Multicriteria heat vulnerability assessment for the Metropolitan region of Toulouse (FR)

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Title

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Degree: Master in Urban Climate & Sustainability

Based on key findings of the IPCC's Sixth Assessment Report (AR6), "It is virtually certain that hot extremes (including heatwaves) have become more frequent and more intense across most land regions". Within this context, better understanding the impact of urban heat has become increasingly relevant. This work aims at contributing to this research area by generating a urban heat vulnerability assessment combining environmental, socio-economic, and demographic data for the Metropolitan region of Toulouse (France). As part of its objectives, the study focuses on the potentials and limitations of composite indexes and heat vulnerability maps as operational tools for urban climate plans. Data collected from different sources (national mapping institute, national statistical institute, metropolitan authority open data repository, and urban weather station network) was employed to perfome a Cumulative Vulnerabilities Assessment (CVA), which assigns different levels of vulnerability to spatial units based on their values of Environmental, Socio-economic, and Susceptible Population scores. Results of the CVA were then crossed with other two heat vulnerability assessments' results obtained from the application of a Principal Component Analysis (PCA) and an Analytical Hyerarchic Process (AHP). The combination of the results from the three methodologies was used to produce a combined heat vulnerability map. Results obtained highlighted hostspots of urban heat related vulnerability in the metropolitan region of Toulouse. Furthermore, the study found that composite indexes can be an effective tool to spatially visualize cumulative vulnerabilities tendency over the metropolitan region; however, they are not sufficient to support decision makers and practitioners in defining what type of intervention would be more appropriate over a specific area. In addition, the study suggests that statistically obtained findings should be accompanied by qualitative field research to complement, better characterize, and describe heat vulnerability.

Keywords

Urban heat, Vulnerability Assessment, Urban Climate Mapping

Originality statement. I hereby declare that this Master's dissertation is my own original work, does not contain other people's work without this being stated, cited and referenced, has not been submitted elsewhere in fulfilment of the requirements of this or any other award.

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GLOSSARY, ACRONYMS AND NOTATION

Glossary

BD ALTI : Vectorial database produced by the French National Institute of Geographic and Forestal Information.

BD TOPO : Vectorial database produced by the French National Institute of Geographic and Forestal Information.

CES OSO : National scale French land use map in raster format (resolution 25 meters), produced annually employing Sentinel-2 satellite products.

Climate Change: “a change of climate which is attributed directly or indirectly to human activity that alters the composition of the global atmosphere and which is in addition to natural climate variability observed over comparable time periods” (IPCC, 2022).

Acronyms

CIEU: *Centre Interdisciplinaire d’Etudes Urbaines* – Center of Interdisciplinary Urban Studies.

CNRM: *Centre National de Recherches Météorologiques* – French National Center of Metereological Research.

GIS: Geographic Information System.

HV : Heat Vulnerability.

IGN: *Institut national de l'information géographique et forestière* - French National Institute of Geographic and Forestal Information. The IGN is a public institution that ensures the production and distribution of geographic information in France.

INSEE: *Institut National de la Statistique et des Etudes Economiques* - French National Institute of Statistics and Economic Studies.

IPCC: Intergovernmental Panel on Climate Change.

LISST: Laboratoire Interdisciplinaire Solidarités, Sociétés, Territoires - Interdisciplinary Solidarity, Societies, Territories Laboratory.

MApUCE : *Modélisation Appliquée et droit de l'Urbanisme: Climat urbain et Énergie* – Applied Modelization and Urbanism right : Urban Climate and Energy. MApUCE iss a research project developed in 2019 and led by a consortium of French research laboratories including CNRM and LISST.

PCAET - *Plan climat-air-énergie territorial* – Climat-Air-Energy territorial plan. The PCAET is a planning tool (mandatory at the metropolitan scale), both strategic and operational, which allows local authorities to tackle all the air-energy-climate issues in their territory.

UHI: Urban Heat Island.

Notation

$\sum$=sum
β= regression coefficient
μ= Sample mean

CHAPTER 1: INTRODUCTION

1.1 Rationale

During the summer of 1995, in the city of Chicago (IL), U.S.A., a heatwave hit the region leaving at least 700 deaths, most of which were declared as heat related (Semenza *et al.*, 1996). Similarly, the summer of 2003 marked a divide in the French and European perception of heatwaves, shifting from inconvenient anecdotic events to acknoledging the risks associated with these climate hazards (Poumadère *et al.*, 2005). The latest, which took place between August 4th and 18th 2003 left an incredibly high death toll accounting for 14,947 deaths registered in France only. Germany, Italy, Spain, The Netherlands, as well as other European countries also registered several heat-related deaths during the same heatwave. Later, in 2010, a similar event led to an estimate of 55,000 heatwave-related deaths in Russia (Shaposhnikov *et al.*, 2014).

According to the World Meteorological Organization (James Douris and Geunhye Kim, 2021), 93% of the natural disaster related deaths in the past 50 years in Europe were linked to extreme temperatures. In the top 10 disasters ranked by deaths, comprised between the period 1970-2019, all the events correspond to extreme temperatures. France has the highest reported number of deaths, linked to heatwaves occurred in 2003, 2006 and 2015 -excluding the European portion of the Russian Federation (Figure 1). Considering the magnitude of these events and the reported trend for the future it is increasingly important to contribute toward the identification of heat vulnerability as a key component in planning, implementing, and monitoring climate change mitigation and adaptations strategies in cities.

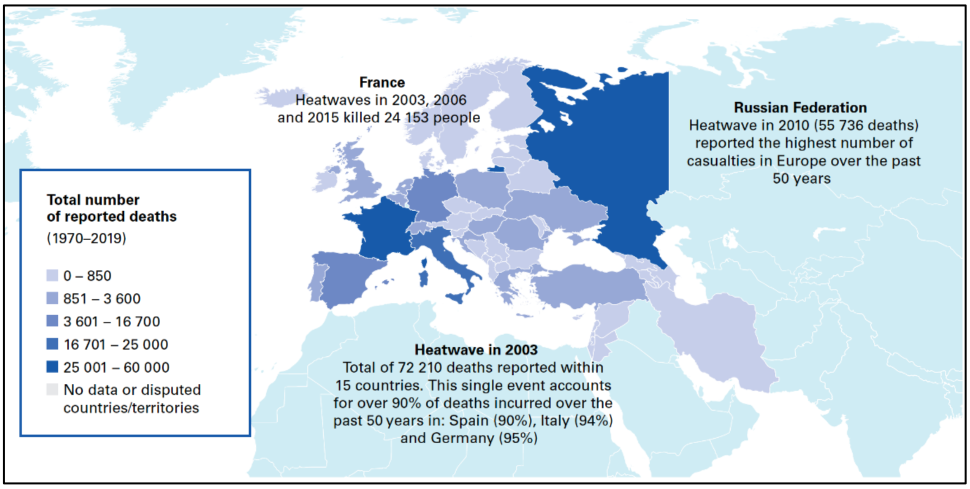


Figure 1. Reported disasters and their related deaths (1970-2019) (WMO, 2021).

Based on key findings of the IPCC's Sixth Assessment Report (2022), "It is virtually certain that hot extremes (including heatwaves) have become more frequent and more intense across most land regions". If the global warming trend observed continues to progress at the same rates, phenomena like the ones listed above are likely to increase frequency and intensity, incrementing potential population exposure. Due to the phenomenon known as "Urban Heat Island" (IPCC), population in urbanized areas are likely to experience higher temperatures compared to those in non-urbanized areas, and therefore be more exposed to heat stress. Furthermore, studies suggest that within the same city, environmental exposure, demographic and socioeconomic differences among urban population sectors can result in different levels of heat vulnerability. Some groups have been identified as being more heat vulnerable compared to others, such as elderly and very young, persons with disabilities and health conditions, persons with lower socioeconomic status, persons socially isolated and minorities, among others (Leal Filho *et al.*, 2018).

Spatially identifying urban heat-related vulnerability can support decision makers in taking informed decisions about where mitigation and adaptation strategies can be implemented, and/or where interventions should most effectively be deployed in case of emergency. Hence, a better understanding of urban heat related vulnerabilities can contribute toward the process of adapting cities to climate change. For instance, 'Toulouse Métropole', local authority responsible for the metropolitan region of Toulouse (FR), and its partners, have developed as part of their climate services, a network of meteorological stations that collect real time data across multiple locations. This research project, is linked with the efforts of the Toulouse Metropolitan authority to develop and improve its climate services. The study, expanding on the existing UHI mapping network developed in the last five years, crosses climate data from Toulouse's urban metereological network with other data related to environmental, social, economic, and demographic information, in order to assess and map urban heat vulnerability in the metropolitan region, and identify hotspots were mitigation and adaptation intervention could be most beneficial.

Within this broad context, this study was developed in the framework of an internship conducted at the 'Laboratoire Interdisciplinaire Solidarités, Sociétés, Territoires' (LISST) at the 'Université Toulouse Jean Jaures' in France (https://lisst.univ tlse2.fr). The work, which lays under the wide Urban Climate thematic, was developed within the team of the 'Centre Interdisciplinaire d'Etudes Urbaines' (CIEU), under the guidance of Julia Hidalgo –senior researcher focused on urban climatology, climate change adaptation and mitigation in urban environments and operational urbanism –and co-guided by Guillaume Dumas –researcher engineer of the 'Centre National de Recherche Météorologiques' (CNRM) and link with the metropolitan local authority 'Toulouse Métropole'. Furthermore, this study was developed in paralel with the LISST internship of Thomas Lagelouze – at the time, master student of the 'Université Grenoble Alpes'– and constitutes a synergic and complementary piece of work further expanding on a common research interest area.

1.2 Aims and Objectives

The aim of this thesis' project is to contribute towards heat vulnerability assessing and mapping in the metropolitan region of Toulouse -France, by integrating urban heat maps with environmental, demographic and socio-economic data.

The following objectives will contribute toward the aim of this research:

- Identification and review of existing literature in the field of heat vulnerability analysis and visualization.
- Recognition of the environmental, geographic, socioeconomic, and demographic data available for the study area.
- Construction of a multi-criteria heat vulnerability assessment based on state-of-the-art heat vulnerability research, available data, and specificities of the study area.
- Production of heat vulnerability maps for the metropolitan area of Toulouse at the finest scale available (commonly understood by urban stakeholders and easily adaptable to other scales) that could be integrated into the authority's climate plan *Plan climat-air-énergie territorial* (PCAET).

1.3 Outline

This work focuses on generating a urban heat vulnerability assessment combining different environmental, socio-economic and demographic variables with the objective of producing a heat vulnerability map for the metropolitan area of Toulouse. Raw variables were collected from different sources and treated according to methodological requirements to compose a single combined dataset. Variables were used to conduct a heat vulnerability assessment through the methodology known as Cumulative Vulnerabilities Assessment (CVA), which assigns different levels of vulnerabilities to spatial units based on their values of Environmental, Socioeconomic and Susceptible Population scores.

In order to analyse and compare different methodologies, results of the CVA, were crossed with other two heat vulnerability assessments (available at the same scale and comprising the same geographical limits) obtained from the application of a Principal Component Analysis (PCA) and an Analytical Hyerarchic Process (AHP). The combination of the results obtained from the three methodologies was then used to produce a combined heat vulnerabilities map in which spatial units have been assigned different confidence levels based on classification consistency across the three methodologies. Different softwares were used in the process, such as ArcGIS Pro, QGIS Desktop 3.22.6, Excel, IBM SPSS Statistics and Photoshop, among others.

The second chapter (pg.17) of this thesis focuses on the state of the art of urban heat vulnerability research, providing an overview on existing definitions, approaches and methodologies adopted at international level. The third section (pg.31) describes the methodology outlined above in detail. The fourth one (pg.49) focuses on the results obtained while the fifth one (pg.61) is centered around the discussion of the results. The final section contains the conclusions, limitations and recommendations for future works.

CHAPTER 2: LITERATURE REVIEW

2.1 Heat vulnerability

While the notion of vulnerability has been nowadays considered in different studies and among different fields, its origins can be largely connected to the field of social sciences and to the notion of social vulnerability. Among diverse definitions, this concept has been explained as a way to measure population resilience to environmental hazards (*Cutter, Boruff and Shirley, 2003*). Within this field, vulnerability is defined as the result of inequalities as factors that define a group or individuals proneness to be impacted by hazard, and as a function of their capacity response and conditions in their environments. This notion of vulnerability has been expanded to other fields. Influences can be found in the basis of heat vulnerability (HV) studies which emerged in medical related research areas such as epidemiology and public health. Such studies have aimed at laying the basis to understand how characteristics of individuals or population groups are associated with the negative impacts of extreme heat exposure on human health (Conlon *et al., 2020*).

Following the definition adopted by Wilhelmi and Hayden (2010) and (Thomas *et al.*, 2019), vulnerability -and HV in particular- can be understood as a function of three components:

1. **Exposure** is influenced by the urban distribution of heat which depends on local meteorological condition and urban climate in combination with urban morphology and land use. Exposure indicators are associated with quantitative environmental data collected or modelled in different ways. Remote sensed imagery (Land Surface Temperature), atmospheric temperature collected through weather stations (urban weather station networks), as well as data collected through loggers installed in buildings or carried across different areas of the city either on foot, bikes, or cars.
2. **Sensitivity** is influenced by diverse factors that are not only connected to the proximity or duration of exposure but are rather a combined effect of socioeconomic and cultural aspects in relation to biological characteristics. For instance, sensitivity can be impacted by health conditions (e.g., cardiovascular diseases) as well as social isolation (e.g., individuals leaving alone), or work conditions (e.g., individual working outdoors).

3. Finally **adaptive capacity** can be understood as the actions that community or individuals can put in place to adapt and cope with hazard's exposure. This needs to be considered at different scales, at community level (e.g., local government emergency response, cooling shelters) but also at household or individual level (e.g., access to AC, awareness, and adoption of protective strategies -showers, light clothes, hydration).

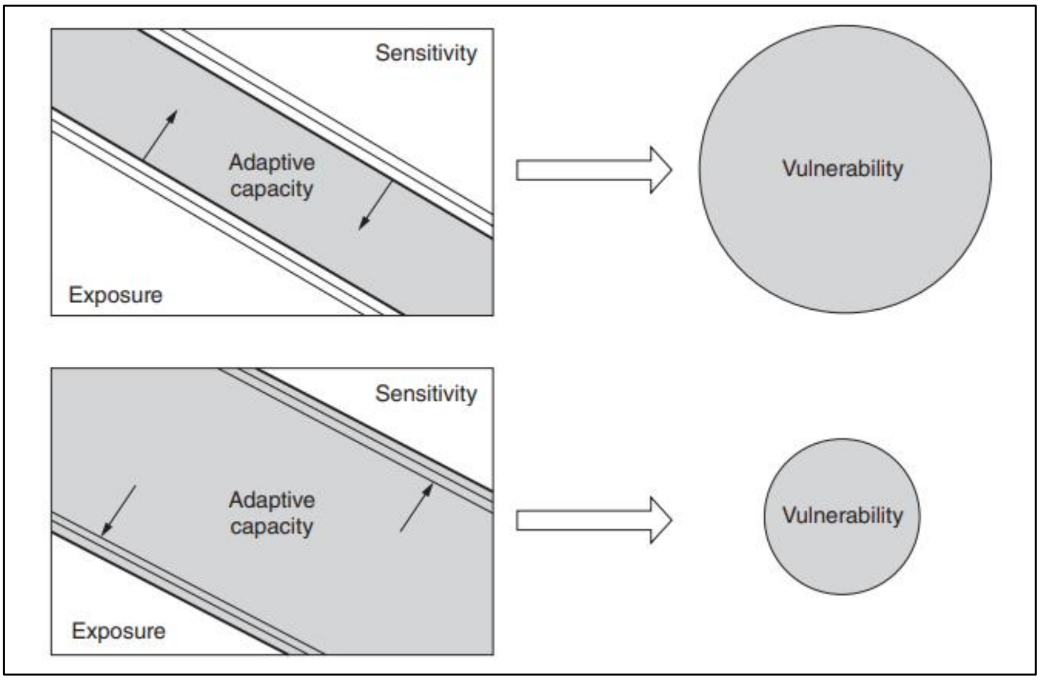


Figure 1. Representation of Vulnerability as a function of Exposure, Sensitivity and Adaptive capacity (Thomas et al., 2019)

While it is not within the scope of this study to explore the different interpretations of vulnerability available in existing literature nor to provide a new definition; it is important for the purpose of clarity to state that vulnerability within this study is understood as social vulnerability of individuals in relation to heat exposure. According to the 'risk geography' approach provided by (Pigeon, 2002), risk can be understood as: "the probability of occurrence of damage taking into account the interactions between physically damaging processes (hazards) and settlement factors (vulnerability)". Within this interpretation, vulnerability is no longer considered as a passive indicator, but it is rather approached as a factor that actively and unequally contributes to the potential damage. Based on this interpretation, vulnerability stems from those settlement conditions influenced by physical, social, economic, cultural, and institutional factors embedded in the urban environment (Figure 2). Hence, for the purpose of this study, vulnerability is approached with the aid of socioeconomic and demographic individual's descriptors that have been identified as positively or negatively influencing the proneness of individuals to incur in damage in relation to their exposure to heat.

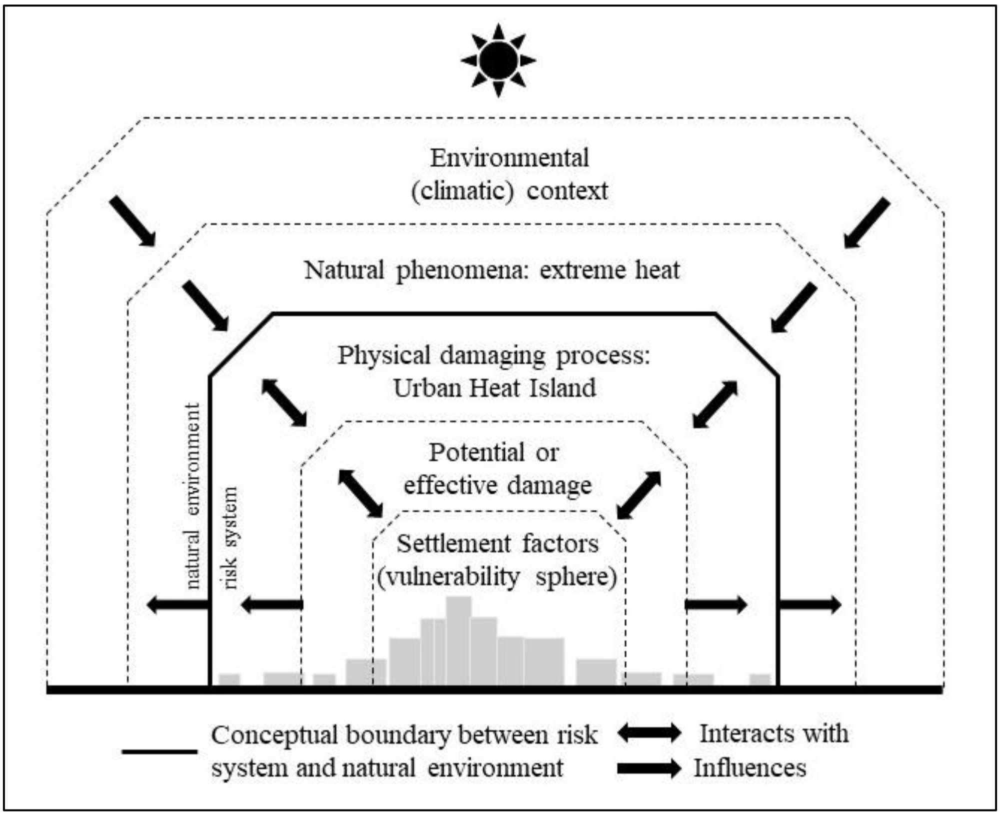


Figure 2. Risk system and natural environment. Extracted, translated, and adapted from Pigeon, 2002. The scheme contains inputs provided by Lagelouze and Hidalgo heat vulnerability scheme contained in Lagelouze (2022)

2.2 Heat vulnerability studies

Several of the initial studies conducted in the field of heat vulnerability belong to the field of epidemiology and public health; these aim at the identification of factors influencing heat related morbidity and mortality within a specific geographic domain. Furthermore, these studies are usually associated with a temporal component related to the manifestation of extreme weather, normally in concomitance with the manifestation of what is referred to as 'heatwaves' (Semenza *et al.*, 1996; Naughton, 2002; Vandentorren *et al.*, 2006). During heatwaves, individuals are likely to be more exposed to heat stress for prolonged period of times. The prolonged exposure, which usually continues overnight, hinders the body capacity to properly recover by limiting biological thermoregulatory mechanisms; this might result in a potentially dangerous increased body temperature (Koppe *et al.*, 2004).

