A Machine Learning Approach to predict Urban Temperatures with Downscaled Climate Data and City Measurement Networks

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1. Introduction

Climate change intensifies heatwaves – now among the deadliest climate hazards. Cities face heightened risks from the **urban heat island (UHI)** effect, where city morphology amplifies extreme heat. While global and regional climate models are increasingly incorporating urban parameterizations, urban-scale downscaling remains **computationally prohibitive**.

We present a **machine learning** approach to downscale 2m air temperature to 100m resolution, integrating:

- Urban morphology (building height, tree cover, elevation)
- Local Climate Zones (LCZs) [1]
- Data from dense urban temperature sensor networks [2]

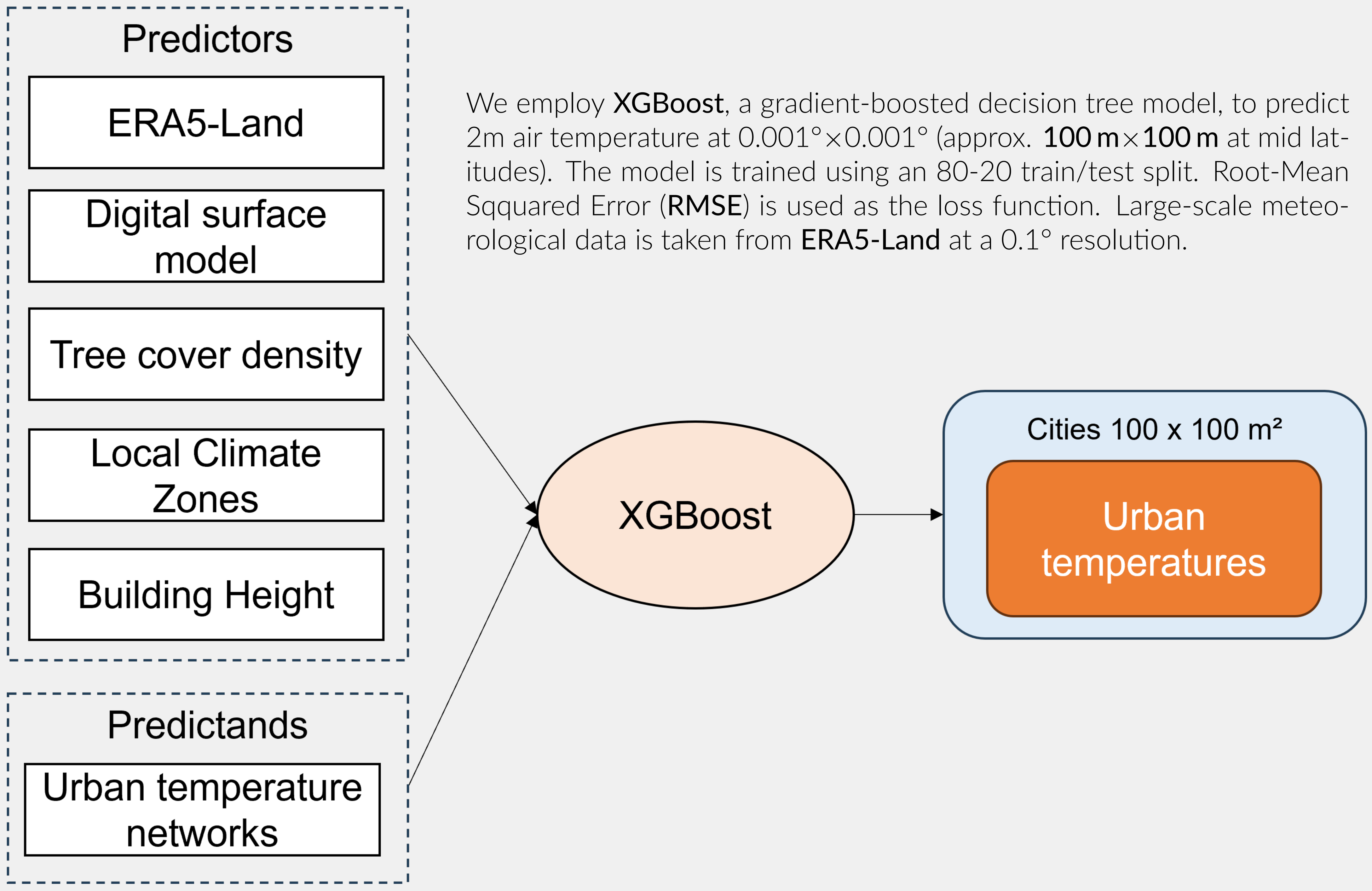
Developed for the EU healthRiskADAPT project, this study enables hyper-local heat risk assessment for the pilot cities of Oslo, Bern, Lyon, and Naples, supporting targeted adaptation strategies.

