

Urban Heat Island Monitoring Using Thermal Infrared Satellite Data in Italian cities

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Abstract

Climate change is driving a sustained increase in global temperatures and an intensification of extreme events, including heatwaves. Urban areas are typically warmer than the surrounding suburban and rural environments, a phenomenon known as the Urban Heat Island (UHI) due to the presence of buildings and inhomogeneous surfaces, which affects surface energy and water exchanges as well as the local meteorology. UHI strongly affect urban climate, ecosystems, air quality, and human thermal comfort, and its impact is exacerbated during heatwaves, with risks for human health. Monitoring and characterizing UHI is crucial for urban planning, climate mitigation and adaptation strategies. The Surface Urban Heat Island (SUHI) can be effectively investigated through the study of the Land Surface Temperature (LST) derived from satellite observations, enabling comprehensive spatial and temporal analyses of urban thermal patterns, including the identification of hot- and cold-spots, and the assessment of mitigation strategies.

In this study, thermal infrared satellite observations of LST are used to characterize the SUHI and its dynamics over selected urban areas in Italy. A decadal dataset is built using Landsat 8 data to analyse long-term evolution. For recent years, Landsat 8 data are combined with ECOSTRESS data, significantly enhancing temporal sampling. This multi-sensor approach enables an improved assessment of urban temperature evolution and its response to climate change.

1. Introduction

Human-induced climate change represents one of the major challenges of the 21st century (e.g., Eyring et al., 2021). Its most evident manifestation is the increase in mean air temperature, with enhanced sensitivity in some regions, including the Mediterranean basin (e.g., Ali et al., 2022), which has been recognized as a climate hotspot (Giorgi, 2006). Climate change also affects wind and precipitation patterns and influences the frequency and intensity of extreme events such as storms, droughts, and heatwaves (e.g., Gulev et al., 2021). In recent years, the Mediterranean region has experienced an increase in the frequency and intensity of heatwaves (e.g., Perkins-Kirkpatrick and Lewis, 2020; Seneviratne et al., 2021; Rousi et al., 2022), with record-breaking temperatures leading to severe impacts on human comfort and health, particularly in large urban areas (see, e.g., Royé, 2017). Urban environments are typically warmer than their rural surroundings, especially during nighttime. This phenomenon, known as the Urban Heat Island (UHI), is associated with land-use changes, urban morphology, and the widespread use of artificial materials, as well as local heat emissions from traffic and air conditioning (Oke, 1982). These factors modify the surface radiative balance and heat and moisture exchanges, affecting urban meteorology, pollutant dispersion, ecosystems, and human thermal comfort. During heatwave conditions, the UHI effect can be significantly amplified, particularly in densely built-up areas with limited vegetation cover (e.g., Founda and Santamouris, 2017). Monitoring the spatial and temporal evolution of UHIs is challenging due to their spatial extent and surface heterogeneity. Indeed, understanding and characterizing UHIs has traditionally relied on numerical urban climate modelling and sparse in situ meteorological networks. While numerical atmospheric models provide valuable insights into boundary layer dynamics and diagnostic forecasts, they face challenges regarding spatial

parameterization, computational costs, and complex input requirements (e.g., Mirzaei and Haghighat, 2010; Di Bernardino et al., 2022). In situ weather stations, on the other hand, offer high temporal continuity but lack the spatial density necessary to capture fine-scale urban thermal heterogeneity. In this context, satellite-based thermal infrared observations provide a unique capability for continuous spatial monitoring across heterogeneous landscapes (e.g., Ward et al., 2016; Sobrino and Irakulis, 2020). Landsat series observations have long served as a benchmark for high-spatial-resolution land surface temperature retrieval at fine urban scales (e.g., Scalabrini et al., 2024). More recently, thermal data from the ECOSTRESS sensor aboard the International Space Station have enabled enhanced spatial detail at 70-meter resolution alongside variable diurnal acquisition times, effectively mitigating the temporal limitations of traditional sun-synchronous platforms (Hulley et al., 2019, 2022). Integrating these satellite thermal infrared observations provides a robust framework for evaluating Surface Urban Heat Islands, identifying thermal hotspots, and supporting urban climate mitigation strategies (Voogt and Oke, 2003; Zhou et al., 2019).

