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Categorisation of urban open spaces for heat adaptation: A cluster based approach

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ABSTRACT

In the context of climate change, adapting a city's open spaces to heat waves and extreme heat is crucial for mitigating the Urban Heat Island effect and ensuring the wellbeing of its inhabitants. However, the heat adaptation potential of open spaces varies within a city. This study develops an objective and replicable method to categorise urban areas based on their open spaces' adaptive capacity and improvement potential to heat waves at the micro-scale. This is achieved using a clustering approach, eliminating manual operations, using openly available data, employing indicators suitable for every urban fabric type, and using the urban block as the analysis unit. The validation of the method in the case study of Bilbao (Spain) demonstrates its capacity to obtain meaningful insights regarding open space heat adaptation potential. An analysis of the resulting categories reveals significant open space improvement potential throughout the city and a varying adaptive capacity that depends on urban density. Categories with the lowest adaptive capacity have median open space ratios between 0.35 and 0.65 and median tree cover ratios between 0.07 and 0.15. Those with the highest adaptive capacity present median open space ratios between 0.8 and 1 and median tree cover ratios between 0.05 and 0.25. The method can aid local policymakers in identifying opportunity spots for hosting adaptation solutions and understanding the challenges the city may face in planning adaptation action. The method's replicability enables it to be applied in other cities, contributing to a broader exploration of climate change adaptation potential.

1. Introduction

The effects of human-induced global warming are already notable. Vicedo-Cabrera et al. [1] recently found that 37 % of heat-related mortality during warm seasons between 1991 and 2018 could be attributed to human-induced climate change. The summer heat wave of 2019 was estimated to be the deadliest extreme event of the year, with approximately 2050 excess deaths in the temperate countries of France, the Netherlands, the UK, and Belgium [2]. Unfortunately, the situation is expected to get worse. The Intergovernmental Panel on Climate Change (IPCC) predicts that in the next 20 years, average global temperatures will rise by at least 1.5 °C above pre-industrial levels [3]. Temperatures across Europe are predicted to rise continuously more than the rest of the world over this century. Projections indicate that by 2071, average temperatures in Europe will increase by 1.2–3.4 °C (SSP1-2.6 scenario) and 4.1–8.5 °C (SSP5-8.5 scenario) [4]. This rise in temperature will be combined with more frequent, intense, and longer heat waves [3]. Cities are especially vulnerable to heat waves and high temperatures due to the Urban Heat Island (UHI) phenomenon, which makes cities warmer than their rural surroundings, thus intensifying the heat in urban areas [5]. The UHI depends on factors such as the presence of vegetation, the Sky View Factor (SVF), the proportions of street canyons, impervious surfaces, or surface albedo [6]. Temperature exposures can also be influenced by micro-scale conditions, creating a variety of microclimates within the local scale [7,8].

Higher urban temperatures increase the use of energy for cooling, reduce outdoor and indoor thermal comfort, increase the concentration of pollutants such as tropospheric ozone, and impact human health and

Abbreviations: IPCC, Intergovernmental Panel on Climate Change; UHI, urban heat island; NDVI, normalised difference vegetation index; LCZ, Local Climate Zone; GIS, Geographical Information System; TCC, tree canopy cover; DSMV, digital surface model of vegetation; OSA, open space amplitude; OSR, open space ratio; RSR, road surface ratio; A, albedo; SVF, sky view factor; DSM, Digital Surface Model; I, imperviousness; SR, solar radiation; PCA, principal component analysis.

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wellbeing [5].To ensure the wellbeing of citizens in future heat wave events, it is essential to successfully adapt our cities to this incoming climate [3]. This is especially relevant for temperate cities, where the built environment is not prepared for extreme high temperatures. For that, effective adaptation tools are needed [9,10]. Changing existing urban open spaces to adapt to climate change is an effective strategy to improve outdoor thermal comfort during extreme heat events. These adaptation solutions also contribute to the regulation of the urban climate at the local scale (by reducing the UHI intensity) and at the micro-scale (by regulating the microclimate) [11–14].

Recent studies in urban climate and climate change adaptation have significantly improved the ability to quantify the effectiveness of heat adaptation solutions [15]. Increasing vegetation, a proven solution to reduce thermal stress and mitigate the UHI effect [16], has been extensively studied. While tree planting is one of the most studied solutions [17–20], shrub planting and increasing grass surface have demonstrated effectiveness, too [14,21]. Other successful solutions are increasing cool pavements and reducing impervious surfaces in urban open spaces [5,13,21,22]. Blue infrastructure, such as water ponds or lakes, has also shown effectiveness [23,24] even though its research is more limited than other solutions [15], and it is challenging to integrate them into existing urban areas. Urban artificial shading is also a well-documented adaptation solution [25,26]. For instance, street sun sails, a non-intrusive street shading solution traditional to south Spanish cities, substantially reduce ground and façade temperatures [27]. Finally, urban interventions oriented to liberate urban space to accommodate adaptation solutions can be considered adaptation solutions, too. For instance, pedestrianisation works that reduce the surface destined for motorised traffic free space that can be used to implement adaptation solutions. An example of this kind of intervention is the Barcelona superblock model [28].

In recent years, efforts have been focused on estimating the effectiveness of urban heat adaptation solutions [15]. These efforts are essential to understanding the potential effects of climate change adaptation solutions and, thus, motivating action and allocating resources [29]. Understanding the benefits is also crucial to support policymakers' decision-making and provide information on resilience monitoring. However, among various constraints in adaptation, the feasibility of implementing effective solutions, including constraints related to physical characteristics, is a significant challenge. This constraint is rarely addressed in urban heat adaptation literature. For instance, Zhang et al. [16] quantified the impact of UHI reduction by transforming low vegetation areas into vegetation areas with a high Normalised Difference Vegetation Index (NDVI). Their work offers essential insights into the potential of vegetation solutions. Nevertheless, it lacks the micro-scale approach needed to consider the feasibility of transforming densely built areas into high NDVI areas.

Not every open space can accommodate identical solutions, and the effectiveness of solutions may change from one open space to another. Bassolino et al. [30] showed that existing dense urban fabrics have limited space to accommodate adaptation solutions, and as a result, their capacity to adapt is reduced. Moreover, other studies have shown that the characteristics of urban areas can increase or hinder the effectiveness of solutions. For example, Kolokotsa et al. [31] proved that in street canyons with a high aspect ratio (height to width ratio), adaptation solution effectiveness is lower because air temperature in those streets is highly influenced by advection. Dimoudi and Nikolopoulou [18] demonstrated that the higher the vegetated-to-built area ratio, the greater the effectiveness in air temperature reduction of tree planting. This conclusion suggests that urban areas with a higher ratio of open space to built areas have a higher adaptive capacity. Zhao et al. [32] found a correlation between tree cooling efficiency and characteristics such as albedo and solar radiation. Previous studies provided insights into adaptation solution effectiveness and identified constraints, yet there is a lack of systematic analyses considering the adaptive capacity of open spaces undergoing adaptation.

The IPCC defines the term adaptive capacity as the capacity of communities and institutions to adopt adaptation solutions [33], and commonly in literature is linked to the ability of individuals or collectives to adapt [34,35]. In this research work, we extend the meaning to the physical capacity that open spaces have to accommodate effective adaptation solutions. Together with adaptive capacity, this paper defines improvement potential as the degree to which a given space can be further enhanced to address extreme heat through adaptation solutions. This term captures the idea that open spaces already well-equipped with adaptation solutions may exhibit limited potential for additional improvement. At the same time, those with fewer interventions present a higher scope for enhancement. For instance, highly vegetated permeable open spaces may have low improvement potential, denoting that their adaptation limit has been reached.

Knowing the adaptive capacity and improvement potential of the different open spaces of a city would allow decision-makers, on the one hand, to have an overview of the adaptation opportunities and adaptation limits of a city and, on the other hand, to determine which adaptation solution is suitable for each open space. However, assessing one by one the adaptive capacity and improvement potential of urban open spaces is time-consuming and costly. Therefore, an urban categorisation approach is fundamental to addressing this issue.

Urban categorisations or classifications aim to sort a given city's elements into groups that share similarities. These groups are the categories, and often, an archetype that represents the typical values of its category is identified [7,36,37]. By assessing the archetype, the variables are reduced, and results can later be extrapolated, allowing localised analyses to be expanded to the city level [38]. Even though categorisations supported by data mining techniques are widely used to reduce simulation or assessment time at the building scale [39,40], their application for predicting the suitability of adaptation solutions is still limited among urban climate or urban adaptation studies.

