Detection and Simulation of Urban Heat Islands Using a Fine-Tuned Geospatial Foundation Model for Microclimate Impact Prediction

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Motivation & Methodology

Key Challenges for Urban Heat Island Modelling and Forecasting

- **Heterogeneous data:** Integrating satellite and meteorological data across scales is complex[1]
- **Disaggregated observations**: Independent data sources cause spatial and temporal gaps[2]
- **Sparse monitoring:** Limited ground truth restricts model validation and fine-scale forecasting[3]
- **Computational demands:** Physical models are costly, and deep learning models need large datasets and lack cross-domain generalizability[4]

Goal:
Therefore, this study applies a geospatial foundation model to detect and simulate urban heat islands, quantify spillover cooling effects, and assess how GFMs perform in settings where traditional approaches often face limitations.

Study Design and Model Architecture

- **Experiment 1 – Empirical Baseline:** Combine LULC and LST data from 2017–2025 to quantify green space cooling and validate GFM outputs against ground truth across 12 European cities
- **Experiment 2 – Future Extrapolation:** Assess the model's capacity to generalize to unseen cities, demonstrated for Brașov (Romania) using EURO-CORDEX climate projections to model future heat hotspots
- **Experiment 3 – Urban Greening Simulation:** Apply guided inpainting to replace built-up zones with vegetation, simulate urban greening, and estimate potential surface temperature reductions to quantify the cooling effect of green interventions

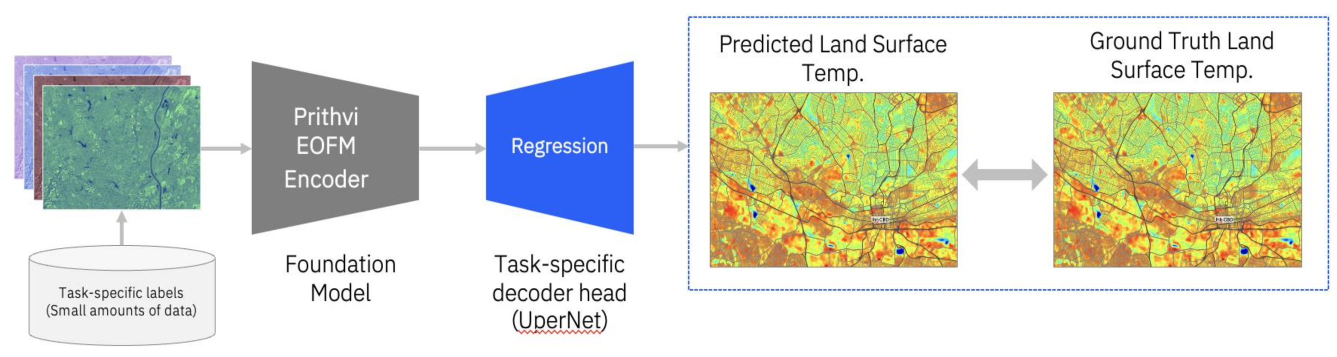

Fig. 2: Overview of the Prithvi foundation model architecture and its fine-tuning pipeline.

