Satellite and ground-based data to monitor urban heat islands. Cases of study: polish and italian cities

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Abstract

Urban Heat Island (UHI) is a significant environmental phenomenon that exacerbates rising temperatures in urban areas, affecting human health, energy consumption, and urban sustainability. This study analyzes UHI intensity in four selected cities—Kraków and Gdańsk (Poland) and Ancona and Termoli (Italy)—using Landsat-8 and Landsat-9 thermal infrared imagery combined with ground-based in situ temperature measurements. The study employs object-based classification using a Random Forest (RF) algorithm, enabling a detailed assessment of land surface temperature (LST) variations across different land cover types.
The results indicate that built-up areas and impervious surfaces exhibit significantly higher temperatures, with LST values reaching 36.5°C in Ancona and 32.2°C in Kraków, whereas vegetated areas show a cooling effect, reducing temperatures by up to 7°C. Coastal cities, particularly Gdańsk and Termoli, display lower UHI intensity but greater LST variability due to maritime cooling and cloud cover effects.
Statistical validation comparing satellite-derived LST with in situ measurements demonstrated a strong correlation in Kraków (r = 0.73) and moderate agreement in Ancona (r = 0.62), while Gdańsk and Termoli exhibited lower correlation values (r = 0.09 and r = 0.003, respectively), attributed to cloud interference and coastal microclimatic effects. The study highlights the importance of integrating remote sensing with ground-based data to enhance UHI monitoring accuracy and proposes urban planning strategies, including increased vegetation cover and heat-resilient urban materials, to mitigate UHI effects.
These findings contribute to the scientific understanding of UHI dynamics in different climatic contexts and provide actionable insights for sustainable urban development. Future research should explore high-resolution thermal datasets and advanced machine learning models for improved urban temperature monitoring.

1. Introduction

Urbanization has significantly altered land use patterns, leading to an increase in surface temperatures in cities and the formation of Urban Heat Islands (UHI). UHI refers to localized temperature anomalies where urban areas exhibit higher temperatures than their surrounding rural regions, primarily due to the extensive presence of impervious surfaces, limited vegetation cover, and anthropogenic heat emissions (Gkatzioura & Perakis, 2024).

The UHI effect has significant environmental and socio-economic consequences. Rising urban temperatures increase the demand for air conditioning, resulting in higher energy consumption and greenhouse gas emissions, thereby contributing to global warming (Nobar & Rahimi, 2024). Prolonged exposure to high temperatures can lead to health problems such as heat stress, cardiovascular diseases, and respiratory illnesses, particularly among elderly individuals and children (Khalili et al., 2024).

Given the growing importance of managing urban climate impacts, remote sensing technologies have become a crucial tool for monitoring and analyzing UHI dynamics. Thermal satellite imagery, such as Landsat-8 and Landsat-9, enables precise detection of spatial surface temperature variations and identification of high-intensity UHI areas (Mathew et al., 2024). Modern approaches, such as the use of hyperspectral imaging for the classification of Local Climate Zones (LCZ), allow for an even more detailed analysis of UHI dynamics (Vavassori, 2024). Additionally, the use of deep learning algorithms enhances the accuracy of mapping and predicting urban temperature changes (Zhou & Bai, 2024**).**

Despite the increasing precision of satellite-based remote sensing methods, ground-based measurements remain a key component for calibrating and validating satellite data. Studies indicate that integrating both data sources improves the accuracy of surface temperature assessments, particularly in diverse urban environments where local climate conditions, air circulation, and land cover types influence temperature distribution (Rees, 2024). This hybrid approach is particularly beneficial in diverse urban environments, where factors such as local climate variations, wind patterns, and land cover heterogeneity influence surface temperature distributions (Ramakreshnan et al., 2018).

This study aims to analyze the spatial distribution and intensity of UHI in four selected cities in Poland and Italy using Landsat-derived thermal remote sensing data and ground-based temperature measurements. By integrating these methodologies, this research seeks to enhance the accuracy of UHI detection and provide quantitative insights into urban thermal anomalies.

The specific objectives of this study are:
1. To identify and map UHI intensity across different urban areas using satellite thermal imagery.

