NEURAL INFORMATION PROCESSING SYSTEMS

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

Jannis Fleckenstein, David Kreismann, Tamara Rosemary Govindasamy, Thomas Brunschwiler, Etienne Vos, Mattia Rigotti

IBM Research

IBM

Motivation

- **Urbanization:** More than 70% of the world's population will live in cities by 2050[1]
- **Urban heat island (UHI) effect**: Cities are on average up to 5°C warmer than surrounding regions[2]
- **Consequences**: Increased energy consumption, health risks, and environmental pollution[3]

Problem Statement

- **Challenges**: Physics-based models require extensive input data, specialist knowledge, and high computing power, and are often designed for data-rich regions[5]
- Classic ML/DL methods limited by high demand for labeled data and low transferability[6]
- **Solution**: Geospatial Foundation Models (GFMs) offer improved generalizability and transferability due to training on large geospatial datasets[7]

1. Cf. Piracha, Chaudhary 2022, p. 1
2. Cf. Santamouri et al. 2013, p. 7 et seqq.
3. Cf. Tan, Jianguo et al. 2010, S. 80; Santamouris et al. 2015, p. 1 et seqq.
4. Cf. Varentsov, Krinitskiy, Stepanenko 2023, p. 16
5. Cf. Ghorbany et al. 2024, p. 18
6. Cf. Farahani et al. 2020, p. 1 et seqq.
7. Cf. Mai, Huang, et al. 2023, p. 2 et seqq.

Methodology

- During **fine-tuning**, the pre-trained encoder is adapted using small amounts of annotated data (e.g., LST labels)
- Through **task-specific decoder heads** (in this case, a regression head), the model generates **high-resolution temperature maps**[8]
- These maps are used for **Urban Heat Island (UHI) analysis**

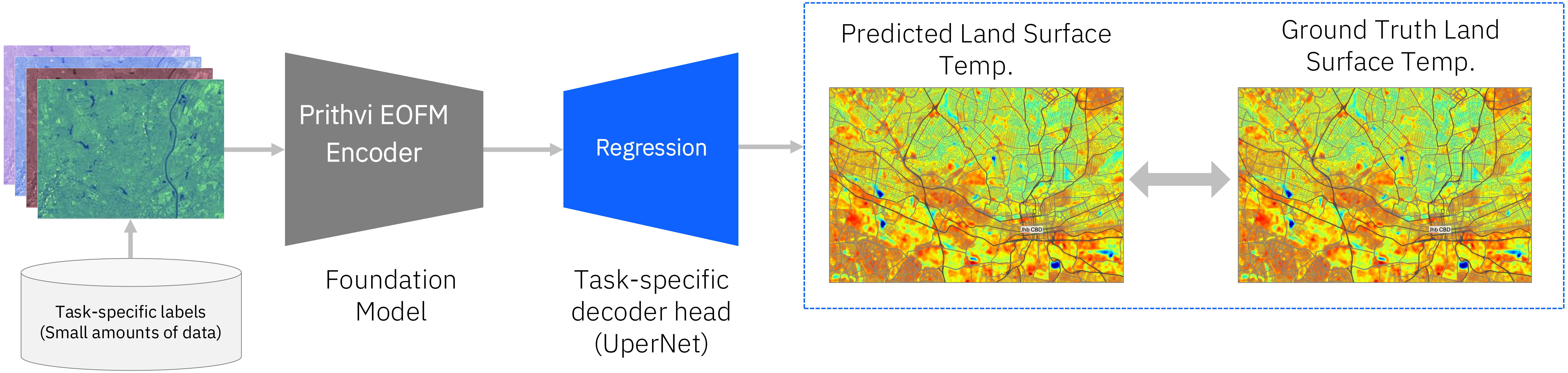

Fig. 2: Overview of the Prithvi foundation model architecture and its fine-tuning pipeline.

