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Article Synergising Machine Learning and Remote Sensing for Urban Heat Island Dynamics: A Comprehensive Modelling Approach

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Abstract: This study evaluates the effectiveness of sustainable urban regeneration projects in mitigating Urban Heat Island (UHI) effects through a place-based approach. Geographic Information Systems (GIS) and satellite imagery were integrated with machine learning (ML) models to analyse the urban environment, human activities, and climate data in Turin, Italy. A detailed analysis of the ex-industrial Teksid area revealed a significant reduction in Surface Urban Heat Island Intensity (SUHII), with decreases of -0.94 in summer and -0.54 in winter following regeneration interventions. Using 17 variables in the Random Forest model, key determinants influencing SUHII were identified, including building density, vegetation cover, and surface albedo. This study quantitatively highlights the impact of increasing green spaces and enhancing surface materials to improve solar reflectivity, with findings showing a 19.46% increase in vegetation and a 3.09% rise in albedo after mitigation efforts. Furthermore, the results demonstrate that integrating Local Climate Zones (LCZs) into urban planning, alongside interventions targeting these key variables, can further optimise UHI mitigation and assess changes. This comprehensive approach provides policymakers with a robust tool to enhance urban resilience and guide sustainable planning strategies in response to climate change.

Keywords: Urban Heat Islands (UHIs); Surface Urban Heat Island (SUHI); remote sensing; Geographic Information System (GIS); machine learning (ML); Local Climate Zones (LCZs); urban planning

1. Introduction

The Urban Heat Island (UHI) effect is a well-documented phenomenon wherein urban areas experience elevated temperatures compared to their rural surroundings. This temperature difference arises primarily from the concentration of buildings, infrastructure, and human activities, which alters the natural energy balance of urban environments. The UHI effect exacerbates problems, such as increased energy consumption, air pollution, and adverse health impacts, particularly during extreme weather events. These issues are further amplified by climate change, making UHI mitigation a critical focus for urban planning and environmental policy [1,2].

Oke [3], a pioneer in UHI research, advanced this understanding by distinguishing two layers affected by urbanisation: the Urban Canopy Layer (UCL), influenced by the built environment, and the Urban Boundary Layer (UBL), which extends above the UCL. UHIs can be measured through air temperature sensors for the UCL, thereby capturing Canopy Urban Heat Island (CUHI) effects, or through thermal remote sensing for the UBL, which measures Surface Urban Heat Island (SUHI) intensity [4,5].

As urban areas expand, the boundaries between urban and rural regions have become less distinct, thus complicating traditional UHI assessments. To address this

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Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/license s/by/4.0/). challenge, Oke and Stewart [6,7] developed the Local Climate Zone (LCZ) classification, identifying 17 zones based on built geometries and land cover. Their research established a strong correlation between settlement size—measured based on population and human activity—and UHI intensity [8].

Urban regeneration projects have emerged as effective strategies for mitigating UHIs, particularly when combined with advanced analytical tools, such as Geographic Information Systems (GIS), remote sensing, and machine learning (ML). These technologies allow for comprehensive analysis by integrating spatial, environmental, and socio-economic data [9–13]. Surface Urban Heat Island Intensity (SUHII) offers a detailed understanding of how urban morphology and land use affect heat distribution at the surface level. Recent advancements in remote sensing [14–17] and ML have enabled the creation of more accurate models to predict UHI dynamics. ML algorithms, such as Random Forest, are particularly effective at identifying key variables that influence SUHII, including vegetation cover, building density, and surface albedo [18–23]. The LCZ classification is used to spatially analyse these variables by dividing urban areas into zones based on their physical and thermal properties, making it a valuable tool for targeted urban planning [17,20].

Building on this foundation, resumed in Appendix A, this study focuses on the city of Turin in northwest Italy through an in-depth analysis of the former industrial Teksid area. To comprehensively analyse the urban environment, GIS data and remote sensing imagery were employed to construct a geodatabase. These tools provided insights into the distribution, evolution, and drivers of SUHII by integrating data from multiple sources to develop a place-based model. ML techniques were then applied to assess the complex relationships between SUHII and urban factors, such as geometry, land use, and materials, thus uncovering patterns that traditional methods may have missed.

The LCZ method was also incorporated to assess the settlement morphologies defined by the Regional Landscape Plan (RLP) of the Piedmont Region. This combined approach offered a deeper understanding of SUHII variations based on urban morphologies and provided a comprehensive framework for urban planners to analyse SUHI. By assembling a geo-package for Turin, key variables influencing SUHII were identified, and non-linear relationships between these variables and SUHII were explored through the ML algorithm. Additionally, SUHII patterns were compared with LCZ morphologies to contextualise the findings and enhance our understanding of UHI behaviour across different urban forms.

This integrated approach not only identifies the key drivers of SUHII but also quantifies the impact of mitigation measures and compensatory solutions in critical urban contexts. It provides urban planners with actionable insights for implementing targeted UHI mitigation strategies, particularly in areas constrained by regulations or historical preservation requirements.

2. Materials and Methods

The methodology adopted in this study, as outlined in Figure 1, integrates four key elements guided by the state of the art, which is detailed in Appendix A. These elements include (i) a place-based analysis using GIS to geo-localise and describe urban characteristics [10–14]; (ii) the use of remote sensing imagery to complement the description of the urban environment and assess SUHII [15–18]; (iii) a data-driven model employing ML to analyse SUHII dynamics [19–24]; and (iv) the LCZ method to categorise typical urban contexts and propose mitigation strategies for UHI effects. This combination of approaches provides a comprehensive framework for studying UHI phenomena, thus offering insights that have not been previously integrated into a single methodology.

In the *pre-modelling* phase, GIS and remote sensing data were integrated to build a detailed geodatabase capturing the spatial–temporal variability in Turin during the years 2000–2001 and 2018; environmental indicators were calculated during pre-processing. These data were spatialised and organised into a geo-package for further analysis, thus

ensuring consistency across the variables. The pre-processing steps also involved cleaning the data and preparing the data for the modelling stage.

In the *modelling* phase, the Random Forest ML algorithm was chosen due to its robustness against overfitting and ease of integration into the ArcGIS Pro environment. The algorithm was applied to simulate SUHII based on identified key variables. Sensitivity analyses were conducted to identify the most SUHI-related factors. Hyperparameter tuning optimised the model's performance, and the results were calibrated to improve prediction accuracy.

Lastly, the LCZ method was integrated to explore the relationship between urban morphologies and SUHII, thus providing insights into how specific urban forms impact heat distribution. By comparing SUHII with LCZ characteristics, this method allowed for the identification of mitigation measures tailored to different urban morphologies, thus enhancing the potential of effective UHI mitigation strategies.



Figure 1. Flowchart of the methodology used to evaluate UHI effects.

2.1. Investigation Area

Turin has historically played a significant industrial role in Italy, particularly as a major hub for automotive manufacturing, with Fiat's production facilities being prominent. This industrial legacy has profoundly influenced the city's urban landscape and contributed to its economic growth. In recent years, Turin has undergone substantial transformation, with numerous regeneration initiatives aimed at revitalising the urban areas once dominated by industry. These interventions have focused on repurposing former industrial sites and integrating green spaces, and they have adopted various strategies to improve liveability, reduce pollution, and promote cultural and recreational amenities, signalling a shift towards a more sustainable and resilient urban environment [25-27].

A key example of these regeneration efforts is the former Teksid area, located in the northern part of the city (as shown in Figure 2). The selection of this site was driven by the need to investigate UHI dynamics within the broader framework of urban regeneration. The Teksid area has undergone extensive redevelopment since its closure in 1992, aligning with the city's overall efforts to revitalise former industrial sites and promote sustainable urban growth [28,29].



