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Walking the heat: why thermal walks matter for high resolution microclimate mapping

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Abstract.
High-resolution microclimate maps are critical for advancing urban climate resilience strategies by providing detailed spatial insights into environmental variables. This study evaluates the performance of using a random forest regressor with single and multiple features to fit interpolated environmental data, including solar radiation, temperature, humidity, and wind speed. Using regression kriging on observations from 42 weather stations distributed on the campus of the National University of Singapore (NUS), spatial environmental variables were mapped at a 5×5 meter resolution. The interpolation process uses various geospatial layers to refine the results and the fine-scale spatial resolution. As a result, this model captures the localized variability of environmental variables. This work contributes to urban climate modeling by advancing the methodological frameworks for microclimate mapping and addressing the growing need for reliable high-resolution environmental data to inform thermal comfort assessments and resilience strategies.

1. Introduction

The intensifying impacts of climate change have led to a steadily increasing global temperature, resulting in more frequent and severe heatwaves, as well as other extreme weather events [1]. These changes are escalating health risks and contributing to increased mortality rates, with heat already recognized as one of the deadliest natural hazards [2]. Addressing these challenges requires the development of climate-resilience strategies that mitigate health risks, particularly in urban areas where populations are most vulnerable [3, 4]. To effectively design such strategies, a detailed understanding of microclimate conditions in the built environment at fine spatial scales is essential. Microclimates exhibit disproportionate impacts on individuals [5] as localized environmental variations can have varying degrees of impact on thermal comfort and perception [3]. Consequently, creating thermally comfortable and livable urban environments requires a comprehensive approach that integrates high-resolution spatial data with more human-centric considerations. This enables the identification of localized temporal and spatial differences.

The study of microclimates relies on various methodologies to capture environmental variations at fine spatial scales. These approaches are shaped by data availability, computational resources, and the desired spatial and temporal resolution of results, each with inherent strengths and limitations [6]. Spatial interpolation techniques are commonly employed to estimate environmental variables where direct observations are unavailable. These methods can be broadly categorized into deterministic approaches (e.g., Inverse Distance Weighted (IDW), Trend Surface Analysis, and Spline Interpolation), geostatistical methods (e.g., Kriging), and hybrid techniques such as Regression Kriging (RK) [6, 7]. Among these, IDW, Kriging, and RK are the most widely used [8]. RK, in particular, combines regression models with geostatistical kriging to capture both large-scale trends and residual spatial autocorrelation. However, its resolution is inherently constrained by the density and spatial distribution of input data, often limited by the scale of available observations. Then, model validation typically relies on cross-validation techniques, comparing predicted values against observed data to assess accuracy [9].

Empirical sensor-based methods and computational modeling techniques, including Computational Fluid Dynamics (CFD) and urban climate models, are widely used in microclimate studies to simulate airflow, heat transfer, and solar radiation, though they are often limited by high computational demands and simplified urban geometries [10]. Recent machine learning and deep learning approaches offer alternatives by capturing nonlinear environmental dynamics and emulating numerical models, enabling high-resolution predictions but requiring substantial computational resources and extensive training data [11, 12]. A persistent challenge is balancing model complexity with computational feasibility to accurately represent fine-scale urban microclimates [13]. Moreover, these methods typically rely on weather station data and often lack pedestrian-level ground-truthing, limiting their ability to account for localized microclimatic conditions relevant to human thermal comfort.

Thermal walks have gained increasing attention as traditional urban climate studies, which rely on fixed weather stations or large-scale datasets, often fail to capture localized microclimatic variations [14, 15]. Given the heterogeneity of thermal conditions in urban environments, human-centered measurement approaches are essential for understanding how pedestrians experience temperature fluctuations in real-world settings. These studies reveal significant spatial and temporal variability in meteorological conditions and human thermal perception, influenced by factors such as Mean Radiant Temperature, solar radiation, humidity, wind speed, and urban morphology, including shading and vegetation. Recent advancements have introduced mobile and stop-and-go measurement techniques to monitor thermal conditions along pedestrian routes, highlighting the role of urban features like built density and greenery in shaping thermal comfort [14, 15, 16]. Mean Radiant Temperature is widely recognized as one of the most complex, influential, and challenging variables to measure and assess in relation to thermal comfort [17, 18].

While regression kriging enables high-resolution interpolation of environmental data, it does not fully capture local microclimatic variations experienced by pedestrians, especially between measurement points. This study expects to use thermal walks to provide valuable ground-truth data to enhance the accuracy of these interpolations.

2. Methodology

This pilot study uses a network of 42 stationary weather stations with 3 meteorological towers capturing various environmental variables at a minutely interval. This study interpolates them using regression kriging to a 5×5 meter grid and fits each individual variable using the gathered thermal walk data of 10 total walks and random forest regressor depicted in Figure 1.

