HeatAdapt: Monitoring and mitigating heat hotspot areas

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Introduction

Responding to global warming and adapting to climate change effects such as heat waves and drought is a key priority of European and national-level Climate Change Adaptation strategies. Regional and city administrations aim to reduce climate change-related health risks and increase human well-being through adequate planning measures such as establishing green and blue infrastructure. Changes in land use (LU) and land cover (LC) play an important role in determining local climate characteristics. Urban Climate, for instance, differs from the surrounding natural areas, showing higher air and surface temperatures, known as the Urban Heat Island Effect, mainly related to changes in the surface radiative properties. By leveraging LULC data (Copernicus Land Monitoring Service), Sentinel 2 data, meteorological INCA data (meteorological analysis- and nowcasting system for Austria), climate models and other auxiliary datasets and integrating Land surface temperature (LST) stemming from ECOSTRESS, we develop a multi-sensor/data multi-resolution downscaling algorithm grounded in the physical representation of LST [1, 2].

Data and Method

In our study, we focus on the development and refinement of an LST downscaling methodology, merging multiple datasets of spatially-explicit LST observations at high temporal and spatial (10 m) resolution. We combine EO-based LST observations captured by ECOSTRESS with higher solution optical imagery (Sentinel-2), LULC information, INCA meteorological data, and other auxiliary datasets to generate temporally and spatially high resolution LST products.

ECOSTRESS:	land surface temperature
INCA:	air temperature, global radiation, wind speed, relative humidity
Land cover:	tree cover density, imperviousness, digital elevation model, water and wetness index
Sentinel 2:	bands B02, B03, B04, B08

Our methodology leverages a super-pixel Convolutional Neural Network (CNN) architecture, adapted from the GHSS2Net-derived model [3]. Our approach consist of two pivotal steps: first, modelling LST at its sensor-specific resolution, based on the physical models [1, 2], to create a dense time series (e.g., 70m in the case of ECOSTRESS). Second, the further refinement and downscaling to 10m resolution. Employing the GHSS2Net-adapted model, optimized for a 5x5 super-pixel input, using 2x2 convolutional kernels without pooling layers to preserve contextual information, our approach achieves significant advancements in spatial prediction accuracy ($R^2 \gtrsim 0.7$) without sacrificing temporal consistency. This efficiency is attributed to the model's design, which prioritizes contextual information retention through its unique convolutional structure and employs dropout regularization and batch normalization to enhance performance.