Figure 2. Technical cartography plant (1955–1969), City of Turin.

Focusing on the specific Teksid area allows for a detailed investigation of how previous land uses (Figure 3a) and subsequent post-industrial regeneration efforts (Figure 3b) influence local climate patterns and Urban Heat Island (UHI) effects.



Figure 3. (a) Former industrial Teksid area in Turin, 1920 (Immagini del cambiamento, archivio CDS5, https://areeweb.polito.it/imgdc/schede/PD04.html). (b) Regeneration program in Spina 3. Google Cartographical Data, 2018.

2.2. Data Collection and Pre-Processing

The data for the city of Turin were organised into a comprehensive geo-dataset based on the following sources:

- Buildings, rivers, parks, greenings, public spaces, squares, parking areas, roads, etc.: BDTRE (Banca Dati Territoriale di Riferimento degli Enti, in Italian) 2018, https://www.geoportale.piemonte.it/geonetwork/srv/ita/catalog.search#/search?any=BDTRE, and the municipal technical map of Torino CTC 1999 (Carta Tecnica Comunale, in Italian), http://geoportale.comune.torino.it/geocatalogocoto/?sezione=catalogo; EAGLE (https://eagle-science.org/about/).
- Land use: Corine land cover 2000 and 2018: https://land.copernicus.eu/en/products/corine-land-cover/cha-2000-2006; https://land.copernicus.eu/en/products/corine-land-cover/clc2018.
- Population and families in 2001, 2011, and 2021 from the National Institute of Statistics (ISTAT in Italian): https://www.istat.it/notizia/aggiornamento-basi-territoriali-2021-2/.
- Climate data: weather station of Politecnico di Torino collected by the LivingLAB: https://smartgreenbuilding.polito.it/; other weather stations in Turin: https://www.arpa.piemonte.it/rischi_naturali/snippets_arpa_graphs/map_meteoweb/?rete=st azione_meteorologica.

Satellite image collection was facilitated through the "STAC API Browser" plugin in QGIS [30]. The pre-processing phase involved using the "Semi-Automatic Classification Plugin" (SCP), which handled radiometric, geometric, and atmospheric correction as well as cloud masking tasks [31,32]. The SCP greatly enhances the accuracy, reliability, and interpretability of raw satellite imagery.

The selected images (in Table 1) span the period when the industrial landscape was dominant, starting from 2000 to 2001, which provides a historical baseline. To capture recent urban regeneration initiatives in the pre-COVID-19 era, images from 2018 were used. This minimises anomalies due to the pandemic's impact on human activities, with both years sharing similar climatic conditions. Table 1 highlights the comparable air temperatures and cloud cover for these years, thus strengthening the analysis's comparability. Additionally, seasonal variation was considered by selecting typical days in winter, summer, and transitional seasons to ensure methodological rigour.

Table 1. Selection of Landsat 7 (for typical days in 2000 and 2001) and Landsat 8 (for typical days in 2018) satellite images for the City of Turin.

| Landsat Product ID | Date | Time | Cloud Cover | Cell size m | Season | Air Temp. °C |
|--|------------------|-------|----------------|----------------|------------|-----------------|
| LC08_L2SP_195029_20180822_20200831_02_T1 | 11 August 2018 | 10:16 | 0.31 | 30 | Summer | 26.2 |
| LC08_L2SP_195029_20180211_20200902_02_T1 | 22 February 2018 | 10:17 | 0.23 | 30 | Winter | 3.8 |
| LC08_L2SP_195029_20180416_20200901_02_T1 | 16 April 2018 | 10:16 | 0.30 | 30 | Mid-season | 17.9 |
| LE07_L1TP_194029_20010824_20200917_02_T1 | 24 August 2001 | 09:59 | 0.04 | 30 | Summer | 26.1 |
| LE07_L1TP_195029_20001218_20211122_02_T1 | 18 December 2000 | 10:07 | 0.05 | 30 | Winter | 2.1 |
| LE07_L1TP_195029_20010527_20200917_02_T1 | 27 May 2001 | 10:07 | 0.10 | 30 | Mid-season | 23.2 |

2.3. Candidate Variables

A sensitivity analysis in the pre-modelling phase identified candidate variables for subsequent modelling, with the formulas and references in Table 2. Most variables were computed using the "Raster Calculator" tool in QGIS, while others, like the Sky View Factor and building density, were derived from BDTRE and processed with QGIS plugins [33,34].

To automate the analysis, Python scripts in the QGIS Python console were used to compute each variable in Table 2. This involved six Landsat images from three seasonal days in 2001 and 2018, covering all census sections, and 30 m × 30 m cells (144,826 cells total) in Turin. The scripts in Python enable the automatic execution by modifying file paths for Landsat bands; these scripts are available at the link: https://ldrv.ms/b/c/8e7ec8768139e3da/EQ likuGRxhNrBo6ArS2j7sBJgMnukcpl gz74R4x H9i7A?e=r9KvJj (accessed on 20 July 2024).

For weather station data, Kriging interpolation was performed using the "Smart Map" plugin in QGIS [35] to fill gaps and create continuous spatial representations, which is recognised as an effective multiquadric method for unbiased interpolation [36,37]. Additionally, the Kernel Density Estimator in ArcGIS Spatial Analyst represented the Built Coverage Ratio (BCR) based on spatial concentration.

The integration of various geographical raster and shapefiles resulted in non-uniform spatial properties, thus necessitating a harmonisation process through reprojection and resampling techniques for modelling consistency. This produced a unified geo-package of geo-datasets, thus enabling seamless integration into the analysis. Spatial representations of candidate variables are shown in Figures 4 and 5 as examples (2 out of the 102 raster outputs are part of the geo-dataset).

| Category | Variables | Formula | Reference |
|------------|---|---|-----------|
| | Normalised Difference Vegetation Index (NDVI) | (NIR-VIS)/(NIR + VIS) | [38-40] |
| | Proportion Vegetation Index (PVI) | (NDVI-NDVImin)/(NDVI-NDVImin) | [38-40] |
| | Normal Difference Water Index (NDWI) | (GREEN-NIR)/(GREEN + NIR) | [41,42] |
| Land Cover | Normal Difference Moisture Index (NDMI) | $(NIR_{short} - SWIR)/(NIR_{short} + SWIR)$ | [38,39] |
| | Albedo | $(\rho \text{NIR} + \rho \text{SWIR})/2(1 - \rho \text{RED})$ | [43,44] |
| | Emissivity | (0.004·PVI) + 0.986 | [43,44] |
| | Solar Reflectance Index (SRI) | $[(SR-SR_{min})/(SR_{max}-NDVI_{min})] \cdot 100$ | [45] |
| | Land Surface Temperature (LST) | $Tc = (K2/(ln (K1/L\gamma + 1))) - 273.15$ (*) | [46] |
| | Buildings and Human Activities | Kernel Density Estimation QGIS tool | [33] |
| Urban | Normalised Difference Built-Up Index (NDBI) | (SWIR – NIR)/(SWIR + NIR) | [47] |
| Geomorphol | Sky View Factor (SVF) | SAGA QGIS tool | [34,48] |
| ogy | Building Coverage Ratio, Building Density | BCR, BD | [14] |
| | Building Volume and Surface-to-Volume ratio | V, S/V | [14] |
| | Relative Humidity | Weather stations' massurements | |
| Weather | Wind Speed and Direction | (Vriging interpolation in Smort Man | [25 27] |
| Stations | Solar Irradiation | (Kriging interpolation in Smart Map | [33–37] |
| | Air Temperature | QGIS tool) | |

Table 2. Candidate variables for enhanced modelling of SUHI dynamics.

