

# Neglecting humidity may lead to overestimated economic impacts of cooling demand

Yohan Choi<sup>1,2</sup>, Shinichiro Fujimori<sup>3,5</sup>, Tomoko Hasegawa<sup>4,5</sup>, Kiyoshi Takahashi<sup>5</sup>, Jun'ya Takakura<sup>5</sup>, Yong-Gun Kim<sup>6</sup>, and Chan Park<sup>7,\*</sup>

<sup>1</sup>Department of Urban Planning and Design, University of Seoul, Seoul, Republic of Korea

<sup>2</sup>Institute of Urban Science, University of Seoul, Seoul, Republic of Korea

<sup>3</sup>Environmental Engineering Department, Kyoto University, Kyoto, Japan

<sup>4</sup>Research Organization of Science and Technology, Ritsumeikan University, Shiga, Japan

<sup>5</sup>National Institute for Environmental Studies (NIES), Tsukuba, Japan

<sup>6</sup>Graduate School of International Studies, Yonsei University, Seoul, Republic of Korea

<sup>7</sup>Department of Landscape Architecture, University of Seoul, Seoul, Republic of Korea

\*Corresponding author. e-mail: chaneparkmomo7@uos.ac.kr

February 3, 2026

## Supplementary Note S1. Statistical Validation of Climate Indicators and Methodological Consistency

### S1.1. Validation of Cooling Degree Day (CDD) Indicators

To ensure the reliability of the long-term cooling energy demand projection, we first validated the explanatory power of different CDD calculation methods using historical panel data. We constructed a country-fixed effect regression model to control for unobserved time-invariant heterogeneity across countries, such as industrial structure, building characteristics, and energy policies. The regression specification is as follows:

$$\ln(E_{r,t}) = \alpha + \beta \ln(GDPpc_{r,t}) + \delta \ln(CDD_{r,t}) + \sum_r \gamma_r D_r + \epsilon_{r,t} \quad (1)$$

where  $E_{r,t}$  denotes the per capita cooling energy demand in region  $r$  at time  $t$ . We tested four different CDD metrics derived from Dry Bulb Temperature (DBT) and Wet Bulb Globe Temperature (WBT) based on Standard and UKMO calculation methods.

Table 1 summarizes the estimation results. The transition from the conventional DBT-based metric to the humidity-adjusted WBT-UKMO metric reveals a significant structural improvement in the model.

- **Signal Clarification:** The  $t$ -statistic for the climate variable ( $\ln CDD$ ) significantly increased from 6.68 (DBT-Standard) to 8.73 (WBT-UKMO), indicating that the WBT-UKMO index captures the variation in cooling demand more precisely.
- **Bias Correction:** Concurrently, the  $t$ -statistic for income ( $\ln GDPpc$ ) stabilized ( $7.71 \rightarrow 6.36$ ). This suggests that the conventional DBT method failed to fully capture climatic impacts,

causing the model to overattribute demand variations to economic factors (omitted variable bias). By incorporating humidity and radiation effects via WBT, we successfully disentangled the pure climatic effect from the economic effect.

Consequently, we selected **WBT-UKMO** as the primary climate input for our projection model, as it provides the most robust empirical evidence for cooling demand sensitivity ( $R^2 = 0.9538$ ).

Although all models exhibited high explanatory power ( $R^2 > 0.95$ ), the WBT-UKMO model recorded the lowest Akaike Information Criterion (AIC) value at 402.86. This indicates that the WBT-UKMO model achieves the best balance between goodness of fit and parsimony compared to the DBT-based models (AIC = 431.82) and the simple WBT model (AIC = 418.45).