8. Cf. Bhamjee, Debary, et al. 2024, p. 1694 et seqq.

Study Regions

- **Thirteen European cities** used to test **model generalization** beyond training data

- **Twelve cities (red dots)** analyzed for **internal** and **spillover cooling** across diverse **hydro-climatic settings**

- **Brașov (blue)** used as an **unseen evaluation city**

- Prague selected for the **in-painting intervention** step

- **Workflow** adaptable to **any urban area**, showing the flexibility of **geospatial foundation models**

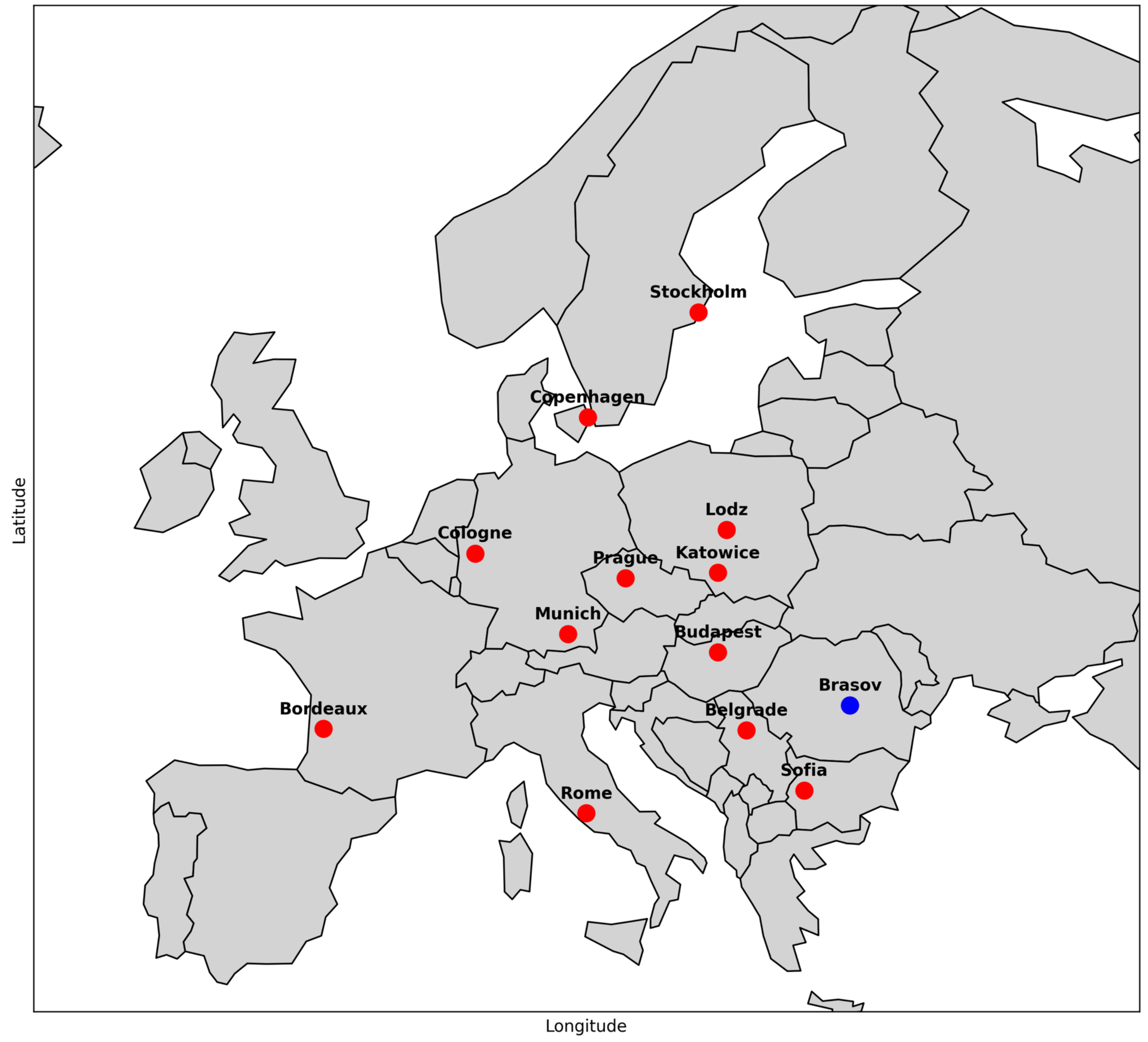

Fig 1: Study regions across twelve European cities (red dots) representing varied urban and climatic conditions. Brașov (blue dot) served as the extrapolation site for model testing.

Experiments

- Tree-covered areas act as natural heat sinks, while heat sources almost only consist out of built area.