^(*) K2, K1, and L_{γ} must be retrieved from Landsat 7 and 8 imagery metadata.

Figure 4 present the Kernel analysis of the BCR for Turin in 2001 and 2018. Higher BCR values indicate denser built-up areas. Despite differences in data accuracy from BDTRE cartographies, there is a clear increase in the BCR, especially in peripheral areas.

Figure 5 displays the NDVI, calculated from satellite imagery using NIR and red wavelengths (Table 2). In 2001, Turin's NDVI was near 0, indicating minimal vegetation. By 2018, urban regeneration significantly increased the vegetation, with NDVI values approaching 1.



Figure 4. Maps of the BCR in Turin (m^2/m^2) in the years (a) 2001 and (b) 2018. Grid UTM Zone 32N.



Figure 5. Maps of the NDVI in August in the years (a) 2001 and (b) 2018. Grid UTM Zone 32N.

2.4. Evaluation of the Surface Urban Heat Island Intensity (SUHII)

This study adopted an approach that used the LST to automatically differentiate between urban and suburban areas, thus avoiding reliance on predefined boundaries, as in traditional methods cited in the introduction. SUHII was calculated by normalising the local LST value using the formula [46]

$$SUHII = \frac{LST - LSTmean}{LSTstdev}$$

A positive SUHII indicates a warmer LST than average, thus highlighting intensified urban areas, while a negative SUHII suggests a cooler LST, typically in peripheral regions. This method allowed for context-independent comparisons of variations across different landscapes.

Figure 6 presents the SUHII derived from satellite imagery of Turin and its surroundings. SUHII is more pronounced in areas with high industrial activity, dense buildings, and minimal vegetation (southeast of Turin). In contrast, areas undergoing urban regeneration (northwest), such as the ex-industrial Teksid area, show cooling effects, indicating UHI mitigation in the 2018 image.



Figure 6. SUHII elaborated from satellite imagery in August: (a) 2001; (b) 2018.

2.5. Correlation Analysis with SUHII

The Pearson correlation coefficient r was used to evaluate the linear relationship between two datasets, such as SUHII and a variable X:

$$r = \frac{\sum(SUHII - SUHII_{avg}) \cdot \sum(X - X_{avg})}{\sqrt{\sum(SUHII^2 - SUHII_{avg}^2)} \cdot \sqrt{\sum(X^2 - X_{avg}^2)}}$$

In this study, r was calculated for a preliminary sensitivity analysis across all 30 m × 30 m cells and census sections in Turin. However, Pearson's coefficient only captures linear relationships, which may not fully represent the complexity of the urban environment. To address nonlinear relationships, a Random Forest model was employed, offering greater flexibility in detecting more complex patterns between SUHII and other variables.

2.6. Machine Learning Modelling: Random Forest Regression

This section presents the model developed to calculate SUHII using a data-driven approach based on the Random Forest (RF) ML algorithm. The RF model was selected due to its ability to manage large datasets and capture complex, non-linear relationships between variables within an urban environment, which is facilitated by the ArcGIS Pro plugin [35]. Prior to integrating the variables into the RF algorithm, hyperparameter tuning was performed using libraries, such as Optuna and Scikit-learn [49]. This process systematically optimised the model's performance by adjusting the hyperparameters (e.g., the variable range, leaf size, and tree depth), thus ensuring that the algorithm operated efficiently.

The geo-package was organised with SUHII as the target variable, while other data and calculated variables served as predictors. The dataset was split into training (80%) and testing (20%) sets. Initially, the RF regression model was trained to learn the relationships between predictor variables and SUHII. The trained model was then validated using the test dataset, with performance assessed through various metrics, such as the Mean Squared Error (MSE), the Root Mean Squared Error (RMSE), and R-squared. To further enhance model accuracy and reliability, a calibration phase was undertaken by adjusting the input parameters and variables. The final model was subsequently used to simulate SUHII across past, present, and future scenarios.

Figure 7 illustrates the operational framework of the model. Beginning with input data organised in a geo-package, the model employs ML algorithms to simulate SUHII by combining variables and iteratively reducing the error between observed and predicted

SUHII values. The RF algorithm generates multiple decision trees, with each using different data combinations. Each tree acts as a decision-making unit by considering certain variables, including the following.

- Leaf size: the minimum number of variables required to stop tree splitting.
- Tree depth: the maximum number of levels a decision tree can reach.

The final prediction is made by averaging the results from all decision trees. A larger number of trees in the forest enhances the accuracy and robustness of the prediction.



Figure 7. Random Forest regression modelling (authors' own elaboration).

The "Forest-Based Classification and Regression" tool in ArcGIS Pro [49] was used to implement the RF algorithm on a standard personal computer, enabling the creation of training and test datasets and the development of a predictive model for large urban datasets. The model's output was compared with SUHII derived from satellite imagery, and a residual analysis was performed to identify discrepancies.

2.7. The UHI Effects of LCZs and Settlement Morphologies

This section explores the application of the qualitative LCZs method, as defined by Stewart and Oke [9], to the settlement morphologies ("morfologie insediative," m.i.) outlined in the Regional Landscape Plan (RLP) for the City of Turin. The goal was to quantitatively assess the similarities between LCZ and m.i. characteristics in relation to SUHII values.

In the initial phase, LCZ types uncommon in Italian cities, such as LCZ 1 (high-rise business districts) and LCZ 7 (informal settlements), were excluded. Thermal, radiative, and metabolic properties were then assigned to each settlement morphology. These properties were defined as follows:

- Thermal properties, quantified by surface admittance (the ability of a surface to exchange heat, influenced by materials, orientation, moisture, and wind);
- Radiative properties, indicated by surface albedo (the ratio of reflected to incident solar radiation, affected by surface colour, roughness, and moisture);
- Metabolic properties, representing anthropogenic heat output (annual average heat flux from human activities and fuel combustion).

The analysis compared the LCZ and m.i. characteristics with SUHII values, proposing mitigation strategies based on their thermal, radiative, and metabolic properties. The objective was to determine whether the SUHII model, combined with LCZs and m.i., could be used to quantify the effects of mitigation interventions and inform more tailored urban planning strategies.

3. Results

3.1. Linear Correlation Analysis Between SUHII and Urban Variables

Table 3 summarises the results from averaging 1000 SUHII values, effectively minimising the influence of anomalous data. Variables with low correlation, such as heat loss surfaces and building heights, are excluded.

The analysis indicates a positive correlation between SUHII and several variables: the Normalised Difference Built-up Index (NDBI), indicating built-up density; the Normalised Difference Water Index (NDWI), representing water content; building density (BD); and building volume (V).

Conversely, negative correlations are observed with vegetation presence (NDVI), vegetation considering atmospheric variations (PVI), moisture (NDMI), surface emissivity (EM), albedo (ALB), solar reflectance and thermal emission capacity (SRI), and the Sky View Factor (SVF). Correlations for SVF, BD, and V are notably low.

These correlations are specific to the City of Turin and this case study; however, the methodology is applicable to other urban areas.

