic zones.

By situating the ECDD indicator within this international methodological landscape, this study extends existing degree-day approaches beyond aggregated normalization and contributes a microdata-based framework for climate-adjusted residential efficiency evaluation.

As shown in Table 1, conventional Energy Use Intensity (EUI) does not account for climatic variability, making cross-regional comparisons potentially misleading. Weather-normalized approaches using HDD/CDD adjust for temperature differences but are frequently applied at aggregated levels and rarely incorporate household-level heterogeneity. Engineering efficiency indicators reflect theoretical performance under standardized conditions but do not capture actual operational behavior.

In contrast, the ECDD indicator integrates explicit degree-day normalization with microdata-based stratification of household characteristics. By calculating energy consumption per degree-day at the end-use level, ECDD reflects the combined influence of climatic demand, dwelling characteristics, and occupant behavior. While it does not represent pure thermodynamic efficiency, it provides a climate-adjusted operational efficiency metric suitable for comparative regional analysis.

Unlike aggregated HDD normalization methods commonly applied in Europe and North America, the present framework incorporates bias-reduced micro-resampled populations, enabling stratified climate-adjusted efficiency analysis at the household level.

Based on the identified limitations of existing climate-adjusted indicators, the following section presents the data sources and methodological framework developed to construct the ECDD indicator and bias-reduced household population.

Table 1. Comparison of ECDD with conventional climate-adjusted energy indicators.

Indicator	Climate Normalization	Household Heterogeneity	End-Use Differentiation	Behavioral Effects Reflected	Typical Application Scale	Main Limitation
Energy Use Intensity (EUI) (kWh/m ² ·yr or GJ/household)	No	Limited	No	Indirect	Building or aggregated regional level	Does not adjust for climatic variability
Weather-Normalized Consumption (HDD/CDD adjusted)	Yes	Limited	Usually no	Indirect	Utility, regional, or national statistics	Often applied to aggregated data; assumes homogeneous behavior
Engineering Efficiency Metrics (e.g., COP, U-value based)	Implicit (design conditions)	No	Yes (equipment level)	No	Equipment or building design level	Reflects theoretical thermodynamic performance, not actual operation
Regression-Based Climate Models	Yes	Partial	Sometimes	Partial	Regional or national datasets	Sensitive to model specification; often lacks micro-level stratification
ECDD (Energy Consumption per Degree-Day)	Yes (explicit DD normalization)	Yes (microdata stratification via HMRP)	Yes (heating, cooling, hot water)	Yes (integrated operational response)	Household-level microdata	Does not isolate pure thermodynamic efficiency

Notes: EUI = Energy Use Intensity. HDD = Heating Degree-Day; CDD = Cooling Degree-Day; DD = Degree-Day. HMRP = Household Micro-Resampled Population. COP = Coefficient of Performance. Climate normalization refers to adjustment for interregional climatic differences in heating and cooling demand.

3. Data and Methodology

3.1. Data Sources

Research on energy efficiency in the household sector can be categorized into two types. The first consists of micro-level studies focusing on individual dwellings or specific appliances [10,11], whereas the second comprises macro-level studies that address regional or aggregate trends. This study belongs to the second category of research.

In this study, in addition to the Statistical Survey on Household CO₂ Emissions (SSH), multiple large-scale national statistical datasets—such as the Survey on Time Use and Leisure Activities and the Family Income and Expenditure Survey—are employed to examine the interrelationships among housing characteristics, household attributes, and climatic conditions. Prior studies in Japan have likewise incorporated degree-day indices as explanatory variables [12,13]. Tanaka [14,15] applied the Regularized Singular Value Decomposition (RSVD) method to SSH microdata to estimate end-use-specific energy consumption at the municipal level across Japan, using degree days as explanatory variables. Other SSH-based studies examined regional differences in CO₂ emissions and variations in energy use according to building type, construction year, and floor area [16].

However, few studies have directly evaluated regional energy efficiency in Japan. Kelly [17] developed a structural equation model to examine the relationships among housing performance, climatic factors, and residential energy intensity in the United Kingdom. Similarly, Canada's Survey of Household Energy Use (SHEU) [18] investigated housing and equipment characteristics nationwide to compare regional energy use patterns. Nevertheless, in these studies, energy efficiency is often treated only qualitatively as the

inverse of energy intensity. However, even in these studies, energy efficiency has been treated only as a qualitative indicator that is inversely related to energy intensity, and quantitative analyses of regional residential energy efficiency that explicitly account for climatic conditions remain limited.

3.2. Inherent Statistical Biases in the Data Sources

One of the main challenges in improving the accuracy of regional analysis using large-scale surveys lies in statistical bias arising from the sampling design. To mitigate this effect, SSH employs a stratified sampling design that divides Japan into 30 strata, defined by the service areas of the ten major electric power companies, and is further subdivided into three urban-scale categories. However, this framework does not fully correspond to the Energy and Climate Classification Zones (ECCZs) defined under Japan's Energy Conservation Act, leaving potential climatic bias unaccounted for.

Tanaka [19] reduced statistical bias in estimating municipality-level CO₂ emissions using the SSH by assigning regional classifications corresponding to the ECCZ and introducing a multilayer correction to adjust for biases in household-size composition and dwelling-type composition. Hoshino and Ogawa [20] also noted that differences in income distribution contribute to regional bias in SSH microdata. These findings suggest that several socioeconomic factors, including household structure, dwelling type, and income class, in addition to the ECCZ, may introduce systematic bias and that controlling for these effects is crucial for ensuring valid regional comparisons.

Table 2 compares the distribution of household size between the population (Population Census [21]) and the SSH. The proportion of one-person households in SSH was approximately half of the population, indicating that a simple tabulation resulted in a dataset biased toward households with two or more members.

Table 2. Comparison of household size shares in the two statistics.

Survey	1 Person	2 Persons	3 Persons	4 Persons	5 Persons or More
Population Census 2020	38%	28%	17%	12%	5%
Household CO ₂ Survey	19%	34%	22%	16%	9%

Notes: Values represent the proportion of households by household size. The Household CO₂ Survey refers to five rounds of the Statistical Survey on Household CO₂ Emissions (SSH).

Table 3 presents the results obtained by first constructing a two-dimensional table of household size distributions by the eight energy conservation law climate zones for both SSH and population, and then calculating the ratio between the corresponding cells (SSH/population). Values close to 1.0 indicate closer agreement between the SSH and population distributions, whereas larger deviations from 1.0 indicate under- or over-representation. In Zones II and V–VIII, the proportion of one-person households was approximately 0.5, indicating substantial underrepresentation, whereas the proportion of households with two or more members exceeds 1.1 and increased with household size relative to the population.

In Zone I, one-person households and households with five or more members were underrepresented, whereas three-person households were overrepresented. Table 4 shows the composition ratios according to dwelling type and year of construction. SSH is characterized by a higher proportion of detached houses and dwellings constructed before 2010 than the population, as reported in the Housing and Land Survey [22].

