

An innovative approach to select urban-rural sites for Urban Heat Island analysis: the case of Turin (Italy)

Original

An innovative approach to select urban-rural sites for Urban Heat Island analysis: the case of Turin (Italy) / Bassani, Francesca; Garbero, Valeria; Poggi, Davide; Ridolfi, Luca; von Hardenberg, Jost; Milelli, Massimo. - In: URBAN CLIMATE. - ISSN 2212-0955. - 42:(2022), p. 101099. [10.1016/j.uclim.2022.101099]

Availability:

This version is available at: 11583/2956207 since: 2022-02-23T09:40:28Z

Publisher:

Elsevier

Published

DOI:10.1016/j.uclim.2022.101099

Terms of use:

This article is made available under terms and conditions as specified in the corresponding bibliographic description in the repository

Publisher copyright

Elsevier postprint/Author's Accepted Manuscript

© 2022. This manuscript version is made available under the CC-BY-NC-ND 4.0 license
<http://creativecommons.org/licenses/by-nc-nd/4.0/>. The final authenticated version is available online at:
<http://dx.doi.org/10.1016/j.uclim.2022.101099>

(Article begins on next page)

An innovative approach to select urban-rural sites for Urban Heat Island analysis: the case of Turin (Italy)

Francesca Bassani^{a,b,*}, Valeria Garbero^b, Davide Poggi^a, Luca Ridolfi^a, Jost von Hardenberg^a, and Massimo Milelli^c

^a*Department of Environment, Land and Infrastructure Engineering, Politecnico di Torino, 10129 Turin, Italy*

^b*Department of Meteorology, Climate and Air Quality, Arpa Piemonte, 10135 Turin, Italy*

^c*CIMA Foundation, 17100 Savona, Italy*

Abstract

A novel metric – the Mean Temperature Difference (MTD) – is proposed for the selection of urban-rural pairs of stations needed in the Urban Heat Island (UHI) quantification. This metric highlights the thermal pattern typical of each weather station with respect to the average one of the area of interest. Afterwards, Principal Component Analysis is adopted to cluster stations into subsets exhibiting similar thermal behaviors. The joint use of MTD and PCA allows one to classify stations objectively and without the need of preliminary assumptions about the station landscapes. An application to the metropolitan area of Turin (Italy) and a comparison with validated methods to select urban-rural pairs demonstrate that the proposed approach is easily interpretable and reliable also when the study area exhibits a non-trivial landscape categorization.

Keywords: Urban Heat Island, urban-rural pairs, MTD

1. Introduction

The meteorological phenomenon known as Urban Heat Island (UHI) is one of the main effects produced by increasing urbanization (Landsberg, 1981; Tzavali et al., 2015) and a significant example of anthropogenic climate modification (Arnfield, 2003). UHI refers to the warmer temperatures experienced by a city with respect to its rural surrounding area, mainly due to the different thermal properties between urbanized and natural lands, anthropogenic heat emissions, human-induced pollution and limited wind blowing among buildings (Oke, 1973, 1976; Rizwan et al., 2008). In the long and well-documented urban heat island literature (Stewart, 2011), UHI has been commonly quantified as the difference, in terms of air temperatures, between pairs of urban and rural measurement sites (Oke, 1973; Kim and Brown, 2021) or between a spatial average of several urban and/or several rural stations (e.g., Hoffmann and Schlünzen, 2013). This difference

*The formal publication is available at <https://doi.org/10.1016/j.uclim.2022.101099>

*Corresponding author

Email address: francesca.bassani@polito.it (Francesca Bassani)

11 is crucial in determining the UHI intensity and requires choosing a non trivial definition of which stations are
12 "urban" and "rural". In his work, Stewart (2007) highlighted the difficulty in the definition of the urban-rural
13 dichotomy, because the demarcation between "urban" and "rural" is artificial and many relevant local-scale
14 aspects should be taken into account. Recent studies tried to address this critical issue by proposing new
15 methods that (i) highlight different thermal behaviors in urban-rural pairs – e.g., the approaches based on the
16 thermal day-to-day variation (Karl et al., 1995; Gough, 2008; Mohsin and Gough, 2012; Tam et al., 2015; Wu
17 et al., 2017; Anderson et al., 2018) or the mean daily excursion (Milelli, 2016) – or (ii) identify the stations
18 called "peri-urban", i.e. those located close to the urban-rural interface, by focusing on the day-to-day warm
19 and cold transitions (Gough, 2020).

20 Another important approach to classify the stations is the Local Climate Zones (LCZs) Classification
21 System proposed by Stewart and Oke (2012). By using criteria concerning aspects that control the local
22 surface climates, this climate-based tool classifies the landscape (i.e., a local-scale area of land) in 17 regions
23 characterized by uniform surface cover, structure, material and human activity. The classification covers
24 both built and natural environments and each zone is characterized by a distinctive near-surface temperature
25 regime.

26 Despite the variety of methods, a key point is that all of them need a preliminary classification of the
27 stations. In order to overcome this possible source of arbitrariness, we propose a novel method, which we
28 call the "Mean Temperature Difference" (hereinafter MTD). The MTD is a data-based approach aiming to
29 recognize and differentiate the thermal behavior of the urban context with respect to its surrounding less
30 populated area. The former is different – in terms of thermal response – from the latter, mainly because of
31 its predominantly impervious land cover type and the presence of sheltering constructions, which trap heat
32 during the day and release it during the night resulting in higher night-time temperatures.

33 The strength of the proposed MTD method is the capability to objectively identify these different thermal
34 behaviors, without assuming *a priori* which sites pertain to the urban and rural categories. In this sense, the
35 MTD approach can complete and be of support to the Local Climate Zones Classification. In fact, as stated by
36 Stewart and Oke (2012), the intention of the LCZs is not to supplant the categories "urban" and "rural" in the
37 heat island issues, but to provide a more conscious and constrained use of these categories when describing
38 the local conditions of the stations.

39 Starting from a group of stations – heterogeneous in terms of LCZs – and adopting the Principal
40 Component Analysis (Jolliffe and Cadima, 2016) as a clustering method, the proposed approach is able to
41 objectively and clearly identify the different thermal behavior of the stations. It allows a clear distinction of
42 what is the typical "urban" pattern, the different "rural" one and also what does not fall into either categories.

43 No choice about whether a site is "urban" or "rural" is made *a priori* and no parameters to calibrate enter the
 44 procedure, so that its results are clear, immediate and easy to apply. This makes the method objective, totally
 45 data-based and unrelated to any preliminary landscape classification.

46 To show the features of the proposed method, we apply it to the city of Turin (Italy) and its surrounding
 47 area, which is characterized by a quite complex morphology (orographic and hydrographic heterogeneity,
 48 different land uses, etc.), making it suitable to test the proposed metric.

49 The paper is organized as follows. Section 2 describes the MTD metric. Section 3 reports the results of
 50 the application of the proposed method to Turin area and highlights its advantages. In Section 4 we discuss
 51 the applicability of the MTD. Section 5 shows the comparison of the MTD-based approach with existing
 52 methods to select proper urban-rural pairs. Finally, some conclusions are drawn.

53 2. Proposed method

54 The idea behind the MTD metric is to detect similar behaviors among stations and it is based on two main
 55 steps: (i) the evaluation of a metric characterizing the thermal behavior of each measurement site, and (ii)
 56 the adoption of the Principal Component Analysis (Jolliffe, 2002; Wilks, 2011), in order to capture common
 57 performances of such metric and to cluster the stations into distinct groups.