Table 3. Application field and linear correlation of the average variables with SUHII (for groups of 1000 data; in red negative correlation, in blue positive correlation).

| | SUHII | NDVI | PVI | NDBI | EMISSIVITY | ALBEDO | SRI | NDMI | NDWI | SVF | BD | \mathbf{V} |
|-----------------|----------|-------|-------|-------|------------|--------|-------|-------|-------|-------|------|--------------|
| minimum | -0.43 | -0.09 | 0.67 | -0.41 | 0.9887 | 0.08 | 25.04 | 0.05 | -0.29 | 0.62 | 0.03 | 2839.00 |
| average | 1.32 | 0.05 | 0.72 | -0.18 | 0.9889 | 0.12 | 25.13 | 0.18 | -0.19 | 0.74 | 0.19 | 3800.08 |
| median | 1.56 | 0.01 | 0.71 | -0.14 | 0.9888 | 0.11 | 25.09 | 0.14 | -0.17 | 0.73 | 0.20 | 3575.28 |
| maximum | 3.05 | 0.25 | 0.79 | -0.05 | 0.9891 | 0.17 | 25.27 | 0.41 | -0.09 | 0.94 | 0.30 | 8053.86 |
| Pearson's corre | lation r | -0.96 | -0.95 | 0.97 | -0.95 | -0.92 | -0.96 | -0.97 | 0.92 | -0.47 | 0.26 | 0.18 |

Figure 8 illustrates the relationship between SUHII and the variables listed in Table 4, confirming the direction of the Pearson correlations. The overall trend is well-defined and supported by a high coefficient of determination (R²). However, exceptions are observed for very low and very high SUHII values, where other variables may influence UHI effects.





Figure 8. Line fit plots of SUHII-related variables.

|--|

| Season | Number of Trees | Number of Randomly Sampled Variables | Leaf Size | Tree Depth Range |
|-----------------|--------------------|---|--------------|---------------------|
| Summer 2018 | 200 | 5 | 1 | 31 |
| Mid-season 2018 | 59 | 5 | 3 | 13 |
| Winter 2018 | 60 | 5 | 5 | 25 |
| Summer 2001 | 59 | 4 | 1 | 39–50 |
| Mid-season 2001 | 164 | 4 | 1 | 38-44 |
| Winter 2001 | 97 | 4 | 2 | 16 |

The independence of the variables was evaluated using multilinear regression. As shown in Figure 9, only the NDVI, NDBI, albedo, and PVI had *p*-values below 0.05. The regression model achieved a high coefficient of determination ($R^2 = 0.9872$), indicating a strong fit.



Figure 9. Multilinear regression of SUHII.

3.2. SUHII Modelling with Random Forest Algorithm

The RF algorithm was optimised using the Optuna tool, with the results shown in Table 4. Key hyperparameters—the number of trees, the sampled variables, the leaf size, and the tree depth—were fine-tuned to enhance model accuracy. In 2001, 4 variables were sampled, and in 2018, 5 were sampled, from over 17 in total. The number of trees and the tree depth varied to capture the model's complexity, thus ensuring optimal performance in both training and testing phases.

Table 5 presents the performance of the RF model. MSE and RMSE values, all under 0.08 and 0.283, indicate minimal prediction errors. High R^2 values (0.853 to 0.997) confirm strong model accuracy, while *p*-values < 0.05 demonstrate statistical significance across seasons and years, thus ensuring robust SUHII predictions.

| Season | MSE | RMSE | \mathbb{R}^2 | <i>p</i> -Value |
|-----------------|-------|-------|----------------|-----------------|
| Summer 2018 | 0.023 | 0.152 | 0.997 | 0.001 |
| Winter 2018 | 0.021 | 0.145 | 0.991 | 0.002 |
| Mid-season 2018 | 0.080 | 0.283 | 0.948 | 0.001 |
| Summer 2001 | 0.045 | 0.212 | 0.994 | 0.001 |
| Winter 2000 | 0.011 | 0.105 | 0.853 | 0.002 |
| Mid-season 2001 | 0.017 | 0.130 | 0.990 | 0.001 |

Table 5. MSE, RMSE, R², and *p*-value of data-driven model with RF algorithm.

Table 6 shows that the mean residuals are close to zero, indicating accurate predictions by the RF model with minimal systematic error. The low standard deviations across seasons reflect consistent predictive performance.

Table 6. Residuals analysis (mean and standard deviation).

| Season | Mean Residuals | Standard Deviation of Residua | |
|-----------------|-------------------|-------------------------------|--|
| Summer 2018 | -0.00041 | 0.0786 | |
| Winter 2018 | -0.00020 | 0.0756 | |
| Mid-season 2018 | -0.00004 | 0.2378 | |
| Summer 2001 | -0.00082 | 0.1052 | |
| Winter 2000 | -0.00013 | 0.0793 | |
| Mid-season 2001 | -0.00026 | 0.0682 | |

Table 7 highlights that in 2001, the topography (DTM), built-up areas (NDBI), and Solar Irradiation were the main factors influencing SUHII. By 2018, the built environment gained greater importance, with the BCR (Building Coverage Ratio) the most influential factor, followed by DTM, NDMI, and the Sky View Factor, indicating increasing urbanisation and its effects on SUHII.

| | 2001 | | | 2018 | |
|------|-----------------------|---------|------|-------------------|----------|
| Rank | Variable | Score | Rank | Variable | Score |
| 1 | DTM | 6102.32 | 1 | BCR | 18023.83 |
| 2 | NDBI | 5555.31 | 2 | DTM | 12137.12 |
| 3 | Solar Irradiation | 4327.89 | 3 | NDMI | 11733.99 |
| 4 | NDMI | 4197.91 | 4 | Sky View Factor | 5901.33 |
| 5 | Albedo | 3251.13 | 5 | NDVI | 4767.62 |
| 6 | Air temperature | 2824.21 | 6 | Emissivity | 4509.74 |
| 7 | NDVI | 2696.72 | 7 | NDWI | 4488.35 |
| 8 | Emissivity | 1950.37 | 8 | Wind speed | 4368.62 |
| 9 | SRI | 1801.58 | 9 | S/V Ratio | 3173.45 |
| 10 | Wind direction | 1575.72 | 10 | Wind direction | 2875.59 |
| 11 | NDWI | 1282.06 | 11 | Relative Humidity | 2757.80 |
| 12 | Wind speed | 1090.55 | 12 | Air Temperature | 2680.04 |
| 13 | Air Relative Humidity | 1035.66 | 13 | Solar Irradiation | 2603.21 |
| 14 | - | - | 14 | SRI | 2572.03 |
| 15 | - | - | 15 | Albedo | 2151.66 |

Table 7. The weight of variables for the UHII in 2001 and 2018.

3.3. Assessing SUHII in the Ex-Industrial Area of Teksid

Analysing SUHII outputs in the Teksid ex-industrial area before and after urban regeneration reveals the effectiveness of the interventions. Figure 10 shows SUHII



predictions for different seasons in 2001 and 2018 at the district level generated by the RF model. A marked decrease in SUHII values was observed in 2018, especially during the summer, suggesting that the regeneration efforts had a significant cooling effect.

Figure 10. Comparison of SUHII in the different seasons of 2001 and 2018 in the ex-Teksid area.

Table 8 compares SUHII variations between 2001 and 2018 across different scales, showing a substantial reduction in 2018. This decreases, especially during summer (-0.944 SUHII), suggests a strong cooling effect from the interventions. However, the reduction is less pronounced in winter (-0.544, heating systems turned on), reflecting the complexity of UHI dynamics and the need for season-specific mitigation strategies.

| Variable | Radius's Distance from Intervention Area [m] | Summer | Spring | Winter | Mean |
|----------------------------------|---|--------|--------|--------|--------|
| UHII (ex-Teksid area) | 0 | -0.944 | -1.037 | -0.544 | -0.841 |
| UHII (district area) | 500 | -0.413 | -0.524 | -0.476 | -0.471 |
| UHII (Turin's municipal area) | within administrative borders | -0.500 | -0.849 | -0.492 | -0.614 |

In Table 9, the analysis of percentage changes in key SUHII variables (NDMI, NDVI, and albedo) between 2001 and 2018 highlights the fact that the NDVI notably increased across Turin, particularly in the ex-Teksid area, with rises of +22%, +17%, and +11% in spring, reflecting successful urban regeneration.