2. Methodology

In this study, the Urban Heat Island is investigated in terms of Surface Urban Heat Island (SUHI), derived from satellite-based Land Surface Temperature (LST). For Landsat 8, Level-1 top-of-atmosphere brightness temperature from Band 10 (10.60 to 11.19 μm) is used to retrieve LST at a resampled spatial resolution of 90 m using the Statistical Mono-Window (SMW) algorithm (Ermida et al., 2020; Scalabrini et al., 2024):

$$LST = A \cdot \frac{T_b}{\epsilon} + \frac{B}{\epsilon} + C \quad (1)$$

where T_b is the top-of-atmosphere brightness temperature, ϵ is the surface thermal emissivity, and A, B, C are algorithm coefficients that account for atmospheric attenuation based on Total Precipitable Water (TPW).

All retrieved Landsat 8 LST scenes are co-registered onto a common spatial grid. SUHI areas are defined dynamically based on the LST spatio-temporal distribution.

Specifically, pixels are identified as belonging to the SUHI area if their temperature exceeds a threshold defined as the spatial mean (μ) of the time-based 90th percentile LST distribution plus half of its standard deviation (σ), adapting the statistical approach from Guha et al. (2017):

$$SUHI: LST > \mu + 0.5\sigma$$

The schematic representation of the SUHI computation pipeline applied to Naples is depicted in Figure 1.

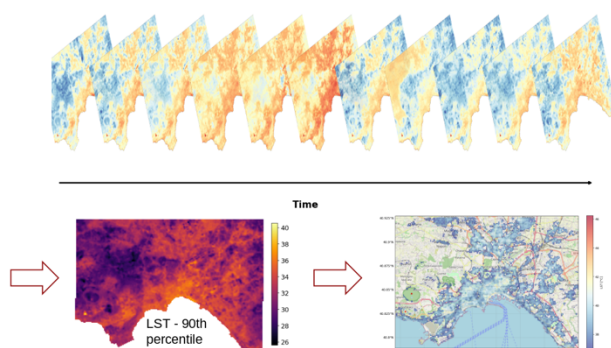


Figure 1. Flowchart of the methodology applied for the LST threshold retrieval.

Long-term temporal dynamics are evaluated using scene-averaged LST values. To identify local surface thermal changes while minimizing seasonal intra-annual variability, pixel-based thermal stability is evaluated by computing the seasonal standard deviation of LST across the multi-year time series.

Data processing and spatial analysis were carried out using open-source Python libraries, including Pandas (McKinney, 2010), GeoPandas (Van den Bossche, 2022), Matplotlib (Hunter, 2007), Xarray (Hoyer and Hamman, 2017), and Rioxarray (Snow et al., 2026).

3. Study area and satellite datasets

The analysis focuses on two coastal cities in Southern Italy characterized by different urban scales and topographic complexities. Naples is located on the Tyrrhenian coast and represents the most densely populated metropolitan area in Italy, with approximately one million inhabitants. The city features complex topography and orography, bounded by the sea, Mount Vesuvius, and the volcanic region of Campi Flegrei, with urban development extending across coastal plains and surrounding hills. Reggio Calabria is situated on the Strait of Messina, with approximately 200,000 inhabitants, presenting a simpler urban layout along a narrow coastal strip backed by steep mountainous terrain, characterized by unique coastal atmospheric and oceanographic interactions. Figure 2 shows the position of the considered cities and a detailed view of the metropolitan scales.

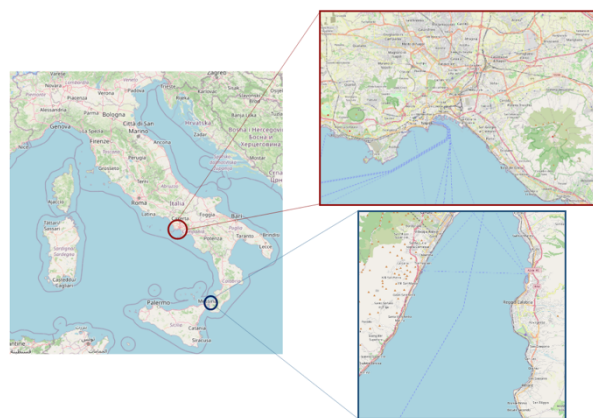


Figure 2. Geographic location of the study areas along with detailed local scale urban domains (© OpenStreetMap contributors).

Landsat 8 is a United States Geological Survey (USGS) satellite launched in 2013, carrying two instruments: the Operational Land Imager (OLI) and the Thermal InfraRed Sensors (TIRS). The spatial resolution of the sensor is 30 m for OLI (with the exception of the panchromatic band, characterized by a 15 m resolution) and 100 m (resampled to 30 m to match OLI resolution) for TIRS data. Its revisit time is 16 days. In late 2021, Landsat 9 was launched with identical characteristics. The joint use of both satellites allows a temporal revisit of 8 days. In the present study, however, only Landsat 8 data have been used.