A common approach used within public health studies is related to comparing data from recorded heatwaves periods with data in which such events didn't happen, with the purpose of identifying factors that might have led to increased deaths. Given the research focus, a recurrent methodological approach consists in the identification of subjects declared dead during heatwaves that are then matched with controls pairs living in the same area, having the same sex and ideally the same age or close to it (Semenza *et al.*, 1996; Naughton, 2002; Vandentorren *et al.*, 2006). Studies following this approach have been conducted in cities such as Chicago (USA) -(Semenza *et al.*, 1996; Naughton, 2002)-, Adelaide, Australia - (Zhang *et al.*, 2016) , Modena, Italy – (Foroni *et al.*, 2007), and across different regions in France –(Vandentorren *et al.*, 2006)-. These studies have utilized data that can be reconducted to main categories comprising demographic (e.g., age, sex, place of residence), medical (e.g., pre-existing health conditions, bed confinement), housing (e.g., n. of rooms and bathrooms, floor, insulation), and behavioural (e.g., living alone, going out of house) factors. Some studies also included information related to awareness and protective measures adopted to react to extreme heat exposure and considered information such as frequency of room ventilation and showering or dressing habits during extreme heat's exposure periods.

These studies have been useful in recognizing groups and subjects at risk by identifying common characteristics among persons impacted by heat exposure. For instance, multiple studies agree on the fact that persons with cardiovascular-respiratory-kidney disease, those with reduce mobility, the very young or those of older age, have higher risks of being impacted by heat. Furthermore, associations between increased risks to heat exposure and the use of antipsychotics and antidepressants or other medicines that impact thermoregulation and can cause dehydration have been discovered (Nordon *et al*., 2009; Westaway *et al.*, 2015). Other associations identified in clinical studies suggest that patients with psychological disorders and metal disabilities are at higher risk of death (Naughton, 2002; Vandentorren *et al.*, 2006) and admissions into emergency rooms during manifestations of extreme heat (Trang *et al.*, 2016; Yoo *et al.*, 2021). Other findings suggest that alcohol and drug users in situation of dependency might be at higher risk due to the effect of such substances on the body; but also due to the impact of heat exposure on the users' capacity to secure substances (Cusack, de Crespigny and Athanasos, 2011). These negative effects can also be exacerbated for those users living in precarious environments, either in shelters or in the streets.

While studies on HV approached from the medical perspective have contributed to the identification of factors impacting morbimortality, their approach present some limitations. Firstly, arguments have been raised about what is known as mortality displacement/harvesting which might influence the classification of heat related death and for which not all studies account (Basu, 2009). Additionally, many of the studies are just limited to studying the effects of heatwaves of specific durations rather than long-term, seasonal, or recurrent exposure. Often exposure is considered only based on regional temperature averages or local data collected from weather stations outside the city. These approaches might miss important data related to the unequal heat distribution at urban scale, the differences of temperature during day and night-time, among other specificities typical of local urban climates. Furthermore, another important gap in these studies, is related to the lack, or just partial incorporation of parameters helpful to assess vulnerability from a socio-economic standpoint.

The incorporation of socio-economic components in HV studies led to an evolution in the approaches used to assess and map vulnerability. For instance, some studies (Harlan *et al.*, 2006; Reid *et al.*, 2009; Johnson *et al.*, 2012) brought to the research community attention the importance of considering social vulnerability components while assessing HV. Furthermore, these studies suggested the importance of focusing on local scale assessments, as an unequal distribution of vulnerability was observed not only between cities, but also between neighbourhoods. To respond to the need of focusing on a local scale, such studies identified the importance of considering the complexity of the built environment and its relationship with local climate. The focus on Urban Heat Island (UHI)-understood as the differences in temperature between the city and its rural surroundings (Oke in Cermak *et al.*, 1995), and the importance of considering the spatial distribution of heat at urban level was introduced into HV studies. This resulted in an increased attention towards the inclusion of environmental data able to describe the thermal environment in detail and at a very small spatial scale - neighbourhood or even block scale (Huang, Zhou and Cadenasso, 2011; Johnson *et al.*, 2012).

With the concomitant introduction of socioeconomic variables and urban climatology, it became evident that heat vulnerability is a complex topic requiring the integration of diverse information and disciplinary approaches.

2.3 HV determinant factors and variables

Several HV studies have been developed based on the integration of multiple criteria. A common approach is based on the development of composite indexes -Heat Vulnerability Indexes (HVIs)- that often considers environmental, demographic, medical and socioeconomic variables. Such variables are frequently selected based on parameters suggested by extensive literature reviews (Leal Filho *et al.*, 2018) or based on their fit with an adopted vulnerability framework (Inostroza, Palme and de la Barrera, 2016). Weighting and aggregations are either done following the advice of experts and local specialists (Räsänen *et al.*, 2019), utilizing statistical methods (Wong *et al.*, 2016) or combining both approaches (Alonso and Renard, 2020). Some researchers assume that all variables contribute equally to vulnerability, hence, to all factors is assigned equal weight (Chow, Chuang and Gober, 2012), some opts for an equal weight distribution between biophysical and socioeconomic parameters (50%-50%) regardless of the number of variables selected (Ho, Knudby and Huang, 2015), while others assign a heavier weight to environmental (75%) and less to socioeconomic (25%) variables like (Mushore *et al.*, 2018). The summary in Table 1 provides an overview on different approaches and parameters used in the field of HV, utilizing both HVI and non HVI related methods.

Table 1.Examples of variables and methodologies that have been used in different heat vulnerability studies

Spatial unit	Variables	Method	Field -study - location -time
City limits of Chicago -based on distribution of death during the target period of the study	**Environmental: -** **Medical:** Cause of death **Demographic-Socioeconomic**: Access to cooling shelter, Lived alone, **Housing:** AC in lobby, AC in home, Lived on top floor, Type of residence (single family -apartment building), Number of rooms	Case control study	**Public health** **Semenza *et al*. 1996 -** Chicago city (city scale) - July 12 through July 16, 1995
City limits of Chicago -based on distribution of death during the target period of the study	**Environmental: -** **Medical**: Cause of death, Confined to bed (yes/no), Able to care for self (yes/no), Amount of alcohol consumed, Current smoker (yes/no), History of condition(and whether medication taken): Asthma, Other lung disease, Heart disease, Liver disease, High blood pressure, Trouble sleeping, Depression, Mental problems, Cancer, Kidney disease, **Demographic-Socioeconomic:** Gender, Race, Ethnicity, Height and weight, Employment status, Ability to speak and read English, Length of residence in Chicago, Length of residence in current home, Number of persons living in home, How often left home in average week, Pet in home (yes/no), Income, Knowledge about and response to heat-wave dangers, Number of group activities per week, Number of social services per week **Housing**: Number and type of fans, Number and type of air conditioners, Whether windows ever opened (yes/no), Number of floors in building, Floor resided upon	Case control study	**Public health** **Naughton *et al*. 2002** - Chicago (city scale) 29 July through August 6, 1999
Eight neighbourhoods in the Phoenix-Mesa Metropolitan area	**Environmental**: Distance from the central city, Population settlement density, Amount of open space, Vegetation density **Medical:-** **Demographic-Socioeconomic:** Median income (US dollars), Poverty rate (percent of population below the US government federal poverty guideline), Educational attainment (percent with less than a high school diploma), Ethnicity (percent Hispanic and Native-, African-, and Asian-American), Age (median, ages 5 and under, or ages 65 and older). (Adaptive capacity) Community network (questionnaire regarding social ties), **Housing :**Quality of houses (cooling system, swimming pool, reflectivity of roof)	Human Thermal Comfort Index Associations between neighbourhood HTCI and other variables tested using one-way ANOVAs and Pearson correlations	**Integrated approach** **Harlan *et al* 2006** - Phoenix-Mesa Metropolitan area - June 1 through August 31, 2003
Case studies and control pairs residences selected across n.3 2003 heatwave impacted locations in France Census unit used as area of influence to select controls	**Environmental:** LST average 200mts radius from place of residency, Vegetation Index calculated 200mts radius from place of residency **Medical:** Cause of death (heat related / cardiovascular / both), Mental disorder or Neurological disease , Cardiovascular disease, Liver, Kidney /Respiratory disease, High blood pressure - Obesity, Able to move -Bed confined **Demographic-Socioeconomic:** Visited other air-conditioned places, Lived alone, Used light clothes or implemented other preventive measures like taking more showers **Housing**: Lived on the top floor, Had A/Insulation in building and age of building, Number of rooms -bathrooms, Number of windows per 50m2	Case control study / Multivariate regression model	**Public health** **Vandentorren *et al*. 2006** - France (national scale /region most impacted HW) - August 8 and 13 of 2003

Spatial unit	Variables	Method	Field -study - location -time
Canton scale (French administrative division unit)	**Environmental:** Average temperature and cantons' cut-off temperature, Ozone concentration levels **Medical**: - **Demographic-Socioeconomic:** Median household income (-), percentage high school graduates in the population aged 15 years and older (-), percentage blue collar workers in the active population (+), unemployment rate (+) **Housing: -**	Heat exposure index/ FDep99 deprivation index (Principal components analysis)	**Public health** **Rey *et al*. 2009** - France (national scale) - 3rd to 15th August 2003
U.S. Census tract unit (2000)	**Environmental:** Percent census tract area not covered in vegetation **Medical:** Percent population ever diagnosed with diabetes **Demographic-Socioeconomic:** Percent population below the poverty line, Percent population with less than a high school diploma , Percent population of a race other than white , Percent population living alone , Percent population ≥ 65 years of age , Percent population ≥ 65 of age living alone **Housing:** Percent households without central AC, Percent households without any AC	Vulnerability Index Spearman's correlation coefficients / Principal Components Analysis	**Integrated approach** **Reid *et al*. 2009** -USA national scale - Census data from 2000 Land use from 2001 Health data 2002 AC 2002
Block group -U.S. census-based unit	**Environmental:** LST mean by block group **Medical: -** **Demographic-Socioeconomic:** median household income, percentage of households under the federal poverty level, percentage of people having a bachelor's degree, percentage of people receiving less than 9 years of education, percentage of White people, percentage of people older than 65, percentage of people that live alone, total crime **Housing: -**	Correlation analysis between LST and social variables	**Integrated approach** **Huang *et al*. 2011** - Baltimore (Gwynn's Falls -includes urban, suburban and rural areas) - 1999/2000 data
U.S. Census tract unit	**Environmental:** Mean summer max T from June 1990-1994 and 2000-2004 Mean summer min T from June 1990-1994 and 2000-2004 Mean normalized differential vegetation index (NDVI) **Medical: -** **Demographic-Socioeconomic:** Population over 65, Median household income, Population of foreign-born noncitizens, Population living in different residences from 5 years prior **Housing:**	HVI -defined as the linear sum of all seven normalized vulnerability measures of equal weight	**Integrated approach** **Chow *et al*. 2011** - Metropolitan Phoenix - I990-2000
U.S. Census tract unit	**Environmental:** Land surface temperature, Normalized difference built-up index , Normalized difference vegetation index **Medical: -** **Demographic-Socioeconomic**: Females age 65 and up , Males age 65 and up , Females age 65 and up living alone , White population , Black population, Females head of household ,Males age 65 and up living alone ,Mean family income in 1989 , Per capita income in 1989 , Mean household income in 1989 , Population 25 and older with less than high school education, Asian population, Population age 65 and older in group living , Other race population ,Hispanic population, Population 25 and older with a high school education, **Housing:-**	HVI (Extreme heat vulnerability index - EHVI) Principal component analysis	**Integrated approach** **Johnson *et al*. 2012** - Chicago – 1995
National Statistics Chilean Institute (INE) census tract	**Environmental:** Land Surface Temperature (LST)**;** Normalized Difference Vegetation Index (NDVI) values **Medical:** (for adaptive capacity) access to medical services, distance from the centroid of a census tract built up area to the nearest health care centre	Vulnerability index / Principal Component Analysis	**Integrated approach** **Inostroza *et al*. 2016** - Santiago de Chile - 2002 to 2010

Spatial unit	Variables	Method	Field -study - location -time
	Demographic-Socioeconomic: (for sensitivity) total number of people of 65 years of age or older, total number of people of five years of age or younger, disabled population - sum of six census categories: i) only blindness, ii) only deafness, iii) only muteness, iv) paralysis, v) mental illness and v) multiple physical disabilities, number of those who live alone: i) single, ii) widowed, iii) divorced and iv) separated. Education- last level of formal education completed but including only the four lowest levels: i) never attended, ii) pre-elementary, iii) special differential and iv) basic/elementary. Unemployment: i) working for a family without monetary payment, ii) looking for a first job, iii) student and iv) permanently unable to work. **Housing: (for adaptive capacity)** communication - based on four categoriespertaining to i) Internet, ii) mobile phone, iii) telephone and iv) computer access. no water supply- as the number of households without running water. materials variable- as the total number of households that use light materials per census tract, based on i) wood lined septum, ii) cement with fibrous materials (a light construction material commonly used in Chile), and iii) waste (tin, cardboard, plastic, etc.)		
France census tract (IRIS)	**Environmental: -** **For physiological index (8 variables):** **Demographic-Socioeconomic:** Children under 5 years old (+), Person aged 6 to 44 years old (-), Person aged 45 to 74 years old Decrease (+), Person 75 years old or older Increase (+), Sex for 45–74 years old The greater the number of women, the more vulnerable they are(+), Sex for over 75 years old The greater the number of women the more vulnerable they are(+), **Medical:** Person affected by chronic or acute pathology (+), Person with psychiatric disorders (+) **For socioeconomic index (40 variables):** **Demographic-Socioeconomic:** Ratio of the number of births domiciled at the mother's home, Average age of the population , % of the population between the ages of 18 and 64 , % of population under 5 years old , % of population over 65 years old ,Ratio of females to males, % of female population , number of employed persons with low-skilled jobs between 15–64 years old , Poverty rate of the entire population , Average age of principal residences over the period 1900 to 2009, , % of apartment type principal residents built between 1990 and 2009 , % population living in low-rent housing , % population in main residence occupied free of charge, % of precarious housing, % of employed women between 15–64 years old , % of employment in the population between 15 and 64 years old , % of the employed population between 15–64 years old working in farming , Unemployment rate of the employed population between 15 and 64 years old , Unemployment rate of employed women between 15 and 64 years old, % employed population with low-skilled jobs , % of retired people in 2012 , % out-of-school population over 15 with no higher education qualification , % population over 15 years out of school with no certificate or diploma, % out-of-school population over 15 years old with long-term education at tertiary institutions , % out-of-school population over 15 years old with higher education , Average annual salary in euros , Number of people receiving adult disabled benefit (ADB) per inhabitant , Median household income in euros, Proportion of social housing (%) **Medical:** Mortality rate (all causes) per 1000 inhabitants , Number of premature deaths from all causes (before the 65 years old) per capita , Number of new long-term care (LTC) admissions per capita, Number of medical professions in 2014 per capita , Number of health institutions of all types (private or public), Number of hospital places (short or long hospitalization) per 1000 inhabitants , % of people suffering from psychiatric disorders (Full-time inpatient active file) in 2012 , Number of psychiatric hospital places per 1000 inhabitants, Number of people on psychotropic treatment per capita, Number of care places per 1000 inhabitants, Length in kilometres from a hospital by isochrones **Housing: -**	For physiological index**:** Analytic Hierarchy Process (experts' panel - prioritization by binary comparison) For socio- economic index: Principal Component Analysis with Varimax rotation	**Public health** **Alonso & Florent Renard 2020** - Great Lyon Area - Data 2012 & 2019

As observed from the literature reviewed, variables utilized to assess vulnerability vary from study to study. It is however possible to recognize recurrent categories used to select HV related parameters:

- **Environmental**, related to data referring to temperatures, land use and vegetation presence. Recurrent approaches see the usage of Land Surface Temperature (LST), regional temperature averages, Normalized Difference Vegetation Indexes (NDVIs), Land Use and Surface cover, among others.
- **Medical** data which is associated with causes of death, pre-existing pathologies, medications, or treatments, which is either retrieved from local medical statistics or using qualitative surveys often conducted with the support of public and private health practitioners.
- **Demographic/Socio-economic** data related to age, sex, education, employment, migratory status, race, income, among other factors. This data is usually extrapolated from the national census. Although information might also be collected from regional or city scale databases.
- **Housing** data which refers to information related to the houses-buildings were people live, date of construction, number of floors, materials, among others. This information is extracted from local authorities' databases, but it might also be collected through field observations and qualitative surveys.

While the spatial scale of analysis also varies among the studies, the most common recurrent spatial unit in the literature reviewed correspond to the census tracts of the different national census. Some studies move from this scale to larger spatial units usually corresponding to some administrative division, neighbourhood, canton, department, region, and so on.

