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High-resolution air temperature maps based on deep learning models may underestimate temperatures at the microscale.

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Introduction

- Estimates of energy demand and heat-related deaths and illnesses have been made to achieve a sustainable city. In doing so, it is essential to know accurate temperatures for the entire city.
- Recently, machine learning and deep learning models have been developed to predict temperature maps based on the relationship between weather station data and predictor variables.
- The usefulness of these algorithms has been confirmed in many studies. However, due to problems in data acquisition, there has been little indication of how well they reflect temperatures at the microscale.
- In Seoul, the S-DoT was installed in 2020 to acquire microscale temperatures regularly.

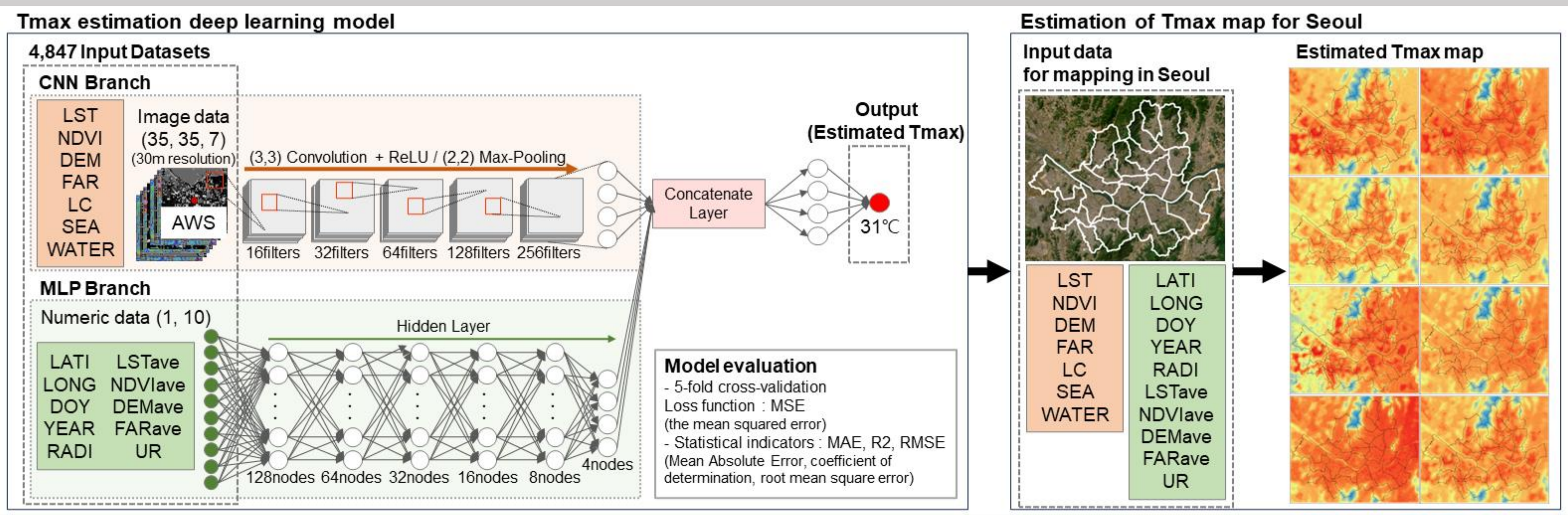
Purpose

- To understand how well high-resolution air Temperature (Ta) maps predicted by the deep learning model depict Ta at the microscale.

Method

1. Mapping the maximum Ta of the day (Tmax) by a deep learning algorithm.

- The deep learning model was constructed as a multi-input model with branches (i.e., convolutional neural network (CNN) and multilayer perception (MLP) branches) and capable of receiving two types of data (i.e., image data and numeric data).
- The 4,847 training datasets consist of predictor variables and the observed AWS Tmax. These datasets have a temporal range of June-September 2015~2020 and a spatial range of meteorological stations throughout South Korea, excluding Jeju Island.
- Predictor variables were selected for factors for which previous studies have revealed direct and indirect influences on Ta determination.
- The Tmax map was estimated for eight days from June to September 2020-2022 in a spatial extent that included a 2-km buffer centered on the Seoul city boundary.