The albedo and the NDMI, representing surface properties, also improved citywide, with more pronounced changes during winter. Negative NDMI values in spring indicate lower rainfall in 2018. Overall, these results demonstrate the positive effects of urban interventions on reducing UHIs through enhanced vegetation and surface characteristics.

| Variable | Scale | Summer | Spring | Winter | Mean |
|----------|-----------|---------|---------|---------|---------|
| | ex-Teksid | +19.46% | +21.79% | +8.23% | +16.49% |
| NDVI | district | +6.41% | +16.61% | +7.61% | +10.21% |
| | Turin | +6.17% | +11.09% | +1.53% | +6.26% |
| | ex-Teksid | +10.07% | -7.41% | +17.89% | +6.85% |
| NDMI | district | +6.77% | -4.27% | +17.69% | +6.73% |
| | Turin | +8.44% | -12.43% | +17.39% | +4.47% |
| | ex-Teksid | +3.09% | +0.63% | +14.86% | +6.19% |
| ALBEDO | district | +1.18% | +0.11% | +13.46% | +4.92% |
| | Turin | +3.72% | +0.23% | +15.40% | +6.30% |

Table 9. Variation (2001–2018) of key variables contributing to UHIs.

Figure 11 illustrates the NDVI map, graphically revealing the increase in vegetation and greenery within the ex-industrial Teksid area in 2018, with the newly established Dora Park prominently located at the centre.





In Figure 12, the Dora Riparia River is clearly visible in both years, alongside the new parks established in 2018. Moisture, whether in soil, vegetation, or air, provides a cooling effect that mitigates UHI impacts.



[0.3;1] Healty and moistened vegetation

Figure 12. The NDMI during mid-season in 2001 and 2018 in the ex-Teksid area.

Figure 13 shows albedo differences between 2001 and 2018. In 2001, darker colors indicate low reflective areas. By 2018, urban regeneration resulted in increased solar reflectance, represented by lighter colors.



Figure 13. Albedo during summer in 2001 and 2018 in the ex-Teksid area.

Figure 14 indicates a significant decrease in SUHII across the entire municipal territory in 2018. An average decrease of -0.614 was observed when considering all three seasons (summer, winter, and spring/autumn).



Figure 14. The model of Surface Urban Heat Island Intensity (SUHII) in 2001 and 2018 using the Random Forest regression.

3.4. The Evaluation of SUHII and Its Mitigation Interventions in Local Climate Zones

In this section, the UHI effects are compared with the characteristics of the LCZs and typical urban settlements for the City of Turin [50].

Table 10 provides average values for surface admittance, albedo, and anthropogenic heat output for the City of Turin [9]. The LCZs consider typical urban areas with low-rise (1–3 stories, height < 9 m), mid-rise (4–9 stories, height 9–24 m), and high-rise (10+ stories,

height > 24 m) buildings. The albedo of asphalt surfaces typically ranges from 0.15 to 0.30, although studies in Italy report values between 0.05 and 0.20 [51]; as such, a value of 0.10 was considered [52]. For asphalt surfaces, such as those at airports and on roads, a value of 0.10 was used, while mining and extractive areas were assigned a value of 0.225.

Some LCZs are not present in the urban area of the City of Turin, and they were neglected in this study (in grey).

| Table 10. Average values of surface admittance, albedo, and anthropogenic heat output; in grey are |
|--|
| the LCZs not identified in the Metropolitan City of Turin. |

| | Surface Admit- tance (J m ⁻² s ^{-1/2} K ⁻¹) | | | Surface Albedo | | | Anthronoconic Usat | |
|----------------------------|---|------|---------|----------------|------|--------------|--------------------|--|
| Local Climate Zone | | | Average | Surface | | | Antihopogenic meat | |
| | | | - | (- |) | | | |
| LCZ 1 compact high-rise | 1500 | 1800 | | 0.10 | 0.20 | | 50 300 | |
| LCZ2 compact mid-rise area | 1500 | 2000 | 1850 | 0.10 | 0.20 | 0.15 | >75 | |
| LCZ 3 compact low-rise | 1200 | 1800 | 1500 | 0.10 | 0.20 | 0.15 | >75 | |
| LCZ 4 open high-rise area | 1400 | 1800 | 1600 | 0.12 | 0.25 | 0.185 | >50 | |
| LCZ 5 open mid-rise area | 1400 | 2000 | 1700 | 0.12 | 0.25 | 0.185 | >25 | |
| LCZ 6 open low-rise area | 1200 | 1800 | 1500 | 0.12 | 0.25 | 0.185 | >25 | |
| LCZ 7 lightweight low-rise | 800 | 1500 | | 0.15 | 0.35 | | >35 | |
| LCZ 8 large low-rise area | 1200 | 1800 | 1500 | 0.15 | 0.25 | 0.20 | >50 | |
| LCZ 9 sparsely built area | 1000 | 1800 | 1400 | 0.12 | 0.25 | 0.185 | >10 | |
| LCZ 10 heavy industry | 1000 | 2500 | 1750 | 0.12 | 0.20 | 0.16 | >300 | |
| LCZ A dense trees | unk | nown | | 0.10 | 0.20 | | 0 | |
| LCZ B scattered trees | 1000 | 1800 | 1400 | 0.15 | 0.25 | 0.20 | 0 | |
| LCZ C bush, scrub | 700 | 1500 | | 0.15 | 0.30 | | 0 | |
| LCZ D low plants | 1200 | 1600 | 1400 | 0.15 | 0.25 | 0.20 | 0 | |
| LCZ E bare rock or paved | 1200 | 2500 | 1850 | 0.15 | 0.30 | 0.10 */0.225 | 0 | |
| LCZ F bare soil or sand | 600 | 1400 | | 0.20 | 0.35 | | 0 | |
| LCZ G water | 1 | 500 | | 0.02 | 0.10 | | 0 | |

* Typical value for asphalt pavements in Italy.

Table 11 joins the characteristics of the LCZs with the settlements' morphologies m.i. from the Regional Landscape Plan (RLP) of Piedmont Region.

Table 11. Association between the settlements' morphologies ("m.i." in Italian) and the LCZs.

| Association of Settlement Morphologies with Local Climate Zones | | | | | | |
|--|---|--|--|--|--|--|
| Settlements' Morphologies by RLP ("Morfologie Insediative m.i." in Italian) | Local Climate Zone (LCZ) | | | | | |
| (m.i. 1)—Consolidated urban areas of major centres | LCZ 2—Compact mid-rise area | | | | | |
| (m.i. 2)—Consolidated urban areas of minor centres | LCZ 3—Compact low-rise area | | | | | |
| (m.i. 3)—Urban fabrics outside of urban centres | LCZ 4—Open high-rise area | | | | | |
| (m.i. 4)—Discontinuous suburban fabrics | LCZ 5—Open mid-rise area | | | | | |
| (m.i. 5)—Organised specialised settlements | LCZ 10—Heavy industry | | | | | |
| (m.i. 6)—Dispersed areas, mainly residential | LC6—Open low-rise area | | | | | |
| (m.i. 7)—Dispersed areas, mainly specialised | LC8—Large low-rise area | | | | | |
| (m.i. 8)—Specialised islands | LCZ E—Bare rock or paved | | | | | |
| (m.i. 9)—Infrastructural complexes | LCZ E—Bare rock or paved | | | | | |
| (m.i. 10)—Rural areas in plains or hills | LCZ 9—Sparsely built area | | | | | |
| (m.i. 11)-Systems of rural nuclei in plains, hills, low mountains | LCZ 9—Sparsely built area | | | | | |
| (m.i. 12)—Mountain villages | LCZ B-Scattered trees + LCZ 9-sparsely built area | | | | | |

| (m.i. 13)—Rural areas in mountains or hills with scattered and dispersed buildings | LCZ B—Scattered trees + LCZ 9—sparsely built area |
|--|---|
| (m.i. 14)—Rural areas in plains | LCZ D—Low plants |
| (m.i. 15)—Mountain pasturelands and high-altitude rural settle- ments | LCZ D—Low plants + LCZ 9—sparsely built area |

Table 12 summarises the average characteristics of surface admittance, surface albedo, and anthropogenic heat output for different m.i.s. Specific land uses—including large commercial structures, hospitals, prison areas, logistics hubs, motorway infrastructures, sports facilities, and cemeteries—exhibited distinct characteristics associated with various LCZs.