Table 1: Comparison of Regression Results by CDD Calculation Methods (Fixed Effect Models)

CDD Metric	DBT-Standard	DBT-UKMO	WBT-Standard	WBT-UKMO
$\ln(\text{GDPpc})$ ( $\beta$ ) ( <i>t-value</i> )	1.918*** (7.71)	1.667*** (6.70)	1.823*** (7.41)	<b>1.577***</b> <b>(6.36)</b>
$\ln(\text{CDD})$ ( $\delta$ ) ( <i>t-value</i> )	0.368*** (6.68)	1.608*** (8.12)	0.961*** (7.67)	<b>2.806***</b> <b>(8.73)</b>
$R^2$	0.9503	0.9527	0.9519	<b>0.9538</b>
<b>AIC</b>	431.82	412.12	418.45	<b>402.86</b>

Note: Values in parentheses are t-statistics. \*\*\* indicates significance at the 1% level.

- **Countries:** Australia, Austria, Canada, France, Greece, Italy, Japan, South Korea, Luxembourg, Netherlands, New Zealand, Portugal, Spain, United States, Argentina, Brazil, Morocco, Croatia, Cyprus, Hong Kong, Malta, Slovenia, Uruguay
- **Period:** 2000-2020
- **Data Source:** IEA Energy End-uses and Efficiency Indicators [1]

## S1.2. Methodological Strategy: Validation vs. Projection

In this study, we employed a dual-model strategy to ensure both statistical robustness and physical plausibility.

- **Regression Analysis (Validation):** The fixed-effect regression presented above served as a validation tool to identify the most effective climate indicator. The results empirically confirmed that cooling demand is highly elastic to humidity-inclusive climatic changes ( $\delta \approx 2.81$ ), justifying the use of WBT-UKMO as a key driver in our projection.
- **Structural Projection (Simulation):** However, for future projections, we utilized a structural bottom-up model (incorporating floor area and AC adoption rates) rather than directly extrapolating the regression coefficients. This is because the log-linear regression assumes constant elasticity, which fails to capture the non-linear saturation effects of technology adoption (S-curve) and physical limits of consumption in the long term.

Our structural projection model explicitly accounts for **market saturation** (as defined by the AC adoption function adjusted for climate saturation) and **technological efficiency**, addressing the

limitations of the linear regression approach. Nevertheless, the strong climate sensitivity identified in the regression analysis ( $\delta$ ) empirically supports the structure of our projection model, where the climate change rate ( $\Delta CDD$ ) acts as a dominant multiplier for future demand growth.

## Supplementary Note S2. Adjustment of AC Adoption Rate Function

In this study, we adjust the functions used to estimate air-conditioning (AC) adoption rates to ensure consistency with (i) a higher indoor temperature setpoint (22°C instead of 18°C) and (ii) alternative cooling degree day (CDD) metrics that incorporate daily temperature extremes and humidity. These adjustments affect only the *climate maximum saturation* component of the AC adoption function; income-related constraints are treated separately in the main model.

### S2.1 Climate maximum saturation based on $CDD_{18}$

The climate maximum saturation function represents the upper bound of AC ownership determined solely by climatic need, assuming no income constraints (i.e., all households who require cooling can afford an air conditioner). This concept was originally developed by [2] using AC ownership data from 40 cities spanning diverse climatic conditions.

[3] revised this relationship to ensure that the saturation curve asymptotically approaches 100%, which is required for global energy modeling. The resulting functional form is:

$$\text{Saturation} = 1 - 0.949 \cdot e^{-0.00187 \cdot CDD_{18}}, \quad (2)$$

where  $CDD_{18}$  denotes cooling degree days calculated with an 18°C base temperature. This formulation has been widely adopted in integrated assessment models and global cooling demand studies [4].

However, the use of an 18°C setpoint implicitly assumes a uniform global preference for indoor thermal comfort, which is unlikely to hold across countries with different climates, building characteristics, and cultural norms regarding indoor temperature.

### S2.2 Shift to a 22°C setpoint

To make the model more contextually relevant, we shift the climate maximum saturation curve from an 18°C to a 22°C setpoint, following the approach of [5]. We estimate a flexible, non-linear mapping between  $CDD_{18}$  and  $CDD_{22}$  using a Generalized Additive Model (GAM):

$$CDD_{18} = f(CDD_{22}), \quad (3)$$

where  $f(\cdot)$  is a smooth spline function fitted to daily climate data from ISIMIP3B.

