Identifying urban profiles with regard to overheating factors

Application to French municipalities

Pauline Besnard, *Baptiste Alglave*, Jérémy Bernard, Matthieu Goussef, Francois Leconte, Erwan Bocher

Scientific context

- **Urban territories** are increasingly exposed to **overheating** processes [Masson, 2000].

  ➠ Threats on populations [Huang et al., 2023]

- Classifying territories with respect to their **sensitivity to overheating** is a critical issue [Wang et al., 2020].
- Still, very **few classifications** with regard to overheating factors.

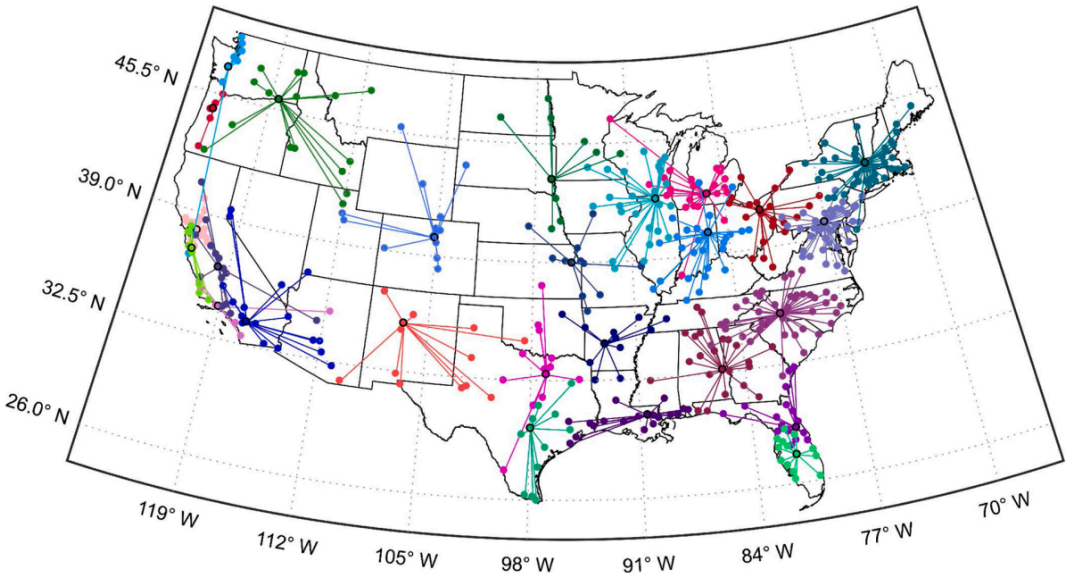
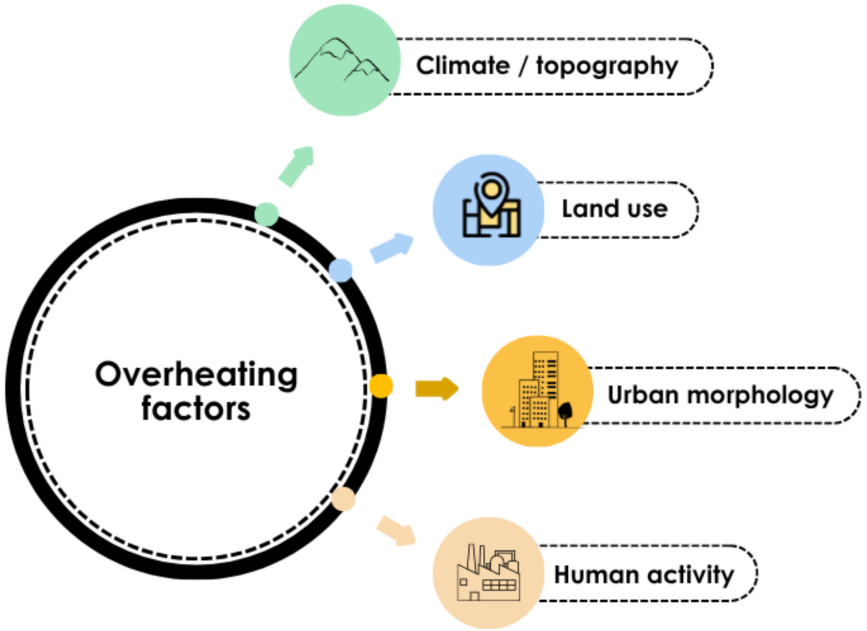


Figure 1: Urban clustering based on geographical distance and 8-day composite daytime LST during a heat wave (July 12–19, 2006).

Urban Overheating Factors



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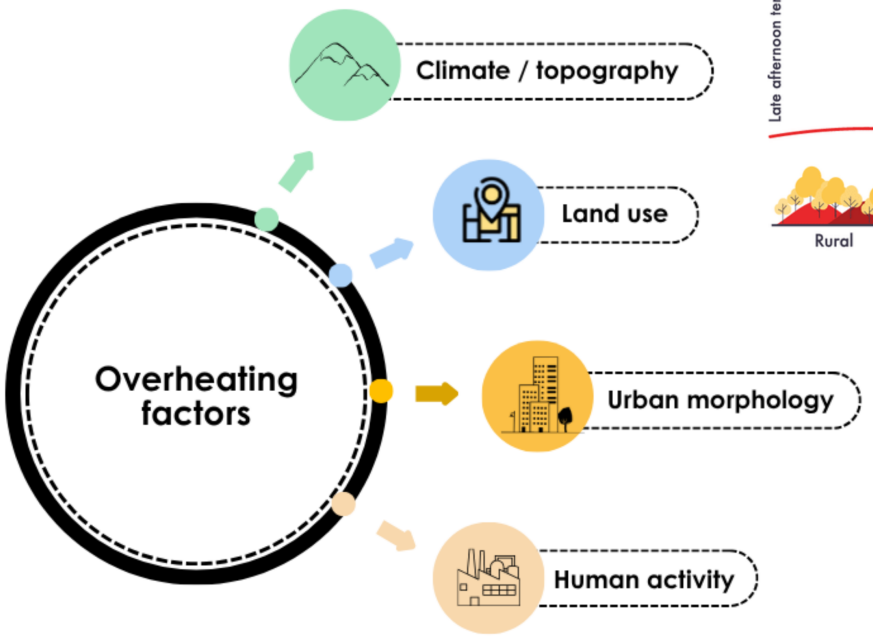
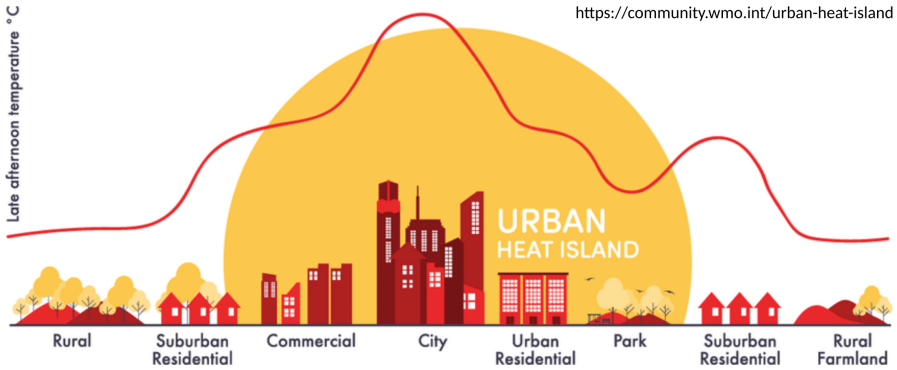
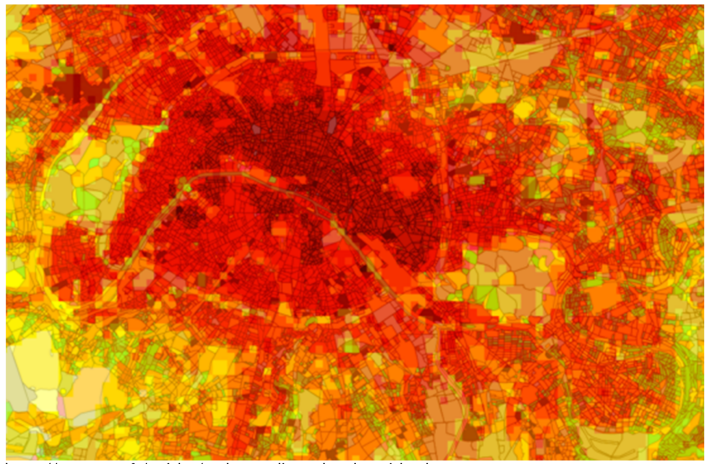




https://community.wmo.int/urban-heat-island



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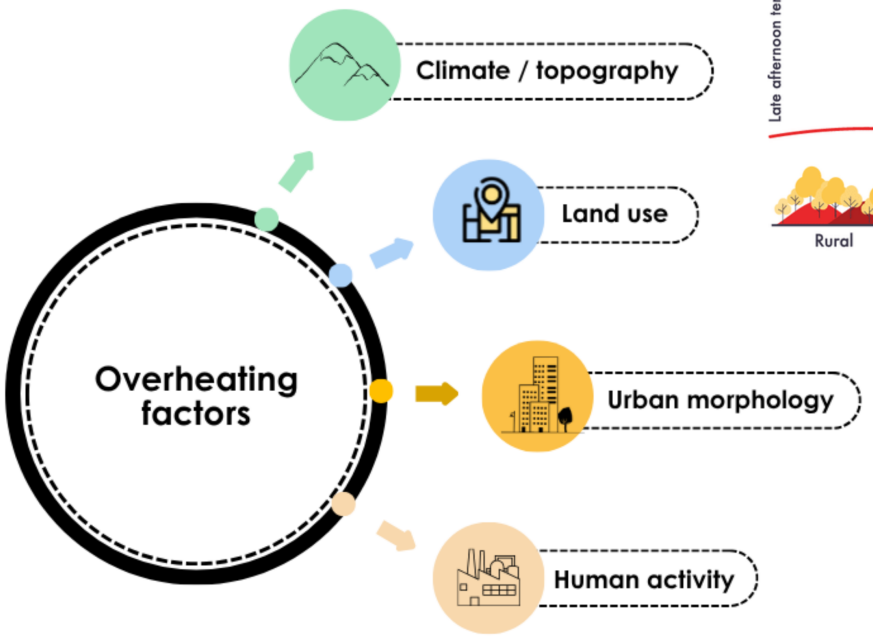

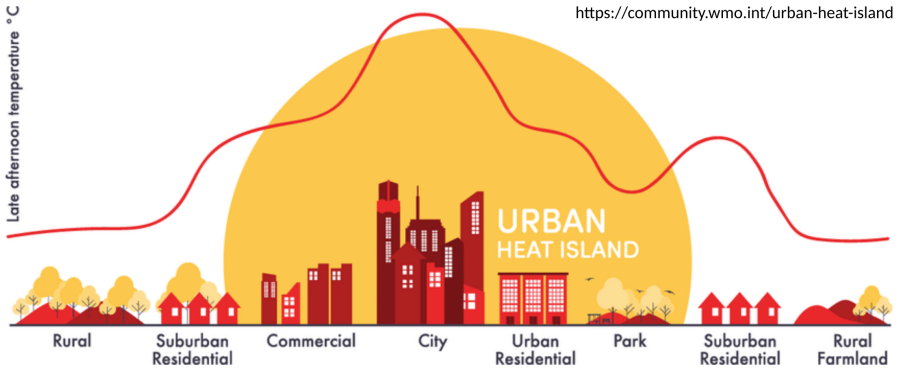

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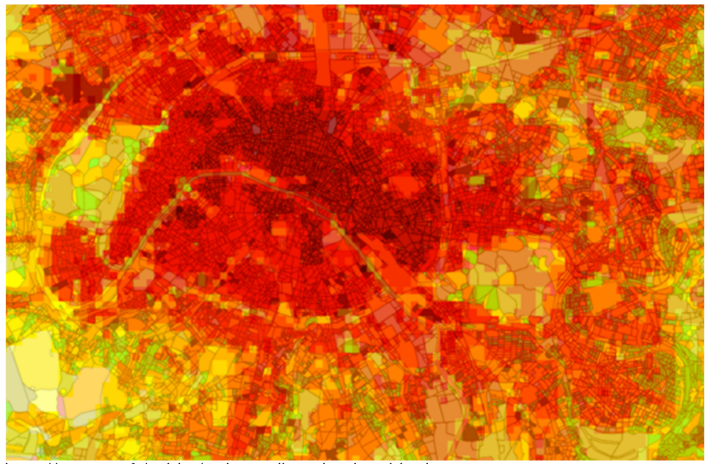

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➠ Data to analyze urban areas and inform spatial planning?

Potential of GIS to analyze urban areas

GIS (Geographic Information System)

➠ store and access massive and comprehensive amount of geographic data to map territories

BD Topo

Database of the elements of the French territory and its infrastructures (administrative boundaries, buildings, hydrography, land use, transport).

IGN
INSTITUT NATIONAL DE L'INFORMATION GÉOGRAPHIQUE ET FORESTIÈRE

OpenStreetMap

Free, participative, global database [Vargas-Munoz et al., 2020]

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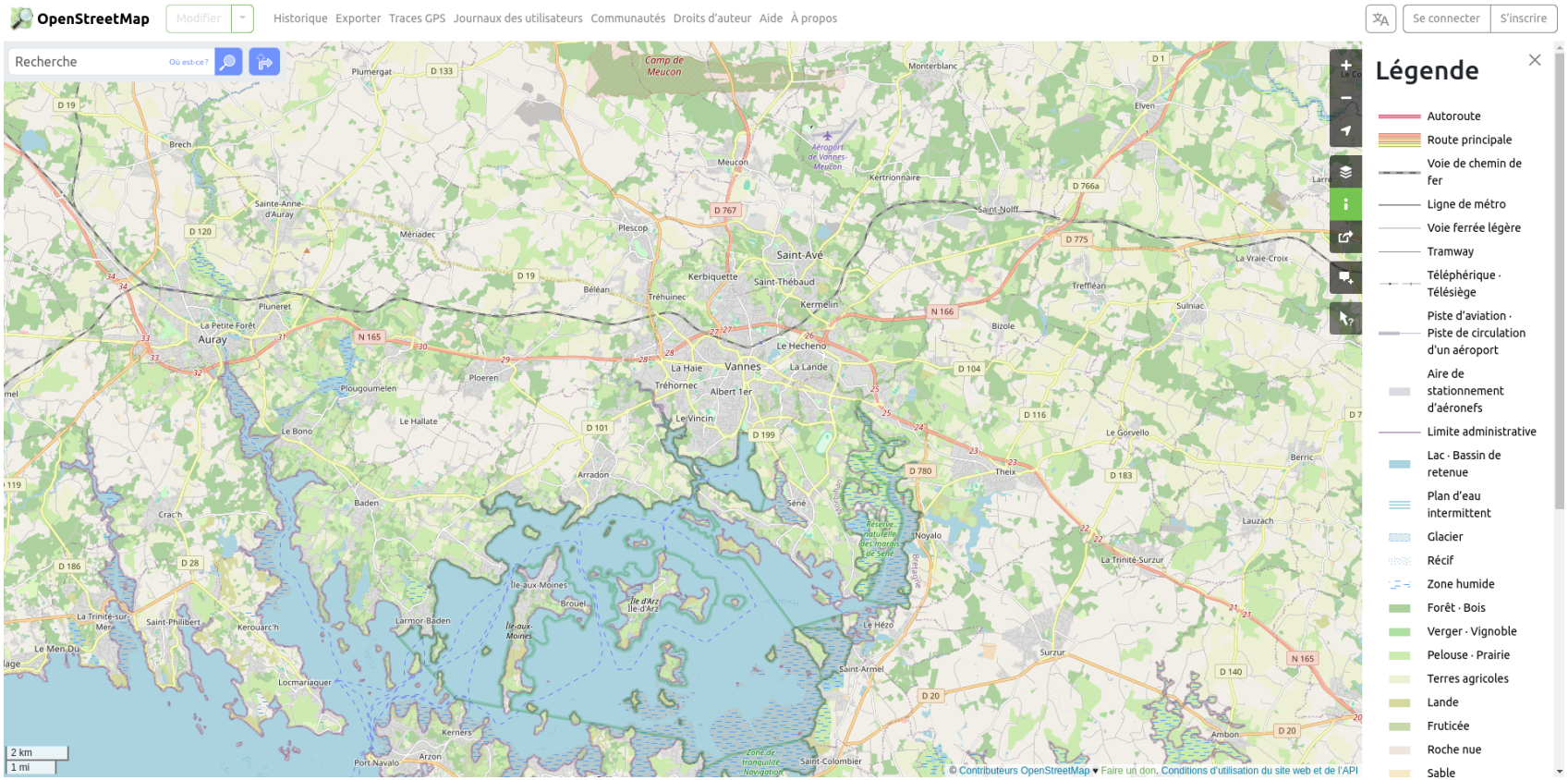

GIS APPLIED TO URBAN CLIMATE

In recent years, GIS tools have been developed to describe and document territories with regard to urban microclimate.