2. Objectives

The present study has the following aims:

- **Downscale** temperature to the urban scale
- Compute **health relevant heat indices** at the urban scale
- Develop an efficent, accurate, and **generalizable** downscaling model

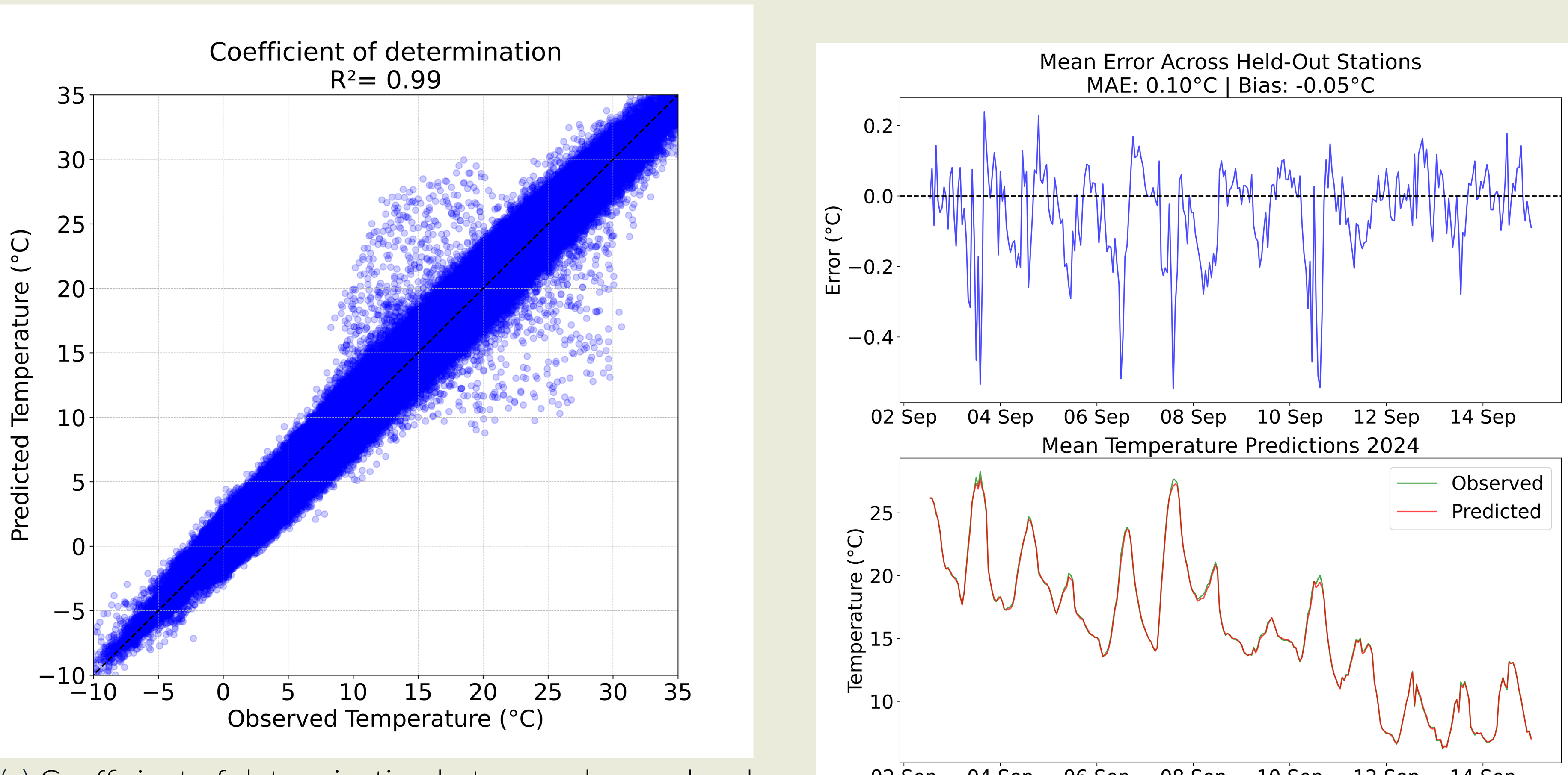
3. Data and Methods



We employ **XGBoost**, a gradient-boosted decision tree model, to predict 2m air temperature at 0.001°×0.001° (approx. **100 m×100 m** at mid latitudes). The model is trained using an 80-20 train/test split. Root-Mean Sqquared Error (**RMSE**) is used as the loss function. Large-scale meteorological data is taken from **ERA5-Land** at a 0.1° resolution.