We then compute  $CDD_{18}$ -equivalent values corresponding to each  $CDD_{22}$  value and apply these transformed values to the McNeil and Letschert saturation function. This procedure preserves the original functional form while adapting it to a 22°C setpoint.

### S2.3 Recalibration for alternative CDD metrics

We further recalibrate the climate maximum saturation curve for four alternative CDD metrics at a 22°C setpoint and 60% relative humidity:

- **DBT-Standard:** daily mean dry-bulb temperature,

- **DBT-UKMO**: daily maximum and minimum dry-bulb temperature,
- **WBT-Standard**: wet-bulb temperature based on daily mean conditions,
- **WBT-UKMO**: wet-bulb temperature based on daily extremes.

Because these metrics imply different relationships between climate and cooling load, we apply the same GAM-based procedure to each metric: we estimate a spline linking each CDD measure to  $CDD_{18}$ , convert each to a  $CDD_{18}$ -equivalent value, and then compute the corresponding saturation curve using Equation (1).

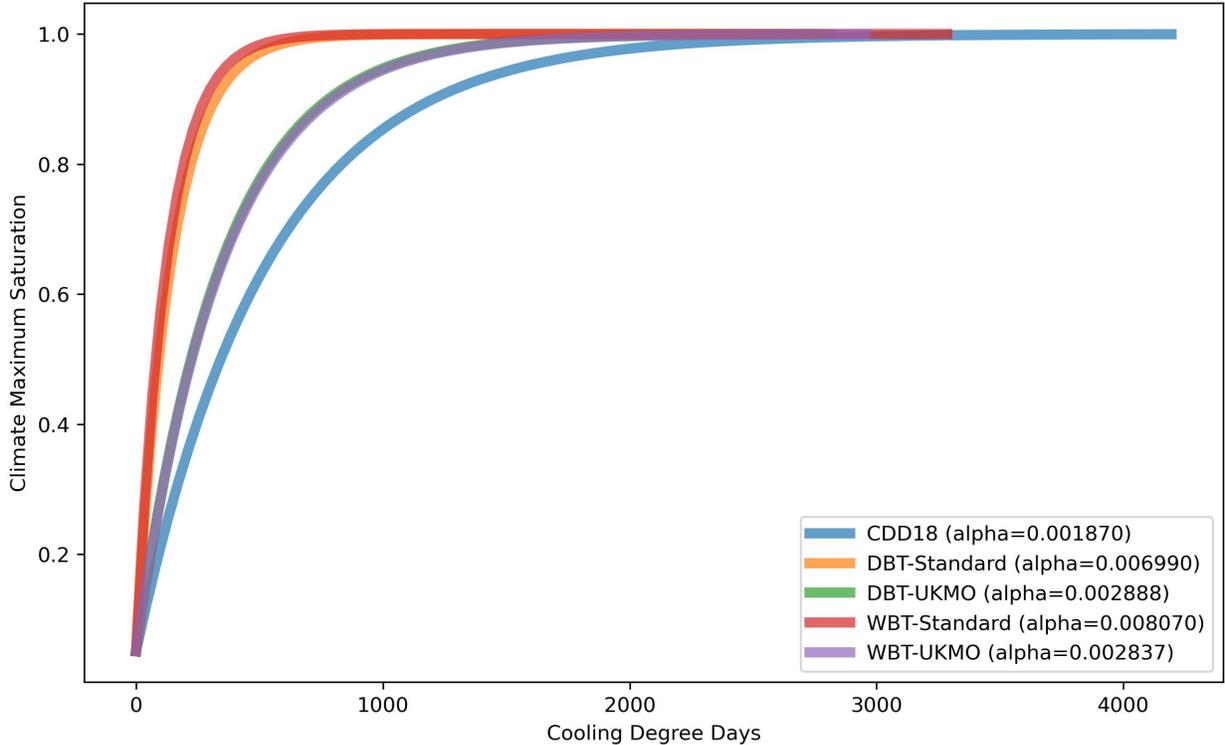


Figure 1: Climate maximum saturation curves for five CDD methods at a 22°C setpoint and 60% relative humidity.

