Integrated day-to-hour downscaling of irradiance and temperature for climate projections

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Introduction

Climate projection data is commonly available at daily time resolution from sources such as CMIP. However, solar PV applications typically require hourly resolution for key variables including irradiance and temperature. We present an integrated framework to downscale daily climate projection variables to hourly resolution.

Comparing downscaling approaches

Day-to-hour downscaling can be performed through different approaches: physical Numerical Weather Prediction (NWP) models, empirical statistical models, and more recently, generative machine learning (GML)-based models. Our approach falls within the statistical category, as it is computationally efficient and does not require High Performance Computing (HPC) resources.

Table 1: Comparison of three different downscaling methods.

Downscaling method	Speed	HPC Requirement	Spatiotemporal downscaling
NWP	Slow	Yes	Yes
GML	Medium	Yes	Yes
Statistical	Fast	No	No *

* While statistical models that can downscale climate projections effectively in both time and space may be feasible, none have been proposed yet.

Training sites per Köppen climate

We train downscaling models for each Köppen climate classification. For each classification, we randomly select 10 locations and acquireSolarAnywhere ® Typical GHI Year (TGY) hourly time series for model training, yielding 310 sites in total.

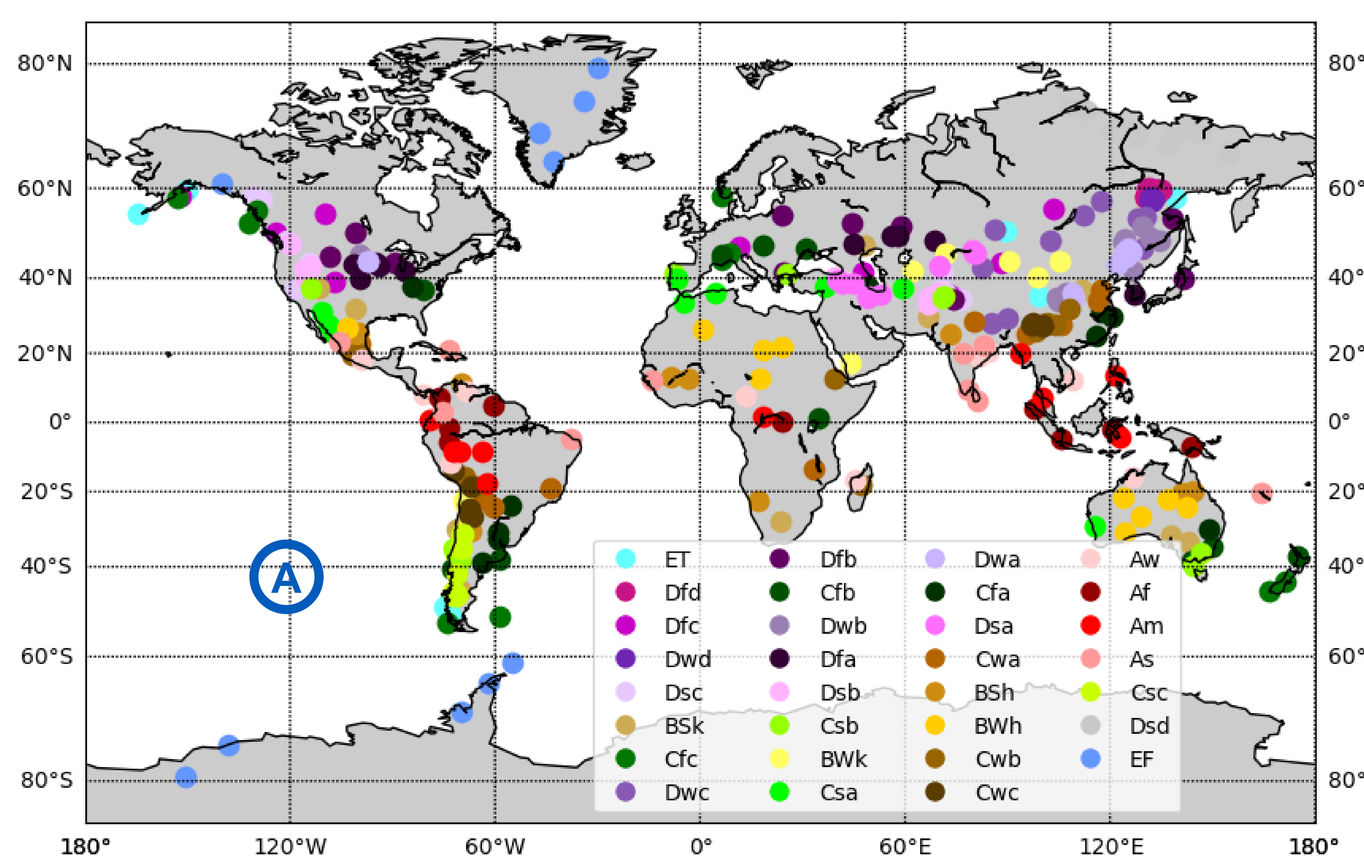

Figure A: Location of sites on a world map selected for model training per Köppen climate classification, as indicated by colors.