58 We start describing the first step. The variable considered for each weather station S is the monthly-
 59 averaged hourly temperature $T_{i,M}^S$, where subscripts $i = 1, 2, \dots, 24$ and $M = Jan, Feb, \dots, Dec$ refer to the
 60 hours and months, respectively. For example, the monthly temperature value at 01:00 hours for January (i.e.,
 61 $T_{1,Jan}^S$) refers to the climatological average over all years of all the temperatures of January registered at
 62 01:00. The metric MTD is defined, for each hour i , each month M and each station S , as:

$$\text{MTD}_{i,M}^S = T_{i,M}^S - \overline{T_{i,M}^S} - \langle T_{i,M}^S - \overline{T_{i,M}^S} \rangle \quad (1)$$

63 in which the overbar refers to a temporal average over all months and hours of $T_{i,M}^S$, and $\langle \cdot \rangle$ represents the
 64 spatial mean among all stations included in the study area (i.e., $\langle \cdot \rangle = \sum_j (T_{i,M})_j / N_S$, where j ranges from
 65 1 to the number of stations N_S). The first two terms at the right-hand side of Eq. (1) define the anomaly of
 66 temperatures at each hour and month compared to their temporal average for that station. The last two terms
 67 remove the mean anomaly across all stations for that hour and month. Positive values of MTD indicate that
 68 the station S , at a certain hour and month, is characterized by higher air temperature anomalies than the mean
 69 of the other stations, while the opposite occurs for negative MTD.

70 In the second step of the proposed method, the MTD values are organized in a matrix to which the
 71 Principal Component Analysis (PCA) is applied. The matrix (hereinafter **MTD**) has dimensions $288 \times N_S$:

72 its rows contain the values $MTD_{i,M}$ corresponding to the 24 hours for every month ($24 \times 12 = 288$), and each
73 column refers to a station S : therefore, **MTD** defines a cloud of 288 points in a N_S -dimensional space.
74 PCA is commonly used in the atmospheric science and it is considered a robust tool in climatology and
75 meteorology (e.g., Lorenz, 1956; Hannachi et al., 2007; Demšar et al., 2013). As described by Wilks (2011),
76 this mathematical technique aims at reducing the dimensionality of a large set of data to another data set, which
77 contains a linear combination of the original variables. The analysis can be conducted on the correlation
78 matrix or on the covariance matrix. PCA applied to the correlation matrix weights all the standardized
79 variables equally, because all have variance equal to the unity; instead, the analysis on the covariance matrix
80 emphasizes the principal components having the largest variances (Wilks, 2011). Therefore, we performed
81 PCA on the covariance matrix of **MTD** so that the information about the variance is included in the clustering
82 of stations. PCA arranges the original dimensions of the data matrix **MTD** onto a new orthogonal space, such
83 that the new axes are oriented in the directions explaining largest variance in the data. These new directions
84 are called principal components and they are chosen in such a way that the greatest variance of the data lies
85 along the first direction (namely, the first principal component), the second greatest variance on the second
86 direction, and so on. The principal components correspond to the eigenvectors of the covariance matrix of
87 **MTD**, while the eigenvalues are a proxy of the variance explained along each principal direction. It follows
88 that, ordering the eigenvalues in descending order from largest to smallest, it is likely that the subspace
89 mapped by the first m principal directions explains most of the variability of the data contained in the **MTD**
90 matrix. That is, it is sufficient to consider this m -dimensional subspace to describe the main features of the
91 original N_S -dimensional space. The quality of the description provided by the m -th subspace can be assessed
92 by comparing the sum of the m eigenvalues – corresponding to the m eigenvectors considered – and the
93 cumulated variance explained by all the eigenvectors, computed as the sum of all eigenvalues. Typically, in
94 the present application the first two principal components (i.e., $m=2$) were sufficient to describe the thermal
95 behavior of the stations, allowing to cluster them on a simple plane. As a consequence, the interpretation of
96 the analysis is straightforward and objective.

97 **3. Case study: Turin (Italy)**

98 *3.1. Stations and data*

99 Turin is located in the North-West region of Italy, at latitude 45.071 N and longitude 7.687 E. The
100 metropolitan area of Turin has a population of almost 1.5 million inhabitants, covering an area of about 600
101 km^2 . The city is at about 100 km (air distance) far from the highest peak of the Alps, at a mean elevation

102 above the sea level of 250 meters and it is surrounded by hills up to 600 m high in the Eastern sector, as
 103 shown in Fig. 1a.

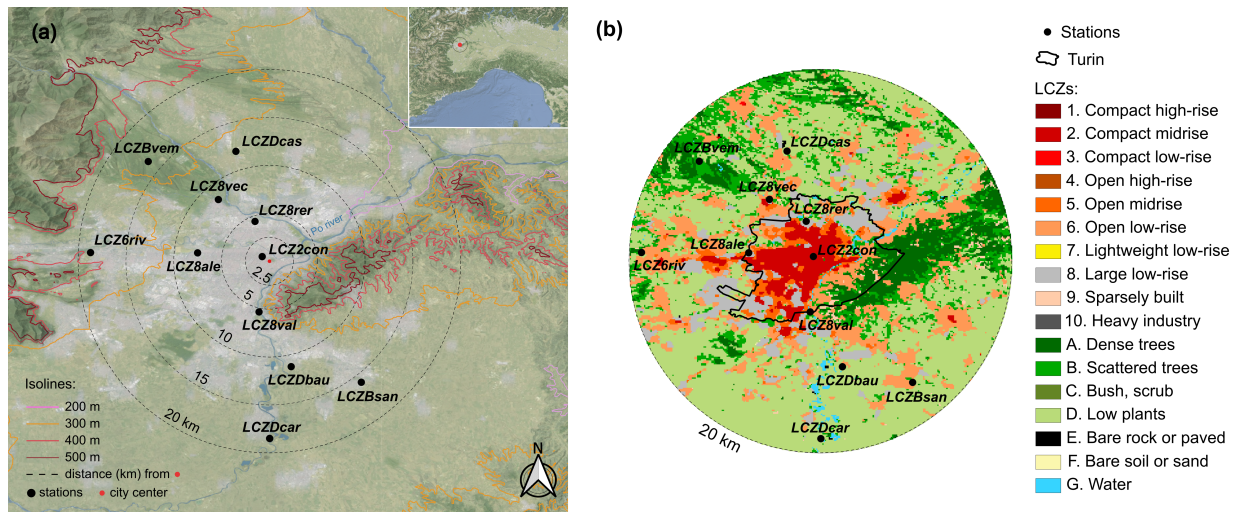


Figure 1: Panel (a): terrain map of the metropolitan area of Turin (North-West of Italy, in the inset), with the principal rivers highlighted in blue and the urbanized area represented in gray. The distance in kilometers of each weather station (black dots) from the city center (red dot, Piazza Castello: lat 45.071 N, lon 7.687 E) is marked with the black dashed isolines, while the colored continuous isolines indicate the elevation above the sea level (meters). Panel (b): LCZ map of the studied area, from Demuzere et al. (2020) (WUDAPT database, Ching et al., 2018).

104 The Po river flows in the South-East of the city and separates the most urbanized area, which is mainly
 105 located on the western bank of the river, from the hills in the East (see Fig. 1a). The Köppen Climate
 106 Classification (Köppen and Geiger, 1936) puts Turin into the Humid Subtropical Climate, namely Cfa (C =
 107 warm temperature, f = fully humid, a = hot summer). According to this, the climate in Turin is warm and
 108 temperate with significant rainfall all over the year. The 11 stations considered in the analysis (see Tab. 1)
 109 provide hourly near-surface temperature data. They belong to the network of the Regional Agency for the
 110 Protection of the Environment of Piedmont Region (Arpa Piemonte) and are distributed around the city of
 111 Turin, with about 20km as maximum distance from the city center (see Fig. 1a). For this study, the selected
 112 stations are chosen on the basis of the longest temporal series available, from January 1st, 2007 to December
 113 31st, 2020 (14 years).

114 According to the Local Climate Zones (LCZ) map (see Fig. 1b), provided for Europe at 100m spatial
 115 resolution by Demuzere et al. (2019, 2020) (WUDAPT database, Ching et al., 2018), six stations fall under the
 116 "Built types" category of Stewart and Oke (2012): Consolata (*LCZ2con*), Rivoli (*LCZ6riv*), Alenia (*LCZ8ale*),
 117 Vallere (*LCZ8val*), Venaria Ceronda (*LCZ8vec*) and Reiss Romoli (*LCZ8rer*). The stations of Santena-Banna
 118 (*LCZBsan*), Venaria La Mandria (*LCZBvem*), Bauducchi (*LCZDbau*), Carmagnola (*LCZDcar*) and Caselle

Table 1: Weather stations for the temperature measurements used in the analysis, sorted alphabetically by their short names, with lat-lon coordinates in decimal degrees, elevation above the sea level (a.s.l., meters) and Local Climate Zones types and definitions (from Stewart and Oke, 2012).