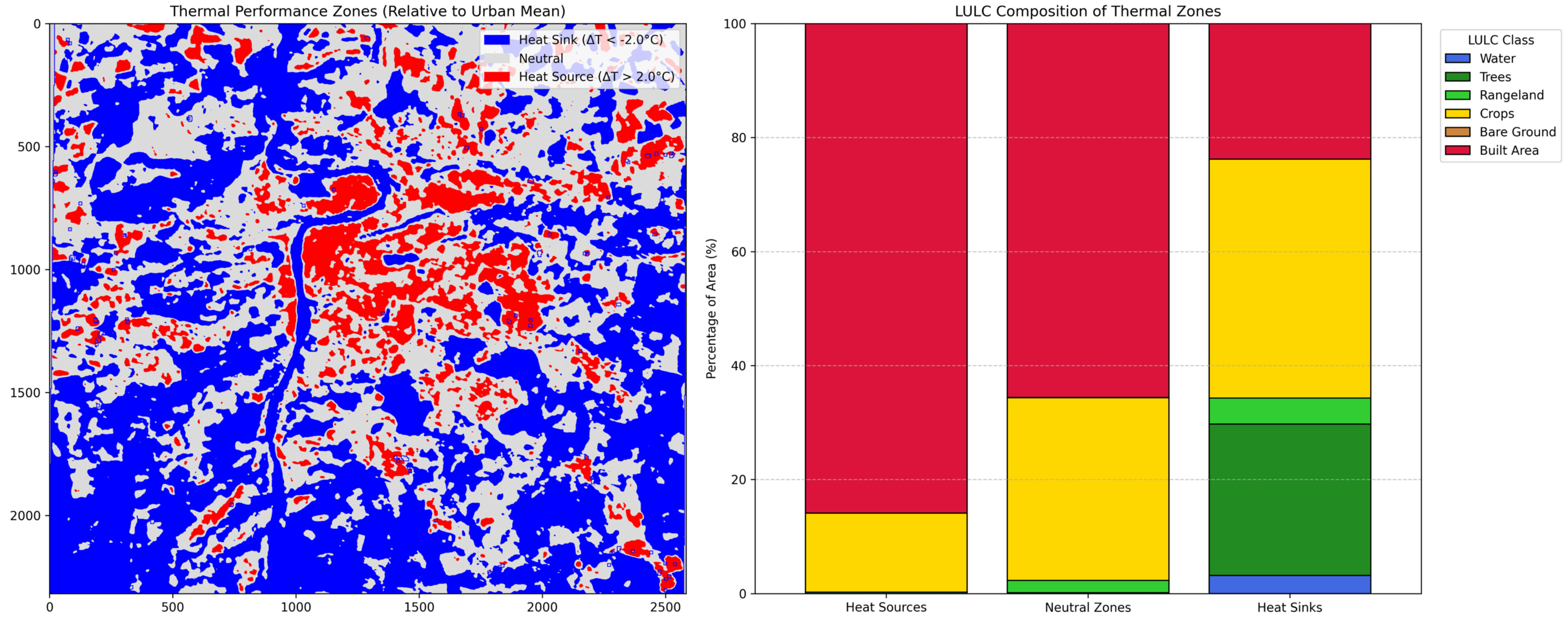

Fig 3: Heat source-sink experiment

- Dense city cores exhibit an average UHI intensity of +3.3 ℃, reflecting clear thermal contrasts shaped by vegetation distribution