Geoclimate
[Bocher et al., 2021]

Wudapt
[Ching et al., 2018]

Zones Climatiques Locales
[Cerema, 2024]

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➠ Rely on the concept of **Local Climate Zone (LCZ)**

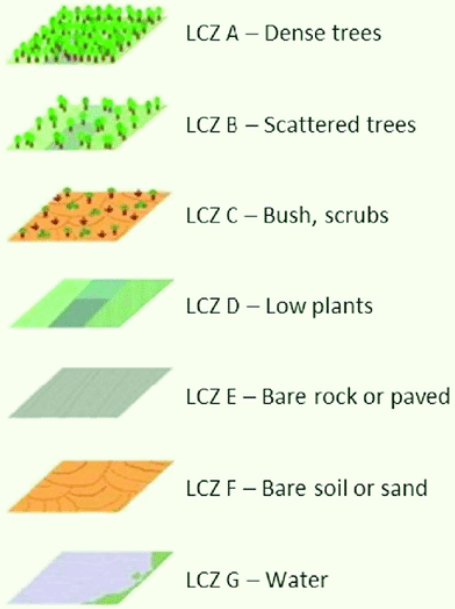
Local Climate Zones (LCZ)

LCZ types

Built types

- LCZ 1 – Compact high-rise
- LCZ 2 – Compact midrise
- LCZ 3 – Compact low-rise
- LCZ 4 – Open high-rise
- LCZ 5 – Open midrise
- LCZ 6– Open lowrise
- LCZ 7 – Lightweight low-rise
- LCZ 8 – Large low-rise
- LCZ 9 – Sparsely built
- LCZ 10 – Heavy industry

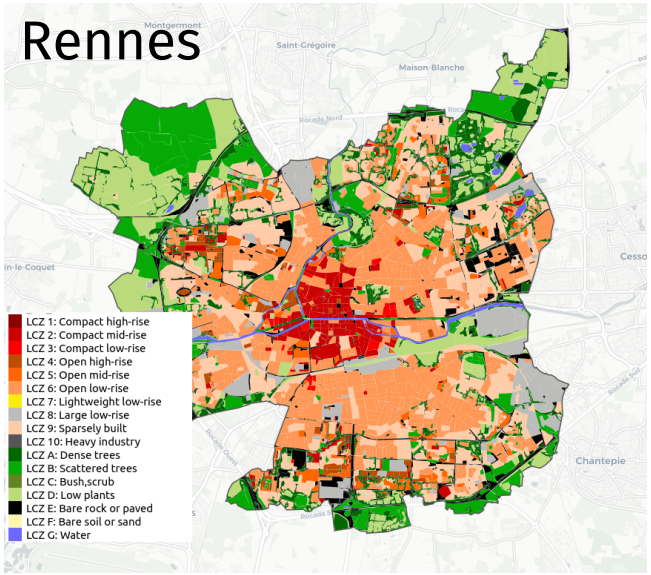
Non-built types

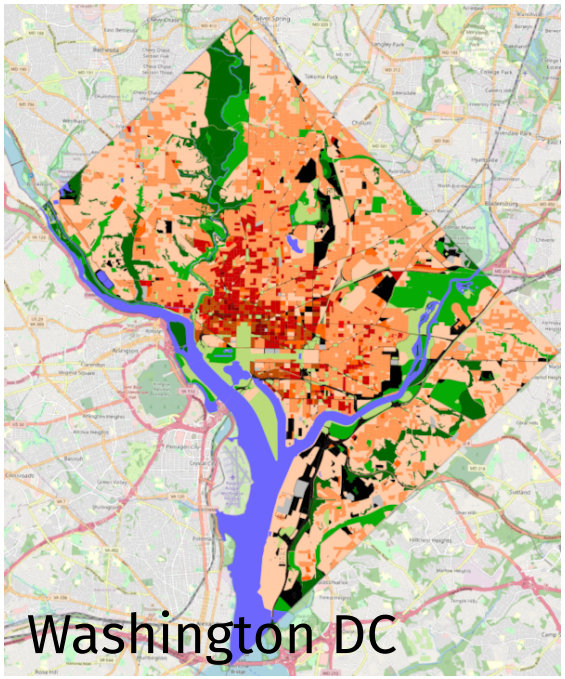


- LCZ A – Dense trees
- LCZ B – Scattered trees
- LCZ C – Bush, scrubs
- LCZ D – Low plants
- LCZ E – Bare rock or paved
- LCZ F – Bare soil or sand
- LCZ G – Water

Local Climate Zones, commonly named „LCZ XX“ (XX from 1 – *Compact high-rise* to G – *Water*).

LCZs from 1 to 9 correspond to urban climate zones defined by Oke (2004).





Scientific issue

Aim of this work: propose a methodological framework for classifying urban areas on the basis of urban overheating indicators.

Data of applications: French municipalities

Method:

- Identify overheating factors $\rightarrow$ define indicators of overheating based on geographic data
- Factorial Analysis of Mixed Data (FAMD) for analysing the indicators combined with k-means for the clustering
- Compare the clusters compared with Urban Heat Island (UHI) model outputs.

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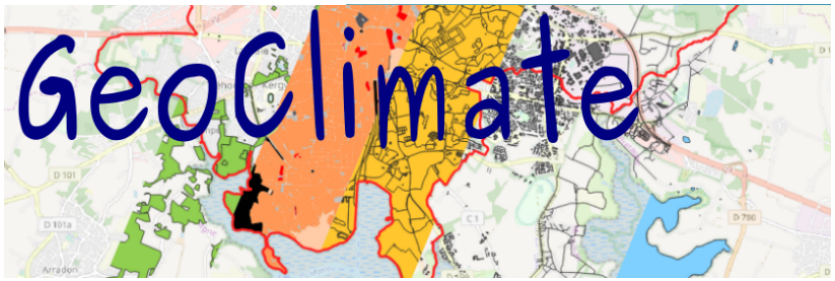
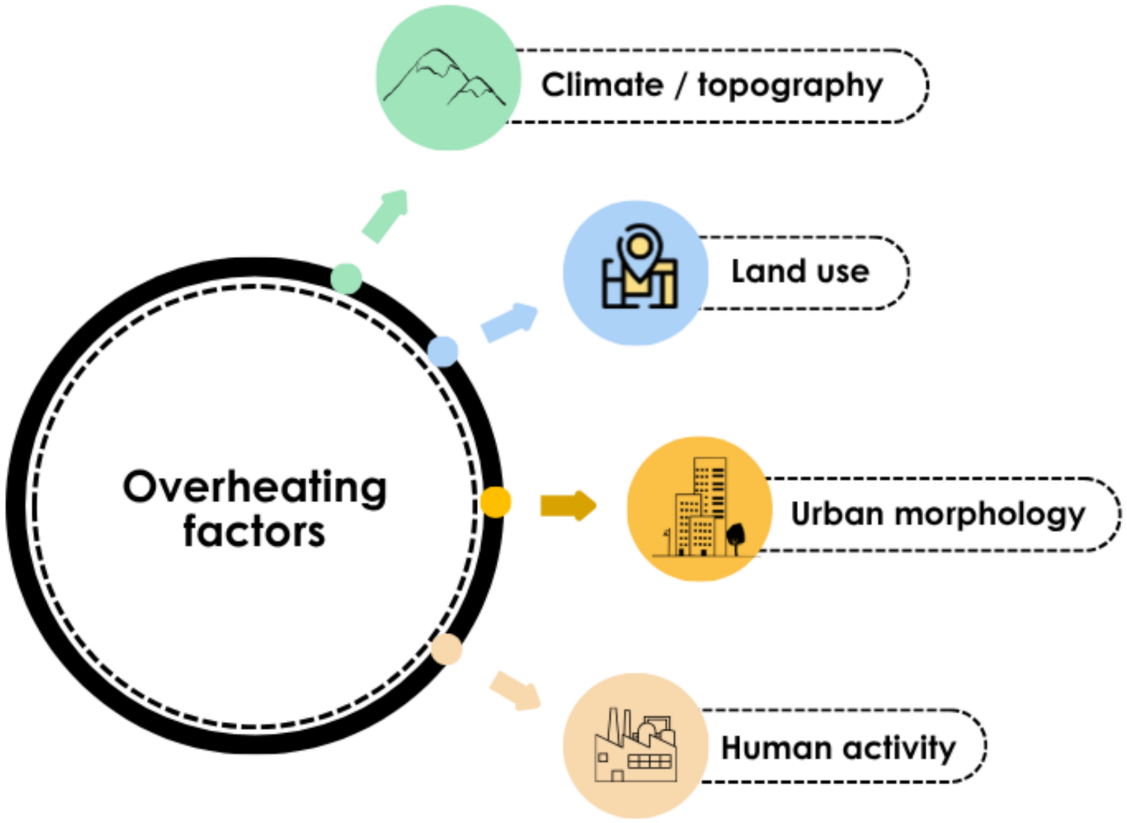


+ additional datasets

Urban overheating factors and indicator definition



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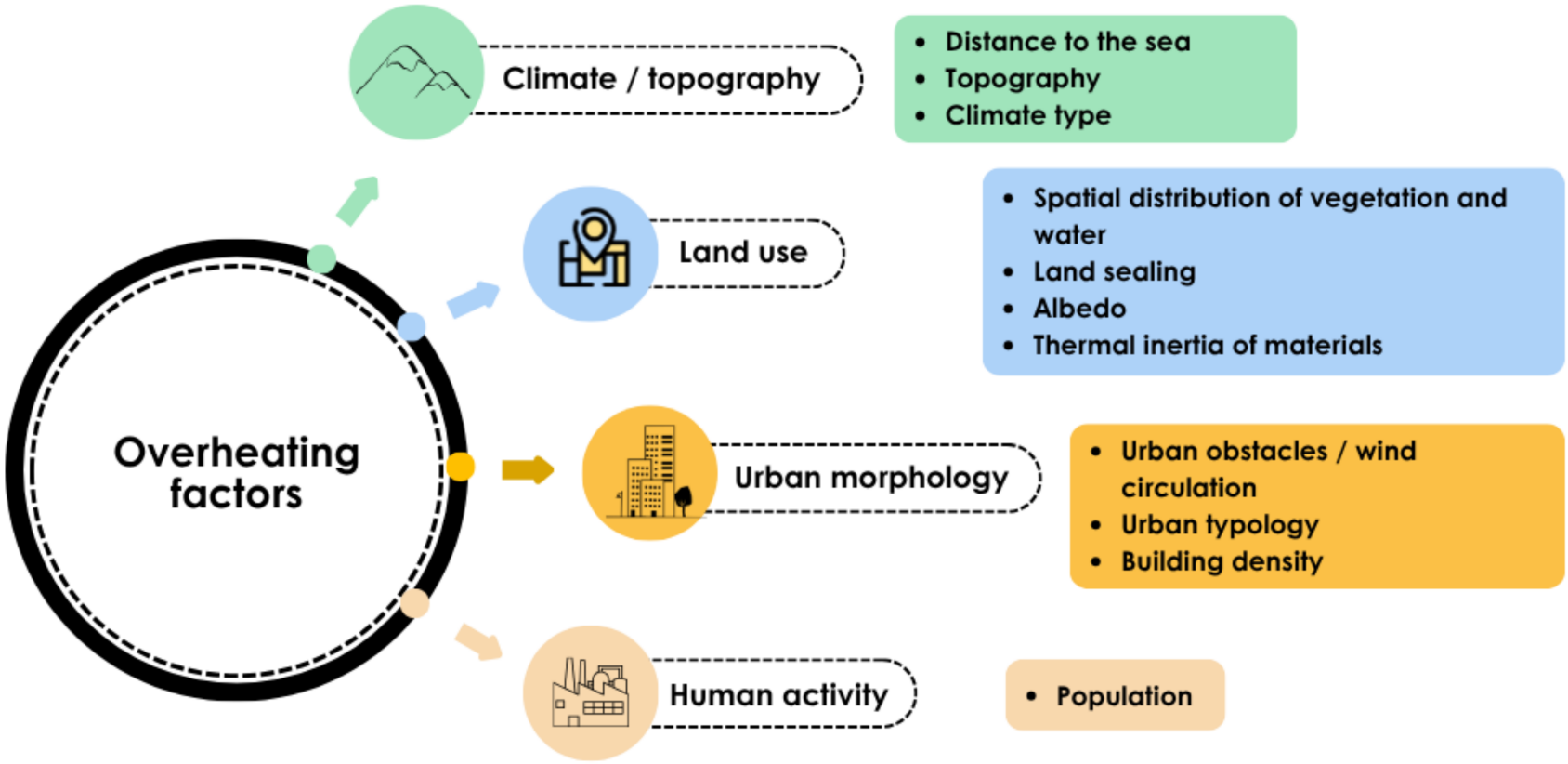


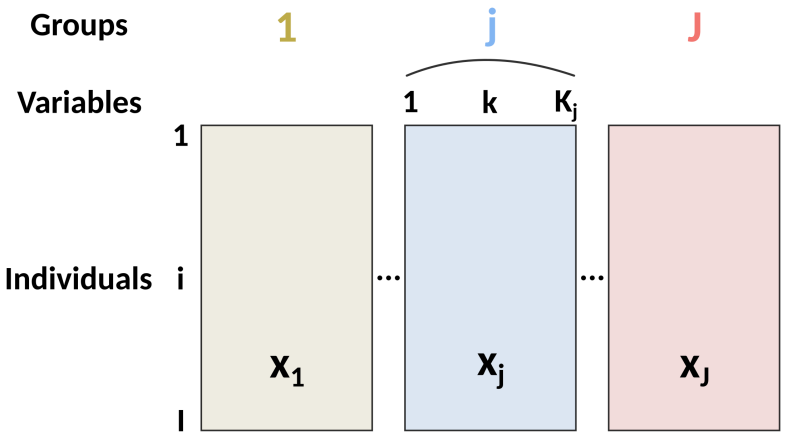
Urban overheating factors and indicator definition

➠ 13 indicators describing overheating factors

Table 1: Variables used in the factorial analysis of mixed data

Class of factor	Variables	Data source (resolution)	Variable type
Climate and topography	Distance of the municipality centroid to the sea	NaturalEarth (1:10e6)	Positive continuous
	Climate type (based on Köppen classification)	kgc package (0.05°)	Categorical
	Topographic Rugosity Index (TRI)	SRTM (30m)	Positive continuous
Land use	Proportion of impervious surface	OSM (Geoclimate)	Proportion
	Mean distance between closest vegetation areas	OSM (Geoclimate)	Positive continuous
	Proportion of vegetation	OSM (Geoclimate)	Proportion
Urban morphology	Number of urban patches	OSM (Geoclimate)	Counts
	Mean surface of the urban patches	OSM (Geoclimate)	Positive continuous
	Proportion of high buildings	OSM (Geoclimate)	Proportion
	Proportion of mid-rise buildings	OSM (Geoclimate)	Proportion
	Proportion of compact buildings	OSM (Geoclimate)	Proportion
	Proportion of non-compact buildings	OSM (Geoclimate)	Proportion
Human activity	Population in the municipality	INSEE (municipaltiy)	Counts

Multivariate analysis



Quantitative or qualitative groups of data

Factorial Analysis of Mixed Data

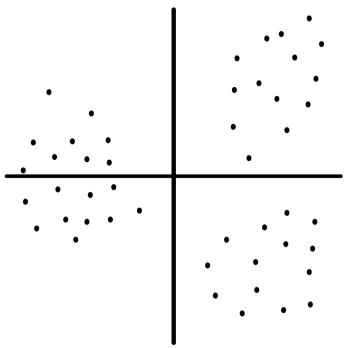
1/ Compute the first eigen-value for each group of variable

2/ Perform PCA on the weighted table

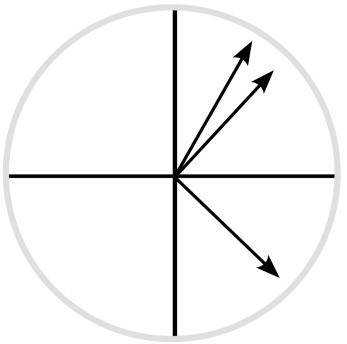
$$\left[\frac{X_1}{\sqrt{\lambda_1^1}};\ldots;\frac{X_j}{\sqrt{\lambda_1^j}};\ldots;\frac{X_J}{\sqrt{\lambda_1^J}}\right]$$

Project variables and individuals in their respective reduced-dimensional spaces

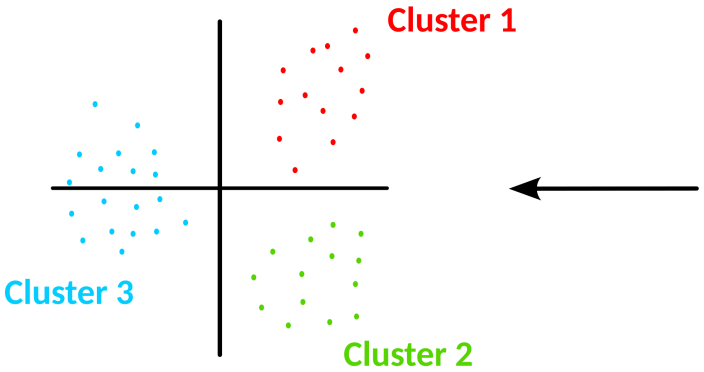
Projection of individuals



Projection of variables



K-means clustering



[Husson et al., 2011]

