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ABSTRACT

Accurate knowledge of climatic conditions is essential for planning and developing a territory, particularly in building construction sector. Determining microclimate zoning could benefit policymakers and building designers in enhancing bioclimatic design and thermal comfort under subtropical conditions. This article presents a new microclimate zoning combining statistical analysis (double nested clustering and K-means partitioning) and GIS-based spatial interpolation . The method was tested on meteorological data from 242 weather data points of Reunion island, and the altitude. The first implementation distinguished three climate zones, most notably separating the east (humid region) from the west (dry region), and a central area (temperate region). The second implementation allows to identify subclimate typologies within the three main climate zones. The representation of the local climate dynamics is portrayed through spatial interpolation. The twelve sub-zones provide a more accurate climatic map of Reunion Island, in tune with observed climates over the territory. Moreover, considering altimetry enabled to include the effect of relief in microclimate zoning. The major result of this study is that our microzoning method is not limited to urban areas, unlike most of the case studies in the literature. By considering meteorological data at a fine spatial resolution, our approach can be applied to a wide range of applications (cities, rural areas, energy, agriculture…).

1. Introduction

The definition of climate typologies and their spatial distribution assists planning and management of the territory while providing information on the local challenges and vulnerabilities that affect natural patterns and productive activities (Cortez, 2021). An accurate climate zoning allows, among other uses, to promote the development of sustainable territories. Urban planners strive to reduce the impact of urban heat islands, considering that the adaptation to climate change is better adressed at the city level, (Perera and Emmanuel, 2018). Furthermore, building construction is a system that reflects an adaptation to environmental conditions. Thus, the study on bioclimatic design in tropical areas reveals a current application of vernacular concepts (vegetation of spaces, large openings, solar protection…). When establishing energy policy, predicting a building's thermal behavior requires a detailed understanding of the local climatic conditions (Xiong et al., 2019). But the disparate distribution of meteorological stations on a region does not always allow the acquisition of exact weather data. The survey conducted by Hao et al., (2021) has shown that, in the case of missing weather data, extrapolating climate type to a neighboring region can lead to the prescription of unsuitable technologies and designs, implying non-optimal energy performances. Therefore, it is necessary to ascertain the distribution of climate characteristics of a locality at a

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small scale. This study is expected to constitute a pillar for various applications as it will help policy makers in implementing building energy efficiency programs, and support decisions in urban planning.

The (RTAADOM, 2016)[1] common to the French overseas territories and the (PERENE, 2009)[2] reference system, govern building design in Reunion Island. These design tools are based on climate zoning, which classify the island's climate according to the land topography and the prevailing winds. The proposed method set out to highlight nuances within a local climate, based on a meteorological data-centered approach. The classification combines a nested double clustering and a k-means partitioning. By using a large spatialized meteorological database from Météo-France, (Faure et al., 2008), we propose a mapping of Reunion Island's microclimates based on a multivariate data analysis. Walsh et al., (2022) suggests that a building performance-based approach is preferable for climatic zoning aiming to support builing policy and guidelines. Although, a holistic strategy, not centered on buildings, allows climate zoning to be employed in other contexts, such as agriculture, geography, hydrology, etc., as long as the climatic parameters chosen are in line with the purpose of the study.

This article is structured as follows. First, we present the existing climate mappings for Reunion Island and a bibliographic review of the most used classification methods. Secondly, we present the chosen climate data classification method and the resulting climate zones are analysed. Using GIS tools, these new climate zones are spatialized. Finally, the map result is compared with previous climate maps.

1.1. Statement of significance

Climate zoning usually takes an overall view of climatic factors, making it ineffective and difficult to implement on a smaller scale. To ensure a sustainable and resilient building stock, it is essential to design and construct buildings able to withstand climatic dynamics, (Verichev and Carpio, 2018; Díaz-López et al., 2021). One climate classification aim is to provide a guideline to help define standard regulation for energy policy and at the city level, support decision in performance-based urban planning. However, an inadequate policy leads to additional costs in terms of energy consumption and to inappropriate requirements challenging to meet for various stakeholders, (Pernigotto et al., 2021). It seems crucial to perform climate zoning at smaller scale to emphasize spatial heterogeneities. Literature suggests effective statistical analysis methods for climate zoning on a territorial scale. However, the originality of the proposed approach comes from the second series of analyses. Indeed, the first clustering enables us to identify the major climatic zones of the region. To define the consistency of each cluster, the Ward method is used. Thus, criteria to define cluster homogeneity is based on minimizing the within-inertia of each cluster (Husson et al., 2010). Inside each major zone, a second clustering is performed to group meteorological points according to their similarities, and thus create new, smaller zones, which we describe as microclimatic zones. Performing a double clustering would allow us to highlight climatic subtypes existing within a main typology of climate. In the case of Reunion Island, the landscape is so undulating that meteorological variations occur on a small scale, hence the need to refine zoning as much as possible. Furthermore, for the most coherent zoning, as much information as possible must be provided as input. The disparate spatial distribution of meteorological stations on a territory does not permit the gathering of precise data for a particular region leading to misclassification. Since they are derived from a forecasting model used by the meteorological operator Météo-France, the databases used in our study are the most current detailed for Reunion Island. The provided database covers the entire territory at a resolution of 3.5 km. This rich data grid will allow further research on resilient building stock at the city level based on the proposed microclimate zoning. The climate zoning is constructed using hierarchical agglomerative classification and k-means partitioning. This technique enables the grouping of regions by similarities. By relying on a statistical classification of recent high resolution meteorological data, we obtain a more accurate depiction of the climate patterns of Reunion Island.

1.2. Brief view of Reunion Island

Reunion Island is a French overseas Department located in the middle of Indian Ocean. The island has a surface area of 2512 km^2 and a population of roughly 900,000 people. Jauze, (1998) draws attention to the unique feature of the island: its core is its periphery, and its periphery is its core. Indeed, the coastline and lower slopes ($<$ 600 m) concentrate 85% of the island's inhabitants, as illustrated in Fig. 1. The capital Saint-Denis and the second economic pole Saint-Pierre, both located in the periphery, confirm this point. Due to the coastal area's saturation, the inhabitants are increasingly migrating to the island's mid-slope. Consecutive crises have exacerbated inequities and the precariousness of the people, notably in terms of housing. As a result, approximately 100,000 individuals (30% of the population) lack proper housing. Moreover, new challenges must be addressed in light of an aging rental stock and the demand for 170,000 dwelling units by 2035 in the context of substantial land pressure, (Département, 2022). Buildings must be designed according to local climate. In the lowlands, the main focus would be to establish a cooling strategy. In the highlands, the confort strategy woul be oriented towards heat storage. Thus, altitude alone is unsuitable to define building guidelines, due to the island's unusually uneven relief and its insular nature. The temperature significantly decreases with altitude. It drops by about 0.6 °C every 100 m.

