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New microclimate monitoring method and data process for investigating environmental conditions in complex urban contexts

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ABSTRACT
The rapid urbanization of the last century coupled with local climate change imputable to anthropogenic actions triggered a huge research effort aimed at investigating urban microclimate. Typically, cities present a variety of microclimates due to the internal variation of their landscapes in terms of morphology, surfaces properties, presence of greenery, etc. Location-specific microclimate conditions affect both (i) building energy needs and (ii) citizens' quality of life. For these reasons, a small-scale analysis from the citizen perspective with high-time-resolution environmental data is required. Recent studies tried to reach that level of precision by using remote sensing, movable observational transects or dense network of weather stations located in specific points of the urban settlement. Within this framework, the current study presents a new bottom-up methodology which aims at identifying granular microclimates within the same built environment. The method consists of a cluster analysis of experimental data collected by a wearable miniaturized weather station which allows the monitoring of outdoor parameters at the pedestrian height and with high-time resolution. Experimental campaigns were conducted in five different case studies, where a planned monitoring path was repeated at different times during the day. The heterogeneity of the context demonstrates the replicability of the proposed method, suitable for clustering different areas of a same urban context characterized by variable local microclimate. The study contributes to better understand the variability of building boundary conditions for energy need prediction and indoor/outdoor environmental comfort assessment.

KEYWORDS
Urban Microclimate, Urban heat island, Outdoor thermal comfort, Monitoring, Environmental quality.

INTRODUCTION
The urban population is continuously growing, and it will reach the 60% of the world population in 2030 according to United Nation predictions (2016). The urbanization process progressively changes land usage, consequently modifying the energy balance in cities leading to the well-known phenomenon of the Urban Heat Island (Oke, 1973;). UHI negatively affects both citizens' health (Serrat et al., 2006;) and building stock energy consumption (Akbari et al., 2001). Moreover, such negative consequences are going to be exacerbated in the next decades due to climate change since extreme weather evens as the heatwaves are predicted to be more intense and more frequent (Founda and Santamouris, 2017). Nevertheless, the complex and heterogeneous morphology of cities causes sensible diversification of the microclimate within the urban canopy layer. As a matter of fact, Jonsson (2004) found out an intra-urban temperature difference of the same magnitude as the detected urban-rural differences in Gaborone, Botswana. Intra-urban temperature differences up to 5°C were also detected in Wien, Austria, by Mahdavi et al. (2017). Moreover, the study

demonstrated how specific microclimate conditions affect the building thermal performance leading to a mean annual heating load variation up to 16.1 kWh/m^2 per year among the analysed areas.
Within the presented framework, the detection of intra-urban microclimate diversifications and how much they are related to different urban structures is a key point for the scientific community. To get this goal, high-spatial-resolution weather data are required. Nowadays, the most common implemented methodologies include: (i) remote sensing (Voogt and Oke, 2003;), (ii) permanent network of weather stations (Paolini et al., 2017), and (iii) observational mobile transects (Hart and Sailor, 2009; Parace et al., 2016). Nevertheless, an investigation procedure focused on the pedestrian perspective is still missing. This work presents a new bottom-up methodology which aims to identify different and distinctive microclimates within the same built environment from raw environmental data collected accordingly to the pedestrian perspective. An innovative monitoring wearable system is presented and the obtained outcomes are post-process through *k-means* clustering procedure. The outlined methodology is applied to five different case studies to test its validity in different urban configurations. The final findings can therefore help policymakers to select suitable mitigation strategies for the most critical areas of their cities in terms of both outdoor thermal comfort and building stock energy consumption.

METHODS

The present work proposes a bottom-up process to detect local urban microclimate conditions based on collected experimental data. The main environmental parameters are monitored by means of a miniaturized wearable weather station which can be easily warren by a pedestrian (Pigliautile and Pisello, 2018). Therefore, the perspective of the monitoring campaign is human centred, and the collected data represent what citizens are subject to, in terms of environmental forcing, air quality, and thermal overheating/overcooling. The collected data are therefore statistically analysed by means of clustering to identify the intra-urban microclimate diversification.