2.4 HV dimensional approaches

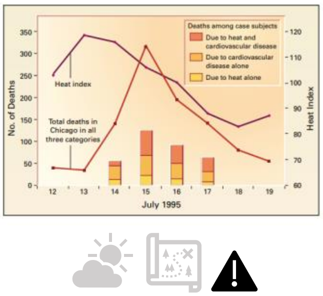
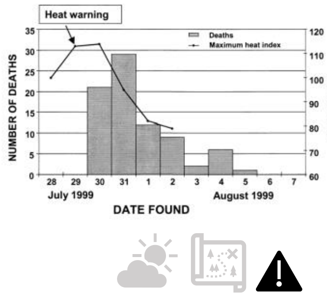
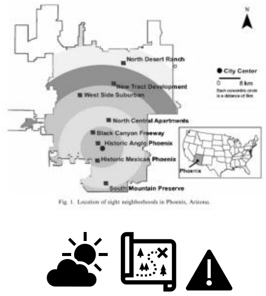
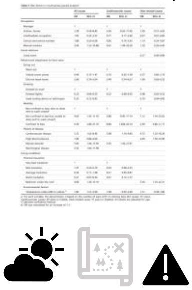
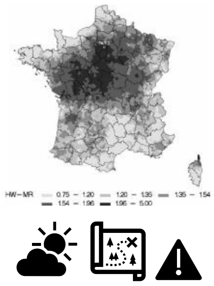
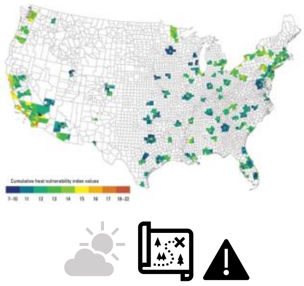
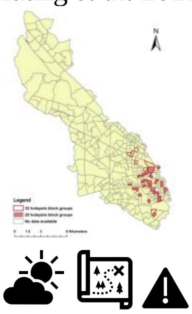
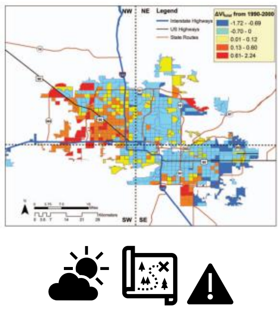
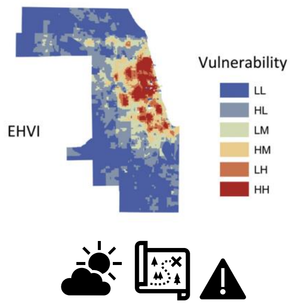
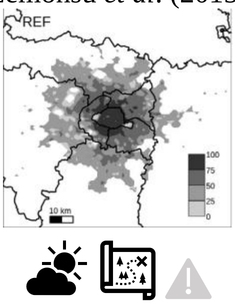
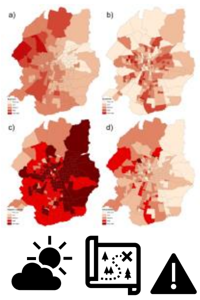
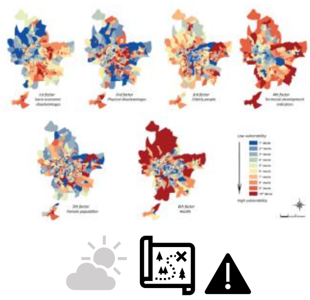
In addition to the determinant factors and variables employed to approach HV in previous studies, it is also possible to identify the dimension through which HV has been approached in the past (Table 2.). From the studies, three main relevant dimensions can be extrapolated:

1. The climatic dimension: which correspond to the characterization of the exposure component, employed to approach the climatic event/context and determining the link between vulnerability and potential damage.

2. The spatial dimension: which allows to spatially situate vulnerability enabling to locate, compare and account for those site-specific components spatially influencing vulnerability.
3. The social dimension: which comprises those aspects of HV influenced by socio-economic determinants with which significant bonds with vulnerability have been identified.

As it can be observed, in some studies heat vulnerability has only been approached through a single dimension or at the intersection of two. It is however within the corpus of works aiming at approaching HV at the intersection of the three dimensions, climatic, spatial, and social that this study positions itself.

Table 2.Dimensions employed to approach heat vulnerability in existing studies

Studies' references, graphic representations, and dimensions		
Semenza *et al.*, 1996 	Naughton *et al.*, 2002 	Harlan *et al.*, 2006 
Vandentorren *et al.*, 2006 	Rey *et al.*, 2009 	Huang *et al.*, 2011 
Huang *et al.* 2011 	Chow *et al.* 2011 	Johnson *et al.* 2012 
Lemonsu *et al.* (2015) 	Inostroza *et al.* 2016 	Alonso & Florent Renard 2020 
1.Climatic dimension 	2. Spatial dimension 	3.Social dimension 

The table summarizes the approach taken by different international studies regarding the three main dimensions identified to approach heat vulnerability, notably the climatic, spatial, and social dimensions. Dimensions here have been represented through synthetic symbols for simplification purposes, however it must be noticed that the way each study approaches the dimensions can differ from case to case.

2.5 HVIs potentialities, limitations, and operational applications

While the potentialities of HVIs as tool to inform heat related interventions to protect people have been recognized (Bao, Li and Yu, 2015), defining, characterizing, measuring, and mapping vulnerability remains challenging. Even though studies dealing with HV have evolved in the last decade, there isn't, up to date, a consistent, agreed upon and robust methodology to construct HVIs (Karanja and Kiage, 2021). Albeit the facility with which HVIs can be relatively easily implemented in diverse contexts, Conlon et al. (2020) have identified how Principal Component Analysis (PCA) –the most commonly used methodology— derived HVIs are influenced by inputs data and mapping methods and how small differences in inputs parameters can lead to completely different results identifying different vulnerability hotspots depending on the researchers' choices. Hence, the importance of approaching HV in a context-specific way that is aware of the limits of the proposed methodologies. Furthermore, while identifying HVIs methodological gaps is fundamental, it is also important to acknowledge that the final selection of variables and methods is also eventually bounded by the type of data available in each specific study area (Inostroza, Palme and de la Barrera, 2016).

For instance, the study conducted by Alonso and Renard (2020) for the metropolitan area of Lyon (France), moved from a unified HVI to a multi-methodological approach that aims toward mapping physiological and socioeconomic vulnerability to heat as two different co-contributing components. Physiological vulnerability was assessed through an Analytic Hierarchy Process, composing an index based on weights assigned to variables by a panel of experts (doctors, nurses, and pharmacists) employing binary comparison. Socio-economic vulnerability was represented through factors extracted from a PCA: socio-economic disadvantages, physical disadvantages, elderly people, territorial development indicators, female population, and health. Each factor was then spatially represented to identify hotspots within the metropolitan region. One of the limitations of the study identified by the authors, is that the vulnerability analysis didn't took into consideration exposure (climatic dimension). Their advice suggests to further build on this approach by crossing the information obtained with urban climatic data as a step to further explore HV.

Recognizing and mapping different vulnerability factors following the multi method approach suggested by Alonso and Renard (2020) can be useful to support local authorities in deploying tailored resources according to the different types of vulnerability. This approach allows an enhanced descriptive spatial visualization of vulnerability in comparison to unified HVI that aggregates all vulnerability factors, some authors claim (Mallen, Stone and Lanza, 2019; Conlon *et al*.2020). While not widely diffused, variations of HVIs have been already adopted by some local authorities -mainly in Europe and USA- who have incorporated HVIs and HV maps into their tools and operational documents tackling climate change adaptation and mitigation. Similarly to the corpus of scientific literature, the approaches and methodologies employed by local authorities and their operational applications, vary largely.

Among the cities that have already adopted HVIs and HV maps: the city of Milan introduced HV maps into their '2020 Air and Climate Plan'; Barcelona introduced a heat vulnerability index map in their 'Climate Plan 2018-2030'; Sevilla utilized HV maps in their '2017 Climate and Sustainable Energies' action plan; Vitoria-Gasteiz produced HV maps based on different climate scenarios within their 'Climate Change Adaptation Action Plan 2021-2030'; New York City incorporated an HVI developed by Madrigano *et al.* (2015) in their 2017- 'Cool Neighborhoods NYC' – a document that identifies the heat adaptation and mitigation strategies for the city; Philadelphia has developed an HVI that is accessible online, which has been used to inform their '2021 Climate Action Playbook', guide community heat relief plans ('Beat the Heat Hunting Park' -2019) and provide citizens with an open resource they can consult to know if they live in a vulnerable area of the city and what resources to cope with extreme heat are available to them in terms of community assets, like cooling shelters, pools and health facilities. In the latter case, HVI and HV maps works both as analytical tool to inform policy/decision makers and as communication/information tool for the community.

For this research, exiting literature suggested the need of working at the finest scale available (Pag.21), incorporating the urban heat exposure component (Pag.29) and crossing it with different data (2.3 HV determinant factors and variables). Hence, it is within this context that the study worked at the smallest available scale in France, incorporating UHI intensity data and crossing it with other environmental, demographic, and socioeconomic data.
In the following chapter the study area of the metropolitan region of Toulouse will be presented in more detail. Furthermore, the chapter will expand on the methodological choices employed to approach heat vulnerability in this study, based on the heat vulnerability theoretical approach set in this chapter and the state of the art presented, over which this study aims to further build.

CHAPTER 3: METHODOLOGY

3.1 Study area -Metropolitan region of Toulouse, France

The study area selected for this project is the Metropolitan region of Toulouse, located in the south-west of France (Figure 3). Toulouse is the capital of the *Occitanie* region, its metropolitan area has an extension of 458.2 km^2, this area comprises 37 *communes* (French administrative division analogue to the terms councils or townships used in other countries) and a population of approximately 800,000 persons according to the 2019 census (Insee, 2022). Toulouse is the fourth largest city in France following Paris, Marseille and Lyon; however due to its extension it is also one of the least densely populated with approximately 1738 hab/ km^2; Paris in comparison has around 8 690 hab./ km^2. The region is crossed by the *Garonne* river; the altitude ranges between a minimum of 102m and a maximum of 273m above sea level. The metropolitan region is inscribed in an area exposed to three different types of temperate climates, notably and oceanic climate with influences of Mediterranean and continental climates.

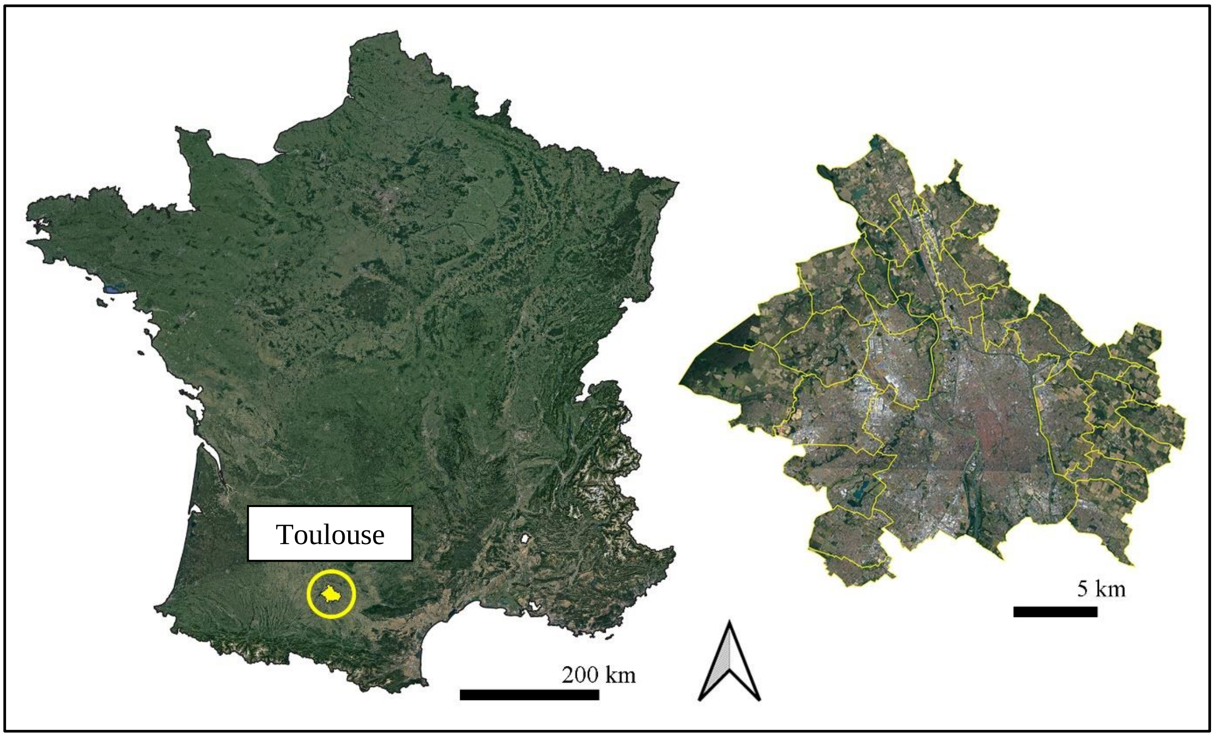


Figure 3.Study area – France –left– and Toulouse metropolitan region contours (including Toulouse's 37 communes) –right–. Base map source: Esri, DigitalGlobe, GeoEye, i-cubed, USDA FSA, USGS, AEX, Getmapping, Aerogrid, IGN, IGP, swisstopo, and the GIS User Community

Toulouse, as other cities, is prone to the phenomena know as Urban Heat Island (UHI), presenting higher temperatures in highly urbanized areas in comparison to the less urbanized rural surroundings. During the days that present favourable conditions in summer, temperatures can reach up to 40 ˚C with winds varying from 2 m.s^{-1} in the morning and evening to 4 m.s^{-1} in the middle of the day– the nocturnal UHI intensity can reach an average of 4 ˚C and peaks of 6 ˚C. The map in Figure 4 shows the typical UHI distribution on a day classified as Local Weather Type 9 (Sunny day, very hot in summer, with north-westerly wind) – according to the classification proposed by (Hidalgo and Jougla, 2018) in which the UHI phenomena is more intense.

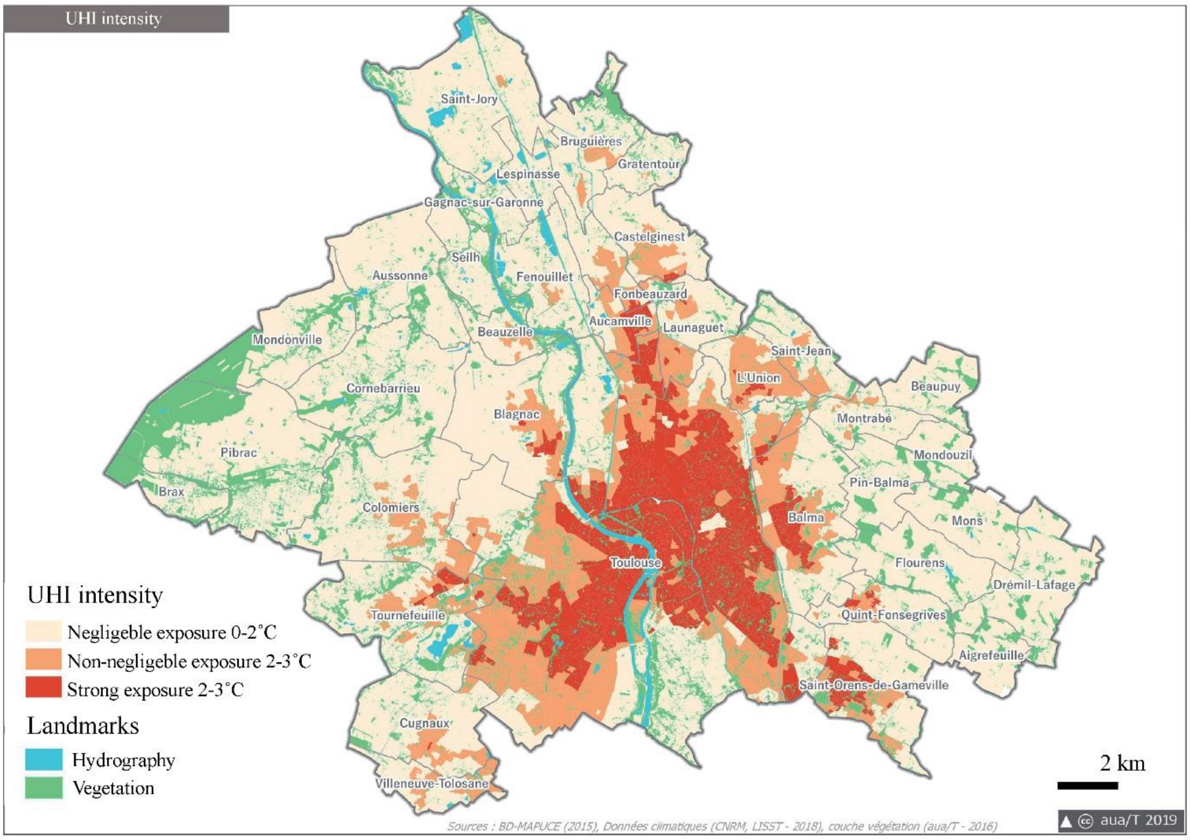


Figure 4.UHI intensity map extracted and translated from the Climatic Atlas of the Metropolitan Toulouse perimeter (Atlas climatique sur le périmètre de Toulouse Métropole) - (aua/T, 2019)

3.2 Heat vulnerability assessment

This study employs the methodology known as Cumulative Vulnerability Assessment (CVA) to assess individuals' heat vulnerability in the urban environment. The methodology is derived from the '*Cumulative Risk Assessment Framework*' developed by the U.S. Environmental Protection Agency (EPA) in 2003. The CVA version employed in this study was adapted to the French context by (Lanier *et al.*, 2019) to analyse environmental inequalities caused by multiple air pollutants exposure in two cities in the north of France. The objective of the methodology is to assess cumulative vulnerability to environmental exposure factors (adapted in this case to urban heat) considering socio-economic and demographic inequality determinants. The methodology allows to characterize and prioritize geographical units based on a cumulative vulnerability score enabling the visualisation of the areas with the highest levels of cumulative vulnerability. The cumulative vulnerability score is obtained through a tri-dimensional matrix composed of an Environmental score (S *env*), a Susceptible Population score (S *pop*) and a Socio-economic deprivation score (S *pop*) - (Figure 5).

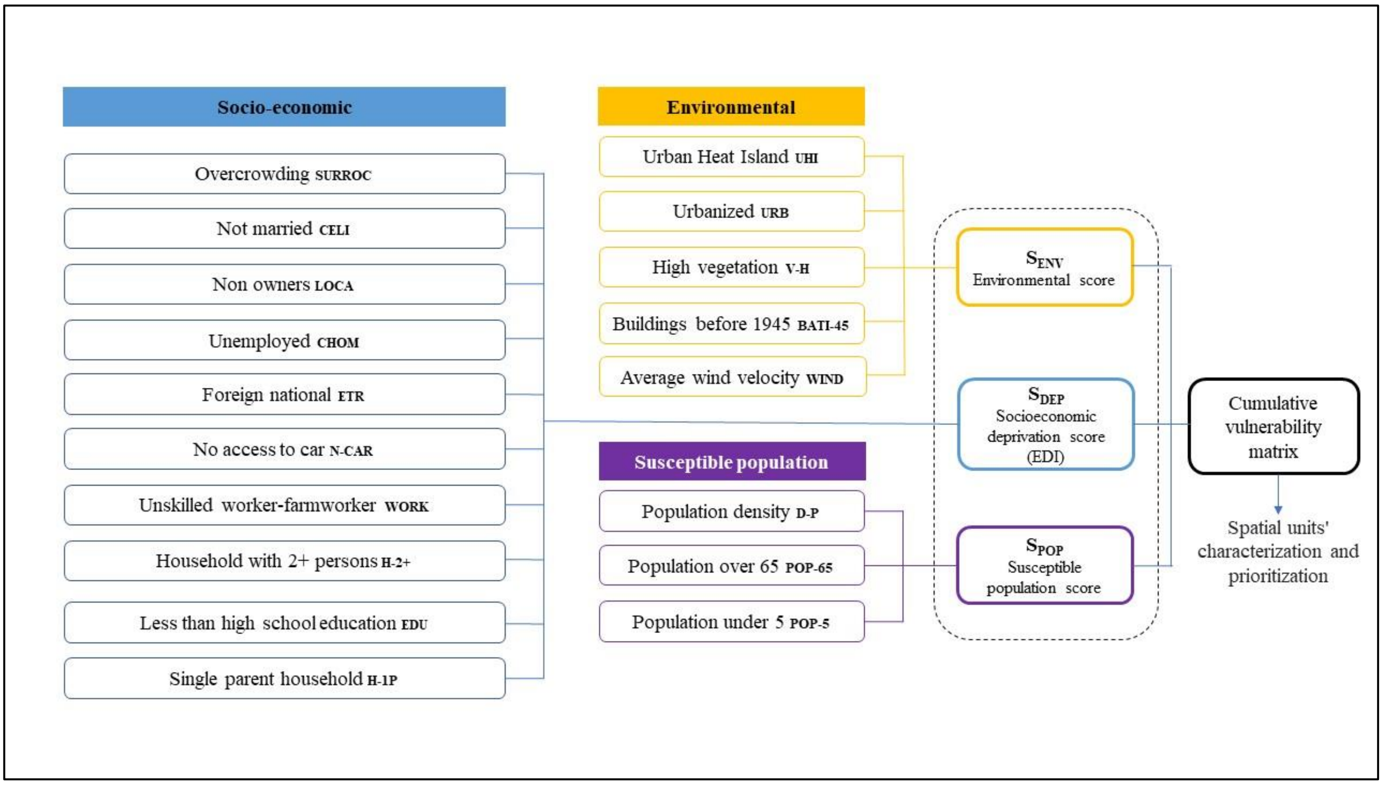


Figure 5.Cumulative Vulnerability Assessment framework adapted to assess heat vulnerability from Lanier et al. (2019)

3.3 Spatial units, selected variables, and post-acquisition treatment

3.3.1 Spatial units

The spatial unit employed for the study is the '*Ilots Regroupés pour l'information Statistique*' (IRIS), which correspond to the smallest census tract unit available in the French census (Insee, 2022). Census data is made freely available by the French National Institute of Statistics and Economic Studies known as Insee. The IRIS units are employed to administratively partition communes of five to ten thousand inhabitants into smaller units comprised in average of two thousand individuals –251 IRIS units compose the metropolitan region of Toulouse (Figure 6). The IRIS unit is the reference scale employed to spatially localize factors/variables of the three CVA components and characterize and compare spatial units.