2. Evaluation of estimated Tmax map using observations.

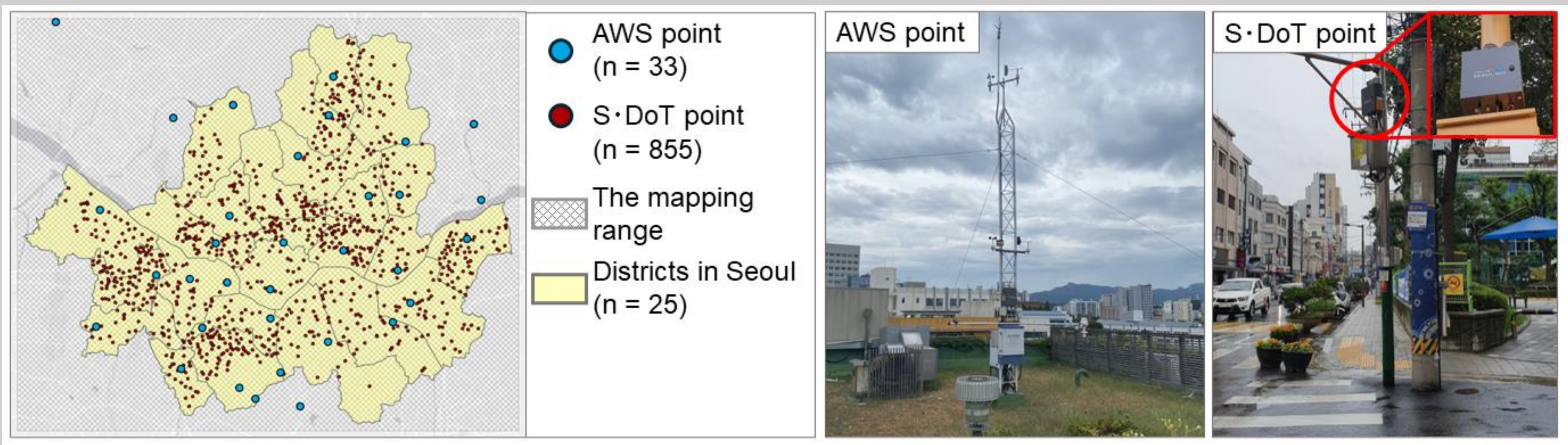
- We verified the accuracy of the map by comparing the estimated Tmax with the observed Tmax at 33 AWS stations in Seoul.
- Using Equation (1), the error between the two groups (Error (AWS)) was examined by date and station.

$$Error\ (AWS) = Estimated\ Tmax\ -\ Observed\ AWS\ Tmax \cdots\ Equation\ (1)$$

3. Comparison of estimated Tmax maps with the microscale Tmax (S・DoT).

- To confirm whether and how accurately the estimated Tmax represents microscale Ta, we compared the estimated Tmax and the Tmax observed by S・DoT using Equation (2).

$$Gap\ (S{\cdot}DoT) = Estimated\ Tmax\ - Observed\ S{\cdot}DoT\text{-}Tmax \cdots\ Equation\ (2)$$



What is AWS

- AWS is an automated weather station operated by the Korea Meteorological Administration (KMA).
- The AWSs are installed according to KMA's strict regulations, and the Ta sensor is placed 1.2 to 2.0 m above the installation surface.