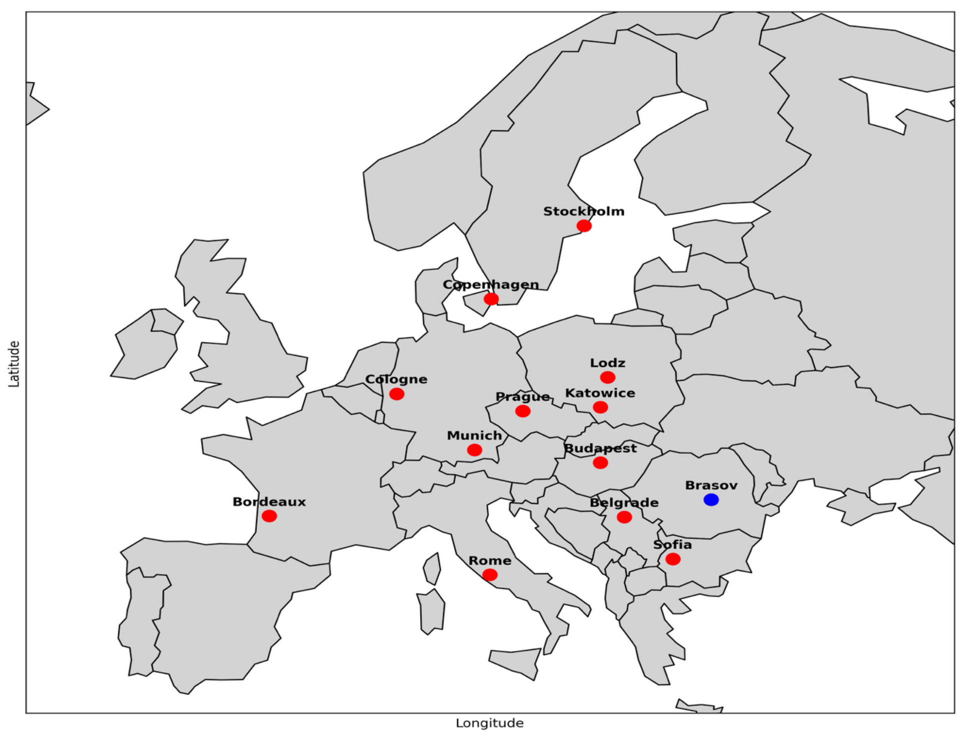

Fig 1: Study regions across twelve European cities (red dots) representing varied urban and climatic conditions. Brașov (blue dot) served as the extrapolation site for model testing.

- **Study Regions:** Thirteen European cities were selected to test the GFM's ability to generalize across a range of diverse urban, geographic, and climatic contexts, capturing variations in land use and environmental conditions, including Brașov (unseen) and Prague (inpainting case).

Experiments

Ground truth internal and spillover cooling patterns

- Dense city cores exhibit an average UHI intensity of +3.3 °C, reflecting clear thermal contrasts shaped by vegetation distribution
- Parks act as cooling sinks, with internal cooling up to −2.6 °C and spillover effects reaching −3.5 °C close to parks