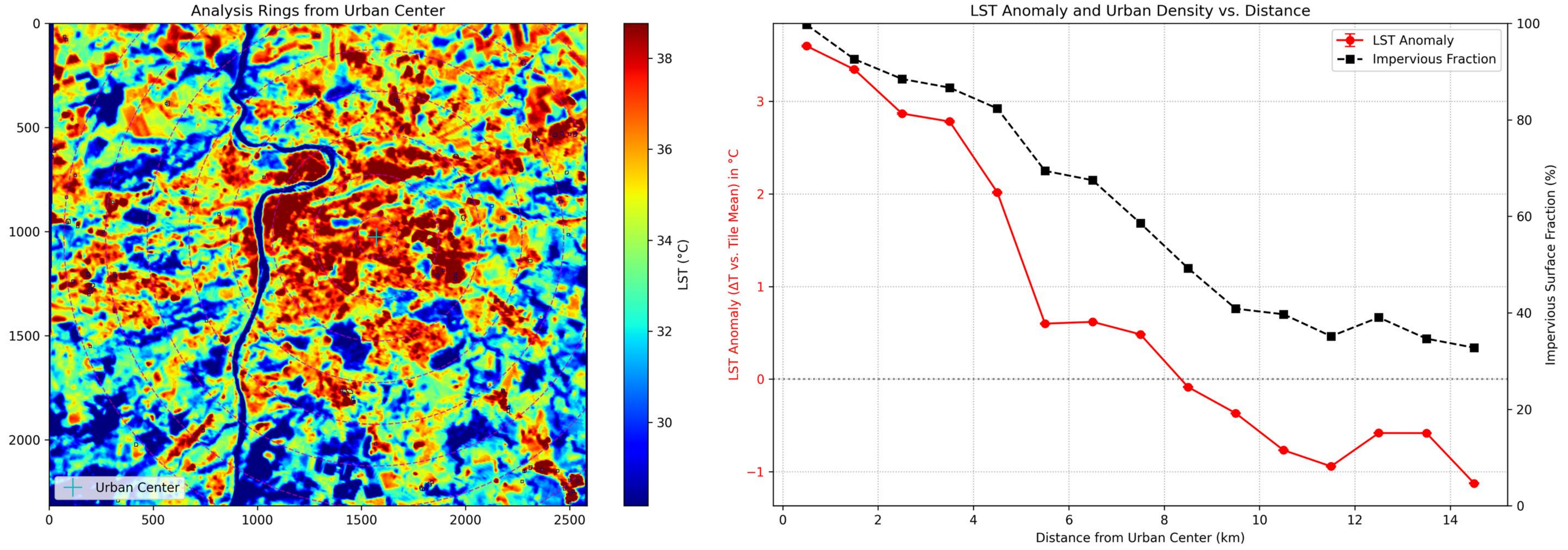

Fig 4: Urban gradient experiment

Experiments

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

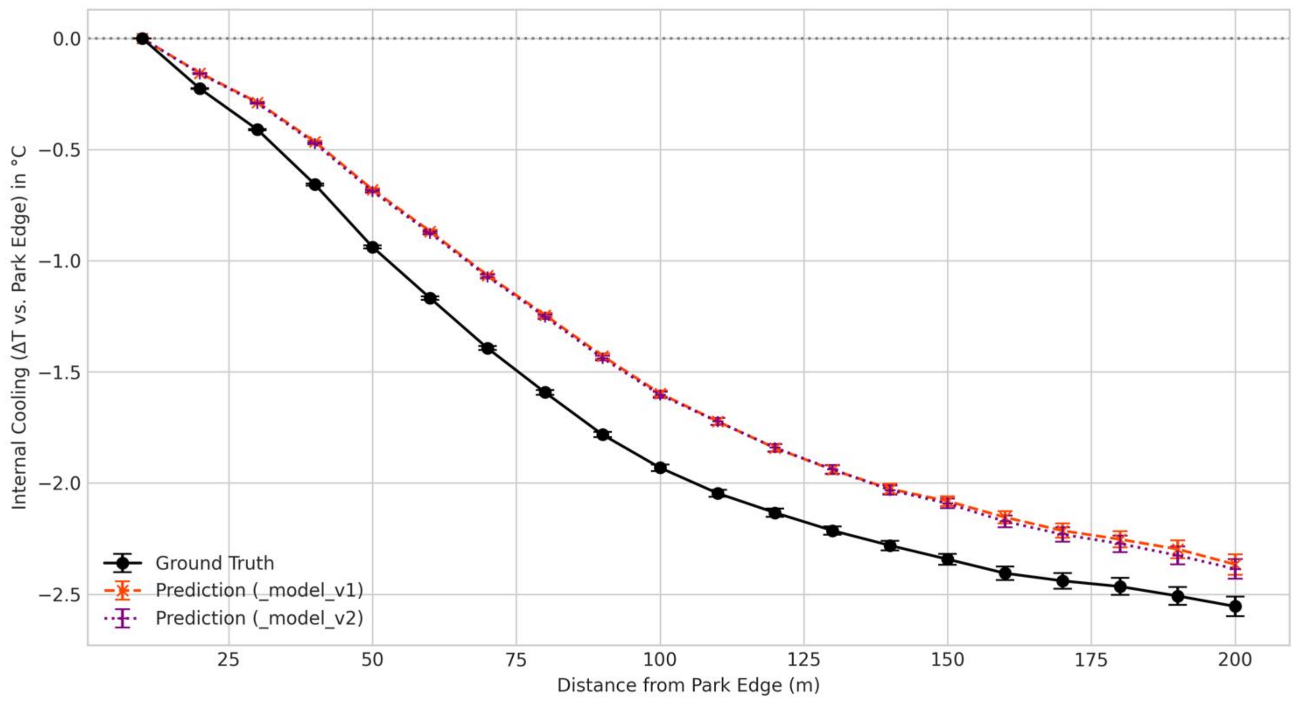

Fig 5: Internal cooling gradient