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2. To compare satellite-derived land surface temperature (LST) with in situ temperature measurements from ground-based sensors.
3. To assess the influence of land cover types on LST variations through statistical analysis of classified urban zones.

2. Study Area

The research has been conducted in selected cities in Poland and Italy (Figure 1). In Poland, the study analyzed Kraków and Gdańsk, two cities with different climatic and urban conditions. Regarding the Italian cities, two cities on the east coast were analyzed: Ancona and Termoli. Ancona is the capital of the Marche Region, while Termoli is a tourist town with approximately 30,000 inhabitants.

Table 1 presents the total population and land area (in km²) for the four cities included in the study: Kraków and Gdańsk (Poland), and Ancona and Termoli (Italy). These parameters provide a comparative basis for analyzing UHI intensity in relation to urban size, population density, and geographical characteristics. Larger cities with higher population densities and extensive built-up areas, such as Kraków and Gdańsk, are expected to exhibit stronger UHI effects, while coastal cities like Ancona and Termoli may experience moderated temperature variations due to maritime influences. The data serve as a reference for understanding the spatial extent of urbanization and its impact on local climate conditions.

Kraków, located in southern Poland, experiences a temperate climate with significant continental influences. The city faces cold winters and hot, dry summers, which, combined with dense

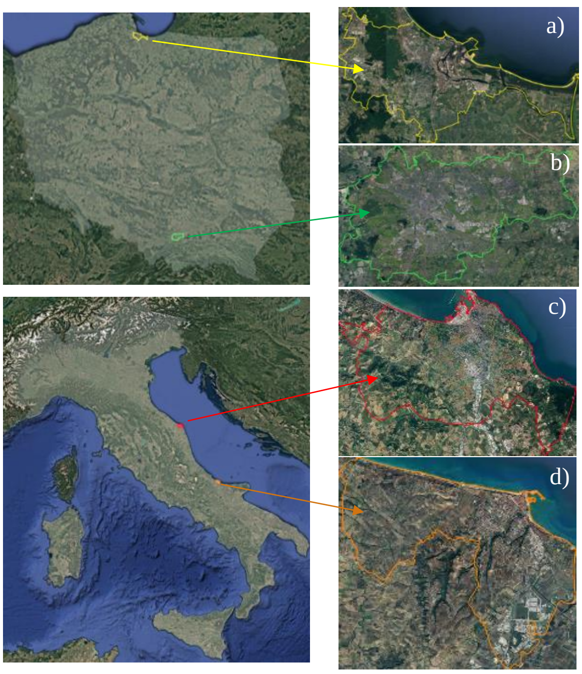

Figure 1. Study area locations overlaid on Google Maps imagery: a) Gdańsk, b) Kraków, c) Ancona, and d) Termoli.

AOI	Population [pers]	Area [km^2]
Kraków	807 644	326,91
Gdańsk	487 834	262,00
Ancona	99 239	123,70
Termoli	31 980	55,00

Table 1. Population and area of the selected study areas.

urban development, contribute to the formation of UHI (Devendran and Banon, 2022). Similar patterns have been observed in other European cities with comparable climates, where urban density exacerbates thermal stress (Okumuş and Terzi, 2022).

Gdańsk, situated in northern Poland on the Baltic Sea, falls within the temperate climate zone with maritime influences. The city experiences milder winters and moderately warm summers, resulting in less pronounced temperature differences between urban areas and surrounding regions (Sharma et al., 2023). Proximity to the sea impacts air humidity, while port and industrial areas add complexity to thermal analysis. These findings align with studies on coastal urban areas and their unique thermal dynamics (Drăguleasa et al., 2023).

In Italy, Ancona and Termoli were analyzed, both located in the central part of the country within the Mediterranean climate zone, facing the coast of the Adriatic Sea. The Mediterranean climate is characterized by hot, dry summers and mild, rainy winters, which help replenish water supplies but also bring strong northwestern winds. Occasionally, there are snowfall episodes along the coast, as well as severe thunderstorms and strong sea swells.