Figure 1. XGBoost flowchart with main variables

4. Results and Discussion



(a) Coefficient of determination between observed and predicted temperatures

(b) Mean error in early September 2024

Figure 2. XGBoost fit metrics

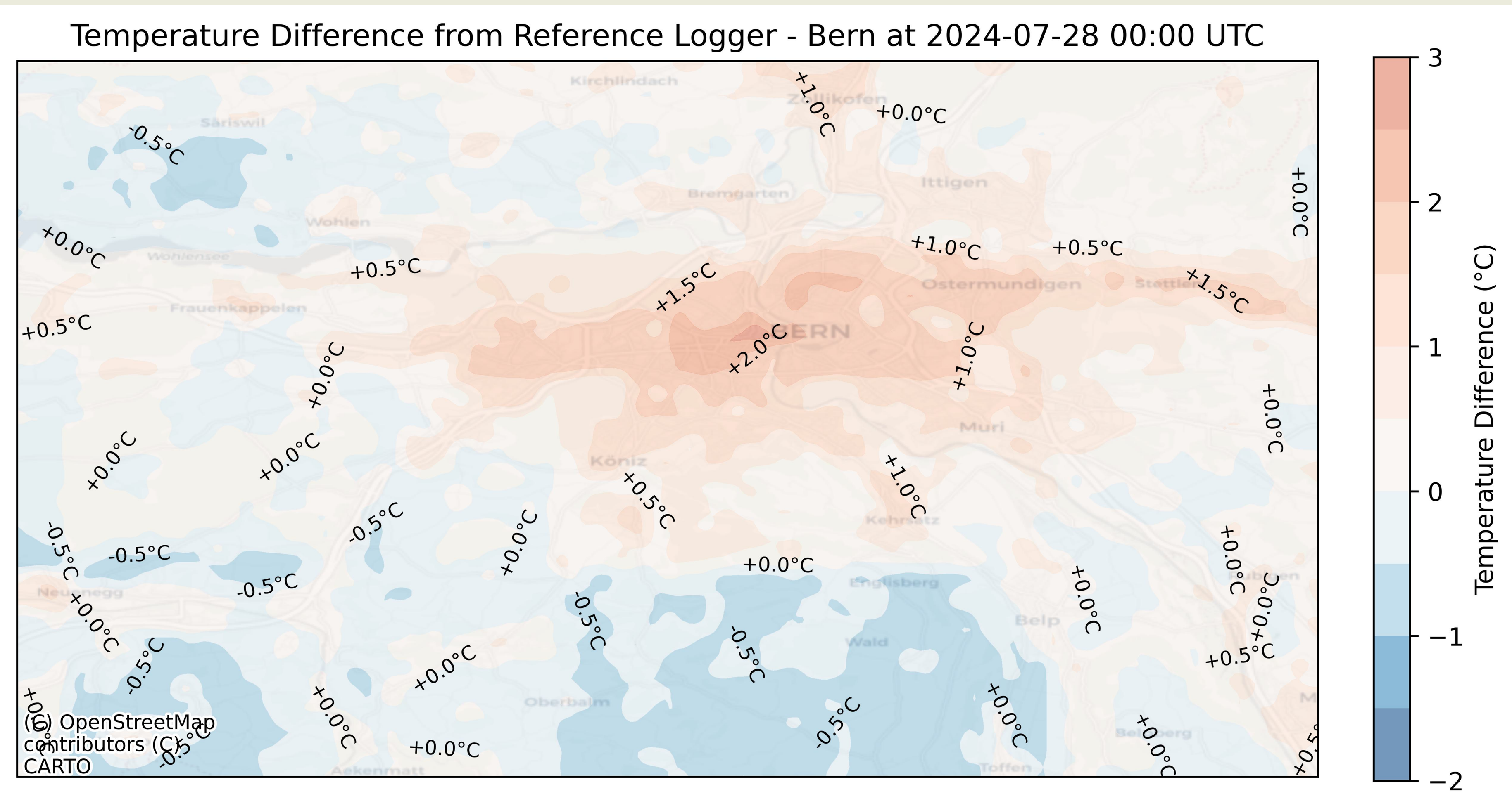


Figure 3. Local temperature minus reference temperature (meteorological station at Zollikofen)

Limitations:

- Discontinuities in the computed temperature field arise (Fig. 3)
- The model's ability to extrapolate accurately to different temporal/spatial ranges is yet to be tested

A proof-of-concept model was trained on **Bern** and **Zürich** urban sensor data from **2018 to 2024**.