Station name	Station short name	Lat (N)	Lon (E)	Elevation (m a.s.l.)	LCZ type and definition
Consolata	<i>LCZ2con</i>	45.0758	7.6783	290	2: Compact midrise
Rivoli	<i>LCZ6riv</i>	45.0800	7.4989	362	6: Open low-rise
Alenia	<i>LCZ8ale</i>	45.0797	7.6108	320	8: Large low-rise
Vallere	<i>LCZ8val</i>	45.0181	7.6750	239	8: Large low-rise
Venaria Ceronda	<i>LCZ8vec</i>	45.1353	7.6325	253	8: Large low-rise
Reiss Romoli	<i>LCZ8rer</i>	45.1125	7.6708	270	8: Large low-rise
Santena-Banna	<i>LCZBsan</i>	44.9447	7.7819	238	B: Scattered trees
Venaria La Mandria	<i>LCZBvem</i>	45.1750	7.5592	337	B: Scattered trees
Bauducchi	<i>LCZDbau</i>	44.9610	7.7086	226	D: Low plants
Carmagnola	<i>LCZDcar</i>	44.8861	7.6861	232	D: Low plants
Caselle	<i>LCZDcas</i>	45.1856	7.6508	300	D: Low plants

119 (*LCZDcas*) are categorized as "Land cover types" (Stewart and Oke, 2012), as shown in Tab. 1.

120 However, the LCZ classification is sometimes the result of unsupervised choices and may lead to assign-
 121 ments which not always match the analysts' expertise. In the following section, the stations are reexamined
 122 in light of the MTD approach. It emerges that sometimes the LCZs are too local to fully characterize the
 123 thermal behavior of the sites and do not consider the effects induced by local surrounding conditions or the
 124 large-scale context around a station, e.g., the distance to the city center or the proximity to the reliefs.

125 3.2. Results: Urban Heat Island

126 The MTD patterns obtained from Eq. (1) are shown in Fig. 2. The emerging patterns already feature
 127 common behavior among groups of stations at a first glimpse. Firstly, three stations – Consolata (*LCZ2con*),
 128 Reiss Romoli (*LCZ8rer*) and Alenia (*LCZ8ale*) – show a central cold area, characterized by negative MTD
 129 values during daytime, while at night hours the temperature anomalies are positive (see the first row of Fig.
 130 2). Secondly, the stations Caselle (*LCZDcas*), Rivoli (*LCZ6riv*) and Vallere (*LCZ8val*), displayed in the
 131 second row of Fig. 2, do not show a well defined hot/cold blob. Finally, in the remaining panels of Venaria
 132 Ceronda (*LCZ8vec*), Venaria La Mandria (*LCZBvem*), Bauducchi (*LCZDbau*), Santena-Banna (*LCZBsan*)
 133 and Carmagnola (*LCZDcar*) an inverse pattern clearly emerges, characterized by positive MTD values during
 134 daytime and negative ones during night times.

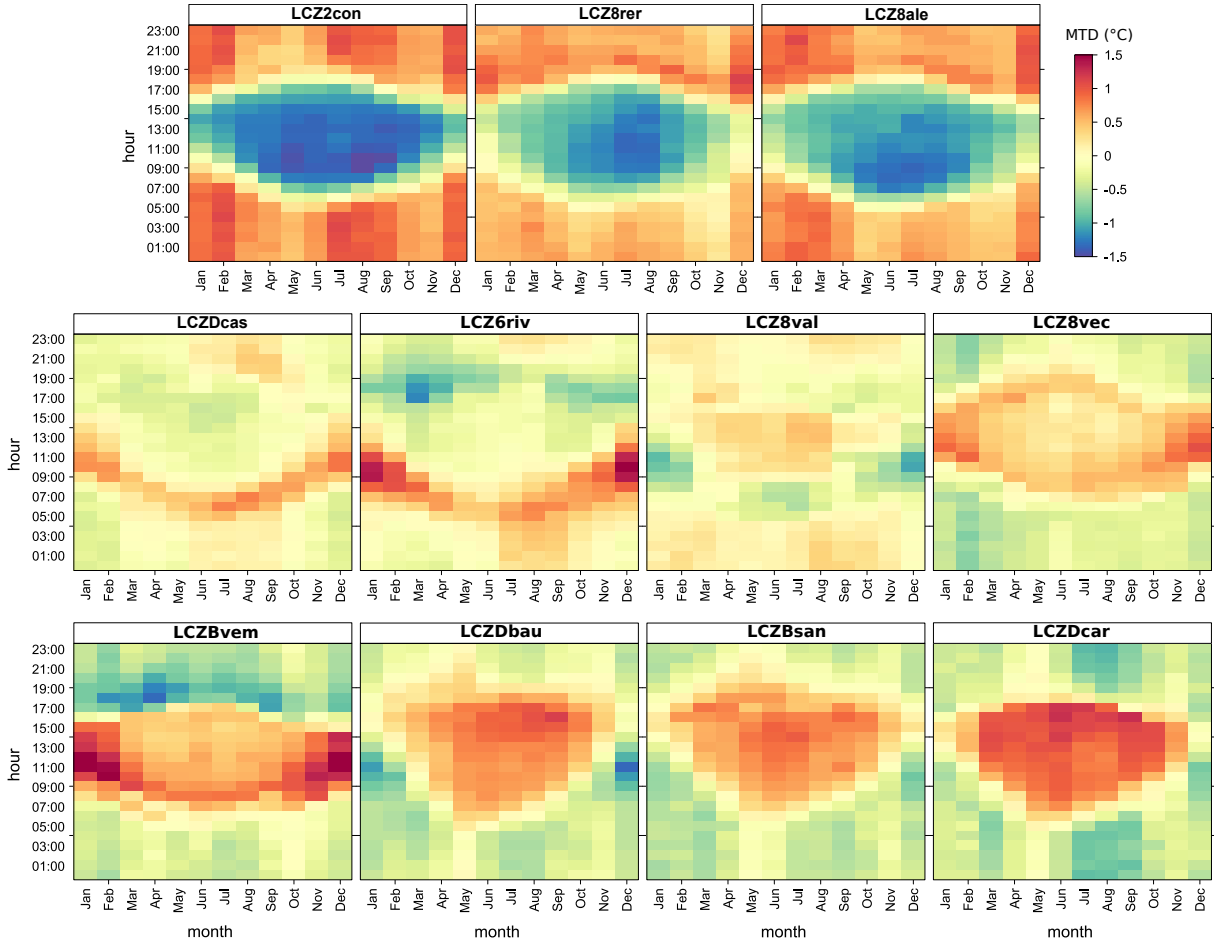


Figure 2: Mean Temperature Difference (MTD): each panel, labeled with the short name associated to each weather station S , represents the $MTD_{i,M}^S$ computed with Eq. 1 (hours i are reported on the y-axis and months M on the x-axis).

135 Figure 3 shows the results of the applications of the Principal Component Analysis to the MTD matrix,
 136 allowing the different behaviors of the stations to be distinguished. As described in Section 2, the first two
 137 principal components clearly emerge. In Fig. 3a the percentage of the explained variance is plotted on the left
 138 y-axis, while its cumulative values are represented as the right ordinate. The first two principal components
 139 (p.c.) explain most of the variance in the data (about $\approx 92\%$) and so they are sufficient to cluster the stations:
 140 in particular, the first p.c. accounts for $\approx 74\%$, while the second p.c. for about 18% . The projection of each
 141 station onto the first and the second principal components are reported along the x- and y-axis of Fig. 3b,
 142 respectively.

