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Research Article

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Posted Date: June 18th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-9021368/v1

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Additional Declarations: No competing interests reported.

Quantum-Inspired Entropic Evolutionary Unsupervised Urban Heat Island and Urban Cool Island Detection Method

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Abstract. Urban Heat Island (UHI) detection in complex urban environments requires analytical methods capable of handling uncertainty, spatial gradualness, and strong land-use heterogeneity. This paper presents a novel unsupervised method for UHI detection implemented in a GIS-based framework that integrates Fuzzy C-Means (FCM) clustering with a quantum-inspired entropic evolutionary optimization strategy aimed at improving clustering initialization and solution stability. The proposed method relies on a probabilistic chromosome representation and an entropy-guided evolutionary mechanism to select initial configurations that mitigate FCM sensitivity to starting conditions in an unsupervised clustering setting, without relying on labelled data. The approach is applied to the city of Naples (Italy) using Landsat 8 remote sensing data, specifically Land Surface Temperature (LST) and Normalised Difference Vegetation Index (NDVI) maps at 30 m spatial resolution acquired during a heatwave event. The optimal number of clusters is determined through internal validity indices. Urban Heat Islands (UHIs) and Urban Cool Islands (UCIs) are identified by analysing cluster centroid distributions in the LST–NDVI feature space and spatially aggregating pixels associated with the hottest and coolest clusters, respectively. A UHI and UCI reliability measure based on mean fuzzy membership values is introduced to support confidence-aware prioritization of both heat mitigation and cooling preservation strategies. A reliability measure based on mean fuzzy membership values is introduced to support confidence-aware prioritization of both heat mitigation and cooling preservation strategies. Test results show that the proposed framework outperforms FCM in terms of accuracy and processing speed; Furthermore, using a reliability measure for the detected UHIs and UCIs provides decision makers with a crucial tool for assessing the reliability of their classification.

Keywords: Quantum Inspired Optimization, Fuzzy C-Means, Fuzzy Entropy, Entropic Evolutionary Algorithms, Urban Heat Islands, Surface Urban Heat Island, GIS-based analysis.

1. Introduction

Urban Heat Islands (UHIs) are among the most pressing challenges faced by contemporary cities under climate change, with direct impacts on public health, energy consumption, and urban liveability (Oke, 1982; Voogt et al. 2003).

The existing literature demonstrates that elevated urban temperatures are closely linked to increased energy consumption (Kolokotroni M. et al. 2012; Kikegawa Y. et al. 2006; Parker J. et al. 20211), air pollution (Sarrat C. et al. 2006; Li H. et al. 2018), biodiversity loss (Ceplová N. et al. 2017; Géron C. et al. 2021), and the health of residents (Tan J. et al. 2010; Goggins W.B. et al. 2012; He,B.-J. et al. 2021), making UHIs a critical concern in urban environmental research.

The increasing frequency and intensity of heatwaves have further amplified the need for reliable analytical tools capable of identifying thermally critical urban areas and supporting climate-oriented planning strategies.

Alongside the study of UHIs, growing attention has been devoted to Urban Cool Islands (UCIs), also referred to as Urban Cold Islands, which represent urban areas characterized by relatively lower surface temperatures compared to their surroundings. UCIs are typically associated with higher vegetation cover, water bodies, permeable surfaces, or favorable urban morphologies, and act as local thermal mitigation zones within overheated urban fabrics. The identification and preservation of UCIs are increasingly recognized as essential components of urban climate resilience, as these areas contribute to reducing thermal stress and enhancing adaptive capacity at the neighborhood scale.

From an analytical perspective, both UHI and UCI detection represents a complex spatial problem. Urban thermal patterns emerge from the interaction of multiple factors, such as land cover, vegetation, and urban morphology, and manifest as continuous and heterogeneous structures rather than as sharply bounded entities, as assumed by traditional UHI definition (Zhou et al., 2014). This intrinsic spatial complexity makes UHI and UCI detection poorly suited to simple threshold-based or binary classification approaches, (Martin P. et al. 2015; Ma Z. 2025), which often fail to capture gradual transitions, overlapping thermal regimes and localized anomalies within dense urban fabrics.

Recent reviews on machine-learning applications for for urban thermal analysis highlight a strong prevalence of predictive and forecasting-oriented approaches, mainly focused on estimating land surface temperature or projecting future thermal scenarios (Snaiki et al. 2025). While these contributions are fundamental for mitigation and adaptation planning, they often assume that UHI patterns are already well-defined in space. As a result, the problem of UHI and UCI detection itself, intended as the identification of coherent and reliable thermal structures under conditions of uncertainty and spatial heterogeneity, remains comparatively underexplored.

In this context, unsupervised data-driven methods have gained increasing relevance, as they allow urban thermal patterns to be identified directly from

remotely sensed data without relying on labelled datasets or predefined thresholds. Among these approaches, fuzzy clustering techniques represent a particularly suitable analytical paradigm, as they explicitly model uncertainty and gradual spatial transitions. By assigning degrees of membership rather than crisp class labels, fuzzy clustering enables a more realistic representation of urban thermal phenomena, which are inherently continuous and spatially diffuse.

Fuzzy clustering techniques represent a shift toward a more flexible analytical paradigm, as they explicitly model uncertainty and gradual spatial transitions, making them particularly suitable for climate-related phenomena characterized by spatial continuity and heterogeneity (Zadeh, 1965; Bezdek, 1981).

Within the broader climate change literature, FCM has been successfully applied to a variety of environmental and hydro-climatic problems, including the regionalization of rainfall patterns, climate trend analysis, and the identification of homogeneous climatic zones, where sharp boundaries between classes are physically implausible (Roy et al., 2024). These studies demonstrate the effectiveness of FCM in capturing gradual spatial variations and uncertainty inherent in climatic systems.

However, despite its proven potential in climate and environmental analyses, the direct application of FCM to Urban Heat Island detection remains relatively limited, with only a few contributions explicitly exploring its use for the identification and characterization of urban thermal patterns. This gap is particularly relevant given that UHI phenomena exhibit spatial continuity and fuzzy transitions analogous to other climate-related variables.

Moreover, although FCM enables a nuanced representation of urban thermal structures through membership-based interpretations, it remains strongly dependent on the initialization of cluster centroids, a well-known limitation that can lead to convergence toward suboptimal solutions and reduced robustness, especially in highly heterogeneous datasets (Bezdek et al., 1987).

Addressing this limitation has motivated a wide body of research on meta-heuristic optimization strategies for FCM initialization.