Table 3. Differences in household size distribution by region between the two surveys.

Climate Zone	1 Person	2 Persons	3 Persons	4 Persons	5 Persons or More
I	0.44	1.2	1.96	1.6	0.41
II	0.48	1.34	1.35	1.43	1.27
III	0.59	1.19	1.13	1.3	1.22
IV	0.66	1.08	1.14	1.23	1.23
V	0.58	1.14	1.17	1.17	1.55
VI	0.47	1.19	1.41	1.46	1.69
VII	0.53	1.16	1.37	1.41	1.53
VIII	0.56	1.11	1.29	1.35	1.57

Notes: Ratio of household share in the Household CO₂ Survey to household share in the corresponding districts in the 2020 Population Census [21].

Table 4. Composition of building type and construction year in the two statistics [22].

Survey	Building Type	Built ≤ 1990	1991–2010	Built ≥ 2011	Total
Housing and Land Survey 2018	Detached	27%	21%	7%	54%
	Apartment	16%	22%	6%	45%
Household CO ₂ Survey	Detached	31%	29%	7%	67%
	Apartment	12%	18%	4%	33%

3.3. Construction of the Household Micro-Resampled Population (HMRP)

As a first step, a Household Micro-Resampled Population (HMRP) was constructed using a resampling approach to reduce statistical bias inherent in the SSH.

The five principal attributes considered as potential bias factors were

- (1) Climatic zone;
- (2) City scale;
- (3) Household size;
- (4) Dwelling type;
- (5) Year of construction.

These are collectively referred to as the Five Stratified Attributes (5-SAs) of residential energy intensity. Furthermore, this study defined 22 regional groups (ECCZ–USRG: 22 regional groups combining energy and climate zones with urban-scale categories) that combined the climatic classification (ECCZ) with urban-scale divisions. These 22 regions were used as basic analytical units, enabling simultaneous adjustment for climatic and urban-scale biases and more precise regional comparisons of household energy efficiency.

To construct the HMRP, microdata from the Statistical Survey on Household CO₂ Emissions (SSH) conducted by the Ministry of the Environment, Japan, were used. Although the SSH is conducted annually with approximately 10,000 households nationwide, it lacks detailed meteorological information corresponding to the actual location of each dwelling. To address this limitation, the dataset was linked to municipal-level meteorological data obtained from the Automated Meteorological Data Acquisition System (AMeDAS [23]). Furthermore, the Regularized Singular Value Decomposition (RSVD) method was applied to decompose each household's annual energy consumption into end-use components.

The RSVD model represents the relationship among the observed energy consumption vector Y , explanatory variable matrix X , and end-use coefficient vector K as shown in Equation (1):

$$Y = XK^T \quad (1)$$

Here, K was estimated through singular value decomposition with an L_2 regularization term to prevent overfitting, minimizing the objective function shown in Equation (2):

$$K^r = \arg \min_K \left\{ \|XK^T\|_2^2 + \alpha \|K\|_2^2 \right\}, \quad \alpha \geq 0 \quad (2)$$

The penalty parameter α , which controls the regularization strength, was determined by identifying the local maximum of the rate of change in the mean squared error (MSE).

The dataset constructed using this procedure was used as the resampled population. A resampled dataset in which the distribution of the Five Stratified Attributes (5-SAs) closely approximated the national population was defined as the Household Micro-Resampled Population (HMRP).

Accordingly, household size distributions were obtained from the Population Census [21], and dwelling type $\times$ construction year distributions were derived from the Housing and Land Survey [22]. Each was independently resampled to approximate the population proportions, and the dataset was generated by minimizing the sum of squared errors between the resampled attribute ratios and the corresponding population ratios. The procedure employed stratified bootstrap sampling with replacement [24,25]. Consequently, the HMRP consisted of approximately 2,500,000 household records structured across 22 regional groups (ECCZ-USRG) $\times$ two dwelling types $\times$ three construction year categories $\times$ five household size classes, resulting in 660 multidimensional cells.

This approach enhanced the randomness relative to the original SSH and reduced information loss owing to the small number of sample cells. Using HMRP, the attribute bias correction for the Five Stratified Attributes (5-SAs) can be omitted, enabling both improved analytical accuracy and greater computational efficiency.

3.4. Definition of Energy Consumption per Degree Day (ECDD)

To evaluate regional residential energy efficiency, this study defined Energy Consumption per Degree Day (ECDD) as

$$ECDD_j = \frac{\sum_{i \in A} \frac{E_{ij}}{XDD_j}}{n^A} \quad (3)$$

where i = household;

n = number of samples;

j = energy end-use category;

XDD_j = degree-day index corresponding to end use j ;

$A = \{i \in H \mid i \text{ belongs to regional group } r\}$;

H denotes the set of all households;

$r = 1, \dots, 22$.

The inverse of the ECDD represents the overall response of energy consumption to climatic load, reflecting not only thermal efficiency, but also behavioral and building adaptation effects. The inverse corresponds to the climate-adjusted energy efficiency indicator.

The degree-days used for the ECDD calculation were defined as cumulative temperature differences exceeding (or below) the base temperature. Three degree-days were used: First, Cooling Degree Days (CDDs (22–24 °C)); second, Heating Degree Days (HDDs (18 °C base)); and Household Energy Degree Days (HEDD (40 °C base)), which serve as a comprehensive climatic index representing household energy uses, such as water heating and other domestic end uses, and are extended versions of the Water Heating Degree Days (WDDs (40 °C base)) proposed by Tanaka [14].

Using the framework described above, the next section presents the empirical results of the ECDD-based regional efficiency analysis.

4. Results

This section analyzes the regional structure of the total and end-use household energy consumption using the resampled household population (HMRP). In particular, the relationships between the three key housing attributes—dwelling type, construction year, and

household size—and climatic conditions expressed by degree days (DDs) were examined. Energy Consumption per Degree-Day (ECDD) was used to quantify the climatic response characteristics of residential energy use.

4.1. Structure of Total Household Energy Intensity

Figure 1 illustrates the relationship between total household energy intensity and the three housing attributes across ECCZ-U22 (22 Combined Regions of Energy and Climate Classification Zones and Urban Scale Categories). The left panel shows a clear positive correlation between household size and energy intensity. Detached houses exhibited 1.3-to-5 times higher energy intensity than apartments, mainly because detached houses generally have larger floor areas and lower insulation and airtightness.