Urban categorisations have been mainly used in urban climate studies to assess UHI intensity or predict microclimate behaviour. Numerous studies in this field use the framework of Steward and Oke's Local Climate Zones (LCZ). LCZ is a classification that describes climate conditions on a local or neighbourhood scale, suitable for a resolution of 1 km $\times$ 1 km [41]. Recent works have developed methods to nuance further this classification. Some of the works have focused on assessing urban climate on a more detailed scale than LCZ by adding block level, street level, or building level characteristics [7,37,42,43]. Others have supplemented LCZ with parameters beyond the physical realm, such as community coping capacity parameters [44]. López-Moreno et al. [42] developed a categorisation to aid energy performance assessment that could be suitable for an adaptive capacity and improvement potential assessment due to the diversity indicators used. However, this categorisation is based on a local classification, so the method is not easily replicable. Even though these approaches demonstrate that data mining and urban categorisation are promising approaches for assessing the issue of urban heat, they are not purposefully developed to explore the possibilities of adaptation.

A few works have developed urban classification methodologies to identify urban area types that have similar urban climate behaviour and adaptation options. However, some of these methods rely on pre-existing classifications, such as Land Cover and Land Use classifications [31,45] or local pre-existing bespoke urban fabric classifications [30]. In the recent work by Sützl et al. [46], they conducted a 250 $\times$ 250 m resolution grid classification based on k-means clustering and used indicators from the urban climate literature. The method effectively identifies urban types with similar surface temperatures; later, these types are used for analysing adaptation options. While being very useful, this work lacks the micro-scale approach needed to closely examine the adaptation options that the urban open spaces have. The assessment unit used, the grid, does not adapt to the morphology of the city, which could overlook micro-scale variables. This hindrance is reflected in the work by Ref. [42], where they concluded that only 37 % of pixels of the size

200 × 200 m had homogeneous characteristics. The classification results using the grid are also more challenging for urban planners or designers to interpret, as they do not reflect real urban structures. On the other hand, the method relies on commonly used urban climate indicators and does not add additional parameters in the classification that can affect adaptation options, such as street width or road surface ratio.

The research work presented here adds to the contributions of these works by including in the categorisation parameters that directly analyse the possibility of applying adaptation solutions by including indicators that: 1) assess the capacity to accommodate solutions, 2) consider the effectiveness of adaptation solutions, 3) evaluate improvement capacity through adaptation solutions. Additionally, the analysis unit used will be suitable for the micro-scale assessment of adaptation options. This way, the present research focuses on identifying urban open spaces that have similar adaptation potential rather than similar UHI magnitude. Therefore, the need for a categorisation method to aid heat wave adaptation actions in open spaces is still evident.

Hence, this research aims to develop an objective, replicable, micro-scale categorisation method for identifying the adaptive capacity and improvement potential of individual open spaces within a city located in a temperate climate. To demonstrate the applicability and replication potential of the method, it is applied in a case study city and the results obtained analysed.

The research work is organised as follows: Section 2 describes the steps followed in the development of the urban categorisation methodology; Section 3 presents the application of the method on a case study; Section 4 includes the results of the study and discussion; Section 5 summarises the study's conclusions.

2. Urban categorisation methodology based on adaptive capacity and improvement potential

The method developed for the urban categorisation is based on the data mining technique of clustering. Data mining refers to the process of extracting from data previously unknown, implicit, potentially helpful information. This information can be used for decision-making or prediction, among other potential uses [47]. The clustering technique is a type of data mining where the goal is to group the data instances based on multiple variables. No classes are defined in the clustering, and the results usually provide an archetypical instance for each cluster. Since cluster analysis was introduced to the study of the built environment, researchers have relied on it to systematically categorise urban areas [7,37,44,48]. One of the first works in this field [48] proved the capacity of cluster analysis to differentiate two neighbourhoods based on morphological indicators. K-means is a widely used clustering algorithm known for its computational efficiency and user-defined cluster number, the *k* value. Unlike other algorithms, such as hierarchical clustering, it does not impose a high computational burden. The low computational requirements and the flexibility to adjust the *k* value make it suitable for explorative methods such as the one presented in this paper. In this work, adaptive capacity and improvement potential indicators conform to the clustering variables, and the resulting clusters are the urban categories. The clustered instances are derived from the spatial analysis unit chosen and the analysis instance closest to the cluster centre is the archetype, which presents the most typical values of the cluster.

The analysis unit has to be adequate for the purposes of the categorisation. Analysis units such as the neighbourhood or census levels would overlook micro-scale characteristics, making them too large for the method. The grid is unsuitable for small heterogeneous cities because it would fail to capture the characteristics of homogeneous urban zones within the predefined square-shaped parcels [42]. Defining the open space boundaries one by one would be excessively time-consuming, hindering the replication of the method on a large area. Consequently, the chosen analysis unit is the urban block defined as the land parcel delimited by the street axis. The choice of the urban block fits the micro-scale, uses commonly publicly available data for its definition, and can be adapted to different urban fabrics. Moreover, the urban block unit is easily understood by urban planners and urban designers. These characteristics make it suitable for the present method. The following sections show the steps followed, which have been guided by the work carried out by Refs. [39,47,48].

2.1. Data preparation

First of all, the urban blocks should be defined and carefully filtered. A street or road axis layer can be used to define the urban blocks. This layer is then converted from a vector line layer to a vector polygonal layer using Geographical Information System (GIS) software. Additional layers like water body boundaries can be used to improve the delimitation of urban blocks. Afterwards, the resulting polygons should be carefully filtered, as including instances that are not of interest to the analysis can alter the cluster analysis results, making them unusable. For instance, the polygons that lay outside the urban areas should be removed, as well as other polygons that lie in areas that are not of interest to the study and are expected to have outlier values, such as river basins.

An inductive process is followed to identify the indicators suitable for the categorisation. The process is explained in Fig. 1. First, a set of possible indicators is created based on a literature review. On the one hand, a list of indicators of open space characteristics linked with the adaptive capacity of the open spaces is added. This list includes indicators related to the possibility of accommodating solutions and indicators related to characteristics that condition the effectiveness of solutions. For instance, "street width" is added because it indicates the possibility of planting trees in the street, and "street height to width ratio" is added because it conditions the effectiveness of specific solutions. On the other hand, indicators linked with the potential for improvement in open spaces are included. For instance, "vegetation cover ratio" is added because it indicates that an open space already has enough vegetation, indicating that tree planting cannot improve that area. Finally, additional indicators found in scientific publications that are relevant to the topic are added, such as literature about urban climate, heat vulnerability and heat coping capacity. This addition is done to ensure that the initial list is not overly narrowed. Afterwards, with the list of indicators in hand (57 in total), filtering is done to ensure that the chosen indicators are aligned with the objectives of the method (Appendix A). For this aim, the following questions are posted.

- Is this indicator linked with urban open spaces' physical adaptive capacity or improvement potential? This question mainly filters indicators that are related to the capacity of individuals or communities to adapt.
- Is applying this indicator objective, replicable, or suitable for micro-scale assessment? This question primarily excludes indicators that do not apply to diverse urban fabrics or must be manually calculated.
- Is open-access data available to feed the indicator? This question excludes indicators with unavailable data or indicators with available data that are not openly accessible. This step is conducted to ensure the method is replicable to different case studies and users. That is, the method is flexible and scalable enough to be implemented regardless of the size and type of urban fabric.

Every indicator with a "no" answer for any of those questions is removed. As a result, 12 indicators are obtained. Finally, the indicators that refer to overlapping characteristics (i.e. vegetation cover and NDVI) are unified to avoid duplicate information. The final list includes 8 indicators. Once the indicator list is decided, each indicator is calculated using GIS software and the database for the clustering is created.

