HeatAdapt: Land surface temperature for monitoring and mitigating heat hotspot areas

Katja Kustura, Matthias Sammer, David Conti, Michael Riffler

GeoVille Information Services and Data Processing GmbH, Sparkassenplatz 2, A-6020 Innsbruck, Austria

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. Changes in land use and land cover play an important role in determining local climate characteristics, primarily by affecting surface radiative properties. In urban areas, this can lead to higher air and surface temperatures, known as the Urban Heat Island effect. By leveraging land use and land cover, Sentinel-2, and meteorological data, as well as the land surface temperature (LST) datasets available from ECOSTRESS, we develop a multi-sensor Convolutional Neural Network framework for LST estimation. The presented methodology provides high-quality LST datasets at a high temporal resolution. This establishes LST as an important parameter for regional and city planning measures – including the development of green and blue infrastructure – aimed at reducing climate change-related health risks and increasing overall well-being within urban areas.

Introduction

Changes in land use (LU) and land cover (LC) are known to influence the local climate characteristics. In particular, the increase in the built-up (sealed) surfaces affects surface radiative properties, making urban areas increasingly warmer than their surroundings and more prone to excess heat, and leading to an urban heat island (UHI) effect. Understanding and managing UHI hotspots is essential for effectively implementing mitigation measures (such as green and blue infrastructure), reducing climate-change related health risks, and developing more sustainable cities.

Land Surface Temperature (LST) is a widely used proxy to investigate the effects of the LULC changes on the surface UHI effect, contributing to an overall understanding of Earth's surface dynamics and the impact of climate trends. Satellite-based LST datasets have been extensively used, for advanced assessments of UHI effects, overcoming the challenges of conducting high-resolution air temperature measurements at a similar scale.

Here, we present a deep-learning-based methodology for LST estimation from LULC, Sentinel-2, and meteorological datasets. The model is effective in generating spatiotemporally dense high quality LST datasets. This paves the way towards the integration of LST in regional and city planning measures and offers a new approach to assess the impact of urban development and land use and land cover changes.

Datasets and methodology

The modelling workflow makes use of the following datasets (Fig. 1), a choice grounded in the physical models for the LST [1,2]:

ECOSTRESS: • 70-m resolution land surface temperature (NASA) – label dataset

INCA: • 1-km resolution meteorological data (ZAMG, Austria)
• air temperature, global radiation, wind speed, relative humidity

Sentinel-2: • 10-m resolution multispectral imagery (Sentinel mission)
• bands B02, B03, B04, B08

Land cover: • tree cover density, imperviousness, water and wetness index (Copernicus Land Monitoring Service)

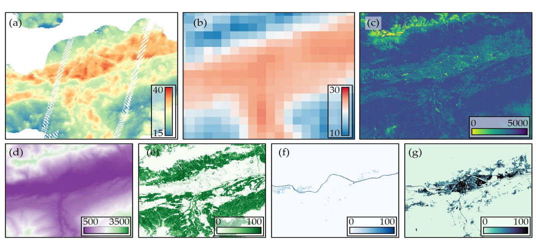

Figure 1: Datasets used in the CNN training. (a) ECOSTRESS land surface temperature in C°, (b) INCA air temperature in C°, (c) Sentinel-2 band B04 reflectance, (d) digital elevation model, (e) tree cover density, (f) water and wetness index, (g) imperviousness.

We utilize a standard Convolution Neural Network (CNN) model to perform LST predictions (Fig. 2, Table 1). Our model is adapted from the Sentinel-2 segmentation and classification CNN configuration [3,4] and modified to address a continuous regression problem of LST estimation. The training is done on the 70 m-resolution ECOSTRESS dataset. The predictions are done in two steps: (i) 70 m resolution (gap filling), and (ii) 10 m resolution (downscaling)

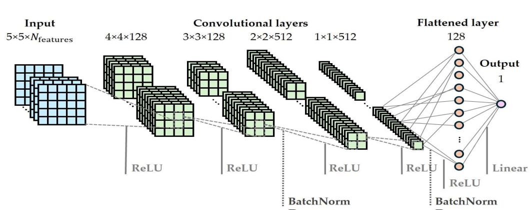

Figure 2: Scheme of the CNN architecture used for the land surface temperature predictions.

input layer	size: 5×5×15		
convolutional layers	kernel size: 2×2; stride: 1×1; filters: 128 (layers 1 and 2), 512 (layers 3 and 4)		
dense layer	size: 128		
activation functions	rectified linear unit ('relu'), for the final layer 'linear'		
optimizer	adam (with inverse time decay); learning rate schedule: initial_lr=0.001, decay_rate=1, steps=1000×number_samples/batch_size		
loss function	mean absolute error		
number of epochs	50	**batch size**	512
train/validation split	80:20	**dropout rate**	0.1

Table 1: Summary of the CNN architecture and hyperparameters.