## S2.4 Interpretation of Supplementary Figure S1

Supplementary Figure S1 shows that all saturation curves retain an exponential shape but differ in steepness (parameter  $\alpha$ ). The **DBT-Standard** curve rises most rapidly with CDD, implying faster growth in AC need at relatively low CDD levels. By contrast, the humidity-adjusted curves (**WBT-Standard** and **WBT-UKMO**) increase more gradually, indicating that regions already exposed to humid heat start from a higher baseline cooling requirement, thereby reducing the marginal effect of additional warming.

The **DBT-UKMO** and **WBT-UKMO** curves lie between these extremes, capturing the influence of diurnal temperature variability. These differences propagate to projected AC adoption and cooling energy demand, as discussed in the main text.

# Supplementary Note S3. Additional Results

## S3.1 Regional Cooling Energy Consumption

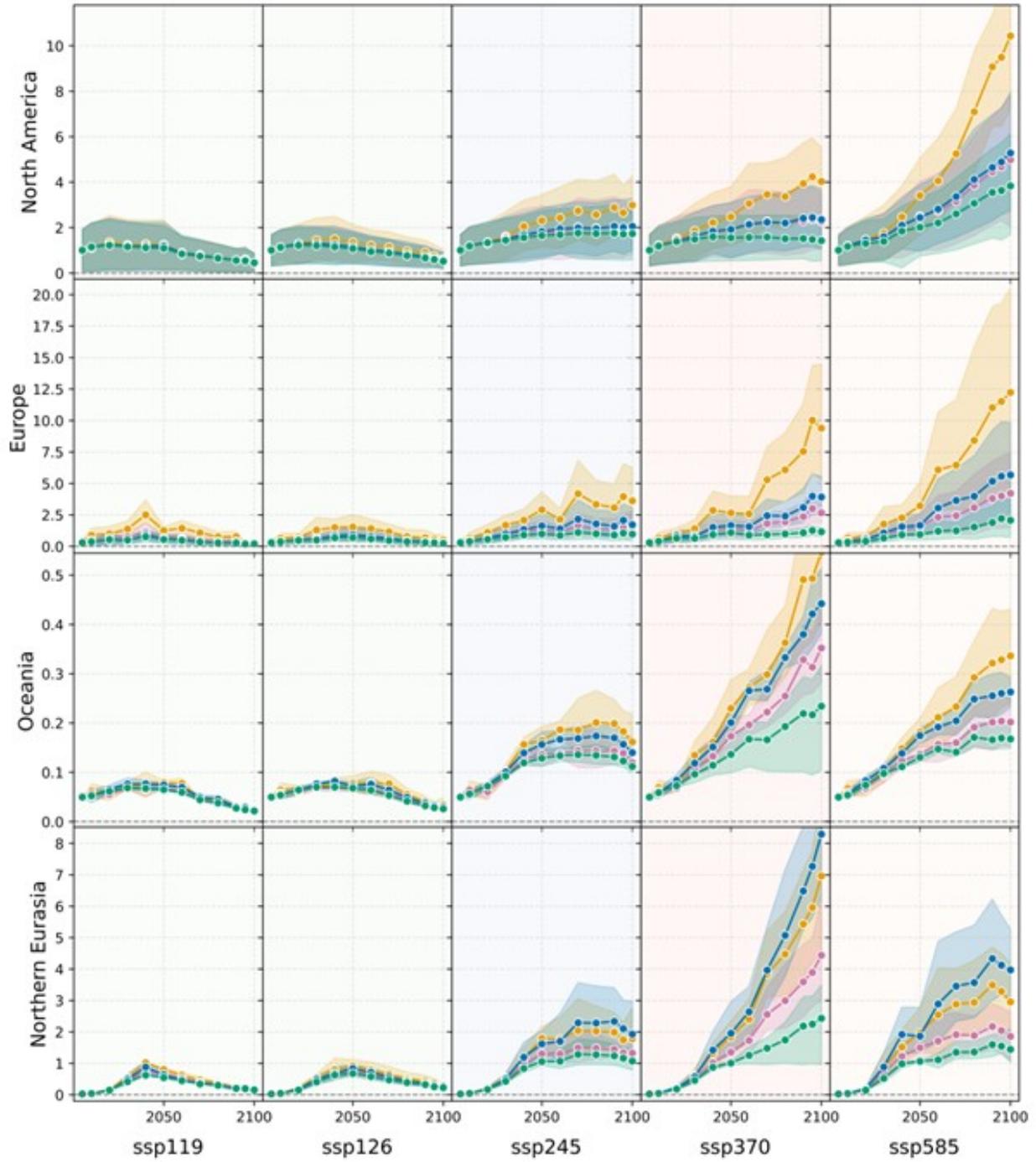


Figure 2: Cooling Energy Consumption in Global North (EJ/yr)