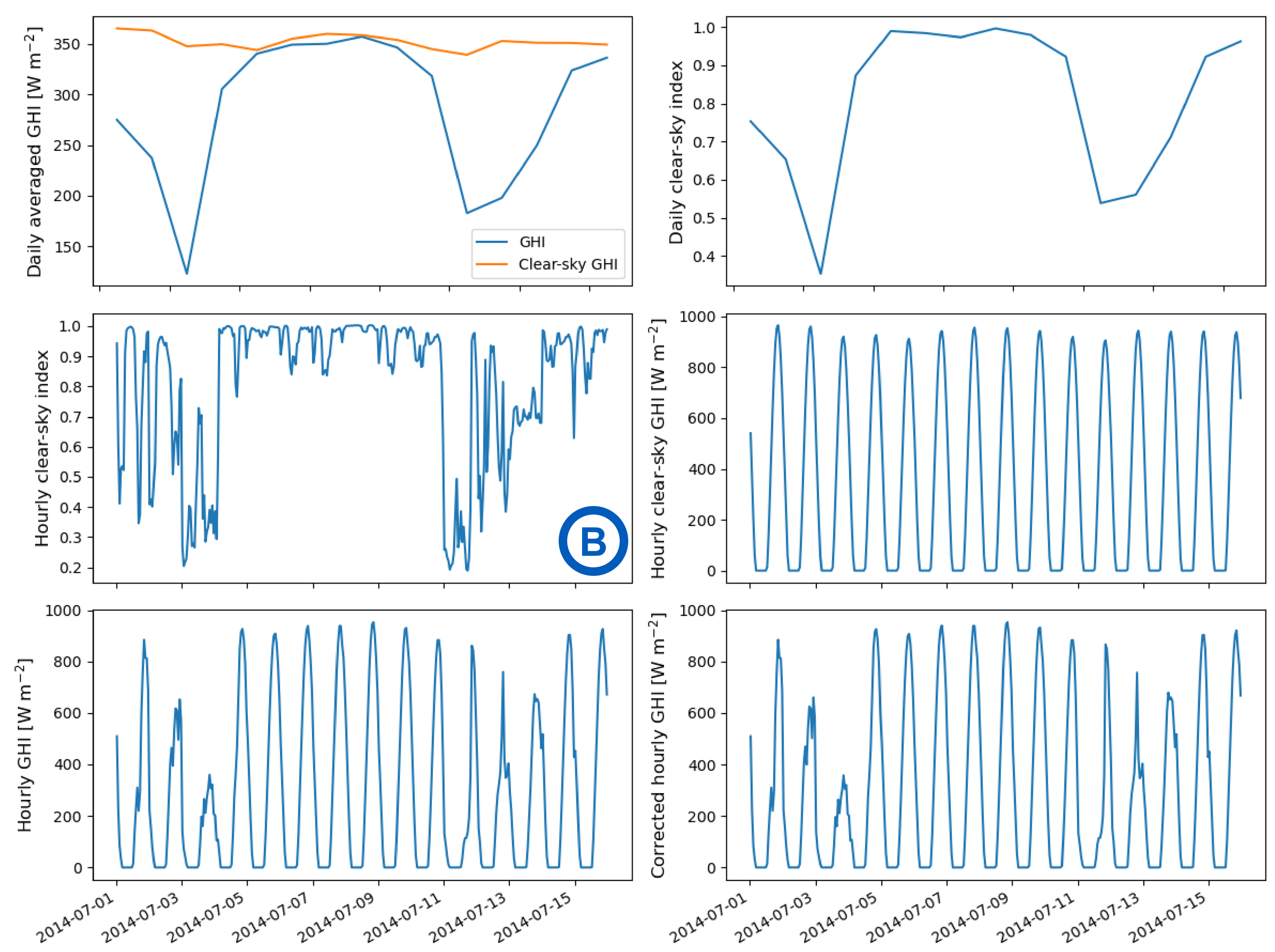

Figure B: Illustration of the downscaling process for Bellevue, WA: (top left) daily-averaged GHI and clear-sky GHI; (top right) daily clear-sky index; (mid left) downscaled hourly clear-sky index; (mid right) downscaled hourly clear-sky GHI; (bottom left) downscaled hourly GHI; (bottom right) corrected hourly GHI conserving daily-averaged GHI from climate models.

Using copula to downscale irradiance

Climate models simulate daily averaged GHI and clear-sky GHI, allowing the derivation of daily clear-sky index. We use a T-copula (one degree of freedom) to downscale the clear-sky index from daily to hourly resolution, as it captures both the distribution and temporal correlation of hourly clear-sky index in the training dataset. This downscaling procedure resembles the hour-to-minute downscaling of clear-sky index inSolarAnywhere's recent 1-minute Typical Year data product. Additionally, daily clear-sky GHI is downscaled to hourly resolution using the following zenith-dependent formula:

$$GHI_{cs}(h) = 24 * GHI_{cs}^{d} \frac{\cos(sza(h))^{1.2}}{\sum_{i=1}^{24} \cos(sza(i))^{1.2}}, \qquad (1)$$

where $GHI_{cs}(h)$ is the downscaled hourly clear-sky GHI, GHI_{cs}^{d} is the daily average clear-sky GHI simulated by the climate model, and SZA is the representative zenith angle capped in the [0, 90] degree range for the hour *h*. Hourly GHI can then be computed from downscaled hourly clear-sky index and downscaled hourly clear-sky GHI, conserving daily averaged GHI simulated by climate models.