Results

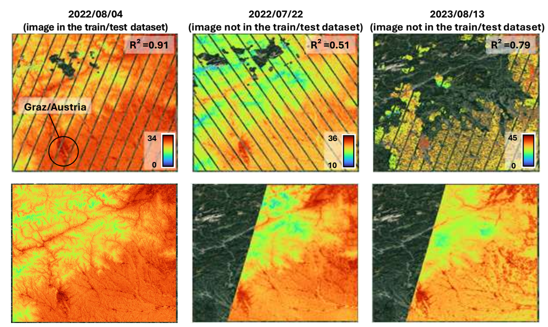

Figure 3: Top row: ECOSTRESS observations. The quality mask is applied, leaving only non-cloudy and best quality pixels. Bottom row: land surface temperature predictions at 70m resolution. Train/test is done on all available summer afternoon observations (June-Aug in both 2022 and 2023). Training and prediction is done on a single Sentinel-2 tile (33TWN).

Visual analysis: The results are generally satisfying since the model predictions and the ECOSTRESS measurements are visually close (Fig. 3).

- The model can fill various gaps in the ECOSTRESS observations.
- The model can correct "grid" artifacts in the ECOSTRESS data.
- The predictions capture the spatial features present in the ECOSTRESS observations, even increasing spatial detail (i.e., enhancing the contrast).
- Visual divergences can occur, but mainly as a few isolated patches (a fraction of the overall image) and outside of urban areas. These artifacts could be due to some spurious model error or problems with the input data (e.g., clouds).

Statistical analysis: We consider the pixel-pairwise temperatures of our predictions and the matching ECOSTRESS measurements. We obtain the prediction error $LST_{\mathrm{prediction}} - LST_{\mathrm{ECOSTRESS}}$ and derive the following statistics for its distribution:

1. Mean absolute error (MAE): loss function for the model training. Our analysis shows that overall, at least 80% of the pixel errors lie in the acceptable ±3°C interval [5].
2. Coefficient of determination (r^2): an absolute and scale-independent measure of how well a model fits data. Most predictions achieve good or acceptable r^2 values (range $r^2 \sim 0.5 - 0.7$), indicating a robust overall fit without the risk of overfitting ($r^2 > 0.95$).

Downscaling: The application of the model is extended to 10 m resolution images to obtain downscaled LST predictions. The trained CNN model operates on a pixelwise basis and can be directly apply it to 10 m resolution input images (Fig. 4).

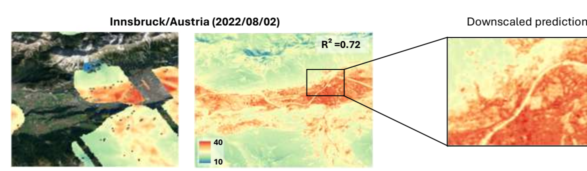

Figure 4: 10 m resolution downscaling of ECOSTRESS observations (Innsbruck, Austria). Left: ECOSTRESS observation with the quality mask applied. CNN model land surface temperature predictions at 70 m resolution (middle) and at 10 m resolution (right).

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. CNN framework for estimating LST from LULC, Sentinel-2 and meteorological data is developed, showing promise in filling the spatial and temporal gaps, thereby providing a heat-monitoring variable which can be used to assess the effect of excess heat within built-up environments, from urban and rural to alpine areas.

Further research activities are needed to generate more robust time-series and downscaling predictions (hyper-parameter tuning, adapting model architecture, validation with in-situ data etc.). Obstacles in scaling the proposed approach stem from non-systematic data quality issues related to ECOSTRESS (insufficient could-masking, offsets in geo-referencing, artefacts), and further development in this direction is needed. Lastly, a comprehensive ground-truth dataset is essential for improving model validation. Greater institutional willingness to make such data available for scientific purposes would significantly enhance these efforts.

References:
[1] Matzarakis A. et al. *Int. J. Biometeorol.* **54**, 131–139 (2010).
[2] Rigo G. et al. *Theor. Appl. Climatol.* **90**, 185–199 (2007).
[3] Corbane C. et al. *Neural Comput. Appl.* **33**, 6697–6720 (2021).
[4] Syrris V. et al. *Remote Sens.* **11**, 907 (2019).
[5] Mansourmoghaddam M. et al. *Remote Sens.* **16**, 454 (2024).

URBIS24
16-18 Sep 2024
ESA/ESRIN, Frascati, Italy

CONTACT:
kustura@geoville.com
sammer@geoville.com

GeoVille
Information Systems and Data Processing GmbH