Variable preprocessing

Counts and positive continuous variables

- log-transformation: $y = log(x + 1)$

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A very common one is the **centered logratio transformation (CLR)**:

$$\text{CLR}(j) = \log\left(\frac{x_j}{\left(\prod_{j'} x_{j'}\right)^{1/J}}\right) = \log\left(x_j\right) - \frac{1}{J}\sum_{j'}\log\left(x_{j'}\right) \quad j = 1, \ldots, J.$$

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Following [Martín-Fernández et al., 2003], a multiplicative replacement strategy gives:

$$r_j = \begin{cases} \delta_j, & \text{if } x_j = 0, \\ \left(1 - \frac{\sum_{k|x_k=0} \delta_k}{c}\right) x_j, & \text{if } x_j > 0, \end{cases}$$

where

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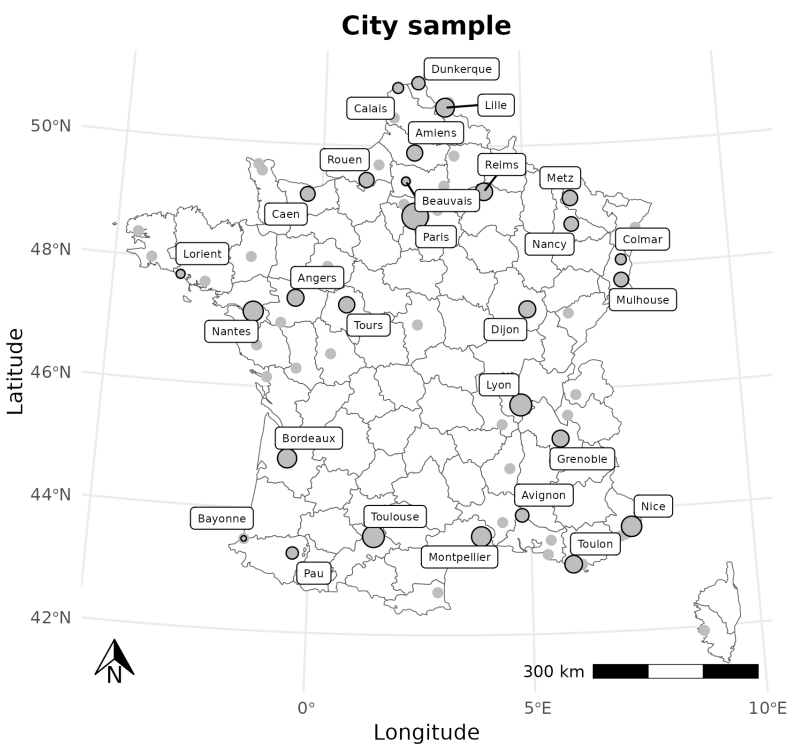
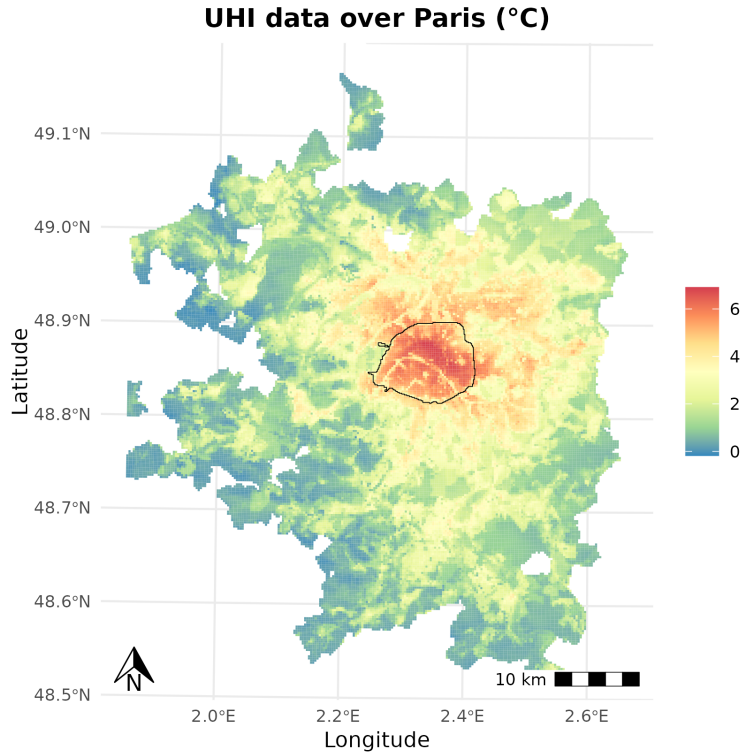
➠ This zero-replacement strategy implies that zeroes are not considered to be essential zeros, but rather values that are too small to be detected.

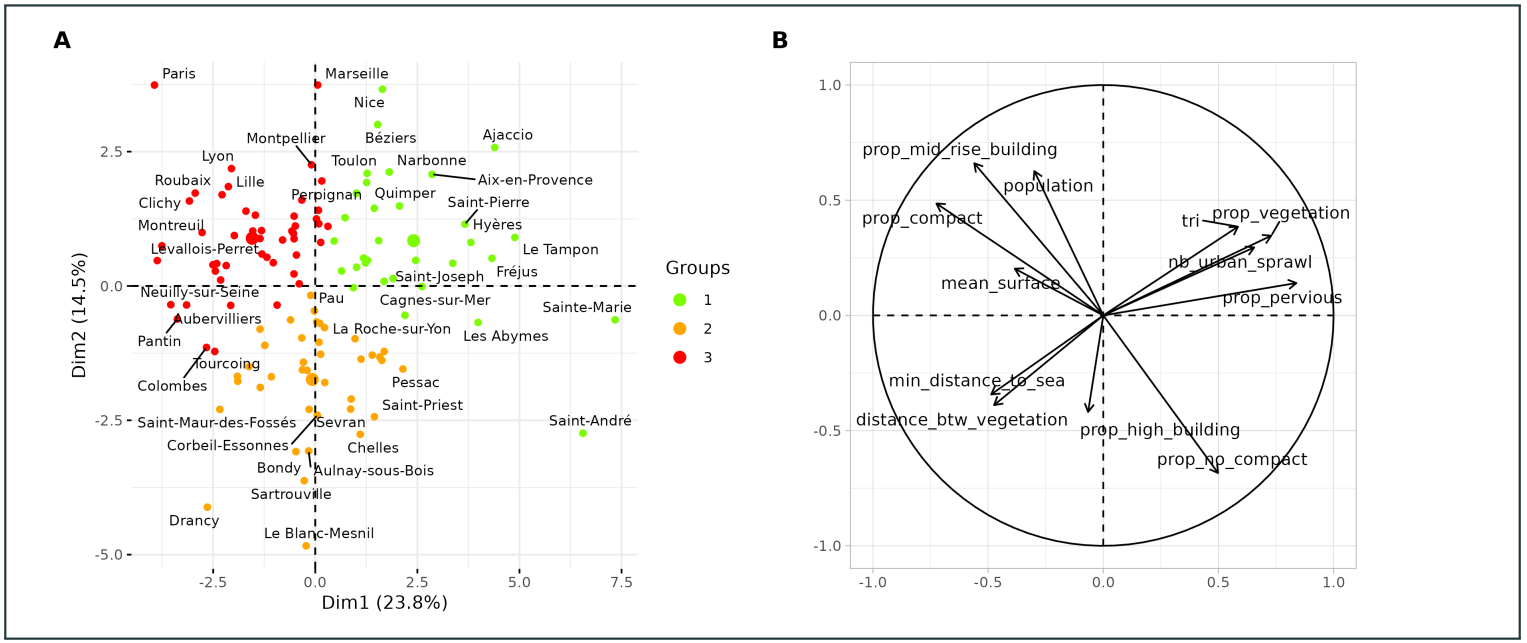
City sample

- Municipalities over 50 000 inhabitants
  - ➠ 120 municipalities (1 individual = 1 municipality)
- UHI model outputs from TEB/SURFEX model (MaPuce project)
  - ➠ 42 urban areas



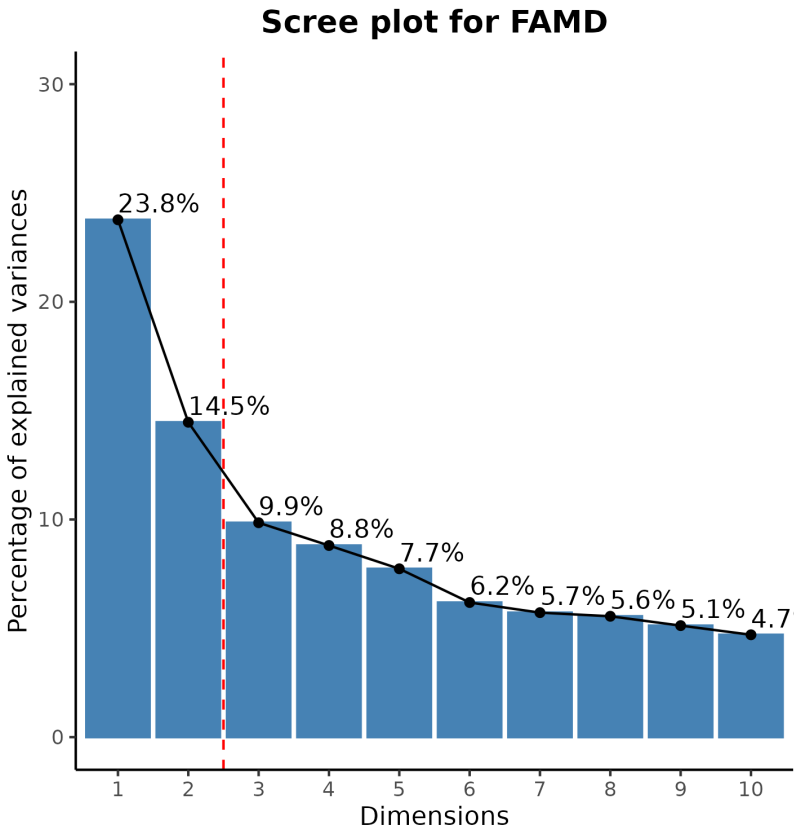


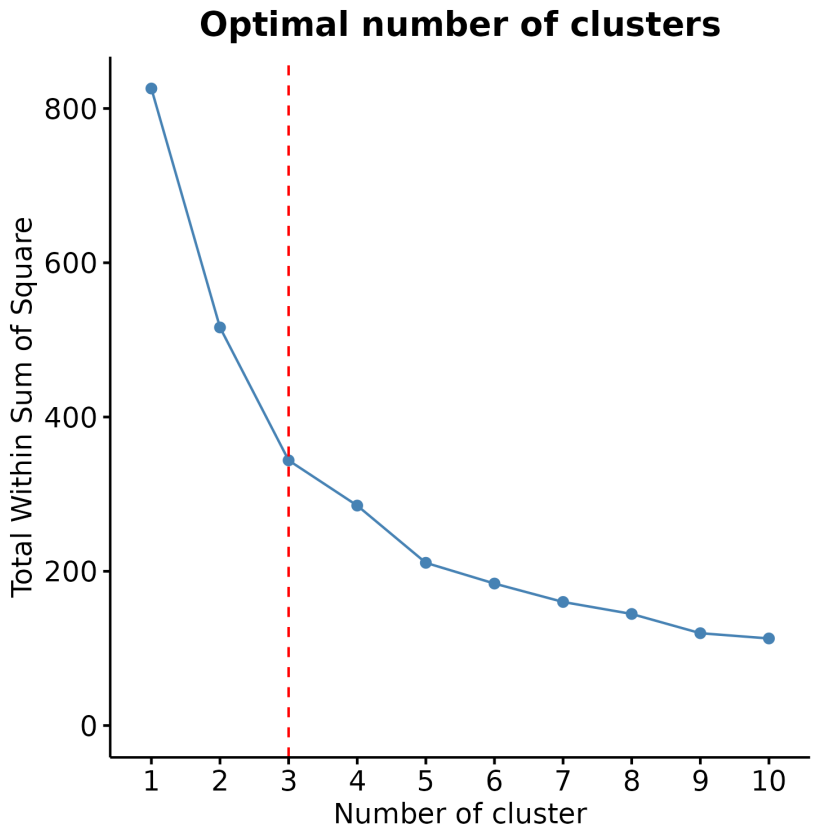
FAMD and clustering results



Results

1. FAMD → filter two first dimensions.
2. Conduct k-means based on the two first dimensions
   → three clusters.





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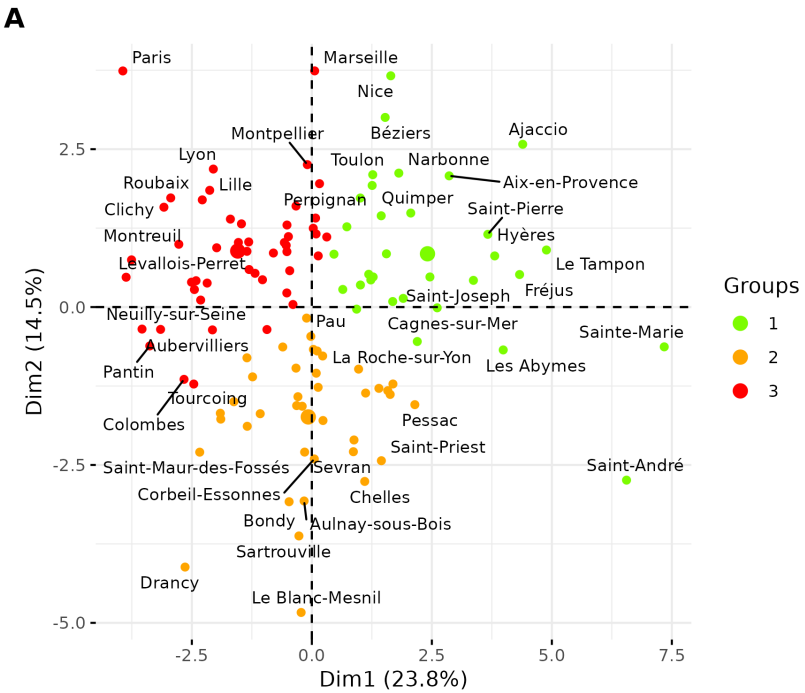
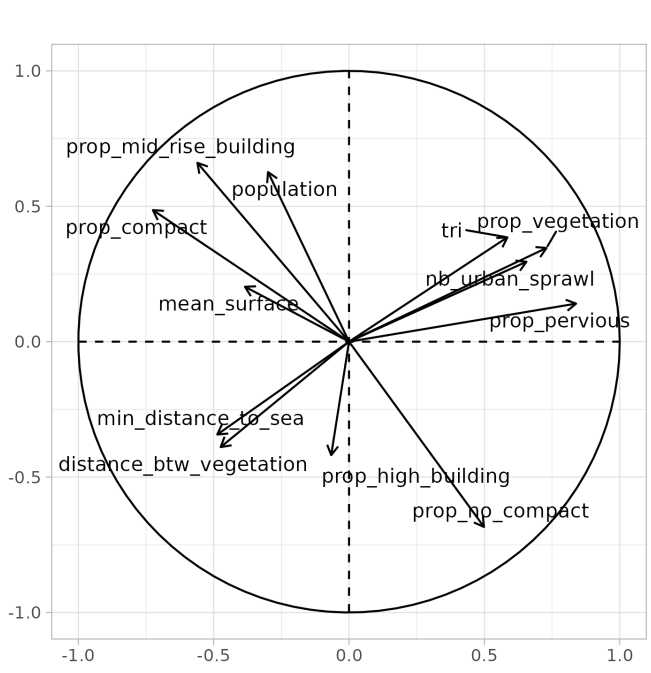




Structuring variables :

- Density and height of the building.
- ”Green” variables, number of urban patches, topography.

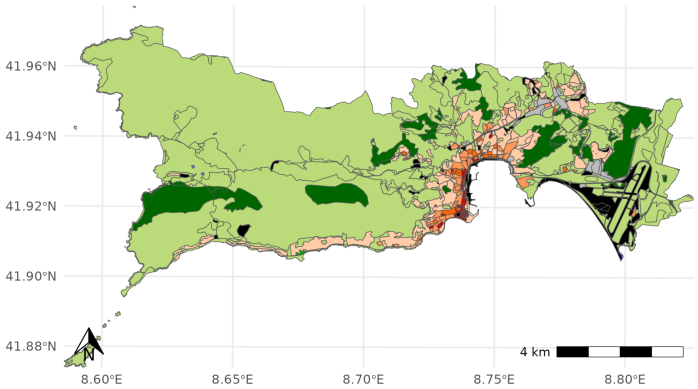
Two main axis of variability:

1/ Vegetalization and cooling variables.

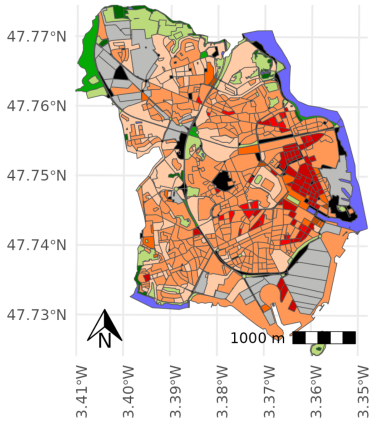
2/ Compact versus non-compact.