The weather stations are on the National University of Singapore (NUS) Campus, which covers an area of about 2 km^2 with various environments like densely built urban areas, as well as public open spaces or greatly and partly vegetated spaces. Singapore is typical in that there are lots of outdoor spaces, as well as semi-outdoor spaces, which are sometimes solely beneath or inside buildings but are fully exposed to environmental hazards. This study uses the same

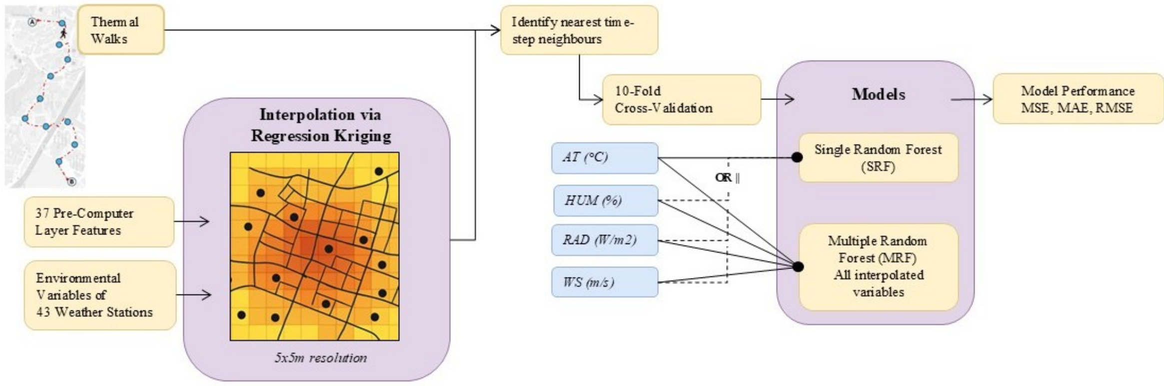

Figure 1: Simplified overview of the experimental setup utilizing environmental variables from the thermal walk and interpolation: Air Temperature (AT), Humidity (HUM), Radiation (RAD), and Wind Speed (WS) to fit the interpolated data.

data as described in this study by Lim et. al. [19]. That model utilized a total of 32 computed layers of feature information for vegetation, buildings, environmental data, mobility data, and simulated data, which were then in a multi-step cluster to improve distinctiveness and accuracy of cluster boundaries. The data was retrieved using available Laserscan data, OpenStreetMap data and then data computed using Ladybug tools (simulated data), in order to then extract the features.

A total of 10 thermal walks were carried out at different times throughout the day, from 9 a.m. to 7 p.m., to capture a wide range of climatic conditions across the campus. Environmental data, including humidity, solar radiation, wind speed, and air temperature, were logged at a 10-second interval. The experimental setup used for these measurements is identical to the one employed by Marcel et al. [20].

For interpolation, regression kriging was performed using PyKrige and scikit-learn at a resolution of 5×5 meters. The following parameters were set for the kriging process: a C-value of 0.001, a gamma of 5, a radial basis function (RBF) kernel, 50 estimators, a random state of 4, and a neighborhood size (n) of 8. These settings were applied to each environmental variable at each timestamp of the thermal walks using the aforementioned campus-wide available station data.

The thermal walk data was aligned with the interpolated dataset by identifying the closest time-step neighbors. The dataset was then subjected to 10-fold cross-validation. As previously depicted in Figure 1, two models were investigated. The first model, "Single Random Forest" (SRF), used a Random Forest Regressor trained individually for each environmental variable to capture the specific relationships between the predictor variables and the target variable. In this approach, the interpolated Air Temperature served as the base and was fitted to the mobile weather station's Air Temperature. The second model, "Multiple Random Forest" (MRF), employed a combined approach utilizing all environmental interpolated available variables as features to train a single target variable. This model was designed to explore the potential impact of multicollinearity or complex interactions, which could introduce noise or obscure relationships, potentially reducing model accuracy compared to the single-feature models. Model performance was evaluated using several metrics, including Mean Squared Error (MSE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE).

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3. Results

Tables 1 and 2 present performance metrics (MSE, MAE, RMSE) for training (A) and test (B) datasets, comparing single-feature (SRF) and multi-feature (MRF) models.

For Air Temperature and Wind Speed, the MRF model demonstrates lower error differences between training and test sets, with Test MSE values of 0.33 (Air Temperature) and 0.34 (Wind Speed), and Test RMSE values of 0.57 and 0.58, respectively, indicating better generalization. Conversely, the SRF model shows higher discrepancies, with Test MSE values of 1.40 (Air Temperature) and 0.66 (Wind Speed), suggesting overfitting.