The indicator **tree canopy cover** ratio (TCC) measures the percentage of open space of an urban block covered by trees. This indicator is linked with improvement potential. It reflects the amount of tree

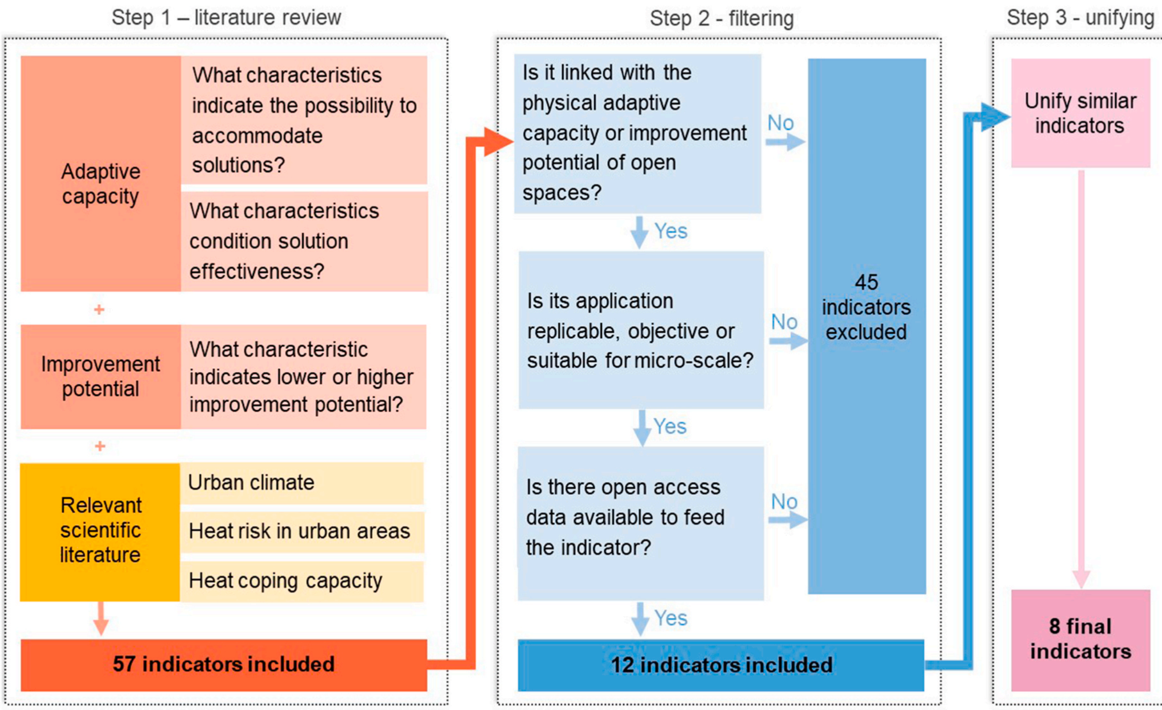

Fig. 1. The process followed for the selection of the indicators.

density in the open space and, therefore, the amount of additional trees that can be planted. For its calculation, a Digital Surface Model of vegetation (DSMV) raster image can be used. From the raster image, pixels with a height value below 2 m are removed. Then, the footprints of buildings are removed. TCC is calculated as the ratio of remaining vegetation pixels on each urban block.

The indicator **open space amplitude** (OSA) quantifies the spaciousness or extent of open areas within an urban block. This indicator is linked with adaptive capacity. In the first indicator list, street width was identified as a critical indicator that reflects the possibility of accommodating adaptation solutions such as trees. However, only some urban areas have defined street canyons, and not every open space is a street. Squares or residual spaces are potential areas for accommodating adaptation solutions too [49]. In order to sort this obstacle, open space amplitude is used instead of street width. A layer with the building footprint is needed to calculate the indicator. Then, a proximity raster layer is created on a GIS software using the building layer as a base. Every point in the open space is then assigned the distance value to the closest building. Finally, the indicator is calculated as the average distance value for every open space pixel within each urban block.

The indicator **open space ratio** (OSR) measures the percentage of open space surface in an urban block concerning the space covered by buildings. This indicator is linked with adaptive capacity. A higher OSR is linked with a higher adaptive capacity of an area since there is more space for accommodating open space adaptation solutions; hence, their effectiveness is more significant [7,18,31].

The indicator **road surface ratio** (RSR) quantifies the percentage of the open space within the block that is destined for roads. This indicator is linked to both improvement potential and adaptive capacity. An open space with many roads has less space to accommodate solutions such as trees, grass, or impervious pavements. Simultaneously, it has improvement potential through pedestrianisation, which has been identified as a crucial action for urban transformation [28]. A vector road layer can be used to calculate this indicator. Then, the layer is rasterised and the building footprints removed. RSR is calculated as the ratio of remaining road pixels on each urban block.

The indicator **albedo** (A) quantifies the solar radiation that is reflected by a surface. It is one of the parameters that Stewart and Oke [6] identified for measuring UHI intensity. In this case, this indicator is linked with the improvement potential, as a lower albedo indicates that a block has the potential for improvement by increasing the albedo of its surface materials. The albedo is calculated using Landsat 8–9 OLI/TIRS C2 L2 reflectance images. The images chosen for the calculation should be taken during summer, with low aerosol concentration and without clouds. The detailed procedure followed to obtain the albedo values from the reflectance images can be found in Ref. [50]. The final value is calculated as the average albedo value of each block.

The **sky view factor** (SVF) indicator measures the visible sky fraction at a given location. On a shallow street canyon, SVF values are closer to 1; as the proportions of the street canyon narrow, the values decrease. This indicator is linked with adaptive capacity. In literature, narrow street canyons have been related to lower effectiveness of adaptation solutions [18,31,51]. Using a Digital Surface Model (DSM), a raster layer is created by assigning an SVF value to each pixel within a block. For that, the UMEP plugin for QGIS can be used. Then, the average SVF of the pixels that lay on an open space within a block is calculated. Finally, the indicator is calculated as the average SVF for every open space point within each urban block.

The indicator **imperviousness** (I) refers to the degree to which a surface is impermeable or resistant to water infiltration. Stewart and Oke [6] relate this parameter to the UHI effect, and reducing the impervious surface is a known adaptation solution for heat wave adaptation [21,52]. This indicator is linked with the improvement potential, as it indicates the potential of decreasing impervious surfaces as an adaption measure. A satellite raster image of the surface imperviousness should be obtained for the calculation, such as a Copernicus imperviousness image. The indicator is calculated as the average value of imperviousness within each urban block.

The indicator **solar radiation** (SR) refers to the amount of solar radiation that reaches the open space surface. The intensity of SR in an open space indicates the potential for the open space to improve by introducing shading solutions; thus, it is linked with improvement potential. The values can be calculated for each pixel of an urban block using an DSM and the plugin UMEP for QGIS. Then, the average SR of the pixels that lay on open spaces is calculated.

Carefully preparing the data is an essential step to ensure that the cluttering results are helpful to the purposes of the analysis. Moreover, the k-means algorithm is sensitive to outlier values, which can distort the results and lead to unproductive categories. Consequently, data has to be cleaned by removing missing and outlier values. Then, variables are normalised to prevent undesired weighting. For that, values are rescaled, transforming them into the [0–1] range by applying the following equation:

$$x_{ij,norm} = (x_{ij} - x_{j,min})/(x_{j,max} - x_{j,min}) \tag{1}$$

Where $x_{ij,norm}$ is the normalised value of variable *j* for block *i*; x_{ij} is the actual value of variable *j* for block *i*; $x_{j,min}$ is the minimum value of variable *j* for all blocks and $x_{j,max}$ is the maximum value of variable *j*. Afterwards, a correlation analysis is performed to exclude dependent indicators that could bias the categorisation. Because the distribution of the data for most of the indicators is non-normal, a *Spearman* correlation analysis is conducted, and *r* (correlation coefficient) and *p* (statistical significance) values are obtained.

2.2. Cluster analysis and validation

Before conducting the cluster analysis, the *k* value needs to be chosen. The *k* value selection and the results' validation are made in an iterative process. First, several *k*-value analyses are conducted, and afterwards, the results for each analysis are evaluated. Since quantitative methods are not always conclusive to select the optimal k value [46], quantitative and qualitative methods are combined. Among the existing validation methods, in this research work internal validation, visual validation, and external validation are blended [53].

First, a gap analysis is conducted as part of the quantitative internal validation. The gap analysis indicates the optimal *k* value by comparing the dispersion of data points within clusters to what would be anticipated under a relevant null reference distribution [54]. Taking the *k* value suggested by the gap analysis, the optimal *k* value and other close *k* values are chosen to perform several cluster analyses. Then, the cluster analysis results are visually validated using the Principal Component Analysis (PCA) scatter plot. The results corresponding to observed meaningful patterns in the plot are selected for external validation. Human judgment is recommended to evaluate the usefulness of the clusters obtained regarding the problem intended to be solved [46], ([55], p. 105), ([56], p. 134).

To make sure that the cluster analysis results are aligned with the aim of the method and the characteristics of the case study city, a qualitative assessment of the results is suggested as external validation. The qualitative assessment is done by evaluating in detail, by expert judgment, the fitness of the cluster results within the reference neighbourhoods of the case study city. These reference neighbourhoods are typified as they share homogeneous characteristics because they were built under the same development project, urban plan or historical period. The blocks within each reference neighbourhood are expected to be categorised in the same cluster. To conduct this external cluster validation, previous knowledge of the case study city is needed. Additionally, historical literature that could aid the selection of the reference neighbourhoods can be used. The aim of this validation is to assess the robustness of the results, by checking that the categories are not influenced by anecdotal variabilities, thus, the clusters are not over-fitted. By evaluating the fit of the clusters among these reference neighbourhoods, the most appropriate *k* value is selected.