2. State-of-the-art climate zoning methods

Despite the relevance of climate classification, there is no up-to-date consensus on the appropriate methodology for its

[1] Réglementation thermique, acoustique et aération pour les bâtiments: thermal, acoustic and ventilation regulations for buildings

[2] PERformances ENErgétiques des bâtiments à La Réunion: Building energetic performance in Reunion Island

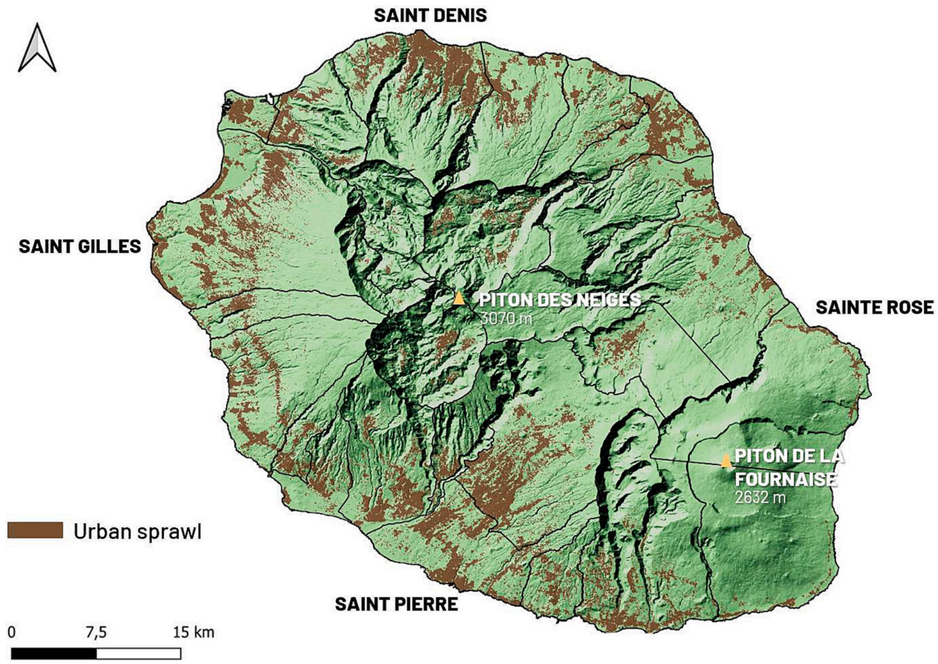


Fig. 1. Urbanization of Reunion island and main cities.

establishment. Previous studies have pointed out that various approaches are currently used for classifications in climate research: classical methods and modern methods.

Classical classifications are based on predefined threshold values that indicate the limits between various preset climate classes, as showed in studies conducted by Belda et al., (2014); Jacobeit, (2010); Sa'adi et al., (2021). The Köppen classification, (Kottek et al., 2006), which is the most well-known classification in this group, is frequently applied for evaluating climate and climate change in geography, hydrology, agriculture, and biology. This approach draws a relationship between rainfall, air temperature, and vegetation distribution. Köppen's classification system is based on a 5-group division of vegetation. Each group is associated with a climate zone: the equatorial climate zones (A), the arid climate zones (B), the warm temperate climate zones (C), the snow climate zones (D), and the polar climate zones (E). According to de Oliveira Aparecido et al., (2016); de Sá Júnior et al., (2011), this classification would imply that climate is a sufficient factor to characterize a specific vegetation type. However, other factors must be considered, such as historical factors, rapid changes in climatic conditions, and human factors, among others, as stated by Zscheischler et al., (2012). Furthermore, inconsistencies have been pointed out between the climate classes revealed by the Köppen classification and the climate types encountered. Peel et al., (2007) affirmed that the insertion of the altitude criterion would help refine the portrayal of climates. This would enhance the extrapolation of climate types identified by Köppen in mountainous regions and areas with a sparse distribution of weather stations. It would prevent the extension of climate types from high-altitude stations to low-altitude locations in the absence of data for the latter. In addition, Sparovek et al., (2008) note the rigidity of the Köppen method regarding the criteria for threshold delimitation. In some cases, various features of the natural landscape implying high changeability of climatic features were included into the same climate class. The classification of Köppen's effectiveness for global studies of climate change over a given period is undeniable. Still, its greatest weakness is the lack of precision in defining the climate zones of a targeted region. It was also judged unsuitable for building comfort study by Attia et al., (2019).

The most commonly used climate classification method for bioclimatic design purposes is the degree-day. The degree-day is the difference between the average temperature outside the building and an arbitrarily set comfort temperature. This reference temperature corresponds to the temperature at which the HVAC system does not need to be activated. As external temperatures vary from region to region, the degree-day allows assessing the energy required to maintain the comfort of buildings in various climate zones. These classical methods are of an arbitrary nature.

In contrast to threshold-based classifications, modern approaches are based on grouping individual objects through statistical analysis. In this category, individuals are grouped into self-generated classes based on statistical criteria that can be imposed for supervised classification or not for unsupervised classification or clustering. Using supervised classification, we can predict the assignment of new observations based on rules we must establish. As Kassambara, (2017) explains, it necessitates prior knowledge of the number of groups in the studied population and the group to which each observation in the population belongs. This approach is not often chosen in the literature and is more commonly associated with local climate zoning (LCZ) (Khan, 2018). The supervised classification algorithm can only be applied to regions with known and detailed climate features. In China, Yang et al., (2008) developed a building climate zoning that proposes bioclimatic design strategies for each zone based on past research. We will favor clustering when the number of groups existing in the population is not known in advance. The objective of unsupervised method is not to seek correlations between individuals but rather to construct homogeneous groups of individuals based on their similarities. In the climatological field, the Euclidean distance measures the similarity between the climate variables of two weather stations, (Cortez, 2021; Fovell and Fovell, 1993; Praene et al., 2019; Sa'adi et al., 2021). Clustering has the advantage of handling a high number of variables, unlike other methods that simplify classification by considering a fewer variables. Zeleke et al., (2022) affirms that supervised classifications multiply uncertainties, making multivariate clustering of high-resolution climate data a more interesting approach. This method has shown its efficiency in climate zoning adapted to a bioclimatic design by combining climatology and building energy performance analysis in studies carried out by Hao et al., (2021); Walsh et al., (2017a, 2017b). Non-hierarchical and hierarchical clustering approaches can be distinguished among clustering techniques. The most popular non-hierarchical method is the k-means method. It allows rapid partitioning of the data set into k clusters. The value of k is preset, and the optimal solution is determined through iterations: each cluster's center will be chosen randomly. Each individual will be assigned to its closest cluster. The aim is to have stable clusters by minimizing the distance between the individuals of the same group— in other words, to reduce dissimilarities within the cluster, explained (Creusier and Biétry, 2014). This iterative approach has a major drawback; the groupings rely on the initial random assignment of variables. The result thus varies at each implementation according to the initial position of the cluster centers. Moreover, the number k of clusters is arbitrarily fixed questioning the possibility of not choosing the optimal number of climate classes, (Gerstengarbe et al., 1999). In their analysis, Unal et al., (2003) identify hierarchical clustering algorithms as ideal for the exploratory stage of the research since they assist in selecting the optimal number of groups. Netzel and Stepinski, (2016) demonstrated that the k-means algorithm performed better than the hierarchical clustering method in the setting of climate zoning. Combining these two techniques might be interesting, as Praene et al., (2019); Zeleke et al., (2022); Sa'adi et al., (2021); Cortez, (2021) did to identify climate classes in hot regions.

These approaches allow us to have global climate zones given a specific region. However, as stated by Young et al., (1997), topography plays a key role in the case of rugged terrain. Indeed, we observe, in these cases, significant variations in wind speed or precipitation. These large variations on a short spatial scale lead to microclimate. Geiger referred to microclimate as a site- or station-specific climate. According to Naiman et al., (2005); Rotach and Calanca, (2003), the study of a microclimate generally considers the atmosphere's dynamic and thermodynamic factors (temperature, humidity, wind speed, etc.) measured in a restricted area.