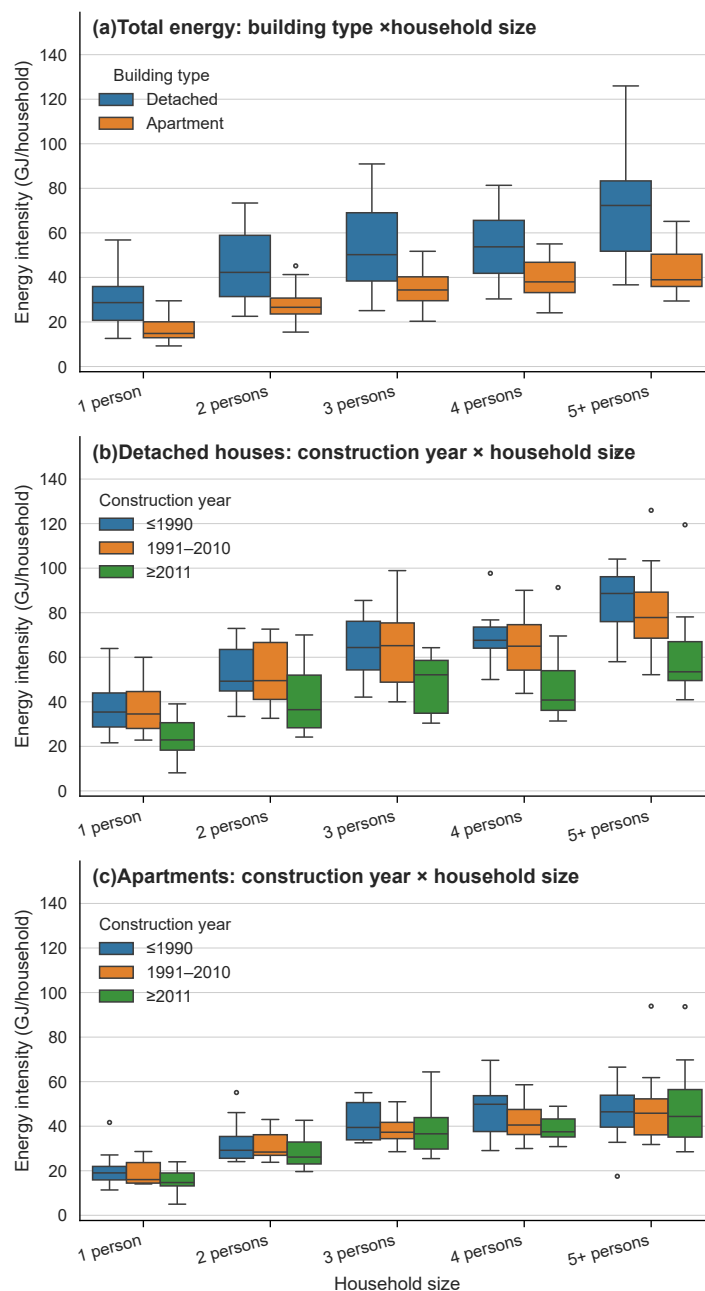


Figure 1. Relationship between total household energy intensity and three housing attributes (building type, construction year, and household size).

The middle and right panels show the relationships between energy intensity and household size by dwelling type and construction year. Newer houses, particularly detached houses, displayed lower energy intensity, particularly detached houses. This trend reflects the progressive reinforcement of energy conservation standards for residential buildings and their associated systems since the 1980s.

4.2. Relationship Between Degree Days and End-Use ECDD

This section presents the relationships between each degree-day index and the ECDD of the corresponding end uses with strong climatic correlations, in relation to the three key housing attributes. Among these attributes, household size is represented by one-person and three-person households as representative cases.

For reference, Table 5 lists the degree-day values by energy conservation law climate zone during the survey period, calculated as household-weighted averages.

Table 5. Climate indicators by ECCZ region.

ECCZ Zone	Mean Temperature (°C)	CDD	HDD	HEDD
I	7.1	0	4001	11,840
II	9.7	34	3272	10,911
III	10.9	76	2940	10,475
IV	12.3	137	2560	9971
V	14.4	252	2020	9209
VI	16.6	394	1487	8410
VII	17.6	433	1223	8069
VIII	23.7	980	49	5881

Notes: Created from AMeDAS [15] meteorological data and HMRP sample reconstruction.

4.2.1. Total Energy Consumption

Figure 2 shows the relationship between total household ECDD and HEDD. Larger HEDD values indicate colder regions. ECDD increased almost linearly in cold regions ($\text{HEDD} \geq 9000$; approximately ECCZs I–V), suggesting lower climate-adjusted energy efficiency as thermal demand increased. In contrast, ECDD remained nearly constant in warmer regions (ECCZs VI–VIII), implying a stable efficiency.

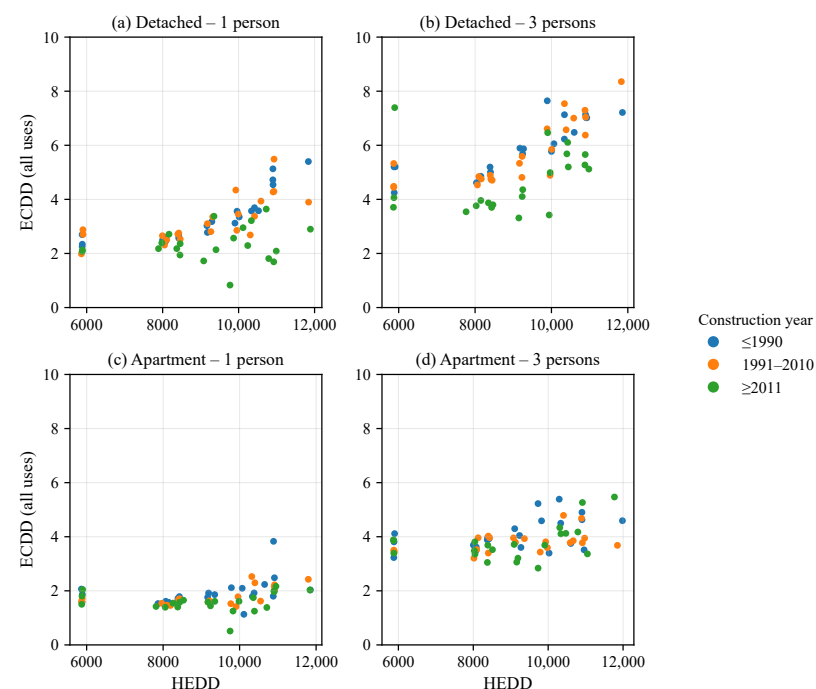


Figure 2. Relationship between HEDD and total household energy intensity by building type and construction year.

Newer houses (built after 2011) exhibited smaller ECDD values, suggesting that energy efficiency improved over time.

4.2.2. End-Use Energy ECDD

Figure 3 shows the relationships between ECDD, degree-days, and housing attributes for three major end uses: heating, cooling, and water heating.

