Local urban weather data generation based on atmospheric reanalysis data to support building energy design in Singapore

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ABSTRACT

Building energy modeling (BEM) is essential for predicting energy use and improving thermal performance in buildings. Traditionally, weather data for BEM comes from built-in tool datasets. Additionally, global atmospheric reanalysis datasets like ERA5, have been used in recent years for BEM. However, the spatial resolution of global atmospheric reanalysis datasets is generally coarse relative to cities, limiting their accuracy in capturing local urban climate effects. Adopting ERA5 as the forcing data, this study examines the use of two urban land surface models, Urban Tethys-Chloris (UT&C) and Urban Weather Generator (UWG), to generate localized weather data for Singapore. The generated local weather data are compared with the data from an on-campus weather station and other weather datasets. Subsequently, these weather datasets are employed as input for an educational building's energy model that has been validated with energy meter data. The results demonstrate a better agreement between the generated local weather data and locally measured data, compared to the original ERA5 data and typical meteorological year weather data. This leads to an improved accuracy in building energy prediction. By leveraging the global availability of atmospheric reanalysis datasets, this framework for generating local weather data can serve as a universally applicable approach to support building energy design in tropical cities.

KEYWORDS

Urban microclimate; Outdoor thermal environment; Urban heat island; Building energy efficiency; Atmospheric reanalysis data; Land surface models

INTRODUCTION

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The building sector accounts for about 30% of global energy use (International Renewable Energy Agency, 2023) and significantly contributes to CO2 emissions, with building operations responsible for 26% and embodied emissions for 7% of total energy system emissions. In tropical countries like Singapore, buildings consume over half of the total electricity supply (International Renewable Energy Agency, 2023). As urbanization and climate change increase energy demands, efforts are being made to reduce energy use intensities.

Building Energy Modeling (BEM) tools are essential for predicting energy use and enhancing thermal performance, relying on precise weather data such as temperature, humidity, solar radiation, and wind speed. Weather data, a key input in BEM, typically comes from tools' built-in datasets that are represented by Typical Meteorological Year (TMY) datasets. In recent years, global atmospheric reanalysis datasets, such as fifth-generation ECMWF atmospheric reanalysis of the global climate (ERA5) and Modern Era Reanalysis for Research and Applications, version 2 (MERRA-2), have been used for BEM as they provide data on past weather conditions (Jiang et al., 2021).

However, weather data from meteorological stations or reanalysis datasets can become outdated over time, making it inadequate for representing recent weather conditions. Moreover, meteorological stations are often located in airports or rural areas, which may differ significantly from the urban environments under investigation. The spatial resolution of global atmospheric reanalysis datasets is generally coarse relative to cities, limiting their accuracy in capturing local climate effects.

To address this, researchers have developed methods for generating urban-specific weather data for BEM, including Computational Fluid Dynamics (CFD) simulations (Bouyer et al., 2011; Brozovsky et al., 2022; Hadavi & Pasdarshahri, 2021) and Urban land surface models (Bueno et al., 2012; Lipson et al., 2023; Paolini & Santamouris, 2023). While CFD simulations are accurate, they can be time-consuming. Urban land surface models offer quicker ways to produce localized weather data. Although urban land surface models have been used in various cities, there is limited focus on tropical climates. Furthermore, there has been little comparative analysis of different urban land surface models for generating local weather data specific to building energy simulations. This study aims to address this gap by evaluating and comparing various datasets and models to assess their effectiveness in predicting building energy consumption in tropical urban areas.

METHODOLOGY

Weather data

Singapore, a typical tropical city near the equator, experiences a wet equatorial climate with consistently high temperatures and annual precipitation of 2300 mm (Jiang et al., 2021). This study zeroes in on the SDE2 building at the National University of Singapore, a representative public building in Singapore. Local weather data is sourced from a weather station located at a bus stop near the building.