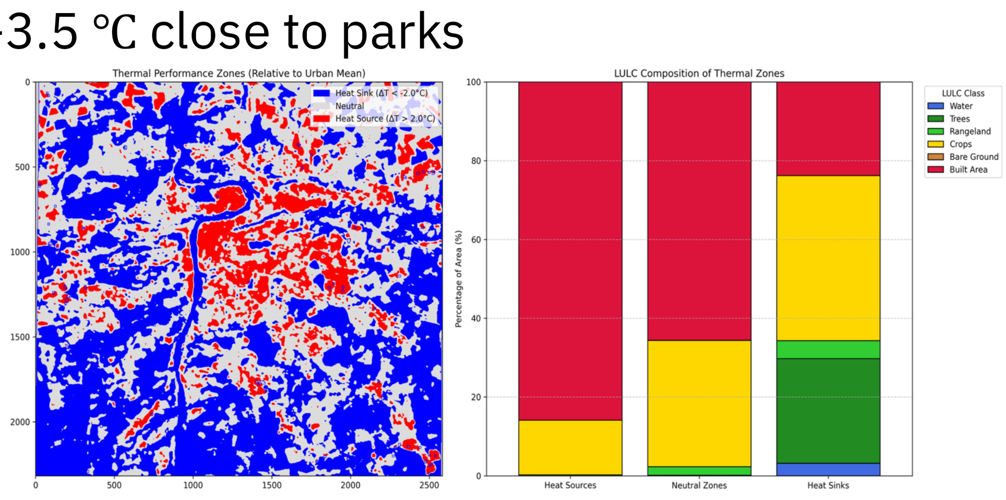

Fig 3: Heat source-sink experiment

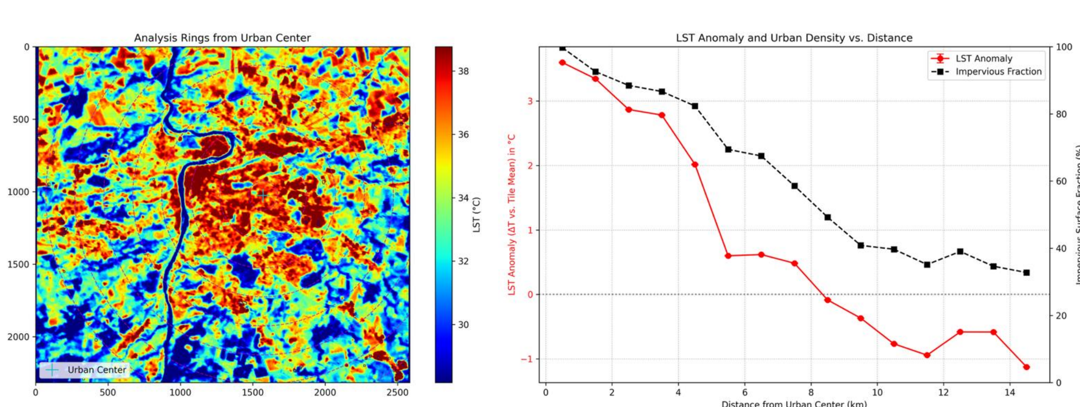

Fig 4: Urban gradient experiment

Model Performance Evaluation and Future Climate Forecasting

- Both models accurately capture the internal cooling gradient, with model V2 showing clear improvements in reproducing spillover cooling patterns

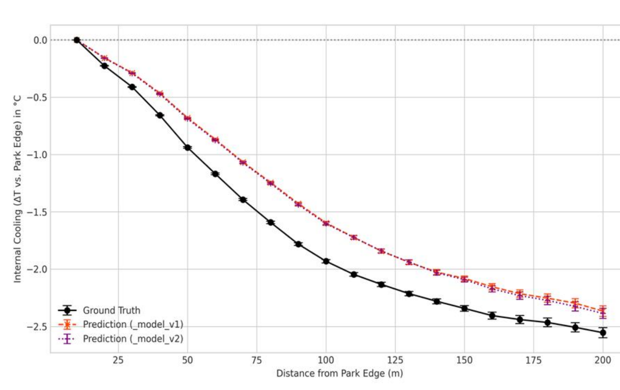

Fig 5: Internal cooling gradient

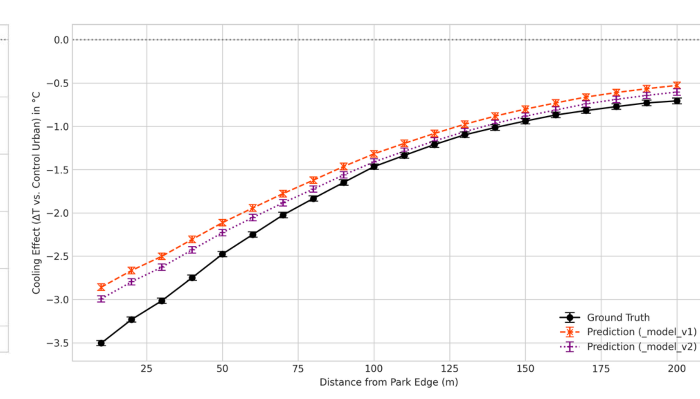

Fig 6: Spillover cooling gradient

- Climate projections reveal a strong intensification of UHIs under RCP 4.5 and 8.5 scenarios toward 2100
- Model V2 robustly extrapolates to unseen extremes, with an MAE of 1.74 °C on the upper 10% of temperatures, reinforcing reliability for future simulations