Using RF to downscale temperature

Once hourly GHI is available, we use a random forest model to derive hourly ambient temperature from GHI along with additional features listed in Table 2. Since climate models simulate daily maximum and minimum temperatures, we only need to predict normalized hourly temperatures, defined as:

$$tnorm(h) = \frac{t(h) - tmin}{tmax - tmin}, \qquad (2)$$

where *t* is the original hourly temperature, and *tmax* and *tmin* are the daily maximum and minimum temperature, respectively.

As shown in Figure C, normalized solar time is the most important feature in predicting hourly temperatures, followed by zenith angle. A 2-fold cross-validation benchmarks the random forest models across all 31 climate zones. Temperature RMSE ranges approximately within [0.5, 1.5] degrees, with tropical climate zones generally exhibiting fewer prediction errors than those in high-latitude and polar regions. As shown in Figure D, the downscaled hourly GHI approximatesSolarAnywhere GHI in terms of daily mean and temporal variability. For temperature, the diurnal pattern, daily extremes, and the time lag between GHI and temperature are well preserved by the downscaling model.

Table 2: Major feature list used in building Random Forest models for temperature.

Feature ID	Full name	Range	Unit
stnorm	Normalized solar time	[-1, 1]	NA
cossza	cos(SZA)	[-1, 1]	NA
tmean	Daily average of temp.	[-273.15, inf]	°C
trange	Daily range of temp.	[0, inf]	°C
ghi	GHI	[0, inf]	W m^{-2}