3. Methodology

This study uses an integrated approach that combines satellite remote sensing and in situ ground measurements to analyze the spatial distribution and intensity of urban heat islands (UHIs) in selected cities. The methodology consists of three main components: processing of satellite imagery, ground-based temperature measurements and comparative analysis of the two data sets. The different stages of the study workflow are shown in the diagram (Figure 2).

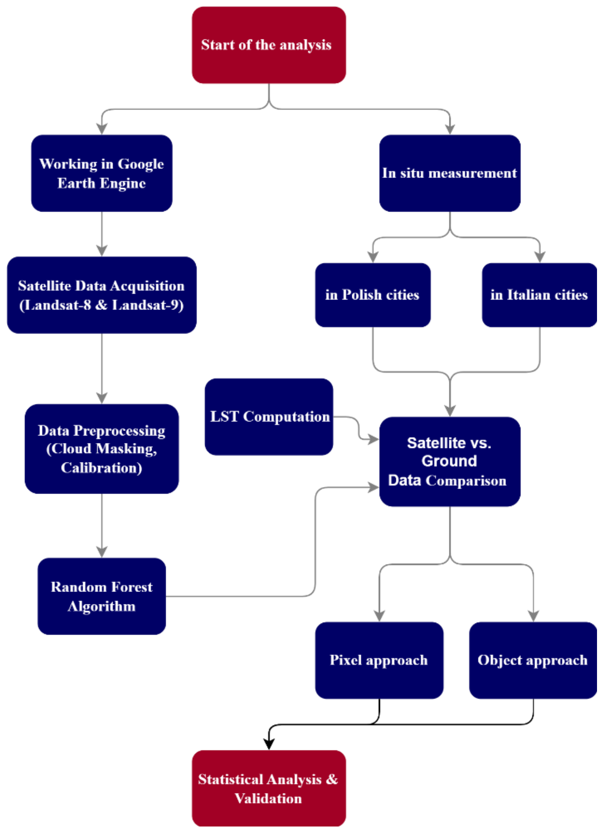

Figure 2. Methodological workflow for the study.

3.1 Satellite Data processing

Landsat-8 and Landsat-9 thermal imagery were used for surface temperature analysis, with data processing conducted in Google Earth Engine (GEE). A list of Landsat image used in the study is presented in Table 2. The study area boundaries were defined using administrative AOI shapefiles, and cloud-free satellite images (cloud cover <15%) were selected for the summer months of 2024. The thermal infrared bands (TIRS-1 and TIRS-2) were used to calculate LST through a standard single-channel algorithm (Avdan and Jovanovska, 2016), incorporating radiometric corrections, atmospheric adjustments (Eq. 1), and emissivity estimation based on the Normalized Difference Vegetation Index (NDVI) (Eq. 2-4). The emissivity correction, derived from NDVI values, allowed differentiation between vegetation and built-up surfaces, improving the accuracy of temperature retrieval.

$$Tb = \frac{K2}{ln(\frac{K1}{L\lambda}+1)} \quad (1)$$

where Tb = brightness temperature (K)
K1, K2 = calibration constants for the Landsat sensor (provided in metadata)
Lλ = TOA radiance

$$LST = \left(\frac{Tb}{\left(1+(0.00115-(\frac{Tb}{1.4388})\right)*\log(Ep)}\right) - 273.15 \quad (2)$$

where Tb = thermal channel
Ep = emissivity, estimated using NDVI-based emissivity model

$$NDVI = \frac{NIR-RED}{NIR+RED} \quad (3)$$

where RED = Red channel
NIR = Near-Infrared channel

$$Ep = 0.004 * NDVI + 0.986 \quad (4)$$

To refine the LST analysis, a Random Forest (RF) classification algorithm was applied (Belgiu & Drăguţ, 2016), segmenting the urban landscape into five primary land cover categories: high vegetation, grassland, built-up areas, parking lots, and bare soil. This object-based classification provided a more structured approach to identifying temperature variations across different urban surfaces compared to conventional pixel-based analyses.

The classification included:

1. High vegetation (e.g., parks, forests)
2. Grass-covered areas
3. Built-up areas (e.g., roads, rooftops)
4. Parking lots (high heat retention surfaces)
5. Bare soil (low vegetation cover)

An average temperature value was counted for each category, allowing a site-based UHI assessment.