143 The physical meaning of these principal components is clear looking at panels (c) and (d) of Fig. 3,
 144 showing the two signals. Let us focus on the signal described by the first principal component (Fig. 3c). It
 145 is characterized by negative temperature anomalies during daytime hours and positive ones during evening

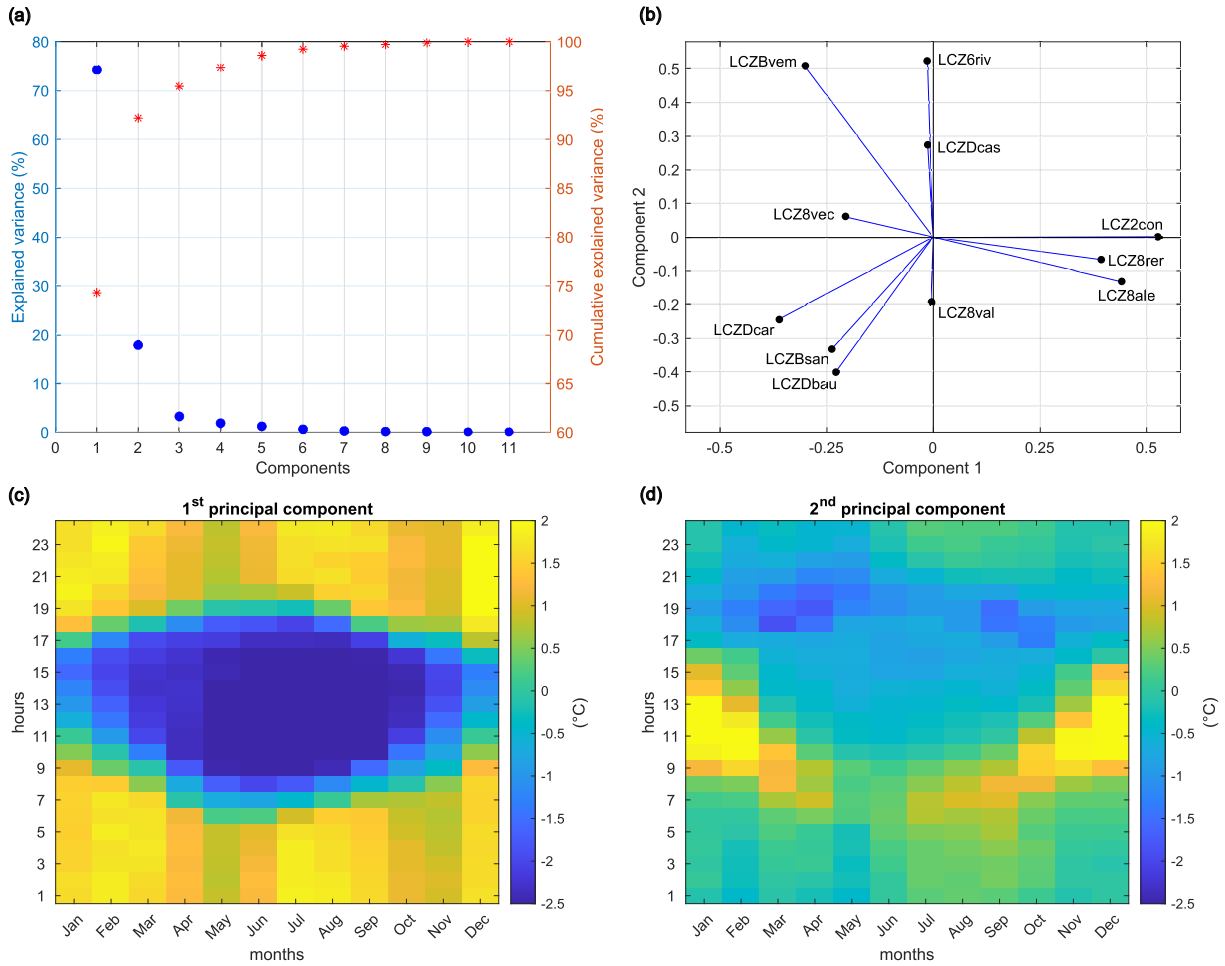


Figure 3: PCA on the matrix MTD: **(a)** percentage of explained variance for each of the 11 components (blue dots, left axis) and their cumulative values (red asterisks, right axis); **(b)** space of the first (x-axis) and second (y-axis) principal components; **(c),(d)** representation of the two principal components of the MTD (color scales in degrees Celsius).

146 and night. This is the typical pattern embedded in the Urban Heat Island phenomenon: in the morning
 147 and early-afternoon, the UHI is low and can even become negative in some cases (Memon et al., 2009),
 148 resulting in the so-called daytime Urban Cool Island (Theeuwes et al., 2015). Then, when the solar radiation
 149 decreases, the urban area retains more heat and cools more slowly than the rural surroundings (Theeuwes
 150 et al., 2017), resulting in positive anomalies of temperatures. We deduce from this pattern that the first
 151 principal component – which corresponds to the highest eigenvalue ($\approx 74\%$ of explained variance) – refers to
 152 the most evident characteristic differentiating the stations: urban vs. rural thermal behavior. The projection
 153 of each station onto the first principal component (x-axis of Fig. 3b), either it is positive or negative,
 154 determines whether a site is characterized by one or the other thermal behavior: the stations of Consolata
 155 (*LCZ2con*), Reiss Romoli (*LCZ8rer*) and Alenia (*LCZ8ale*) are characterized by substantially positive values,

156 while negative projections correspond to Venaria La Mandria ($LCZBvem$), Venaria Ceronda ($LCZ8vec$),
 157 Carmagnola ($LCZDcar$), Santena-Banna ($LCZBsan$) and Bauducchi ($LCZDbau$). Instead, an almost null
 158 projection onto the first p.c. means that the thermal behavior cannot be assigned to urban or rural patterns.
 159 This is the case of Rivoli ($LCZ6riv$), Caselle ($LCZDcas$) and Vallere ($LCZ8val$).

160 The general pattern described by the first p.c. (Fig. 3c) can be made station-specific by multiplying
 161 it by the projection of the station of interest onto the first principal component, thanks to the fact that the
 162 principal components form an orthonormal base. As an example, consider two stations characterized by a
 163 positive and a negative projection onto the first p.c., namely Consolata ($LCZ2con$, positive) and Carmagnola
 164 ($LCZDcar$, negative), and examine one temporal slot, e.g., 01UTC in January. We define $E_{i,M}^{PC}$ as the
 165 value corresponding to the considered instant in time (hour $i = 1$ and month $M = Jan$), derived from the
 166 representation of the first principal component ($PC = 1$) in Fig. 3c: $E_{1,Jan}^{PC=1} = 1.63$. The value of the
 167 projection of Consolata onto the first principal component is 0.54 (see Fig. 3b). The MTD associated with
 168 this station is $MTD_{1,Jan}^{LCZ2con} = 0.90^\circ\text{C}$ (see panel $LCZ2con$ in Fig. 2), and it can be obtained by multiplying
 169 $E_{1,Jan}^1$ by 0.54: $MTD_{1,Jan}^{LCZ2con} \approx 1.63 \cdot 0.54 = 0.88^\circ\text{C}$. The centesimal digits missing for obtaining the exact
 170 value 0.90°C (in Fig. 2) derive from the additional contribution of the other principal components. To sum up,
 171 at 01UTC in January the temperature at Consolata is $\approx 0.90^\circ\text{C}$ warmer than the average of all other stations.
 172 This behavior reflects the UHI effect and it is mainly due to the urban characteristics of this site, which is
 173 confirmed also by its LCZ class. Instead, the station of Carmagnola is characterized by a negative projection
 174 onto the first principal component, equal to -0.35 (Fig. 3b): $MTD_{1,Jan}^{LCZDcar} \approx 1.63 \cdot (-0.35) = -0.57^\circ\text{C}$. As
 175 above, a good approximation of the actual $MTD_{1,Jan}^{LCZDcar} = -0.38^\circ\text{C}$ displayed in Fig. 2 would be obtained
 176 adding $E_{1,Jan}^2 \cdot (-0.25)$, where (-0.25) is the projection of Carmagnola onto the second principal component
 177 (Fig. 3b).