3. The case study of bilbao

The urban categorisation methodology was tested in Bilbao's case study (northern Spain, 43.25°N, 2.93°W). The study area includes all urban neighbourhoods within the municipality of Bilbao. Bilbao covers an area of 40.59 km^2 and has 342,484 inhabitants, making a population density of 8437.64 individuals/km^2. Health risks caused by heat waves in Bilbao are projected to increase by 7–12 % between 2011 and 2040 a by 16–25 % between 2071 and 2100 (RCP 4.5) [57], underscoring the need for effective heat adaptation action in the city.

The method was applied with the aid of Matlab and QGIS software. Matlab is a programming and numerical calculation software, and in this work, it was used for data analysis and data visualisation. QGIS is an open source GIS, and in this work, it was used for data gathering, processing and visualisation.

The layers used to define the urban blocks were the road axis and river basin boundary provided by the regional government and the municipality, as well as the municipal boundary available at the cadastre. Using the software QGIS, the polygons laid in rural neighbourhoods were removed, as well as those lying in the river basin and under developed urban areas (i.e. *Zorrotzaurre* island). The rural neighbourhoods were identified according the land zoning of the local General Urban Planning Plan.

Finally, narrow blocks with an area-to-perimeter ratio smaller than five were automatically removed. These instances were mainly small residual surfaces derived from the intersection of roads and were generated because road axes were used to define the urban blocs. These instances were not relevant to the purpose of the method but were large in number, which could have altered the clustering results. By this filtering, 879 instances were removed, remaining 1373. The included and excluded instances are shown in Fig. 2.

Afterwards, the data that feeds the indicators was imported into QGIS for processing. In Table 1, indicators, data source, dimension (adaptive capacity or improvement potential) and references are summarised. For the case of Bilbao, no road surface data was openly available to feed the RSR indicator, so instead, it was obtained by multiplying the street axis by 3 m (the minimum lane width).

Once the indicators were calculated for each urban block, the case study database was created. This database was cleaned, the values normalised and checked for correlations. The correlation analysis resulted in the exclusion of the variable SR, due to its significant correlation with OSR, SVF and OSA (Fig. 3).The variables OSR and OSA, and OSA and SVF showed a high positive correlation too, but to a lesser extent than SR. After evaluating the results of the cluster analysis with

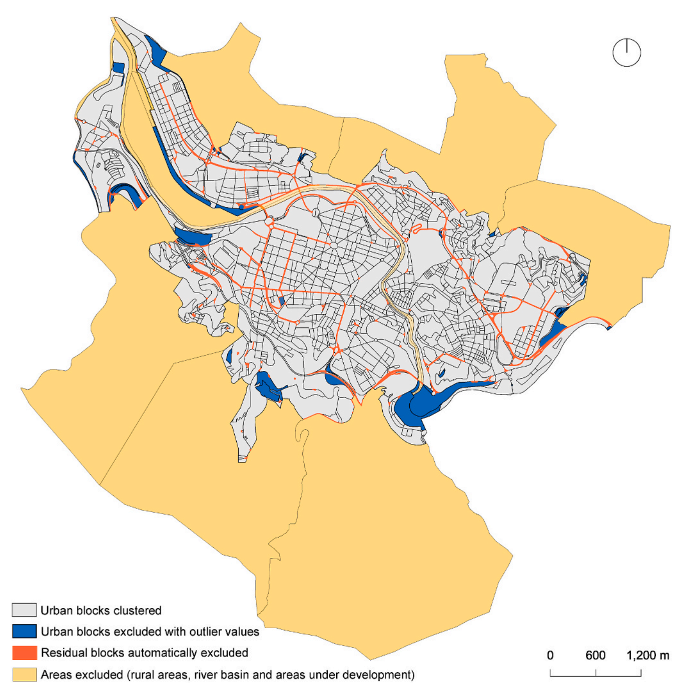

Fig. 2. Included and excluded urban blocks.

Table 1
Indicators used in the case study.

Indicator	Dimension	Data source	References
Tree canopy cover ratio (TCC)	Improvement potential	Digital Surface Model of Vegetation (DSMV). Spanish National Centre for Geographic Information	[11,17,18,21,58,59]
Open space amplitude (OSA)	Adaptive capacity	Bizkaia Cadastre (regional cadastre)	Suggested by the authors
Road surface ratio (RSR)	Improvement potential and adaptive capacity	Basque Government	Suggested by the authors
Open space ratio (OSR)	Adaptive capacity	Bizkaia Cadastre (regional cadastre)	[7,18,31]
Albedo (A)	Improvement potential	Landsat	[6,60]
Sky view factor (SVF)	Adaptive capacity	Digital Surface Model. Spanish National Centre for Geographic Information	[18,31,51]
Imperviousness (I)	Improvement potential	Copernicus	[6,21,52]
Solar radiation (SR)	Improvement potential	Digital Surface Model. Spanish National Centre for Geographic Information	[51,61]

	OSR	A	SVF	I	SR	TCC	RSR
OSA	0.84	-0.20	0.80	-0.67	0.86	0.19	-0.43
	OSR	-0.08	0.81	-0.71	0.96	0.23	-0.33
		A	-0.14	-0.02	-0.11	0.07	0.00
			SVF	-0.72	0.92	0.23	-0.37
				I	-0.75	-0.53	0.51
					SR	0.24	-0.38
						TCC	-0.44
							RSR

Fig. 3. r values of the correlation analysis conducted. The p-value is $p < 0.005$ for every variable pair.

these variables included, the decision to keep them was taken, since each of them represents a different relevant characteristic of the adaptation potential of open spaces.

Qualitative and quantitative methods were combined to select the optimal k value. As a quantitative method, a gap analysis was conducted. The gap analysis was conducted using the Matlab evaluation object “GapEvaluation” [62] and the search method “firstMaxSE”. The smallest k value satisfying the following criteria (eq. (2)) is suggested as the optimal k value:

$$\mathrm{Gap}(k) \geq \mathrm{Gap}(k+1) - \mathrm{SE}(k+1) \tag{2}$$

Where $\mathrm{Gap}(k)$ represents the gap value for the clustering solution for k, and $\mathrm{SE}(k+1)$ is the standard error for the clustering solution for $k+1$.

Following the gap analysis, the gap suggested that the optimal k value was 7 (Fig. 4). Taking $k = 7$ as approximate, a cluster analysis for $k = 5$, $k = 6$, $k = 7$, $k = 8$ and $k = 9$ was conducted for later assessing quantitatively the fitness of the results by visual inspection of the PCA and expert validation. The visual inspection of the PCA scatter plots showed a satisfactory fitting criterion for all k values (Fig. 5). For the expert validation, the reference neighbourhoods were chosen based on the authors’ knowledge on the city and literature about the urban development of Bilbao [63–66]. The chosen neighbourhoods were checked on-site to confirm that the blocks’ characteristics within each neighbourhood were uniform. The neighbourhoods of the old quarter, modernist housing developments from the 40’s and 60’s, low density housing developments of early XXth century and urban developments of the XXIst century were chosen in the case of Bilbao (Fig. 6).

The k values of 8 and 9 were the first discarded, as they failed to capture the homogeneity of the reference neighbourhoods “Medieval old quarter”, “Grupo Santutxu” and “San Inazio”. Between the remaining k values, $k = 6$ was chosen as the final, as it succeeded in capturing best the homogeneity of the reference neighbourhoods, even “San Inazio” and “Otxarkoaga.” The distribution of the clusters for $k = 5$, $k = 7$, $k = 8$, and $k = 9$ and the location of the reference neighbourhoods are shown in Appendix B. The distribution of the clusters for $k = 6$ are shown in Fig. 7.

4. Results and discussion

4.1. Description of the categories

The application of the method in the case study city resulted in a categorisation of the urban blocks of Bilbao in 6 categories. These categories are distributed in the city as shown in Fig. 7. A critical inspection of the statistical data and the archetype blocks (Fig. 8) allowed a description of the categories regarding their adaptive capacity and improvement potential. Each category was labelled with a descriptive name for easier identification.