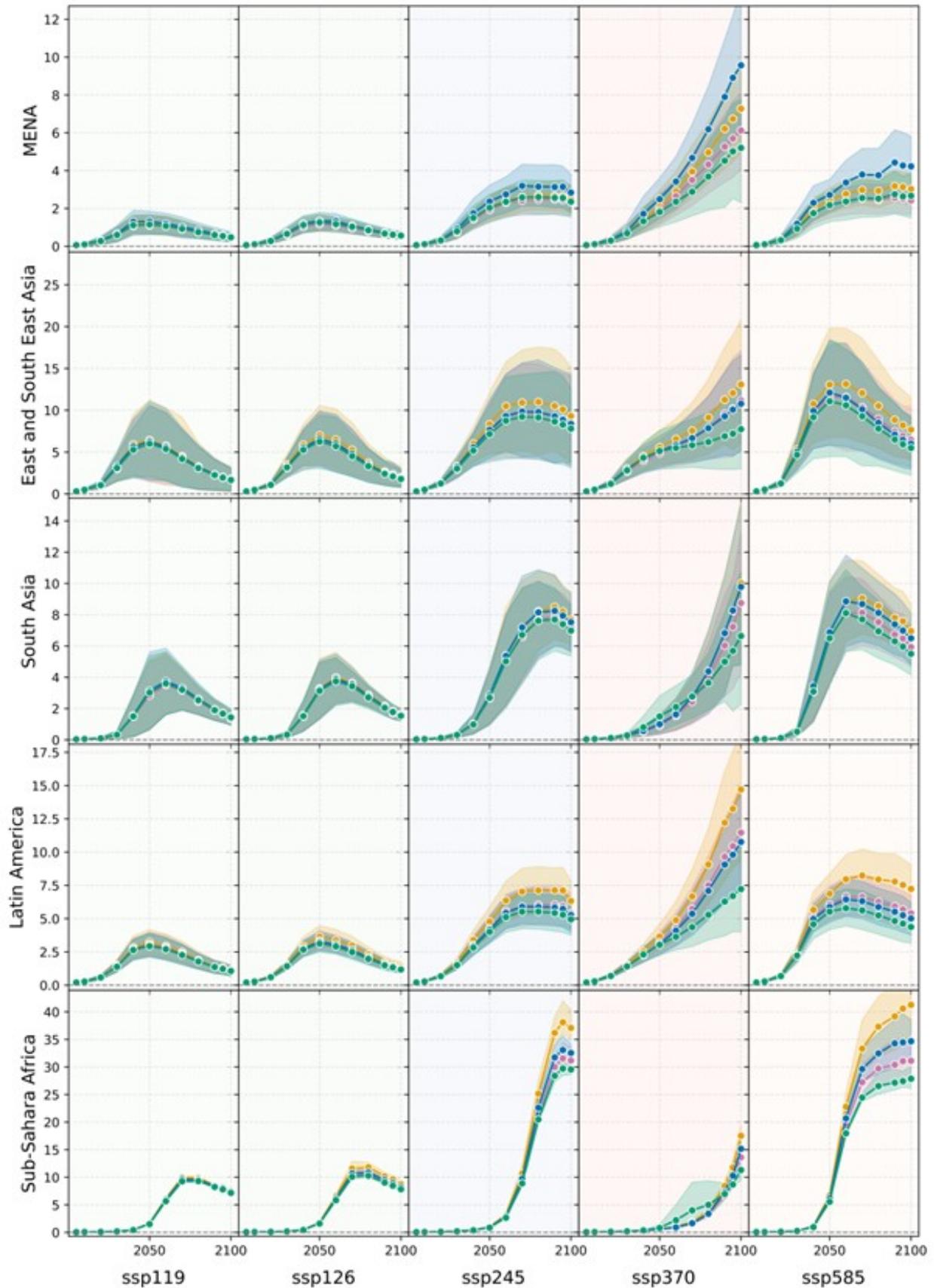


Figure 3: Cooling Energy Consumption in Global South (EJ/yr)

### S3.2 Residential Cooling Energy Share

Here we provide an explanation for the residential cooling energy share and additional details related to our results presentation. The **residential cooling energy share** is defined as the proportion of total residential energy consumption that is attributable to cooling energy use. In other words, it quantifies what fraction of overall residential energy demand is dedicated to air conditioning. This metric is particularly useful for assessing the significance of cooling demand in relation to total residential energy use, especially when comparing across different climate scenarios and CDD calculation methods.

Mathematically, the residential cooling energy share ( $S_{\text{cool, res}}$ ) is expressed as:

$$S_{\text{cooling, res}} = \frac{E_{\text{cooling, res}}}{E_{\text{Total, res}}} \quad (4)$$

where  $E_{\text{cooling, res}}$  is the total energy consumed by residential cooling and  $E_{\text{total, res}}$  is the total residential energy consumption.

Supplementary Figure 4 presents the projected residential cooling energy share for each CDD calculation method in the years 2050 and 2100. This figure enables a direct comparison of how different CDD approaches affect future projections of the cooling energy share. For each region, the dashed line along the x-axis indicates the 2020 baseline value, providing a reference point for understanding how future trajectories diverge from historical levels under various scenarios and calculation methods.