178 The previous example shows that the correspondence between the projection of the stations onto the
 179 first principal component and their thermal pattern is very clear. A first group, characterized by positive
 180 projections ($LCZ2con$, $LCZ8rer$ and $LCZ8ale$), resembles exactly the signal shown in Fig. 3c, where warmer
 181 temperatures are experienced during night. Therefore, its thermal behavior is associated with a typical urban
 182 pattern in the UHI effect, as already discussed by Milelli (2016) and Garbero et al. (2021). The LCZ-based
 183 classification assigned to the stations belonging to this group confirms these findings, since the combined
 184 effect of buildings and the mostly paved surface cover – typical of LCZ classes number 2 and 8 – greatly
 185 influences the surface energy and radiation balance (Oke, 1982).

186 A second group of stations exhibits the opposite temperature pattern with respect to the one shown in
 187 Fig. 3c, having a negative projection onto the first p.c.: $LCZBvem$, $LCZ8vec$, $LCZDcar$, $LCZBsan$ and

188 *LCZDbau*. We associate this thermal pattern with the rural surroundings of the city, characterized by colder
189 temperatures during the night and by higher early morning heating rate than over the city (Johnson, 1985;
190 Theeuwes et al., 2015). As before, some considerations can be drawn in light of the LCZs assignment. In
191 agreement with the authors' expertise, the described rural thermal pattern is coherent with the land cover types
192 B (scattered trees) and D (low plants) associated with the stations of Santena-Banna (*LCZBsan*), Venaria La
193 Mandria (*LCZBvem*), Bauducchi (*LCZDbau*) and Carmagnola (*LCZDcar*). Note that *LCZBsan*, *LCZDbau*
194 and *LCZDcar* were adopted as rural stations also in Milelli (2016) and Garbero et al. (2021). However, the
195 LCZs assignment of Venaria Ceronda (*LCZ8vec*), namely the "Large low-rise" built type, seems too local
196 to fully characterize its rural thermal pattern emerging from PCA. Actually, the LCZ class number 8 would
197 relate this station to a mostly paved surface with few or no trees, but the PCA shows that its thermal behavior
198 is instead more aligned with the rural class.

199 Figure 3b also shows that the projection onto the first principal component is almost zero for *LCZ6riv*,
200 *LCZDcas* and *LCZ8val*. This means that for these three stations the contribution of the first principal
201 component ($E_{i,M}^{PC=1}$) weights less than the second p.c. and, therefore, the signal characterizing these sites
202 looks like panel (d) of Fig. 3. Before focusing on the meaning behind the second principal component, the
203 near-absence of the projection onto the first principal component in *LCZ6riv*, *LCZDcas* and *LCZ8val* reveals
204 that Rivoli, Caselle and Vallere exhibit an intermediate thermal behavior with respect to the other stations
205 characterized by substantially positive or negative projections. Note that this intermediate behavior is not
206 necessarily homogeneous among these stations. PCA only highlights that their thermal pattern differs from
207 all other sites characterized by positive or negative projections and, therefore, these three stations should be
208 considered carefully for UHI studies. It is also important to point out that also the LCZs assignment for
209 *LCZ6riv*, *LCZDcas* and *LCZ8val* is questionable and appears too local to take into account the real conditions
210 affecting the temperatures measured by the sensors. The site of Rivoli (*LCZ6riv*) is designated as "Open
211 low-rise" built type, but its thermal behavior is not classified as urban by the PCA probably because of the
212 proximity to the reliefs and the distance from the city of Turin. Caselle station (*LCZDcas*) is assigned to the
213 "low plants" land cover type D, but the PCA does not classifies it as rural. Actually, *LCZDcas* is located in
214 the perimeter area of an airport, at about 200 m from the airstrip and only 600 m far from the closest town
215 and the effective presence of low plants is true in the immediate surroundings of the site only. Finally, the
216 "Large low-rise" built type associated with the station of Vallere (*LCZ8val*) does not show an urban thermal
217 behavior, because it is located close to a park. Therefore, the LCZs assignments are not always able to clearly
218 distinguish the urban and rural thermal patterns, since we observed that same LCZ type corresponds in some
219 cases to different thermal behaviors.

Let now focus on the signal described by the second principal component (Fig. 3d), which explains about the 18% of the total variance and captures other aspects (with respect to the first component) related to the stations. This signal is characterized by positive anomalies of temperature after sunrise and negative ones when the solar radiation decreases. We note that southern sites, such as Vallere (*LCZ8val*), Bauducchi (*LCZDbau*), Santena-Banna (*LCZBsan*) and Carmagnola (*LCZDcar*), are characterized by a negative projection onto the second principal component, meaning that these stations experience a later warming in the morning and an earlier cooling in the evenings. This behavior can be ascribed to the different thermal regime existing between the northern and southern portion of the considered area. In the North, the stations are closest to the reliefs and more subject to ventilation, while in the South their location in the Po valley yields to a more frequent inversion in the usual vertical temperature gradient. The colder air near the ground induces a delay in the warming up in the morning and an earlier cooling down in the evening, and it is associated with foggy conditions, as frequently observed in that area (Cassardo et al., 2002). In particular, the Southern stations registered a mean (over the 14 years of the analysis) of 88 foggy days/year, while the Northern ones 17 days/year only (Arpa Piemonte, 2020). Therefore, we suggest that the second principal component is related to the geographical position of the stations, mainly to their elevation – and so proximity to reliefs – and latitude. The high correlation between the projection onto the second principal component and (i) the elevation of the sites (Pearson’s coefficient of correlation ≈ 0.86) and (ii) their latitude (correlation ≈ 0.75) supports our hypotheses.

4. Applicability of MTD

The Urban Heat Island intensity varies from city to city and its quantification is largely affected not only by the geography and climate of the site, but also by the datasets available to researchers. In this context, the proposed method is conceived to be general and applicable even when the data are not as rich as it is for the case study analyzed here.

The first matter to address is the temporal scale of the UHI analysis. In the last decades, different scales were focused on, ranging from climatic scales (e.g., Rosenzweig et al., 2005; Parker, 2010) to seasonal analyses – e.g., summer heat waves (Founda and Santamouris, 2017) or waves in winter months (Giridharan and Kolokotroni, 2009) – to the negative effects of UHI during night hours in health and welfare studies (Tan et al., 2010). There is no single choice, but the selection of the time scale has to agree with the aims of the specific Urban Heat Island study of interest.

If there is no particular purpose other than the characterization of the thermal behavior of stations, the annual time scale represents the most appropriate choice to fully grasp the thermal pattern. In any case, one

of the main advantages of the proposed MTD is to be as general as possible and, therefore, adaptable to any temporal scale of interest.

Once the time scale has been chosen – we considered the annual scale in the Turin case study described in the previous section – a second question concerns the duration of the available measures. In order to test this aspect, we applied the MTD method by increasingly reducing our range of data (i.e., 14 years, 13 years, and so on) and we observed that only one year of observations is enough for the MTD to work. In Appendix A we show that the first principal component of the PCA exhibits the same thermal pattern associated to an urban or rural behavior as in Section 3.2. It follows that the metric MTD appears capable of exploiting the data very effectively, even if obviously the longer the period of observations is, the more the results will not be affected by the particular conditions observed in the considered 12 months.

The time resolution of measures is another key aspect. In the Turin test case, we adopted the hourly time step, which is one of the most widely used in UHI literature (Santamouris, 2007; Oh et al., 2020; Kim and Brown, 2021). However, the robustness of the MTD has been tested also against a coarser temporal resolution: by considering a 3 hour time step (e.g., Pakarnseree et al., 2018, used this sampling time). In this study, we consider a subset of our original data with temperature measurements at 00, 03, 06, 09, 12, 15, 18 and 21 UTC. Again, the method proves to work very well, since the resulting clustering of stations is equal to that obtained with the hourly temperatures (results are shown in Appendix A).