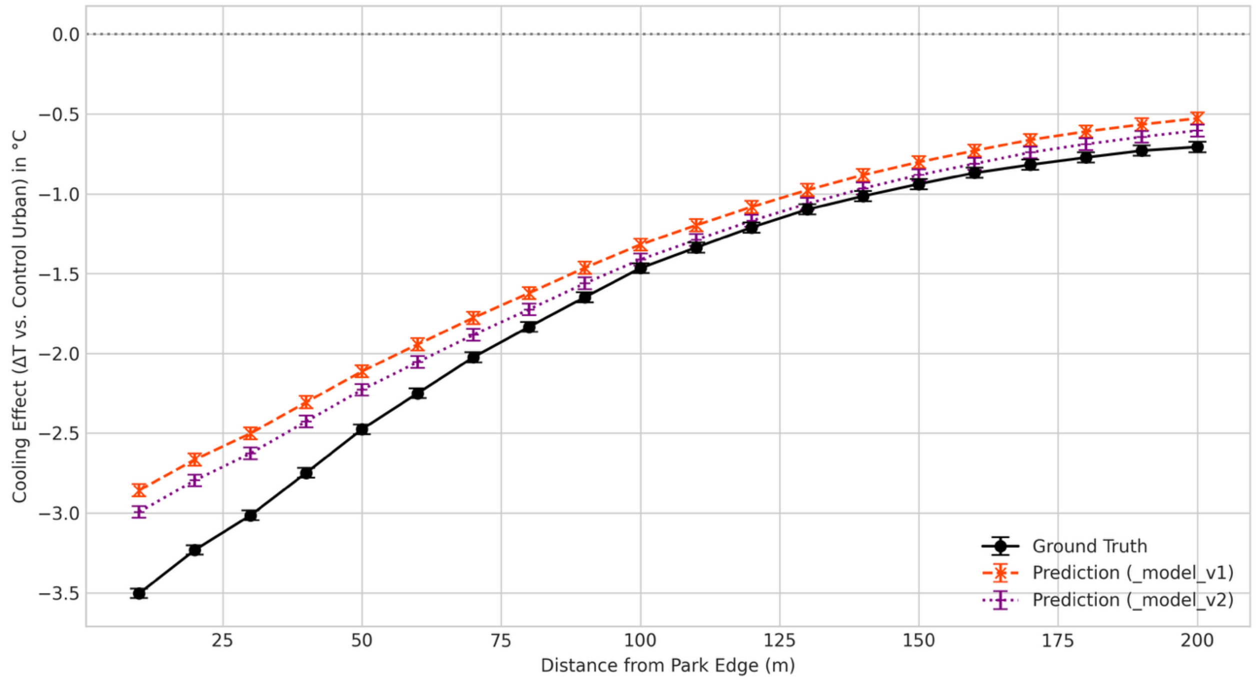

Fig 6: Spillover cooling gradient

- 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 ℃ on the upper 10% of temperatures, reinforcing reliability for future simulations