Table 12. Association between settlement morphologies and the characteristics of LCZs.

| Note | Asso LCZ and | ciation of l m.i. by RLP | Surface Admittance | Surface Albedo | Anthropo- genic Heat Output |
|--|-----------------|-----------------------------|---|-------------------|-----------------------------------|
| | | | (J m ⁻² s ^{-1/2} K ⁻¹) | (-) | (W m ⁻²) |
| | m.i. 1 | LCZ 2 | 1850 | 0.15 | 75 |
| | m.i. 2 | LCZ 3 | 1500 | 0.15 | 75 |
| | m.i. 3 | LCZ 4 | 1600 | 0.185 | 50 |
| | m.i. 4 | LCZ 5 | 1700 | 0.185 | 25 |
| * With refineries (former m.i. 8) | m.i. 5 * | LCZ 10 | 1750 | 0.16 | 300 |
| | m.i. 6 | LCZ 6 | 1500 | 0.185 | 25 |
| * With large commercial structures, purification plants, hospitals, military and prison areas (former m.i. 8), ware- houses, rail junctions, logistics hubs, and nodes (former m.i. 9) | m.i. 7 * | LCZ 8 | 1500 | 0.20 | 50 |
| * Contains only mining areas/extraction plants | m.i. 8 * | LCZ E | 1850 | 0.225 | 0 |
| * Contains runways (albedo value variation *) | m.i. 8 * | LCZ E * | 1850 | 0.10 * | 0 |
| * With energy production systems (e.g., photovoltaic sys- tems) | m.i. 9 * | LCZ E | 1850 | 0.225 | 0 |
| * With motorway infrastructures (change in albedo value *) | m.i. 9 * | LCZ E * | 1850 | 0.10 * | 0 |
| * With theme parks, campsites, sports facilities, golf clubs, cemeteries (former m.i. 8) | m.i. 10 * | LCZ 9 | 1400 | 0.185 | 10 |
| | m.i. 11 | LCZ 9 | 1400 | 0.185 | 10 |
| | m.i. 12 | LCZ B + LCZ 9 | 1400 | 0.1925 | 10 |
| | m.i. 13 | LCZ B + LCZ 9 | 1400 | 0.1925 | 10 |
| | m.i. 14 | LCZ D | 1400 | 0.20 | 0 |
| | m.i. 15 | LCZ D + LCZ9 | 1400 | 0.1925 | 10 |

* For some specific categories of m.i.s, the associations with LCZs were re-defined, as indicated in the column Note.

Figure 15 shows that for the urban area, it is possible to distinguish the LCZ 2 (compact mid-rise), the LCZ 3 (compact low-rise), and the LCZ 4 (open high-rise); in the suburbs, it is possible to distinguish the LCZ 9 (sparsely built), the LCZ 10 (heavy industry), and the LCZ E (bare rock or paved).



Figure 15. Cartographic representation of LCZs' and urban settlements' m.i.s for the city of Turin and its surroundings (as specified in Table 12).

Figure 16 compares anthropogenic heat output from LCZs with SUHII values for August 2021, revealing clear correspondences. These are particularly evident in productive areas, such as the industrial zone in the southwest of Turin (light-green circles), the northeast (yellow circle), and the Teksid area (light-blue circle).



Figure 16. Comparison between the results of the SUHII model in August 2021 (on the left) and the anthropogenic heat output of Local Climate Zones (on the right).

Settlement morphologies requiring priority for UHI mitigation were identified based on thermal, radiative, and metabolic properties. The SUHII analysis in Figure 16 shows the highest surface admittance in consolidated urban fabrics (m.i. 1), specialised islands (m.i. 8), infrastructure complexes (m.i. 9), and areas outside of the urban centre (m.i. 4). Lower albedo values were found in specialised islands (m.i. 8), infrastructure complexes (m.i. 9), and consolidated fabrics (m.i. 1, m.i. 2). The highest anthropogenic heat output was recorded in organised specialised settlements (m.i. 5).

Table 13 establishes a priority order for UHI mitigation, aiding energy governance at both urban and building scales.

| Priority Order | Thermal Properties | Radiative Properties | Metabolic Properties |
|-------------------|--|--|--|
| 1 | Consolidated urban areas of major centres (m.i. 1) | Specialised islands (m.i. 8) * | Organised specialised settlements (m.i. 5) |
| 2 | Specialised islands (m.i. 8) * | Infrastructural complexes (m.i. 9) * | Consolidated urban areas of major and minor centres (m.i. 1, m.i. 2) |
| 3 | Infrastructural complexes (m.i. 9) * | Consolidated urban areas of major and minor centres (m.i. 1, m.i. 2) | Urban fabrics outside of centres (m.i. 3) |
| 4 | Organised specialised settlements (m.i. 5) * | Organised specialised settlements (m.i. 5) * | Dispersed areas, mainly specialised (m.i. 7) |
| 5 | Discontinuous suburban fabrics (m.i. 4) | | |

Table 13. Settlement morphologies with worse thermal, radiative, and metabolic properties (in a priority order for UHI-mitigation interventions).

The type of intervention to mitigate an UHI, however, greatly depends on the type of territorial context. The LCZ approach recommends targeting thermal, radiative, and metabolic properties and tailoring strategies to specific settlement morphologies. Table 14 outlines some of these interventions.

Table 14. Interventions to mitigate the UHI based on improving thermal, radiative, and metabolic properties of settlement morphologies.

| Properties (To Improve | Settlement Morphologie | s Types of Interventions |
|---------------------------|---|---|
| Thermal properties | Consolidated urban areas of major centres (m.i.1) Specialised islands (m.i. 8) * Infrastructural complexes (m.i. 9) * Organised specialised set tlements (m.i.5) * Discontinuous suburban fabrics (m.i. 4) | Use of cool materials with a high Solar Reflectance Index (SRI) for roofs and pavements; they provide cooler surfaces by combining a high albedo with a high thermal emissivity in the infrared spectrum. Green roofs, or rooftop gardens, which provide shadows and reduce the temperatures of roofs and the surrounding air. Planting trees and increasing vegetation coverage. Trees and vegetation lower surface and air temperatures through shading and evapotranspiration; shaded surfaces can be cooler by 11–25 °C compared to peak temperatures of unshaded materials; evapotranspiration, alone or in combination with shading, can help reduce peak summer temperatures by 1–5 °C (EPA - US). Urban cooling systems, like water parks, fountains, or evaporative surfaces, contribute to cooling the surrounding environment. Use of permeable materials that allow water to infiltrate the soil and contribute to cooling through evapotranspiration and more water content; they also drain excess water during heavy rainfall events, known as "water bombs". Promote passive cooling strategies that reduce energy use inside of buildings (e.g., natural ventilation, evaporative cooling, geothermal cooling). Adopt building and urban certification systems that ensure minimal and optimal use of energy considering the climatic conditions and the best technologies on the market in accordance with environmental protocols in order to achieve higher certification scores (ITACA Urban scale certification, GBC Historic Building Protocol, LEED® Protocol). |
| Radiative properties | Specialised islands (m.i. 8) * Infrastructural complexes (m.i.9) * Consolidated urban areas of major and minor cen- tres (mm ii. 1, 2) | High solar reflectance or albedo materials for the external surfaces of buildings, such as roofs, walls, and pavements, with high albedo combined with a high thermal emissivity in the infrared spectrum. Adopting building and urban certification systems that ensure minimal and optimal use of energy considering the climatic conditions and the best technologies on the market in accordance with environmental protocols in order to achieve higher certification scores (ITACA Urban scale certification GBC Historic Building Protocol LEED® Protocol) |