In ecological research, Luo and Zhou, (2006) emphasized the crucial role of accurately defining microclimates. Indeed, the latter are essential for wildlife habitat selection or plant breeding in the case of revegetation projects.

In building physics, it will mostly be a definition of the microclimates in an urban area to help urban planners and designers adjust strategies to the local context. The fact is that urbanized areas tend to produce and retain more heat than rural areas, thus creating an urban heat island effect, (Dimoudi et al., 2013; Joshi et al., 2022; Zheng et al., 2018). According to Hermawan and Švajlenka, (2022), environmental elements such as topography, vegetation, presence of water, and urban morphology coupled with building envelope elements (shape, materials, orientation, ventilation) define the urban microclimate. Lehnert et al., (2021); Xue et al., (2020); Feng and Liu, (2022) identified three main methods used to identify and map these local climate zones:

- Based on field measurements and authors' knowledge (supervised classification),
- Based on geographic information systems (GIS),
- Based on remote sensing imagery.

Local Climate Zoning (LCZ) is the most popular method adressing the subject at a city level, considering cities as one of the major factor of environmental global changes, (Bechtel et al., 2015). The LCZ classification was established to counter the shortcomings of urban-rural distribution, identifying 17 patterns based on surface structure, land cover and human activities, (Bechtel et al., 2015; Stewart and Oke, 2012). In accordance with LCZ, ventilation zone is developped on the basis of urban ventilation, building height, street structure and compactness during performance-based planning, (Zhao et al., 2020; He et al., 2020). These studies showed the impacts of urban morphology on local climate, admitting that urbanization plays a key role in comfort level, it can either induce heat islands or allow to have a sufficient natural ventilation for urban heat island mitigation, (He et al., 2019).

3. Existing climate zoning of Reunion Island

There are two main seasons on the island. The austral summer extends from November to April. This is the period when solar radiation is the most abundant and the temperatures are the highest. The days are the longest and the rainiest with cyclonic risks. February is the wettest month on the island (on average, 1.5-m rainfall at the Sainte-Rose meteorological station). The austral winter (May to October) is marked by shorter days and lower daytime temperatures. The season is relatively dry, cool, and less humid, with a predominance of east and southeast trade winds. In the west of the island, there is nearly no precipitation (4.2 mm in July in Saint-Gilles, whereas there is 700 mm of water in the east during the wettest month). Indeed, there is a marked longitudinal disparity. Due to its proximity to Tropic of Capricorn ($-21^\circ\ 07'$ S; $55^\circ\ 31'$ E), Reunion Island is prone to a regime of southeasterly trade winds. On the windward (eastern) side, these trade winds bring high humidity and precipitation nearly all year. However, compared to the windward side, the leeward (western) side recieves significantly less rainfall, with a high degree of seasonal variation. Consequently, the western side is dryer and thermal winds are frequent (sea and land breezes).

Since the 1980s, several researchers have been interested in classifying the island's climates. The studies tend towards oriented or interdisciplinary analyses, whose final objective will be to adjust the input typology (climatological, topographical, agricultural, hydrological, etc.) according to the final needs of the targeted sector. We identified five existing climate maps differing by their classification strategy (See Table 1):

- Bioclimatic zoning according to Cadet, (1980) providing insights into the flora of Reunion and dividing the island into five climate zones;
- Morphoclimatic zoning according to Bougère, (1987) based on soil erosion and geological typologies, rainfall and relief, giving five climate zones;
- World climate classification of Köppen-Geiger, updated by Peel et al., (2007), based on vegetation and precipitation, exposing 8 climate zones;
- Climate zoning of the PERENE, (2009) reference frame, which results from the superposition of layers of meteorological data, revealing four climate zones;
- Climate zoning of the RTAADOM, (2016), thermal, acoustic and ventilation Regulations based on PERENE, splitting the island into three climate zones by considering topography.

Although several climate zonings have been carried out, the ones of Cadet, Bougère and Köppen are unsuitable for thermal building design. PERENE proposed the first climate classification tailored for building conception. However, the administrative division of this zoning brings ambiguity and inconsistency: for instance, Saint-Pierre located at the southern edge of Zone 1 is set apart from Zone 2, based only on administrative frontiers that do not justify this distinction. In 2016, the island was assigned the first thermal regulation, RTAADOM, (2016), aiming to standardize and normalize the construction typologies across French overseas territories while proposing technical solutions to make dwelling energy efficient. The altimetric split seems to offer results more in agreement with the climatic dynamics. Nevertheless, the territorial division into three classes appears to have limitations when observing climatic cohesiveness. Indeed, despite their differences, the East and West coast climates share the same features regarding this regulation.

4. Methods

This study is structured in three main parts as shown in Fig. 2:

- Climate classification;
- Subclimate classification;
- Mapping.

The climate classification is the statistical partitioning of global meteorological data covering the entire Reunion Island. This zoning method over a territory has already been tested by numerous athors throughout literature (Praene et al., 2019; Zeleke et al., 2022; Xiong et al., 2019; Cortez, 2021; Jacobeit, 2010; Pernigotto et al., 2021). First, the meteogeorological data undergo a principal components analysis. This preliminary step aims to reduce high-dimensional dataset while preserving patterns and trends. It accomplishes this by converting the data into fewer dimensions that serve as feature summaries of the initial dataset. Furthermore, the PCA allows us to identify the principal plane on which we will project the clustering results later. A hierarchical agglomerative clustering is then performed to find the optimal number of clusters. After determining the number of optimal clusters, iterative calculations strengthen the partitionning. The purpose of this K-means partitionning is to highlight groups of similar objects; in our case climate groups. The next phase is the subclimate classification. We initiate the process described previously within each climate group. The second series of statistical analysis allows us to identify climate subclasses within climatic classes, which we categorize as microclimates. The last phase is the microclimate zones mapping using geographical interpolation.

4.1. Data preprocessing

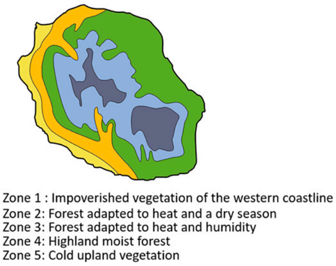
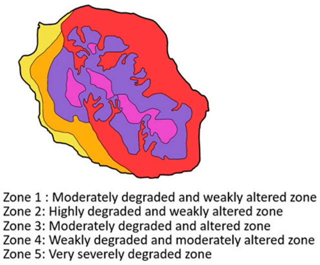
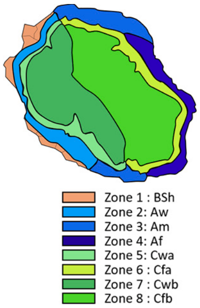
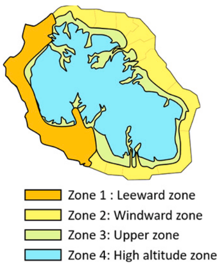
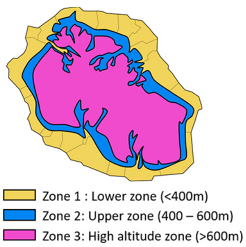
Since the end of 2006, Météo-France[3] has been using a high-resolution operational model called ALADIN set up by Faure et al., (2008). This model offers climate data with a 3.5 km high resolution. It also enables precise modeling of the airflow around the topography of Reunion Island. The ALADIN model's output is used for this survey:

- Daily minimum and maximum relative humidity (%);
- Daily cumulative global solar radiation (J/cm^2);
- Daily average wind speed (m/s);
- Daily minimum and maximum temperature (°C);
- Daily cumulative rainfall (mm).