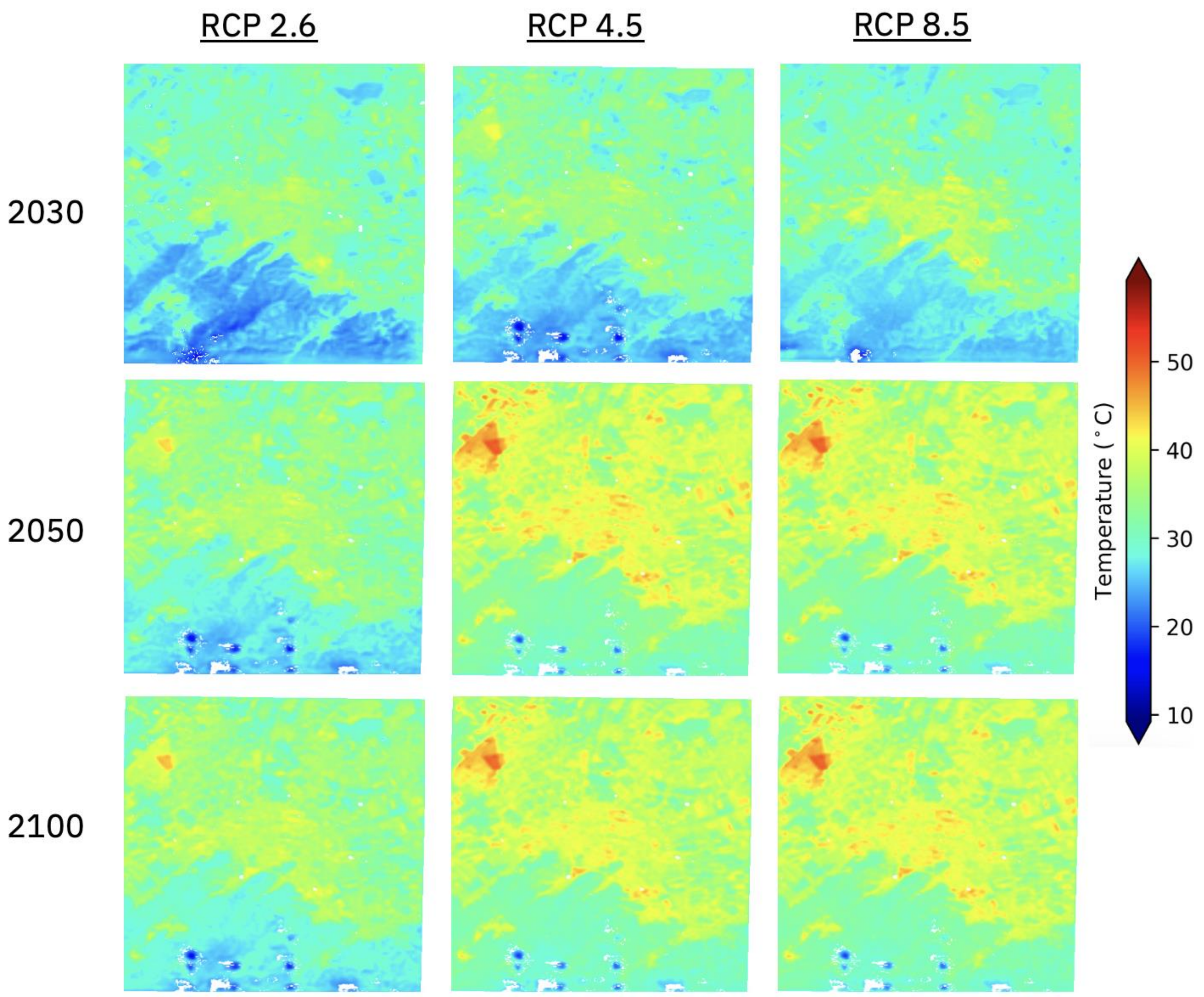

Fig 7: Projected UHI extent under RCP 2.6, 4.5, and 8.5 for 2030, 2050, and 2100 in Brasov.

Experiments

- The greening intervention increases NDVI and lowers local LST by several degrees, confirming vegetation-driven cooling