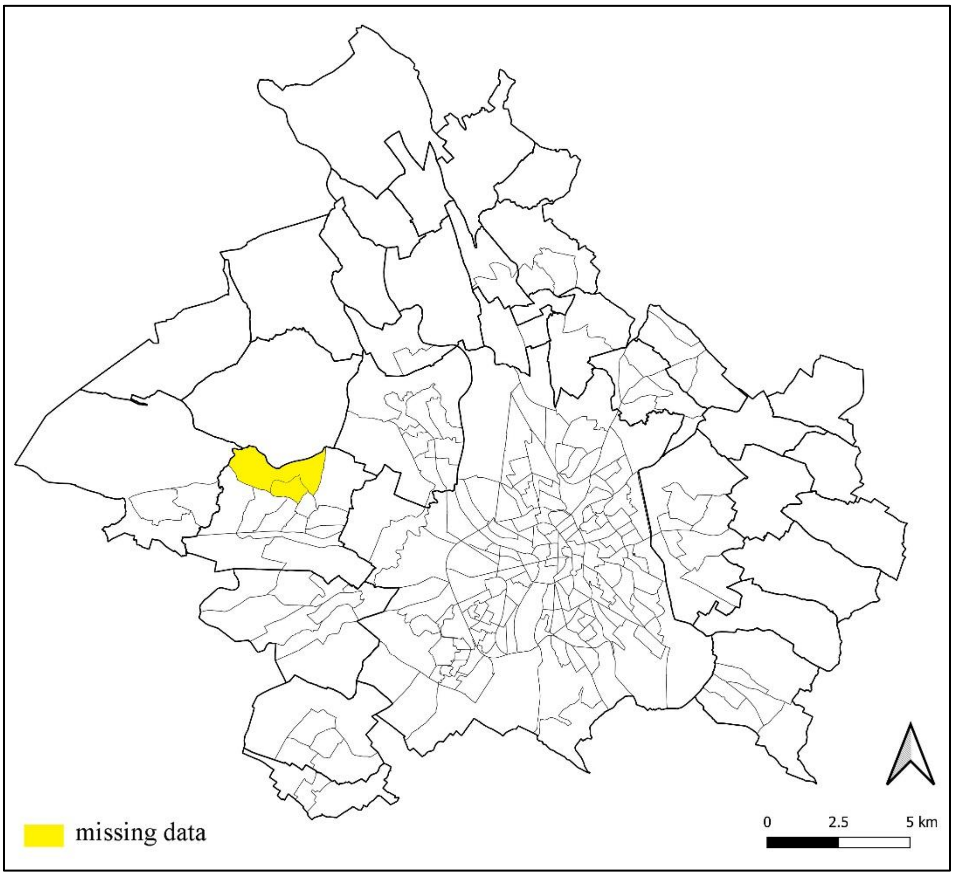


Figure 6. n.251 IRIS units composing the metropolitan region of Toulouse

3.3.2 Variables

A total of 18 variables were selected to quantitatively characterize individuals' heat vulnerability, as defined in Chapter 2. The variables were selected based on their contribution to the three components employed to characterize heat vulnerability in this study (Table 3):

Environmental component; Susceptible Population component and Socio-economic deprivation component. Variables for the Environmental and Susceptible Population components were selected based on existing literature and their previous use to characterize heat vulnerability. The sole exception to this is represented by the variable *UHI intensity* (UHI) and *Average Wind Velocity (WIND)* which were available at the scale of the Metropolitan area of Toulouse but are not commonly employed –presumably due to availability constrains.

Variables in the Socio-economic component were retained based on their contribution in the creation of the French- European Deprivation Index -EDI- (Pornet *et al.*, 2012; Merville *et al.*, 2022), an index employed to measure context-specific socio-economic deprivation. Additional details regarding the construction of the index are provided in the next sections (Pag.38). Finally, variables selection was eventually limited by data availability over the study area. Due to missing data, out of the 251 IRIS units composing the ensemble of the metropolitan region of Toulouse, 249 were retained and two were removed from the analysis.

Table 3.Variables selected according to the three main components employed to characterize heat vulnerability: Environmental component; Susceptible Population component and Socio-economic deprivation component.

n.	Variable	Code	Impact on vulnerability	Treatment post-acquisition	Source	Reference in heat vulnerability studies
			Environmental component			
1	UHI Intensity	UHI	+	GIS	Toulouse Metropole - CNRM	None of the studies consulted employed this variable directly; other temperatures data such as LST or average temperatures are employed instead
2	Urbanized % (Build-up surface)	URB	+	GIS	CES- OSO	Conlon *et al.* (2020); Koman *et al.* (2019); Mitchell and Chakraborty (2018); Benmarhia *et al*. (2017); El-Zein and Tonmoy, (2015); Lemonsu *et al.*, (2015); Johnson *et al*. (2012)
3	High Vegetation%	V-H	-	GIS	CES - OSO	Conlon *et al*. (2020); Koman *et al.*, (2019); Benmarhnia *et al.*, (2017); Inostroza *et al*. 2016; Johnson *et al*. (2012); Chow *et al.* (2011); Reid *et al.* (2009); Vandentorren *et al*. (2006),
4	Buildings built before 1945	BATI 45	+	Variables aggregation	Insee	(Hayes, Berry and Ebi, 2019); Aminipouri, Knudby and Ho, (2016); Inostroza *et al*. (2016); Lemonsu *et al.* (2015);
5	Average wind velocity	WIND	-	GIS	Ibitolu (2020)	None of the studies consulted employs wind velocity data directly
			Susceptible Population component			
6	Population density	D-P	+	GIS	Insee -BD TOPO- IGN	Mitchel and Chakraborty (2018); El-Zein and Tonmoy (2015); Lemonsu *et al.* (2015); (Wolf, McGregor and Analitis, 2014); Harlan *et al* (2006);
7	Population over 65	P-65	+	/	Insee	Faye *et al.* (2021) ; Alonso and Renard (2020); Koman *et al.* (2019);Hayes, Berry and Ebi, (2019); Inostroza *et al*. (2016); Johnson et al. (2012); Harlan *et al.* (2006)
8	Population less than 5	P-5	+	/	Insee	Faye *et al.* (2021) ; Alonso and Renard (2020); Koman et al. (2019); Inostroza *et al*. (2016); Bao *et al.* (2015)
			Socio-economic deprivation component			
9	Overcrowded households	SUROC	+	/	Insee	Conlon et al. (2020); Hayes et al. (2019); (Hayes, Berry and Ebi, 2019); Benmarhnia *et al*. (2017); El-Zein and Tonmoy (2015)
10	Non-married	CELI	+	/	Insee	Inostronza *et al.* (2016); Gronlund *et al.* (2014)
11	Non-owners	LOCA	+	/	Insee	Koman *et al.* (2019); Benmarhnia *et al.* (2017); El-Zein and Tonmoy (2015); English *et al.* (2013)
12	Unemployed	CHOM	+	/	Insee	Ebi *et al.*, (2021a,2021b); Alonso and Renard (2020); Hayes and Poland (2018); Benmarhnia *et al*. (2017); Inostroza *et al.* (2016); Rey *et al*. 2009
13	Foreign national	ETR	+	/	Insee	Benmarhia *et al.* (2017); Eisenman *et al.* (2016); El-Zein and Tonmoy (2015); (Wolf, McGregor and Analitis, 2014); Chow *et al.* (2011);
14	No access to car	N-CAR	+	Variables aggregation	Insee	Watkins *et al.*, (2021); Koman *et al.* (2019); Aminipouri, Knudby and Ho (2016); English *et al.* (2013);
15	Unskilled worker-farmworker	WORK	+	Variables aggregation	Insee	Ebi *et al*. (2021a,2021b); Hayes, Berry and Ebi, 2019); Eisenman *et al.* (2016)
16	Household with 2+ persons	H-2+	+	/	Insee	None of the heat vulnerability studies consulted employed this variable (EDI)
17	Less than high school education	EDU	+	/	Insee	Alonso and Renard (2020); Inostroza *et al*. (2016); Johnson *et al.* (2012); Huang *et al.* (2011); Harlan *et al.* (2006)
18	Single parent household	H-1P	+	/	Insee	None of the heat vulnerability studies consulted employed this variable (EDI)

3.3.3 Post-acquisition treatment

Most variables employed were sourced from the Insee databases directly at the IRIS scale and didn't require any treatment. Variables **4/14/15** are not directly issued by Insee but are rather the result of addition or subtraction operations applied to aggregate available variables to produce the "new" variables employed. For variable **2** and **3**, remote sensed imagery was employed to extract urbanized surface and high vegetation surface coverage employing the raster calculator tool contained in the Geographical Information System software ArcGIS Pro. Surfaces were calculated over the IRIS units employing the zonal statistic tool available in the software package. The percentage of coverage was then calculated based on the overall spatial unit surface. Similarly, variable **6** was calculated crossing the number of inhabitants on each IRIS provided by Insee, with the surface of the spatial unit.

Variable **1** –UHI intensity–, was available in the form of grid data which was then transposed to the IRIS units employing the zonal statistic tool previously mentioned. The *majority* value instead of a zonal average was chose to represent the UHI; this choice aims at retaining intensity's majority rather than the average comprising minimum and maximum values. Similarly, for Variable **5**, available in the form of data point grid of 250m x 250m a zonal statistic was calculated over each IRIS. Data points were joined over the spatial units and then wind velocity values were calculated for each IRIS.

3.4 Cumulative Vulnerability Assessment

Once variables were ready to be employed in the Cumulative Vulnerability Assessment, the first step of the methodology consists in the calculation of three scores composing the final index, for each spatial unit –Environmental Score (S *env*), Susceptible Population Score (S *pop*) and Socio-Economic Deprivation Score (S *dep*).

3.4.1 S env- Environmental Score

The Environmental score, that reflects urban heat, was determined employing five variables:

- UHI intensity (UHI) which represents the intensity of the nocturnal urban heat island in comparison to the rural surrounding.

- Urbanization percentage (URB) which represents the build-up surface comprising buildings and impervious surfaces such as parking, roads, and others.
- High vegetation surface coverage percentage (V-H) which negatively contributes to heat due to the evapotranspiration effect and shade provided by trees.
- Buildings built before 1945 (BATI-45) which comprises all the constructions completed before 1945 that were considered in this study as more likely not having proper thermal insulation, resulting in higher indoor thermal stress for users. It has to be pointed out that this estimation doesn't account for potential renovations aiming to improve thermal insulation buildings might have been subject too, which necessarily result in an overestimation.
- Average wind velocity (WIND), represented by the average velocity of winds at pedestrian height (2m) and wind at 10m above the average urban canopy height, which constitute a negative contribution to heat.

To calculate the S *env* score each spatial unit is first ranked from the lowest value to the highest, according to the value of each one of the environmental component variables. The S *env* score for each spatial unit is then calculated using (1).

$$S\ env_i = \sum_{p=1}^{5} n_{i,p}$$

(1)

The S *env* of the i est geographical unit is obtained by the sum of the ranks (m) for each parameter (p). Spatial units are ranked over the final S *env* score.

3.4.2 S pop- Susceptible population Score

The Susceptible population score comprises variables selected based on previous literature review findings that have identified groups of people more susceptible to extreme heat. Notably, the elderly –represented here by the over 65 years old group (P-65) and the very young, here considered as 5 years old or less (Pop-5), are well known age groups with significant difficulties to adapt to heat. For the former, due to their reduced capacity to cope with heat due to normal aging physiological deterioration. For the latter, due to the lack of self-sufficiency, reduced communication capacity and non-completely formed physiologies. Furthermore, the variable population density (D-P) is retained as, to a higher number of individuals is associated a higher number of persons with potential health issues, disabilities or other characteristics that can result in increased vulnerability to heat.

The process to calculate the S *pop* score is the same described in the previous S *env* section. The (2) is employed to obtain the score for each spatial unit. Spatial units are then ranked over the obtained score.

$$S\ pop_i = \sum_{p=6}^{8} n_{i,p}$$

(2)

3.4.3 S dep- Socio-economic deprivation Score

The Socio-economic deprivation score is calculated using the methodology developed by Pornet et al. (2012) and updated by Merville et al. (2022), the French- European Deprivation Score (EDI). This index was conceived to characterize socio-economic deprivation by combining data from the European Union Statistics on Income and Living conditions survey (EU-SILC) with variables of the French Insee census. A summary of the steps to build the EDI are shown in Figure 7.

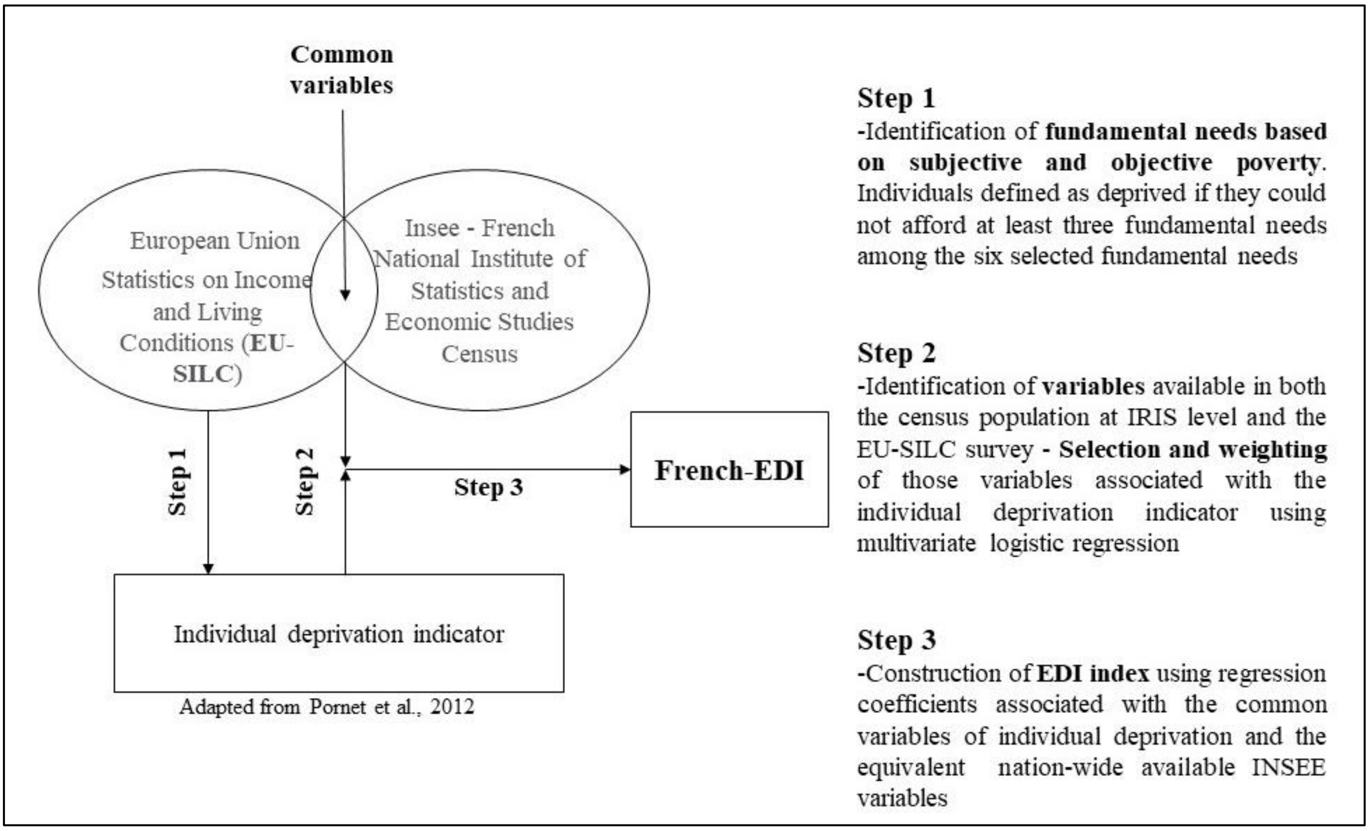


Figure 7. French- European Deprivation Index (EDI) construction scheme with a summary of the main steps to obtain the final index.

Based on the last updated EDI, developed by Merville et al. (2022), variables and weighting factors presented in Table 4 are retained to compose the final socio-economic deprivation index.

Table 4. French-EDI weighting factors and variables

β= regression coefficient /weighting factor	**Code**	**Variable**
0.25	H-2+	Household with 2+ persons
0.39	CELI	Non-married
0.44	SUROC	Overcrowded households
0.50	N-CAR	No access to car
0.64	EDU	Low level of education
0.73	ETR	Foreign National
0.84	LOCA	Non-owner
0.97	CHOM	Unemployed
0.97	WORK	Unskilled worker-farmworker
1.11	H-1P	Single parent household

$$S\ dep_i = \sum_{p=9}^{18} \beta_i n_i$$

S dep = socioeconomic deprivation index
n= variable
β= regression coefficient /weighting factor

(3)

The S *dep* score of the *i* est geographical unit is obtained using (3). Since variables have different scales, before the calculation of the score, features are scaled using the *Normalization by the mean* method employing (4). This prevents variables' magnitude to disproportionately impact the final score. Spatial units are then ranked over the final S *dep* score.

$$x' = \frac{x - \mu}{\max(x) - \min(x)}$$

x' = Mean normalized value
x= Original value
μ= Sample mean
max(x)= Maximum value of x
min(x)= Minimum value of x

(4)

3.3.4 3D cumulative vulnerability matrix

The results of the three scores are employed to build a tri-dimensional vulnerability matrix which enabled the identification and prioritization of the geographical units with higher cumulative levels of vulnerability. Spatial units are ranked based on their final score on each component and are then discretize as described next. IRIS are divided into six quantiles (S1: lowest exposure/ S6: highest exposure) based on the environmental component, and into four quantiles over the susceptible population (Q1: lowest susceptibility-Q4: highest susceptibility) and socio-economic deprivation components (Q1: lowest socio-economic deprivation-Q4: highest socio-economic deprivation). This discretization choice prioritizes the environmental component over the other two to strength the environmental (heat exposure) dimension.