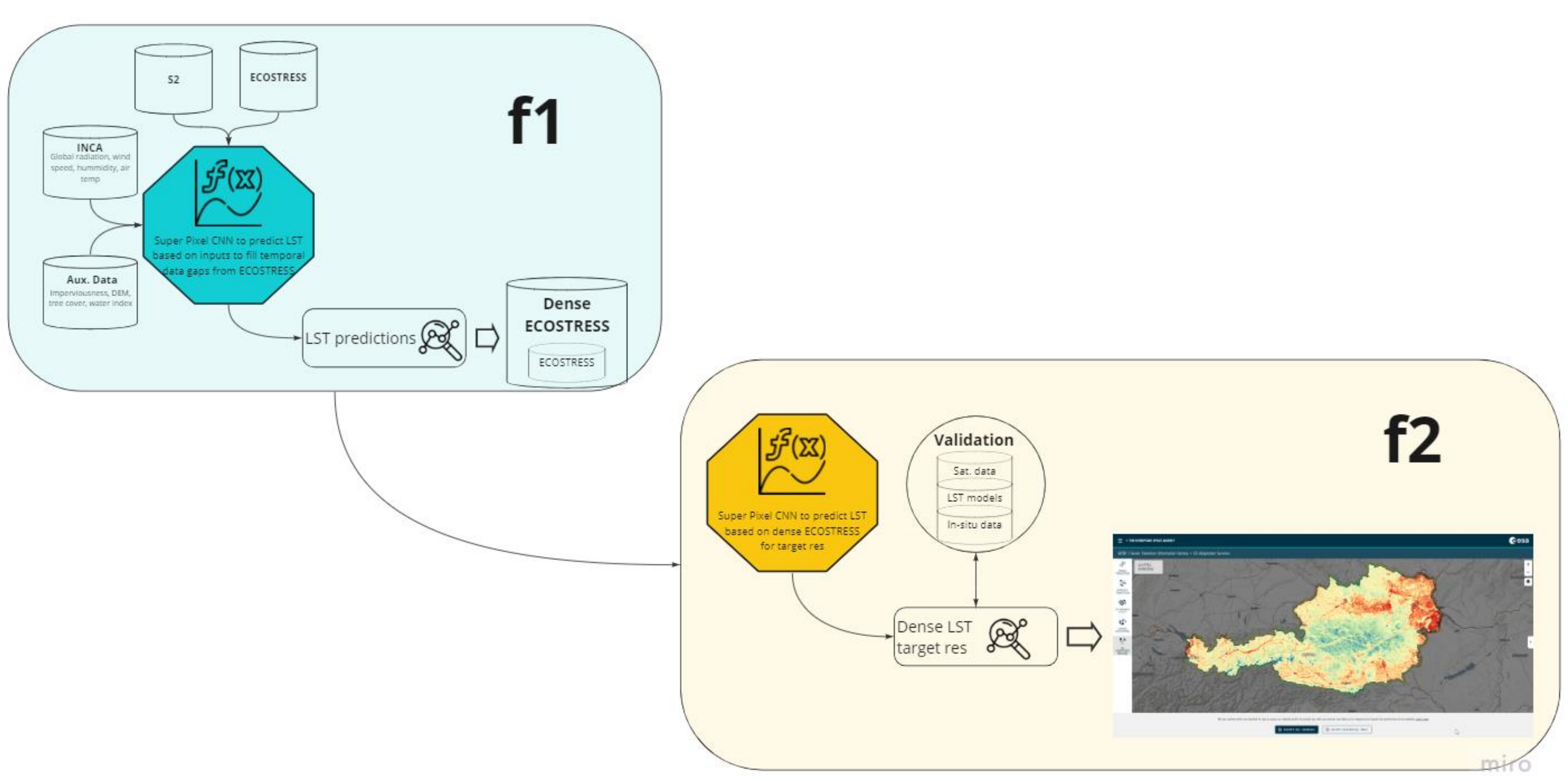

Figure 1: Overview of the technical goas. (f1) Creating dense land surface temperature time-series data based on ECOSTESS, INCA and Sentinel 2 products, and respective derivatives and various land cover products using super-pixel CNN. (f2) Applying super-pixel CNN in the process of downscaling land surface temperature data to 10m resolution.

References:

[1] Matzarakis, A., Rutz, F. & Mayer, H. Modelling radiation fluxes in simple and complex environments: basics of the RayMan model. Int. J. Biometeorol. 54, 131–139 (2010).

[2] Rigo, G., Parlow, E. Modelling the ground heat flux of an urban area using remote sensing data. Theor. Appl. Climatol. 90, 185–199 (2007).

[3] Corbane, C., Syrris, V., Sabo, F. et al., Convolutional neural networks for global human settlements mapping from Sentinel-2 satellite imagery. Neural Comput & Applic (2020).