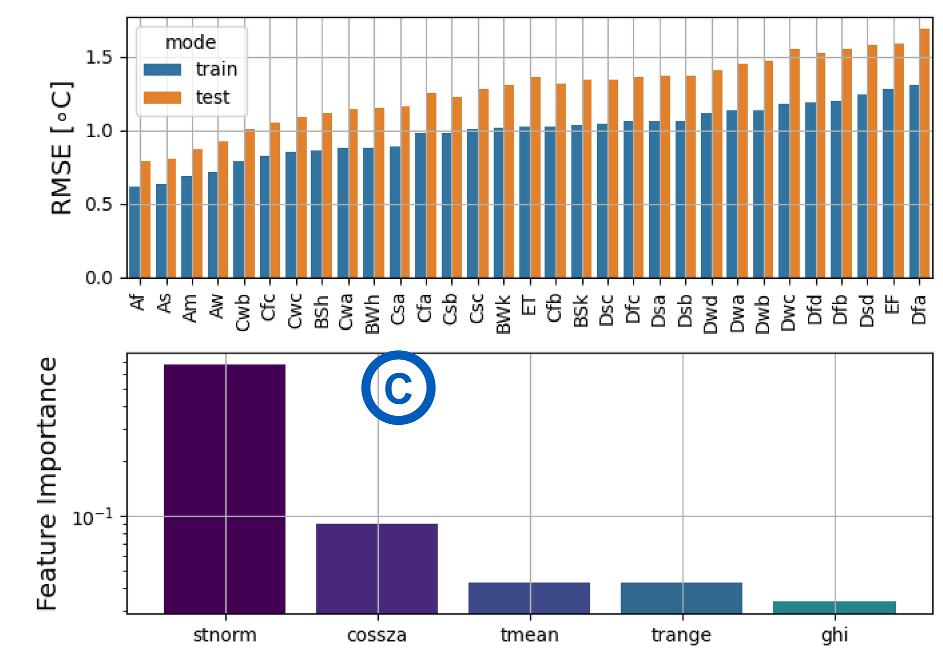

Figure C: (top) RMSE in training and testing mode across 31 Köppen climate zones; (bottom) Feature importance ranking averaged over all Köppen climate zones.

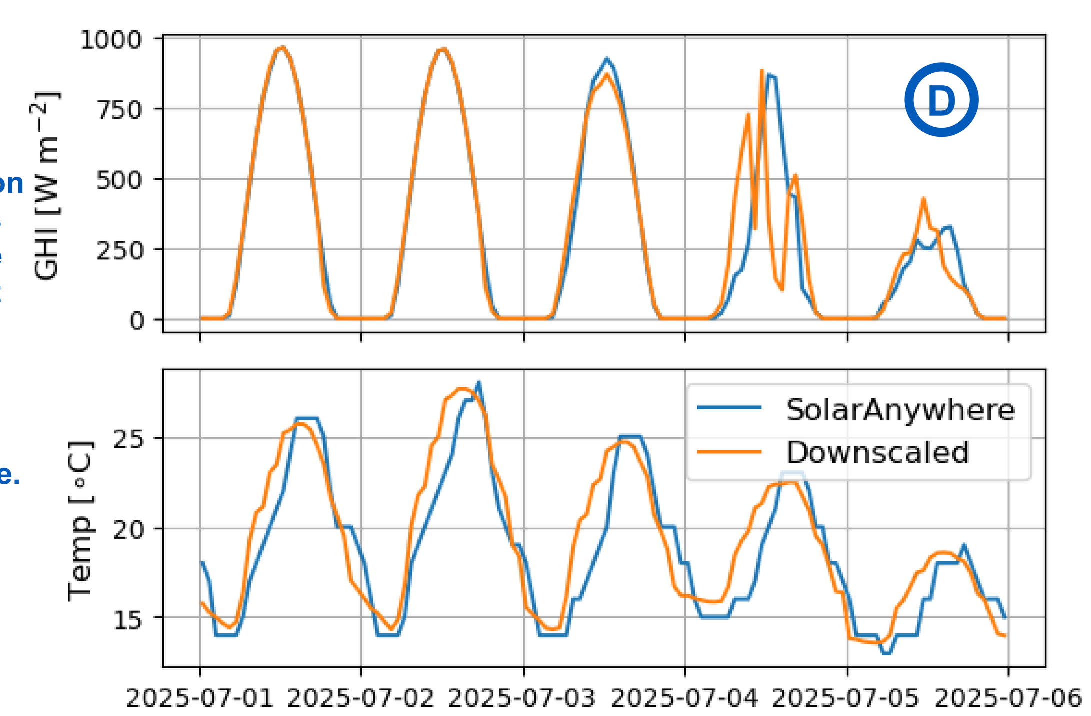

Figure D: Comparison of hourly time series from SolarAnywhere Typical Year product and from the proposed downscaling model for (top) GHI, and (bottom) temperature.

Conclusions

We present an integrated downscaling framework that enables efficient conversion of daily climate projections into hourly irradiance and temperature suitable for solar energy modeling. The T-copula method accurately captures temporal variability and distributional characteristics of irradiance, while the random forest models successfully reconstruct diurnal temperature structure and daily extremes. This lightweight approach offers a practical alternative to computationally intensive NWP and GML downscaling techniques, making hourly climate projection data accessible for broader energy-system applications.

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