Table 1: Resulting metrics for Model 1 "Single Random Forest" (SRF), with (A) representing the metrics for the Training dataset and (B) representing the metrics for the Test dataset.

Measure	(A) MSE	(B) MSE	(A) MAE	(B) MAE	(A) RMSE	(B) RMSE
Air Temperature (°C)	0.19	1.40	0.31	0.85	0.44	1.18
Wind Speed (m/s)	0.10	0.66	0.23	0.60	0.31	0.81
Radiation (W/m²)	4644.62	25693.85	40.46	95.60	68.15	160.21
Humidity (%)	4.14	29.59	1.52	4.11	2.03	5.44

For Humidity, the MRF model significantly outperforms SRF, achieving lower Test MSE (5.19 vs. 29.59) and RMSE (2.28 vs. 5.44). However, the MRF Test MSE (5.19 vs. 0.73 for training) highlights potential variability, indicating instability despite mitigating overfitting.

For Radiation, both models exhibit overfitting, with high Test MSE (25,693.85 for SRF; 14,716.55 for MRF) and RMSE (160.21 for SRF; 121.10 for MRF). These results suggest Radiation's complexity makes it challenging for both models to generalize effectively.

Table 2: Resulting metrics for Model 2 "Multiple Random Forest" (MRF), with (A) representing the metrics for the Training dataset and (B) representing the metrics for the Test dataset.

Measure	(A) MSE	(B) MSE	(A) MAE	(B) MAE	(A) RMSE	(B) RMSE
Air Temperature (°C)	0.05	0.33	0.13	0.34	0.21	0.57
Wind Speed (m/s)	0.05	0.34	0.16	0.41	0.23	0.58
Radiation (W/m²)	2096.57	14716.55	26.33	70.09	45.79	121.10
Humidity (%)	0.73	5.19	0.51	1.38	0.86	2.28

Figure 2 illustrates an exemplary run for each environmental variable presented as a line chart, where the interpolated data (Int_) serves as the feature, and the Mobile Weather Station (mWST_) data represents the target variable. The chart compares the resulting values from the Single Random Forest (SRF) and Multiple Random Forest (MRF) models over a selected 30-minute timeframe. The SRF model exhibits substantial fluctuations and spikes across all environmental variables, particularly for Air Temperature and Humidity, when compared to the MRF model. In contrast, the predictions for Radiation and Wind Speed show only slight differences between the SRF and MRF models.

Notably, the interpolated data for Air Temperature and Humidity generally displays a stable trend, with only brief periods of rapid fluctuation. In comparison, the interpolated data for Wind

Speed and Radiation demonstrates more variability, though the fluctuations are less pronounced than those observed in the Air Temperature and Humidity data. The mWST data follows a similar pattern, though significant discrepancies are evident when comparing the mWST values to the interpolated data—both in terms of absolute values and the timing and duration of certain fluctuations.