Due to the influence of land's elevation on the climate, the literature has shown how important it is to include the altitude in climate zoning, (Kottek et al., 2006). The topography of Reunion Island is traced using a digital elevation model from the Shuttle Radar Topography Mission System with a 90 m resolution. We measured the elevation of each of our weather points using the SRTM file in raster format on the geographic information system tool QGIS. Our dataset consists of seven climatic variables and three geographical variables (longitude, latitude, altitude) measured on 896 points spread over the territory of Reunion Island. A preprocessing of the data

[3] Official service of meteorology and climatology in France.

Table 1
Existing climate zoning for Reunion Island.

	Existing climate classifications		
Reference	Climate maps	Field of application	Classification approach
Bioclimatic classification, (Cadet, 1980)		Botanics, agriculture biology	Vegetation description based on meteorology
Morphoclimatic zoning, (Bougère, 1987)		Scenology, geology, volcanology, hydrology	Connecting soil erosion and geological typologies, rainfall and relief
Köppen-Geiger Classification, (Peel et al., 2007)		Hydrology, geography, agriculture, biology or climatology	Climate characterization according to vegetation and rainfall
PERENE Climate zoning, (PERENE, 2009)		Architecture and building	Meteorological data layers superposition
RTAADOM Climate zoning, (RTAADOM, 2016)		Architecture and builing	Classification according to land elevation

using the software Rstudio, RStudio Team, (2020) was required to clean up our database and remove the sea-based points from the spatial grid and the missing observations. Principal components analysis in R will replace missing values with the average of the observed variables as the default, which could bias our results, mainly when there are multiple missing values. In the case of our study, our matrix's dimension decreased from 896 × 10 to 242 × 10.

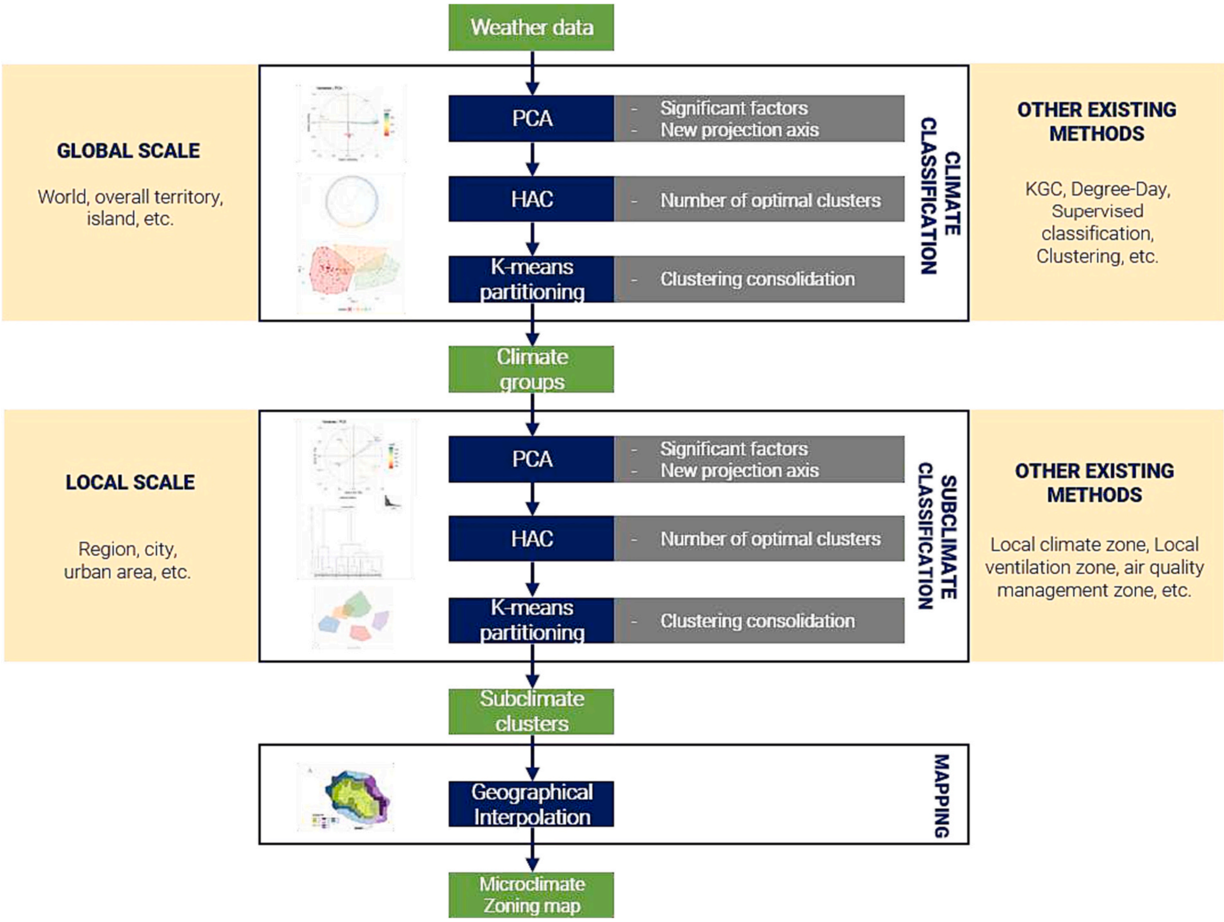


Fig. 2. View of the proposed methodology.

4.2. Clustering

4.2.1. Principal component analysis

Principal component analysis, or PCA, is widely used as a preliminary process to minimize the dimensionality of huge data set. This statistical approach attempts to represent the variance of the data set using a reduced number of components, choosing ease and rapidity of analysis over redundancy and noise in the information. Principal component analysis combines variables so that the resulting variables (i.e., principal components) are uncorrelated and contain the essential information from the original data set. The calculation is done through an iterative process in order to retain the largest share of variance within the first components. It is the same as picking only the most influential variables on the total variance of the database, (Zscheischler et al., 2012; Jollife and Cadima, 2016). The Kaiser criterion is used to define the number of components to be considered. Kaiser stated that only components whose eigenvalue $\lambda > 1$ should be selected (Kaiser, 1960). The first two projection planes are generally sufficient for visual analysis, with the axes (principal components, denoted Dim.) as factors. The subspace created will serve as a projection plane for the rest of the study.

4.2.2. Hierachical clustering analysis and k-means partitioning

Following this step, we performed hierarchical clustering on the principal components. Hierarchical Agglomerative Classification (HAC) is carried out, then is consolidated by the k-means.

HAC methods are ideal for the exploratory phase of research, (Unal et al., 2003). They use an iterative process to agglomerate data points. The 242 stations are grouped following the Ward's criterion until they form one single big cluster. The Ward's criterion involves aggregating two clusters. The basic principle of this algorithm is to minimize the total variance within a cluster.

The Silhouette method is used to define the optimal number of clusters. Average Silhouette Width evaluates the performance of a clustering. It assesses the inter-cluster distances and the within cluster distances to determine how well an individual fits into its assigned cluster. The Silhouette coefficient value range between -1 and 1, where 1 reflects a well-performed partitionning. The peak value of the silhouette coefficient corresponds to the optimal number of clusters.