| | Organised specialised set- | |
|------------|----------------------------|--|
| | tlements (m.i. 5) * | |
| | | • Provide dedicated roads (non-communal lanes) for public urban transportation in |
| | | order to make the service more convenient compared to private vehicles. |
| | | • Ensure the continuity of urban cycling paths by planning a functional system that |
| | | facilitates systematic travel from home to work and from home to school. |
| | Organised specialised set- | • Implement specific regulatory provisions for urban development instruments as |
| | tlements (m.i. 5) | well as building regulations (also for productive settlements) with the aim of employing |
| | Consolidated urban areas | bioclimatic construction technologies, eco-tech, and climate-proof materials. |
| | of major and minor cen- | • Research and use the Best Available Technologies (BATs), especially for industrial |
| Metabolic | tres (m.i. 1, m.i. 2) | processes. |
| properties | Urban fabrics outside of | • Implement specific energy efficiency measures (building retrofit measures, re- |
| | centres (m.i. 3) | placement of public lighting sources and fixtures, regulation and control systems for Dis- |
| | Areas of predominantly | trict Heating Network, etc.). |
| | specialised dispersion | • Utilise renewable energy sources (e.g., photovoltaic installations on rooftops, geo- |
| | (m.i. 7) | thermal energy, sharing energy with Renewable Energy Communities-RECs). |
| | | • Adopt building and urban certification systems that ensure minimal and optimal |
| | | use of energy considering the climatic conditions and the best technologies on the market |
| | | in accordance with environmental protocols to achieve higher certification scores (ITACA |
| | | Urban scale certification, GBC Historic Building Protocol, LEED® Protocol). |

4. Discussion

This study offers valuable insights into Urban Heat Island mitigation in the Metropolitan City of Turin by combining Random Forest modelling with LCZs. This integrated approach enables the identification of targeted mitigation strategies tailored to the unique morphological and environmental characteristics of urban areas, thus providing a more precise solution than previous UHI studies that analysed approaches individually. Our integrated methodology aims to quantitatively demonstrate, through a case study analysis, the effects of mitigation interventions following urban regeneration on UHIs.

Many prior studies have emphasised generalised interventions, such as enhancing green infrastructure or improving albedo, but they often limited their considerations to correlations without adequately addressing local urban morphologies and their interrelations.

Our findings suggest that mitigation strategies should vary across different land-use types and settlement forms, highlighting the significance of thermal, radiative, and metabolic properties. For instance, compensatory measures in consolidated urban fabric, where bioclimatic urban planning and UHI mitigation strategies can only be partially applied, present a recurring challenge for UHI management. This research demonstrates that dense urban areas, which are more vulnerable to heat islands, can benefit from alternative strategies, such as improving surface reflectivity (albedo) and incorporating water-based cooling systems.

As observed in the Teksid area, where several mitigation interventions have been applied—including increasing greenery, improving reflectivity, and enhancing humidity with vegetation—this study advances prior work by providing a method to quantify the effectiveness of these interventions through RF modelling to evaluate their impact across diverse urban zones.

Furthermore, by emphasising the need for integrated, adaptive strategies and community involvement, this research contributes significantly to the fields of urban planning and climate resilience, thus providing actionable insights for future urban development. By connecting UHI mitigation with frameworks like the "Mayors Pact" and regional initiatives, such as PEARs, this research situates UHI interventions within a broader context of climate adaptation and resilience.

However, these findings are place-based and may not be generalisable to other urban contexts with different climatic or cultural conditions. Additionally, reliance on detailed urban morphological data for LCZ classification may limit applicability in cities lacking such data. Future research should explore the adaptability of this approach in diverse urban environments by incorporating projected climate change impacts for a more comprehensive understanding of UHI mitigation strategies.

5. Conclusions

This research significantly facilitates the understanding of the UHI phenomenon in the Metropolitan City of Turin by employing an innovative methodology that integrates Random Forest (RF) modelling with LCZs. The analysis revealed a substantial reduction in the SUHII of -0.94 in summer and -0.54 in winter in the Teksid area, which is attributable to targeted urban mitigation interventions, such as increased vegetation (higher NDVI), higher albedo, and reduced impervious surfaces (lower Built Coverage Ratio). These results quantitatively demonstrate the effectiveness of urban regeneration efforts in mitigating UHI effects in a historically industrial context.

These findings underline the critical role of environmental factors, including albedo and surface emissivity, in shaping urban thermal profiles. The integration of quantitative and qualitative analyses allowed for the identification of tailored mitigation strategies that align with the unique morphological characteristics of different urban areas.

The key findings are the following.

- Effective Mitigation Strategies: This study highlights those specific interventions, such as enhancing green infrastructure and improving surface reflectivity, that can significantly reduce UHI intensity in dense urban areas. Almost 1 point of the SUHII decreased in the Teksid area after mitigation.
- Methodological Innovation: By combining machine learning with geospatial data, this research establishes a robust framework for future studies on UHIs, thus allowing for precise modelling and assessment of mitigation strategies across diverse urban landscapes. GIS, ML, and LCZs are included in a single methodology.
- Policy Recommendations: The results advocate for a shift in urban planning practices towards a more integrated, place-based approach that incorporates climate considerations across various sectors, thus promoting coordinated actions that address UHIs.

The methodology can be replicated in other urban contexts by utilising freely available GIS and satellite data to create localised UHI models. By fostering community engagement and collaboration among stakeholders, this research provides a roadmap for cities to implement effective, adaptive strategies for a climate-resilient future.

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| Nomenclat | ure |
|----------------|---|
| BCR | Building Coverage Ratio |
| DTM | Digital Terrain Model |
| GIS | Geographic Information System |
| LCZ | Local Climate Zone |
| LST | Land Surface Temperature |
| m.i. | Settlements' morphologies ("morfologie insediative" in Italian) |
| MSE | Mean Squared Error |
| NDBI | Normalised Difference Built-Up Index |
| NDMI | Normalised Difference Moisture Index |
| NDVI | Normalised Difference Vegetation Index |
| NDWI | Normalised Difference Water Index |
| NIR | Near InfraRed |
| PVI | Proportion Vegetation Index |
| QGIS | Quantum GIS |
| R ² | Coefficient of determination |
| RF | Random Forest |
| RMSE | Root Mean Squared Error |
| S/V | Surface-to-Volume ratio of buildings |
| SRI | Solar Reflectance Index |
| SUHII | Surface Urban Heat Island Intensity |
| SVF | Sky View Factor |
| SWIR | Short-wave Infrared |
| UHI | Urban Heat Island |
| UHII | Urban Heat Island Intensity |
| V | Building volume |
| VIS | Visible |