Results

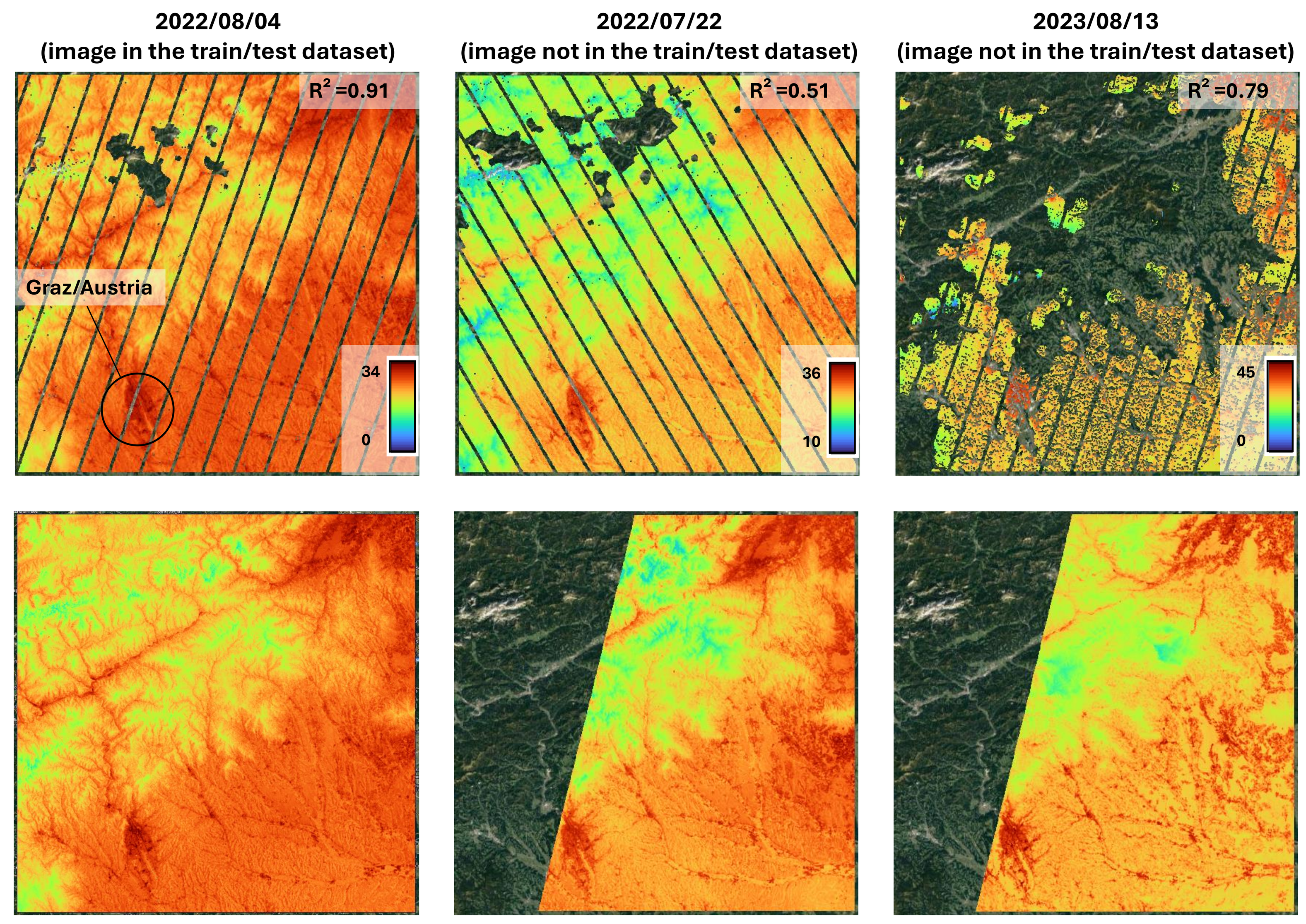

Figure 2: Top row shows ECOSTRESS data used for the training. The quality mask is applied, leaving only non-cloudy and best quality pixels. Bottom row shows f1 results (land surface temperature predictions at 70m resolution). Train/test is done on all available summer afternoon observations (June-Aug in both 2022 and 2023). Training and prediction is done on a single Sentinel 2 tile (33TWN).