To drive the urban land surface model, this study uses ERA5 data from the European Centre for Medium-Range Weather Forecasts, which provides global meteorological variables at a $0.25° \times 0.25°$ resolution. Parameters include 2 m air temperature, surface

pressure, 2 m dewpoint temperature (for relative humidity), 10 m u- and v-component wind speeds, surface solar radiation, and total sky direct solar radiation (for diffuse solar radiation). We employed two urban land surface models, the Urban Tethys-Chloris model (UT&C) and Urban Weather Generator (UWG) to improve the accuracy of ERA5, and to develop local weather data. Urban parameters are derived from data near the target building. The same urban parameters are input into the two models to obtain the results, as shown in Table 1.

UT&C integrates ecosystem modeling with urban canopy schemes to assess the effects of vegetation on urban climate and hydrology. It uses an infinite urban canyon approximation to model complex urban systems, incorporating urban geometry, energy budgets, water budgets, and vegetation processes (Meili et al., 2020). The Urban Weather Generator (UWG) simulates mean energy fluxes across an urban canyon. It accounts for the energy exchange between the urban boundary layer and urban canopy governed by factors such as radiation, sensible and latent heat fluxes to the atmosphere, thermal storage capacity, and anthropogenic heat emitted into the urban canopy. It provides detailed information on heat transfer, infiltration, ventilation, and other factors, allowing for the estimation of heating and cooling loads for urban blocks (Bueno et al., 2012).

Table 1 Urban Parameters used in urban land surface models

Parameters	Value
Building coverage Ratio	0.25
Average Building Height (m)	22.5
Width of Roof (m)	33.0
Canyon Width (m)	99.0
Canyon Orientation (°)	20
Tree Crown Radius (m)	8.0
Tree Height (m)	13.25
Tree Distance to Wall (m)	13.0
Vegetated Ground Proportion	0.7
Impervious Ground Proportion	0.3

For comparison, a Typical Meteorological Year (TMY) dataset from the International Weather for Energy Calculation (IWEC) is used. This TMY data is developed based on 644 months measured at Changi Airport, Singapore (Huang et al., 2014). Additionally, the TMY-ERA5 dataset is used for reference. This dataset combines typical meteorological year data with ERA5 data to provide a global average of historical weather (Wu et al., 2023).

Building energy model

The open-source building energy simulation program, EnergyPlus is employed in the present study. We categorize different zones based on their functions and locations within the building. Each floor has distinct layouts and allocations for different room types. The multi-story building model is built to represent the actual floors, rooms, windows, and external shadings.

By adopting the recorded building cooling load, the model was calibrated using genetic algorithms for optimization. The setting of building construction materials, schedules

of electrical appliances, and occupancy are based on model calibration and actual information of SDE2 building. The calibration process aimed to minimize the Coefficient of Variation of Root-Mean-Square Error (CV(RMSE)), comparing actual and simulated cooling demands. Both CV(RMSE) and Normalized Mean Bias Error (NMBE) were used to evaluate calibration success, following:

$$CV(RMSE) = \left(\frac{1}{\bar{m}}\right) * \sqrt{\frac{\sum_{i=1}^{n}(m_i - s_i)^2}{(n - p)}} * 100 \qquad (1)$$

$$NMBE\ (\%) = \left(\frac{1}{(n - p) * \bar{m}}\right) * \sum_{i=1}^{n}(m_i - s_i) * 100 \qquad (2)$$

where m_i and s_i are the measured and simulated values respectively, $\bar{m}$ is the mean of the measured values, n is the number of data points, and p is the number of adjustable model parameters that equals 1. The resulting NMBE is 0.25% and CV(RMSE) is 29.56%. According to ASHRAE Guideline 14 (ASHRAE, 2014), a good model fit requires an NMBE within ±10% and a CV(RMSE) below 30%, indicating the model has acceptable predictive capabilities.