Classical genetic algorithms (Goldberg, 1989) and swarm intelligence methods, such as Particle Swarm Optimization, have been extensively explored to improve clustering robustness and convergence stability (Maulik U. et al., 2000, 2003; Hatamlou A. et al., 2013; Silva Filho, T. M. et al., 2015; Kuo R. J. et al., 2012). However, these approaches often require repeated executions and introduce additional computational complexity, especially when applied to large and heterogeneous datasets.

Recent advances in quantum-inspired evolutionary computation offer a promising direction in this sense. Quantum Genetic Algorithms (QGAs), originally introduced by Narayanan A. et al., 1996, extend classical genetic algorithms by encoding solutions as probabilistic quantum chromosomes, enabling enhanced exploration of the solution space. Quantum-inspired evolutionary algorithms have demonstrated superior performance compared to conventional genetic algorithms in a wide range of optimization problems (Han K. et al., 2002; Laboudi Z. et al., 2012), while remaining fully implementable on classical hardware. Comprehensive reviews of quantum-inspired metaheuristic algorithms further confirm their

effectiveness and growing adoption across different application domains (Montiel R., 2020).

By simulating key principles of quantum computation on classical hardware, quantum-inspired algorithms enhance global search capabilities without the need for actual quantum machines.

In this work, we adopt the Quantum Entropic Evolutionary Fuzzy C-Means (QEE-FCM) algorithm originally proposed by Di Martino and Sessa (2022), which introduces a quantum-inspired evolutionary strategy to optimize the initialization of cluster centroids in Fuzzy C-Means by minimizing fuzzy entropy. The QEE-FCM algorithm has been previously validated in non-spatial clustering contexts, demonstrating its ability to enhance clustering accuracy and stability by reducing the sensitivity of FCM to initial conditions.

The primary objective of this research is to test a framework that improves the accuracy and execution speed of UHI/UCI detection methods using an unsupervised approach based on FCM, which utilizes the quantum-inspired entropy evolutionary method QEE-FCM to optimize cluster initialization. Our method detects UHIs and UCIs in urban settlements from multispectral satellite images of Land Surface Temperature (LST) and Normalized Difference Vegetation Index (NDVI) taken during heatwaves.

After determining the final clusters, the framework also adopts a robust cluster selection method that identifies the UHIs and UCIs, determining the formation of plateaus in the LST-NDVI feature plane.

A key aspect of the proposed approach lies in the use of fuzzy membership values to quantify the reliability of the detected UHIs and UCIs. UHIs and UCIs characterized by higher membership-based reliability values are therefore identified as critical urban areas and, respectively, cooling areas, with a high degree of certainty throughout their extension.

The proposed framework is implemented and tested on the city of Naples (Italy) using Landsat-derived thermal and spectral indicators. The results show that the quantum-inspired entropic evolutionary strategy enhances the accuracy and spatial coherence of UHI. In addition, the proposed framework enables a reliability interpretation of the detected UHI patterns through fuzzy membership analysis.

1.1 Related Works

The detection and characterization of UHIs have been extensively investigated through remote sensing–based analyses, leveraging thermal and spectral indicators to capture spatial patterns of urban overheating (Almeida C. R. et al. 2021; Zhou D. et al. 2018). Early approaches primarily relied on threshold-based classifications, such as simple LST differences between urban and rural areas. However, these methods have been proven inadequate for representing the variability and complexity of contemporary urban environments, where thermal patterns rarely exhibit sharp boundaries. Recent studies highlight a clear methodological shift toward data-driven approaches, including machine learning techniques such as (e.g., random forests and artificial neural networks) and unsupervised clustering algorithms (e.g., K-means and fuzzy C-means), which enable a more nuanced and

spatially accurate identification of urban thermal patterns (Im et al., 2025; Ahmed et al., 2025). Among these, a large share of data-driven UHI studies focuses primarily on prediction and regression tasks, where machine-learning models are trained to estimate LST values or forecast future thermal conditions. In these frameworks, UHI detection is often treated implicitly, as a by-product of predicted temperature fields, rather than as a distinct analytical problem requiring dedicated methodological treatment. While predictive machine learning approaches have demonstrated high accuracy, they are inherently characterized by substantial methodological and data complexity. Most supervised models require large, heterogeneous, and spatially extensive training datasets, often combining remote sensing products with detailed meteorological records, urban morphology descriptors, land-use information, and, in some cases, socio-economic variables. The acquisition, preprocessing, and harmonization of such datasets entail significant costs and technical effort, frequently limiting model applicability to data-rich contexts and constraining their transferability across different cities. Consequently, many predictive UHI models remain strongly context-dependent and difficult to generalize beyond the specific urban areas for which they were trained.

Within this context, unsupervised clustering techniques have become particularly relevant, as they allow the identification of thermal structures without the need for labelled datasets. Unsupervised learning algorithms were used to partition thermal patterns into data-driven clusters, which are subsequently interpreted and, where appropriate, compared with existing scientific classifications of the study area. The number of clusters is typically varied to explore alternative thermal configurations and to identify the scenario that best captures the underlying spatial structure of urban heat patterns.

Several studies have explored unsupervised and hybrid data-driven strategies for UHI-related analyses. Magyari-Sáska et al. (2024) observed that only a limited proportion of previous studies relied on rigorous predefined thresholds, further supporting the transition toward automated and adaptive hotspot detection approaches. Peña Acosta et al. (2024), applied time-series clustering methods (K-means and K-prototypes) to classify urban street types, achieving a 50–70% reduction in data collection requirements while maintaining high classification accuracy. Although not explicitly focused on UHI detection, these studies highlight the advantages of unsupervised and adaptive clustering strategies for handling complex urban datasets, reinforcing their relevance for urban thermal analysis.

Among unsupervised approaches, fuzzy clustering methods have received limited attention in UHI analysis, despite their ability to represent gradual spatial transitions and overlapping thermal regimes. Unlike hard classification techniques, fuzzy models assign degrees of membership to clusters, enabling a more realistic description of urban thermal behaviour and supporting the interpretation of UHIs as continuous phenomena rather than sharply delimited zones.

Fuzzy C-Means (FCM) has been widely adopted in remote sensing as an unsupervised clustering technique operating in multi-feature spaces, particularly to address spectral mixing and gradual transitions between classes. Previous applications of FCM include vegetation and water body classification based on spectral indices (Afirah et al., 2017), impervious surface mapping through the joint use of built-up indices and Land Surface Temperature (Wicaksono, 2021), flood

extent identification from multi-index satellite imagery (Krishna et al., 2017), and the delineation of homogeneous environmental or hydrological regions (Choubin et al., 2017). Despite its widespread use in remote sensing, the application of FCM to urban climate studies has remained comparatively limited. Fuzzy logic has been widely used to assess heat-wave hazard and risk by combining temperature-related indicators with socio-environmental variables (Keramitsoglou, I. et al. 2013), as well as to delineate Urban Heat Island Formation Zones (UHIFZs) through multi-criteria spatial inference integrating LST, vegetation, topography and built-environment factors (Alshayeb MJ et al. 2025).