Specifically, L1 brightness temperature data (Earth Resources Observation and Science (EROS) Center, 2020) have been used to derive a 90 m-resolution LST, using the 100 m-resolution ASTER Global Emissivity Dataset (NASA JPL, 2014) resampled to the same grid and the NCEP/NCAR reanalysis (Kistler et al., 2001) as ancillary inputs. The ASTER dataset provides the ground emissivity (ϵ) in Equation 1, while the atmospheric reanalysis provides the A, B, C coefficients derived from a lookup table based on total precipitable water. The obtained LST dataset is composed of 76 cloud-free, quality-checked nighttime images for Naples, and 100 images for Reggio Calabria.

With the aim of enhancing temporal sampling and spatial resolution, Landsat 8 data have been compared and used jointly with ECOSTRESS L2 LST data (Hook and Hulley, 2022). ECOSTRESS is a NASA sensor mounted on the International Space Station in late 2018, featuring a variable revisit time (1 to 3 days) and a 70 m spatial resolution (Fisher et al., 2020). Nighttime, cloud-free, and quality-checked images were selected, resulting in a dataset of 40 images for Naples and 75 images for Reggio Calabria. Figures 3 and 4 show the temporal data distribution from 2014 to 2025 and the monthly sampling breakdown for Naples and Reggio Calabria, respectively. The addition of ECOSTRESS data leads to a substantial increase in scene availability starting from 2018. It is worth noting the uneven monthly distribution across both datasets, with the majority of the observations concentrated in summer months (peaking in July) and lower coverage during winter.

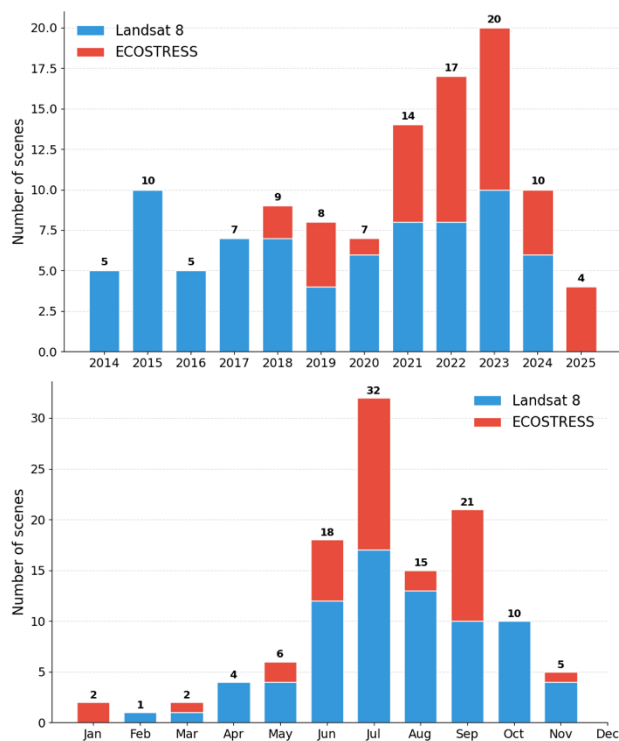


Figure 3. Temporal data availability over the years (top panel) and seasonal distribution breakdown (bottom panel) for Naples (blue: Landsat 8; red: ECOSTRESS).