An important question about the applicability of the MTD concerns the minimum number of weather stations required for the method to work. Turin has a relatively consistent number of measurement sites, but this may not be the case for other cities. In order to test this point, we performed a detailed sensitivity analysis, by re-evaluating the MTD performances using different subsets of the original 11 stations (see Appendix A). By excluding the stations identified as rural by our method (in Section 3.2), the PCA still identifies an urban thermal behavior and a different one. On the contrary, when considering the rural stations only, the main pattern described by the signal is different and cannot be related to urbanity/rurality. This result is a warning that the considered stations are not a good choice in selecting urban/rural pairs for UHI.

Finally, we evaluated the method on a different dataset and geographic domain: the city of Cuneo, in North-Western Italy. Cuneo is located at a higher mean elevation above the sea level (about 550 m a.s.l.), has a smaller number of inhabitants than Turin (about 60000) and has only two weather stations available, namely Cuneo Camera di Commercio *LCZ2ccc* and Cuneo Cascina Vecchia *LCZ6ccv* (see Appendix A). In the surroundings of the city, the station of Boves *LCZDbov* (575 m a.s.l.) is the only one suitable for this kind of analysis. In addition, the hourly temperatures are available for 18 months only (from July 2019 to December 2020). The Köppen Climate Classification (Köppen and Geiger, 1936) puts Cuneo into the

283 Temperate Oceanic Climate, namely Cfb. Being at the foot of the Alps, Cuneo receives more snow during
 284 winter than Turin (Arpa Piemonte, 2020). Even in this completely different domain, the MTD works very
 285 well (see Appendix A): *LCZ2ccc* is deemed as urban, *LCZDbov* as rural and *LCZ6ccv* exhibits an intermediate
 286 behavior between the other two.

287 The minimum number of stations for the application of our method is two, namely the intrinsic number
 288 to the Urban Heat Island definition, provided that the selected sites exhibit a different thermal behavior
 289 (highlighted in the signal of the PCA) in terms of urbanity or rurality.

290 5. Discussion and Conclusions

291 The proposed method aims to cluster common behaviors among the available measurement stations, in
 292 order to detect the most representative urban-rural pairs for Urban Heat Island quantification in the studied
 293 area. The example of Turin shows that the MTD turns out to be an effective metric able to grasp the main
 294 differences – in terms of thermal behavior – among the stations.

295 Given the widely recognized difficulty of the proper selection of urban-rural pairs, the metric which we
 296 propose can complement the methods already existing in literature, and provides an additional tool in the UHI
 297 research topic for the landscape classification. In this line, it is instructive to compare the results (for the Turin
 298 area) of our approach with those of three consolidated methods: (i) the Day-to-Day variation introduced by
 299 Karl et al. (1995) and further developed by Gough (2008), (ii) the mean daily excursion described by Milelli
 300 (2016) and (iii) the ratio between warm and cold day transitions recently presented by Gough (2020).

301 The Day-To-Day (DTD) temperature variation detects urban stations when a site exhibits increasing
 302 day-to-day variation in the daytime maximum temperature. Figures 4a-b show the results of this metric:
 303 DTD is evaluated as the absolute difference between the temperatures of adjacent days for a given period
 304 of time (e.g., month) and is calculated both for daily temperature minimum (nighttime, DTD T_{\min}) and
 305 daily temperature maximum (daytime, DTD T_{\max}). According to Oke (1981, 1982), urban stations exhibit
 306 lower nocturnal temperature variability because urbanized areas trap the radiative energy, inducing a slower
 307 convective heat loss than the surrounding rural areas. Therefore, the effects of urbanization are associated
 308 with the lowest DTD T_{\min} . Results shown in Fig. 4a highlight a first cluster corresponding to the three urban
 309 stations – i.e., Consolata (*LCZ2con*), Reiss Romoli (*LCZ8rer*) and Alenia (*LCZ8ale*) – and this classification
 310 is consistent with what we found by the proposed MTD method. The DTD metric for T_{\min} identifies a second
 311 cluster characterized by higher values of the day-to-day variation, but it is quite difficult to separate possible
 312 intermediate behaviors, at least in an objective way. It follows that the DTD method classifies all other stations
 313 – Venaria La Mandria (*LCZBvem*), Venaria Ceronda (*LCZ8vec*), Carmagnola (*LCZDcar*), Santena-Banna

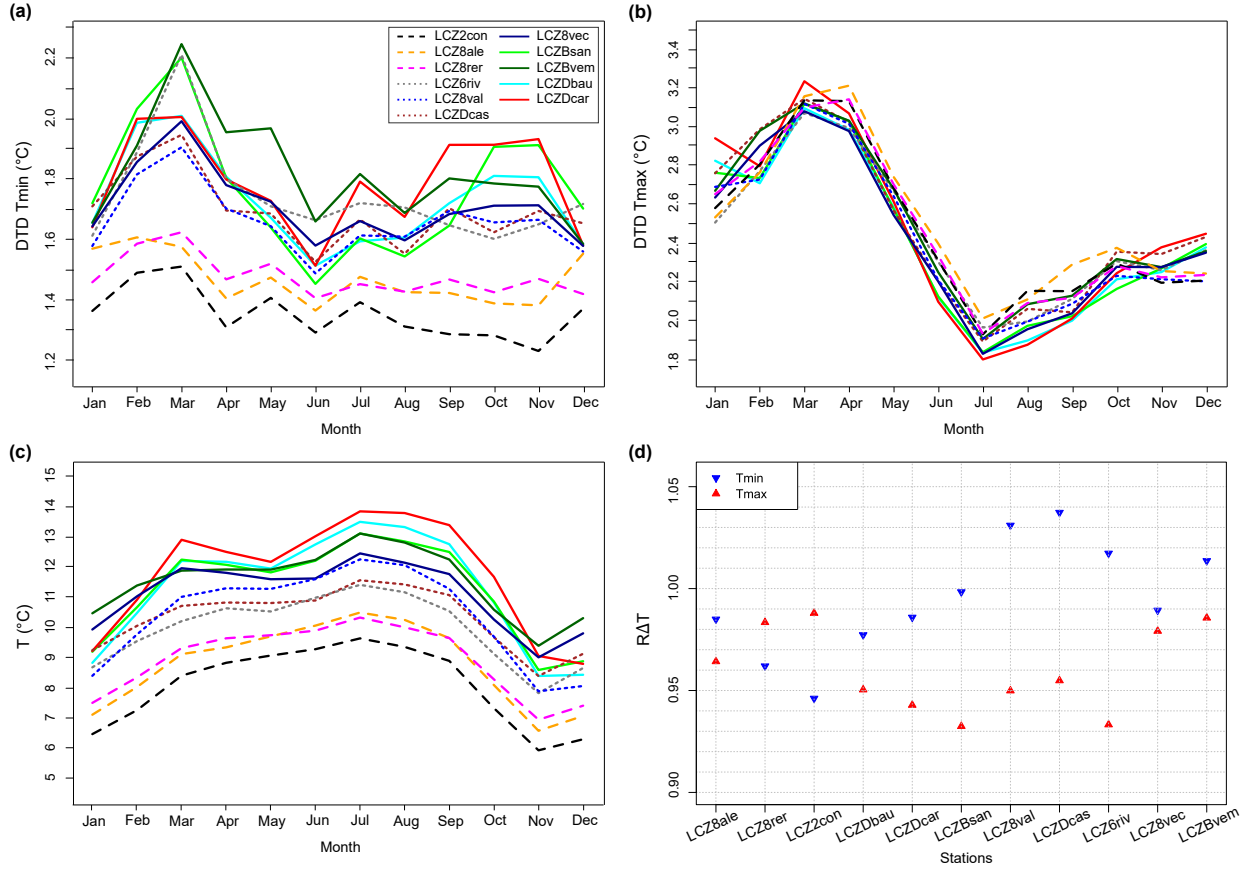


Figure 4: Panels (a) and (b): Day-To-Day (DTD), i.e., the average monthly DTD variation of nighttime (T_{\min} in (a)) and day (T_{\max} in (b)) temperatures (Anderson et al., 2018). The different line styles refer to the thermal behaviors characterizing the stations, obtained through the Mean Temperature Difference (MTD). The dashed lines correspond to stations with positive projection onto the first principal component of the PCA, associated with an urban thermal pattern; the continuous lines refer to stations which projection onto the first p.c. is negative (rural thermal pattern); the dotted lines correspond to the stations characterized by an almost null projection onto the first p.c. Panel (c): mean daily excursion of temperature, i.e., the monthly average of $T_{\max} - T_{\min}$ (Milelli, 2016); this panel refers to the same legend reported in (a). Panel (d): warm to cold transition ratio (R ΔT) for the minimum (downwards blue triangles) and maximum (upwards red triangles) temperature of the day (Gough, 2020).