While these approaches effectively manage uncertainty and gradual transitions, they are inherently knowledge-driven and require predefined membership functions and expert-defined rules, limiting their scalability and transferability across different urban contexts. Only a limited number of studies have employed FCM in conjunction with land surface temperature in urban contexts. These applications have generally focused on the fuzzy discretization of LST values (e.g., low, medium, and high temperature classes) or on supporting ancillary analyses, such as the assessment of public urban parks located in high-LST areas (Wicaksono, 2022), rather than on the direct identification of Urban Heat Island patterns as emergent thermal structures. Consequently, the potential of FCM as a fully data-driven fuzzy clustering approach for UHI detection in a multi-feature space remains largely underexplored. A recent contribution by Cafaro et al. (2025) introduced a GIS-based framework integrating Landsat-derived LST and NDVI within an FCM clustering scheme, demonstrating improved UHI detection performance compared to traditional fixed-threshold approaches.

Although FCM offers a flexible and conceptually appropriate framework for modelling gradual thermal transitions, its performance is known to be strongly influenced by the initialization of cluster centroids (Ahmed M et al. 2002). In heterogeneous urban contexts, different initial configurations can lead to divergent clustering outcomes, affecting both spatial coherence and convergence stability. This sensitivity represents a critical limitation when FCM is applied to large-scale spatial urban datasets, where repeated executions or heuristic initialization strategies are often required to obtain consistent results.

To address this limitation, several studies have explored the integration of FCM with metaheuristic optimization techniques aimed at enhancing the global search capability during the initialization phase (Abdussamad S. et al. 2020; Wang H. et al. 2007). Classical evolutionary algorithms and swarm intelligence methods—such as Genetic Algorithms and Particle Swarm Optimization—have been widely adopted to improve clustering robustness and reduce the risk of convergence toward local minima (Maulik U. et al., 2000, 2003; Hatamlou A. et al., 2013 ; Silva Filho et al., 2015; Kuo et al., 2012). While these approaches generally improve clustering accuracy, they often introduce additional computational complexity and require multiple runs to achieve stable solutions, which can limit their applicability to large and heterogeneous datasets.

In parallel, quantum-inspired computational intelligence has emerged as a promising alternative paradigm for addressing complex optimization problems. By simulating principles derived from quantum computation—such as probabilistic state representation and superposition—on classical computing architectures,

quantum-inspired algorithms enhance exploration of the solution space while remaining computationally feasible. Within this framework, QGAs have been successfully applied to clustering problems, demonstrating improved diversity preservation and convergence behavior compared to classical evolutionary approaches (Narayanan A. et al., 1996; Han K. et al., 2002; Laboudi Z. et al., 2012; Montiel R., 2020).

Several quantum-inspired fuzzy clustering variants have been proposed to mitigate FCM sensitivity to initialization. Ye A. et al., 2016 introduced the Improved Quantum Genetic Algorithm FCM (IQGA-FCM), while Patel O. et al., (2015) proposed QIE-FCM to optimize the number of clusters and the fuzzifier parameter. More recently, Bharil N. et al., (2019) presented EQIE-FCM, which simultaneously optimizes the number of clusters, the fuzzifier, and the initial cluster centers using a quantum-inspired evolutionary strategy. Although these methods enhance clustering robustness, they typically require a high number of iterations, leading to increased computational costs.

To overcome these limitations, Di Martino and Sessa (2022) proposed the Quantum Entropic Evolutionary Fuzzy C-Means (QEE-FCM) algorithm, which introduces an entropy-guided fitness function based on fuzzy entropy to optimize centroid initialization while maintaining computational efficiency. By explicitly minimizing clustering fuzziness during the evolutionary process, QEE-FCM improves both solution stability and convergence behavior compared to other quantum-inspired FCM variants. Despite its proven effectiveness in benchmark clustering and non-spatial applications, the integration of QEE-FCM within GIS-based frameworks for UHIs and UCIs detection has not yet been investigated. This gap directly motivates the present study.

In the following section, the theoretical foundations of fuzzy entropy and the Quantum Entropic Evolutionary Fuzzy C-Means (QEE-FCM) algorithm are introduced. In section 3, the proposed quantum-inspired entropic evolutionary framework for unsupervised Urban Heat Island detection is formally introduced. Section 4 then presents the experimental application of the method to the city of Naples (Italy) and discusses the resulting UHI patterns and reliability analysis. Finally, Section 4 concludes the paper by outlining the main contributions, methodological advantages, and directions for future research.

2. Preliminaries

2.1 Fuzziness of fuzzy clusters

Let $X = \{x_1, x_2, \ldots, x_N\}$ be a finite set of elements and let $F(X) = \{u(x_1)/x_1, u(x_2)/x_2, \ldots, u(x_N)/x_N\}$ be a finite fuzzy set defined on X, where $u(x): X \rightarrow [0,1]$ is the membership degree of x to F(X).

The fuzzy entropy is a measure of the fuzziness of fuzzy sets (Ishikawa and Mieno, 1979). The fuzzy entropy of of F(X) is defined as:

$$H(F(X)) = \frac{1}{N}\sum_{j=1}^{N} h(u_j) \tag{1}$$

where h: [0,1] → [0,1] is a continuous function called fuzzy entropy function; it is monotonically increasing in [0, ½] and monotonically decreasing in [½, 1], assuming the value 0 for $u(x_j) = 1(0)$, that is, in cases where the j*th* element x_j certainly belongs or certainly not belongs to F(X).

De Luca and Termini (De Luca and Termini, 1972, 1979) propose the following fuzzy entropy function to measure the fuzzy entropy of a fuzzy set:

$$h^*(t) = \begin{cases} 0 & \text{if } t \in \{0,1\} \\ -t\log_2 t - (1\text{-}t)\log_2(1-t) & \text{if } 0 < t < 1 \end{cases} \tag{2}$$

The De Luca and Termini fuzzy entropy is used in (Di Martino and Sessa, 2018, 2021) to evaluate the fuzzy entropy of spatial entities in GIS-based applications. In (Cardone and Di Martino, 2024) it is applied to evaluate the fuzziness of trapezoidal strong fuzzy partitions.