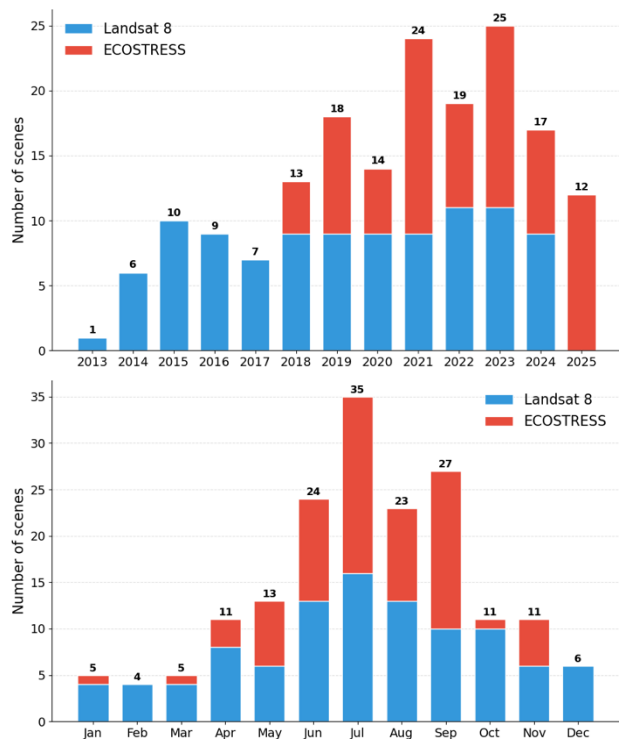


Figure 4. Temporal data availability over the years (top panel) and seasonal distribution breakdown (bottom panel) for Reggio Calabria (blue: Landsat 8; red: ECOSTRESS).

4. Results and discussion

Figure 5 presents the spatial extent of the nighttime SUHI derived independently from Landsat 8 and ECOSTRESS datasets over Naples. Discrepancies in the identified SUHI boundaries, threshold values, and absolute temperatures arise naturally from differences in sensor characteristics, acquisition times, spatial resolutions, and retrieval algorithms. Despite these operational differences, the two sensors display strong spatial consistency. Both datasets successfully identify the high-density historical city centre and the port infrastructure as primary urban thermal hotspots. The finer spatial resolution of ECOSTRESS enables the detection of localized urban structures, such as airport runways (visible in the SUHI maps near 40.87° N, 14.30° E), which are partially blurred or omitted in Landsat 8 observations due to pixel mixing. The SUHI threshold temperature derived from Landsat is around 32 °C, with maximum values within the SUHI footprint reaching 39 °C. For ECOSTRESS, the threshold temperature is approximately 25 °C, with maximum values reaching 29 °C, highlighting offset differences that require future inter-calibration.

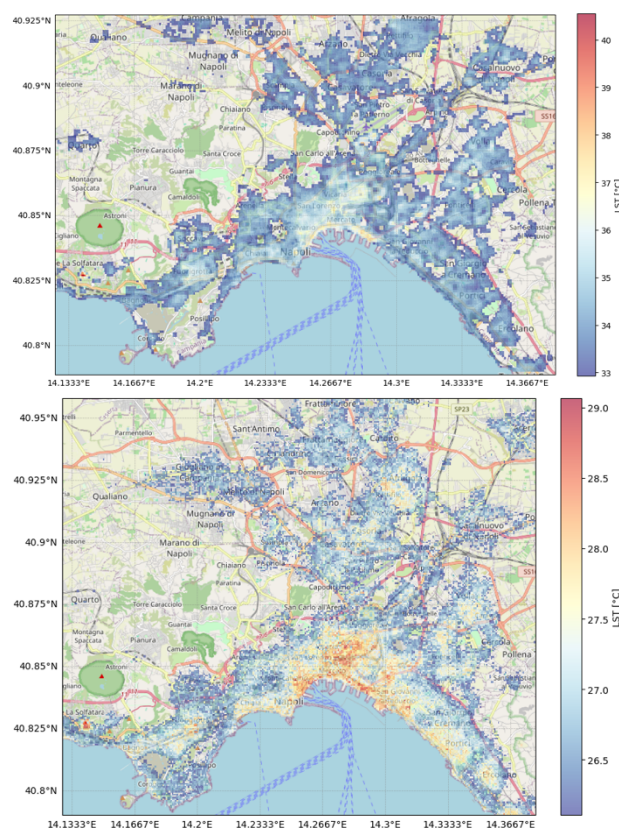


Figure 5. Delineation of nighttime SUHI footprints over Naples derived from Landsat 8 (top panel) and ECOSTRESS (bottom panel).

Similar spatial agreement was observed for Reggio Calabria (Figure 6). The higher ECOSTRESS spatial resolution allows for finer urban detail, registering peak temperatures in the same spatial hotspots identified by Landsat 8. Similarly, the ECOSTRESS-derived SUHI map includes the airport runway (located in the south-western part of the city near 38.075° N, 15.645° E), which was omitted in the Landsat-derived footprint. For Reggio Calabria, the threshold LST values are approximately 32 °C and 26 °C for Landsat and ECOSTRESS, respectively.