K-means method allows a quick partitionning of individuals into K clusters, where K is the optimal number of clusters previously determined through HAC. Each cluster's centroid is randomly selected, and each individual is assigned to its closest cluster. After any assigments, a new calculation is made to determine the cluster's centroid or vector mean. From this partition, the distance between individuals and centers is checked and variables can shift from one cluster to another. Indeed, the aim of k-means partitionning is to group similar points by reducing the intra-cluster distance. The Euclidean distance determines the similarity given:

$$W(C_k) = \sum_{x_i \in C_k} (x_i - \mu_k)^2$$

Where,

- x_i represents a data point belonging to the cluster C_k.
- μ_k is the mean value of the points within the cluster C_k.

The cluster partitionning is consolidated through iterative calculations. This algorithm always converges, the iteration stops once the clusters have stabilized.

The climatic points are grouped according to their similarities and the optimal number of clusters, thereby giving us a global overview of the climate classes on the territory of Reunion Island. The particularity of our study is that we attempt to determine the existence of climate subzones through an embedded clustering. To do so, a hierarchical clustering of principal components is carried out in each previously formed cluster.

4.3. *GIS-based mapping*

The clusters obtained are projected onto a map of Reunion Island to get climate and topographic zoning. The study uses a set of climatic data distributed over a tightly meshed spatial network. Spatial interpolation is nevertheless necessary to smooth our microclimate map. Interpolation is based on the correlation between spatially close objects: an unknown point will have more similarities with an observed nearby point than an observed point far away. In our case, we opted for the inverse distance weighting (IDW) method which is the most used interpolation approach. The value of a point is estimated by averaging the values of the points located in its immediate surroundings, weighted by the inverse of the distance of each point, (Praene et al., 2019).

5. Results and discussion

5.1. *Climate clustering*

Following the procedure indicated in Fig. 1 2 around Reunion Island. According to the Kaiser criteria, only components with an eigenvalue $\lambda > 1$ are retained for analysis, i.e., the first components in the case of our study, as shown in Table 2. The first two axes of the analysis express 67.4% of the total inertia of the data set; this indicates that this plane represents 67.4% of the entire variability of the cloud of individuals (or variables). This is a significant proportion, and the first plane so appropriately depicts the variability present in a major fraction of the active dataset.

This step aims to define the projection map of the principal components shown in Fig. 3, which will be used for the description of the main properties of each cluster. The correlation circle, Fig. 3, highlights the contribution of temperature (Tmax and Tmin), altitude, and relative humidity to the construction of Dimension 1. The variables longitude and precipitation mostly contributes to the creation of Dimension 2. The cluster's features will be assessed based on how they translate to the axis. The hierarchical clustering on principal components yields 3 clusters to be projected on the plan (1.2).

The first cluster, which corresponds to the highlands, has low average temperature and high relative humidity. Cluster 2 represents the east and southeast coasts. A strong wind regime and a significant rainfall mainly characterize it, experiencing heavy rain and strong winds. The third cluster coincides with the west, northwest and southwest coastlines and is characterized by high temperatures, intense solar radiation, and lower-than-average height, see Fig. 4.

This partitioning resulting from the statistical analysis accurately reflects the natural East-West zonation of the island: the windward coast is subject to hot and humid winds coming from the equator, and the leeward coast is less rainy and protected from the winds by the mountainous ranges. It cross-checks the zoning of PERENE and RTAADOM by pointing out that the coastal climate is split in two and that the central part has a distinct climate due to the rugged topography. These first results emphasize the significance of altimetry in climatic classification. Similarly to the RTAADOM, (2016), there are three clearly defined climate groups with three average altitude levels:

- Cluster 1: High altitude area with an average elevation of 1375 m;
- Cluster 2: East zone with an average elevation of 530 m;

Table 2
PCA results.

	Dim1	Dim2
Eigenvalue	4.38	2.36
Cumulative % of variance	43.79	67.39

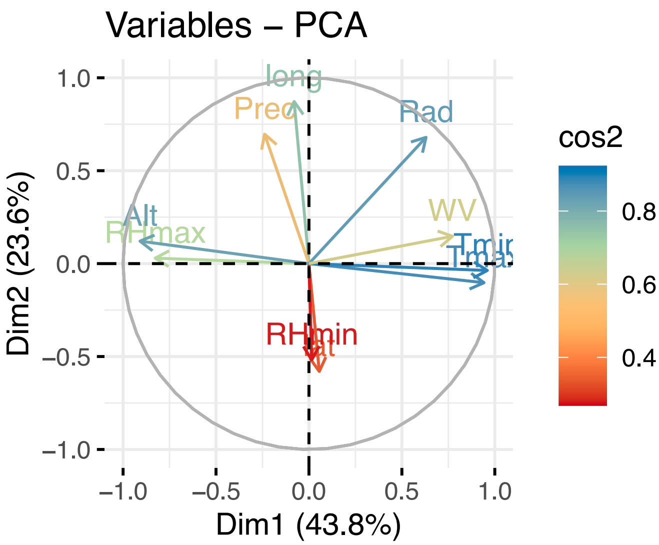


Fig. 3. Projection of the variables on the plan (1.2).

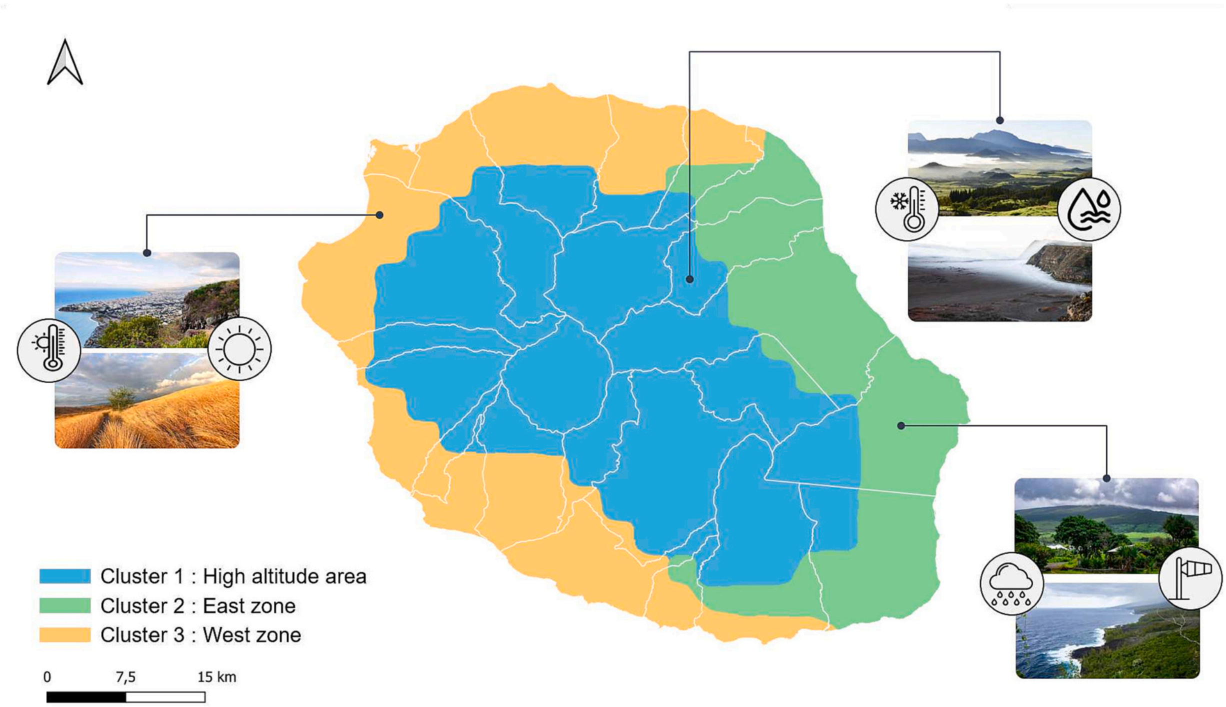


Fig. 4. Cluster visualization and climatic features illustration.