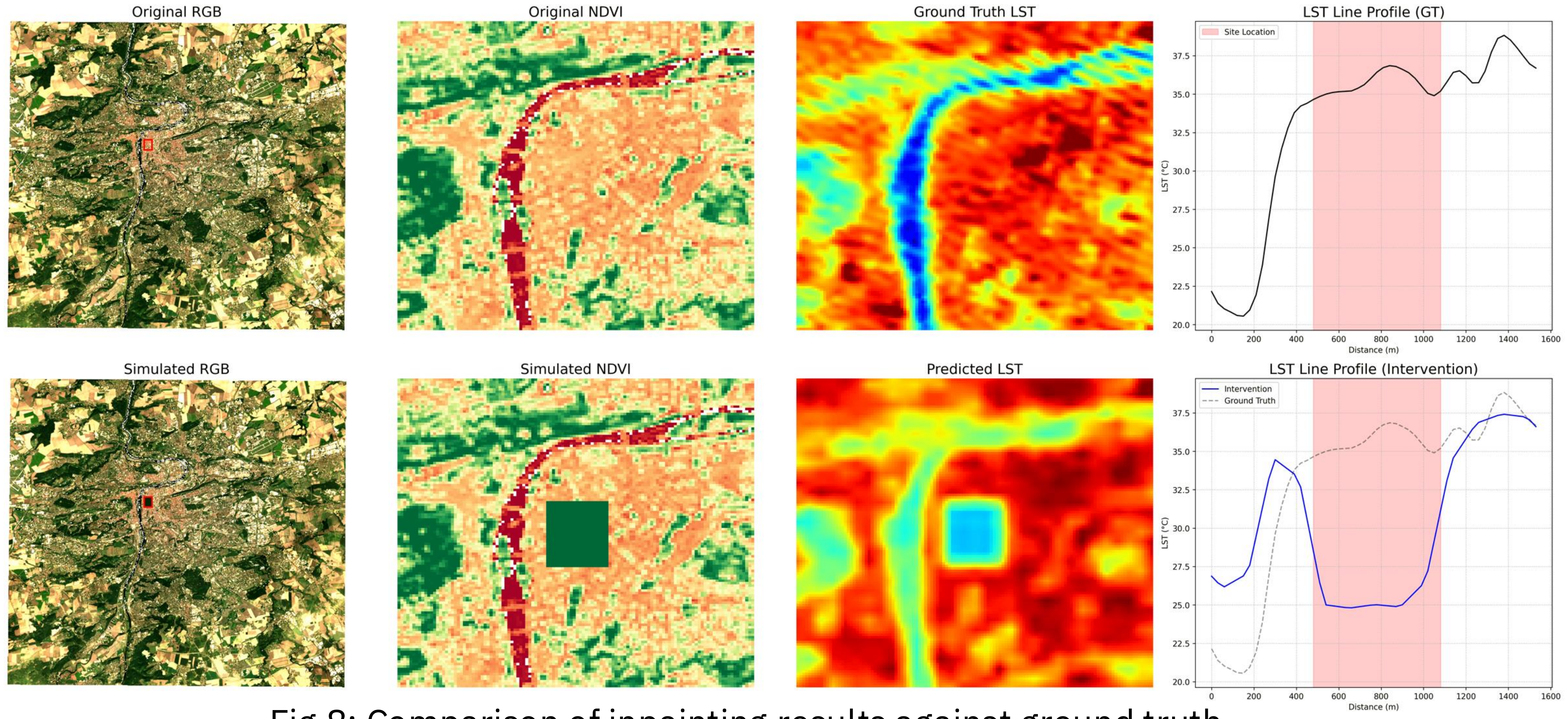

Fig 8: Comparison of inpainting results against ground truth data in Prague.

- Cooling reaches –6 ℃ inside the park and extends up to –3℃ within the first 50 meters