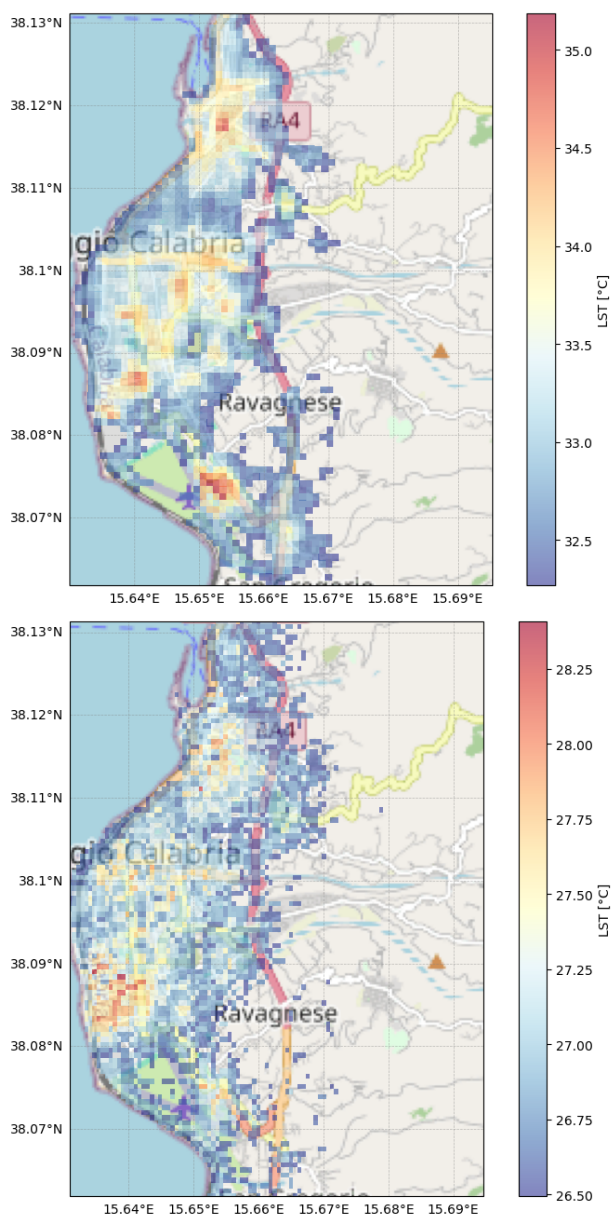


Figure 6. Delineation of nighttime SUHI footprints over Reggio Calabria derived from Landsat 8 (top panel) and ECOSTRESS (bottom panel).

Maximum observed LST values reach around 35 °C for Landsat and 28 °C for ECOSTRESS. As observed in Naples, these systematic offsets must be addressed in future work, as they stem from variations in acquisition times, atmospheric correction models, and observation periods.

While Landsat 8 provides an 11-year observation window, its 16-day nominal revisit period, compounded by cloud contamination, results in an irregular temporal distribution. The integration of ECOSTRESS data from late 2018 onwards substantially increases temporal density in recent years; however, strong seasonal sampling biases remain, with observations heavily skewed toward clear-sky summer months and sparse coverage in winter. Consequently, raw LST time series do not exhibit a statistically significant decadal warming trend without prior radiometric cross-calibration and temporal normalization. Addressing these sampling asymmetries is a prerequisite for robust trend extraction.

Nevertheless, when considering scene-averaged LST values (Figure 7), Landsat and ECOSTRESS LST dynamics show comparable ranges. Spatial averaging mitigates local resolution discrepancies, and temporal differences are constrained when examining single observation points, as opposed to derive a temporal-based dynamic area, where the length of the dataset play a pivotal role.

Both cities display scene-averaged LST values ranging from approximately 8 °C to 35 °C.

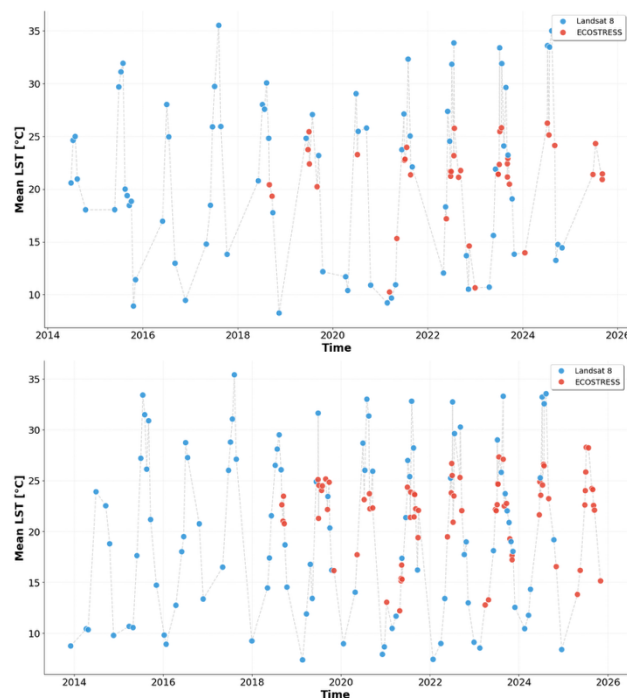


Figure 7. Scene-averaged LST time-series for Naples (top panel) and Reggio Calabria (bottom panel) covering the multi-year observation period.