In (Di Martino and Sessa, 2022) the fuzziness of a fuzzy clustering is measured by using the De Luca and Termini fuzzy entropy (1) Let C be the number of fuzzy clusters and let $V = \{v_1, v_2, \ldots, v_C\}$be the set of the centroids of the clusters. In FCM the membership degree of the j*th* element to the i*th* cluster is given by

$$u_{ij} = \frac{1}{\sum_{r=1}^{c}\left(\frac{\|x_j - c_i\|}{\|x_j - c_k\|}\right)^{\frac{2}{m-1}}} \tag{3}$$

In (Di Martino and Sessa, 2021) the fuzziness of the i*th* cluster given by:

$$H_i = \frac{1}{N}\sum_{j=1}^{N} h^*(u_{ij}) \quad i=1,\ldots,C \tag{4}$$

H_i varies between 0 and 1. The lower the fuzziness of the i*th* cluster, the greater the cluster compactness and separability from other clusters (Cardone and Di Martino, 2020; Cardone et al.,2021).

The fuzziness Fs of the clustering is measured in (Di Martino, Sessa, 2021) as the average of the fuzzy entropies of the C clusters:

$$Fs = \frac{1}{C}\sum_{j=1}^{N} H_i \tag{5}$$

Fs ranges from 0 to 1. It is always equal to 1 for crisp clusters. The greater the fuzziness of the clustering, the more blurred the clustering is and the less compact and well separable the clusters are.

2.1 The QEE-FCM algorithm

QEE-FCM is a variation of FCM proposed in (Di Martino and Sessa, 2020) in which a QGA algorithm is used in a preprocessing phase to optimize the selection of the initial cluster centroids.

Let $\{\mathbf{x_1},..,\mathbf{x_N}\}$ be a set of data given by N points in R^n where $\mathbf{x_j} = (x_{1j}, x_{2j},\ldots,x_{nj})^T$; furthermore, let C be the number of clusters. Each cluster centroid $\mathbf{v_j}$ in the n-dimensional space of the features is stored with in $B_1 + B_2 + .. B_n$ bits, where B_h is the number of bits needed to store the value of the h*th* feature.

The number of bits used to store the values of the C cluster centroids is given by:

$$K = C \cdot \sum_{h=1}^{n} B_h \qquad (6)$$

To find the best values of the initial cluster centroids a QGA method is applied in which each quantum chromosome (QC) is composed by K quantum genes (QGs). The h*th* QG is given by a qubit, where each qubit is randomly collapsed in a bit.

After the collapsing phase the resultant chromosome is given by a K-bit long binary string.

In Fig 1 the process applied to transform a QC in the set of cluster centroids is schematized. In the example in figure, are considered C = 6 clusters. Each QC is composed of 48 QGs, where eight QGs are used to represent a cluster centroid. After collapsing, a classical chromosome is obtained whose alleles are integer values from 0 to 255, encoded in 8 bits; they are the values of the centroids of the six clusters.

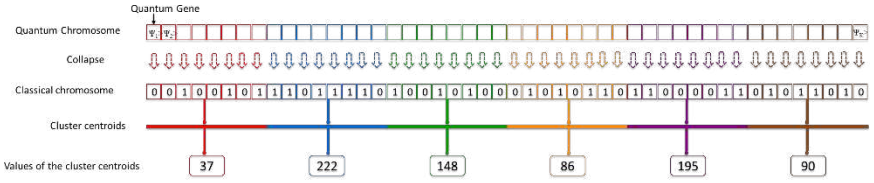


Fig.1. Schema of the process used to obtain the cluster centroids starting from a QC.

The quantum population is composed by a number of N_c QCs, where each QC is given by a superposition of 2^k states with the same probability $1/2^k$.

Let $|\psi_{hi}> = \alpha_{hi}|0> + \beta_{hi}|1>$ i = 1,…,k, h = 1,…, N_c be the i*th* QG of the h*th* QC. It is initially setting $\alpha_{hi} = \beta_{hi} = 1/\sqrt{2}$, so that there is an equal probability that the QC collapses to 0 or 1.

Then the fitness value of each conventional chromosome is measured as well. It is obtained calculating the fuzziness FS of the corresponding clusters by (4). If Fs(h) is the fuzziness of the clusters in the h*th* chromosome, the fitness assigned to the h*th* chromosome is given by

$$Ft_h = 1 - Fs_h \qquad (7)$$

The maximum fitness value is 1, corresponding to the fitness of a solution whit perfectly crisp cluster.

In QEE-FCM the quantum gate operator proposed in (Zhou and Sun, 2005) is applied to evolve the QP. This operator executes a quantum rotation to change the phase angle of each QG, where the probability of measuring state '1' or '0' is related to the fitness of the current solution.

Below is shown in pseudocode the QEE-FCM algorithm. The parameters to be set are the set of data points, the number of chromosomes N_C, the number of cluster C, the maximum number of iteration I_{max}, and the stop iteration error η. The stop iteration error is a threshold to be fixed to the difference between the clustering fuzziness of the best solution and the one measured in the previous iteration. The output is given by the set of optimal initial cluster centroids; it can be used as initial cluster centroids for FCM.

Algorithm 1: QEE-FCM

Input: Set of data points
Number of cluster C
Maximum iterations I_{max}
Number of chromosomes Nc
Stop iteration error η

Output: Optimal initial cluster centroids

```
A quantum population given by Nc QCs is created
A conventional population given by of Nc K-binary strings is created
Ft_Best := 0        // the best fitness is initialized to 1
Ft_BestPrev := 1    // the best fitness in the previous iteration is initialized to 0
numIter := 0   //the number of iteration is initialized to 0
For h = 1 to Nc       // Initialize the QCs
    For i = 1 to k
        α_hi := 1/√2
        β_hi := 1/√2
        Ft_h := 0   // the fitness of the hth QC is initialized to 0
    Next i
Next h
Repeat
    numIter := numIter +1
    Ft_BestPrev := Ft_Best
    For h = 1 to Nc       // Collapse the QCs
        For i = 1 to k
            Generate a random number r where 0 ≤ r ≤ 1
            If |α_i|^2 ≥ r Then
                b_hi := 1
            Else
                b_hi := 0
```

End if

Next i

For j = 1 to **C**

Compute the values of the components of the centroid of the j*th* cluster

Compute the membership degree of each element to the j*th* cluster by (3)

Compute the fuzzy entropy H_j of the j*th* cluster by (4)

$Fs_h := Fs_h + H_j$

Next j

$Fs_h := Fs_h / C$

$Ft_h := 1 - Fs_h$

If $Ft_h > Ft_{Best}$ **Then**

$Ft_{Best} := Ft_h$

End if

Next h

If $(Ft_{Best} - Ft_{BestPrev} > \eta)$ and $(numIter \leq I_{max})$ **Then**

Execute the quantum evolution operator to the QCs

End if

Until $(Ft_{Best} - Ft_{BestPrev} > \eta)$ and $(numIter \leq I_{max})$

Return the centroids of the C clusters

Results of comparative tests performed on classification datasets of the UCI machine learning repository in (Di Martino and Sessa, 2022) highlight that QEE-FCM outperforms other genetic FCM variations both in terms of accuracy and CPU times.