314 (*LCZBsan*), Bauducchi (*LCZDbau*), Rivoli (*LCZ6riv*), Caselle (*LCZDcas*) and Vallere (*LCZ8val*) – as rural
 315 and, differently from our MTD approach, seems unable to grasp the intermediate behavior. As described in
 316 Anderson et al. (2018), even smaller differences between the sites emerge when we consider DTD T_{\max} (see
 317 Fig. 4b).

318 The second term of comparison we consider is the mean daily excursion proposed by Milelli (2016),
 319 calculated as the difference between the monthly averaged maximum and minimum temperatures (Fig. 4c).

Here, the three stations Consolata (*LCZ2con*), Reiss Romoli (*LCZ8rer*) and Alenia (*LCZ8ale*) are clearly marked by a limited daily excursion, indicating a non-sufficient cooling during the night and therefore – according to the UHI definition – they are related to a urban landscape. This is in agreement with what detected with the MTD metric. However, even in this case a non clearly distinguished group of stations shows an intermediate behavior, i.e., a gradual transition from the low to the high daily excursion groups emerges. See for example the stations of Caselle (*LCZDcas*), Rivoli (*LCZ6riv*), Vallere (*LCZ8val*) and Venaria Ceronda (*LCZ8vec*) in Fig. 4c.

Finally, the application of the ratio between the warm and cold transitions is shown in Fig. 4d. By considering Canadian temperatures, Gough (2020) found a metric sensitive to what he called "peri-urban" landscapes, in particular focusing on the warm to cold transition ratio, $R\Delta T$, calculated for minimum temperatures T_{\min} . Figure 4c illustrates the results both for T_{\min} and T_{\max} . Gough (2020) identified the threshold for T_{\min} (i.e., $R\Delta T= 1.05$) above which a group of stations is deemed peri-urban. If we adopt this threshold, no station falls above this limit; therefore, in the case of Turin, the value $R\Delta T= 1.05$ appears not to be adequate to detect intermediate thermal behaviors. This is not surprising because of the different climate in Canada. Using the outcomes of our MTD approach, a new *ad hoc* threshold equal to 1.016 would allow one to classify Vallere (*LCZ8val*), Caselle (*LCZDcas*) and Rivoli (*LCZ6riv*) in a different thermal behavior, which we call intermediate since it differs from the urban and rural but has no internal coherence. However, a slightly different value (lower or higher than 1.016) would provide very different results: e.g., if $R\Delta T= 1.01$ also the station of Venaria la Mandria (*LCZBvem*) would pertain to the intermediate behavior, while for $R\Delta T= 1.02$ the only stations with an intermediate pattern would be Vallere (*LCZ8val*) and Caselle (*LCZDcas*). Note that $R\Delta T (T_{\min})$ for the remaining stations – ascertained as urban (Alenia (*LCZ8ale*), Reiss Romoli (*LCZ8rer*) and Consolata (*LCZ2con*)) and rural (Bauducchi (*LCZDbau*), Carmagnola (*LCZDcar*) and Santena-Banna (*LCZBsan*)) according to the MTD – form two well separated groups and therefore clearly differentiate from the intermediate landscapes, as in Gough (2020).

In a nutshell, the consolidated methodologies, when are applied to the Turin area, agree on the classification of the urban and rural stations, and identify the same urban-rural sites detected by our Mean Temperature Difference method. However, likely due to the complexity of the Turin landscape, the attribution of intermediate thermal behaviors is not straightforward and the consolidated methods seem not to be able to give an objective and unique characterization of this pattern. In contrast, the proposed Mean Temperature Difference seems to be suitable in this area: in light of the Principal Component Analysis, the three stations Rivoli (*LCZ6riv*), Caselle (*LCZDcas*) and Vallere (*LCZ8val*) are characterized by near-zero projections onto the first principal component. In this way, the subjectivity is minimized, since no thresholds or graphic interpre-

tations are needed, differently from the other methods existing in literature. In fact, since the first principal component is associated with the urbanity or rurality of a site, a missing projection onto this component implies a thermal behavior which is neither clearly urban or rural, but rather an intermediate one which is not necessarily characterized by an internal coherence. This observation is also confirmed by the different Local Climate Zones associated to the stations *LCZ6riv*, *LCZDcas* and *LCZ8val*. Their thermal behavior is not captured by the first principal component, but it is synthesized by the second p.c. emerging from the PCA, which is associated to other geographically-based features characterizing the stations.

To summarize, the combined use of MTD metric and PCA represents a robust tool to characterize the sites in the Urban Heat Island context. The method has been proven (i) to well reproduce the thermal behavior of the metropolitan area of Turin, (ii) to agree with existing and widely validated methods for the distinction between the urban and rural stations, and (iii) to be easily interpretable.

Aware of the impossibility to totally eliminate some kind of subjectivity in the task of selecting urban-rural pairs, we aim at providing an additional tool to discern the landscape categories for the Urban Heat Island quantification. The metric which we suggest can be combined with the existing methods, especially when the study area does not offer a trivial categorization into urban or rural stations.

Acknowledgments

The authors thank the Regional Agency for the Protection of the Environment of Piedmont Region (Arpa Piemonte) for the data used in this paper. Barbara Cagnazzi and Daniele Gandini are acknowledged for having provided the fog statistics. This work is funded by the RISK-GEST Project-PITEM RISK, Interreg 2014-2020 Alcotra IT-FR, the MISTRAL 2017-IT-IA-0144 Program Connecting Europe Facility (CEF) and the 2019-2021 Agreement between National Department of Civil Protection and Arpa Piemonte.

Appendix A. Results of the applicability of the MTD

Sensitivity analysis to evaluate to which extent the MTD method is applicable (attached file).

References

- Anderson, C.I., Gough, W.A., Mohsin, T., 2018. Characterization of the urban heat island at Toronto: Revisiting the choice of rural sites using a measure of day-to-day variation. *Urban Climate* 25, 187–195.
- Arnfield, A.J., 2003. Two decades of urban climate research: a review of turbulence, exchanges of energy and water, and the urban heat island. *International Journal of Climatology: a Journal of the Royal Meteorological Society* 23, 1–26.