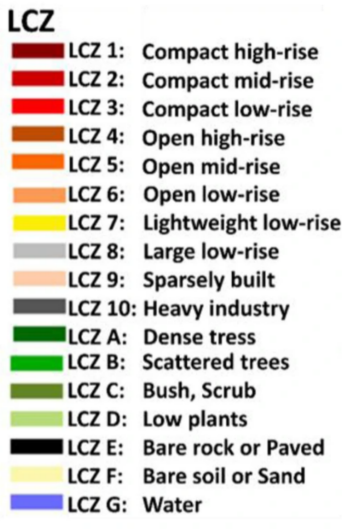
Results

Cluster 1 Ajaccio

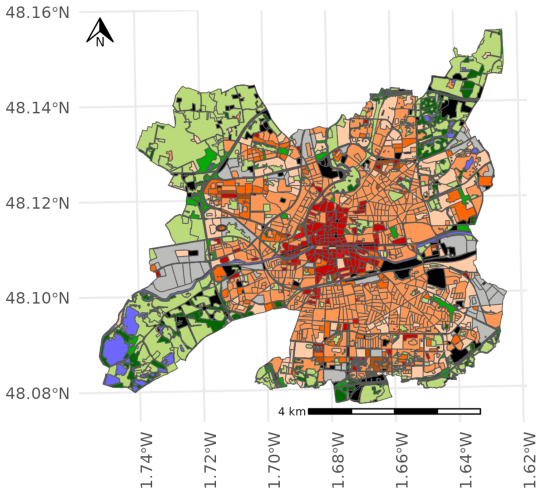


Cluster 2 Lorient

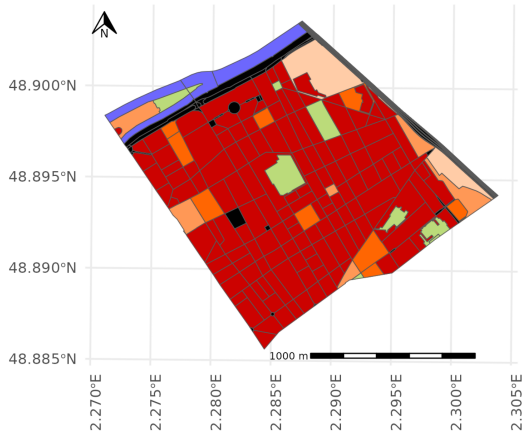




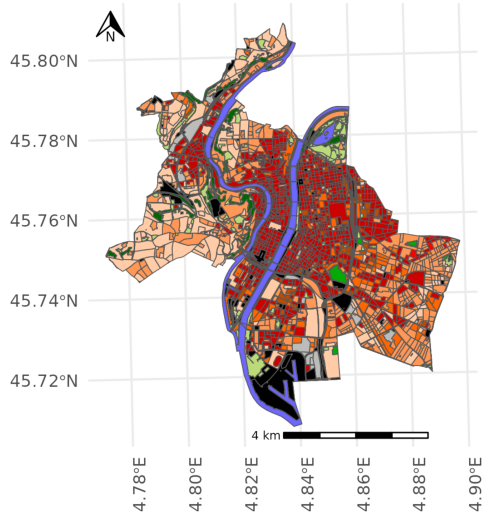
Cluster 3 Rennes



Cluster 3 Levallois-Perret

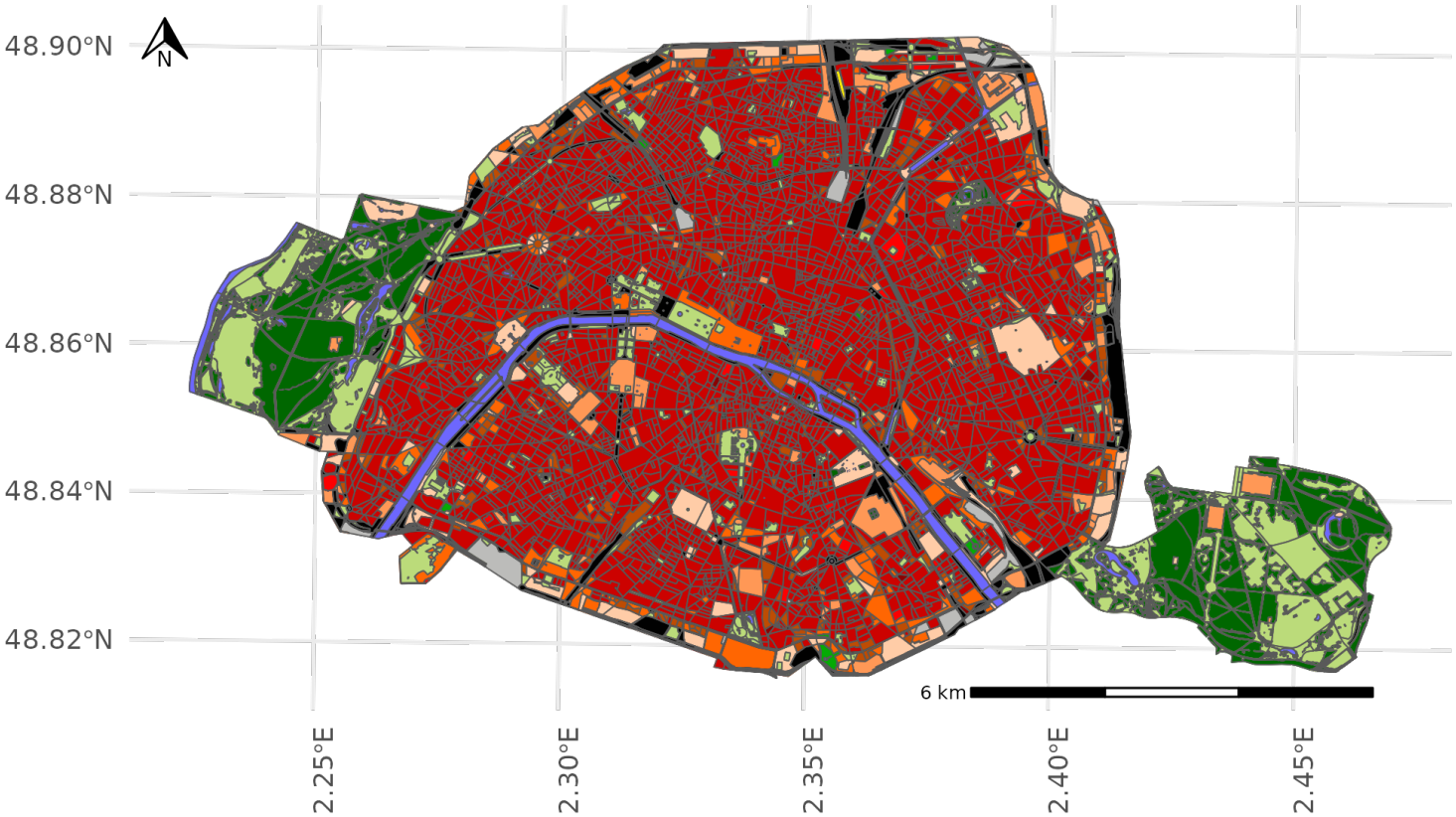


Cluster 3 Lyon

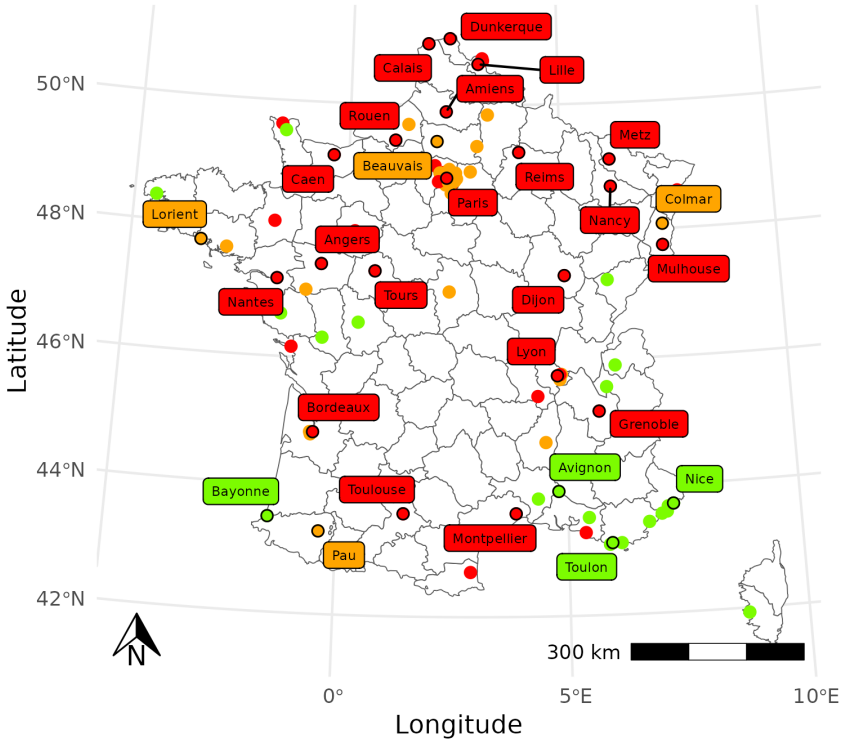


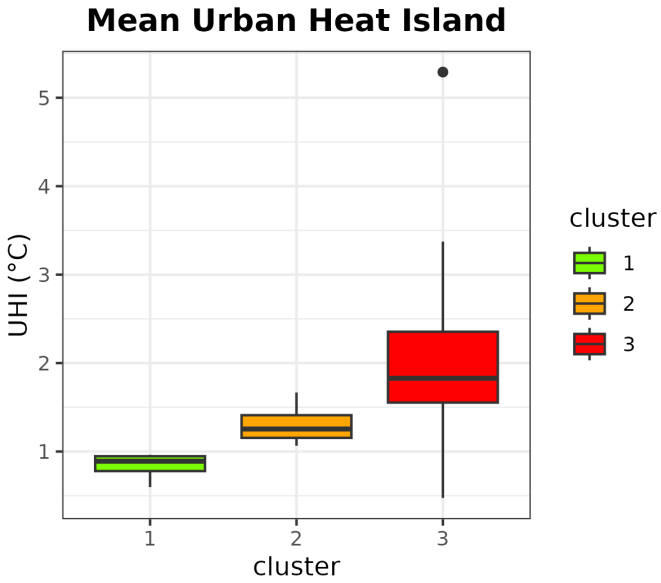
Results

Paris = outlier



Results

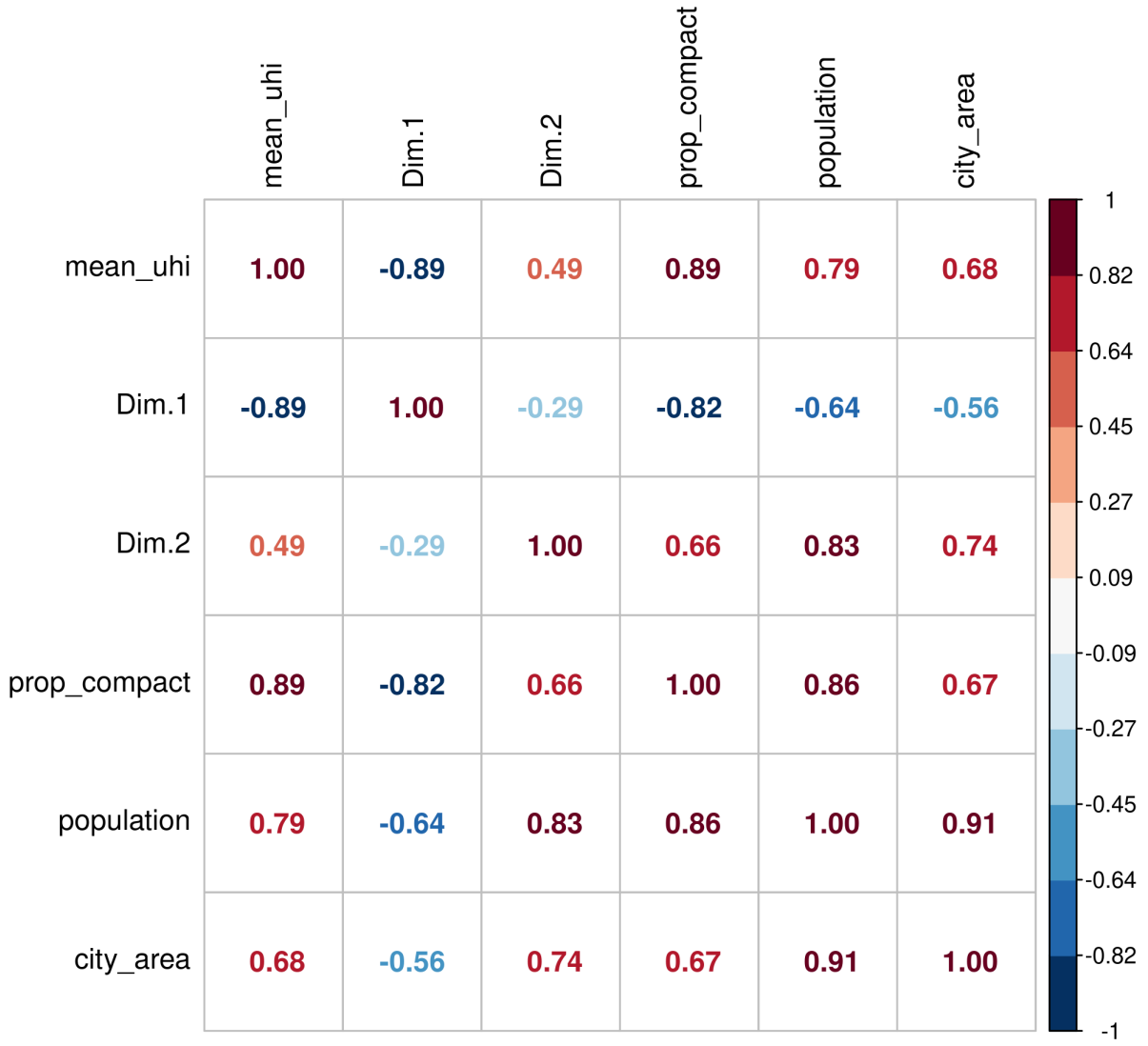




- **Cluster 1:** coastal or mountainous, high permeability, several urban patches.
- **Cluster 2:** single urban sprawl, low permeability, non-compact LCZ.
- **Cluster 3:** dense urban fabric, many urban barriers, minimal permeability.

Results

Correlation between the mean urban heat island and some key variables of the analysis.



Discussion

We identified (1) municipality profiles with regards to overheating factors and (2) the main variables that drive these profiles.

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The intent of this work is to propose a **methodological framework** to identify such city profiles.

Steps of the methodological framework

1. For each overheating factor, identify geographic indicators that describe these factors.
2. Select the urban territories of interest (administrative units, geographical extent) and compute the geographic indicators.
3. Identify profiles from the data through statistical analysis.
4. Confront these to some physical measure of overheating.

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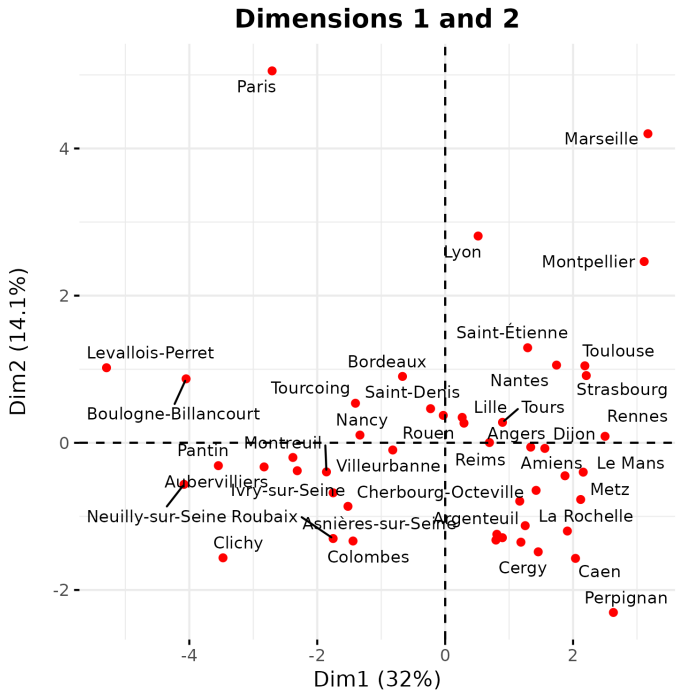
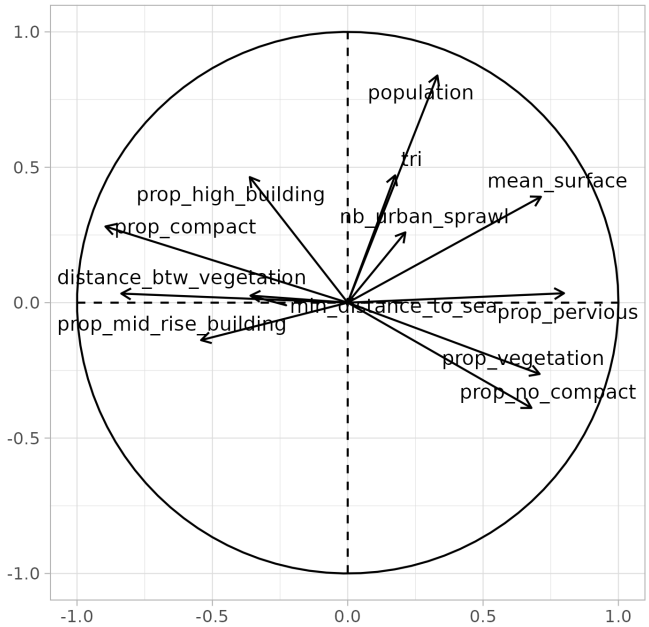
4. Confront these to some physical measure of overheating.