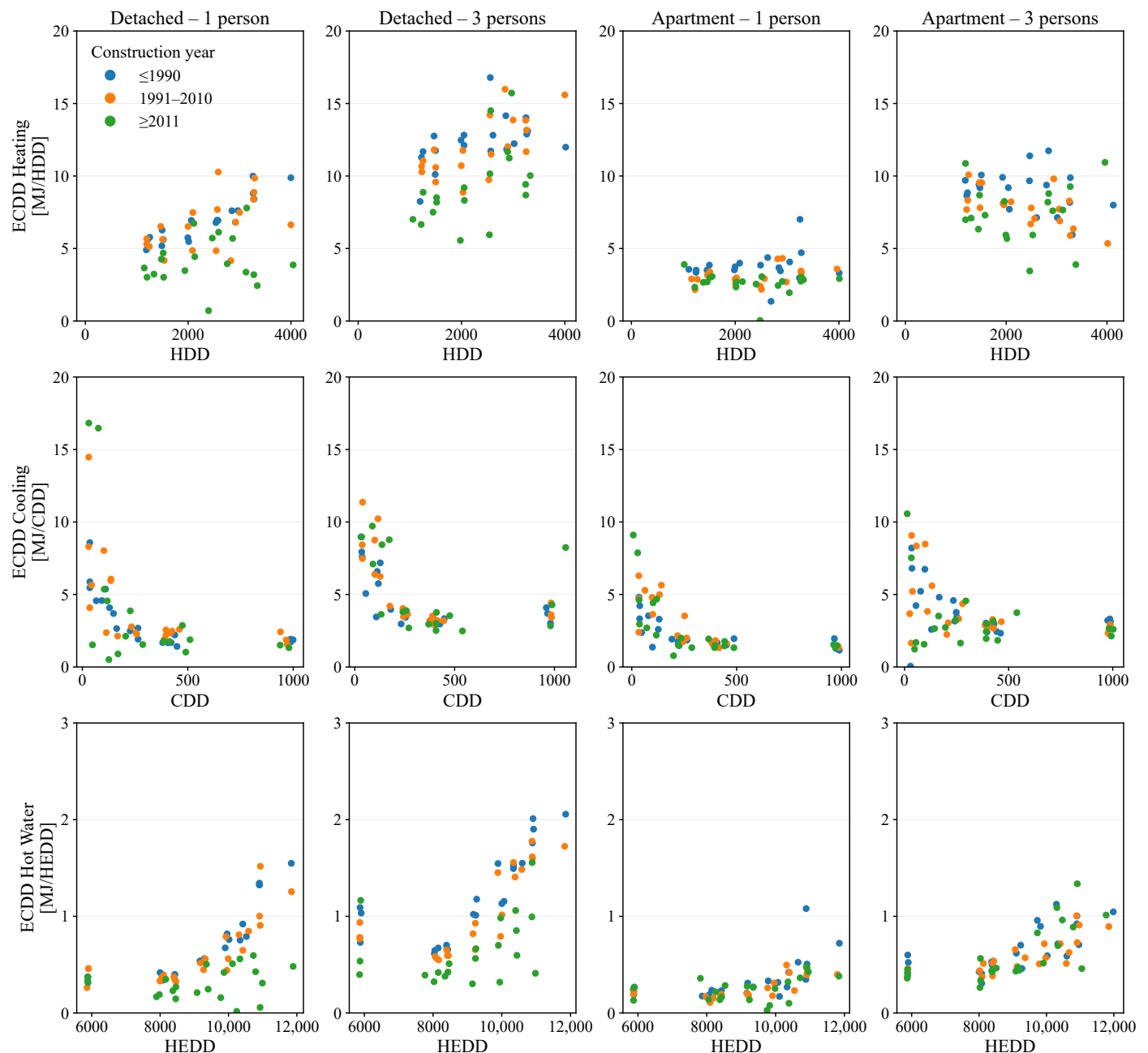


Figure 3. Relationships between end-use ECDD and various indices incorporating degree days.

4.2.3. Heating

For heating, ECDD exhibited a positive correlation with HDD, particularly in colder regions, indicating lower efficiency per unit of heating demand. Newer dwellings showed smaller ECDD values, reflecting improved insulation owing to successive revisions of Japan's building energy standards. This relationship is weaker for apartments, likely because of the greater thermal stability associated with shared walls and smaller exposed surface areas.

4.2.4. Cooling

For cooling, ECDD exhibited a negative correlation with CDD, and overall inspection indicated a nonlinear relationship. It tended to be larger (less efficient) in colder regions. However, in warmer regions (ECCZ Zone V and below), ECDD converged to an approximately constant value of 3.0. This can be attributed to the operational characteristics of air conditioning systems.

In colder regions, intermittent use leads to higher startup loads and unstable temperature control, whereas in warmer regions, continuous operation is more common than in colder regions, resulting in a more stable and efficient performance.

4.2.5. Water Heating

For water heating, ECDD decreased in warmer regions, indicating more efficient operation. In colder regions, ECDD increased linearly with HEDD, primarily because of the greater heat losses associated with the larger temperature differences between the supply water and ambient air.

Newer dwellings showed lower ECDD values, reflecting the widespread adoption of high-efficiency water-heating systems.

These results indicate that the use of ECDD makes it possible to evaluate quantitatively how energy consumption in each end-use category responds to climatic conditions and housing characteristics.

4.3. Climatic Degree-Day Model of ECDD

Based on the results presented in Section 4, we constructed an ECDD estimation model (Equation (4)) using degree days and three housing attributes—building type, construction year, and household size—across 22 regions, as explanatory variables, and the results are summarized in Table 6. This model expresses ECDD as an exponential function of a linear combination of degree-days and housing attributes, enabling simultaneous quantification of climatic sensitivity and housing characteristics.

$$\text{ECDD} = \exp (\beta_0 + \beta_1 \text{XDD}/1000 + \beta_2 \text{Size} + \beta_3 \text{Age}) \quad (4)$$

where

ECDD is the energy consumption per degree-day (MJ/DD);

XDD is the corresponding degree-day (HDD, CDD, or HEDD);

Size is the number of household members (capped at 5);

Age is the construction year (1: before 1990, 2:1991–2010, 3: after 2011).

Because XDD enters the model in exponential form, the negative coefficient does not contradict the observed increase in ECDD under higher thermal load; it reflects the non-linear scaling embedded in the specification.

Table 6. Degree-Day model for ECDD and its regression coefficients.

Detached House Model—Regression Coefficients						
End-Use	Spec	β_1	β_2	β_3	β_0	R^2
Heating	*	−0.223	0.221	−0.064	3.160	0.57
	**	−0.224	0.221	−	3.067	0.54
Cooling	*	−0.981	0.172	0.116	1.101	0.57
	**	−0.991	0.174	−	1.280	0.56
Hot Water	*	0.171	0.208	−0.153	−2.242	0.83
	**	0.168	0.206	−	−2.450	0.82
Total Energy	*	0.078	0.215	−0.046	0.262	0.94
	**	0.078	0.214	−	0.199	0.94

Table 6. Cont.

Apartment House Model-Regression Coefficients						
End-Use	Spec	β_1	β_2	β_3	β_0	R^2
Heating	*	−0.319	0.264	−0.049	3.181	0.62
	**	−0.320	0.263	−	3.106	0.61
Cooling	*	−0.733	0.150	0.017	0.963	0.62
	**	−0.731	0.149	−	0.989	0.61
Hot Water	*	0.118	0.237	−0.035	−2.457	0.87
	**	0.118	0.237	−	−2.510	0.84
Total Energy	*	0.024	0.240	−0.017	0.283	0.95
	**	0.024	0.240	−	0.258	0.95

Notes: Rows marked with * represent models that account for the building construction year (housing age-considered models). Rows marked ** represent models that did not account for building construction years (housing-age-unconsidered models).