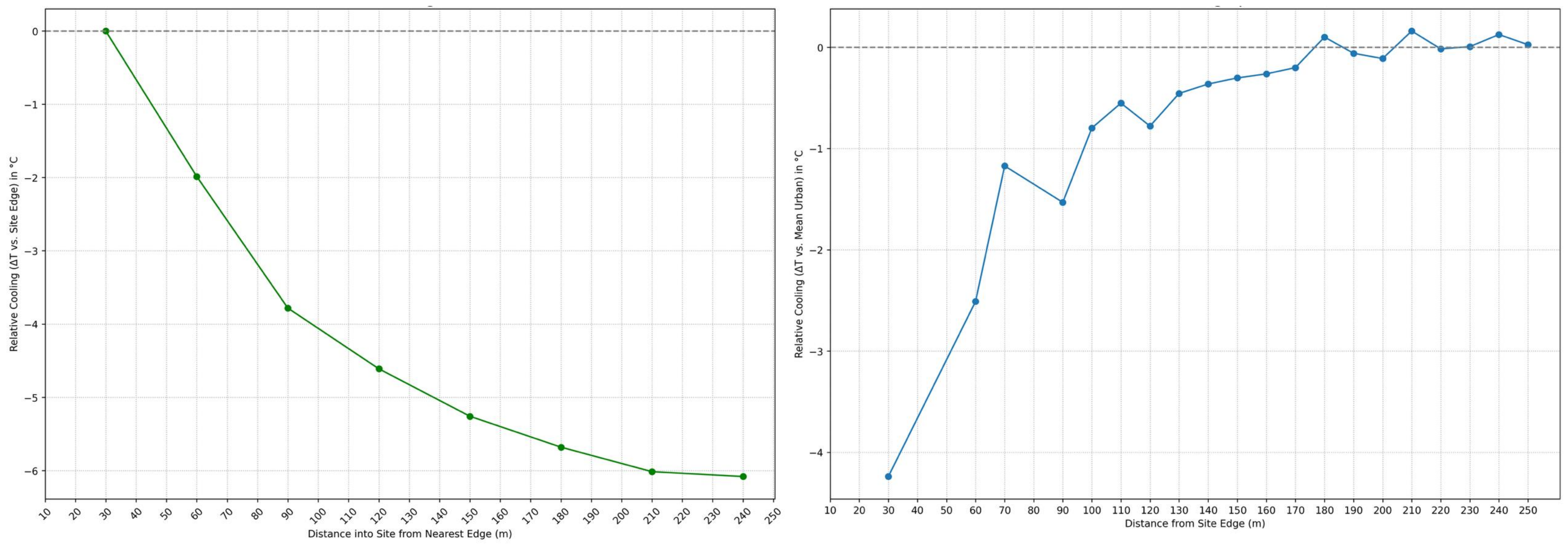

Fig 9: Cooling phenomena of the proposed intervention area.

Results

- **Cooling Analysis:** Benchmarked V1 and V2 performance in capturing park and spillover cooling. V2 outperformed V1 in every metric

	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 during all metrics

	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 indicates the best value and underline indicates the second-best.

Literature

Bhamjee, Muaaz; Debary, Hiyam; Gaffoor, Zaheed; Govindasamy, Tamara; Mahlasi, Craig; Fiaz, Mustansar; Vos, Etienne; Klein, Levente; Makhanya, Sibusisiwe; Watson, Campbell; Kuehnert, Julian (2024): Detection and Characterization of Urban Heat Islands with Machine Learning. In: IGARSS 2024 - 2024 IEEE International Geoscience and Remote Sensing Symposium, pS. 1693–1699. doi: 10.1109/IGARSS53475.2024.10641750.

Farahani, Abolfazl; Voghoei, Sahar; Rasheed, Khaled; Arabnia, Hamid R. (2020): A Brief Review of Domain Adaptation. arXiv: 2010.03978 [cs.LG].

Ghorbany, Siavash; Hu, Ming; Yao, Siyuan; Wang, Chaoli (2024): Towards a Sustainable Urban Future: A Comprehensive Review of Urban Heat Island Research Technologies and Machine Learning Approaches. In: Sustainability 16.11. issn: 2071-1050. doi: 10.3390/su16114609.

Mai, Gengchen; Huang, Weiming; Sun, Jin; Song, Suhang; Mishra, Deepak; Liu, Ninghao; Gao, Song; Liu, Tianming; Cong, Gao; Hu, Yingjie; Cundy, Chris; Li, Ziyuan; Zhu, Rui; Lao, Ni (2023): On the Opportunities and Challenges of Foundation Models for Geospatial Artificial Intelligence. arXiv: 2304.06798 [cs.AI].

Piracha, Awais; Chaudhary, Muhammad Tariq (2022): Urban Air Pollution, Urban Heat Island and Human Health: A Review of the Literature. In: Sustainability 14.9234. issn: 2071-1050. doi: 10.3390/su14159234.

Santamouri, M.; Asimakopoulos, D.; Assimakopoulos, V.D.; Chrisomallidou, N.; Klitsikas, N.; Mangold, D.; Michel, S.; Santamouris, Mat; Tsangrassoulis, Aris (2013): Energy and Climate in the Urban Built Environment, pS. 1–402. isbn: 978-1-134-25790-4. doi: 10.4324/9781315073774.

Varentsov, Mikhail; Krinitskiy, Mikhail; Stepanenko, Victor (2023): Machine Learning for Simulation of Urban Heat Island Dynamics Based on Large-Scale Meteorological Conditions. In: Climate 11.10. issn: 2225-1154. doi: 10.3390/cli11100200.