Appendix A

| N° | Year | Place | Scale | Object | Factors | Methodology | Results | Keyword |
|----|------|-------|-------|---|--|--|--|---------------|
| 3 | 1833 | LDN | Urban | Analysis and characterisation of the climate of London. | Atmospheric conditions. | Systematic observa- tions of factors at reg- ular intervals throughout the day to assess long-term cli- mate trends in the city. | Howard provided a comprehensive un- derstanding of Lon- don's climate and detailing factors. | Investigation |
| 4 | 1976 | VAN | Urban | Causes of the UHI: Canopy and Boundary Layers. | Surface proper- ties, land use, and atmospheric conditions. | Differentiate spatial heat island patterns within Urban Canopy and Boundary Layers. | The study found a clear differentiation between Canopy and Boundary Layer UHIs, influenced by various factors. | Investigation |
| 5 | 1982 | VAN | Urban | Investigating the physical pro- cesses driving the UHI effect. | Surface cover, building materi- als, anthropo- genic heat, weather condi- tions, urban mor- phology. | Comparing energy fluxes between urban and rural areas quan- tifies the UHI's effect on temperature dis- parities. | Urban areas have higher night-time temperatures than rural areas, high- lighting the im- portance of urban energy balance. | Investigation |

| _ | | | | | | | |
|----|------|-----|-------|---|---|---|-----|
| 9 | 2017 | BRA | Urban | Develop and val- idate a GIS-based extension model capable of accu- rately calculating UHII. | Urban geometry and meteorologi- cal data. | They collected urbanThe outcome is ageometry and meteor-computational toolological data, appliednamed THIS ena-a mathematical modelbling simulation ofto estimate the UHII,hypothetical urbanand validated it using scenarios and assess-empirical data inment of the impact ofMATLAB.urban geometry. | GIS |
| 10 | 2018 | SZ | Urban | Ventilation corri- dor planning to mitigate UHIs. | Built environ- ment, wind pat- terns, land use distribution. | GIS-based case study Recommendations to analyse wind envi- ronments by mapping in Shenzhen to im- urban features, as- sessing wind patterns, comfort through and pinpointing suita- ble corridors for natu- ral ventilation. tilation corridors. | GIS |
| 11 | 2018 | НК | Local | The study mapped the spa- tial distribution of nocturnal UHIs using the Local Climate Zone framework. | Climate data and urban morphol- ogy data (total street length, per- vious surface fraction, Sky View Factor). | GIS, GPS, and Landsat 8 images were used Identification of UHI alongside Multiple hotspots through the Linear Regression statistical models, (MLR) and Partial with the statement Least Squares Regres- sion (PLSR) to analyse have significant in- the spatial distribu- tion of nocturnal velopment. UHIs. | GIS |
| 12 | 2019 | HIJ | Urban | Develop and im- plement a GIS- based model for mitigating the UHI effect in Hi- roshima. | Urban morphol- ogy, vegetation, density of popu- lation, surface types. | GIS to analyse various urban parameters af- fecting heat absorp- tion and retention. They collected data to create spatial models for predicting heat distribution across the city. | GIS |
| 13 | 2021 | TRN | Urban | Smart rooftops. | Roof suitability, context, codes, regulations. | A method to assessData analysis techrooftop renovationniques (GIS), designopportunities bystrategies, and impleevaluating energymentation frame-savings, thermalworks to optimise thecomfort, and envi-use of urban rooftopsronmental/economicfor sustainability.benefits was intro- duced. | GIS |
| 14 | 2022 | TRN | Urban | Outdoor thermal conditions at the urban scale. | Urban morphol- ogy, vegetation, outdoor thermal comfort, Sky View Factor, mean radiant | Utilised geospatial as sessment QGIS [UMEP-SOLWEIG (QGIS)], DSM, and field measurements to evaluate outdoor | GIS |

| | | | | | temperature, ur- ban surfaces. | thermal comfort on ar urban scale. | with high spatial and temporal resolution or for the pre-design phase of little neigh- bourhoods. | |
|----|------|-----|---------------|--|---|---|--|---------------------|
| 15 | 2013 | XIA | Re- gional | Landsat 8 im- agery for consid- ering factors like climate, soil, veg- etation, and ac- quisition timing. | Pervious and im- pervious surface, LST. | They conducted re- mote sensing analysis to grasp how impervi- ous surface expansion affects local Land Sur- face Temperature dy- namics in the subtrop- ical city. | Growing impervious surfaces had in- creased Land Surface Temperatures, show- ing urbanisation's impact on subtropi- cal city temperatures. | Remote sensing |
| 16 | 2019 | USA | Re- gional | UHI phenome- non in 54 US cit- ies over 15 years, examining its correlation with temperature changes, weather conditions, and urban warming trends. | UHI, tempera- ture variation, climate zones, weather condi- tions, urban warming trends. | They analysed UHI intensity across cities using satellite data under different tem- perature conditions. Statistical methods were used to evaluate changes in the UHII concerning tempera- ture variations. | In 38 out of 54 US cit- ies, UHI intensity de- creases as tempera- tures rise, regardless of the climate zone. This is propelled by rural area changes, particularly during moist weather, with- out a significant UHI effect increase in warming cities. | Remote sensing |
| 17 | 2021 | LX | Re- gional | Local weather types of data based on Coper- nicus Land Moni- toring Service cli- mate variables dataset. | Thermal patterns (seasons); hourly air temperature, specific humidity, rela- tive humidity, and wind speed data. | Likely involved col- electing and processing Lisbon's temperature and weather data, cat- egorising local weather types, and correlating them with UHI intensity varia- tions across the metro- politan area. | UHI intensity esti- mated in an R script using various factors. | Remote sensing |
| 18 | 2022 | CN | Urban | Ventilation corri- dor planning to mitigate UHIs. | LST, atmospheric data. | A systematic ap- proach combining data collection (satel- tite images), quantita- tive analysis, and vali- dation to effectively identify urban ventila- tion corridors. | Seven primary venti- lation corridors pri- marily consisted of water bodies and green land areas, while four secondary ventilation corridors were mainly com- posed of roads. | Remote sensing |
| 19 | 2022 | SZ | Urban | Relationship be- tween the mor- phological spatial pattern of green space and UHI intensity using | Urban morphol- ogy, land cover, morphological characteristics of green spaces, population, buildings. | Employed machine learning methods to analyse the connec- tion between the spa- tial arrangement of green spaces and the UHI effect. | The UHI intensity was negatively corre- lated with the cores, perforations, and loops of green space but positively corre- lated with islets. | Machine learning |

| machine learning | |
|--|--|
| methods. | |
| 20 2021 NAP Urban 20 2021 NAP U | e Machine learning |
| Satellite data (Landsat 8) and ground meas- urements were pro- to simulate and phology, type, cessed with ENVI and 21 2021 WH Urban mitigate extreme production stage, MATLAB to apply UHI effects in a scale, and inter- factory area. nal structure. mitigating extreme UHI effects in a fac- tory area. | t Machine learning |
| 22 2022 MAD Wadelling SHUI UHI modelling using GIS and machine Development of an add-in (ArcUHI) for albedo, DTM, 22 2022 MAD Uthing accu- vith high accu- racy using Ran- dom Forest re- gression (RFR). Building height, albedo, DTM, Iteration, and mapping data pre-processing, model training, vali- dation, and mapping areas. Development of an add-in (ArcUHI) for automated model- ling of the UHI ef- fect. | Machine learning |
| 23 2022 AMD Urban Employed a ma- chine learning al- LULC maps, BI, gorithm to pre- dict factors. NDMI, MNDWI. Satellite imagery and More than 70% of th ground-based meas- urements to train the 40% in winter would algorithm by incorpo- rating factors to char- temperature zones acterise the surface UHI phenomena. present situations. | e l Machine learning |
| 24 2023 AU Na- tionalo | - e l Machine n learning - |

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