4.4. Prediction of Energy Intensity Using ECDD

Using the parameters estimated from Equation (4), simulations were conducted to examine the relationship between the annual mean temperature (T) and total energy consumption. Degree Days (DDs) were converted from temperature using Equation (5), which was derived from regression analyses of regional meteorological data (DD–T relationships) during the HMRP survey period.

$$T = \begin{cases} -0.00396 \cdot HDD + 22.4 & (R^2 = 0.98) \\ 0.0147 \cdot CDD + 10.7 & (R^2 = 0.83) \\ 40 - HEDD/365 & (R^2 = 1.00) \end{cases} \quad (5)$$

Figure 4 shows simulated total energy intensity by dwelling type and household size. As the mean temperature increased, the total energy intensity decreased. Detached houses exhibited a nonlinear decline, whereas apartments exhibited a nearly linear decrease, indicating greater climatic sensitivity in detached dwellings. The left panel of Figure 4 presents the results by dwelling type and household size, showing that one-person households living in detached houses exhibit energy intensity levels comparable to, or higher than, those of apartment households with three or more members in regions where the annual mean temperature was below 12 °C. In warmer regions, the difference narrowed and fell below 10% in the warmest zone, ECCZ-U22 (Zone VIII). The right panel of Figure 4 shows the total energy intensity by the year of construction for three-person households. Newer houses displayed lower energy intensities, reflecting improvements in thermal insulation and equipment efficiency.

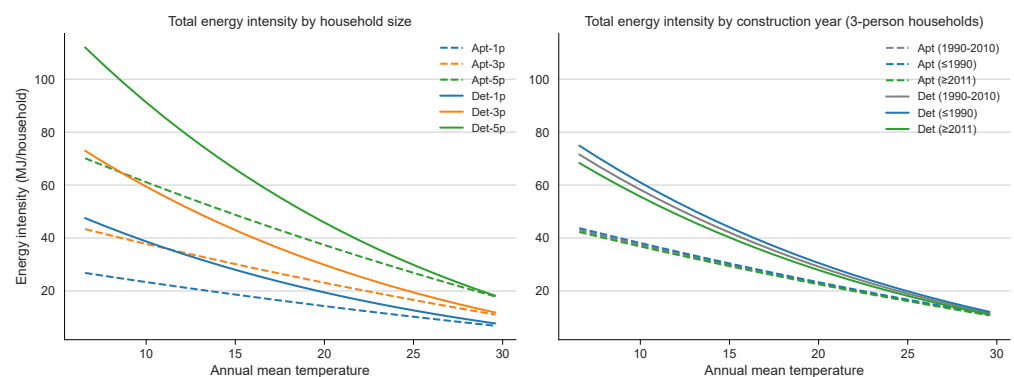


Figure 4. Relationships between annual mean temperature and total household energy intensity. Note: The left panel shows the results by household size, and the right panel shows the results by construction year for 3-person households. Solid lines indicate detached houses and dashed lines indicate apartments.

Figure 5 shows the relationship between end-use energy intensity and annual mean temperature. In the top row of the figure, which corresponds to the heating end use, heating demand increased nonlinearly as the annual mean temperature decreased. At 7 °C (Zone I), convergence was not yet reached, whereas apartments showed convergence below 13 °C (Zones I–IV). For cooling, energy demand increased with increasing temperature, but the rate of increase slowed as ECDD declined. In addition, for detached houses, newer dwellings exhibited a higher energy intensity, which may reflect the increased retention of internally generated heat resulting from improved thermal insulation.

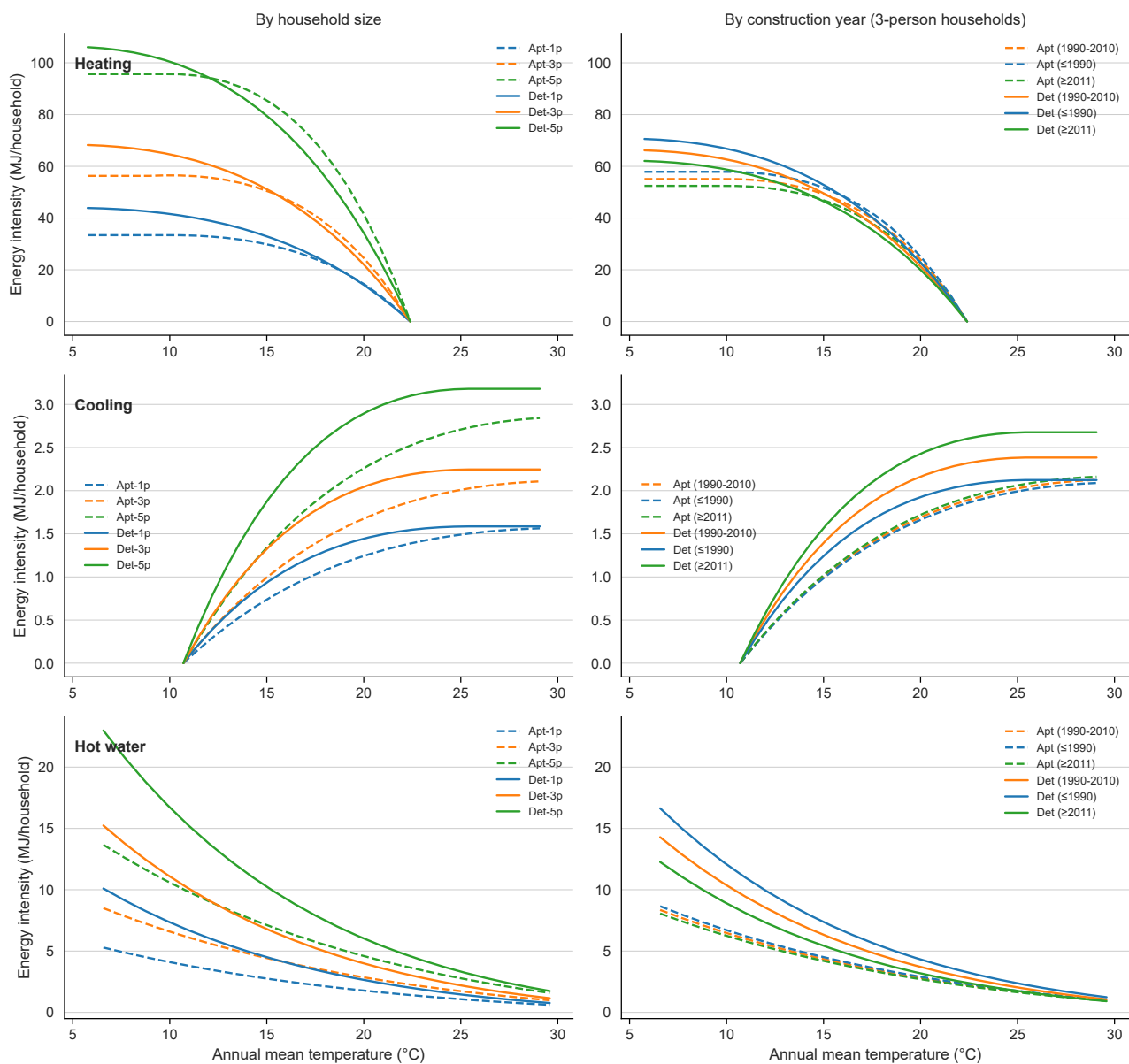


Figure 5. Annual means of temperature and end-use energy intensity.