From our data, we are able to build interpretable city profiles relative to overheating factors, but this is not a definitive classification.

Many choices in this work are open to debate and we will discuss these now.

Exploring the cluster of heat-sensitive cities

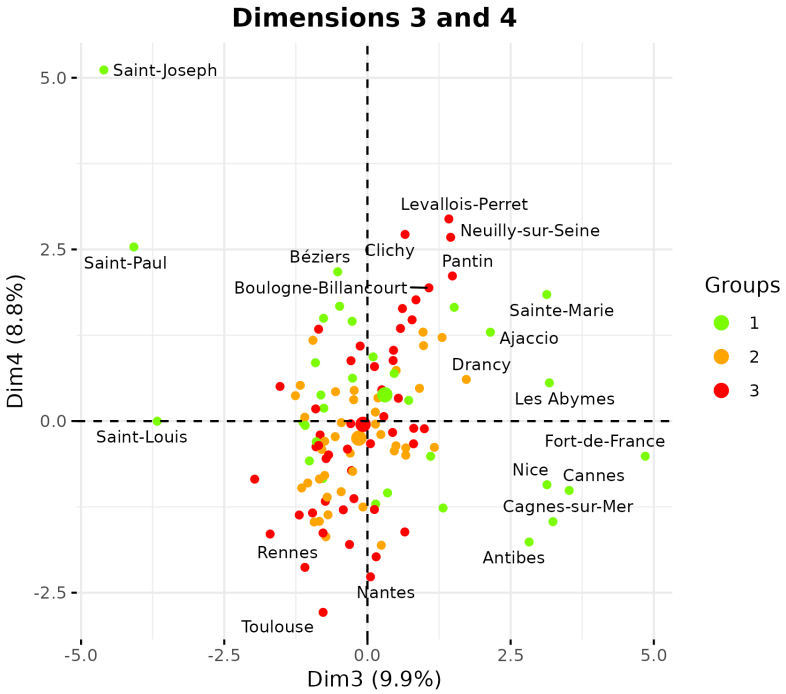


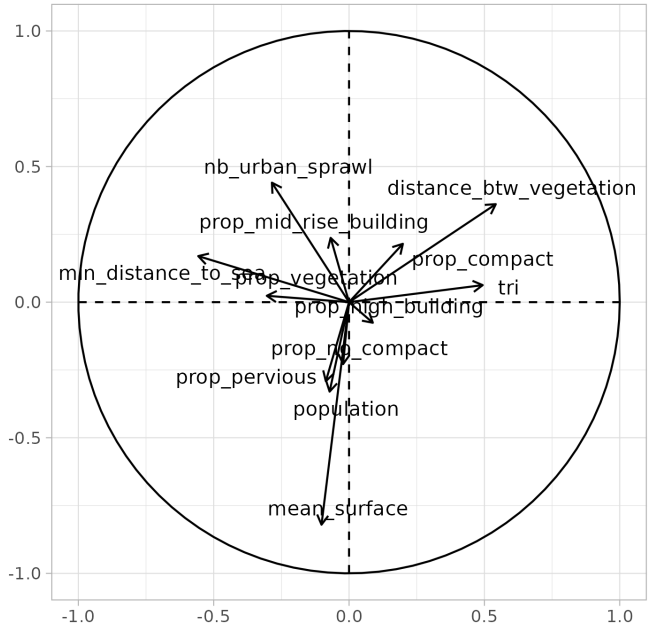


→ known relationship: non-compact versus compact

→ and some new one: ‘population’ distinguishes from ‘compact’

Exploring the next dimensions of the FAMD

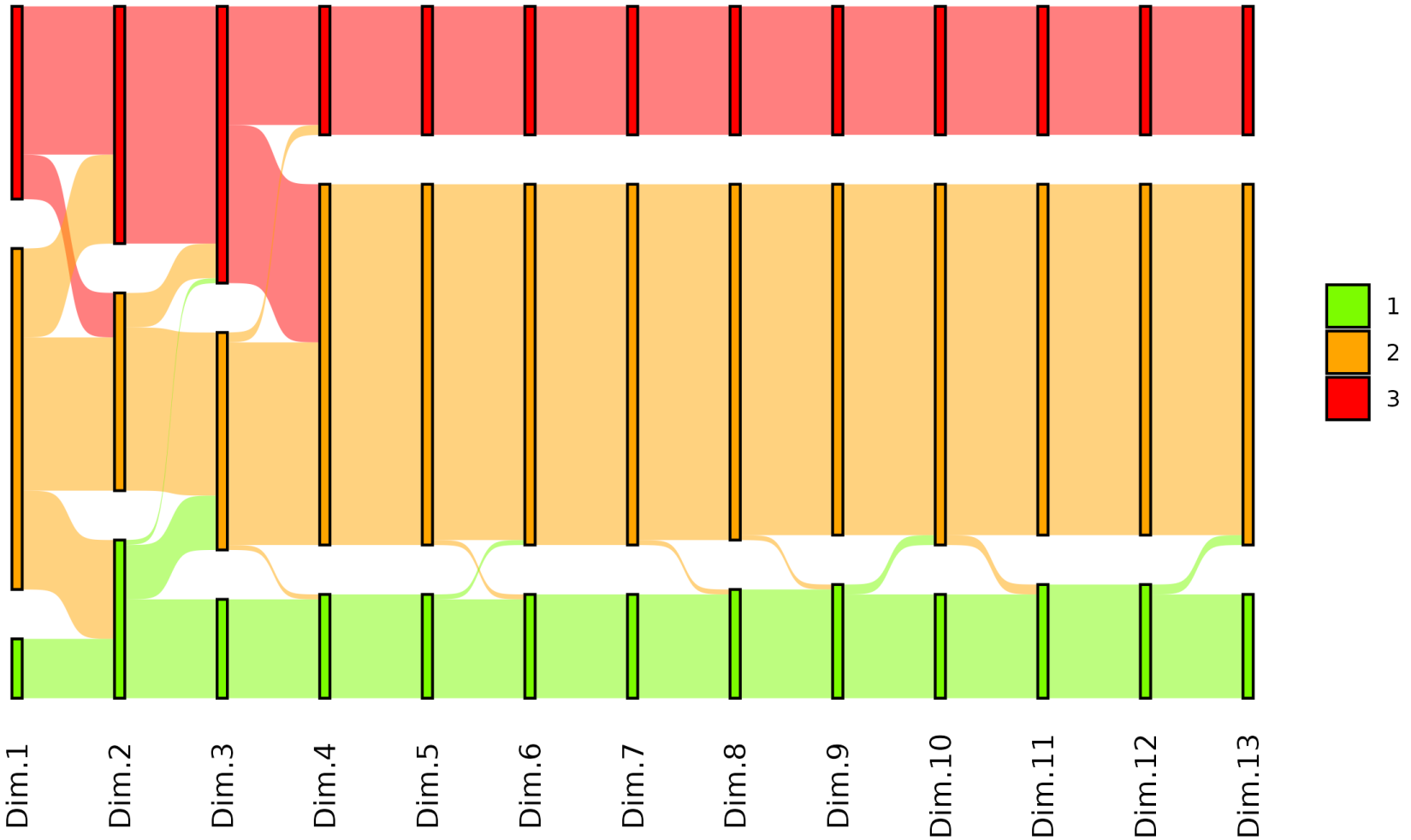




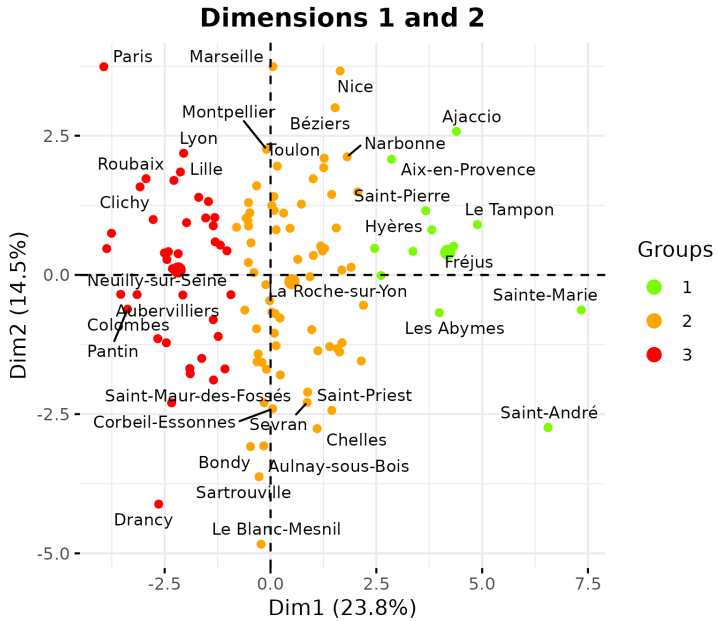
→ 3^{rd} dimension: topography and distance to the sea

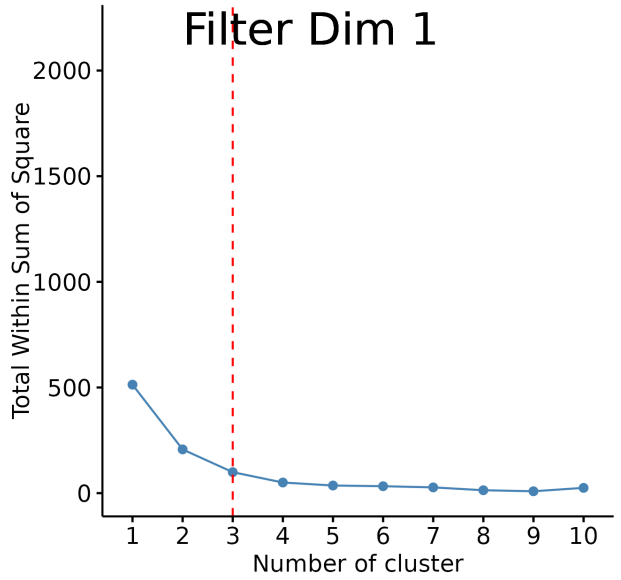
→ 4^{th} dimension: surface of the urban patches

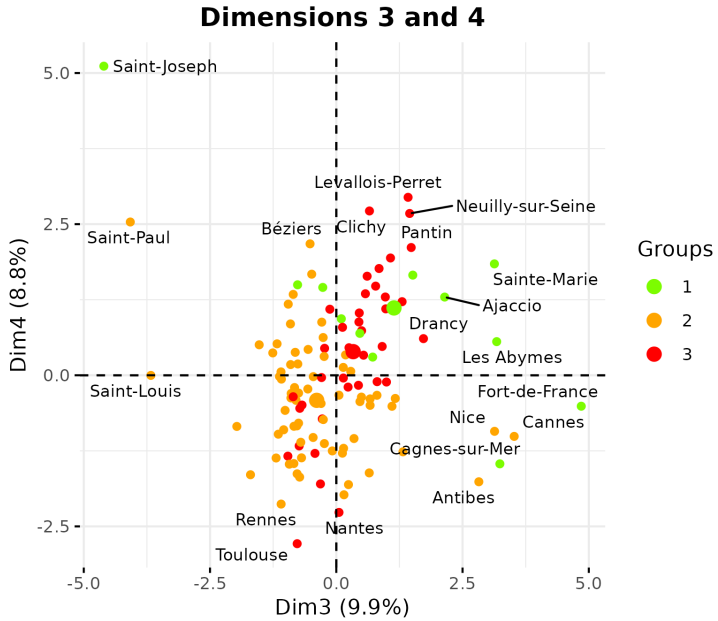
Effect of the number of AFMD dimensions in the clustering