Monitoring campaigns

The monitoring system is a miniaturized weather station coupled with GPS tracer to link the collected environmental data to their site-specific location, i.e. latitude, longitude, altitude and attitude. The system is settled upon a common bike helmet and records all the parameters listed in (Pigliautile and Pisello, 2018) every 2 seconds, such as air temperature, relative humidity, global solar radiation, wind speed, CO_2 concentration, and geographical coordinates.
Five different monitored case studies are here presented. Every case study deals with different urban contexts as summarized in Table1. All the monitoring pathways were planned to pass through areas characterized by different (i) geometrical configuration, (ii) orientation, (iii) amount of anthropogenic sources, and (iv) greenery. The equipped operator covers the same pathway at least twice during a day, i.e. around midday and around sunset, to have both (i) space and (ii) time daily variation of the key environmental parameters. Moreover, the length of each pathway allows to complete a single recording session in less than one hour on foot, so all the parameters fluctuation can be assumed to be space- and no time-dependent.

Table 1. Monitoring campaigns details

Case study	Typology	Start Time	Day	Length	
Knossos Palace archaeological site, Greek	Open area	9:00 a.m.	07/04/2017	1.2 km	~40 minutes
		3:00 p.m.		1.6 km	~40 minutes
		7:00 p.m.		1.3 km	~40 minutes

Gubbio historic centre, Italy	Packed, historical	8:30 a.m.	08/02/2017	2.6 km	~45 minutes
		2:30 p.m.		2.8 km	~45 minutes
		6:30 p.m.		2.7 km	~45 minutes
New York City (Soho), USA	Packed, low rise building	1:00 p.m.	11/30/2017	2.4 km	~35 minutes
		6:30 p.m.	11/28/2017	2.4 km	~35 minutes
New York City (Upper East Side), USA		2:00 p.m.	11/29/2017	3.7 km	~45 minutes
		5:30 p.m.	12/01/2017	3.6 km	~45 minutes
New York City (Wall Street), USA	Packed, high rise building	11:45 a.m.	11/29/2017	-	~25 minutes
		5:00 p.m.	11/30/2017	3.3 km	~25 minutes

Data analysis

After having collected the abovementioned data, we grouped them adopting the k-means algorithm (Lloyd, 1982) which classifies data through a priori fixed *k* number of clusters. This allowed us to figure out potential relationships within the huge amount of observations derived from the monitoring sessions. The iterative grouping procedure minimizes the distance between the observations belonging to the same cluster and, in turn, maximizes the distance among observations belonging to different clusters. The algorithm minimizes the following objective function:

$$J(V) = \sum_{j=1}^{k} \sum_{i=1}^{n} \left(\left\| x_i^{(j)} - c_j \right\| \right)^2 \qquad (1)$$

where, $\| x_i^{(j)} - c_j \|$ is the chosen Euclidian distance between an observation $x_i^{(j)}$ and its cluster centre c_j, i.e. its centroid. The authors assumed three different numbers of final clusters *k*, i.e. 2, 5, and 8, to get the sensitivity of such bottom-up approach in determining the intra-urban microclimate variation. Moreover, we grouped data considering a 3D reference space defined by three environmental parameters which are recognized as affecting the citizens well-being: (i) the global solar radiation (W/m^2), (ii) the CO_2 concentration (ppm), and (iii) the apparent temperature (°C). The obtained data partitions are therefore analysed in terms of their spatial distribution linking the belonging cluster and the GPS coordinates of each observation. The length of each segment, defined by space-contiguous observations belonging to the same class, is calculated and only segments longer than 5m are considered for the analysis. Figure 1 summarizes the adopted methodology for the data analysis.