AOI	Date [yyyy-mm-dd]	Time [hh:mm:ss]	Mission
Kraków	2024-08-29	09:32:13	Landsat 9
Gdańsk	2024-08-18	09:49:27	Landsat 9
Ancona	2024-08-10	09:52:34	Landsat 8
Termoli	2024-08-28	09:40:45	Landsat 8

Table 2. The Landsat images collection.

3.2 Ground-Based Temperature Measurements

To ensure the accuracy and validation of satellite-derived LST values, ground-based thermal sensors were strategically deployed within each study area. The placement of sensors was designed to capture temperature variations across diverse urban land cover categories, which influence local thermal dynamic:

- areas with dense tree cover known for their cooling effect
- moderate vegetation areas influencing urban microclimates
- zones with significant heat retention due to impervious materials
- impervious surfaces with high heat absorption)
- exposed surfaces with variable thermal properties

The in situ measurements were recorded in synchronization with Landsat overpass times to ensure direct comparability between satellite and ground-based observations. Data logging was conducted every 10 minutes. However, during the data collection in Gdańsk and Termoli partial cloud cover was present at the time of the Landsat overpass. As a result, only a subset of sensor data could be used—specifically from sensors located in cloud-free areas. This limitation affected the spatial coverage of the validation dataset, particularly in certain built-up and vegetated regions that were obscured by clouds. Consequently, a filtered dataset was utilized for the comparison with satellite-derived LST, ensuring that only reliable and unobstructed data points were considered for validation.

3.3 Comparative Analysis and Accuracy Assessment

A key aspect of this study was the comparative evaluation of satellite-derived LST values within situ temperature measurements obtained from ground-based thermal sensors. This validation process aimed to assess the accuracy, reliability, and potential biases of remote sensing data in capturing the spatial distribution and intensity of UHI across the selected study areas. To achieve a reliable validation, two complementary analytical approaches were employed.

3.3.1 Pixel-based comparison: In the pixel-based approach, ground temperature measurements were directly compared with corresponding Landsat-derived LST values at identical geographic coordinates. Each sensor location was precisely georeferenced to match 30m-resolution Landsat pixels, ensuring that only aligned data points were included in the analysis. The primary objective of this approach was to identify potential discrepancies between satellite and ground-based measurements due to factors such as sensor calibration differences, land surface emissivity variations, and atmospheric effects.

The analysis involved calculating statistical error metrics to quantify the deviations between satellite-derived and ground-based LST values: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Bias (Systematic Error), Pearson’s Correlation Coefficient (r) (Eq. 5-8).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(LSTsat_i - LSTground_i)^2} \quad (5)$$

$$MAE = \frac{1}{n}\sum_{i=1}|LSTground_i - LSTsat_i| \quad (6)$$

$$BIAS = \frac{1}{n}\sum_{i=1}(LSTsat_i - LSTground_i) \quad (7)$$

$$r = \frac{\sum_{i=1}^{n}\left(LSTground_i - \overline{LSTground}\right)\left(LSTsat_i - \overline{LSTsat}\right)}{\sqrt{\sum_{i=1}^{n}\left(LSTground_i - \overline{LSTground}\right)^2}\sqrt{\sum_{i=1}^{n}\left(LSTsat_i - \overline{LSTsat}\right)^2}} \tag{8}$$

where: LST_{sat} = temperature from Landsat images
LST_{ground} = ground sensor temperature
$\overline{LSTsat}$ = mean temperature from Landsat images
$\overline{LSTground}$ = mean ground sensor temperature,
n = number of points

These metrics provide an indication of the reliability of Landsat thermal imagery for UHI studies and help refine the methodologies for urban heat mapping.

However, in Gdańsk and Termoli the presence of partial cloud cover during the Landsat overpass posed a challenge for validation. Only sensor locations within cloud-free regions were included in the comparative analysis to minimize potential atmospheric distortions. The affected areas were excluded from direct pixel-based validation, and the results for Gdańsk, Termoli were interpreted with this limitation in mind.