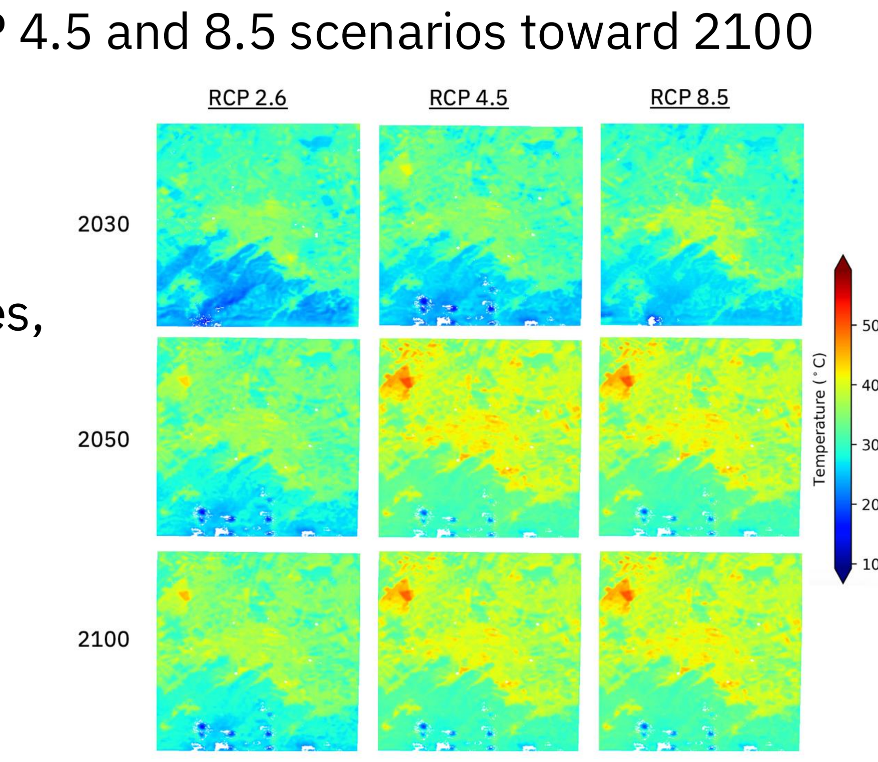

Fig 9: Projected UHI extent under RCP 2.6, 4.5, and 8.5 for 2030, 2050, and 2100 in Brasov.

Inpainting-Based Simulation of Urban Greening for Urban Heat Island Mitigation

- The greening intervention increases NDVI and lowers local LST by several degrees, confirming vegetation-driven cooling
- Cooling reaches −6 °C inside the park and extends up to −0.5 °C within 150 m

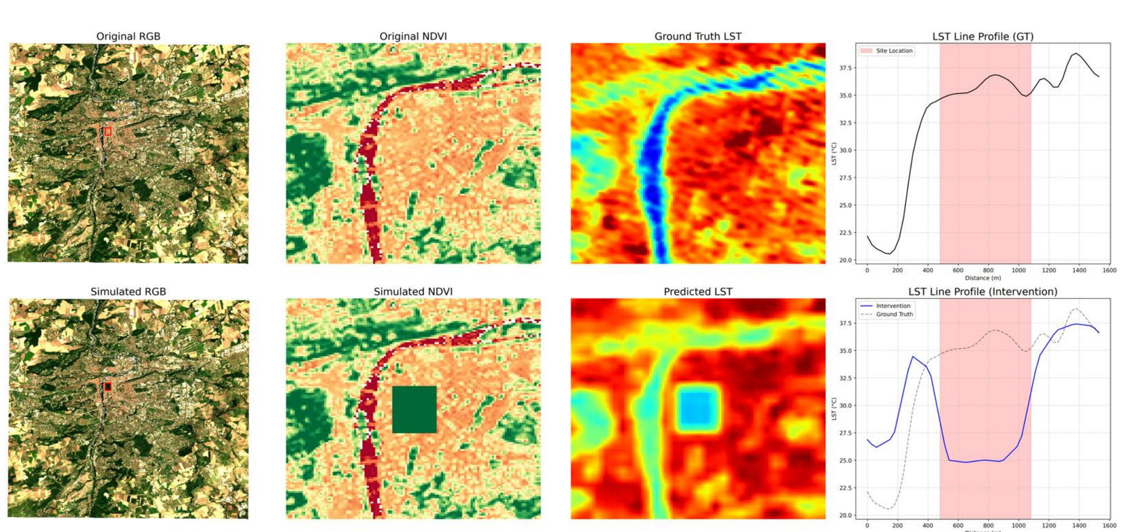

Fig 7: Comparison of inpainting results against ground truth data in Prague.