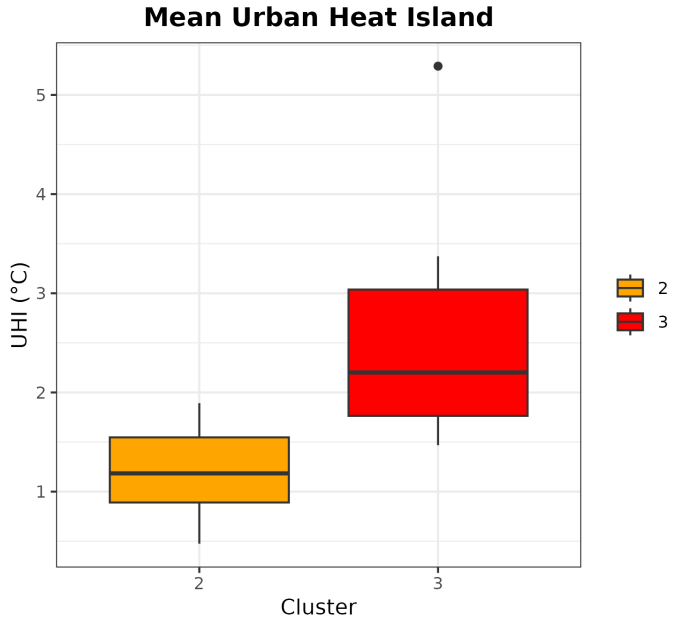


Effect of the number of AFMD dimensions in the clustering









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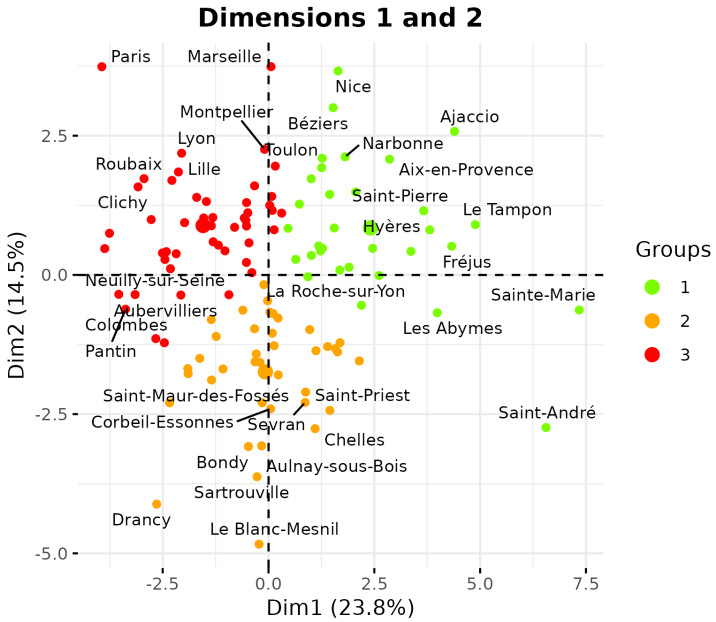
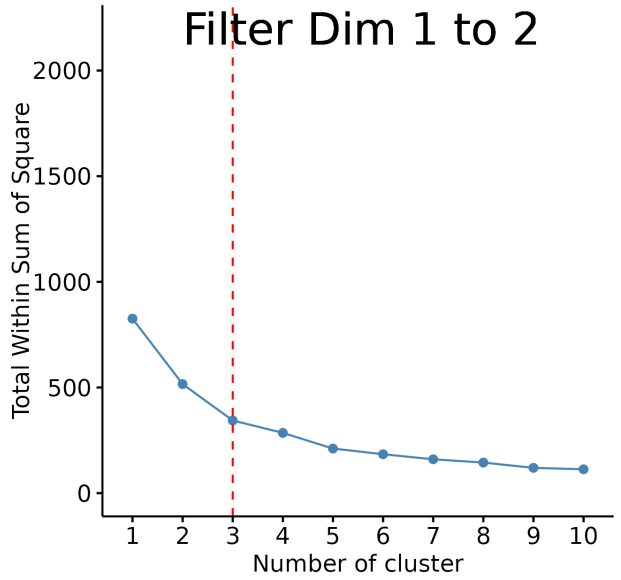
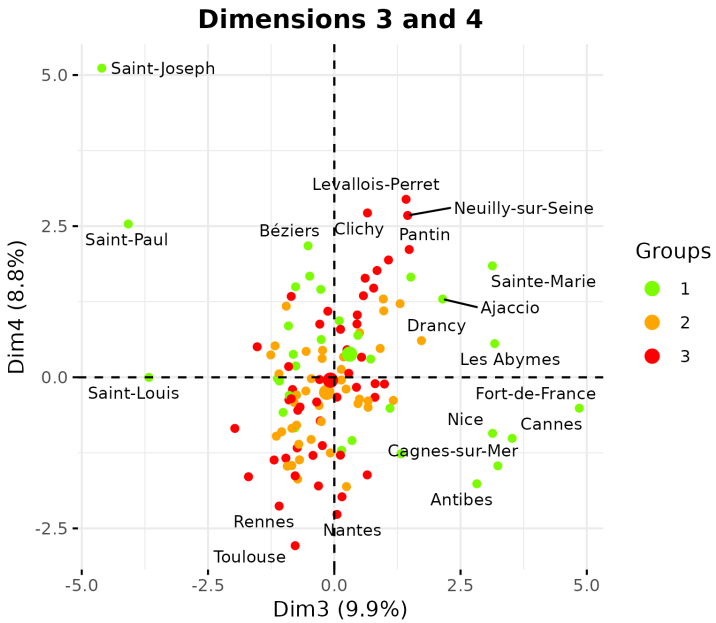
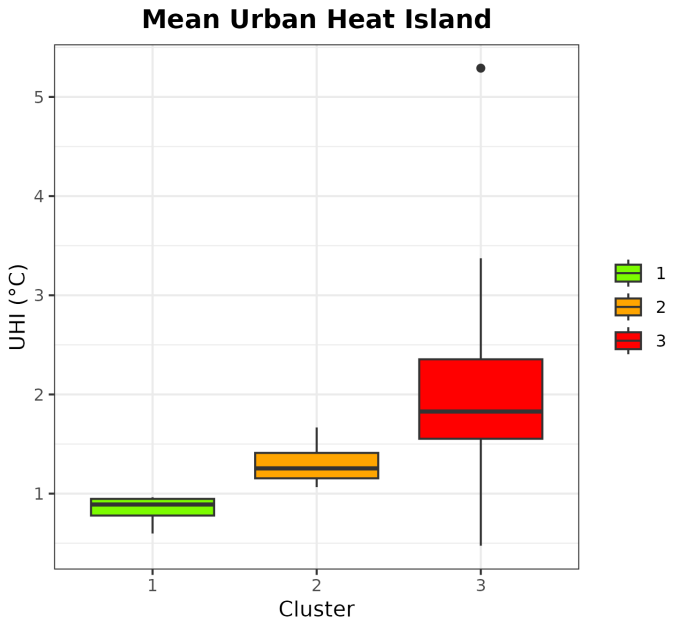
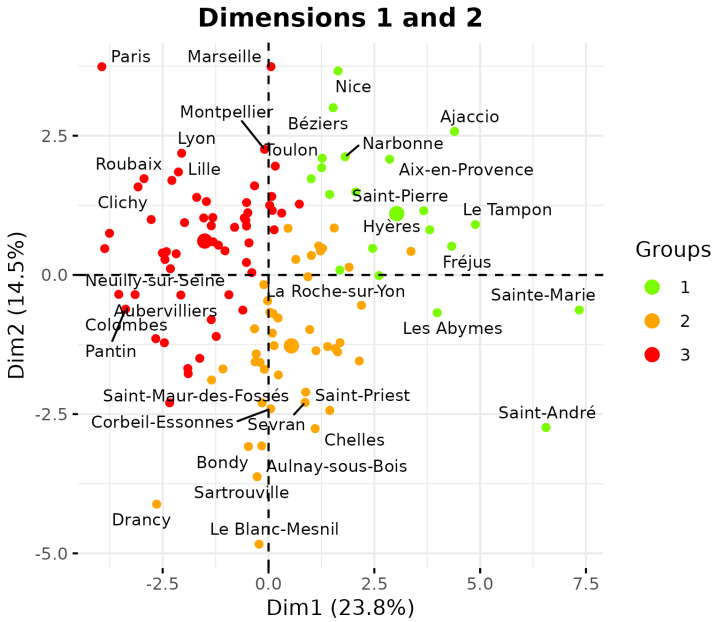


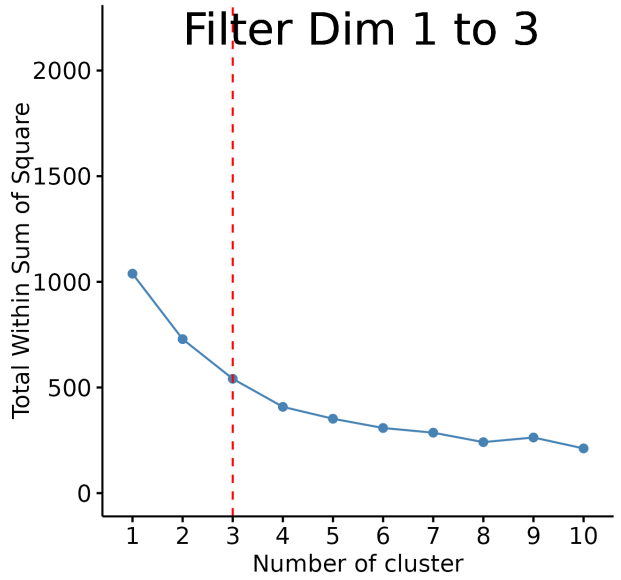


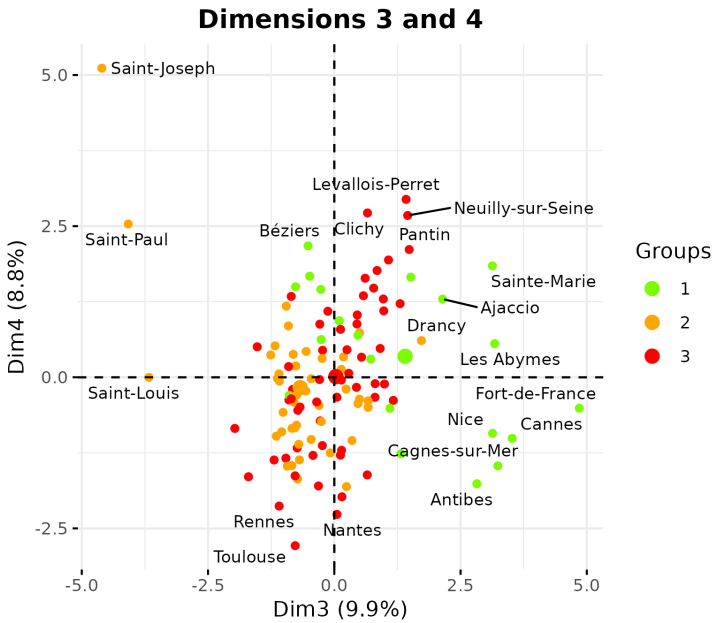


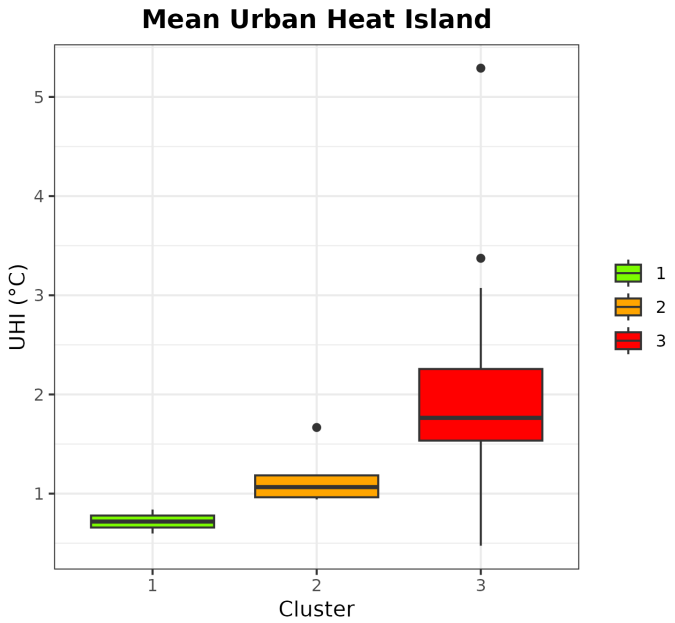


Effect of the number of AFMD dimensions in the clustering

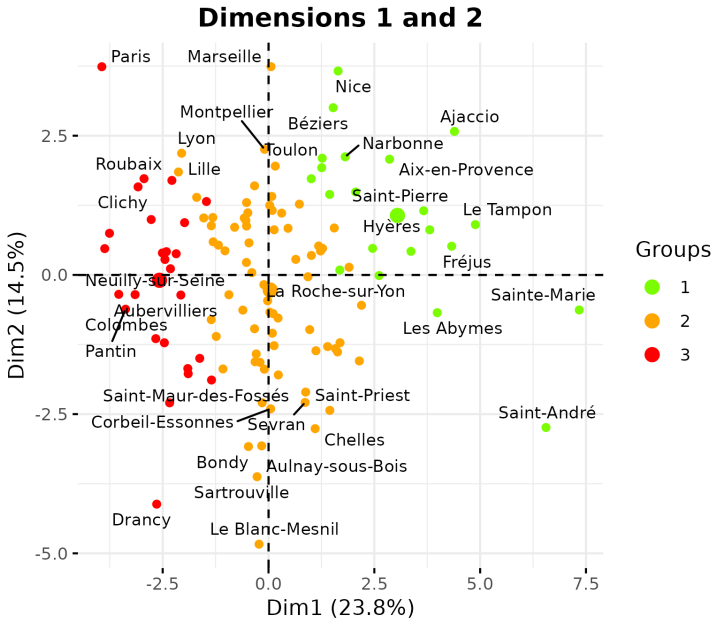


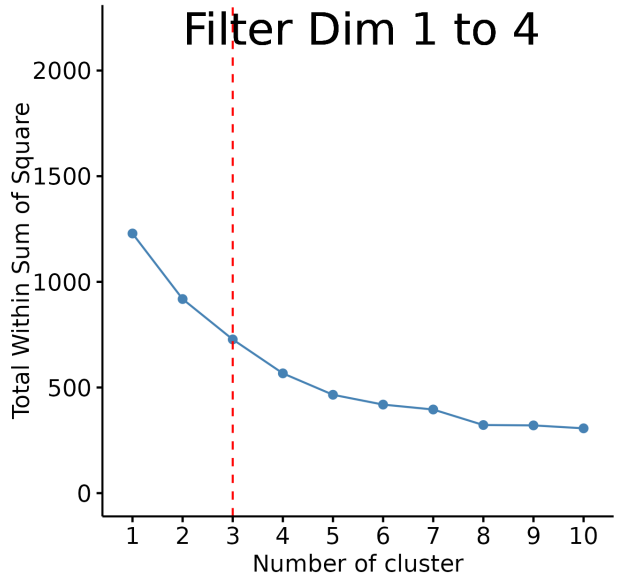


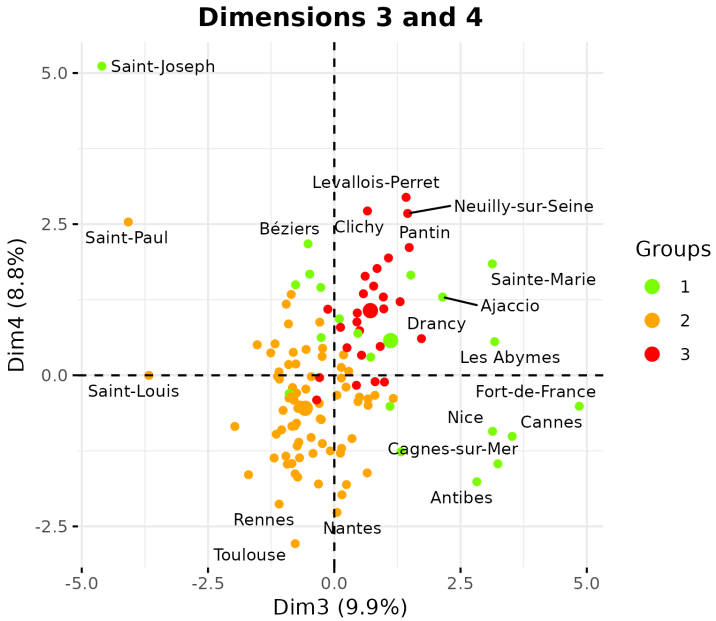


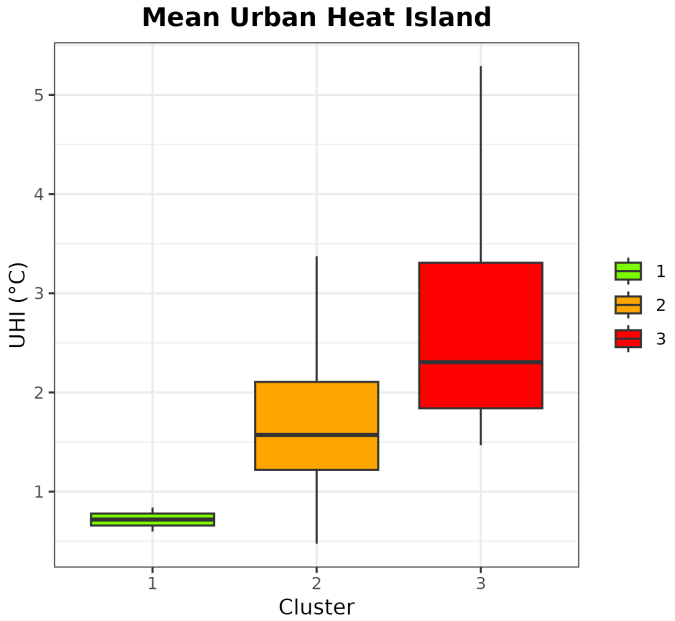


Effect of the number of AFMD dimensions in the clustering

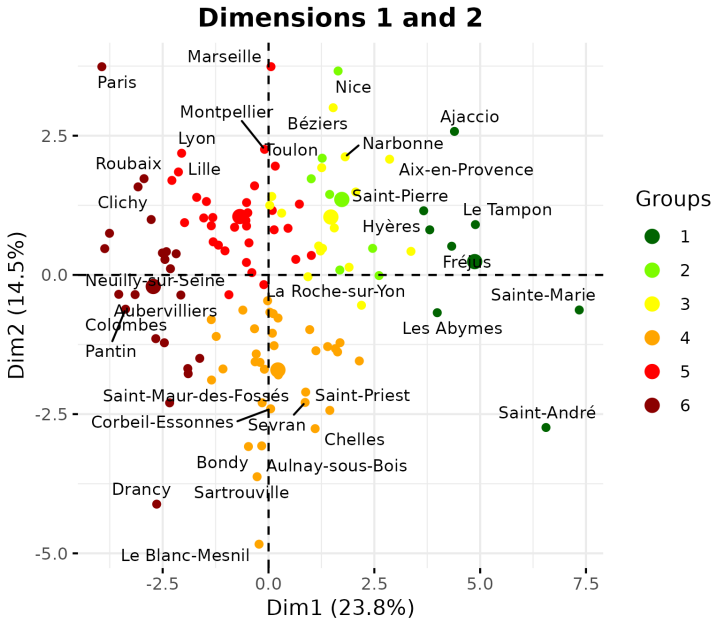


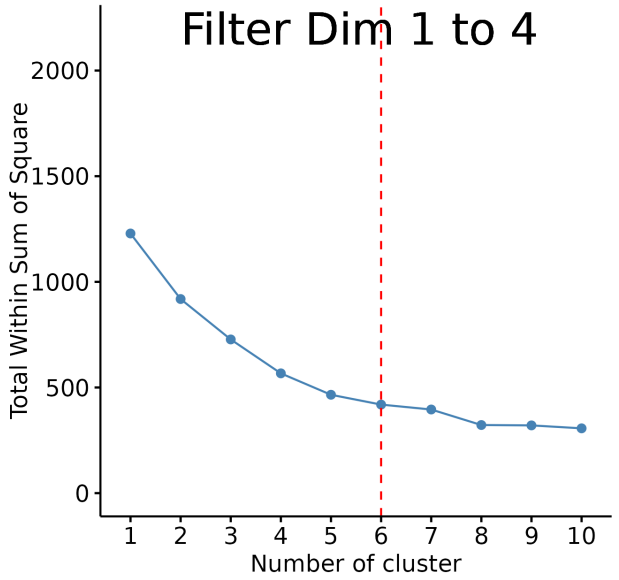


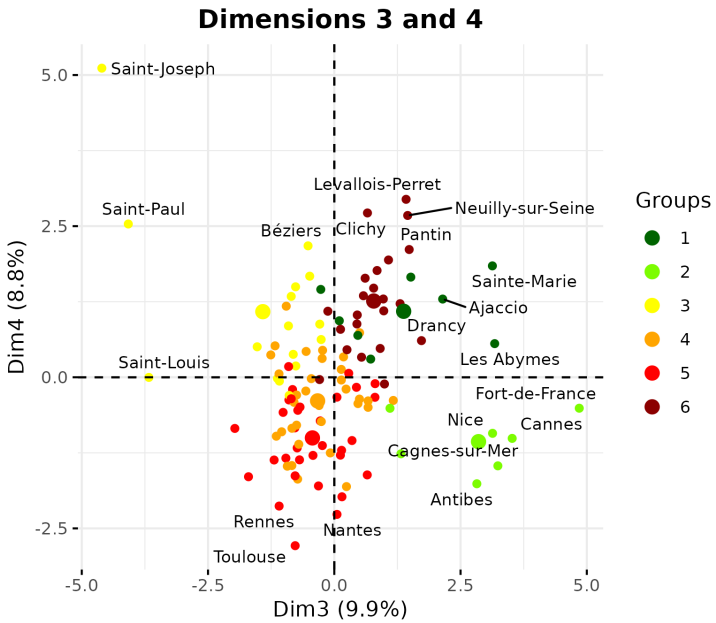


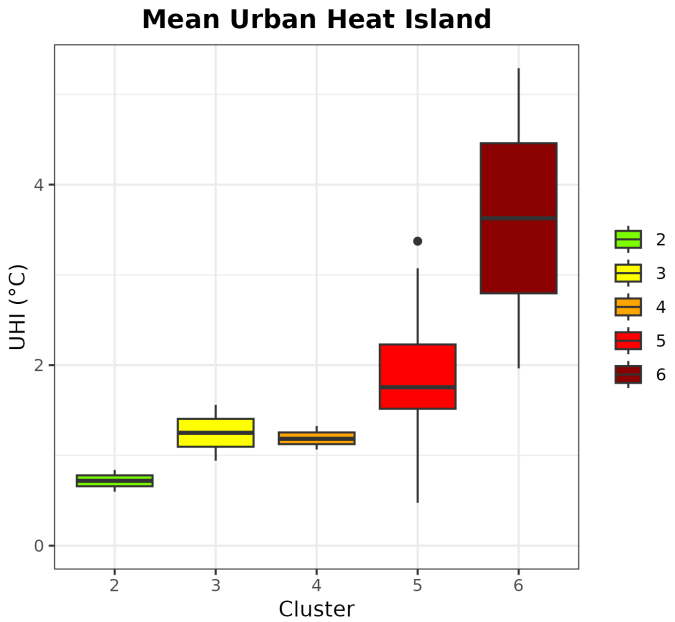


Propose a finer classification









Extending the analysis

Geographically

Consider a wider area (Europe, Africa, Asia, America)

Administratively

Consider urban units rather than municipalities

By including the within structure of the city

The within-structure of city can affect overheating.