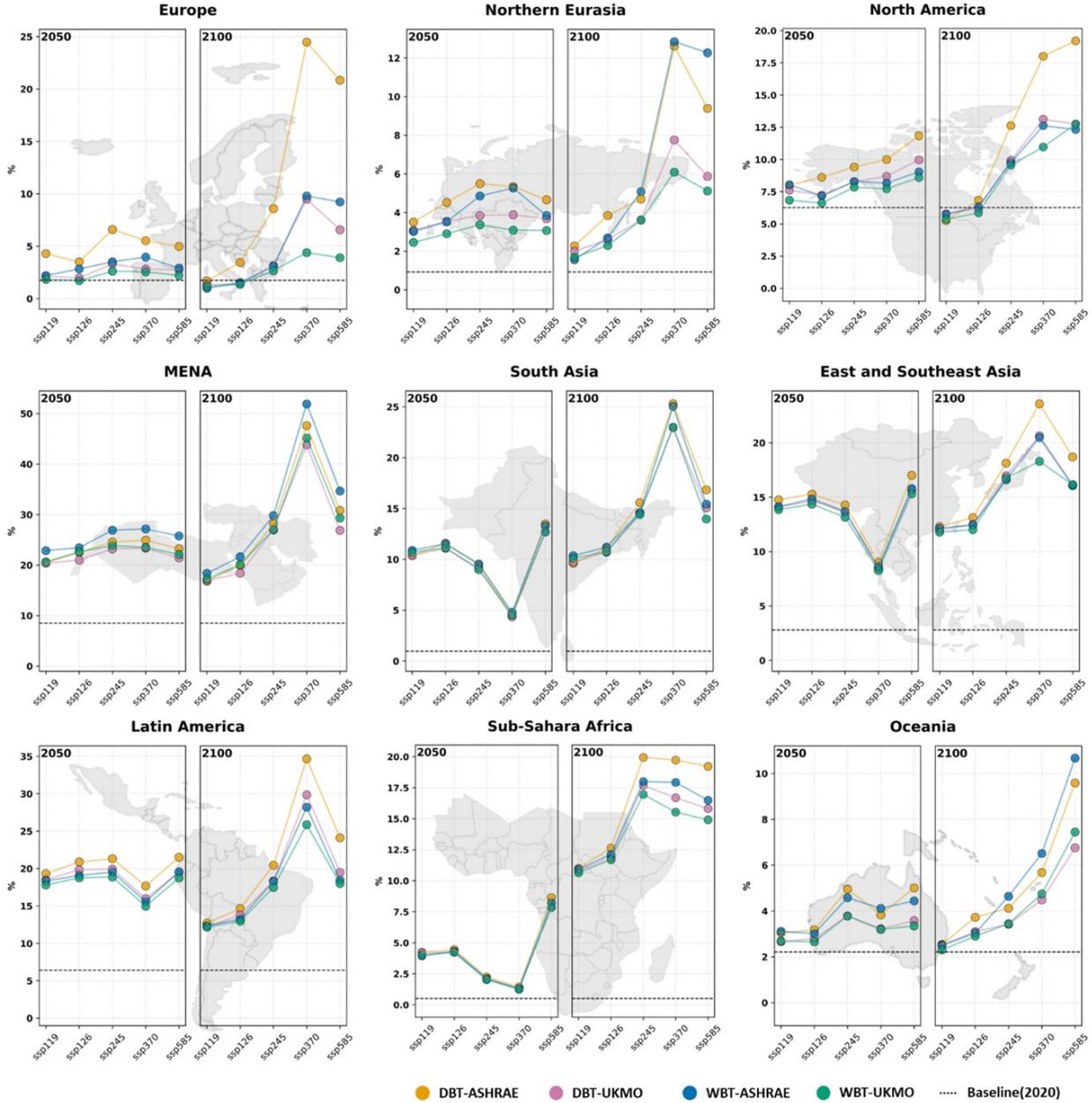


Figure 4: Residential cooling energy share in 2050 and 2100 by CDD calculation method. The dashed line along the x-axis represents the 2020 baseline share for each region.

## References

- [1] International Energy Agency. Energy end-uses and efficiency indicators – July 2025 edition. Database (2025). URL <https://www.iea.org/data-and-statistics/data-product/energy-end-uses-and-efficiency-indicators>. Accessed 20 January 2026.
- [2] Sailor, D. J. & Pavlova, A. A. Air conditioning market saturation and long-term response

- of residential cooling energy demand to climate change. *Energy* **28**, 941–951 (2003). URL <https://www.sciencedirect.com/science/article/pii/S0360544203000331>.
- [3] McNeil, M. A. & Letschert, V. E. Future air conditioning energy consumption in developing countries and what can be done about it: The potential of efficiency in the residential sector. Tech. Rep., Lawrence Berkeley National Laboratory (2008). URL <https://escholarship.org/uc/item/64f9r6wr>.
- [4] Isaac, M. & van Vuuren, D. P. Modeling global residential sector energy demand for heating and air conditioning in the context of climate change. *Energy Policy* **37**, 507–521 (2009). URL <https://www.sciencedirect.com/science/article/pii/S0301421508005168>.
- [5] Andrijevic, M., Byers, E., Mastrucci, A., Smits, J. & Fuss, S. Future cooling gap in shared socioeconomic pathways. *Environmental Research Letters* **16**, 094053 (2021). URL <https://doi.org/10.1088/1748-9326/ac2195>.