- The model is able to capture **intra-daily temperature fluctuations** accurately
- The **UHI** can be observed clearly on Figure 3, reaching a maximum of **2.5°C** in the old town of Bern
- **Tropical nights** (min. night-time temperature > 20°C) would not be captured in the example of Figure 4 without a hyper local urban temperature field

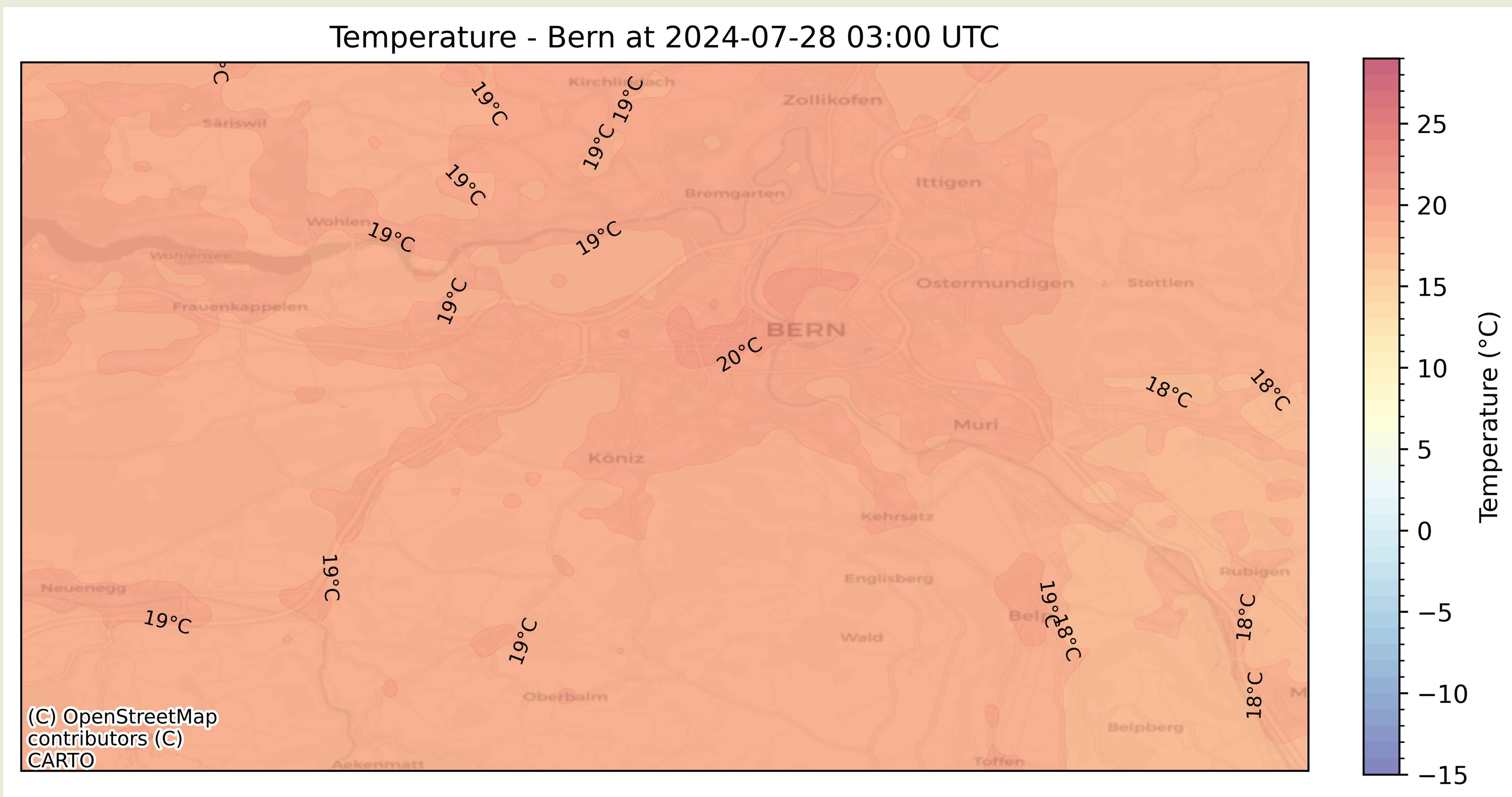


Figure 4. Bern temperature field on a "non" tropical night

5. Conclusion

This machine learning approach successfully leverages ERA5-Land predictors in order to downscale climate data to 100m resolution and capturing the UHI effect. While the model shows promise, computational artifacts remain and improvements are necessary.

Next steps:

- Expand training to 12 European cities and multiple years and seasons
- Compute health relevant heat indices

References

[1] Matthias Demuzere, Jonas Kittner, Alberto Martilli, Gerald Mills, Christian Moede, Iain D. Stewart, Jasper van Vliet, and Benjamin Bechtel. A global map of local climate zones to support earth system modelling and urban-scale environmental science. *Earth System Science Data*, 14(8):3835–3873, 8 2022.

[2] Moritz Gubler, Andreas Christen, Jan Remund, and Stefan Brönnimann. Evaluation and application of a low-cost measurement network to study intra-urban temperature differences during summer 2018 in Bern, Switzerland. *Urban Climate*, 37:100817, 5 2021.

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