3.3.2 Object-based analysis using Random Forest classification: While pixel-based comparisons offer direct one-to-one validation, object-based analysis was also implemented to account for land cover variations and reduce spatial mismatches between datasets. The object-based approach involved:

- classifying urban land cover types into predefined categories
- computing the average LST for each classified object in both satellite-derived and in situ datasets
- comparing temperature variations within each land cover category to assess the consistency between satellite and ground measurements

This method mitigates issues associated with spatial resolution differences, sensor-specific temperature deviations, and mixed-pixel effects, which are common challenges in UHI studies.

4. Results

This section presents the analysis of Urban Heat Island (UHI) intensity in selected Polish and Italian cities based on Landsat-8 and Landsat-9 satellite imagery and ground-based temperature measurements. The findings highlight spatial differences in temperature distribution, the impact of land cover types, and the validation of satellite-derived LST against in situ data.

The retrieved LST values from satellite imagery indicate significant variations in urban heat distribution across the study areas. Figures 3 and 4 illustrate the spatial patterns of UHI intensity, with higher temperatures concentrated in densely built-up and impervious surface areas, while lower temperatures were observed in vegetated zones and near water bodies.

Kraków exhibited the highest UHI intensity among the studied cities, with LST values reaching 32.2°C in built-up areas compared to 26.2°C in vegetated zones. Gdańsk, due to maritime influences, displayed a more balanced temperature distribution, with an average urban LST of 29.8°C, while vegetated areas remained at 26.1°C. In Italy, Ancona recorded the highest LST, with urban temperatures exceeding 36.5°C, particularly in industrial and commercial districts. Termoli, a smaller coastal city, exhibited moderate UHI effects, with urban areas averaging 34.5°C.

These results suggest that urban morphology, land cover type, and proximity to water bodies play crucial roles in modulating local temperature variations and UHI intensity.

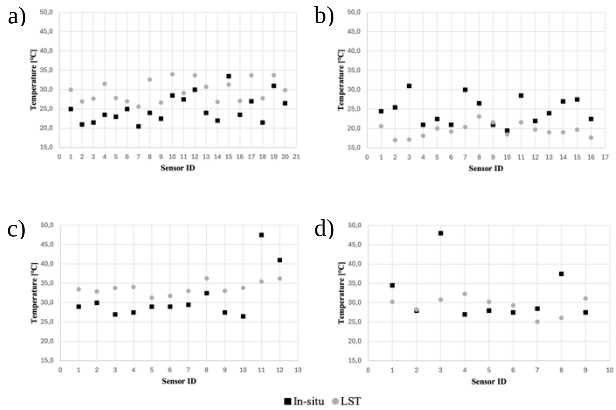

Figure 3. Comparison of in situ and satellite-derived land surface temperature (LST) measurements for: a) Kraków, b) Gdańsk, c) Ancona, and d) Termoli.

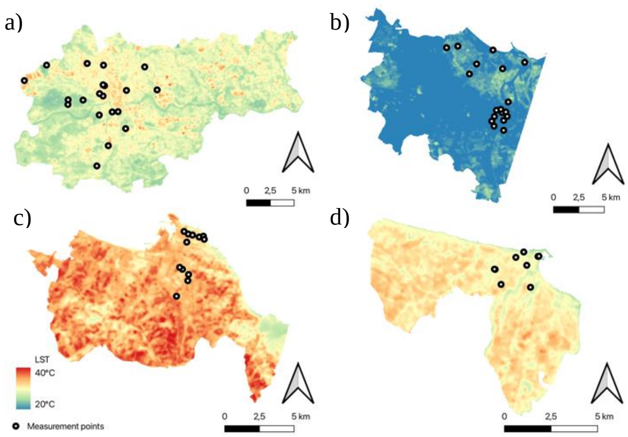

Figure 4. Spatial distribution of calculated land surface temperature (LST) for: a) Kraków, b) Gdańsk, c) Ancona, and d) Termoli, with ground-based measurement points overlaid.