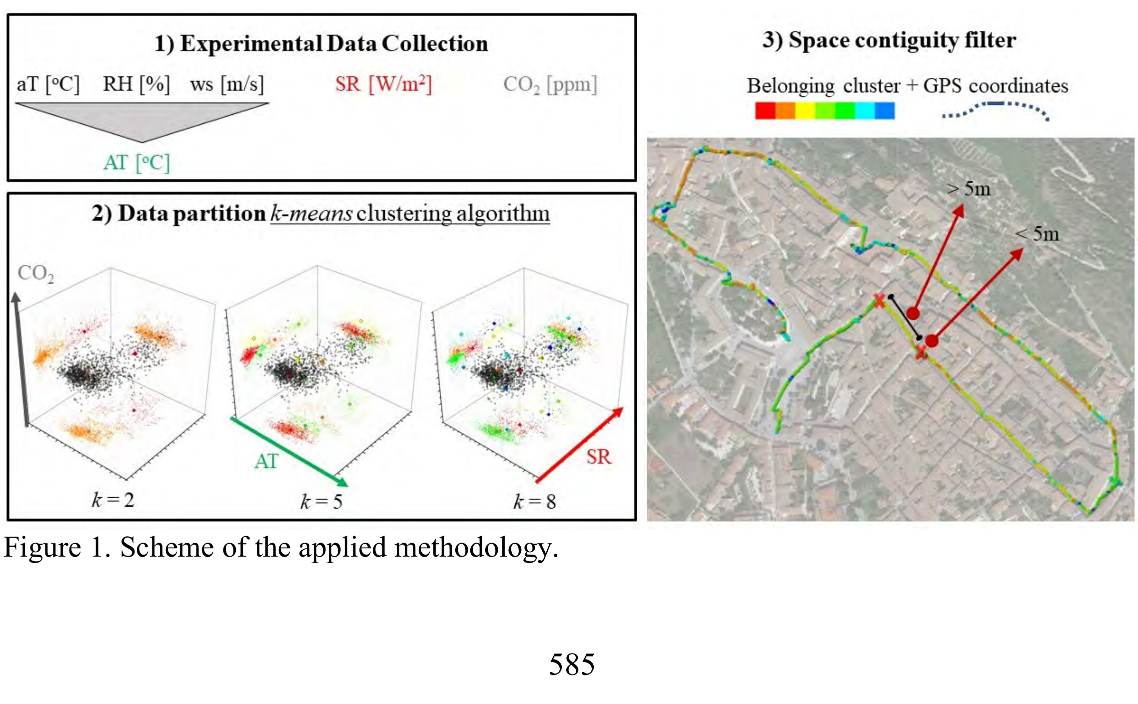
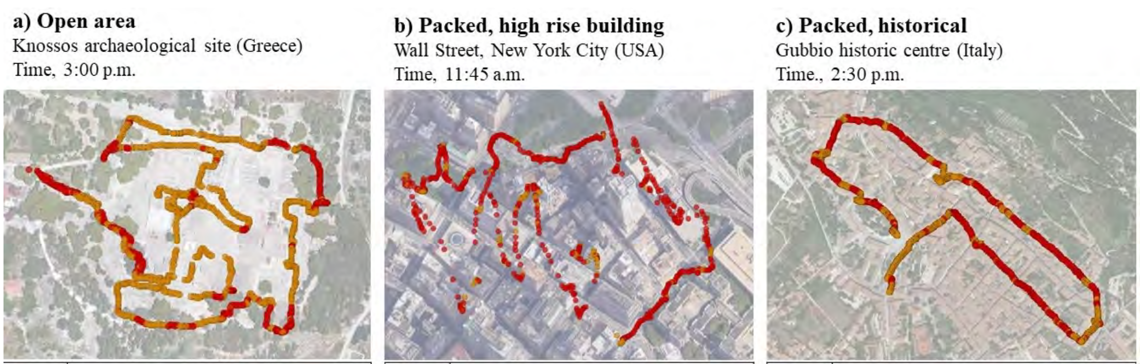


Figure 1. Scheme of the applied methodology.

RESULTS

The presented analysis aims to find out different microclimate conditions within all the considered case studies. The application of the *k-means* algorithm with a *k* value of 2 recognizes the solar radiation as the main driver of the clustering procedure. As a matter of fact, the two centroids representative of the data subgroups are mainly distinguished by their values of solar radiation. Such differences are more evident at midday and in low density urban areas, i.e. the Knossos palace archaeological site, where a maximum centroids' distance of 733.4 W/m^2 is highlighted in terms of solar radiation (Figure 2a). On the contrary, less evident is the data partitioning due to solar access at pedestrian level within the more packed urban contexts, i.e. the three monitored areas of New York City. In particular, the partition of data collected in New York City high-rise building settlement, i.e. Wall Street (Figure 2b), is driven by the CO_2 concentration which presents the widest range of collected values. Therefore, the two data sub-groups are identified by centroids which are really close in terms of apparent temperature and solar radiation, i.e. 0.6°C, 0.1°C and 4.5 W/m^2, 6.1 W/m^2 at day- and night-time respectively but differ from each other for 130 ppm and 100 ppm of CO_2 concentration at 2:00 p.m. and 5:30 p.m. respectively.