Cumulative vulnerabilities level of each spatial unit are obtained multiplying the values of each class. IRIS cumulative vulnerabilities can assume a value ranging from 1 –in the case of an IRIS with S1 x Q1 x Q1, which correspond to the lowest level of vulnerability—to 96 –for an IRIS with S6 x Q4 x Q4 values, which correspond to the highest level of vulnerability. All the possible values contained within the tri-dimensional matrix are displayed in Figure 8. CVA Tri-dimensional Cumulative Vulnerabilities Matrix. Based on the final level of vulnerability, each IRIS is classified in eight different classes following a ranking from the lowest vulnerability level A (matrix value=1) to the highest vulnerability level H (matrix value=96). Finally, a colour is assigned to each class to produce a CVA heat vulnerability map.

S dep	S pop	S env					
		S1	S2	S3	S4	S5	S6
Q1	Q1	1	2	3	4	5	6
	Q2	2	4	6	8	10	12
	Q3	3	6	9	12	15	18
	Q4	4	8	12	16	20	24
Q2	Q1	2	4	6	8	10	12
	Q2	4	8	12	16	20	24
	Q3	6	12	18	24	30	36
	Q4	8	16	24	32	40	48
Q3	Q1	3	6	9	12	15	18
	Q2	6	12	18	24	30	36
	Q3	9	18	27	36	45	54
	Q4	12	24	36	48	60	72
Q4	Q1	4	8	12	16	20	24
	Q2	8	16	24	32	40	48
	Q3	12	24	36	48	60	72
	Q4	16	32	48	64	80	96

CVA
- A (1)
- B (2 - 5)
- C (6 - 10)
- D (12 - 18)
- E (20 - 32)
- F (36 - 54)
- G (60 - 80)
- H (96)

Figure 8. CVA Tri-dimensional Cumulative Vulnerabilities Matrix

3.3.5 Characterization of spatial units' profiles

To allow profiling and comparison among IRIS units' cumulative vulnerabilities, in addition to the final S *env*, S *pop* and S *dep* scores, spatial units' vulnerability is described employing the normalized values of the raw variables contained in the different components. Radar charts visualizations are created to display the three components' scores and the normalized values of the environmental and susceptible population components. The selected variables are normalized using the *min-max* normalization method employing (5. The normalized variables assume a new value comprised between min 0 and max 1, which allows an easier comparison among geographical units.

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)}$$

x' = Normalized value
x= Original value
max(x)= Maximum value of x
min(x)= Minimum value of x

(5)

Each geographical unit can then be compared with another based on its overall level of cumulative vulnerabilities and through the normalized values of the environmental and susceptible population component descriptors. As the socio-economic deprivation component is comprised of a set of ten differently weighted variables, a simplified visualization of the normalized variables poses more challenges. Hence, the socio-economic deprivation score is displayed as a single value. A summary of all the CVA steps described above is provided in Figure 9.

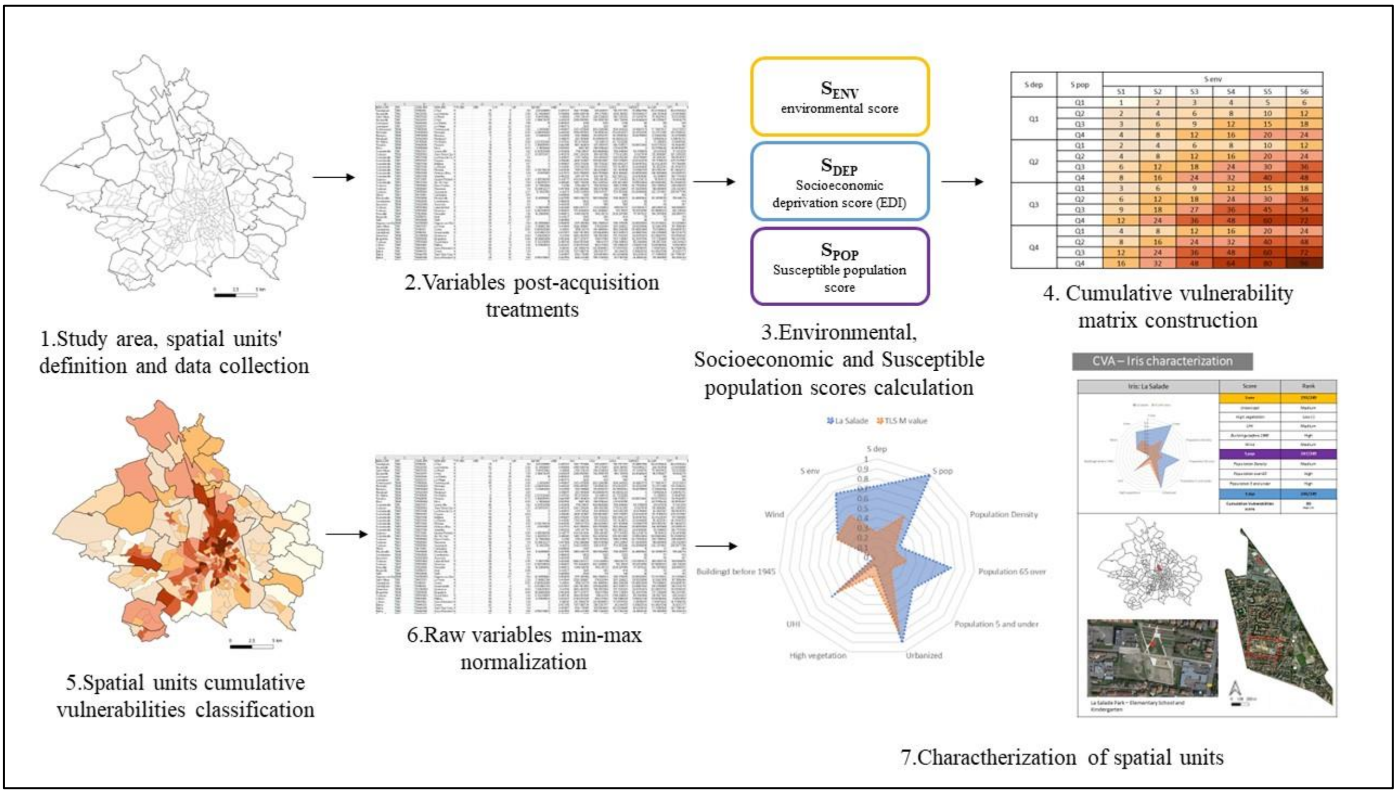


Figure 9. Summary of CVA methodological steps

3.4 Composite Vulnerability Index Construction

In addition to providing a Cumulative Vulnerability Assessment for the metropolitan region of Toulouse, this study aims to provide a composite vulnerability index combining the results of three different heat vulnerability assessments conducted over the same area. The first one is the CVA object of this study and the other two are part of a complementary and synergic study conducted at LISST over the same period by Lagelouze (2022). The results of a Principal Component Analysis (PCA) and an Analytic Hierarchy Process (AHP) were combined with the results of the CVA to provide a unified index through a methodology developed for this study.

3.4.1 Principal Component Analysis (PCA)

The Principal Component Analysis (PCA) is a methodology largely used in the existing heat vulnerability literature (Bao et al. 2015). The PCA is a multivariate statistical technique first developed by Pearson (1901) and employed in different research areas. The objective of the methodology is to analyse a dataset and extract "the important information […], to represent it as a set of new orthogonal variables called principal components" (Abdi and Williams, 2010). The variables regrouped in the components are joined based on the *goodness of fit* of the data fluctuation reciprocity between the sets of variables. Based on how "good" is this fit, some components can be prioritized over others. In this case, the methodology identifies the principal components that describe heat vulnerability based on a series of input variables selected based on the literature review conducted by Lagelouze (2022). A list of the variables employed in the study is available in the annex section.

3.4.2 Analytic Hierarchy Process (AHP)

The Analytical Hierarchic Process (AHP) is a methodology employed in decision making; it was developed by R.W. Saaty between 1971-1975 and has fund different "applications in multicriteria decision making, planning, resource allocation and conflict resolution" (Saaty, 1987). The methodology doesn't focus on exact measurements, but rather on the proportions between them, using relative measurement to simplify analysis and decision making (Brunelli, 2015). In the context of Lagelouze (2022) study, variables are grouped based on the expertise of the analyst and according to their association with heat vulnerability components: Sensitivity, Exposure and Adaptive Capacity. The AHP allows then to establish comparisons between geographical units by following an additive approach that regroups heat vulnerability descriptors based on the relative measures provided by the methodology rather than the exact measured value of each variable. The same variables employed in the PCA analysis were employed in the AHP.

3.4.3 Inter-method composite vulnerability index

The composite index's results of the PCA and AHP methodology are expressed in a normalized distribution of continuous variables ordered from 0 (min cumulative vulnerabilities) to 1 (max cumulative vulnerabilities). On the other hand, the CVA's composite index results are expressed in a categorical ordinal distribution. This index assumes values from A (min cumulative vulnerabilities) to H (max cumulative vulnerabilities).

To build a composite index that combines the results of the three methodologies, results had to be expressed in a way that allows equal classing and interclass comparison. The first step of the composite index compiling methodology proposed, consists in classifying the results of the three methodologies in five equal quantiles as described in Figure 10.

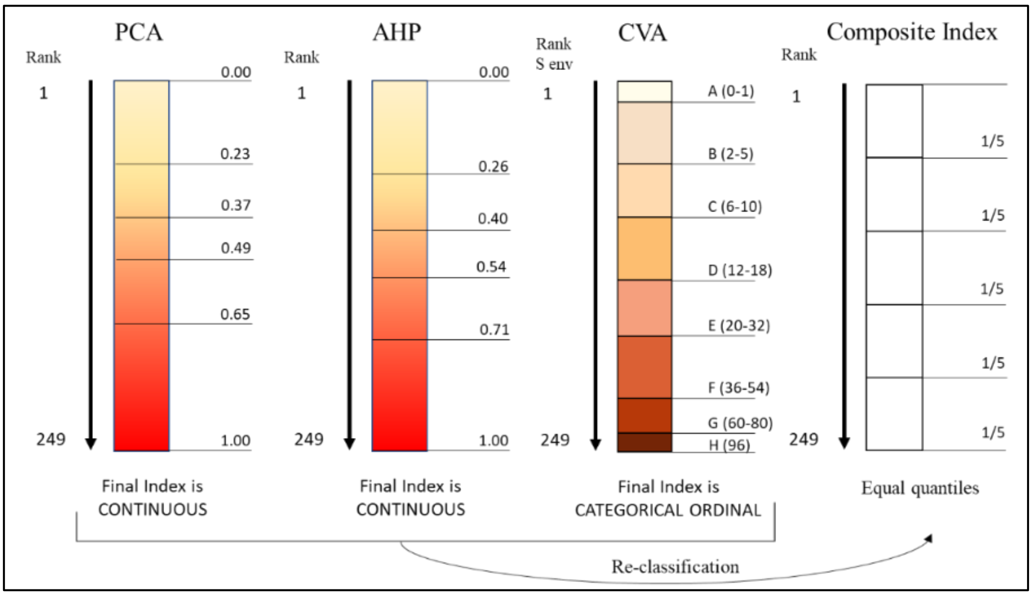


Figure 10. PCA-AHP-CVA results re-classification in equal quantiles

Classifying the results of the AHP and PCA in five quantiles doesn't pose any challenge as the final index results of both methodologies assume a value comprised between 0 and 1. Hence, it is possible to equally split the results in five classes based on their associated rank. Geographic units from 1 to 49 will be in the first quantile, those from 50 to 99 will be in the second, and so on for the other classes. However, the final cumulative vulnerabilities values within CVA classes are common to all the units contained within the classes. For example, all the spatial units contained in the most vulnerable class H, will all have the same level of vulnerability. To overcome this, spatial units within the same class (A-B-C-D-E-F-G-H) were ranked based on their S *env* (Environmental score) values (Figure 11) – this choice is in line with the previously mentioned CVA methodological approach of strengthening the environmental component over the other two.

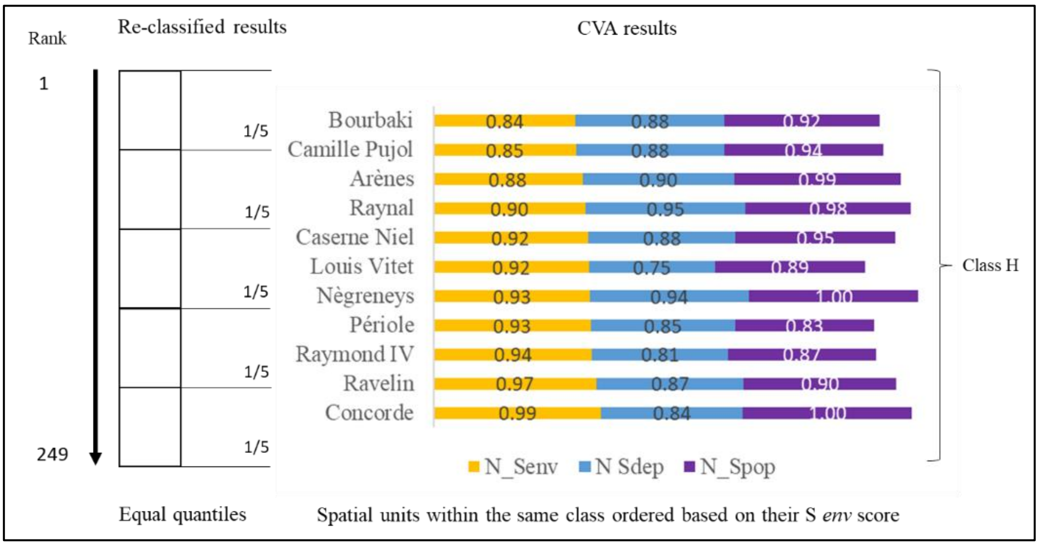


Figure 11. CVA results re-classification based on S env score values

In the following step, the equally classed results of the three methodologies were crossed. Spatial units belonging in the same quantile in three or at least two out of three of the methodologies were retained in the same class in the final composite index. To classify those IRIS units that were classed differently across the three methodologies, their quantile class based on the average ranking of AHP-CVA-PCA was employed. The same value was employed to rank the spatial units within the final composite index quantiles. Figure 12 provides a summary of the overall process. The final index was then used to construct a composite heat vulnerability map.

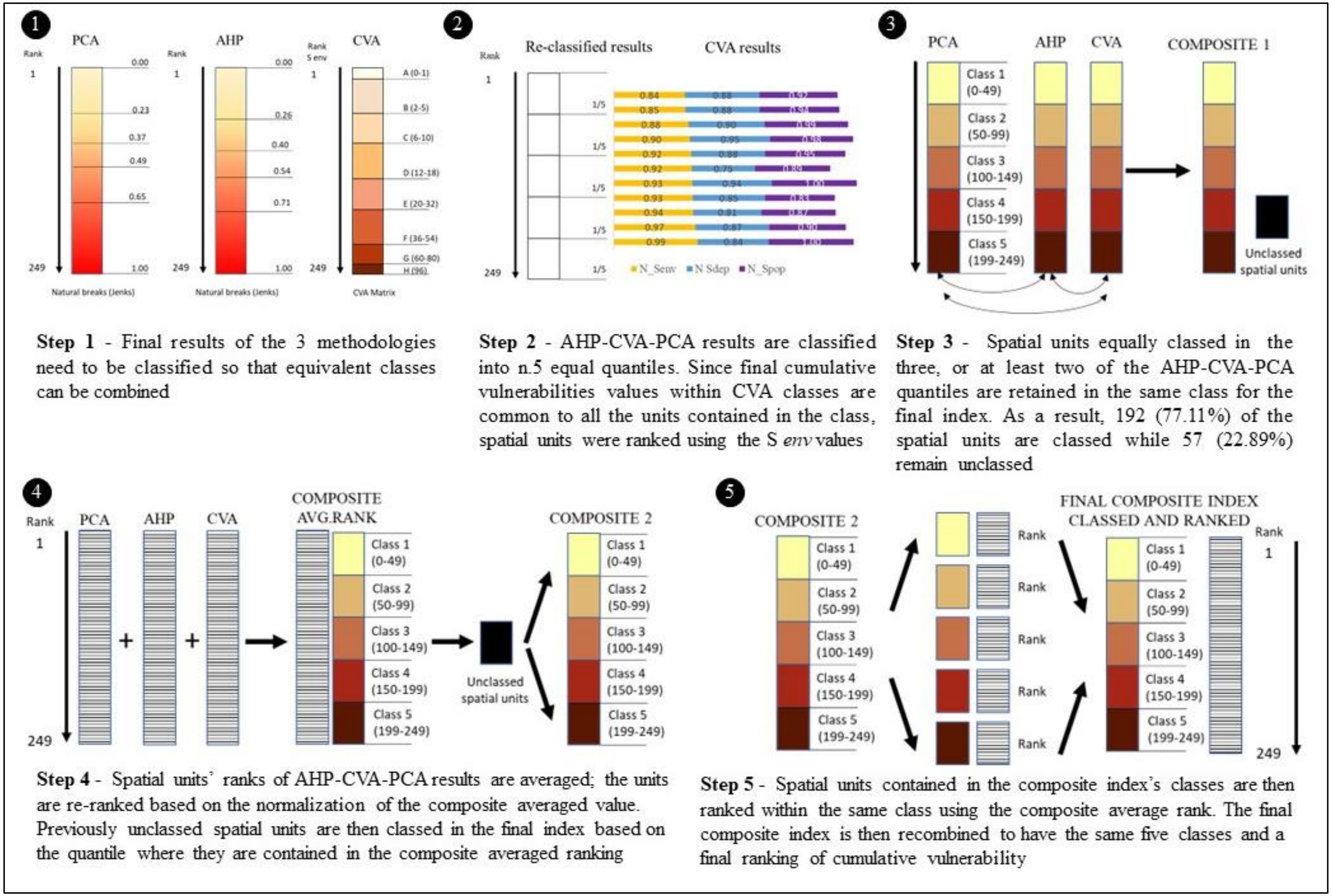


Figure 12. Summary of the methodology employed to compile the composite index combining the results of AHP-PCA-CVA

CHAPTER 4: RESULTS

4.1 Cumulative Vulnerability Assessment results

4.1.1 Environmental Score (S env)

Based on the variables selected to describe the environmental dimension, the IRIS units with the highest Environmental Score are located in the commune of Toulouse and are somehow distributed around the city centre with some interruptions in presence of the *Garonne* river corridor and the wider area of the Parc du Confluent towards the southern edge of the commune. Other pockets with high S *env* values are in the city centres of the satellite towns surrounding Toulouse such as *Balma, L'Union, Aucamville, Blagnac, Colomiers, Tournefeuille and Cugnaux and Villeneuve-Tolosane*. On the other hand, those communes in the east (*Beaupuy, Mondouzil, Montrabé, Pin-Balma, Mons, Flourens, and Quint-Fonsegrives*) and west (*Pibrac and Mondonville*) edges of the metropolitan region are characterized by the lowest S *env* values. Results of the S *env* score are summarized in the Environmental score map in Figure 13.