$\rightarrow$ build geographical indicators representing these structures

➠ More robust and exhaustive classification

A probabilistic PCA for handling zero values

The zero-replacement strategy for compositions relies on some arbitrary choices.

The main advances to account for essential zeroes in compositions come from microbial research where micribiome data are considered as compositions [Zeng et al., 2023].

A probabilistic PCA for handling zero values

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The main advances to account for essential zeroes in compositions come from microbial research where micribiome data are considered as compositions [Zeng et al., 2023].

Consider a latent variable model where $\mathbf{Y}$ is the matrix of variables and $\mathbf{Z}$ are the latent variable. $\boldsymbol{\theta}$ and σ are the parameters.

$$\begin{aligned} \mathbf{Y} \mid \mathbf{Z}, \boldsymbol{\theta}, \sigma &\sim \mathcal{L}(\mathbf{Z}, \sigma^2 \mathbf{I}), \\ \mathbf{Z} \mid \boldsymbol{\theta} &\sim \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma}), \\ \boldsymbol{\Sigma} &= \mathbf{B}\mathbf{B}' \end{aligned}$$

where $\mathbf{B}$ is low rank ($n_{col}(B) < n_{col}(Y)$).

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where B is low rank ($n_{col}(B) < n_{col}(Y)$).

Do we model zeroes in $\mathcal{L}()$ or in Z?

$\rightarrow$ in $\mathcal{L}()$: several zero-inflated distributions such as zero-inflated dirichlet, beta, logistic-normal.

$\rightarrow$ in Z: modeling zeroes and positive values through delta models.

Take home message

Main points:

- **Very few classifications** of cities based on their sensitivity to overheating.
- Here, **classification based on 120 French municipalities** using 13 indicators related to climate, land use, morphology, and human activity.
- Factorial Analysis of Mixed Data (FAMD) $\times$ k-means clustering $\rightarrow$ **3 urban profiles** with differing levels of vegetation, density, and permeability.
- These clusters show **strong relation with UHI model outputs**.

Limits and perspectives:

- Extend to other countries/continents
- Look at a finer scale to the inner structure of the city
- Adapt the methodology to better account for heterogeneous data types
  $\rightarrow$ probabilistic PCA

Thank you for your attention!

Happy to take questions? 😊

Internship application to PEPR Maths-Vives - Any candidate ?

References i

Aitchison, J. (1982).
The statistical analysis of compositional data.
Journal of the Royal Statistical Society: Series B (Methodological), 44(2):139–160.

Aitchison, J. and J. Egozcue, J. (2005).
Compositional data analysis: where are we and where should we be heading?
Mathematical Geology, 37(7):829–850.

Bocher, E., Bernard, J., Wiederhold, E. L. S., Leconte, F., Petit, G., Palominos, S., and Noûs, C. (2021).
Geoclimate: a geospatial processing toolbox for environmental and climate studies.
Journal of Open Source Software, 6(65):3541.

References II

Cerema (2024).
Local climate zones dashboard.
https://cartagene.cerema.fr/portal/apps/dashboards/08066acd23974111be1584a5761fd6b9.
Accessed: 2025-11-18.

Ching, J., Mills, G., Bechtel, B., See, L., Feddema, J., Wang, X., Ren, C., Brousse, O., Martilli, A., Neophytou, M., et al. (2018).
Wudapt: An urban weather, climate, and environmental modeling infrastructure for the anthropocene.
Bulletin of the American Meteorological Society, 99(9):1907–1924.

Greenacre, M. (2021).
Compositional data analysis.
Annual Review of Statistics and its Application, 8(1):271–299.

References III


Huang, W. T. K., Masselot, P., Bou-Zeid, E., Fatichi, S., Paschalis, A., Sun, T., Gasparrini, A., and Manoli, G. (2023).
Economic valuation of temperature-related mortality attributed to urban heat islands in european cities.
Nature communications, 14(1):7438.


Husson, F., Lê, S., and Pagès, J. (2011).
***Exploratory multivariate analysis by example using R*, volume 15.**
CRC press Boca Raton.


Martín-Fernández, J. A., Barceló-Vidal, C., and Pawlowsky-Glahn, V. (2003).
Dealing with zeros and missing values in compositional data sets using nonparametric imputation.
Mathematical Geology, 35(3):253–278.

References iv

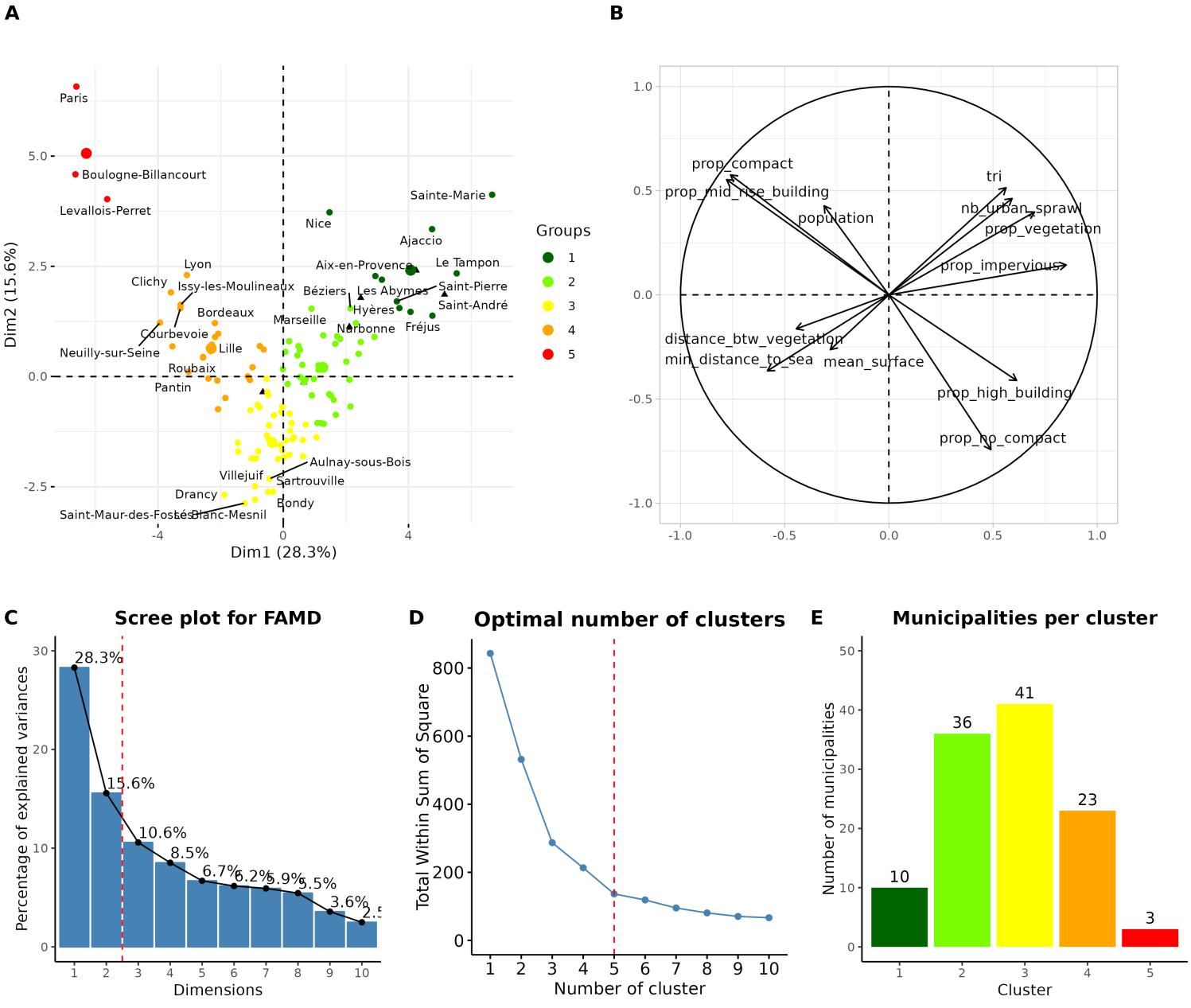
Masson, V. (2000).
A physically-based scheme for the urban energy budget in atmospheric models.
Boundary-layer meteorology, 94:357–397.

Vargas-Munoz, J. E., Srivastava, S., Tuia, D., and Falcao, A. X. (2020).
Openstreetmap: Challenges and opportunities in machine learning and remote sensing.
IEEE Geoscience and Remote Sensing Magazine, 9(1):184–199.

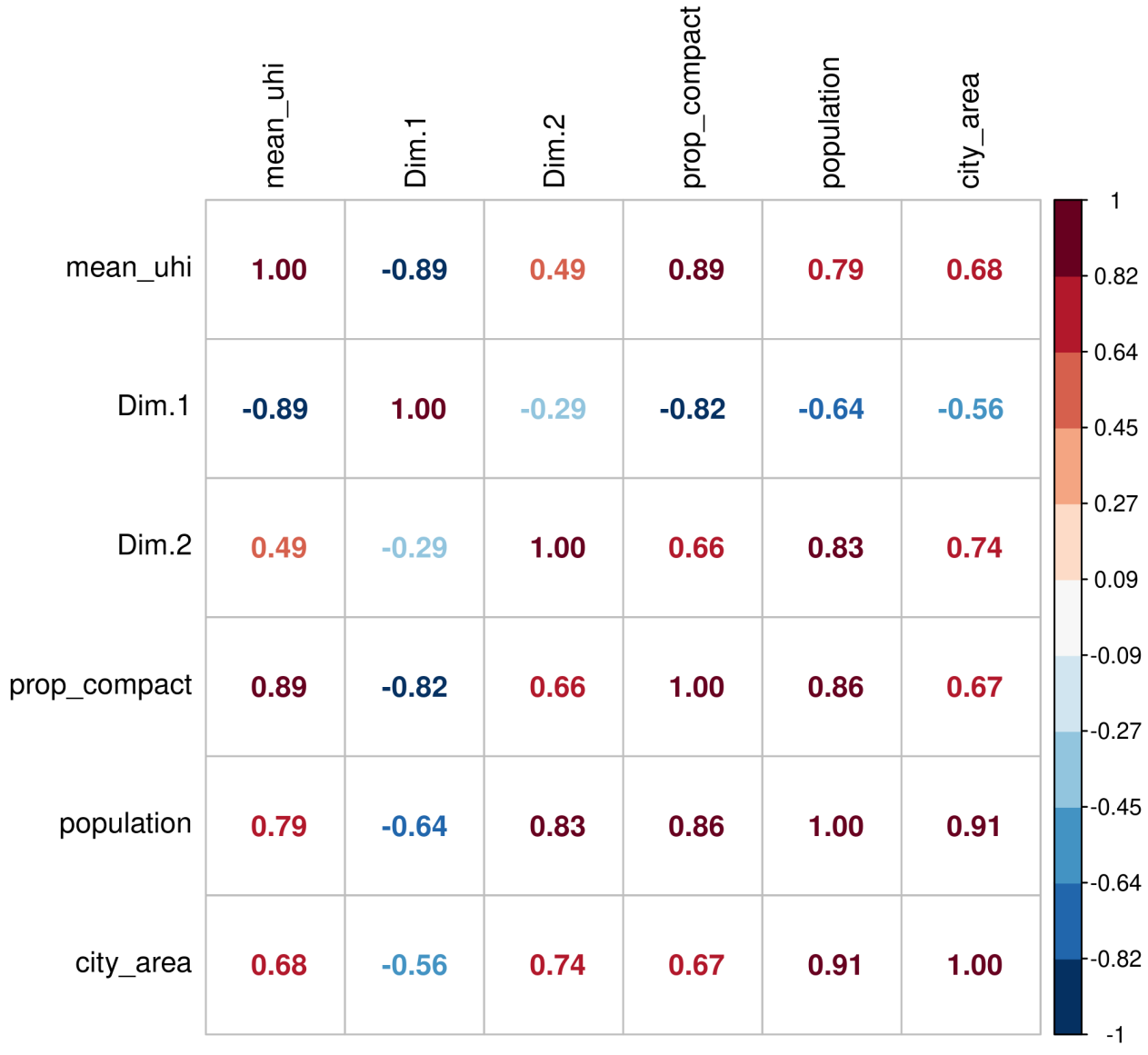
Wang, C., Wang, Z.-H., and Li, Q. (2020).
Emergence of urban clustering among us cities under environmental stressors.
Sustainable Cities and Society, 63:102481.


Zeng, Y., Pang, D., Zhao, H., and Wang, T. (2023).
A zero-inflated logistic normal multinomial model for extracting microbial compositions.
Journal of the American Statistical Association,
118(544):2356–2369.

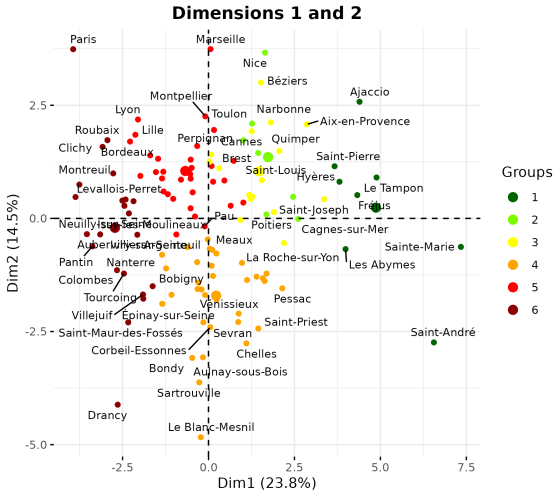
Appendices

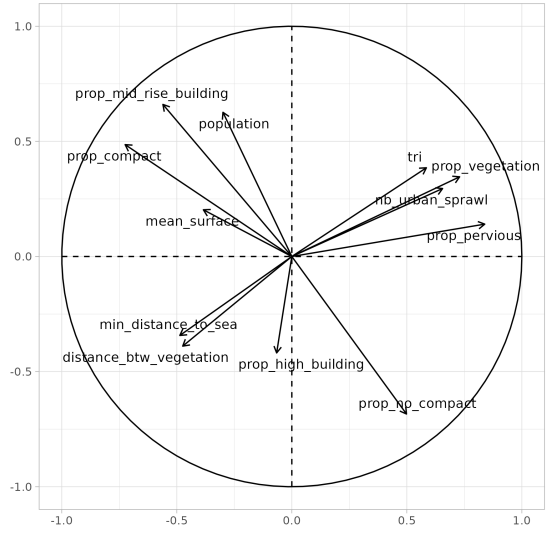

A
Paris
Boulogne-Billancourt
Levallois-Perret
Sainte-Marie
Nice
Ajaccio
Lyon
Aix-en-Provence
Le Tampon
Clichy
Issy-les-Moulineaux
Béziers
Les Abymes
Saint-Pierre
Saint-André
Bordeaux
Hyères
Marseille
Courbevoie
Narbonne
Fréjus
Neuilly-sur-Seine
Lille
Roubaix
Pantin
Aulnay-sous-Bois
Villejuif
Sartrouville
Drancy
Bondy
Saint-Maur-des-Fossés
Le Blanc-Mesnil
Dim2 (15.6%)
Dim1 (28.3%)
Groups
1
2
3
4
5
B
prop_compact
prop_mid_rise_building
population
tri
nb_urban_sprawl
prop_vegetation
prop_impervious
distance_btw_vegetation
min_distance_to_sea
mean_surface
prop_high_building
prop_no_compact
C
Scree plot for FAMD
Percentage of explained variances
Dimensions
28.3%
15.6%
10.6%
8.5%
6.7%
6.2%
5.9%
5.5%
3.6%
D
Optimal number of clusters
Total Within Sum of Square
Number of cluster
E
Municipalities per cluster
Number of municipalities
Cluster
10
36
41
23
3