For water heating, energy demand was greater in colder regions, showing a negative and nonlinear relationship with annual mean temperature. In colder regions, energy demand for water heating was higher because the temperature difference between the ambient air and supply water was larger. In addition, when hot water is distributed through piping, heat loss from the pipes further increases energy demand. Conversely, in warmer regions, a smaller temperature difference is expected to result in lower energy demand for water heating. Furthermore, the lower water-heating energy intensity observed in

newer dwellings is likely attributable to the adoption of newer and more energy-efficient water-heating equipment.

These results confirm that the ECDD model can quantitatively reproduce the regional characteristics of residential energy consumption as a function of mean temperature and degree-days. This model provides a unified analytical framework applicable to future climate change scenarios and regional evaluations of residential energy-saving policies.

While the empirical results reveal distinct regional patterns, their interpretation requires consideration of behavioral and structural factors, which are discussed in the following section.

5. Discussion

5.1. Behavioral Interpretation of Climate-Adjusted Efficiency

While the ECDD indicator is normalized by degree-days and therefore adjusts for climatic demand, the results suggest that operational and behavioral factors play a substantial role in shaping regional residential energy performance. In particular, the relative stability of ECDD observed in warmer climatic zones (Zones VI–VIII) indicates that thermal demand alone does not fully explain variations in energy consumption per degree-day.

In colder regions, heating demand increases nonlinearly as degree-days rise, and ECDD tends to converge at higher thermal load levels. This tendency is consistent with previous studies examining the relationship between climate and energy demand [26]. Such convergence may reflect both structural factors, such as improvements in insulation standards, and behavioral adaptations, including reduced indoor set-point temperatures and the practice of partial space heating under severe cold conditions.

Previous international research has shown that occupant behaviors—such as thermostat settings, window-opening frequency, and heating operation schedules—can substantially influence actual energy consumption, often exceeding the impact of improvements in building envelope performance [27–29]. Furthermore, the widely reported “performance gap” between predicted and measured energy use underscores the importance of behavioral and operational factors in residential energy consumption [30].

In addition, it has been noted that space heating in Japan is often localized rather than whole-house-based, and indoor temperatures tend to be lower than those observed in European countries [31,32]. These cultural and behavioral characteristics may partly explain the convergence of ECDD observed in colder regions.

In contrast, in warmer regions where cooling degree-days are relatively high but seasonal extremes are shorter in duration, behavioral diversity becomes more pronounced. Household decisions regarding air-conditioning usage—such as intermittent cooling, tolerance for higher indoor temperatures, or reliance on natural ventilation—may moderate energy consumption. As a result, ECDD in these zones may reflect cultural and behavioral adaptation rather than purely technological efficiency. This interpretation is consistent with international evidence on the building energy performance gap, which highlights discrepancies between theoretical and actual energy performance due to user practices.

Importantly, because ECDD is derived from observed energy consumption normalized by climatic demand, it captures the integrated outcome of building characteristics and occupant operation. Therefore, the inverse of ECDD should not be interpreted as a measure of pure thermodynamic efficiency. Instead, it represents a climate-adjusted operational efficiency that includes behavioral responses to thermal demand. This distinction is particularly relevant when comparing regions with similar building standards but differing occupancy patterns or lifestyle practices.

These findings suggest that policy measures aimed solely at improving building envelope performance may not fully translate into reductions in climate-adjusted energy intensity unless accompanied by behavioral interventions. Information campaigns, smart-

meter feedback, and adaptive comfort strategies may therefore play a complementary role in enhancing residential energy performance across climatic regions.

Future research should disentangle behavioral elasticity from structural efficiency by integrating time-use data or smart-meter-based occupancy profiles, thereby refining the interpretation of climate-adjusted indicators such as ECDD.

5.2. Methodological Implications of the ECDD Framework

Beyond behavioral interpretation, the ECDD framework carries methodological implications for climate-adjusted energy analysis. Unlike conventional Energy Use Intensity (EUI), which compares total consumption across regions, ECDD explicitly normalizes energy use by climatic demand at the end-use level. This allows for the separation of thermal load from operational response, providing a more refined indicator of performance.

Furthermore, the integration of the Household Micro-Resampled Population (HMRP) reduces sampling bias and enhances statistical representativeness. Many international studies rely on aggregated utility-level data, which may obscure household heterogeneity. In contrast, the microdata-based stratification employed in this study enables simultaneous adjustment for climate, dwelling type, construction year, and household size.

Although ECDD does not isolate pure thermodynamic efficiency, it offers an operational efficiency metric that is more consistent with real-world residential energy use. This distinction may contribute to bridging the gap between engineering-based performance evaluation and empirically observed consumption patterns.

5.3. International and Policy Implications

The findings also have broader international implications. In many regions, building energy policies emphasize envelope performance standards and equipment efficiency improvements. However, the results suggest that climate-adjusted operational efficiency depends not only on structural upgrades but also on occupant adaptation patterns.

Compared with European and North American studies that apply HDD-based normalization at aggregated scales, the ECDD framework demonstrates the feasibility of integrating climate normalization with micro-level demographic adjustment. This approach may be particularly relevant in countries experiencing rapid demographic aging or household size reduction.

From a policy perspective, combining structural measures with behavioral interventions—such as smart-meter feedback, adaptive comfort strategies, and demand-side management—may be necessary to achieve sustained improvements in climate-adjusted residential efficiency.

5.4. Transferability and International Applicability

Although this study is based on Japanese microdata, the ECDD framework is conceptually transferable to other national contexts where large-scale residential energy surveys are available. Comparable datasets include the Residential Energy Consumption Survey (RECS) in the United States, the Survey of Household Energy Use (SHEU) in Canada, and EU-SILC-linked energy consumption datasets in Europe. In many of these contexts, climate normalization is applied at aggregated regional or national scales; however, demographic heterogeneity and sampling bias are not always explicitly addressed.

Recent European building stock studies have demonstrated that climatic variability, demographic change, and housing characteristics jointly shape residential energy demand trends [7,33,34]. These studies emphasize the importance of structural and compositional effects in understanding energy consumption patterns, yet climate normalization is frequently implemented at macro scales without integrating household-level bias correction.