Category 1, labelled “old high density”, can be found in the whole city, with a higher concentration in the older areas. It represents 12.68 % of the urban surface included in the analysis. This category is characterised by dense urban blocks with high building density. The adaptive capacity of the blocks in this category is limited due to their low OSR and low OSA. The limited space reduces the possibility of accommodating or extending solutions. Moreover, the reduced SVF complicates the implementation of adaptation solutions such as

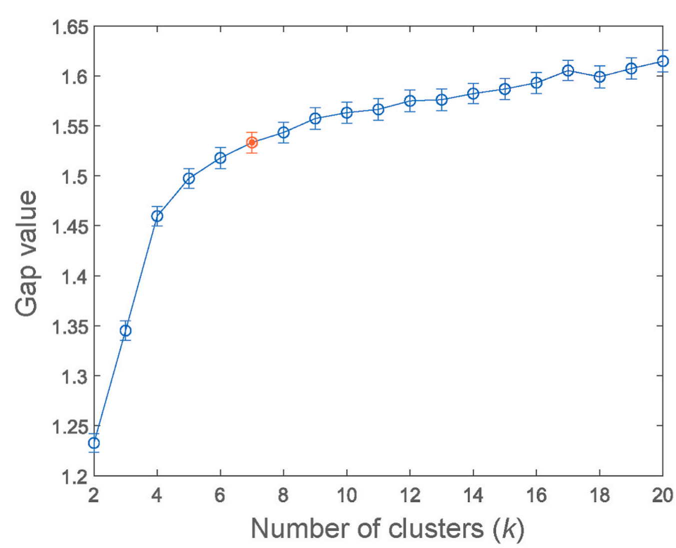

Fig. 4. Optimal k-value resulting from the gap analysis.

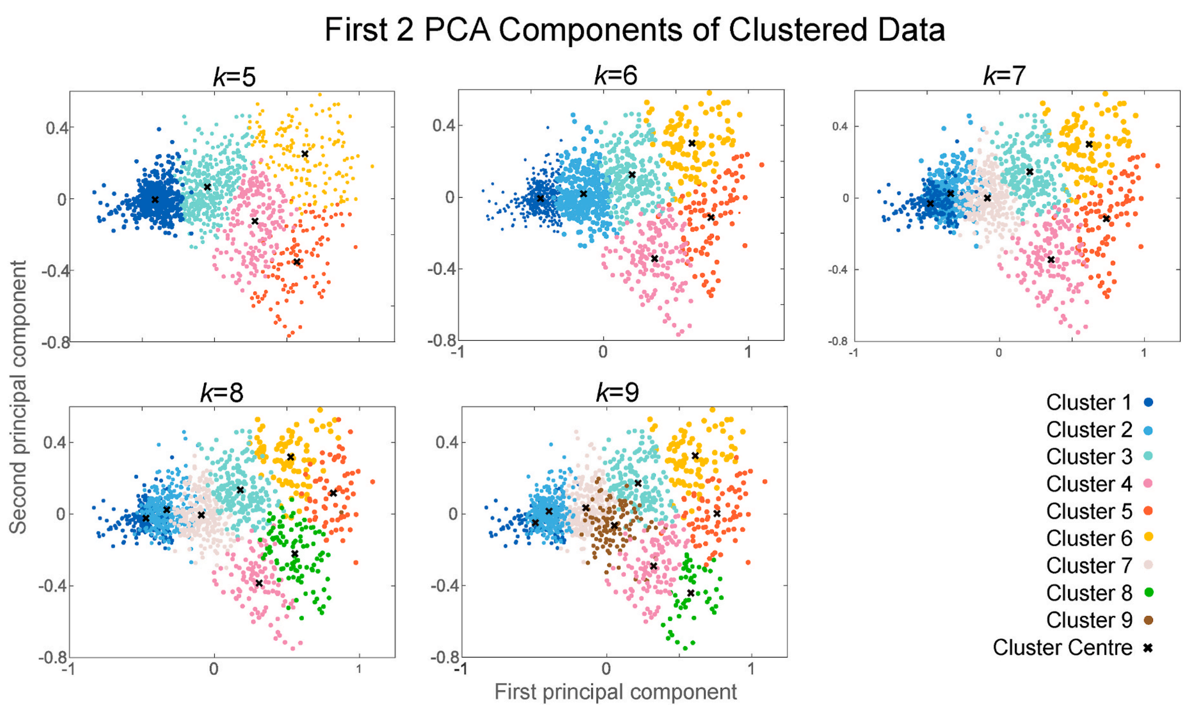

Fig. 5. Scatter plots of the two first principal components of cluster analysis for k = 5, k = 6, k = 7, k = 8 and k = 9.

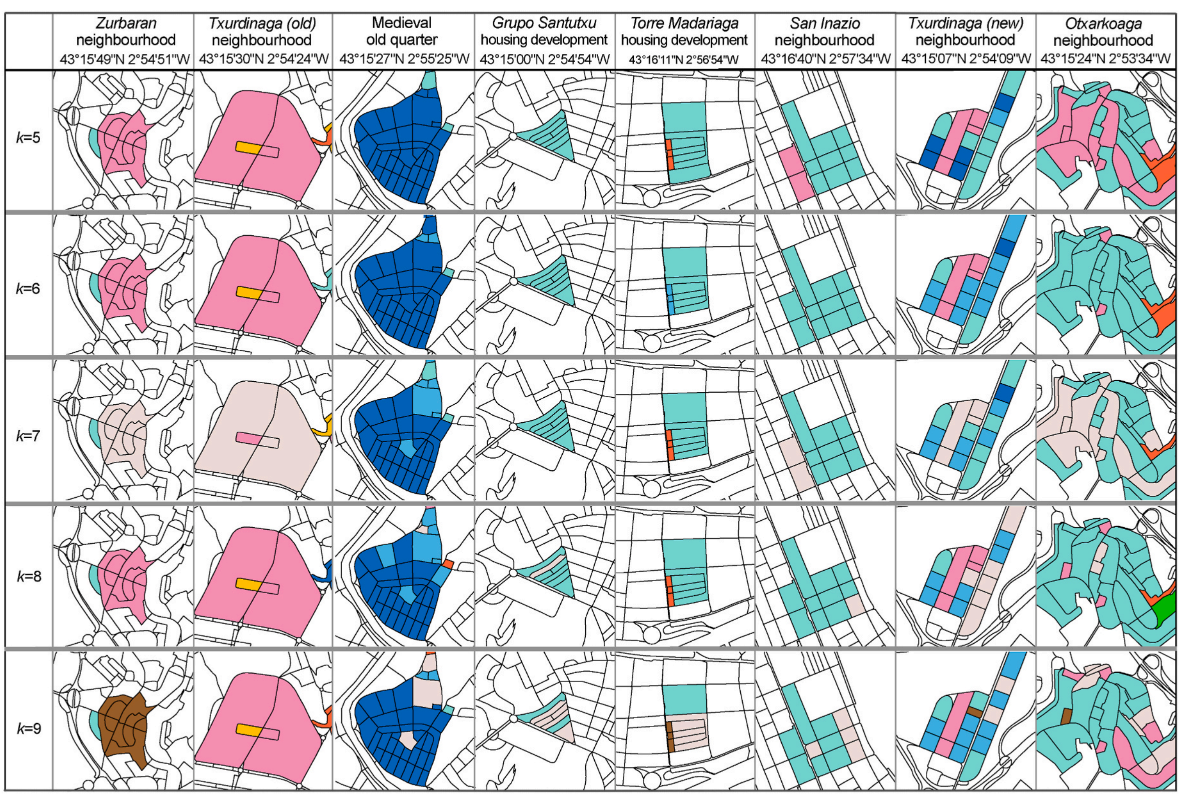

Fig. 6. Comparison of the reference neighbourhoods at each k cluster analysis. The colours represent the cluster value of the urban block on each k = n cluster analysis. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

tree planting or cool pavements, as the effectiveness of these solutions would be hindered by the proportions of the street canyons [18, 31,51]. On the contrary, the streets in Category 1 are suitable for implementing textile solar protection in the street to provide shade, similar to those used in southern Spain [27]. An additional limitation of this block category is that a significant part of the instances lay in historic urban areas, which could hinder dramatic alterations of the existing urban areas, limiting the adaptive capacity. Regarding improvement potential, the high road density ratio indicates a great improvement potential through pedestrianisation works. The TCC