3. The proposed UHI detection method

We proposed a novel unsupervised urban heat island (UHI) detection algorithm, in which a variation of the fuzzy c-means (FCM) algorithm is executed on remotely sensed land surface temperature (LST) and normalized difference vegetation index (NDVI) image data to detect hotspots in urban settlements. Fig. 2 shows a flow diagram of the UHI detection method.

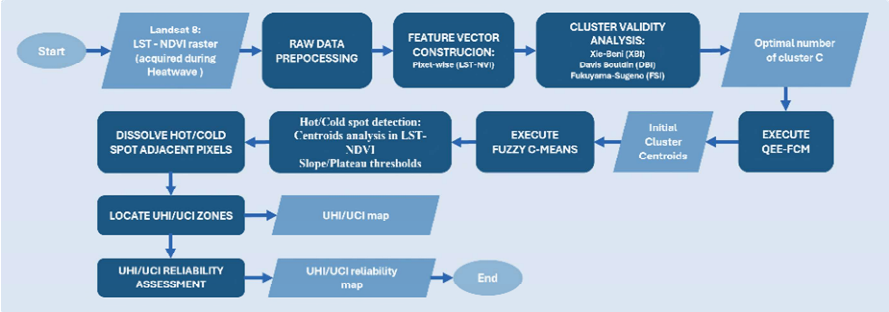


Fig.2. Flow diagram of the proposed UHI detection method

In the preprocessing phase LST and NDVI raster data covering the urban study area are acquired from Landsat 8 multispectral imagery during heatwave events. The two raster datasets are georeferenced and resampled to a unified spatial resolution (30m), obtaining a vector raster data where each pixel is represented as a two-dimensional 30x30 m. feature vector combining thermal and vegetative information. These vectors serve as input for the clustering process.

To determine the optimal number of clusters are measured the tree well-known validity indices, Xie–Beni (XB), Davies–Bouldin (DB) e Fukuyama–Sugeno (FS), evaluating the inter-cluster separation and the intra-cluster compactness.

The strategy used to determine the number C of clusters is as follows:

- to ensure the stability of the solutions, FCM is run multiple times, determining the most frequent value obtained for the optimal number of clusters for each of the three indices;
- if the three indices provide different values, the smallest value is selected. This is the most robust solution because it introduces fewer degrees of freedom, making it less sensitive to noise and less dependent on initialisation. It is also less prone to topological instability of the clusters.

The QEE-FCM algorithm is used to determine the optimal number of clusters. Then, in line with Di Martino and Sessa (2022), a variation of FCM is executed to obtain the final clusters, in which the initial cluster centroids are those returned by QEE-FCM rather than being randomly determined. This prevents local minima from being trapped and speeds up convergence.

Once the final clusters have been determined, each pixel is labelled with the identifier of the cluster to which it belongs with the highest membership degree. Additionally, each pixel is assigned a value indicating its membership degree.

Following Cafaro et al. (2025), heat, hot and coldspots are extracted by analysing the trend in the plot graph showing the values of the centroids of the clusters in the LST-NDVI plane. hotspots are identified as all the clusters located beyond a predefined hotspot threshold (hot threshold line). Likewise, coldspots are

identified as all the clusters located below a predefined coldspot threshold (cold threshold line). These thresholds are determined at the points where the LST-NDVI line forms plateaux, as shown in Fig. 3.

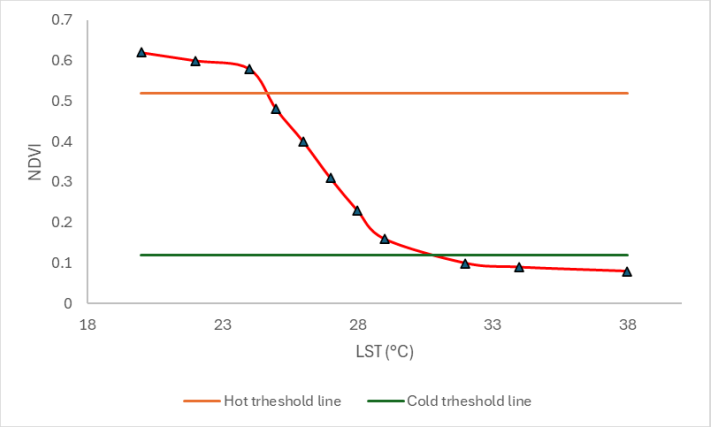


Fig.3. Example of plot of the cluster centroids in the plane (LST-NDVI) and setting of the hot and cold threshold lines

All spatially adjacent pixels belonging to clusters labelled as hot (or cold) spots are combined to form a polygon that defines a UHI (or UCI) zone within the urban study area. The output of this phase is a thematic map that highlights the detected UHIs and UCIs in the urban study area.

This approach enables UHI boundaries to be defined more accurately than in traditional approaches, where they are determined by identifying the boundaries between dense urban areas and peri-urban areas. These traditional approaches introduce subjective errors and are ineffective when the urban area under study is a dense metropolitan area with no clear division between urban and peri-urban areas.

The reliability of each UHI or UCI is assessed by considering the mean value of the membership degree to the corresponding cluster of the spatially adjacent pixels that generated it. This value ranges from 0 to 1: the greater the reliability associated with a UHI (UCI), the smaller the uncertainty in identifying the area as such. This phase generates a thematic map called the 'Reliability Map', in which the UHIs and UCIs are classified according to their reliability.

Analysing the reliability map allows decision makers to assess the degree of uncertainty in the UHIs (UCIs) detected in the urban area under study. UHIs with high reliability values indicate areas of particular concern where a warmer microclimate develops compared to other urban areas. This warming, likely caused by high building density, human activity and sparse vegetation, can pose significant health risks to residents during heatwaves. Conversely, UCIs with high reliability

values represent safe cooling zones capable of mitigating the effects of urban heatwaves.

4. Application on a case study

This section presents and discusses the results of testing the framework on the urban area of the city of Naples, Italy.

To conduct the tests, the framework was implemented in a Python environment using the Python libraries ArcPy of the ESRI GIS tool ArcGIS Pro 3.4 for all GIS-based spatial analysis capabilities and the Python libraries Pygad 3.0 for implementing the quantum genetic functions and the rotation gate.

4.1 The case study of Naples (Italy)

The framework was tested using the city of Naples, Italy, as a case study. The city is particularly susceptible to urban overheating due to its dense impermeable surfaces and limited green spaces. Naples has a relatively small territorial area of 11,727 hectares, but a very high population density of around 8,566 people per square kilometre. The metropolitan area has a population of around 295,700, while the municipality of Naples itself has a population of approximately 1,004,500.