The importance of climate-adjusted building performance assessment has also been highlighted in the IPCC Sixth Assessment Report (WGIII), which identifies operational effi-

ciency in buildings as a key mitigation pathway requiring improved empirical evaluation frameworks [35]. Similarly, recent IEA reports underscore that improvements in building energy performance remain uneven across countries and that operational energy use often diverges from theoretical design expectations [36].

The methodological contribution of this study lies in integrating three components within a unified framework: (1) explicit degree-day normalization at the end-use level, (2) microdata-based stratified resampling to reduce compositional bias, and (3) operational interpretation of climate-adjusted efficiency. This structure is not inherently specific to Japan and can be replicated in other countries with appropriate microdata access.

Moreover, many industrialized countries are experiencing demographic transitions characterized by aging populations and shrinking household sizes. Because household composition significantly affects energy intensity per capita, incorporating demographic stratification into climate-adjusted efficiency metrics may become increasingly important in international comparative research.

From a policy perspective, the ECDD framework provides a bridge between engineering-based performance evaluation and empirically observed energy use. By distinguishing climate-adjusted operational efficiency from pure thermodynamic performance, it offers a more realistic basis for evaluating the effectiveness of building standards, retrofit policies, and behavioral interventions under varying climatic conditions.

Future research should test the general applicability of the ECDD framework in different climatic and institutional settings, thereby assessing its potential as a standardized climate-adjusted residential efficiency indicator in international comparative studies.

5.5. Limitations

This study has several limitations. First, although the HMRP reduces sampling bias, the original SSH microdata do not include detailed time-use information or appliance-level operational data. Therefore, behavioral mechanisms are inferred indirectly rather than observed directly.

Second, degree-day normalization assumes a uniform base temperature, which may not fully capture regional adaptive comfort thresholds. Future studies should examine the sensitivity of ECDD to alternative base temperature assumptions.

Third, the analysis is based on Japanese residential data, and cross-country validation is required to assess the general applicability of the ECDD framework.

Building on the methodological and empirical findings, the final section summarizes the key contributions and implications of this study.

6. Conclusions

This study introduced Energy Consumption per Degree-Day (ECDD) as a climate-adjusted operational efficiency indicator and applied it within a bias-corrected microdata framework derived from Japan's Statistical Survey on Household CO₂ Emissions (SSH). By combining explicit degree-day normalization with a Household Micro-Resampled Population (HMRP), the proposed framework enables statistically consistent regional comparison of residential energy performance while accounting for demographic heterogeneity.

The empirical findings yield three principal insights. First, heating and water-heating ECDD values exhibit nonlinear relationships with degree-days and converge under high thermal demand, indicating that climate-adjusted operational efficiency stabilizes despite increasing climatic load. Second, cooling-related ECDD shows weaker climatic sensitivity and a negative correlation with cooling degree-days, suggesting a substantial role for behavioral adaptation and operational practices. Third, regional variations in climate-adjusted efficiency are jointly shaped by climatic exposure, dwelling characteristics, and household

composition, demonstrating the necessity of integrating demographic stratification into efficiency assessment.

Beyond the Japanese case, the methodological contribution of this study lies in bridging aggregated climate normalization and micro-level residential modeling. Compared with conventional HDD-based normalization applied at national or utility scales in Europe and North America, the ECDD–HMRP framework provides a microdata-based, bias-controlled operational efficiency metric. This structure improves cross-regional comparability by explicitly accounting for both climatic and compositional effects, thereby addressing limitations inherent in traditional Energy Use Intensity (EUI) metrics and design-based thermodynamic indicators.

From a broader international perspective, the framework responds to emerging global challenges, including climate variability, population aging, and shrinking household size. As many industrialized countries face similar demographic and climatic transitions, incorporating both degree-day normalization and demographic adjustment may become increasingly important for accurate residential efficiency evaluation.

Policy implications extend beyond structural retrofitting. While improvements in building envelope standards and equipment efficiency remain essential, the results indicate that climate-adjusted operational efficiency is significantly influenced by occupant behavior and adaptive practices. Therefore, structural measures should be complemented by demand-side management, smart-meter feedback, and behavioral interventions to achieve sustained improvements in residential energy performance.

Several limitations warrant attention. The analysis relies on annual survey data without detailed time-use or appliance-level monitoring, and the assumed base temperatures for degree-day calculation may not fully capture adaptive comfort differences across regions. Future research should integrate high-resolution smart-meter data and cross-national applications to test the generalizability of the ECDD framework.

Overall, this study demonstrates that integrating climate normalization, microdata-based bias correction, and end-use differentiation provides a more realistic and internationally transferable framework for evaluating regional residential energy performance. By reframing efficiency as climate-adjusted operational response, the ECDD approach offers a methodological advancement over conventional aggregated normalization metrics and contributes to a more nuanced understanding of residential energy use under climatic and demographic change.

Author Contributions: Conceptualization, A.T., Y.T. and Y.H.; methodology, A.T.; investigation, A.T.; writing—original draft preparation, A.T.; writing—review and editing, A.T.; visualization, A.T.; supervision, Y.T. and Y.H. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data presented in this study are available on request from the corresponding author on reasonable request. The data are not publicly available due to privacy policies.

Acknowledgments: This study was conducted using microdata from the Statistical Survey on Household CO₂ Emissions (SSH) provided by the Ministry of the Environment, Japan, through the Research Committee on the Use of Household CO₂ Statistics Data of the Japan Society of Energy and Resources. The authors express their gratitude to the Ministry of the Environment for granting access to this dataset.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Ministry of the Environment, Japan. Statistical Survey on CO₂ Emissions from the Household Sector. Available online: <https://www.env.go.jp/earth/ondanka/ghg/kateiCO2tokei.html> (accessed on 2 April 2025). (In Japanese)