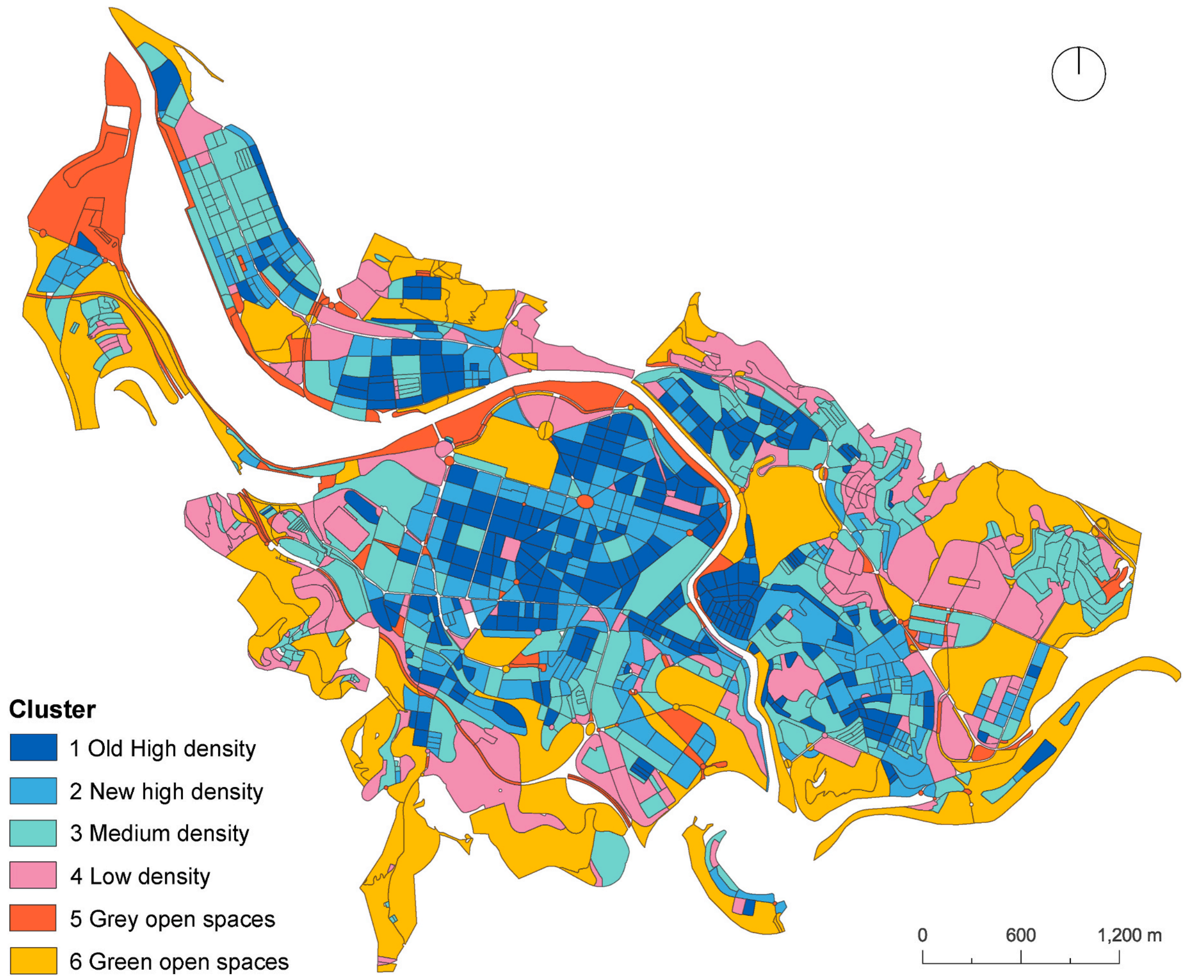

Fig. 7. Urban block category distribution within the city of Bilbao.

ratio is low, and the imperviousness is high. Therefore, there is a high potential for improvement in these two areas. The visual inspection of the archetype block shows the presence of block courtyards, which are potential areas for accommodating adaptation solutions.

Category 2, labelled "new high density", is mainly distributed within the city centre and surrounding neighbourhoods. It represents 12.64 % of the urban surface included in the analysis. These urban blocks present similar values to Category 1 but have a lower RSR, lower albedo values, and slightly higher OSR values. In the city centre, the blocks of these clusters are concentrated around the street "Gran Vía de Don Diego López de Haro", a broad avenue covered with trees. In the peripheral neighbourhoods, the urban blocks of this category are located in highly dense neighbourhoods, generally from newer developments than Category 1. The lower albedo values are indicative of the use of darker roof materials in these new buildings. Their low OSR and OSA hinder the adaptive capacity of the blocks in this category. However, regarding the improvement potential, the lower albedo values indicate an improvement potential by increasing surface albedo. The visual inspection of the archetype block shows limited open spaces with narrow proportions and flat dark roofs. These roofs, even if they are not part of the open space network, represent an opportunity for implementing adaptation solutions that may have an impact in the microclimate.

Category 3, labelled "medium density", is primarily found in the peripheral neighbourhoods of the city, with some urban blocks in the city centre near squares or wide avenues. It represents 18.76 % of the urban surface included in the analysis. It is characterised by having medium OSR values and low OSA values. Regarding the adaptive capacity, the medium OSR values indicated a medium adaptive capacity that the narrowness of the open spaces could hinder. Regarding the improvement potential, the high imperviousness and low TCC ratio indicate a potential for improvement by increasing pervious surfaces and vegetation. The visual inspection of the archetype block shows narrow open spaces with some broader residual spaces. These spaces are generally impervious and present a low tree density, indicating that they are areas of potential improvement.

Category 4, labelled "low density," is mainly found in the peripheral neighbourhoods of the city. It represents 16.35 % of the urban surface included in the analysis. It is characterised by a high OSR, medium OSA and a relatively high TCC ratio. Regarding adaptive capacity, the OSR, OSA, and SVF levels indicate that this category can accommodate effective solutions. Even if this category has one of the highest TCC ratios, it is below 0.3, indicating improvement potential by tree planting. The visual inspection of the archetype block shows the presence of large parking lots, which are potential areas for accommodating adaptation solutions.

Category 5, labelled "grey open spaces", is sparsely distributed within the city, with a slight concentration around the river sides. It represents 6.54 % of the urban surface included in the analysis. This category is characterised by having a very high OSR, OSA and imperviousness. The urban blocks within this category are generally residual spaces between roads or large open spaces with low vegetation cover and high imperviousness. The adaptive capacity of the blocks in this category is high due to their OSR and OSA levels. TCC is low, even lower than highly built-up clusters. This trait denotes an

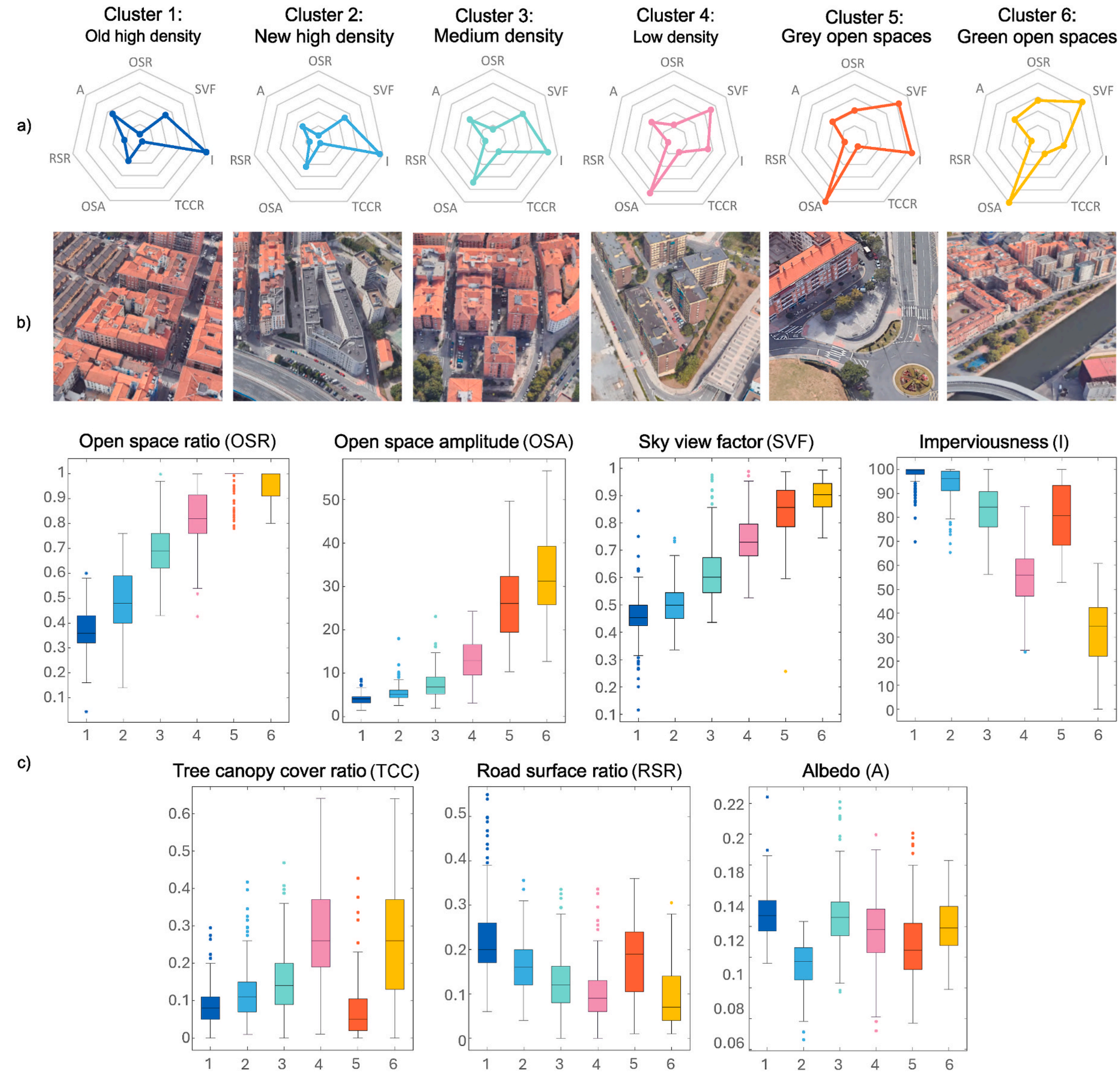

Fig. 8. (a) Normalised variables of each urban block archetype. (b) Aerial image of the archetype blocks (source google earth). (c) Boxplot of variables. The boxes extend from the first quartil to the third quartil of the data. The whiskers represent the lower and upper limits of the non-outlier values. The dots represent outlier values.