The city's climate is classified as subtropical and slightly continental, with a near absence of intermediate seasons. It is characterised by increasingly intense rain showers alternating with extended periods of drought. In recent years, Naples has experienced an increasing frequency of heatwaves lasting several days throughout the summer months. In many parts of the historic centre and newly developed areas, the increased use of impermeable surfaces such as asphalt and concrete has exacerbated the risk of thermal accumulation in summer. This phenomenon has become more severe due to the increasing frequency and duration of heatwaves.

Input data necessary for UHI hotspot detection consists of LST and NDVI raster datasets derived from remotely sensed Landsat 8 satellite imagery. These datasets were acquired on 30 July 2022 during a recorded heatwave event lasting 28 consecutive days from 15 July to 11 August 2022.

The LST index is obtained from Thermal Infrared Sensor (TIRS) Bands 10 and 11, which measure surface thermal radiation. Temperature values range from a minimum of 28°C to a maximum of 56°C. This is shown in Fig. 4.

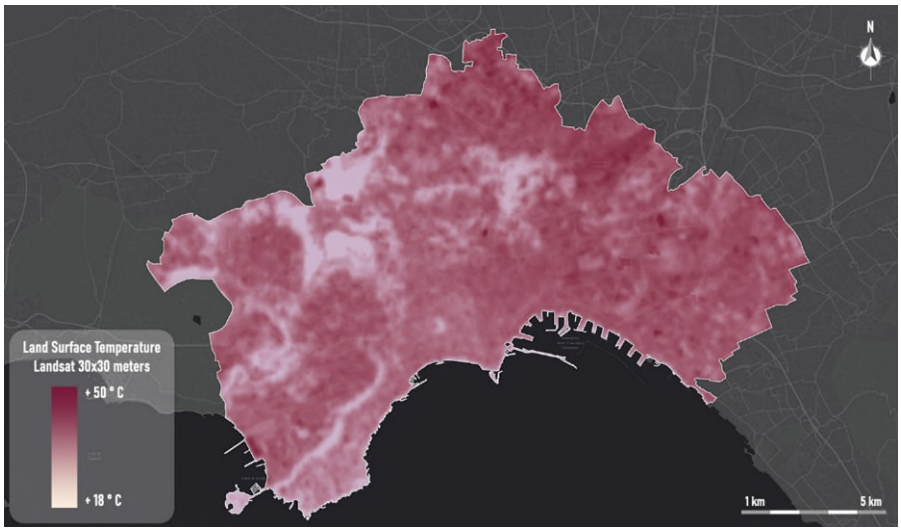


Fig.4. Spatial distribution of the LST on the city of Naples (Italy)

The NDVI index, which has a domain between -1 and +1, is derived from the spectral bands of the Landsat Operational Land Imager (OLI). It records values ranging from a minimum of -0.16 to a maximum of +1.

The NDVI was processed to match the spatial resolution of the LST dataset to ensure accurate data integration for subsequent analysis. Standard preprocessing techniques were applied to the LST and NDVI values, including atmospheric correction, resampling, and reprojection to a common spatial resolution of 30 metres.



Fig.4. Spatial distribution of the NDVI index on the city of Naples (Italy)

The result of the data processing phase consisted of a dataset composed of 131,186 data points where each data point is a two-dimensional vector containing the normalized LST and NDVI values.

4.2 Presentation and discussion of the results

To determine the optimal number of clusters FCM was executed 20 times on the dataset, varying the number of clusters from 2 to 10 each time and measuring the three validity indices XB, DB e FS. For all three indices, the most frequent value of the optimal number of clusters is 9, as shown in Table 1; for this reason, the number C of clusters was set to 9.

Validity idex	Most frequent optimal C value	Absolute frequency	Relative frequency
XB	9	18	0.9
DB	9	15	0.75
FS	9	18	0.9

Tab 1. Most frequent values of the optimal number of clusters C measured with the three indices XB, DB and FS.

To execute QEE-FCM the following parameters are fixed (Tab.2):

Parameter	Value
Number of cluster C	9
Maximum iterations I_{max}	300
Number of chromosomes Nc	500
Stop iteration error η	$1x10^{-3}$

Tab 2. Values fixed for the QEE-FCM parameters.

QEE-FCM terminates after 77 iterations.

Then, FCM was executed setting the values of the centroids of the initial clusters to the ones obtained from QEE-FCM. The parameter assigned in FCM are the fuzzifier m, the maximum number of iterations I_{max} and the stop iteration error ε, given by a threshold to the maximum difference between an element u_{ij} of the partition matrix and the same element determined in the previous iteration. FCM stops if this maximum difference is less than ε or if the maximum number of iterations, $I_{max,}$ has been exceeded.

In order to increase the accuracy of the results, the stop iteration error ε was set to $1x10^{-5}$.

The values of the parameter fixed to execute FCM are shown in Tab. 3.

Parameter	Value
Number of cluster C	9
Fuzzifier m	2
Maximum iterations I_{max}	300
Stop iteration error ε	$1x10^{-5}$

Tab 2. Values fixed for the FCM parameters.

FCM terminates after 153 iterations. The values of the centroids of the final nine clusters are shown in Table 4.

ID cluster	LST	NDVI

1	46.466	0.201
2	48.280	0.206
3	45.144	0.255
4	43.752	0.328
5	42.263	0.444
6	40.505	0.579
7	38.311	0.686
8	35.767	0.782
9	32.371	0.810

Tab 4. Centroids of the final nine clusters.

To measure the benefits of QEE-FCM in terms of execution speed, the FCM algorithm was run again, but this time randomly setting the initial centroids of the clusters. This time the convergence was achieved only after 282 iterations, resulting in the same nine clusters as in Table 4.

In Fig. 5 are shown the trend of the iteration error obtained by running FCM after fixing the initial centroids of the clusters obtained by QEEFCM (QUEE-FCM+FCM), and the trend of iteration error obtained by running FCM by randomly fixing the initial centroids of the clusters (FCM).