RESULTS

Dry Bulb Temperature

The comparison across weather datasets on a typical parameter, dry bulb temperature is analyzed here. Figure 1 shows the hourly diurnal variations in dry bulb temperature from February to December 2019 using six datasets. Local data exhibits significant diurnal fluctuations with a 5°C range and a peak temperature of 31.23°C around noon, indicating that other datasets underestimate peak temperatures. UT&C-ERA5 aligns relatively closely with the local one, particularly for peak temperature timing and magnitude. ERA5 and TMY-ERA5 show minimal diurnal variation with differences under 1.3°C between day and night. UWG-ERA5, reflecting the impact from the urban surfaces, generally shows higher temperatures throughout the diurnal cycle, maintaining a similar fluctuation pattern.

Figure 1 (b) displays the monthly mean temperatures, highlighting the Urban Weather Generator's enhanced performance compared to ERA5, indicating a closer alignment with local data. Figure 1(c) illustrates the variability in dry bulb air temperature, with ERA5 and TMY-IWEC showing broader interquartile ranges similar to Local, while ERA5, UWG-ERA5, and TMY-ERA5 have narrower ranges. Figure 1(d) shows hourly results for March, the hottest month, with UT&C-ERA5 correcting peak value biases better than other datasets.

Mean Bias Error (MBE), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE) are used for the measurement of fit, which can be expressed as:

$$MBE = \left(\frac{1}{m}\right) * \sum_{i=1}^{m}(F_i - O_i) \qquad (3)$$

$$MAE = \left(\frac{1}{m}\right) * \sum_{i=1}^{m} |F_i - O_i| \tag{4}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{m}(F_i - O_i)^2}{m}} \tag{5}$$

where m is the number of observations, F_i and O_i are forecasted and observed values of day i, respectively. Table 2 shows the result of MBE, MAE, and RMSE, indicating UT&C-ERA5 provides the most accurate result considering both magnitude and variability.
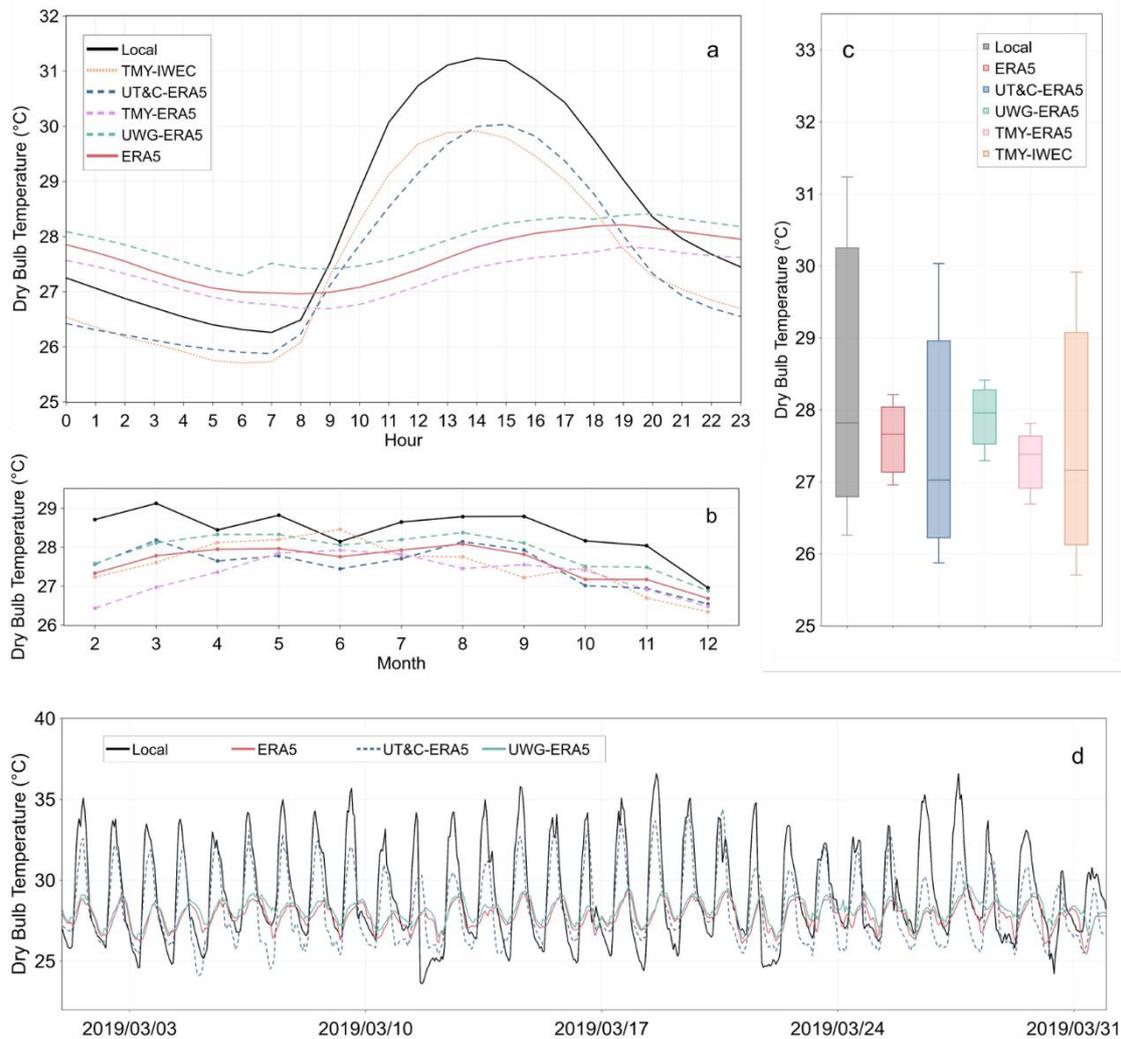