excellent improvement potential through increasing pervious surfaces and tree cover. The high RSR also shows improvement potential by reducing road surface to accommodate adaptation solutions. The visual inspection of the archetype block shows a residual open space between roads that, even if small in size, presents an opportunity for accommodating adaptation solutions.

Category 6, labelled “green open spaces”, is formed by urban parks and green areas of the urban boundary. It represents 26.74 % of urban surface. It presents the typical values of green spaces, such as high OSR, low imperviousness or low RSR. These traits make the category suitable to host adaptation solutions, showing great adaptive capacity. Regarding improvement potential, even though the TCC is high compared to other clusters, it is still low, with a median value of 0.25, denoting that there is room for improvement. The visual inspection of the archetype block confirms this fact, showing that most of the block’s trees are medium to small and lack extensive clustered tree areas.

Looking at the value ranges of the indicators (Fig. 8), some collinearity is observed between OSR, OSA, and SVF and between imperviousness and TCC ratio. Even if this could indicate redundancy among the indicators used for the categorisation, the median values and the value ranges have different trends. This fact highlights that the indicators are offering additional information. If these indicators were excluded, these nuances between the categories would have been lost. For instance, clusters 4 and 6 have similar median values for TCC ratio, but cluster 6 has lower imperviousness than cluster 4. This implies that cluster 6 has a higher proportion of grass surface uncovered by trees than 4, indicating higher improvement capacity and major impact of potential adaptation actions.

An overview of the categories shows significant dissimilarities within the city regarding the adaptive capacity of the open spaces. Categories 1 (“old high density”), 2 (“new high density”), and 3 (“medium density”), mainly due to their low OSR, reveal limited space to accommodate adaptation solutions in their open spaces. On the contrary, categories 4 (“low density”), 5 (“grey open spaces”), and 6 (“green open spaces”) display a high adaptive capacity. Regarding improvement potential, most categories, even those with a higher TCC ratio, show significant improvement potential. These findings are in line with previous studies on the city of Bilbao. For instance, Fernández de Manuel et al. [67]

concluded that most of Bilbao's urban green spaces are grasslands, which contribute less to ecosystem services than clustered trees.

Overall, the results show that the city of Bilbao is dense and has limited open space to accommodate solutions. Thanks to the application of the method, it is possible to conclude that the city's urban area is homogeneous in terms of albedo, road surface ratio, and, to a lesser extent, tree canopy cover and imperviousness. This indicates that city-level policies could be adopted to enhance urban heat adaptation. Finally, the method is also helpful in identifying urban blocks suitable for intensive interventions, such as those categorised as category 6 "grey open spaces."

4.2. Achievements and limitations of the method

The application of the method in the case study demonstrates its capacity to categorise urban open spaces according to their adaptive capacity and improvement potential for heat waves. Moreover, the results obtained and their semantical and statistical description reveal that the method can provide meaningful insights for decision-making regarding the adaptation potential of urban open spaces. This approach can provide adequate city-scale adaptive capacity and improvement potential overviews without time-consuming analysis.

The application of the method in the case study proved that.

- The method can identify relevant categories to assess the adaptive capacity and improvement potential of open spaces to heat waves.
- The categorisation is done objectively by using the clustering approach.
- The method is replicable in temperate cities of different sizes, locations and urban fabrics because (i) the replicability in larger cities is ensured by avoiding time-consuming manual operations, (ii) the replicability in different locations is ensured by using indicators that are easily fed with openly available data, and (iii) the replicability in different urban fabrics is ensured by using analysis instances and indicators that are not specific to any urban fabric. This is reflected in the fact that different urban blocks in size and form are categorised together when their characteristics regarding climate change adaptation are similar.
- The method is suitable for identifying micro-scale characteristics. For instance, the method is able to identify urban blocks that contain squares or wide streets in neighbourhoods with a regular street layout.

This work develops a novel method to identify different open spaces regarding their adaptive capacity and improvement potential in case of heat waves in cities. This is a novel approach with great profitability for urban design, with special emphasis on urban regeneration. Previous categorisations in the field of heat adaptation and mitigation aimed at diagnosing the current UHI or microclimate of the open spaces rather than understanding the potential for future interventions.

On the other hand, in comparison to an LCZ method, the method is fine-tuned to identify opportunity areas at the micro-scale in the case study in which it is applied. The method is able to identify within a dense neighbourhood, squares, linear open spaces or residual urban spaces with the potential to host adaptation solutions. These type of urban spaces would be oversighted with an LCZ approach or other similar methodologies [37,43,46]. The main limitation of the method lies on the variability of the result. Due to the characteristics of the clustering technique, the method has different outputs for each case study, making the comparison of results between case studies unproductive. This characteristic is a drawback compared to an LCZ classification since LCZ classifications can be used to compare different case study cities. However, this method is not intended to be used to compare different cities with each other, as the LCZ is, but to have an overview of the adaptation potential of the city considering its urban design. Nevertheless, the method is flexible enough to admit increasing or reducing the number of indicators depending on the particularities of the cities.

The UHI magnitude may vary within the urban blocks of the same category due to factors such as their location in the city or the characteristics of the blocks nearby. Therefore, to prioritize the areas for intervention, it is recommended to supplement the present method with a risk assessment at the city level. This assessment should consider the characterisation of the UHI within the city and the distribution of the vulnerable population [61,68].

5. Conclusions

Cities will suffer more and more heat waves in the future, and adapting their open spaces to extreme temperatures is essential to ensure the wellbeing of the urban inhabitants. To promote the adaptation of cities to climate change, we need to provide policymakers with tools that facilitate the decision-making involved in the adaptation process. While previous studies have advanced in categorising urban areas according to their climatic behaviour or heat vulnerability, a method that categorises open spaces according their potential to adapt at the micro-scale is still lacking. Subsequently, this research provides a method to categorise open spaces according to their adaptive capacity and improvement potential. This method is demonstrated to be objective, replicable, and suitable for micro-scale assessment. The application of the method in a case study has proven the ability of the method to provide meaningful insight into the adaptation of open spaces to heat waves with limited and accessible data at the micro-scale level.

The categorisation results have enabled us to identify that the potential for improvement of the case study city is significant. Hence, adaptation limits have yet to be reached. For instance, the urban block category "green open spaces" has a median tree cover ratio of 0.25, denoting that tree cover can be intensified even in the greener areas of the city. On the contrary, the adaptive capacity of the city is diverse, with varying degrees of adaptive capacity between urban block categories. While some urban blocks present the ideal characteristics to accommodate solutions that are expected to be effective, in the more dense blocks, solutions beyond business-*as*-usual will have to be explored if adaptation actions want to be taken. The most dense urban block categories "old high density" and "new high density" cover more that 25 % of the categorised urban surface and have median open space ratios below 0.5, indicating that the integration of adaptation solutions in a relevant part of the city is going to be challenging.

This method can aid stakeholders involved in urban planning and climate change adaptation to plan action and allocate resources. The results of the method are valuable for urban designers too. Having an overview of a city's adaptation potential can help stimulate designers' creativity to include adaptation measures in their designs. Moreover, knowing the hinders and opportunities for adaptation within a city can help to frame urban design projects as adaptation actions.

In moving towards a better understanding of urban adaptation to heat waves, it is crucial to acknowledge that this categorisation method is a first step. The following phases of this research should shift the focus towards systematically simulating diverse adaptation options within each category. These simulations will identify each open space's most effective context-specific adaptation solution. Furthermore, the replicability of the method offers possibilities for its use in other cities or even regions. The journey of urban climate change adaptation is ongoing, and this work not only contributes to the understanding of the matter of adaptation to heat waves in a specific case study city but also offers a categorisation method that can be used for a broader exploration of climate change adaptation potential in diverse cities.