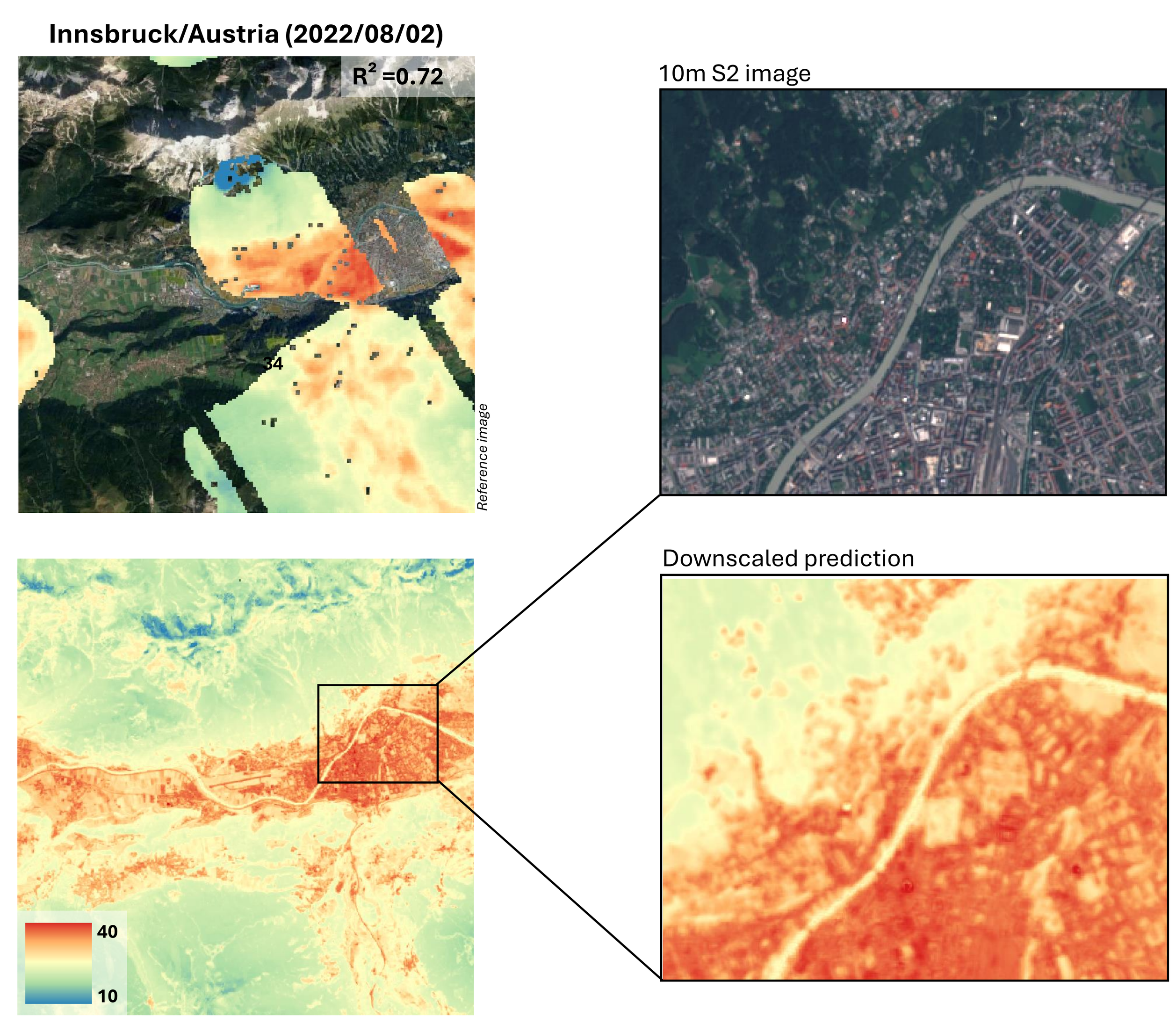

Figure 3: Top left shows ECOSTRESS data over Innsbruck, Austria with the quality mask applied. Bottom left shows f1 results (LST predictions at 70 resolution). Bottom right shows f2 results (LST downscaled to 10m resolution). Top right shows the Sentinel 2 10m image covering the same area, for reference.

Summary and Outlook

This study is a part of the Green Transition Information Factory and aims at demonstrating the combined use of Earth Observation and Climate Modelling data to generate and provide actionable knowledge and decision support focusing on heat hotspots and heat stress i.e., the effect of excess heat within built-up environments from small settlements to large cities, as well as rural or mountainous areas.

Employing a super-pixel CNN yields promising results with spatio-temporal predictions between > 0.5 and < 0.9 R^2. However, further R&D activities are needed to generate more robust time-series and downscaling predications (e.g. hyper-parameter tuning, adapting model architecture, validation with in-situ data etc.). Major obstacles in scaling the proposed approach, however, stem from severe data quality issues related to ECOSTRESS (e.g. insufficient could-masking, offsets in geo-referencing, artefacts). These issues are non-systematic and thus are difficult to address in an automated way. Further research in this direction is needed. Lastly, the lack of comprehensive ground-truth data limits validation efforts. It would be desirable if there were a greater willingness at institutional level to make such data available for scientific purposes.

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