2. Agency for Natural Resources and Energy, Ministry of Economy, Trade and Industry, Japan. *FY2018 Public Relations Survey Project on Electricity Supply and Demand Measures*; The Institute of Energy Economics: Tokyo, Japan, 2020; p. 899. (In Japanese)
3. The Institute of Energy Economics, Japan, Econometric Analysis Unit. *Handbook of Energy and Economic Statistics*; The Energy Conservation Center: Tokyo, Japan, 2021; p. 357. (In Japanese)
4. Andrade, C.; Mourato, S.; Ramos, J. Heating and Cooling Degree-Days Climate Change Projections for Portugal. *Atmosphere* **2021**, *12*, 715. [\[CrossRef\]](#)
5. Song, Y.; Du, A.; Cui, T. Using the Degree-Day Method to Analyze Central Heating Energy Consumption in Cities of Northern China. *Sustainability* **2024**, *16*, 1008. [\[CrossRef\]](#)
6. Mehregan, M.; Naminezhad, A.; Vakili, S.; Delpisheh, M. Building Energy Model Validation and Estimation Using Heating and Cooling Degree Days (HDD–CDD) Based on Accurate Base Temperature. *Energy Sci. Eng.* **2022**, *10*, 3638–3649. [\[CrossRef\]](#)
7. Tsemekidi Tzeiranaki, S.; Bertoldi, P.; Diluiso, F.; Castellazzi, L.; Economidou, M.; Labanca, N.; Ribeiro Serrenho, T.; Zangheri, P. Analysis of the EU Residential Energy Consumption: Trends and Determinants. *Energies* **2019**, *12*, 1065. [\[CrossRef\]](#)
8. Li, J.; He, K. Climate Change Has Increased Household Electricity Consumption: An Adaptive Behavioral Perspective. *China Econ. Q. Int.* **2025**, *5*, 57–71. [\[CrossRef\]](#)
9. Quintana, D.I.; Cansino, J.M. Residential Energy Consumption: A Computational Bibliometric Analysis. *Buildings* **2023**, *13*, 1525. [\[CrossRef\]](#)
10. Yamada, T.; Yamamoto, H.; Nagata, Y. Model analysis of the electrification rate of residential water heating by housing vintage and type to achieve diffusion scenarios for residential heat-pump water. *J. Jpn. Soc. Energy Res.* **2024**, *45*, 31–39. (In Japanese)
11. Azhar, N.; Arif, F.; Khan, A.B. Framework for energy performance measurement of residential buildings considering occupants' energy use behavior. *Eng. Proc.* **2023**, *44*, 15. [\[CrossRef\]](#)
12. Miura, S. Study of the regional characteristics of energy consumption and housing use throughout Japan. *J. Archit. Plan. (Trans. AIJ)* **1998**, *510*, 77–83. (In Japanese) [\[CrossRef\]](#)
13. Tanaka, A. Time-series change of residential energy consumption structures. *J. Jpn. Soc. Energy Res.* **2019**, *40*, 21–27. (In Japanese)
14. Tanaka, A. Decomposition of residential energy consumption and estimation of renewable energy usage. *J. Jpn. Soc. Energy Res.* **2022**, *43*, 25–32. (In Japanese)
15. Tanaka, A. Research a statistical model to differentiate refrigeration usage from seasonal fluctuations in residential electricity demand. *J. Jpn. Soc. Energy Res.* **2024**, *45*, 136–142. (In Japanese)
16. Matoba, H.; Sugiyama, M.; Matsuoka, A.; Shimoda, Y.; Yamaguchi, Y. Analysis on differences of energy consumption among households by simulation and statistics. *J. Jpn. Soc. Energy Res.* **2020**, *41*, 209–218. (In Japanese)
17. Kelly, S. Do more energy-efficient homes consume less energy? Structural equation model of England's residential sector. *Energy* **2011**, *36*, 5610–5620. [\[CrossRef\]](#)
18. Natural Resources Canada, Office of Energy Efficiency. *2003 Survey of Household Energy Use (SHEU)*; Government of Canada: Ottawa, ON, Canada, 2005; pp. 2–32.
19. Tanaka, A. Estimation of environmental burden of residential housing by Bayesian approach on a municipal Level. *J. Jpn. Soc. Energy Res.* **2023**, *44*, 265–273. (In Japanese)
20. Hoshino, Y.; Ogawa, J. Analysis of energy prices and expenditures by region, energy composition, and income level based on individual data from a Household CO₂ emissions survey. *J. Jpn. Soc. Energy Res.* **2021**, *42*, 194–203. (In Japanese)
21. Statistics Bureau of Japan. 2020 Population Census of Japan. Available online: <https://www.stat.go.jp/data/kokusei/2020/kekka.html> (accessed on 1 April 2025). (In Japanese)
22. Statistics Bureau of Japan. Housing and Land Survey of Japan. 2018. Available online: <https://www.stat.go.jp/data/jyutaku/2018/tyousake.html> (accessed on 1 April 2025). (In Japanese)
23. Japan Meteorological Agency. Automated Meteorological Data Acquisition System (AMeDAS). Available online: <https://www.data.jma.go.jp/obd/stats/etrn/index.php> (accessed on 1 April 2025). (In Japanese)
24. Cochran, W.G. *Sampling Techniques*, 3rd ed.; John Wiley & Sons: New York, NY, USA, 1977; pp. 107–175.
25. Luo, W.; Lai, H.C. A weighted residential bootstrap method for multilevel modeling with sampling weights. *J. Behav. Data Sci.* **2021**, *1*, 89–118.
26. Sailor, D.J. Relating residential and commercial sector electricity loads to climate—Evaluating state level sensitivities and vulnerabilities. *Energy* **2001**, *26*, 645–657. [\[CrossRef\]](#)
27. Stevenson, F.; Leaman, A. Evaluating housing performance in relation to human behaviour: New challenges. *Build. Res. Inf.* **2010**, *38*, 437–441. [\[CrossRef\]](#)
28. Huebner, G.M.; Shipworth, D.; Hamilton, I.; Chalabi, Z.; Oreszczyn, T. Understanding electricity consumption: A comparative contribution of building factors, socio-demographics, appliances, behaviours and attitudes. *Appl. Energy* **2016**, *177*, 692–702. [\[CrossRef\]](#)
29. Harvey, L.D.D. Reducing energy use in the buildings sector: Measures, costs, and examples. *Energy Effic.* **2009**, *2*, 139–163. [\[CrossRef\]](#)

30. Oreszczyn, T.; Hong, S.H.; Ridley, I.; Wilkinson, P.; Warm Front Study Group. Determinants of winter indoor temperatures in low-income households in England. *Energy Build.* **2006**, *38*, 245–252. [[CrossRef](#)]
31. Yoshino, H.; Hong, T.; Nord, N. Total energy use in buildings—Analysis and evaluation methods. *Energy Build.* **2017**, *152*, 124–136. [[CrossRef](#)]
32. Matsubara, N. Changes and issues in research on the evaluation of the indoor thermal environment of houses in Japan from the viewpoint of a warmth-preservation lifestyle. *J. Hum.-Environ. Syst.* **2022**, *25*, 1–16. [[CrossRef](#)]
33. Ürges-Vorsatz, D.; Cabeza, L.F.; Serrano, S.; Barreneche, C.; Petrichenko, K. Heating and cooling energy trends and drivers in buildings. *Renew. Sustain. Energy Rev.* **2015**, *41*, 85–98. [[CrossRef](#)]
34. Gillett, W.B.; Kalogirou, S.A.; Morthorst, P.E.; Norton, B.; Ornetzeder, M. Perspectives on decarbonisation of existing buildings in Europe. *Renew. Energy* **2025**, *242*, 122490. [[CrossRef](#)]
35. IPCC. Buildings. In *Climate Change 2022: Mitigation of Climate Change*; Working Group III Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change; Shukla, P.R., Skea, J., Slade, R., Al Khourdajie, A., van Diemen, R., McCollum, D., Pathak, M., Some, S., Vyas, P., Fradera, R., et al., Eds.; Cambridge University Press: Cambridge, UK, 2022; pp. 957–1049. [[CrossRef](#)]
36. International Energy Agency (IEA). *Energy Efficiency 2023*; IEA: Paris, France, 2023. Available online: <https://www.iea.org/reports/energy-efficiency-2023> (accessed on 20 February 2026).

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.