4.1 Object-based classification and temperature variations

The object-based classification approach enabled a more detailed assessment of temperature variations across distinct urban surfaces compared to traditional pixel-based LST analysis. By segmenting the landscape into homogeneous objects, spatial noise was reduced, enhancing the accuracy of LST assessments. The results of the object-based analysis (Figure 5) reveal significant variations in LST across different land cover categories in Kraków (an inland city) and Ancona (a Mediterranean coastal city). The mean LST values and standard deviations for each land cover type are presented in Table 3.

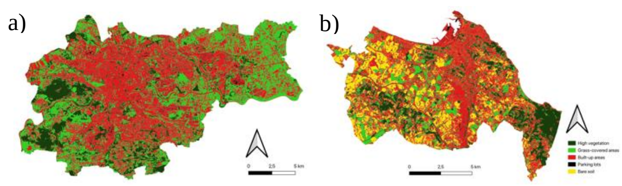

Figure 5. Random Forest classification over a) Kraków AOI b) Ancona AOI.

Land Cover class	Kraków		Ancona	
	Mean [°C]	Stdv	Mean [°C]	Stdv
High vegetation	26.16	1.28	31.16	2.42
Grass-covered areas	27.87	1.40	33.58	1.73
Built-up areas	29.76	1.91	35.18	1.97
Parking lots	32.22	1.60	35.12	1.68
Bare soil			36.53	1.51

Table 3. LST statistics by land cover class – Kraków and Ancona AOI

The results confirm that vegetation plays a critical role in mitigating UHI intensity (Table 3). In both cities, areas covered by dense vegetation exhibited the lowest LST values, with mean temperatures of 26.16°C in Kraków and 31.16°C in Ancona. This cooling effect is attributed to evapotranspiration, shading, and lower thermal inertia of vegetated surfaces compared to impervious materials.

In contrast, built-up areas and parking lots significantly contributed to urban warming. In Kraków, built-up surfaces reached an average LST of 29.76°C, whereas in Ancona, this value was notably higher at 35.18°C. The elevated temperatures in these areas are due to thermal absorption by materials such as asphalt, concrete, and metal roofing, which retain and release heat over time.

Parking lots exhibited some of the highest LST values, exceeding 32°C in Kraków and 35°C in Ancona, as these surfaces are highly impervious, lack vegetation, and receive direct solar radiation. Bare soil areas recorded the highest LST values, reaching 36.53°C in both cities, emphasizing the role of exposed, dry surfaces in extreme heating.

A systematic difference in LST values between Kraków and Ancona was observed, emphasizing the influence of local climatic conditions on UHI intensity. Ancona exhibited higher LST values across all land cover types, with an average increase of 5–6°C compared to Kraków. This discrepancy is attributed to higher solar radiation and lower atmospheric moisture in the Mediterranean climate (Drăguleasa et al., 2023). In contrast, Kraków’s inland location and higher vegetation coverage contributed to greater thermal regulation, particularly in vegetated areas where temperatures remained below 28°C.

4.2 Validation of satellite LST with ground-based data

The accuracy of Landsat-derived LST measurements was evaluated by comparing them with ground-based temperature measurements using both pixel-based and object-based validation approaches. The results of this comparison are presented in Table 4.

Statistic parameter	Krakow	Gdansk	Ancona	Termoli
RSME	5.21	6.26	5.84	7.49
MEA	4.85	5.17	5.23	5.50
BIAS	4.63	-5.09	2.44	-2.55
RSME after BIAS	2.39	3.64	5.31	7.04
MEA after BIAS	1.81	3.00	3.63	5.78
r	0.73	0.09	0.62	0.003

Table 4. Statistical comparison between satellite-derived LST and in situ temperature measurements

Kraków exhibited the strongest correlation (r = 0.73) between satellite and ground-based LST values, suggesting high reliability of Landsat-derived temperatures in inland environments. Ancona demonstrated moderate agreement (r = 0.62), while Gdańsk and Termoli showed low correlation (r = 0.09 and r = 0.003, respectively).

These discrepancies are primarily due to partial cloud cover during image acquisition in Gdańsk and Termoli, leading to higher RMSE values and temperature underestimation in affected areas. Additionally, Termoli’s proximity to the Adriatic Sea resulted in localized thermal variations and wind-driven cooling effects, which affected Landsat LST accuracy.