- Cluster 3: West zone with an average elevation of 257 m.

But unlike the RTAADOM, this grouping highlights the differences between the East and West climatic features, as shown in Fig. 4.

The results are also consistent with PERENE classification (PERENE, 2009). Indeed, the PERENE reference frame results from a classification obtained by overlapping already mapped raw weather data layers. This implies that classification thresholds have been previously assigned to these mappings, unlike clustering. In our case, weather stations are grouped depending on their similarities rather than depending on classes that we would have predefined ourselves. But the PERENE climate zoning and the global clustering concur in highlighting the disparity between the East, the West, and the central part of the island; with specificity for our study for which the so-called "upper zone" is not being represented, and must therefore have been merged into cluster 1 or cluster 2.

Standard deviation quantifies a dataset's distribution relative to its mean. High values in Table 3 reflect heterogeneity across the formed groups, e.g., the altitude shows significant variability within cluster 1. We perform a second clustering to classify the most similar points into subclasses to remove as much heterogeneity as possible.

5.2. Climate subzoning

A second clustering was performed within the three clusters that had previously formed following the methodology shown in Fig. 2. At the completion of each PCA, the first two axes are retained. The three resultant projection planes translate respectively 60.26%; 67.67%; 65.68% of information. The double hierarchical clustering yields a final result of 12 subgroups, which main features are described according to the principal components. The clustering results were projected on a map of Reunion Island, Fig. 5.

The sub-clustering of former Cluster 1 results in 4 subclasses, noted A,B,C,D. The distribution of each individual according to their distinctive characteristics is shown in Table 4, which asserts the homogeneity within the new clusters. Zones 1 are mostly distinguished by high altitudes. This partitioning makes Cluster 1-D stand out. The 1-D region corresponds to the volcanic mountain of La Fournaise. As a result, we observe the features of heavy rainfall, intense radiation for a high-altitude area, and a consistent wind regime. The properties of 1-D differ from those of the other cluster 1 subclasses. This highlights the importance of using a layered categorization to accurately identify microclimates to comprehend the existing climatic subtleties.

The second clustering splits the eastern part of the island into 5 climate microzones, presented in Table 5. The altimetry of microzone 2-A is about equal to the average altitude value of microzones 1. High altitude causes medium-to-low temperature conditions. But the heavy annual precipitation maintains their belonging to the main cluster 2. Microzone 2-E, located in the north-east part of the island is another noteworthy microzone. Its hot yearly temperatures are comparable to the temperature of cluster 3, but the microzone cumulates about 8.89 mm of rainfall annualy.

The subclustering of the last group yields 3 microzones, shown in Table 6. It can be seen in Fig. 5, that the northern and southern parts of the island are grouped in the same microclimate category due to their high exposure to solar radiation and winds and their hot temperatures. The mid-altitude zones 3-A (located in North and South) also have the same characteristics, the main ones being higher than cluster 3 average rainfall and relative humidity. The microzone is also colder.

5.3. Comparison with existing climate zones of Reunion Island

Although other climate zonings have been carried out for Reunion in specific fields of application, the lack of precision regarding the methodology and hypothesis make it difficult to compare the results. In the case of the zoning carried out by Cadet, (1980), the west coast is divided into two parts. Cadet's classification demonstrates that an altitudinal gradient is considered. However, it is not always continuous throughout the entire island's perimeter. Thus this gradient allows you to distinguish the coastal zone from the middle altitude, for example, on the west coast. In the east and in the west mid-slope area, the climate seems to be hot and humid. The upper lands and the cirques are grouped in two zones where humidity and cold are dominant characteristics. We note that this climatic distribution divides the island from east to west. The pluviometry, essential parameter in the botanical study, had to contribute to this analysis. The climatic limits of Bougère, (1987), considering soil erosion, are close to those of Cadet. It shows a real dichotomy between the East and the West and the upper zone seems to be more scattered. The initial classification subdivided Reunion's area into three main zones, as noted in the RTAADOM. According to Réchou et al., (2019), there is a significant asymmetry (east/west) between the

Table 3
Standard deviation of each cluster according to their characteristic features.

	Variable	sd in category	Overall sd
Cluster 1	Altitude	478.83	648.07
	Relative humidity (max)	1.84	4.07
	Solar radiation	217.16	274.07
	Wind velocity	0.34	0.81
	Temperature (max)	2.09	3.19
	Temperature (min)	2.20	3.75
Cluster 2	Precipitation	3.25	3.59
	Solar radiation	205.49	274.07
	Temperature (min)	2.17	3.75
	Relative humidity (min)	3.57	4.59
	Temperature (max)	2.06	3.18
	Wind velocity	0.66	0.81
	Altitude	432.33	648.07
Cluster 3	Temperature (max)	1.59	3.18
	Temperature (min)	1.49	3.75
	Wind velocity	0.87	0.81
	Solar radiation	229.28	274.07
	Relative humidity (min)	3.32	4.59
	Precipitation	1.52	3.58
	Altitude	241.37	648.07
	Relative humidity (max)	3.21	4.07

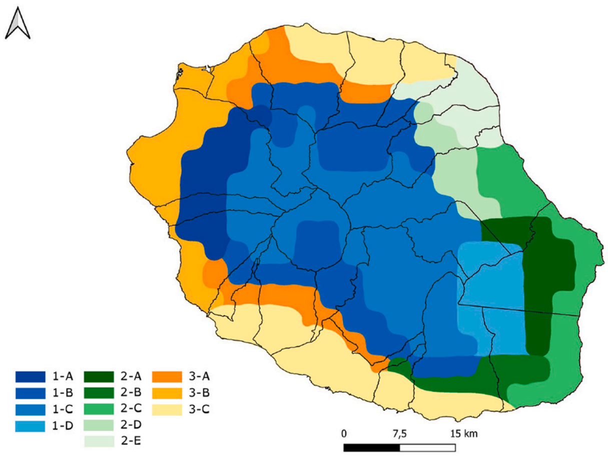
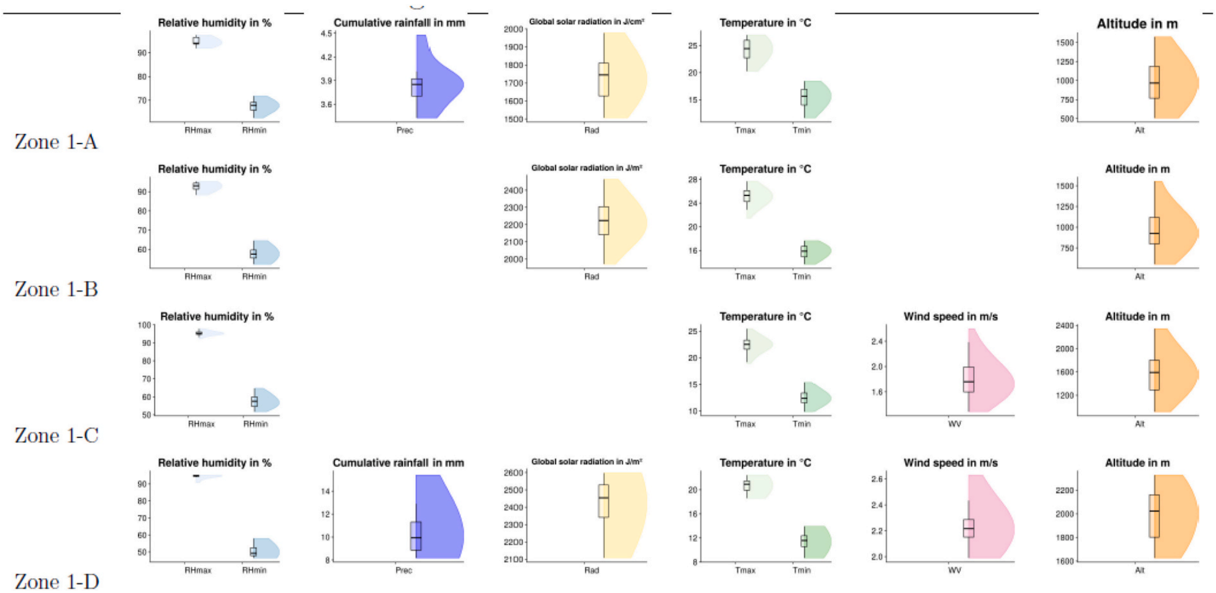