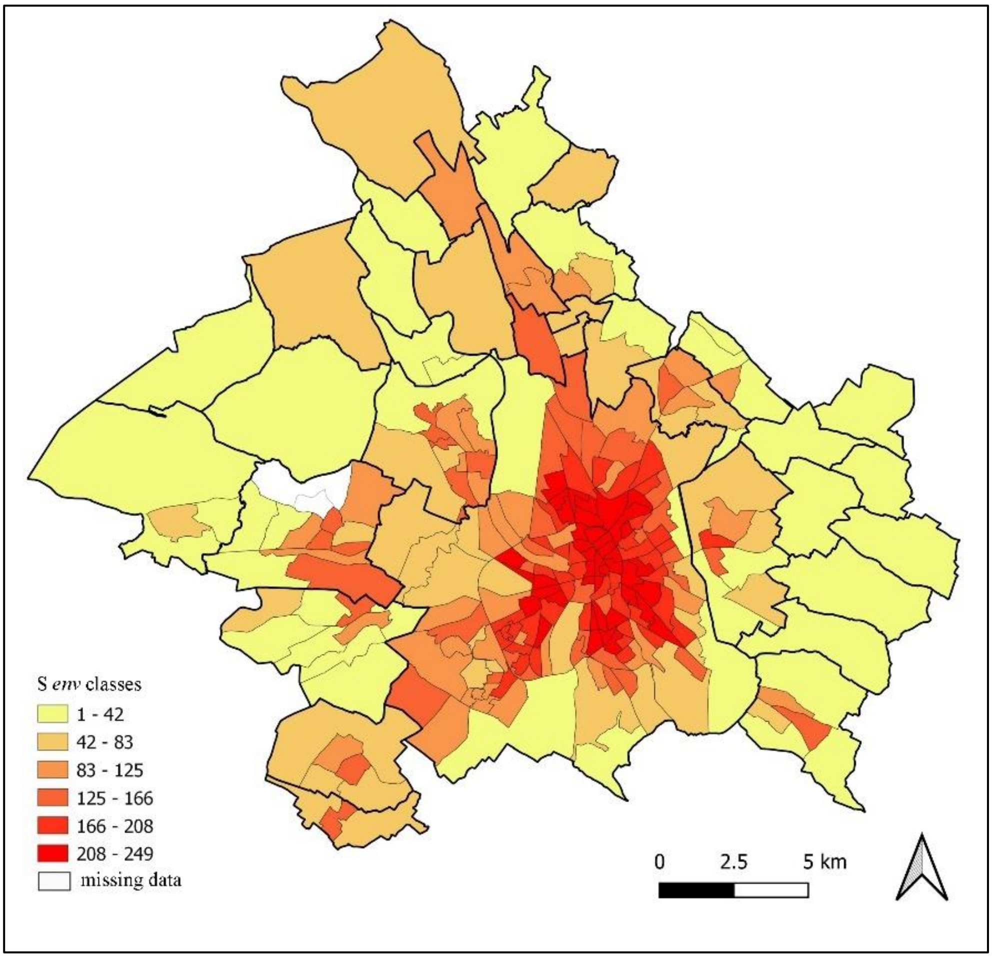


Figure 13. Environmental score map S env

The results of the S *env* are explained through the different composing factors (Figure 14). The UHI intensity is stronger towards the centre of the commune of Toulouse, especially in the neighbourhoods surrounding the city centre with a higher concentration of IRIS towards the east side of the *Garonne* River in comparison to the west. The Urbanization component follows a similar distribution with the city centres of Toulouse and the surrounding communes emerging over the least built-up geographical units in the rest of the metropolitan region. Most of the buildings constructed before 1945 are located towards the historical city centre of Toulouse, however, some smaller clusters are in located in the surrounding communes of *Colomiers*, *Balma*, *Saint-Jory* and *Bruguières*.

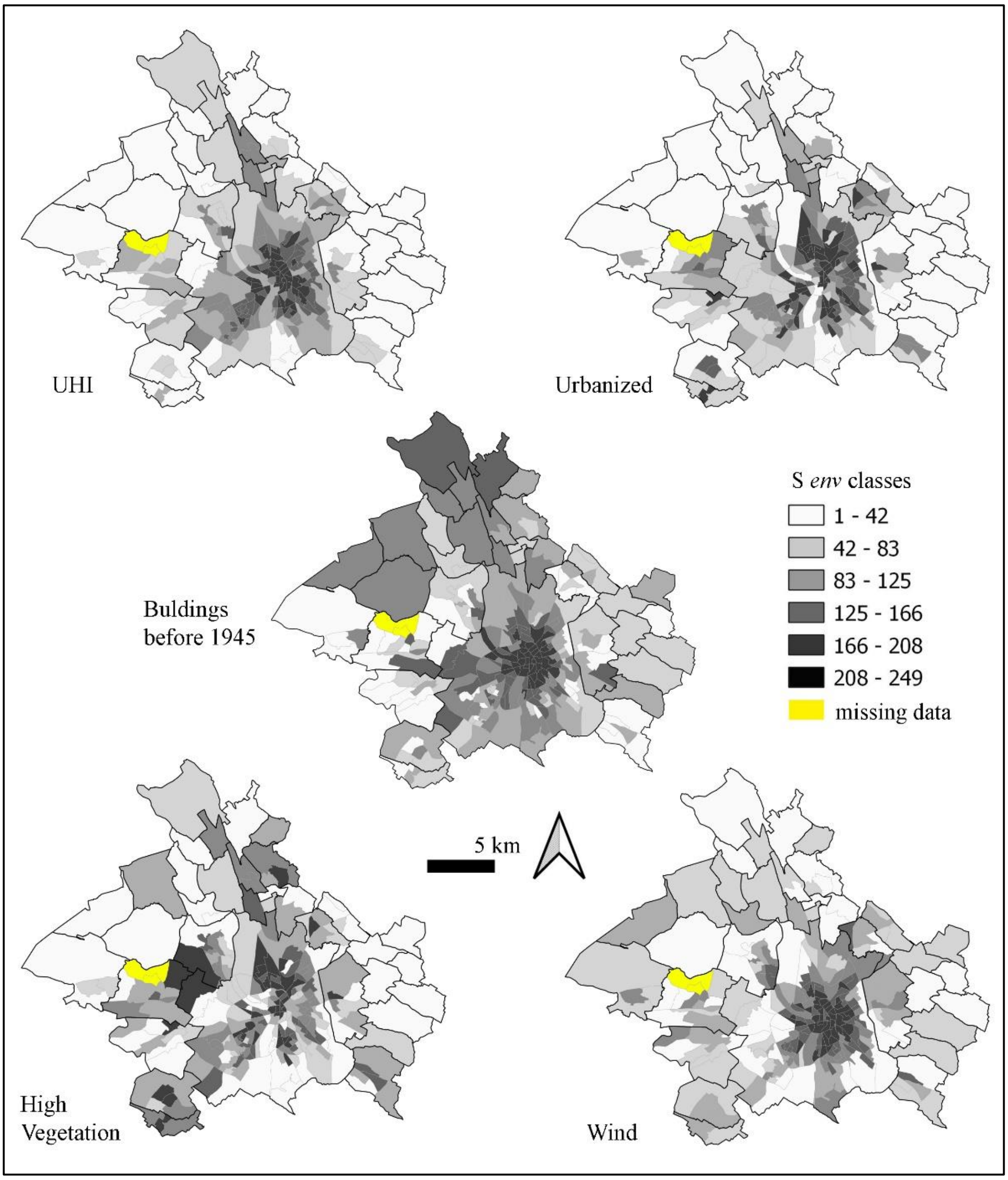


Figure 14. Environmental score composing factors

The high vegetation component shows that most of the less vegetated areas correspond to the highly urbanized areas in the commune of Toulouse, where there are little to no trees compared to the most vegetated areas in correspondence of the *Garrone* river -*Parc du Confluent*, and the forests in the communes of *Pibrac* and *Mondonville* located on the western edge of the metropolitan region (Figure 15). Other areas that come out for their low vegetation levels are the city centres communes around Toulouse like *Cugnaux* and *Villeneuve-Tolosane* in the south-west, *Castelginest*, *L'Union* and *Balma* in the east and north-east. An important cluster of poorly vegetated IRIS units occurs at the intersection of the communes of *Blagnac, Colomiers* and the north-west portion of Toulouse where several industrial-commercial buildings and the international airport of Toulouse are located. Finally, the average wind velocity component shows lower winds toward the centre of the commune of Toulouse with the addition of some IRIS units in the communes of *Saint-Orens-de-Gameville*, *Blagnac* and *L'Union*.

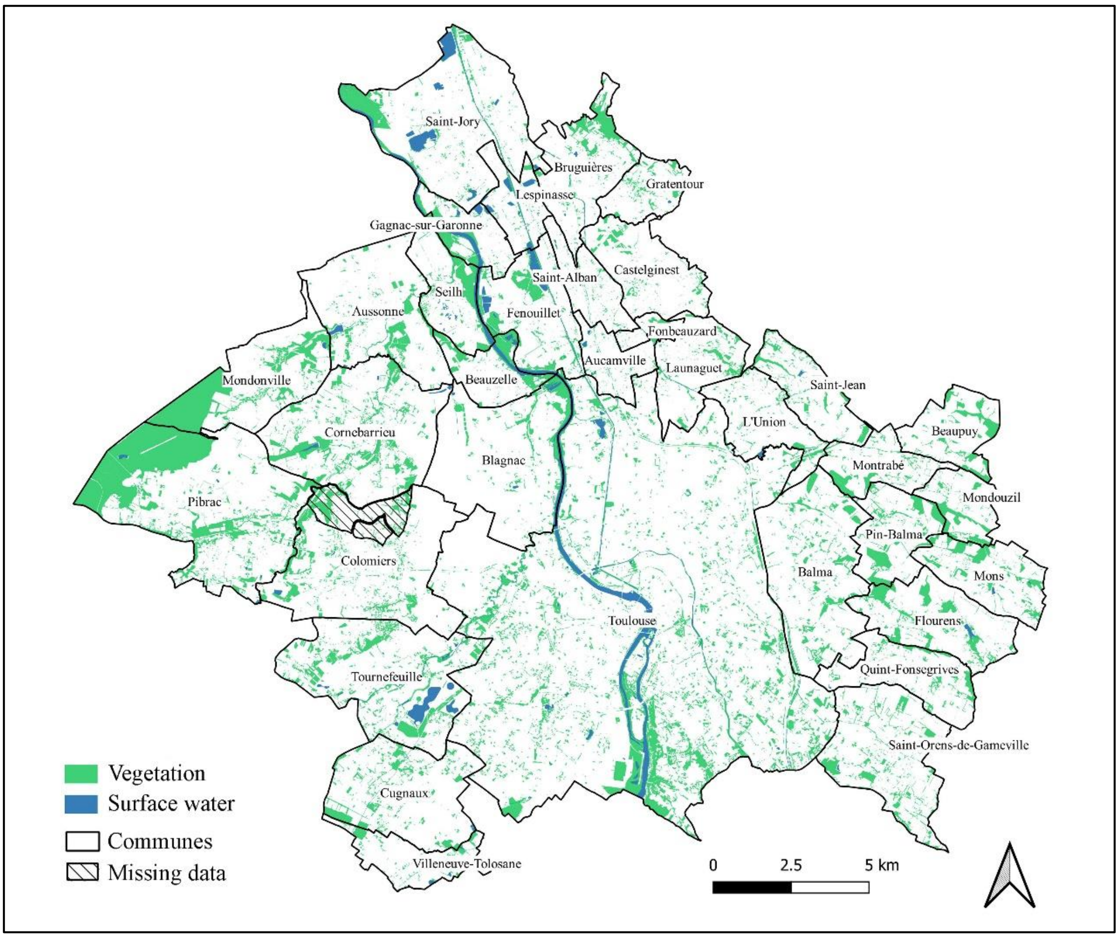


Figure 15. Vegetation and surface water map of the metropolitan region of Toulouse

4.1.2 Susceptible population score (S pop)

The susceptible population score results (Figure 16) show three patterns of susceptible population distribution for the metropolitan region:

-first in the commune of Toulouse the north-east quadrant shows the higher concentration of susceptible IRIS, other quadrants also host IRIS with high level of susceptible population in the surrounding neighbourhoods rather than in the city centre.

-secondly, a cluster of susceptible population is identified in the communes located in the north and north-west of the metropolitan region.

-a third group is then composed by the city centres of the communes surrounding the city of Toulouse, in particular *Colomiers, Tournefeuille, Cugnaux, Villeneuve-Tolosane* and *Quint-Fonsegrives*.

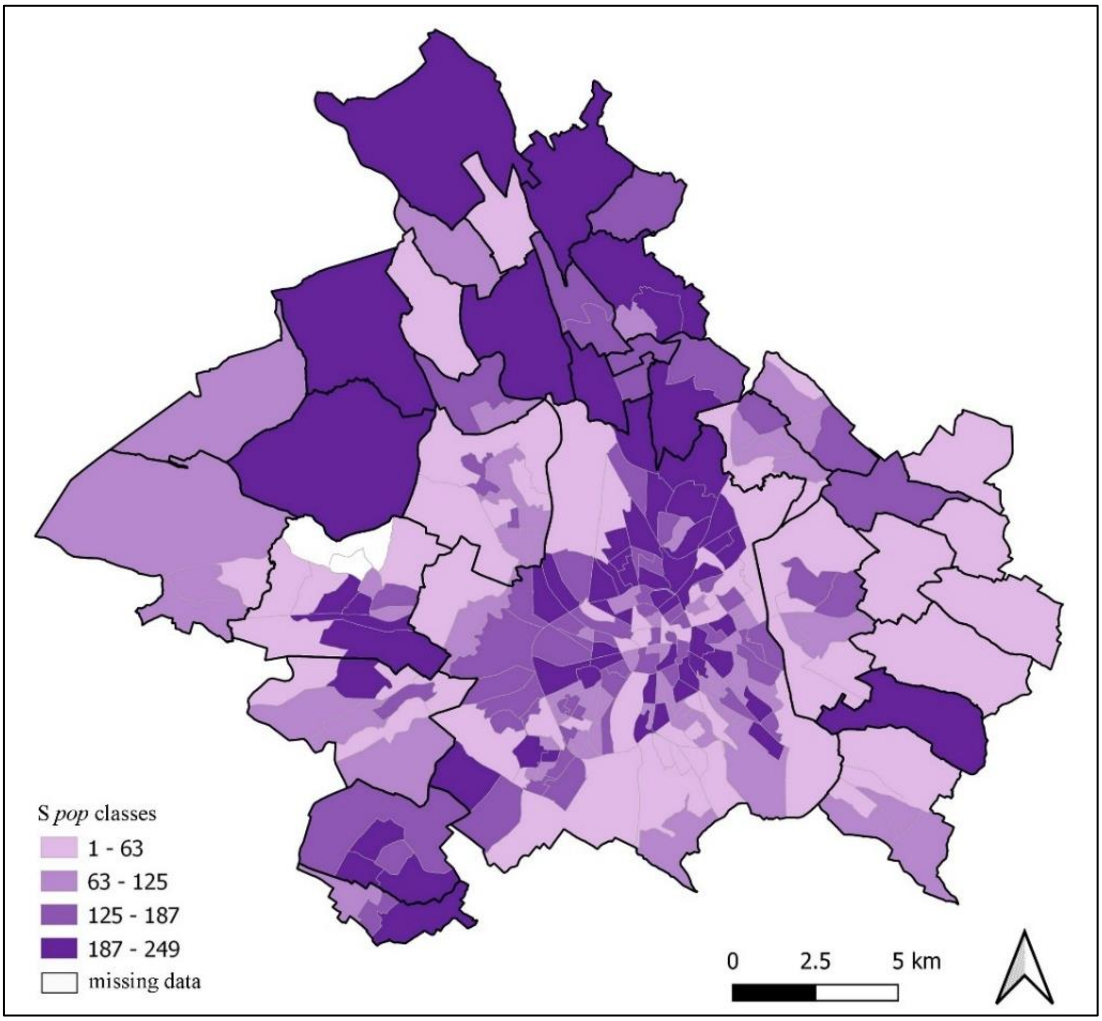


Figure 16. Susceptible population score map S pop

As it can be observed in Figure 17. the concentrations in the commune or Toulouse as well as in some of the surrounding city centres' communes are impacted by the population density factor while the other clusters identified are connected to the presence of both, higher level of population over 65 and higher presence of population over 5 –with a higher concentration toward the north and north-west of the metropolitan region.

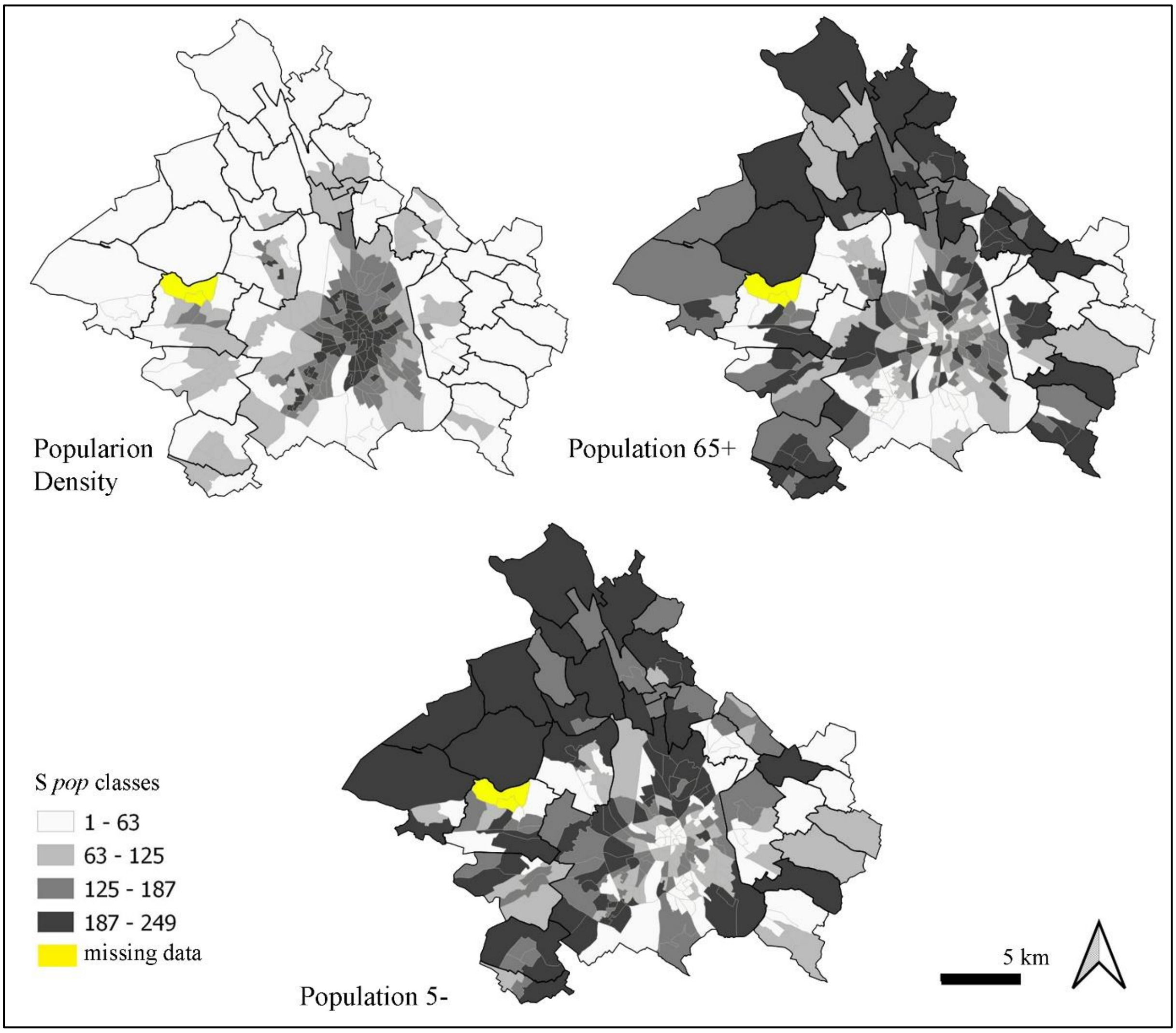


Figure 17. Susceptible population score factors

4.1.3 Socio-economic deprivation score (S dep)

Social economic deprivation measured through the French-EDI score is heterogeneously distributed across the metropolitan region (Figure 18). Some of the most socio-economically vulnerable IRIS can be associated with Toulouse peripheral neighbourhoods as well as those areas known as *quartier prioritaire de la politique de la ville* (like le *Mirail*, *les Arènes*, *Bourbaki*, *Empalot*, *Négreneys*, among others) which represent neighbourhoods defined as disadvantaged by the local authorities. Several peri urban IRIS units classed in the highest level of vulnerability, and located outside the commune of Toulouse, are influenced by the concentration of factors such as low education levels, agricultural and unskilled workers, and single-parent households (Figure 19). The communes located on the west side of the metropolitan area are those identified as having the lowest level of socio-economic deprivation. Once again, the town centres of the communes surrounding Toulouse also emerge over other IRIS units.