Despite temporal gaps, the decadal Landsat 8 dataset proves highly effective for spatial vulnerability mapping. Computing the pixel-based seasonal standard deviation reveals areas experiencing pronounced surface changes over time. For instance, applying a high-variability threshold above 5.5 °C during summer months in Naples highlights specific localized clusters. Inspection of these high-variability pixels directly corresponds to major infrastructure modifications, such as recent ground construction and surface alterations within Naples Airport (Figure 8), as confirmed via historical optical imagery.

Similar findings are observed with the ECOSTRESS dataset (Figure 9). The pattern and intensity of variability differ slightly due to the shorter time frame (2018–2025). Highly variable pixels in the airport area were linked to surface modifications, including rooftop photovoltaic installations. Beyond single infrastructure projects, this simple statistical metric allows for rapid identification of localized thermal anomalies and hotspots caused by land-use changes within urban domains.

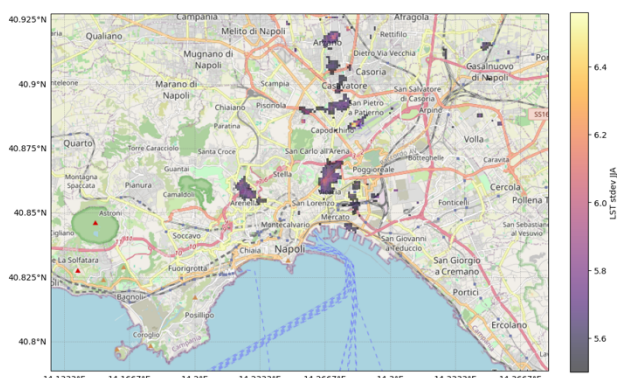


Figure 8. LST variability map (LST standard deviation) in Naples derived from Landsat 8 data. Only pixel with standard deviation above a 5.5 °C are shown.

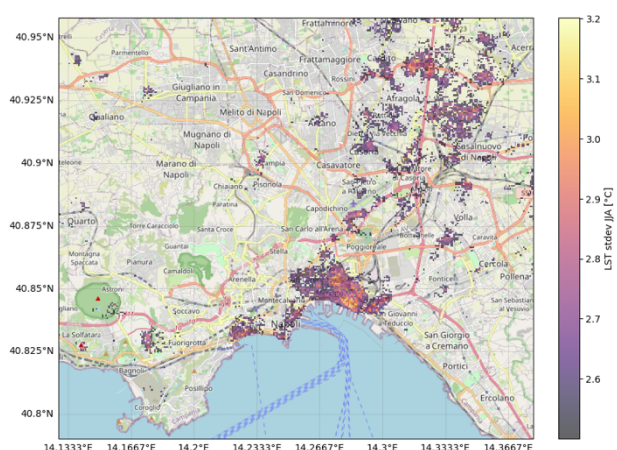


Figure 9. LST variability map (LST standard deviation) in Naples derived from ECOSTRESS data. Only pixel with standard deviation above a 2.5 °C are shown.

5. Conclusion and future perspectives

This preliminary study demonstrates the feasibility and utility of combining multi-sensor thermal infrared observations to assess urban thermal environments and variability. Both Landsat 8 and ECOSTRESS accurately delineate major SUHI hotspots, with ECOSTRESS offering superior detail for fine-scale urban features. However, long-term trend analysis requires careful temporal harmonization and bias correction due to irregular satellite revisit cycles and cloud filtering.

To transition from a preliminary baseline to a fully robust monitoring framework, future efforts will focus on harmonizing LST algorithms between Landsat 8, Landsat 9, and ECOSTRESS to enable joint spatial-temporal analyses, alongside validation against in situ observations. Furthermore, incorporating Landsat 9 acquisitions will double the Landsat temporal sampling, while integrating daytime observations will allow for the characterization of diurnal SUHI dynamics.

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Colorado, USA (<https://psl.noaa.gov/>). Map data copyrighted by OpenStreetMap contributors and available from <https://www.openstreetmap.org>.

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