What is S・DoT

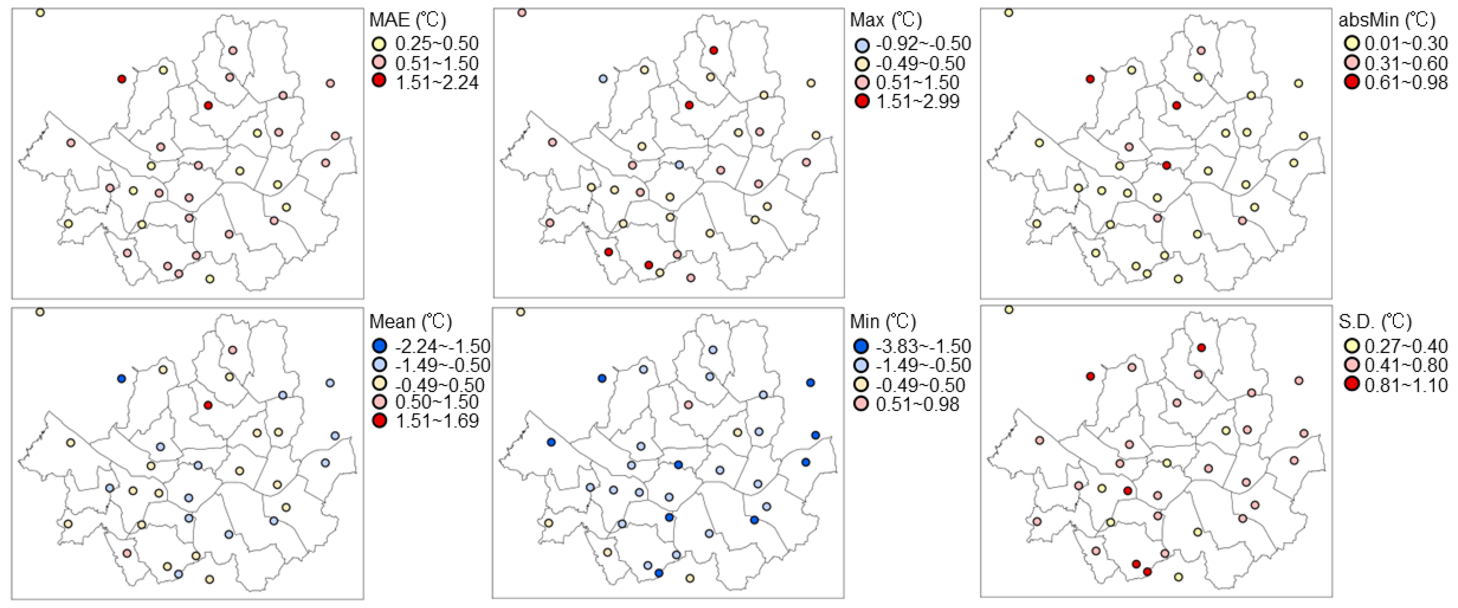
- S・DoT is a ground-based observation system operated by Seoul since April 2020, and it collects ten types of data, including Ta, PM10, PM2.5, humidity, illumination, and noise.
- There are more than 855 stations in Seoul, and most of these stations are installed on CCTV poles at a height of approximately 2-3 m.

Results

1. The performance of the deep learning model and the Tmax map results were validated.

- The best performance of the deep learning model with CNN and MLP branches with the best performance exhibited MAE, RMSE, and R2 values of 0.87 ℃, 1.11℃, and 0.91, respectively.

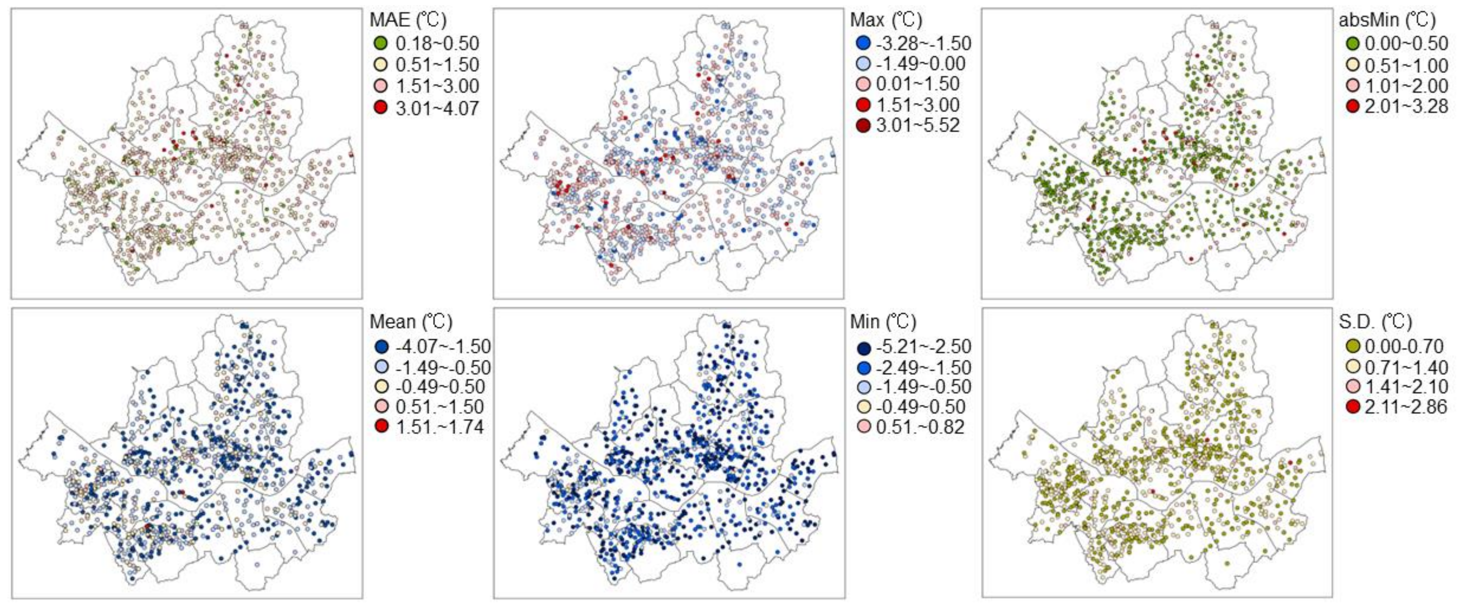
Date	Basic statistics (℃)					
	MAE	Mean	Maximum	Minimum	absMin	SD
2020-06-15	0.701	-0.061	2.211	-3.704	0.008	1.019
2020-07-17	1.054	-0.794	1.434	-3.835	0.073	1.02
2020-09-19	0.579	-0.312	1.971	-2.538	0.019	0.721
2021-06-02	0.784	-0.082	2.364	-2.07	0.06	1.009
2021-07-20	0.744	-0.06	2.987	-2.031	0.064	0.952
2022-06-21	0.689	-0.206	1.774	-1.954	0.028	0.87
2022-07-15	0.762	-0.505	1.08	-2.234	0.009	0.778
2022-08-16	0.665	-0.486	0.98	-1.583	0.011	0.654