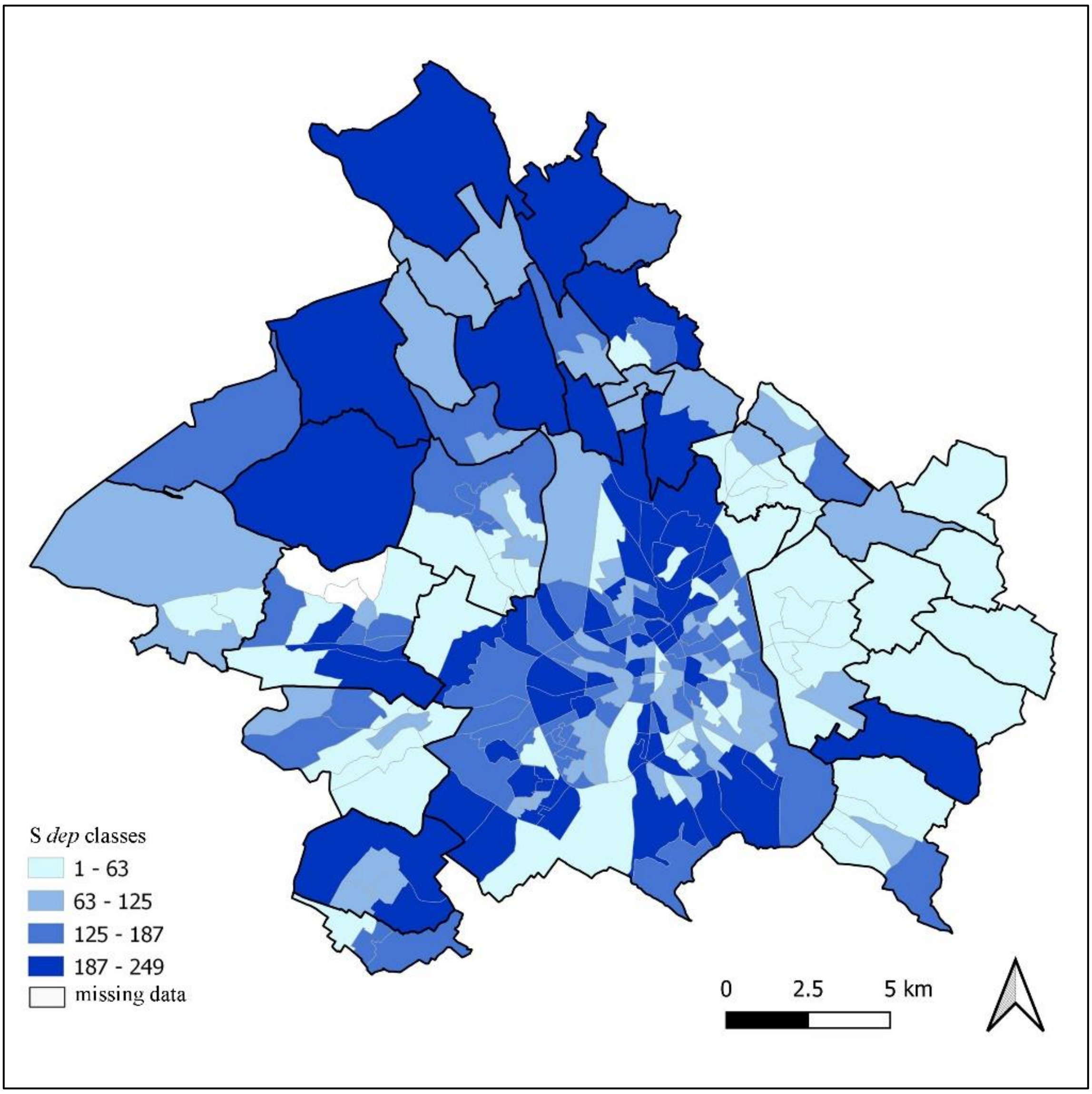


Figure 18. Socio-economic deprivation score map

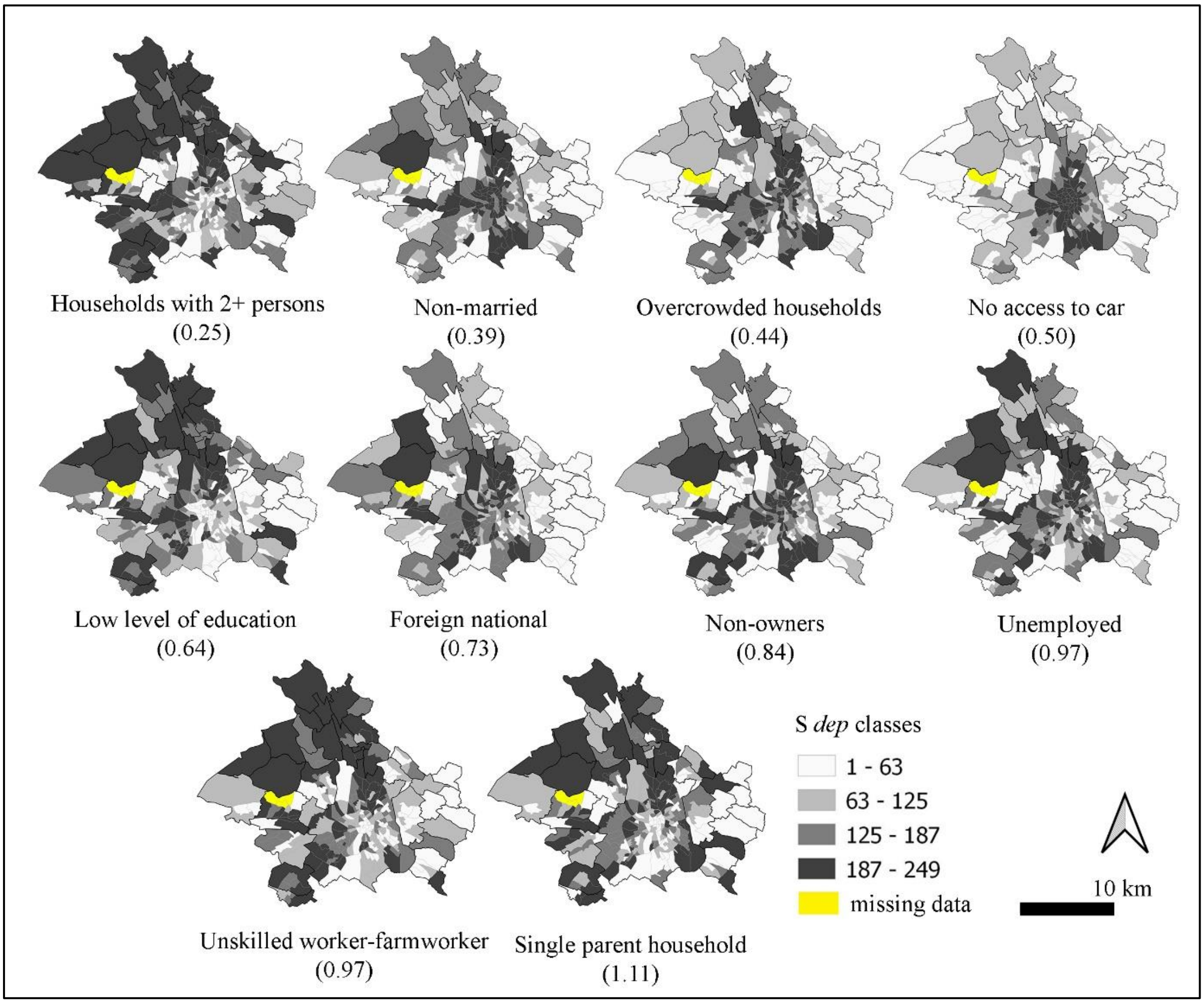


Figure 19. Socio-economic deprivation score factors

4.1.4 CVA index results

Based on the results of the Cumulative Vulnerability Assessment conducted in the metropolitan region of Toulouse (Figure 20), the IRIS units classed in the highest vulnerability class H (Figure 21) correspond to:

-the cluster composed by the IRIS units *Raynal, Nègreneys, Concorde, Périole* and *Raymond IV*, a group of geographical units gathered around the train station of *Toulouse Matabiau*.

-towards the west, relatively to the above cluster, the neighborhood of *Bourbaki*, already mentioned as one of the *quartiers prioritaires de la politique de la ville (QP).*

-southwards from the train station and on the east banks of the *Canal du Midi*, the IRIS of *Louis Vitet* and *Camille Pujol*.

-on the west side of the *Garonne* river, the IRIS *Arénes* and *Ravelin* and toward the south *Caserne Niel*.

IRIS in the next vulnerability class (G), in descending order, are also all comprised within the commune of Toulouse, with the exclusion of *Cabirol-Ramssiers* in the commune of *Colomiers* and *Les Violettes* in the commune of *Aucamville*. A sample of IRIS units's cumulative heat vulnerabilities profiles tables is available in Appendix 1. CVA IRIS units profiles - S *env-S pop-S dep* descriptors' tables.

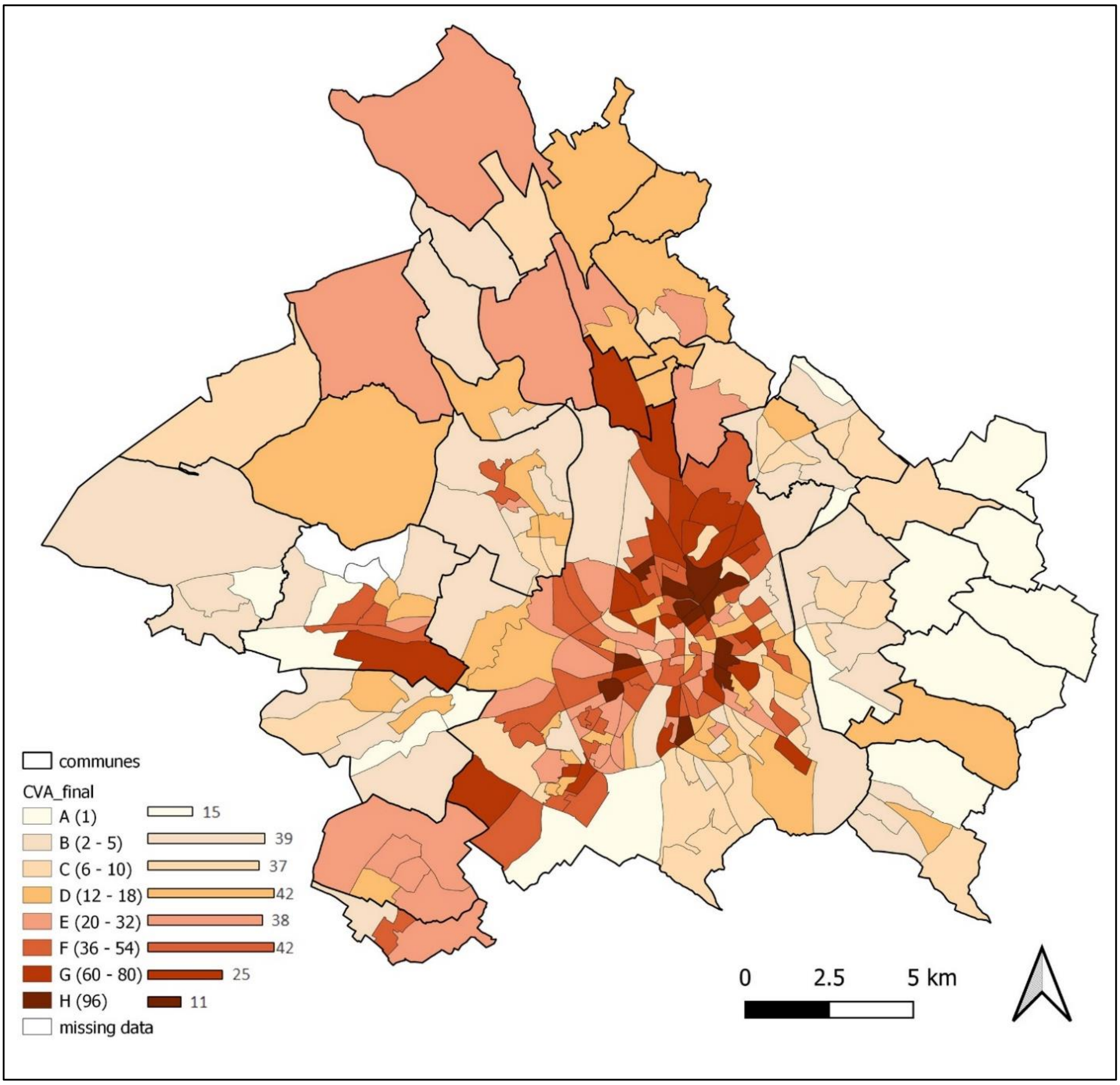


Figure 20. CVA heat vulnerability map

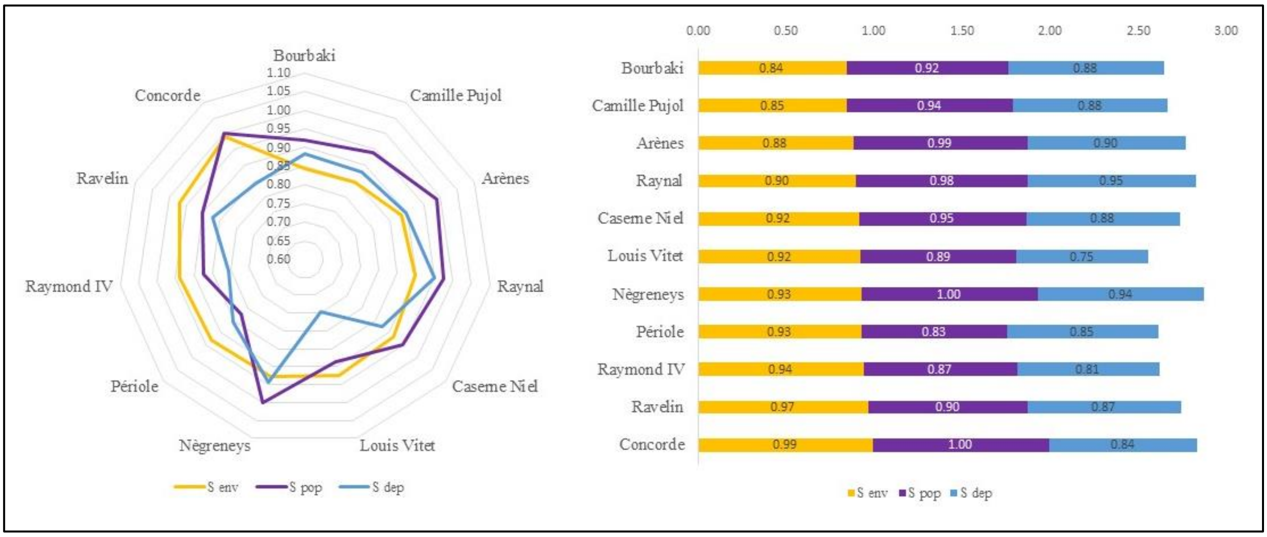


Figure 21. CVA heat vulnerability class H scores

4.2 Composite index results

As explained in Chapter 3 heat vulnerability assessments' results of a Principal Component Analysis (PCA) and an Analytic Hierarchy Process (AHP) were crossed with the results of the Cumulative Vulnerability Assessment (CVA) to produce a composite index of heat vulnerability that takes into consideration the three different methods (Figure 22). It must be reminded that, while the input variables employed differ to some extent between the CVA and the AHP-PCA (Appendix 2. Variables employed in the study conducted by Lagelouze (2022).), the final aim of the three methodologies is the same. Hence, such composite index allows a more comprehensive cumulative vulnerabilities visualization over the metropolitan region of Toulouse compared to the results of a single methodology. The comprehensive visualization, however, poses some analytical interpretation's challenges that will be addressed in Chapter 5.

Following the first composite classification step, 77.5% (193/249) of the IRIS units were classed in one of the five quantiles of the inter-method composite index. Out of the 193 units, 57 (22.9%) were equally classed across the three methods, and 136 (54.6%) were equally classed across two out of the three methods. The rest, 56 units (22.5%) weren't equally classed across methods. Those units were classed based on their average class. Table 5 and Figure 23 show the results of the classification process, including the percentage of classification consistency following the first classification step.