Fig. 5. Microclimatic zoning of Reunion Island.

Table 4
Highland microclimate zones main features.



windward and leeward zones, particularly in terms of rainfall. This research on the spatial and temporal variance of precipitation emphasizes the significance of the island's rugged interior terrain. This confirms the importance of altimetry as a fundamental variable in zoning within our topographic context.

Nevertheless, in order to establish an energy efficiency program, parameters in line with building design must also be evaluated.

This is the case of our study which integrates temperatures, solar radiation, relative humidity, rainfall and wind speed. With rainfall as the primary determinant, the famous Köppen classification underscores the East/West division. This zoning is the closest to our microclimate zoning by identifying 8 climate classes. It shows that the island is not “only” tropical, it also presents more diversified climates which can be dry, oceanic or even temperate. The vegetation along the northeast coastal belt is roughly uniformn, giving the global reading of two large climate zones. The southwest is more divided with a change of zone that seems to reflect the change in altitude. The classification is mainly estabished by the relationship between climate and vegetation, stating that observation of vegetation and a fixed temperature threshold are sufficient to determine a climate type. Thus, Koppen classifies generic and global climate types, but does not account for the fine scale variability of Reunion's climate. It has indeed been stated by Young et al., (1997) that topography and geomorphology lead to abrupt variations in climate. An accurate microclimate zoning must therefore include the usual weather parameters as well as spatial parameters and not be limited to the observation of climatic effects such as vegetation which evolve according to climate conditions. Making our proposed methodology a basis for a smaller scale climatic approach that can

Table 5
East coast microclimate zones main features.

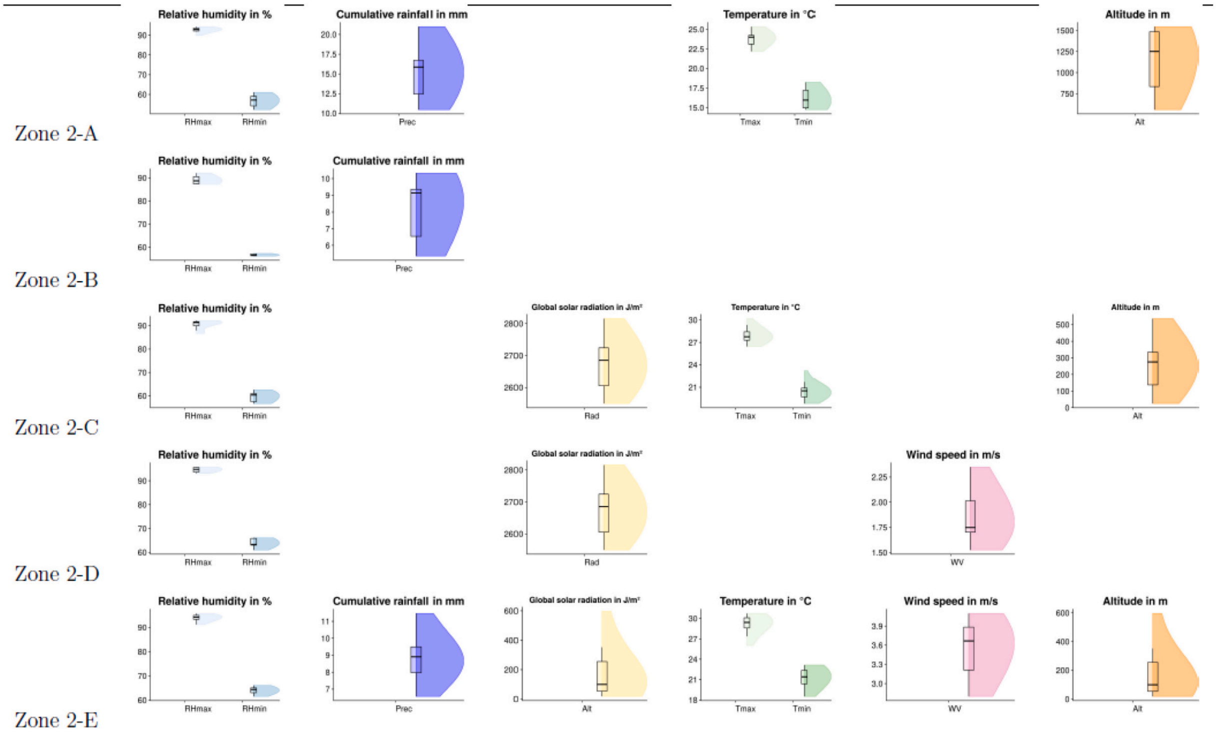
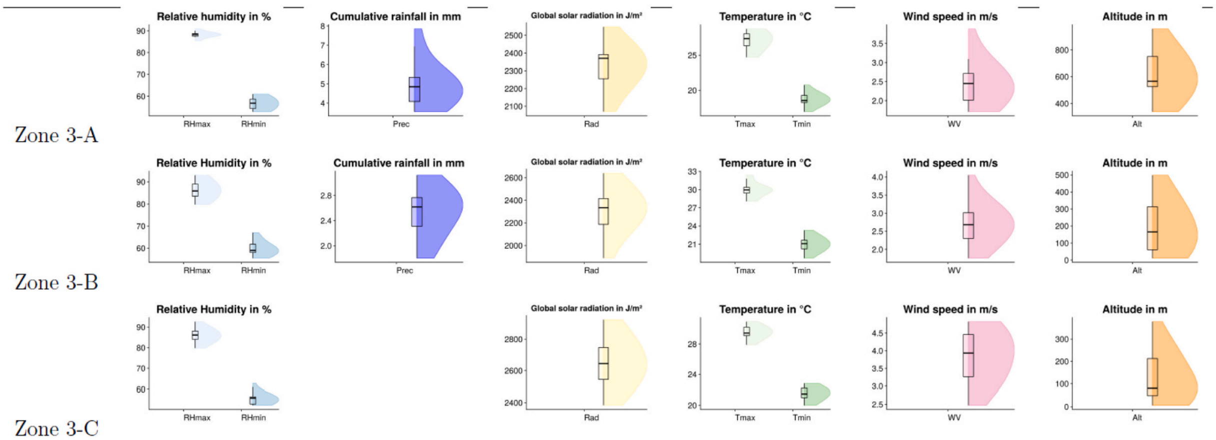


Table 6
West coast microclimate zones main features.



be reapplied to other territories, in particular to mountainous landscapes, like Reunion Island.