2. Tmax at the microscale tended to be higher than the estimated Tmax map, with a maximum gap of more than 5.0°C.

- This gap between the estimated Tmax and S・DoT-Tmax is highly influenced by the station installation environment

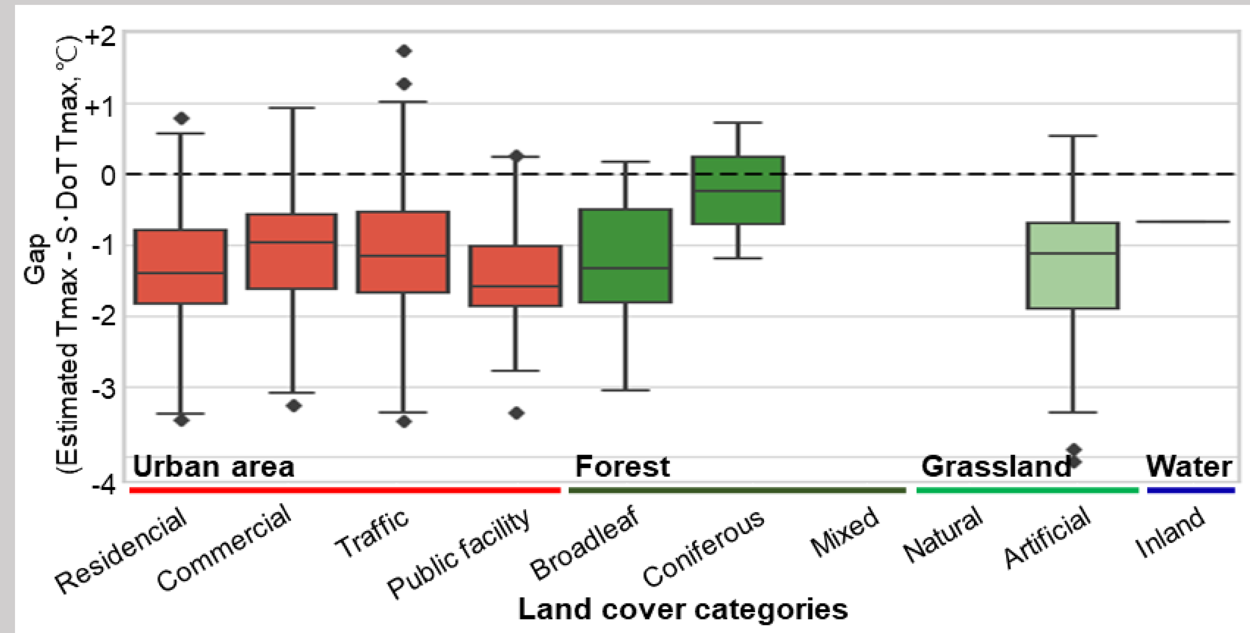
Date	Basic statistics (℃)					
	MAE	Mean	Maximum	Minimum	absMin	SD
2020-07-17	1.26	-1.04	3.89	-4.54	0.0	1.14
2020-09-19	1.68	-1.59	1.41	-5.21	0.0	1.25
2021-06-02	1.10	-0.89	1.72	-4.41	0.0	1.04
2021-07-20	1.10	-0.86	4.58	-3.54	0.0	1.02
2022-06-21	1.30	-1.12	1.96	-4.59	0.0	1.15
2022-07-15	1.30	-1.13	5.52	-4.84	0.01	1.13
2022-08-16	1.66	-1.58	3.68	-4.56	0.0	1.11