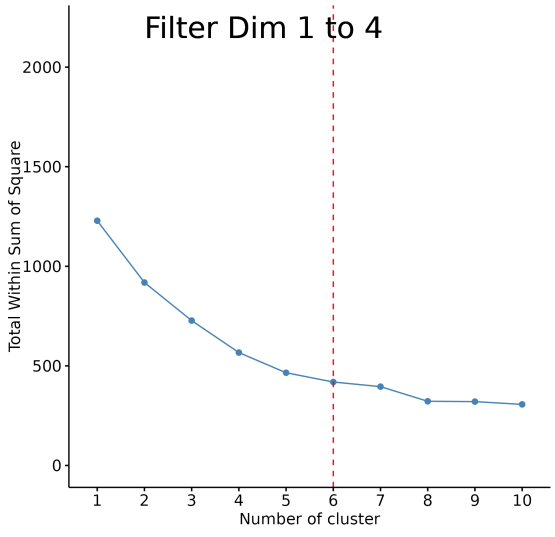
Appendices

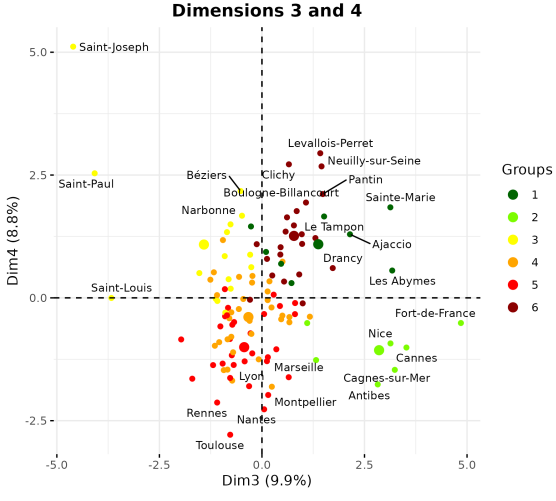

mean_uhi
Dim.1
Dim.2
prop_compact
population
city_area
mean_uhi 1.00 -0.89 0.49 0.89 0.79 0.68
Dim.1 -0.89 1.00 -0.29 -0.82 -0.64 -0.56
Dim.2 0.49 -0.29 1.00 0.66 0.83 0.74
prop_compact 0.89 -0.82 0.66 1.00 0.86 0.67
population 0.79 -0.64 0.83 0.86 1.00 0.91
city_area 0.68 -0.56 0.74 0.67 0.91 1.00
1
0.82
0.64
0.45
0.27
0.09
-0.09
-0.27
-0.45
-0.64
-0.82
-1

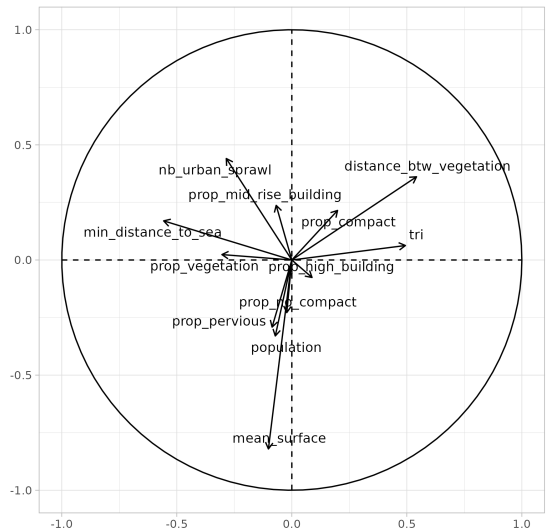
Appendices

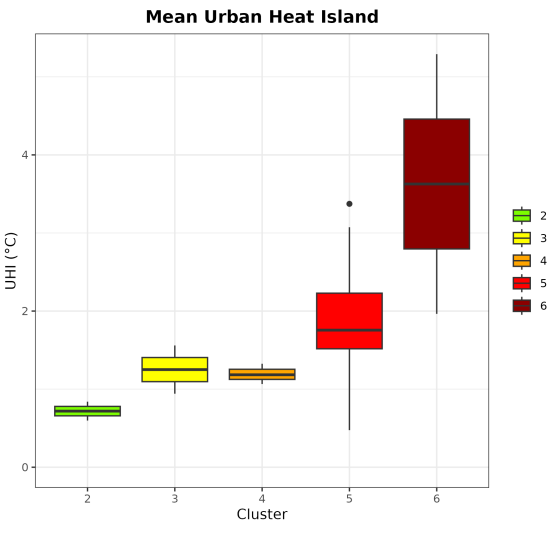

Dimensions 1 and 2
Dim1 (23.8%)
Dim2 (14.5%)
Groups
1
2
3
4
5
6


prop_mid_rise_building
population
prop_compact
tri
prop_vegetation
nb_urban_sprawl
mean_surface
prop_pervious
min_distance_to_sea
distance_btw_vegetation
prop_high_building
prop_no_compact

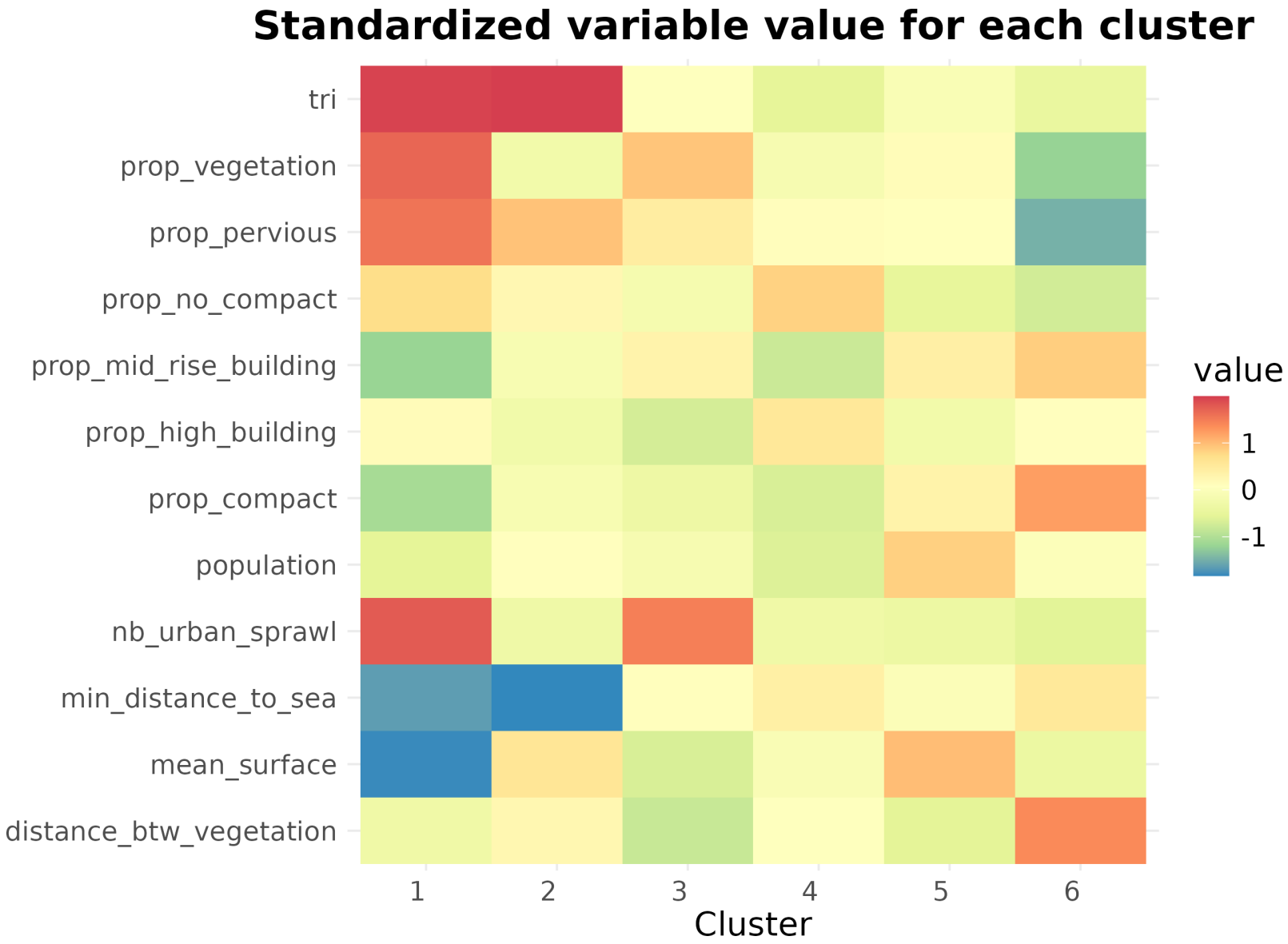

Filter Dim 1 to 4
Total Within Sum of Square
Number of cluster


Dimensions 3 and 4
Dim3 (9.9%)
Dim4 (8.8%)
Groups
1
2
3
4
5
6

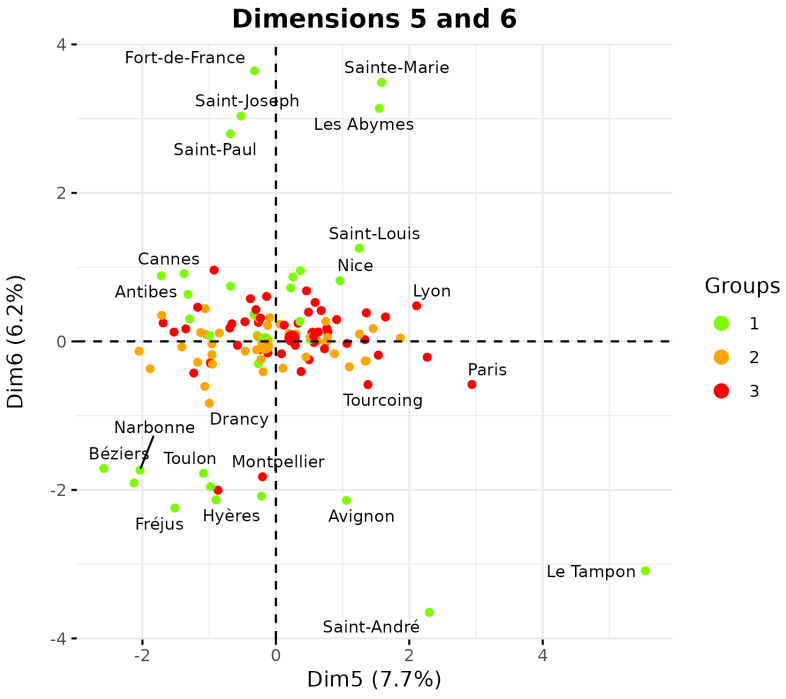

nb_urban_sprawl
distance_btw_vegetation
prop_mid_rise_building
min_distance_to_sea
prop_compact
tri
prop_vegetation
prop_high_building
prop_no_compact
prop_pervious
population
mean_surface

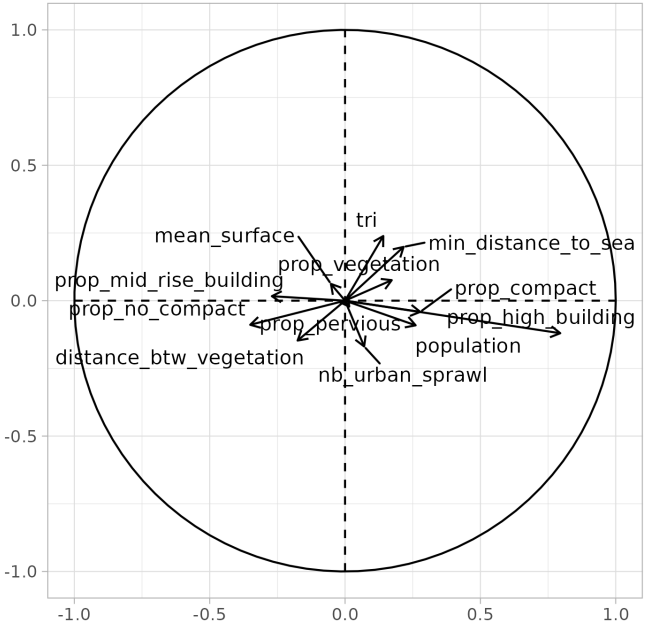

Mean Urban Heat Island
UHI (°C)
Cluster

Appendices

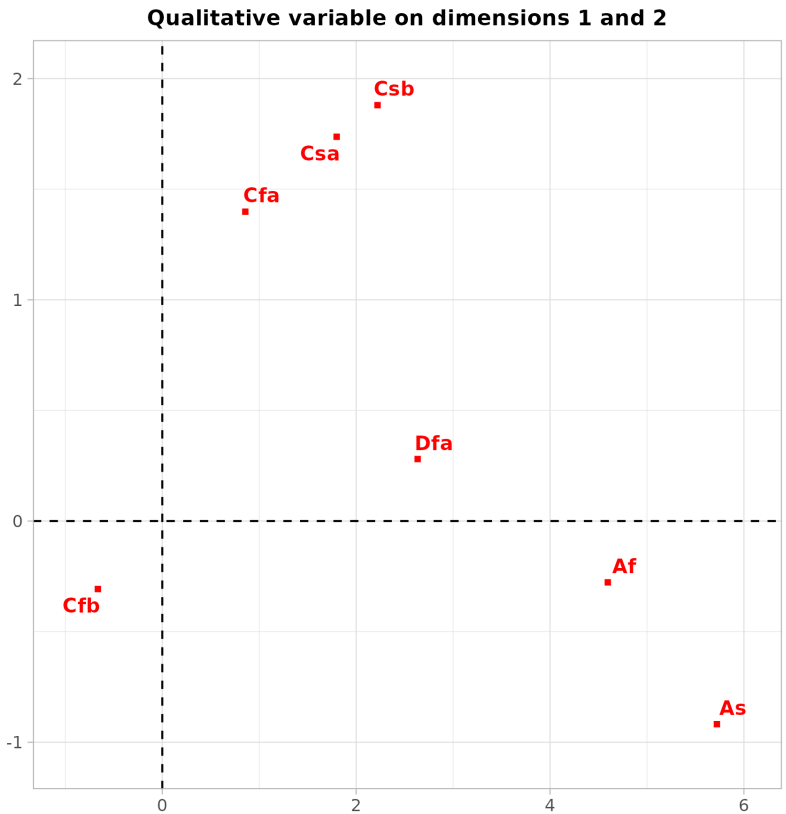

Standardized variable value for each cluster
tri
prop_vegetation
prop_pervious
prop_no_compact
prop_mid_rise_building
prop_high_building
prop_compact
population
nb_urban_sprawl
min_distance_to_sea
mean_surface
distance_btw_vegetation
1
2
3
4
5
6
Cluster
value
1
0
-1

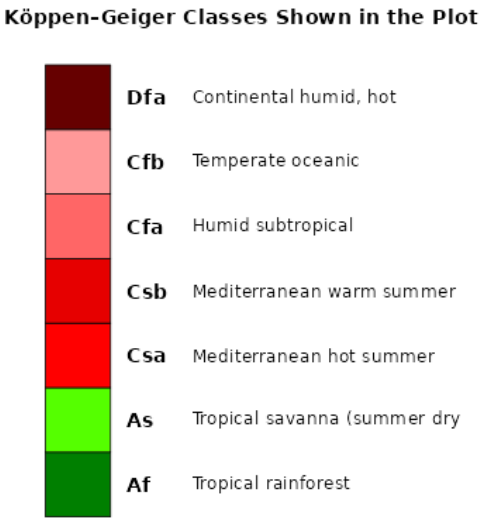
Appendices


Dimensions 5 and 6
Fort-de-France
Sainte-Marie
Saint-Joseph
Les Abymes
Saint-Paul
Saint-Louis
Cannes
Nice
Antibes
Lyon
Paris
Tourcoing
Drancy
Narbonne
Béziers
Toulon
Montpellier
Fréjus
Hyères
Avignon
Le Tampon
Saint-André
Dim6 (6.2%)
Dim5 (7.7%)
Groups
1
2
3


mean_surface
tri
min_distance_to_sea
prop_vegetation
prop_mid_rise_building
prop_compact
prop_no_compact
prop_high_building
prop_pervious
population
distance_btw_vegetation
nb_urban_sprawl

Appendices


Qualitative variable on dimensions 1 and 2
Csb
Csa
Cfa
Dfa
Af
Cfb
As
2
1
0
-1
0
2
4
6


Köppen-Geiger Classes Shown in the Plot
Dfa Continental humid, hot
Cfb Temperate oceanic
Cfa Humid subtropical
Csb Mediterranean warm summer
Csa Mediterranean hot summer
As Tropical savanna (summer dry
Af Tropical rainforest