5.4. Discussion

Among the several methods used to identify climatic types, the most popular one is the Köppen classification. It is an empirical classification based on natural vegetation distribution. From Köppen's point of view, vegetation stands as a key factor in describing climate in a region. The other criterion used is temperature annual range. The identified relationship between climate and vegetation is broadly acknowledged to be ecologically relevant, (Chen and Chen, 2013). Therefore, the classification has been widely utilized to monitor climate variability over multiple time intervals and changes in ecosystem conditions. The state of art demonstrates that a zoning approach responds to a particular thematic application purpose, such as agriculture, biodiversity, land use planning, etc. In this way, zoning must be viewed as a tool for characterizing a territory and must be selected based on our requirements. For urban or building comfort studies, Koppen's parameters are, therefore, insufficient. It was not initially developped for building oriented research. According to Attia et al., (2019), Köppen's classification is unsuitable to formulate recommandations for building codes and energy efficiency programs. Minimum data requirements include temperature, wind, and solar radiation. Our study examines five climate parameters: temperature, relative humidity, solar radiation, precipitation, and wind speed. These parameters help keeping a view at the atmospheric conditions of a given region. Moreover, to elude the rigidity of Köppen's classification in frontiers delimitation, (Peel et al., 2007) recommended including altitude in the analysis, particularly for mountainous regions. The current study has found that altimetry is indeed a major component in climate type organization. The effectiveness of Köppen's climate classification for global studies of climate tendency (hydrology, geography, agriculture, etc.) is undeniable. But the lack of precision in the zoning is its greatest weakness.

Considering technological advancements and meteorological data availability, several countries around the world are now subject to climate zoning to assess energy efficiency in buildings. Attia, (2022) recommends Cooling Degree Days (CDD) and Heating Degree Days (HDD) methods. According to Walsh et al., (2017b), it is one of the most used method for climatic zoning applied to building energy efficiency programs. The choice of the reference base temperature is a crucial issue in the use of degree days. The temperature base at which HVAC systems is not required is arbitrarly chosen, making CDD and HDD subjective approaches. Whereas the proposed methodology uses unsupervised classification. Instead of using a predetermined temperature threshold, the clustering is based on statistical similarities between meteorological stations. Moreover, the reduced input variable of degree day techniques makes it more adapted to cold climates and less reliable for hot humid regions, (Walsh et al., 2017b). Indeed, this classification only considers temperature. It disregards some important climatic factors such as solar radiation, humidy and wind velocity which affects the local climate of an area.

Litterature is lacking concerning the definition of microclimate applied to built environment policies.

Usually, climatic zoning is associated with urban forms and buildings. The LCZ lays on the relationship between the building density of a space and climatic data. Similarly, other methods, such as precinct ventilation zone developped by He et al., (2019), rely on the same approaches by emphasizing urban form and ventilation. Zheng et al., (2018) admitted that cities are warmer and more polluted than rural areas. This statement are corroborated by the work of Yang et al., (2019) confirming that urban architecture patterns is a significant driver of climate change. Our proposed classification is placed prior to this step. Indeed, it is crucial to establish an accurate climate zoning providing reliable meteorological informations, to be able to optimize urban forms. Thus, this study is not only limited to one meteorological variable but focuses on global meteorological data generally used within the framework of building performance. Adressing questions of comfort, climatic characteristics expressed through air temperature, humidity, wind speed and solar radiation are retained. In addition, these existing local-scale zoning can be assigned to the category of supervised classification used for urban microclimates studies and building energy consumption to predict temperature, wind, precipitation, etc. (Xue et al., 2020). The main limitation of supervised method is its incapacity of introducing additional classes that were not in the original data classification. Whereas we provide an unsupervised classification method that avoids the requirement of labeled categories.

In recent years, many modern building developments have been climate-insensitive, requiring energy to ensure comfort in winter and summer (Grimmond et al., 2010). The design of sustainable cities adresses issues of energy efficiency among buildings. As stated in the report of ENSAM, (2021), buildings are considered as a continuum of dweller-housing-building-district-city-territory. Thus, carrying out microclimatic zoning allows us to promote the deployment of sustainable area. Having accurate local climate data is crucial for policy makers and stakholders. Indeed, thinking and designing sustainable tropical cities require an adaptation of urban morphologies in total adequacy with the local climatic conditions. A tightly meshed spatial distribution of this information allows to implement a specific planning and not generic models on the whole territory.

In the case of Reunion Island, population density is greater in coastal zones, as described in section 1.2. These zones are strongly urbanized and particularly vulnerable (prone to sea level rise, tropical storms and cyclones), they involve land use planning specific to a subtropical environment. The microclimate zoning tells us that the climatic requirements vary along the island's shore. In the eastern side, buildings have to cope with heavy rainfall all year; cities, on their part, must deal with risks of flooding and soils permeability. The western side is marked by hot temperatures and strong solar radiation. City planners should design neighborhoods and cities to mitigate the effects of the heat island phenomenon. The latter can be reduced through various strategies by enhancing wind flow and green spaces that serve as thermal buffers and avoiding the mineralization of urban places. In addition, the bioclimatic design encourages the reduction or elimination of active systems (air conditioning) at the building scale in subtropical conditions by promoting natural ventilation, solar protection, and vegetation in the immediate built environment.

The advantage of microclimate zoning is its ability to underscore nuances of global climate zones. Moreover, unsupervised classification creates climatic subclasses specific to the region under study. The proper climatic input variables allow to apprehend the bioclimatic design issue. It facilitates the development of comfortable, climate-responsive buildings with lower energy demand and consequently addresses the sustainable city challenge at the building level.

6. Conclusion and perspectives

In the context of climate change, climate zoning appears to be a valuable tool for identifying vulnerable areas, managing land use, and planning the development of cities responsive to environmental policies. No agreement has currently been made upon which method is the most effective. However, the choice of the approach and meteorological input variables must be in line with the specific purpose of use, whether botanical, geological, or architectural. This study set out to propose a new method of climate classification to apprehend spatial climate variability. We presented a multivariate clustering that combines a nested double clustering method and a k-means partitioning. This method aims at defining climate classes and subclasses, associated with the microclimates of a geographical area. Reunion Island was used as a case study. We performed the clustering from a spatialized meteorological database consisting of climatic and geographical variables relevant to the study of atmosphere's conditions. Three climatic clusters have been identified. The clustering method has then been reproduced within each cluster to build classes within classes. The spatialization of the twelve resulting subclasses allows redefining the contours of the microclimate map of Reunion Island. The new map shows similarities with existant climate zoning maps of Reunion Island, namely the climate zonings of PERENE reference frame and the RTAADOM. This reinforces the importance of the altitude variable in climate study of regions with uneven relief. The findings contribute on our understanding of climate at a local level and can be used as a guide to the adaptation of climate-responsive strategies at a smaller scale, including building performance regulations and performance-based urban planning. It lays the groundwork for resilient and sustainable city development and design.

The method is easily reproducible to other geographical areas. It could even be extended to the world scale to be compared to the current climatic classifications, such as that of Köppen-Geiger. Further work will seek to use the built climate zoning to understand the constraints of a zone to propose an architectural map offering typical, frugal, and comfortable architectures adapted to each microclimate. And in a forthcoming stage, the study is expected to be useful for urban planning and design.

Declaration of Competing Interest

None.

Data availability

The authors do not have permission to share data.

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