Figure 1 *Dry bulb temperature in the study period (a) hourly-averaged diurnal variation; (b) monthly mean variation; (c) boxplot across datasets. (d) hourly data variation of Local, UT&C-ERA5, ERA5 and UWG-ERA5 in March, 2019.*

Table 2 *Evaluation by error metrics on Dry Bulb Temperature performances of different weather datasets*

	TMY-IWEC	ERA5	UT&C-ERA5	UWG-ERA5	TMY-ERA5

MBE	-0.90	-0.80	-0.87	-0.50	-1.18
MAE	1.75	1.72	1.32	1.70	1.97
RMSE	2.34	2.30	1.67	2.21	2.64

Energy Prediction

To evaluate the performance of generated weather datasets for BEM, building energy simulations are conducted using multiple weather datasets as inputs. The two indexes mentioned in model calibration, NMBE and CV(RMSE), continue to be used in statistical comparison. Note that the simulated building cooling load with the Local weather data, is considered as the benchmark for comparative analysis. The hourly building cooling load obtained from the other five weather datasets is compared with this benchmark. The calculated NMBE and CV(RMSE) are listed in Table 3. Results of UT&C-ERA5 show a significant overrating while the others underestimate the cooling load. Compared to the original ERA5, UT&C-ERA5 and UWG-ERA5 provide results with a better agreement with Local. Specifically, UWG-ERA5 exhibits the lowest NMBE, and UT&C-ERA5 exhibits the lowest CV(RMSE).

Table 3 *Evaluation by error metrics on BEM performances using different weather datasets*

	TMY-IWEC	ERA5	UT&C-ERA5	UWG-ERA5	TMY-ERA5
NMBE (%)	4.35	4.50	-3.59	2.34	9.49
CV(RMSE) (%)	24.21	16.84	15.43	16.74	23.44

CONCLUSION

This study explores the approach to generating local weather data using urban land surface models, and evaluates the performance of the generated data as inputs for building energy simulation in Singapore.

A comparative analysis of weather data specific to building energy simulations is performed. We demonstrate that adopting the two urban land surface models, UT&C and UWG, can significantly improve the accuracy of ERA5 reanalysis weather data for local use. An example is given in dry bulb air temperature. Subsequently, they can improve the performance of building energy prediction to different degrees. This work highlights that the proposed reanalysis-data-based approach provided valuable data morphing and building energy simulation framework in the tropical city.

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