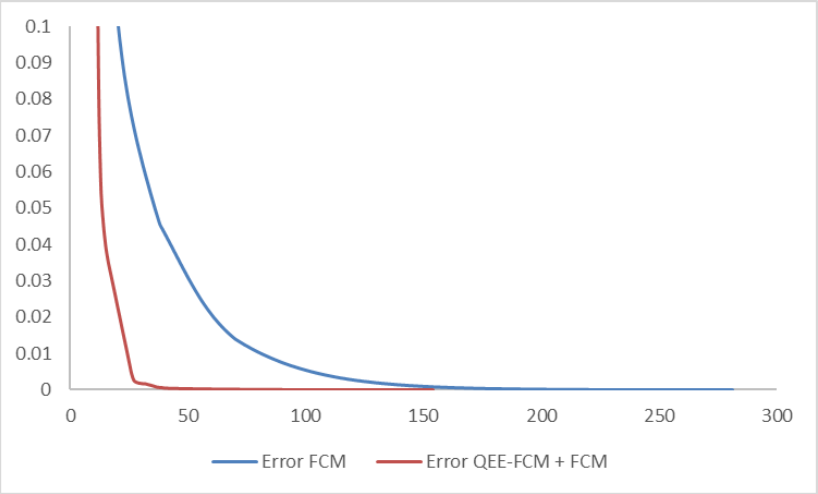


Fig.5. Trend of the iteration error executing QUEE-FCM+FCM and executing FCM.

With an upper value of the Stop iteration error ε equal to 10^{-3}, using the values of the initial cluster centroids determined by QEE-FCM, convergence is achieved with less than 50 iterations. Instead, by initially setting the values of the cluster centroids randomly, over 150 iterations are necessary to reach convergence.

This result demonstrates that QEE-FCM performs better than FCM in terms of execution time, reaching convergence much faster than FCM. This performance advantage can be crucial for UHI detection where large satellite imagery and input data are required.

Each pixel is labelled with the identifier of the cluster to which it belongs with the highest membership degree. The thematic map in Fig. 6 shows the city partitioned by the nine clusters.

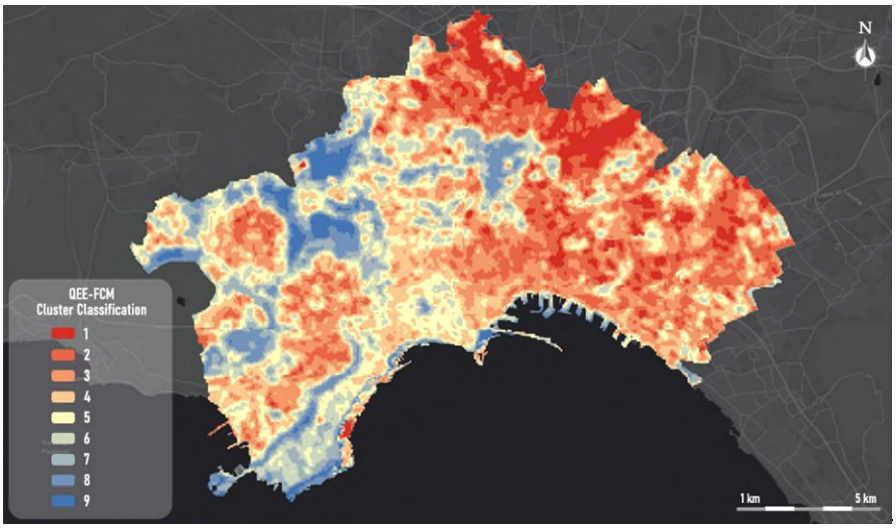


Fig.6. Thematic map showing the distribution of urban areas of the city of Naples by cluster

The hot and cold threshold lines are determined setting the two plateau zones of the trend of the final cluster centroids in the (LST-NDVI) plane (Fig. 7). The two plateau zones are obtained fixing the hot threshold point to the point on the curve where the slope of the curve exceeds the value 4% and fixing the cold threshold point to the point of the curve where the slope of the curve decreases below the value 4%.

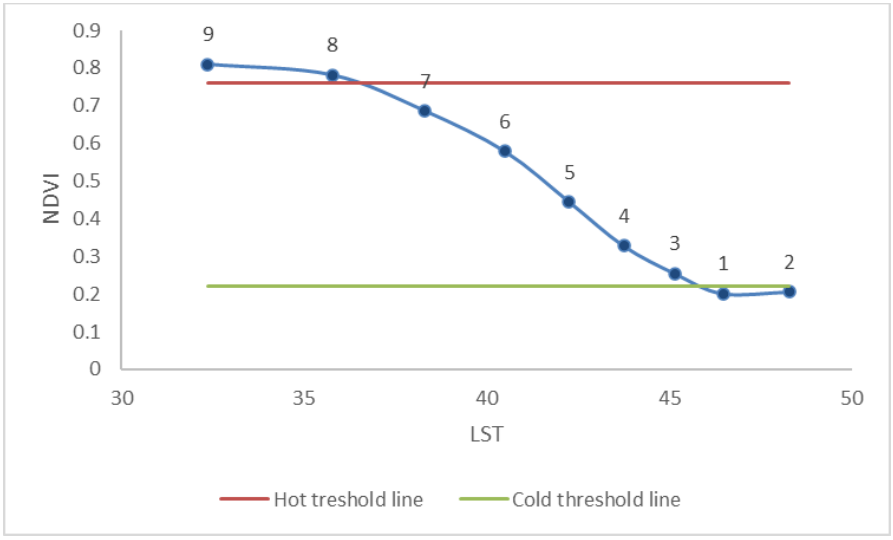


Fig.7. Trend of the cluster centroids in the plane (LST-NDVI) and the hot and cold threshold lines

Pixels belonging with the highest membership degree to clusters 8 and 9 were labelled as hotspots; those belonging with the highest membership degree to clusters 1 and 2 were labelled as coldspots. Then, all adjacent ixels labeled as hotspots (coldspots) are dissolved to form polygons labeled as UHIs (UCIs).

The UHIs and UCIs detected are shown on the thematic map in Fig. 8.

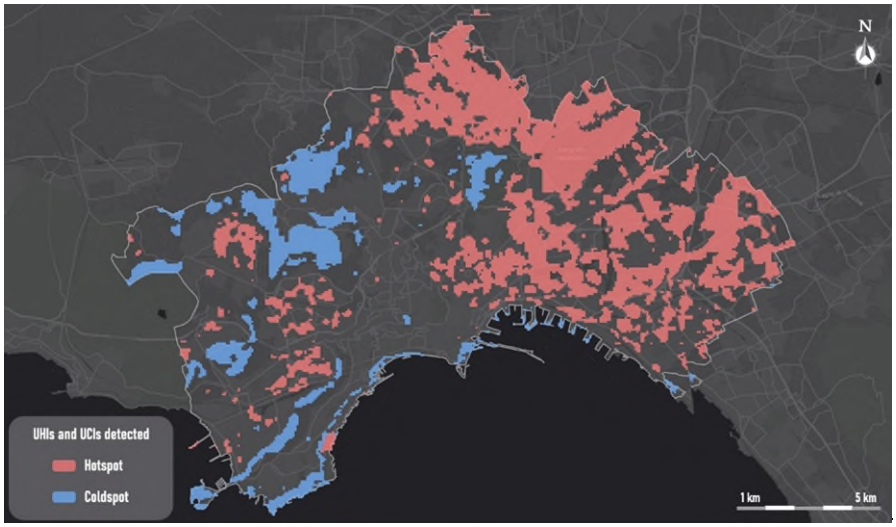


Fig.8. UHIs and UCIs detected in the city of Naples

The UHIs cover a total area of 27.29 square kilometrers. Urban areas in hotspots are those with the highest building density and the lowest number of parks and wooded areas; they are mainly located in the historic center and in dense urban areas to the west, north and east of the city.