- 381 Arpa Piemonte, 2020. Annual Climatic Report (in Italian). [https://www.arpa.piemonte.it/](https://www.arpa.piemonte.it/rischinaturali/tematismi/clima/rapporti-di-analisi/annuale.html)
382 [rischinaturali/tematismi/clima/rapporti-di-analisi/annuale.html](https://www.arpa.piemonte.it/rischinaturali/tematismi/clima/rapporti-di-analisi/annuale.html). [Online; accessed 22-
383 November-2021].
- 384 Cassardo, C., Forza, R., Manfrin, M., Longhetto, A., Qian, M., Richiardone, R., Balsamo, G., et al., 2002. The
385 Urban Meteorological Station of Turin, in: 11th Symposium on Acoustic Remote Sensing, ISAC/CNR.
386 pp. 311–320.
- 387 Ching, J., Mills, G., Bechtel, B., See, L., Feddema, J., Wang, X., Ren, C., Brousse, O., Martilli, A., Neophytou,
388 M., et al., 2018. WUDAPT: An urban weather, climate, and environmental modeling infrastructure for the
389 anthropocene. *Bulletin of the American Meteorological Society* 99, 1907–1924.
- 390 Demšar, U., Harris, P., Brunson, C., Fotheringham, A.S., McLoone, S., 2013. Principal component analysis
391 on spatial data: an overview. *Annals of the Association of American Geographers* 103, 106–128.
- 392 Demuzere, M., Bechtel, B., Middel, A., Mills, G., 2019. Mapping Europe into local climate zones. *PloS one*
393 14, e0214474.
- 394 Demuzere, M., Bechtel, B., Middel, A., Mills, G., 2020. European LCZ map. https://urlsand.esvalabs.com/?u=https%3A%2F%2Ffigshare.com%2Farticles%2Fdataset%2FEuropean_LCZ_map%2F13322450%2F1&e=78898b00&h=9a0f73a7&f=y&p=n. [Online; accessed
395 15-June-2021].
- 396 15-June-2021].
- 397 15-June-2021].
- 398 Founda, D., Santamouris, M., 2017. Synergies between Urban Heat Island and Heat Waves in Athens
399 (Greece), during an extremely hot summer (2012). *Scientific reports* 7, 1–11.
- 400 Garbero, V., Milelli, M., Bucchignani, E., Mercogliano, P., Varentsov, M., Rozinkina, I., Rivin, G., Blinov,
401 D., Wouters, H., Schulz, J.P., et al., 2021. Evaluating the urban canopy scheme TERRA_URB in the
402 COSMO model for selected European cities. *Atmosphere* 12, 237.
- 403 Giridharan, R., Kolokotroni, M., 2009. Urban heat island characteristics in London during winter. *Solar*
404 *Energy* 83, 1668–1682.
- 405 Gough, W., 2008. Theoretical considerations of day-to-day temperature variability applied to Toronto and
406 Calgary, Canada data. *Theoretical and Applied Climatology* 94, 97–105.
- 407 Gough, W.A., 2020. Thermal signatures of peri-urban landscapes. *Journal of Applied Meteorology and*
408 *Climatology* 59, 1443–1452.

- 409 Hannachi, A., Jolliffe, I.T., Stephenson, D.B., 2007. Empirical orthogonal functions and related techniques
410 in atmospheric science: A review. *International Journal of Climatology: A Journal of the Royal Meteorological Society* 27, 1119–1152.
411
- 412 Hoffmann, P., Schlünzen, K.H., 2013. Weather pattern classification to represent the urban heat island in
413 present and future climate. *Journal of Applied Meteorology and Climatology* 52, 2699–2714.
- 414 Johnson, D., 1985. Urban modification of diurnal temperature cycles in Birmingham, UK. *Journal of*
415 *Climatology* 5, 221–225.
- 416 Jolliffe, I.T., 2002. *Principal Component Analysis*. Springer New York.
- 417 Jolliffe, I.T., Cadima, J., 2016. Principal component analysis: a review and recent developments. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* 374,
418 20150202.
419
- 420 Karl, T.R., Knight, R.W., Plummer, N., 1995. Trends in high-frequency climate variability in the twentieth
421 century. *Nature* 377, 217–220.
- 422 Kim, S.W., Brown, R.D., 2021. Urban heat island (UHI) intensity and magnitude estimations: A systematic
423 literature review. *Science of The Total Environment* , 146389.
- 424 Köppen, W., Geiger, R., 1936. *Das geographische System der Klimate Handbuch der Klimatologie*. Ed. W.
425 Köppen and R. Geiger 1.
- 426 Landsberg, H.E., 1981. *The urban climate*. Academic press.
- 427 Lorenz, E.N., 1956. Empirical orthogonal functions and statistical weather prediction .
- 428 Memon, R.A., Leung, D.Y., Liu, C.H., 2009. An investigation of urban heat island intensity (UHII) as an
429 indicator of urban heating. *Atmospheric Research* 94, 491–500.
- 430 Milelli, M., 2016. Urban heat island effects over Torino. *COSMO Newsletter* 16, 1–10.
- 431 Mohsin, T., Gough, W.A., 2012. Characterization and estimation of urban heat island at Toronto: impact of
432 the choice of rural sites. *Theoretical and Applied Climatology* 108, 105–117.
- 433 Oh, J.W., Ngarambe, J., Duhirwe, P.N., Yun, G.Y., Santamouris, M., 2020. Using deep-learning to forecast
434 the magnitude and characteristics of urban heat island in Seoul Korea. *Scientific reports* 10, 1–13.

- 435 Oke, T.R., 1973. City size and the urban heat island. *Atmospheric Environment* (1967) 7, 769–779.
- 436 Oke, T.R., 1976. The distinction between canopy and boundary-layer urban heat islands. *Atmosphere* 14,
437 268–277.
- 438 Oke, T.R., 1981. Canyon geometry and the nocturnal urban heat island: comparison of scale model and field
439 observations. *Journal of climatology* 1, 237–254.
- 440 Oke, T.R., 1982. The energetic basis of the urban heat island. *Quarterly Journal of the Royal Meteorological*
441 *Society* 108, 1–24.
- 442 Pakarnseree, R., Chunkao, K., Bualert, S., 2018. Physical characteristics of Bangkok and its urban heat island
443 phenomenon. *Building and Environment* 143, 561–569.
- 444 Parker, D.E., 2010. Urban heat island effects on estimates of observed climate change. *Wiley Interdisciplinary*
445 *Reviews: Climate Change* 1, 123–133.
- 446 Rizwan, A.M., Dennis, L.Y., Chunho, L., 2008. A review on the generation, determination and mitigation of
447 Urban Heat Island. *Journal of environmental sciences* 20, 120–128.
- 448 Rosenzweig, C., Solecki, W.D., Parshall, L., Chopping, M., Pope, G., Goldberg, R., 2005. Characterizing
449 the urban heat island in current and future climates in New Jersey. *Global Environmental Change Part B:*
450 *Environmental Hazards* 6, 51–62.
- 451 Santamouris, M., 2007. Heat island research in Europe: the state of the art. *Advances in building energy*
452 *research* 1, 123–150.
- 453 Stewart, I.D., 2007. Landscape representation and the urban-rural dichotomy in empirical urban heat island
454 literature, 1950–2006. *Acta Climatologica et Chorologica* 40, 111–121.
- 455 Stewart, I.D., 2011. A systematic review and scientific critique of methodology in modern urban heat island
456 literature. *International Journal of Climatology* 31, 200–217.
- 457 Stewart, I.D., Oke, T.R., 2012. Local climate zones for urban temperature studies. *Bulletin of the American*
458 *Meteorological Society* 93, 1879–1900.
- 459 Tam, B.Y., Gough, W.A., Mohsin, T., 2015. The impact of urbanization and the urban heat island effect on
460 day to day temperature variation. *Urban Climate* 12, 1–10.

- 461 Tan, J., Zheng, Y., Tang, X., Guo, C., Li, L., Song, G., Zhen, X., Yuan, D., Kalkstein, A.J., Li, F., et al., 2010.
462 The urban heat island and its impact on heat waves and human health in Shanghai. *International journal*
463 *of biometeorology* 54, 75–84.
- 464 Theeuwes, N.E., Steeneveld, G.J., Ronda, R.J., Holtslag, A.A., 2017. A diagnostic equation for the daily
465 maximum urban heat island effect for cities in northwestern Europe. *International Journal of Climatology*
466 37, 443–454.
- 467 Theeuwes, N.E., Steeneveld, G.J., Ronda, R.J., Rotach, M.W., Holtslag, A.A., 2015. Cool city mornings by
468 urban heat. *Environmental Research Letters* 10, 114022.
- 469 Tzavali, A., Paravantis, J.P., Mihalakakou, G., Fotiadi, A., Stigka, E., 2015. Urban heat island intensity: A
470 literature review. *Fresenius Environmental Bulletin* 24, 4537–4554.
- 471 Wilks, D.S., 2011. *Statistical methods in the atmospheric sciences*. volume 100. Academic press.
- 472 Wu, F.T., Fu, C., Qian, Y., Gao, Y., Wang, S.Y., 2017. High-frequency daily temperature variability in China
473 and its relationship to large-scale circulation. *International Journal of Climatology* 37, 570–582.