4.3 Comparison of pixel-based and object-based validation

Pixel-based validation allows direct comparison of satellite-derived and in situ temperature measurements in the corresponding geographic coordinates, but is highly sensitive to pixel blending effects, especially in urban areas, where a single 30-meter pixel can cover different types of land cover. Previous studies have shown that differences in spatial resolution between satellite data and ground measurements significantly impact RMSE values, leading to increased variance and localized errors in built-up areas and heterogeneous landscapes (Drăguleasa et al., 2023; Mansourmoghaddam et al., 2023; Singh et al., 2022). In this study, RMSE values for pixel-based validation ranged from 5.21°C in Kraków to 7.49°C in Termoli, reflecting the impact of variations in land surface emissivity and atmospheric distortions.

On the other hand, the object-based validation approach, which groups similar land cover types into homogeneous units, provided a more generalized assessment of UHI dynamics. This technique reduces spatial noise and mixed-pixel errors, offering a more stable representation of temperature variations across different land cover types (Rousta et al., 2023). The use of object-based methods in LST validation has been increasingly recommended in recent studies (Mansourmoghaddam et al., 2023), as it enhances the correlation between satellite-derived and ground-based measurements, particularly in structured urban environments where land cover categories can be clearly distinguished.

Despite these advantages, object-based validation has its limitations. While it provides a more structured approach to LST assessment, it inherently lowers spatial resolution by aggregating temperature values within classified land cover units, potentially masking localized thermal anomalies (Drăguleasa et al., 2023). Additionally, the accuracy of this method depends on the precision of land cover classification, as misclassification of urban surfaces—such as mistakenly categorizing vegetated areas as built-up zones—can introduce systematic errors.

A systematic difference in validation accuracy was observed between inland and coastal cities, aligning with previous studies highlighting the influence of local climatic conditions on LST retrieval (Sharma et al., 2023). The presence of maritime effects in Gdańsk and Termoli, along with partial cloud cover during Landsat image acquisition, contributed to greater discrepancies between satellite and in situ temperatures, resulting in significantly lower correlation values (r = 0.09 in Gdańsk and r = 0.003 in Termoli). These results support earlier findings that atmospheric conditions, particularly humidity and wind patterns, can distort LST retrieval accuracy in coastal environments (Knutzen et al., 2023).

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In summary, while pixel-based validation offers high spatial resolution and allows for detailed temperature comparisons at specific locations, it is more susceptible to errors arising from mixed-pixel effects and land surface heterogeneity. Object-based validation, in contrast, improves agreement between satellite and in situ measurements by reducing spatial noise. The findings of this study reinforce existing research arguing for a combined approach that integrates both pixel-based and object-based methodologies to achieve a more robust assessment of UHI intensity (Bokaie et al., 2016). This is particularly important in urban climate research, where accurate temperature mapping is essential for developing mitigation strategies and guiding urban planning decisions aimed at reducing heat stress in densely built-up areas.

5. Conclusions

This study analyzed Urban Heat Island (UHI) intensity in Kraków, Gdańsk, Ancona, and Termoli using Landsat-8/-9 thermal imagery and ground-based temperature measurements. The findings confirm that urban morphology, land cover, and proximity to water significantly influence temperature variations, with built-up areas reaching 36.5°C in Ancona and 32.2°C in Kraków, while vegetation lowered temperatures by up to 7°C.

Validation of Landsat-derived LST showed high agreement in Kraków ($r = 0.73$) and moderate in Ancona ($r = 0.62$), but low in Gdańsk ($r = 0.09$) and Termoli ($r = 0.003$) due to cloud cover and coastal variability, increasing RMSE values (up to 7.49°C). Object-based classification improved LST accuracy by reducing mixed-pixel effects, allowing better differentiation of land cover impacts on UHI.

UHI mitigation should focus on expanding urban greenery, using reflective materials, and integrating blue infrastructure to reduce heat retention and enhance cooling. Higher-resolution thermal datasets (e.g., ECOSTRESS, UAV sensors) and multi-seasonal analyses are needed to refine UHI assessments. Planned research will further integrate AI-based classification and multi-sensor data fusion will improve climate adaptation strategies and urban resilience.

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