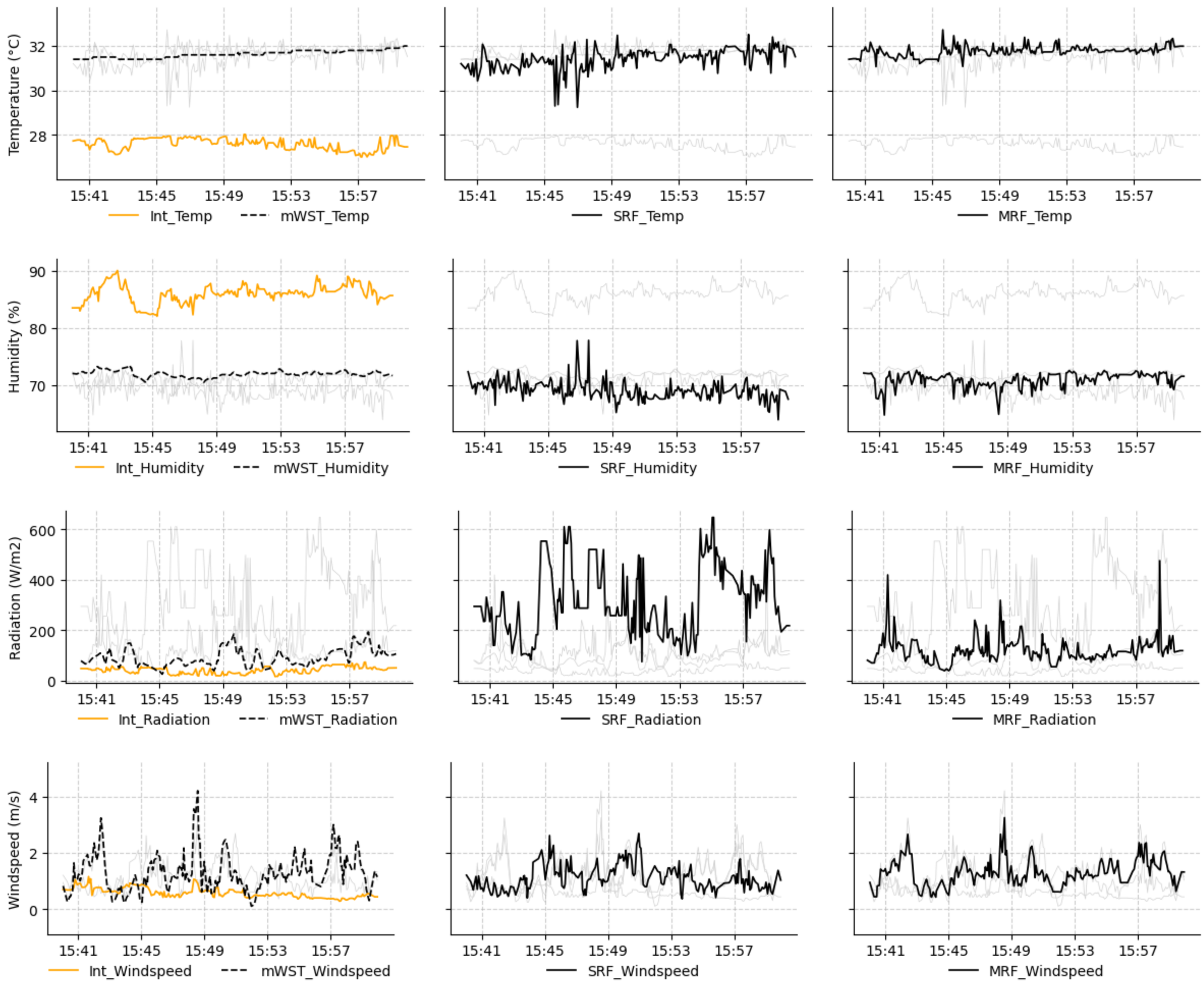

Figure 2: Results for each environmental variable conducted with (1) the interpolated (Int_) and mobile weather station data (mWST_), (2) Single Random Forest (SRF), and (3) Multiple Random Forest (MRF).

4. Discussion and Conclusion

This study integrated regression kriging with Random Forest (RF) modeling to optimize high-resolution microclimate maps, using ground-truth measurements obtained during thermal walks.

However, the dataset was relatively small and confined to daytime measurements, with no structured approach to the timing or execution of thermal walks. Additionally, nighttime thermal variations were not considered. Expanding the dataset to include a greater number of thermal walks conducted across various times of day, including nighttime data, would offer a more comprehensive representation of environmental conditions and enhance the generalizability of the results. Additionally, while regression kriging and Random Forest models produced fine-scale predictions, the models exhibited sensitivity to specific environmental conditions. In particular, Air Temperature and Humidity demonstrated notable overfitting in the Single Random Forest (SRF) model, with large discrepancies observed between the training and test datasets and or overfitting.

In contrast, solar radiation—a well-established dominant driver of local thermal variability that sharply differentiates sunlit and shaded microenvironments and strongly influences pedestrian thermal comfort—was comparatively better captured against the Mobile Weather Station (mWST) data. This suggests the models could reflect the fluctuations between shaded and unshaded conditions, which critically affect thermal perception at the pedestrian scale. However, sensor lag in mobile measurements may have introduced temporal offsets, reducing synchronization with spatially interpolated predictions and contributing to some inconsistencies. The Multiple Random Forest (MRF) model, which integrated multiple environmental features, demonstrated more robust performance, consistently capturing the complex relationships between variables and improving prediction accuracy.

During the comparison between interpolated data and Mobile Weather Station (mWST) measurements revealed significant discrepancies, particularly for Air Temperature and Humidity, possibly due to overfitting of the interpolation model. Nevertheless. the difference highlights the challenges of using interpolated data to represent pedestrian-level microclimatic experiences, where local variations and dynamic factors might not captured by weather stations play a significant role in thermal comfort, thus underscores the need for more extensive ground-truthing to enhance reliability and accuracy.

In conclusion, the study highlights the value of accurately modeling pedestrian-level microclimates for urban planning. By combining regression kriging with Random Forest, it offers a method to create detailed climatic maps that aid in designing climate-responsive and resilient environments. While promising, the approach requires further refinement, especially through the inclusion of nighttime data and more thermal walk measurements, to enhance predictive accuracy.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this manuscript, the authors used generative AI tools to assist with language refinement and proofreading. All AI-assisted content was thoroughly reviewed and verified by the authors, who take full responsibility for the integrity and accuracy of the publication.

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