CRediT authorship contribution statement

Ane Villaverde: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation. **Irantzu Álvarez:** Writing –

review & editing, Validation, Software, Methodology, Data curation. **Eduardo Rojí:** Writing – review & editing, Validation, Supervision, Methodology, Conceptualization. **Leire Garmendia:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Ane Villaverde reports financial support was provided by Basque Government. Ane Villaverde reports financial support was provided by Spanish Ministry of Science, Innovation and Universities. Leire Garmendia reports financial support was provided by Basque Government. Leire Garmendia reports financial support was provided by Spanish Ministry of Science, Innovation and Universities. Irantzu Alvarez reports financial support was provided by Basque Government. Irantzu Alvarez reports financial support was provided by Spanish Ministry of Science, Innovation and Universities. Eduardo Roji reports financial support was provided by Basque Government. Eduardo Roji reports financial support was provided by Spanish Ministry of Science, Innovation and Universities. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A

Table A. 1
Indicators obtained in step 1.

Indicator	Is it related to the (physical) adaptive capacity or improvement potential?	Is its application replicable, objective or suitable for micro-scale?	Is there open access data available to feed the indicator?
Albedo	Yes	Yes	Yes
Annual sun radiation	Yes	Yes	Yes
Available family income	No	–	–
Average building height	No	–	–
Basic education of the population	No	–	–
Building façade albedo	Yes	Yes	No
Built underground	Yes	Yes	No
Built-up surface ratio	Yes	Yes	Yes
Business in ground floor ratio	No	–	–
Connectivity	No	–	–
Continuity (angular)	No	–	–
Courtyard surface	Yes	Yes	No
Density of basic services	No	–	–
Diversity of citizen organisations	No	–	–
Employment density	No	–	–
Exposition to predominant winds	Yes	No	–
Fabric density	Yes	Yes	Yes
Feminization of aging	No	–	–
Firemen access	No	–	–
Global accessibility	No	–	–
Global movement flow	No	–	–
Gross floor area per block	No	–	–
Imperviousness	Yes	Yes	Yes
Local accessibility	No	–	–
Local movement flow	No	–	–
Number of buildings per area	No	–	–
Number of buildings per urban block	No	–	–
Number of trees	Yes	Yes	No
NDVI	Yes	No	Yes
Pavement width	Yes	Yes	No
Pedestrian area in street	Yes	Yes	No
Pedestrian to non-pedestrian ratio	Yes	Yes	No
Percentage of individuals with care needs	No	–	–
Population ageing	No	–	–
Population density	No	–	–
Presence of immigrant population	No	–	–
Public and private walkable areas (green, unbuilt, pavement, bike line, landscaped courtyards and private garden areas)	Yes	Yes	No
Public space area	Yes	Yes	No
Residential to non-residential ration	No	–	–
Road surface ratio	Yes	Yes	Yes
Solar irradiation per m^2	Yes	Yes	Yes

(*continued on next page*)

Table A. 1 (*continued*)

Indicator	Is it related to the (physical) adaptive capacity or improvement potential?	Is its application replicable, objective or suitable for micro-scale?	Is there open access data available to feed the indicator?
Open space amplitude	Yes	Yes	Yes
Street aspect ratio	Yes	No	–
Street length	No	–	–
Street orientation	Yes	No	–
Street width	Yes	No	–
Summer sun radiation in open space	Yes	Yes	Yes
Surface admittance	Yes	Yes	No
Sky View Factor	Yes	Yes	Yes
Terrain roughness	No	–	–
Total above-ground built-up area per building	No	–	–
Traffic intensity	Yes	No	No
Type of urban fabric	Yes	No	–
Urban block area	No	–	–
Urban block perimeter	No	–	–
Urban block proportion	No	–	–
Vegetation cover	Yes	Yes	Yes
Water bodies	Yes	No	–

Table A. 2
Indicators obtained in step 2.

Indicator	Overlapping indicator
Albedo	No
Annual sun radiation	Yes
Built-up surface ratio	Yes
Fabric density	Yes
Imperviousness	No
NDVI	Yes
Public space area	Yes
Road surface ratio	No
Open space amplitude	No
Summer sun radiation in open space	Yes
Sky view factor	No
Vegetation cover (this indicator was adapted to “Tree canopy cover ratio” to fit data availability)	Yes
Solar irradiation per m^2	Yes

Appendix B

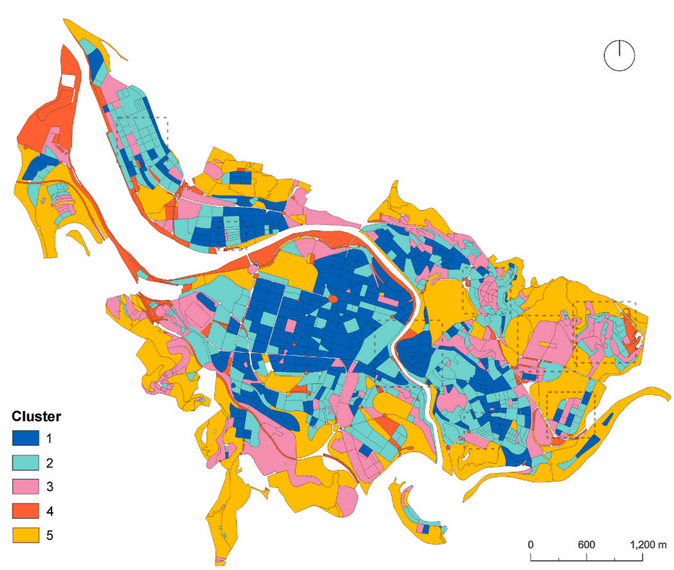

Fig. B 1. Urban block category distribution within the city of Bilbao for k = 5. The dashed lines indicate the location of the validation neighbourhoods.

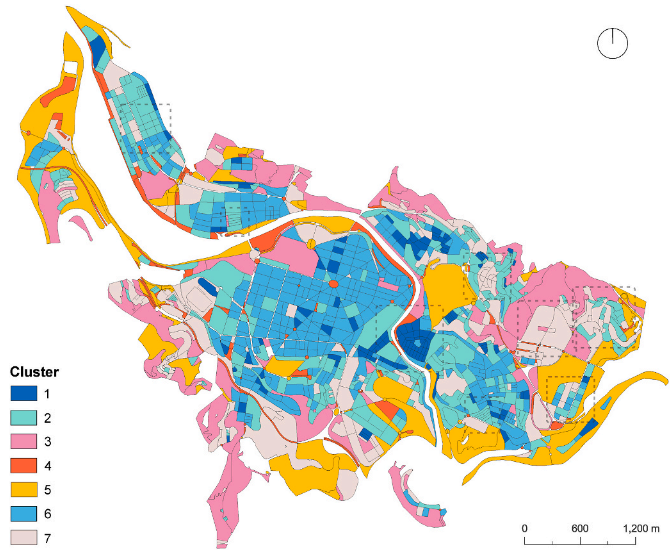

Fig. B 2. Urban block category distribution within the city of Bilbao for k = 7. The dashed lines indicate the location of the validation neighbourhoods.

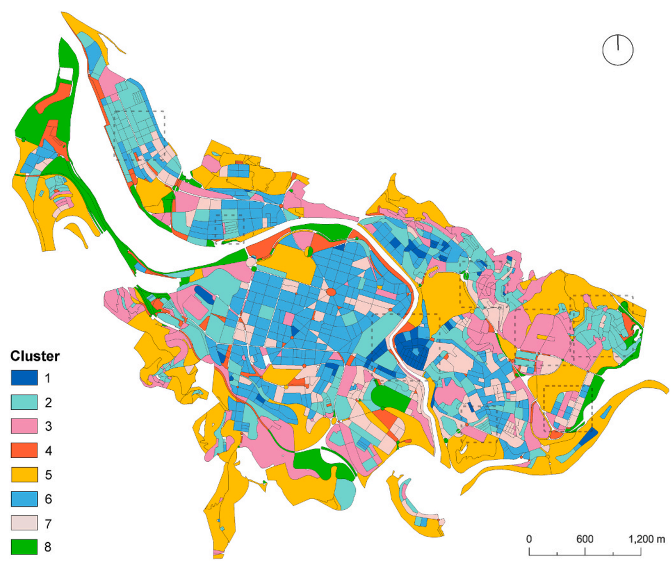

Fig. B 3. Urban block category distribution within the city of Bilbao for k = 8. The dashed lines indicate the location of the validation neighbourhoods.

Fig. B 4. Urban block category distribution within the city of Bilbao for k = 9. The dashed lines indicate the location of the validation neighbourhoods.

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