The UCIs cover a total area of 8.98 square kilometrers. Urban areas in coldspots are those with the lowest building density and the highest number of urban parks and wooded areas; they are mainly located in the western area of the city, including the main urban parks and wooded areas.

Finally, the reliabilities of the UHIs and of the UCIs are obtained; reliability values range between 0.57 and 0.94. The UHIs and UCIs reliability maps are obtained by partitioning the [0,1] reliability domain into three classes, labelled Low, Medium and High, defined in Table 5.

Range of values	**Reliability**
Less than 0.6	Low
Between 0.6 and 0.7	Medium
Greater than 0.7	High

Tab 5. Classification of the reliability index.

The UHI and UCI reliability maps are shown, respectively in Fig. 9 and in Fig. 10.

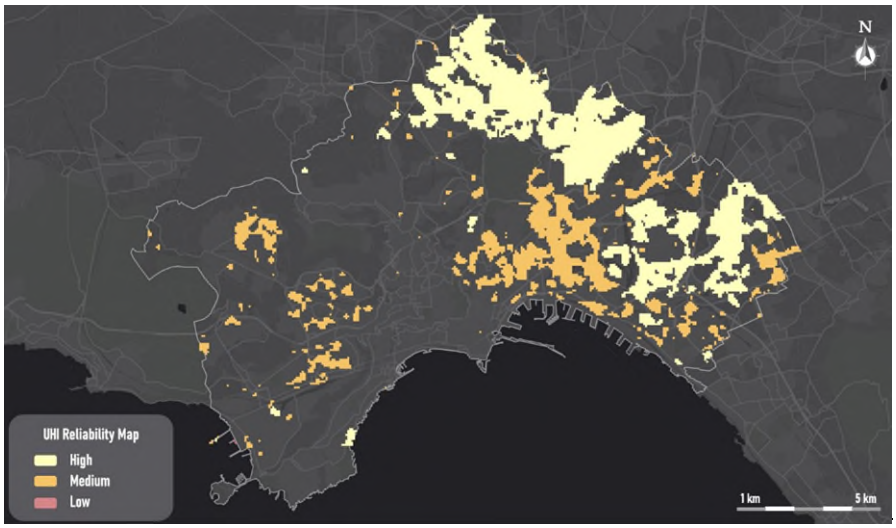


Fig.9. UHI reliability map in the city of Naples.

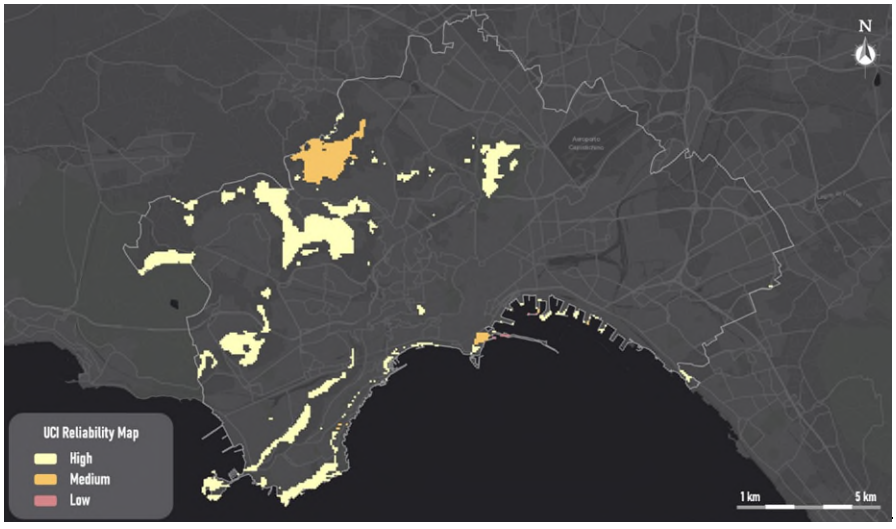


Fig.10. UCI reliability map in the city of Naples.

As shown in the map in Fig. 9, all detected UHIs are classified as High or Medium. In particular, the UHIs with High reliability are areas to the north and east of the city with a high homogeneity in terms of the presence of built structures and impermeable open spaces and the absence of green soils.

Likewise, the UCIs in the UCI reliability map in Fig. 10 are classified as High or Medium. The UCIs with High reliability are green areas northwest of the city;

they are made up of mainly wooded green areas with a homogeneous coverage of living tree species with a high presence of broadleaf trees.

These result highlights that the proposed UHI detection method provides valuable information regarding the reliability of the detected UHIs and UCIs, attributing a higher reliability to UHIs and UCIs with homogeneous soil characteristics.

5. Conclusions

In this work a new framework is proposed based on the quantum-inspired fuzzy c-mean variation QEE-FCM to detect UHIs and UCIs in urban settlements during heatwaves.

The framework is implemented on a GIS platform. The dataset consists of Land Surface Temperature and Normalized Difference Vegetation Index indices obtained from satellite images taken during heatwave periods. QEE-FCM is used to optimize the initialization of cluster centroids.

The framework was tested on a study area consisting of the city of Naples. The results showed that the proposed method is significantly faster than the FCM-based UHI detection method. Furthermore, it provides a reliability measure of the detected UHIs and UCIs, which allows for assessing the reliability of their location and extent.

Future evolution of the research will be focused on improving the accuracy of the detection of UHIs and UCIs, taking into consideration, in addition to the LST and NDVI indices, further measures that can contribute to determining more thoroughly the behaviour of urban soils during heat waves.

Acknowledgements The article has been developed within the context of the project RETURN (Multi-Risk sciEnce for resilienT commUnities undeR a changiNg climate)—the extended partnership that aims to strengthen research chains on environmental, natural and anthropogenic risks at national level and promote their participation in strategic European and global value chains.

Author contributions All authors contributed to the design and implementation of the research, to the analysis of the results and to the writing of the manuscript.

Funding Not applicable.

Data availability Authors confirm that all relevant data are included in the article.

Ethics approval Not applicable.

Declarations

Competing interests The authors declare no competing interests.

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