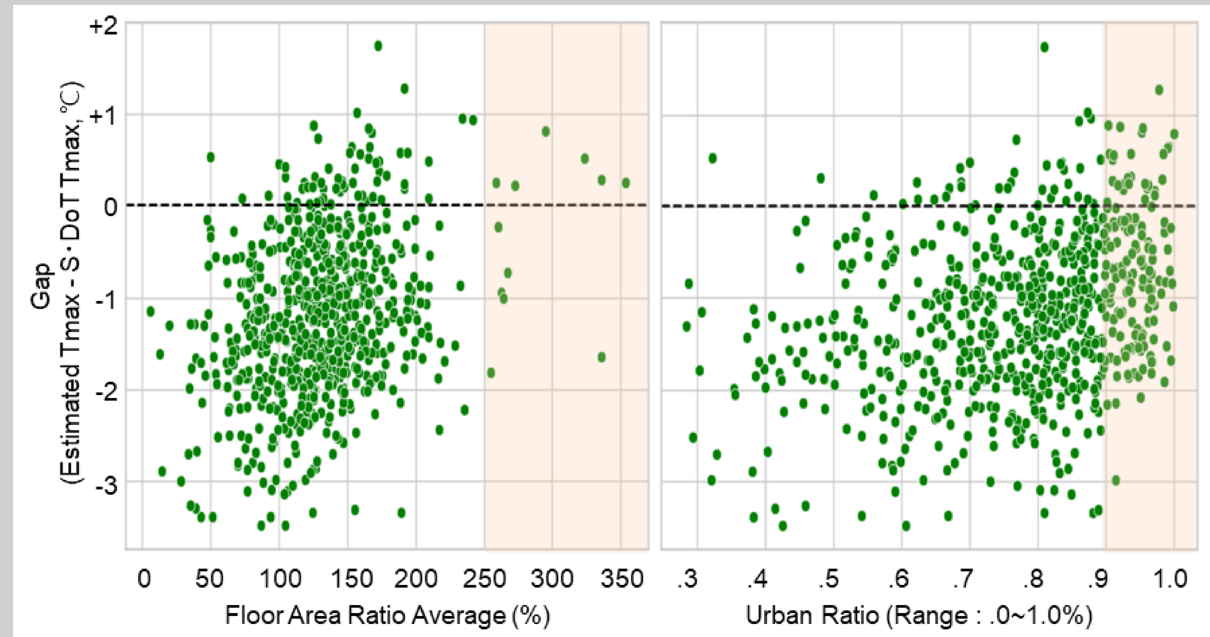


Discussion

2. Microscale high temperatures may be unpredicted, especially in areas susceptible to the heat island effect.

- The gap between S・DoT and estimated Tmax appears larger for urban and artificial cover.
- Gap values decreased when the S・DoT were located at a floor area ratio (FAR) greater than 250% and urban cover ratio greater than 90%; Error may have decreased as the Sky View Factor (SVF) increased and urban heat island intensity weakened.





Conclusion

- Estimation Ta using deep learning algorithms can help identify high/low Ta areas within a city.
- However, it was found that estimated Ta maps can miss high Ta at the microscale by up to 5.0°C or more.
- Knowledge of unpredictable high temperatures in microclimates is helpful in areas such as energy demand calculations and health management.

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