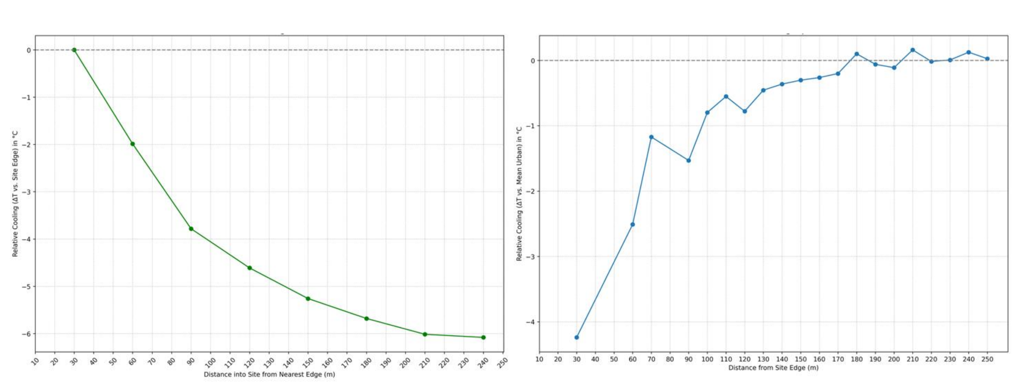

Fig 8: Cooling phenomena of the proposed intervention area.

Conclusion

Results

- **Cooling Analysis:** Benchmarked V1 and V2 performance in capturing park and spillover cooling. V2 outperformed V1, reducing MAE from 0.302 °C to 0.199 °C

	V1			V2		
Experiment	MAE	RMSE	MBE	MAE	RMSE	MBE
Internal Cooling	0.240	0.257	+0.240	0.231	0.249	+0.231
Spillover Cooling	0.302	0.339	+0.302	0.199	0.243	+0.199

Table 1: Performance comparison of model variants for the two key cooling experiments. The best value per metric between V1 and V2 is underlined.

- **Extrapolation Test:** Compared V1 and V2 across baseline, random, and high-heat setups. V2 performed best, accurately extrapolating 3.6 °C beyond training data

	V1			V2		
Model Variants	MAE	MSE	RMSE	MAE	MSE	RMSE
Baseline	1.95	7.25	2.69	2.81	12.94	3.60
Random Data Split	1.80	6.26	2.50	1.77	**5.80**	**2.41**
High-Heat Scenario (90th)	1.96	7.05	2.66	**1.74**	6.37	2.52

Table 2: Performance comparison of model variants using MAE, MSE, and RMSE. Bold indicatesthe best value and underline indicates the second-best.

Potential Methodological Improvements

- Evaluate the use of **T2M** instead of **LST** for improved **UHI** prediction and comparability with meteorological observations
- Align **ERA5** and **EURO-CORDEX** datasets to reduce uncertainty from temporal and spectral mismatches
- Integrate **additional geospatial variables** (albedo, soil moisture, elevation) to enhance predictive accuracy

Key Findings and Next Steps

- **Strong generalization** to unseen data with stable performance under extrapolation conditions
- **Plausible** responses to simulated land use changes, such as vegetation increase
- **Practical tool** for predicting and simulating urban heat island intensity across diverse urban settings
- Potential to support **urban heat mitigation strategies** (e.g., greening, cooling interventions)

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1. Powers et al. 2017, p. 2
2. Zhao, Q. et al. 2022, p. 2 et seqq.
3. Varentsov, Krinitskiy, Stepanenko 2023, p. 16
4. Farahani et al. 2020, p. 1 et seqq.