The two data sub-groups are equally distributed in space in the open site of Knossos and in the packed historic centre of Gubbio at 2:30 p.m. The low solar radiation data in Knossos, i.e. centroid's value of solar radiation equal to 53.5 W/m^2, 94.8 W/m^2, and 60.3 W/m^2 at 9 a.m., 3:00 p.m., and 7:00 p.m. respectively, correspond to the areas shaded by the existing greenery. Similarly, the low and high radiation clusters in Gubbio, i.e. centroids' radiation of 101.7 W/m^2 and 776.7 W/m^2 respectively, identify urban canyons mainly characterized by different orientations, i.e. north-south and east-west oriented respectively (Figure 2c). On the other hand, low incoming solar radiation areas are prevalent in the monitored zones of New York City. Nevertheless, areas with high level of incoming radiation are mainly concentrated in north-south oriented canyons and at crossroads.



a)

Class	Centroid coordinates AT [°C]	SR [W/m^2]	CO_2 [ppm]
● 1	34.1	94.8	360
● 2	35.8	828.2	379

b)

Class	Centroid coordinates AT [°C]	SR [W/m^2]	CO_2 [ppm]
● 1	10.7	25.9	406
● 2	11.3	21.4	535

c)

Class	Centroid coordinates AT [°C]	SR [W/m^2]	CO_2 [ppm]
● 1	38.8	101.7	315
● 2	41.5	776.7	320

Figure 2. Spatial distribution of the two data clusters (k=2) obtained for the monitored open area (a), packed high rise (b), and packed historical configuration (c).

The data partition into 5 sub-groups generates diversified clusters in terms of both solar radiation and CO_2 concentration values in all the considered case studies. Therefore, such partition identifies different microclimate situations of low and high incoming solar radiation combined with less or more polluted air conditions. The generated clusters depict quite well the distinction among open areas and different typologies of urban canyons in all the packed urban case studies, especially during day-time. Moreover, such partition highlights site-specific critical conditions in terms of CO_2 concentration level just before traffic-lights almost in all the monitored areas of New York. This condition is particularly evident in SoHo (Figure 3) where data clusters related to detected high level of CO_2 concentration, i.e. 600 ppm and 514 ppm in correspondence of low and high solar radiation values respectively, continuously cover up to a maximum of 46 m for a total amount equal to the 13.4% of the whole monitored path length.

Packed, low rise building
SoHo, New York City (USA)
Time, 1:00 p.m.

Class	Centroid coordinates		
	AT [°C]	SR [W/m²]	CO_2 [ppm]
● 1	7.7	356.7	445
● 2	6.7	74.5	501
● 3	7.2	66.1	424
● 4	7.0	73.8	600
● 5	7.7	231.2	514

Figure 3. Spatial distribution of the five data clusters (k=5) obtained in SoHo, New York City.

Nevertheless, not the whole 5 data sub-groups can be considered representative of site-specific conditions. The application of the minimum length filter, i.e. 5 m, reduce up to 67.1% the total amount of recorded data in the open archaeological site of Knossos. It means that the environmental parameters in mainly open and natural areas are more sensitive to temporary weather changes rather than being affected by specific spatial configurations.
Finally, the clustering procedure with 8 pre-defined number of classes does not show up further significant intra-urban variations of the monitored environmental parameters leading to redundant fragmentations of the data samples.

DISCUSSIONS
The statistical analysis of the collected data provides an intra-urban detection of specific microclimate conditions. The spatial distribution of each generated data cluster shows distinctive urban configurations along the monitored pathways during day-time and with a *k* of 2. The availability of incoming solar radiation at pedestrian height is depicted as the most influencing parameter for the microclimate diversification. The selection of 5 final clusters points out a relatively more detailed intra-urban microclimate detection considering also other environmental parameters, i.e. CO_2 concentration variation. Nevertheless, such high number of classes, i.e. 5, is not suitable for open areas, i.e. Knossos archaeological site, where the environmental parameters fluctuations are more time- than space-dependent. Finally, the selection of 8 final data clusters seems to be too much detailed for the detection of site-specific microclimate conditions also in high urbanized and packed contexts.

CONCLUSIONS
The presented bottom-up approach to detect the intra-urban microclimate variation shows its promising effectiveness being applied in different contexts and seasons. The statistical data analysis through *k-means* algorithm can identify those areas presenting similar configuration within each case study. The proper number of final clusters depends on the monitored context

typology in order to obtain spatially significant data sub-grouping. A further development of this work will focus on the evaluation of the right *k* value for each defined urban configuration typology.
Nevertheless, the outlined data clusters are associated to peculiar comfort conditions within the same urban context. Therefore, the presented methodology could help urban policymakers to figure out criticalities. A rank of risk in terms of human health or building stock energy consumption peak can be assigned to the obtained environmental data clusters. In this way, areas needing priority intervention can be easily highlighted.

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