Table 5. Inter-method composite index classes' classification consistency table

Classification consistency	Class 1	Class 2	Class 3	Class 4	Class 5
CVA-AHP-PCA	19	7	6	7	18
2 out of 3	27	29	24	31	25
Class assigned based on avg.	0	14	21	20	1
tot (of 249)	46	50	51	58	44
% of units classed	100%	72%	59%	66%	98%

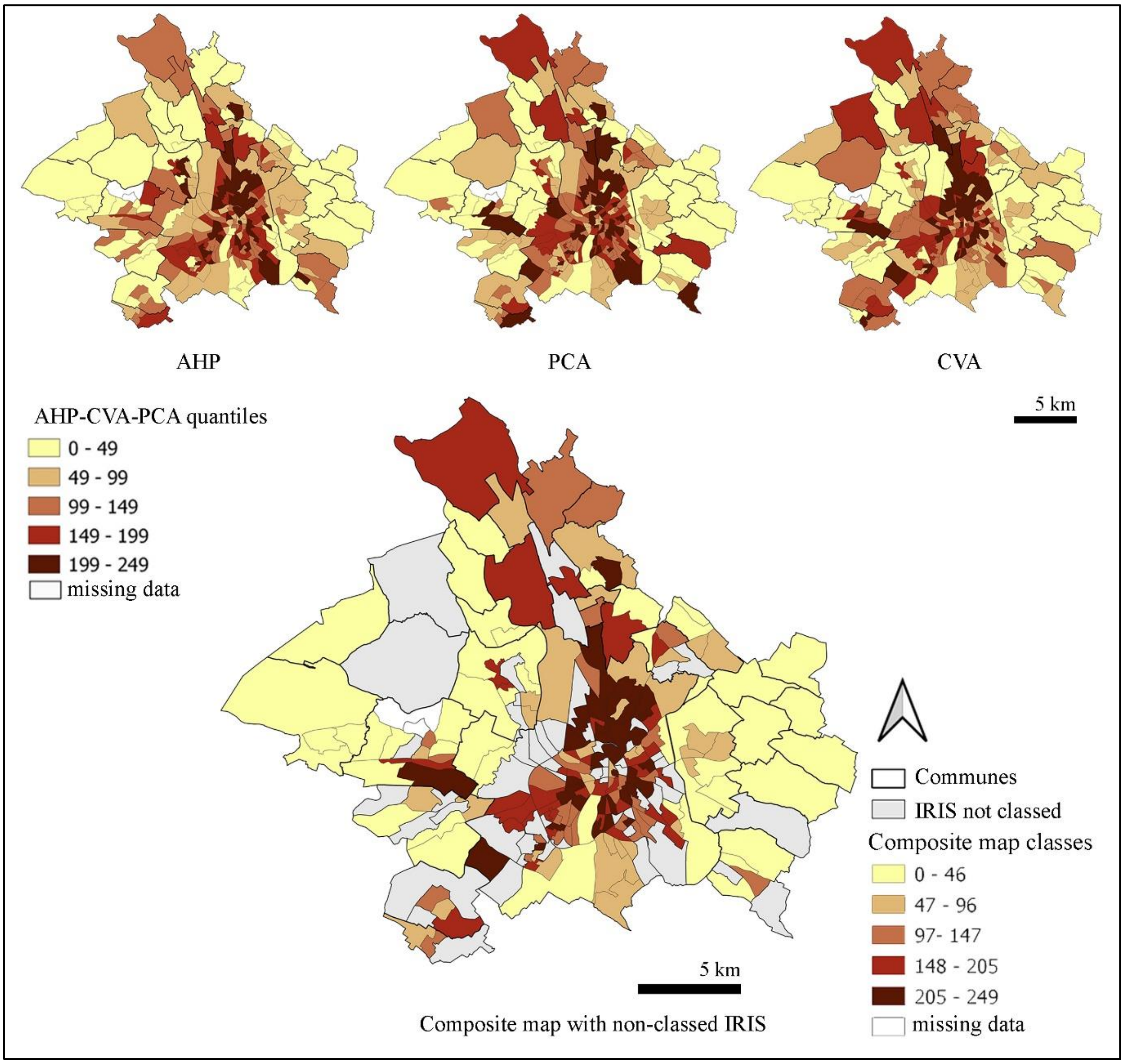


Figure 22. Maps of inter-method composite index construction – above, maps of the AHP-CVA-PCA results—below, composite maps following the first classification step

Classification consistency across the three methodologies was higher in the lowest and highest quantiles, achieving 100% and 98% consistency respectively. The percentage is then gradually reduced toward the centre. In class 3 only 59% of the geographical units were equally classed in three or at least two of the methodologies and 41% were classed according to their average rank.

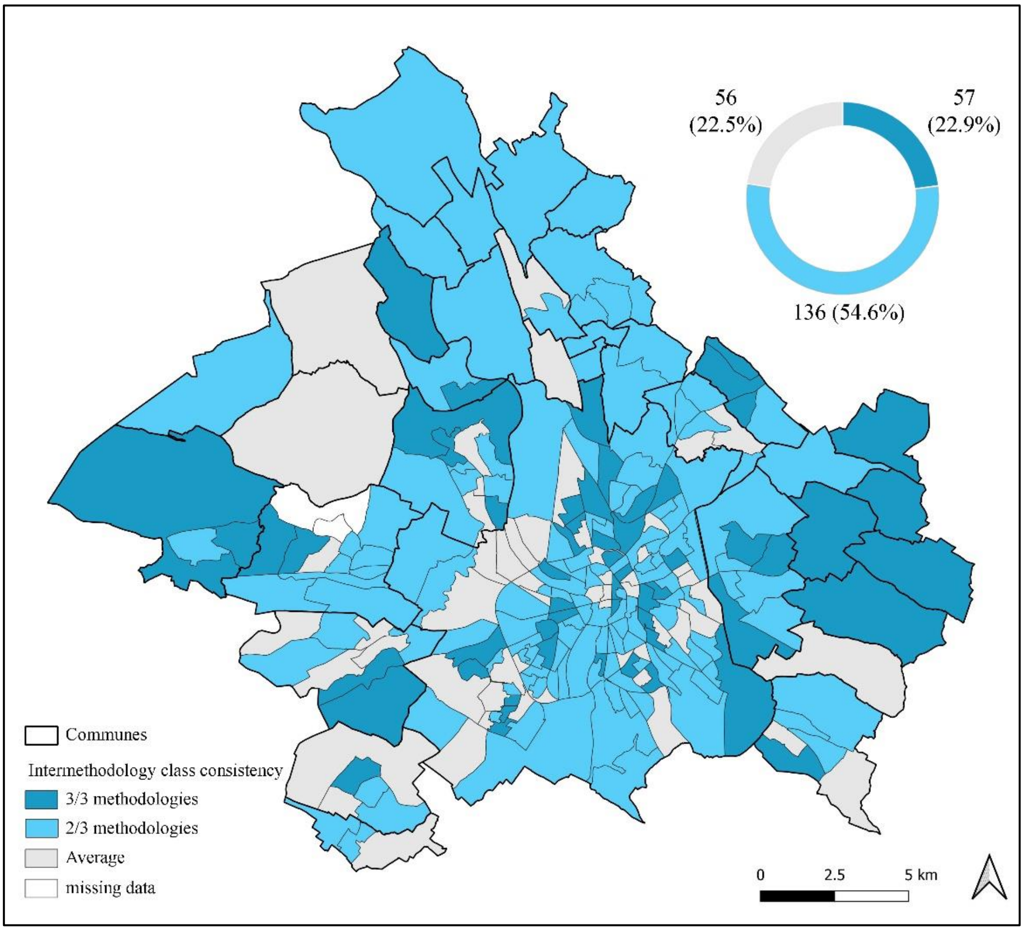


Figure 23. Inter-method composite index classes' classification consistency map

Results of the three-method composite index (Figure 24) show a cluster of geographical units with high levels of cumulative vulnerabilities located in the north-east of the communes of Toulouse. Higher levels of vulnerability in this area were consistent across the three methodologies. Furthermore, within the same commune, IRIS in the previously mentioned *quartiers prioritaires de la politique de la ville* have emerged. Additional IRIS with higher levels of vulnerability have been fund towards the centre –in lower numbers— and mostly in neighbourhoods in the outskirts and peri urban areas of the city of Toulouse. Other units emerged in the communes of *Colomiers* and *Castelginest*.

IRIS classed in the second cumulative vulnerabilities quantile are also mostly contained within the commune of Toulouse. However, a group of units in this class was also identified in the communes located towards the north of the metropolitan region, in addition to the city centers of *Blagnac, Colomiers, Cugnaux* and *Villeneuve-Tolosane*. Cumulative vulnerabilities are the lowest in the communes in the east and west of the metropolitan region as well as along the *Garonne* corridor, crossing south to north, specially outside the city of Toulouse. A detailed table of the composite index classification, including the results of the AHP, CVA and PCA is available in the annex section of this document (Appendix 3. AHP-CVA-PCA Results table).

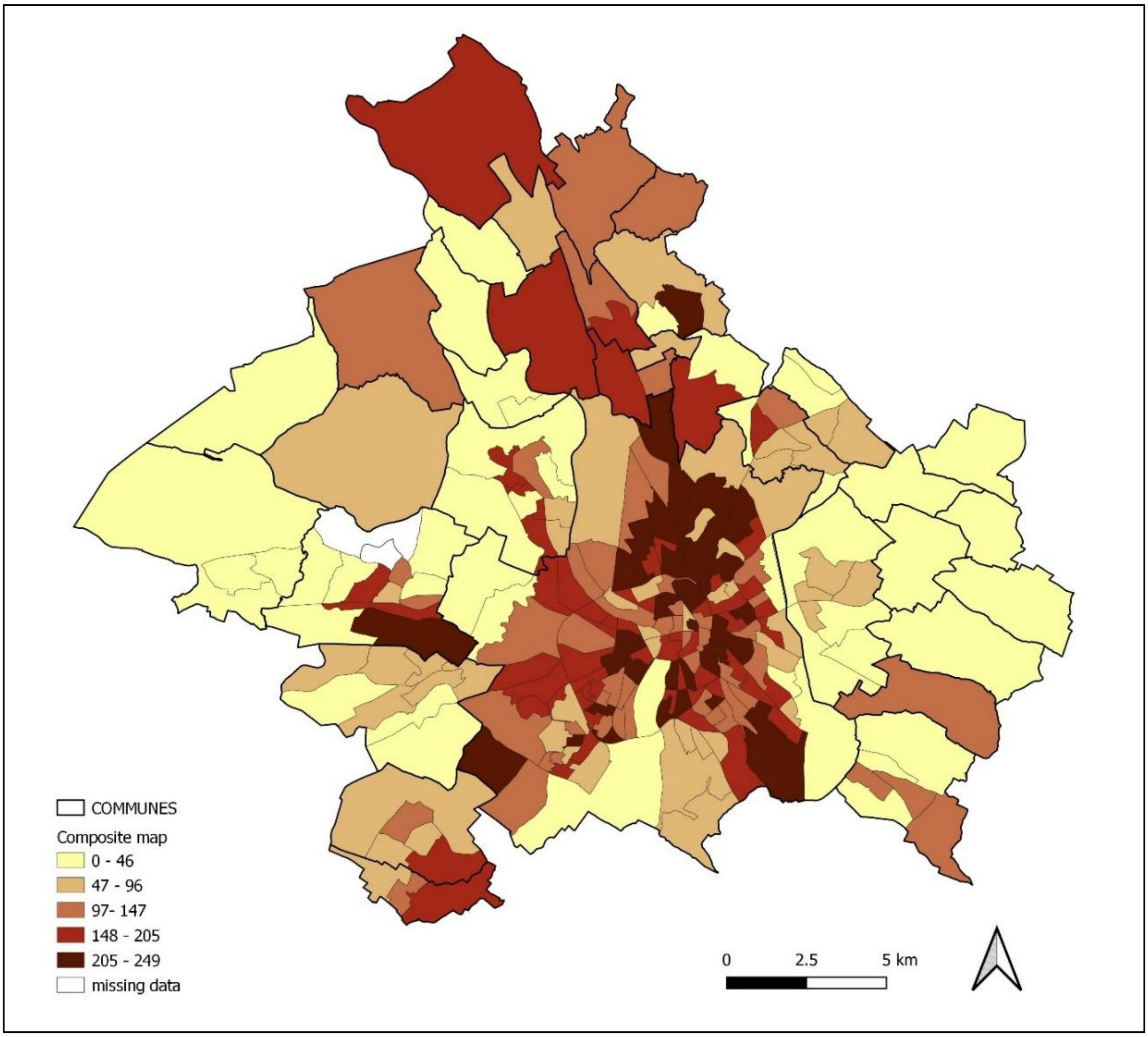


Figure 24. Inter-method cumulative vulnerability composite index map

CHAPTER 5: DISCUSSION AND CONCLUSIONS

Within the current climate change scenarios and in light of the growing concerns related to the increase in heat extremes –in particular in urban context– a number of researchers (Alonso and Renard, 2020; Conlon *et al*. 2020 ; Mallen *et al*. 2019 ; Inostroza *et al*. 2016 ; Bao *et al.* 2015) have approached the "problem" of heat vulnerability providing different conceptual approaches and evaluation methodologies. The same applies to the local authorities (Milan, Barcelona Sevilla, Vitoria-Gasteiz, New York, Philadelphia) that, confronted with the urgency of incorporating heat adaptation and mitigation strategies into their climate plans, have adopted heat vulnerability maps and/or indexes to inform their operational choices. Despite the existing corpus of works addressing heat vulnerability there isn't to date a commonly agreed upon definition, quantification methodology nor analytic approach.

Within this context, and with the aim of discussing existing heat vulnerability assessments' approaches and methodologies, this work proposes to reflect on the topic by:

1. performing a Cumulative Vulnerability Assessment (CVA) over the metropolitan region of Toulouse.
2. constructing a composite cumulative vulnerabilities index comprising the results of three methods (AHP-CVA-PCA) applied over the same region.

In the following section, the document will discuss the findings related with the points presented so far, potential operationalizations, limitations, and suggestions for further studies.

5.1 Variables selection and impact

Following a thorough review of the three methods included in this study, it can be argued that one of the most important pieces to take into consideration when approaching heat vulnerability is the definition of the variables that will be employed to characterize and quantify it. Three factors seem to come into play to influence variable choices. First, the conceptual approach or definition adopted to describe heat vulnerability –meaning the choices the researcher takes based on its own expertise and the subjective affinity with one approach or another. Secondly, once a conceptual framework has been established, a decision on the variables that "better" describe the phenomenon and are most suitable with the conceptual framework chosen must be made. This will be normally informed by previous studies in the field. Thirdly, but not less important, is the factor of data availability over the study area, which will ultimately dictate what variables can or cannot be employed in a study.

Furthermore, once the choices have been operated and the variables selected, additional challenges emerge. One example of this is related to the temporal gap between data acquisition of demographic and socio-economic data and the moment in which they become publicly available. A several-years gap, in a context of fast paced urban transformation can translate in a significant misrepresentation. Another example can be related to the validity of proxies employed to describe a particular phenomenon. In the AHP and PCA conducted by Lagelouze (2022) the variable topography was selected as a proxy for wind, hence considered as a negatively contributing factor in terms of heat exposure. However, following the analysis performed for the CVA it was established that in the context of metropolitan Toulouse, altitude doesn't represent an effective proxy for wind velocity distribution over the region (Figure 25). The above are of course only exemplificatory representations of the importance of variable selection and how these have can have important impacts on the study.

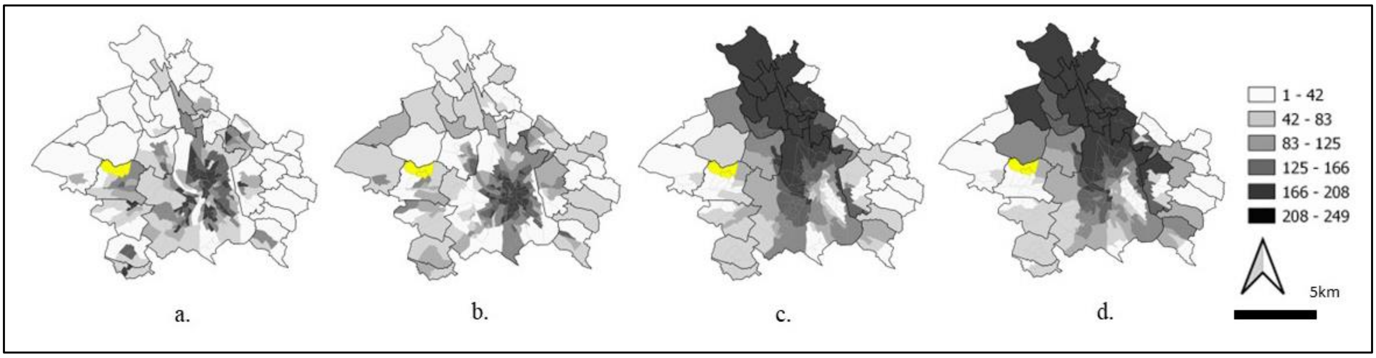


Figure 25. a. Percentage of urbanized surface; b. Average wind velocity; c. Digital Elevation Model majority height; d. Topography majority height. Results are displayed in six classes from the lowest quantile (1-42) to the highest (208-249).

5.1 Scale and spatial units'

In this work, IRIS units were selected as the spatial unit scale to conduct the study over the metropolitan region of Toulouse. This choice was dictated by the fact that this is the smallest scale at which socio-economic and demographic information are publicly made available in in France. The methodology, however, could have been applied both at a coarser or finer scale. For a study at a more detailed scale, INSEE makes available individuals' data to credited researchers and research facilities. This would allow an even more detailed characterization of individuals' vulnerability. For instance, employing the urban islets scale used in the framework of the French National Agency for Research project MApUCE (Plumejeaud-Perreau *et al.*,

2015) it would be possible to combine very detailed information related to urban morphology, climate and population's characteristics at the urban block scale. On the other hand, the study could also be adapted to employ a bigger scale, which might be helpful for operational purposes. In the context of the metropolitan region of Toulouse, this could be done employing the scale of the *Quartiers de la politique de la ville* (City Policy Neighborhoods) which is an administrative partition employed by French local authorities to tackle urban, economic and social issues; or at the scale of the *Communes* which could be helpful to convey information at a larger scale. Other scales are of course possible in other international contexts, depending on local data availability and administrative geographical delimitations.

5.2 Composite indexes' structure and results interpretation

As it has been already mentioned, the three methods employed in this study (AHP-CVA-PCA) represent different approaches to assess the same phenomenon. While the final index result for all the methodologies is conceptually the same: a series of spatial units' vulnerability levels over a spatial conglomerate –the composition of the indexes varies, both conceptually and in terms of composing factors. This, and the fact that there isn't a common heat vulnerability threshold reference scale, makes a comparison of the results on the sole vulnerability score impossible. However, an analysis of trends and spatial vulnerability distributions can be performed as well as an analytical characterization of the vulnerability descriptors behind such trends and spatial distributions. To do so, it is necessary to understand the indexes 'composition and analyse in detail the contributing factors.

The CVA composite index (Figure 26) is made of three factors (scores). The factors are composed combining variables equally (S *env* – S *pop*) and unequally weighted (S *dep*). The final vulnerability score is the result of a multiplicative operation, with the environmental score having the greatest multiplication factor. While the final vulnerability value doesn't provide any information on itself (besides, of course the overall vulnerability class), the composing scores are associated with thematic "buckets" that provide descriptive information over a particular unit allowing a simplified first level of synthetic characterization.

For instance, while analysing the associated scores of the highest quantile of the CVA results, it can be observed how the most vulnerable units are associated with high normalized values in the three scores. IRIS units toward the first part of the list instead show some units with important S *env* score, hence high exposure values, but comparatively lower socio-economic deprivation values and susceptible population presence. Willingly to take a further analytical step it is possible to visualize each component's score through the normalized or raw variable values providing an even more detailed description of the geographical unit.

The AHP index (Figure 27) is also made of three factors (Sensitivity, Exposure, and Adaptive Capacity), each factor is composed of equally weighted variables. The final index in this case is additive and results from the addition of the three factors (with adaptive capacity negatively contributing). Similarly to the CVA, results can be visualized through the factor's values associated with each of the three components. Eventually, as described before, the factors can be further detailed through the normalized or raw variables values to provide further information on the spatial units. In the AHP, each composing factor equally $(\frac{1}{3})$ contributes towards the result regardless of the composing variables and values associated with them. Conceptually, Exposure, Sensitivity and Adaptive Capacity assume then the same importance towards describing the final vulnerability level. In this case, the "richness" of variables through which a factor is composed (for instance, six in the case of the Sensitivity factor compared to three in Adaptive Capacity) doesn't influences the final result.

The PCA (Figure 28) finally is composed of five factors statistically aggregated and then summed to compose the final vulnerability index score. Factors are composed of differently weighted variable values based on the PCA assigned weight. While results can still be observed through the values of each component, it is impossible in first instance to associate the score of the factors to one or another contributing factor because variables are not thematically grouped. Some researchers, in what I would consider a subjective attempt, tend to assign thematic labels to the factors (Alonso and Renard, 2020; Hulley *et al.*, 2019) to facilitate results interpretation. This might however represent a misleading exercise as factors are grouped only based on their statistical association with no thematic influence (other than that exerted by the choice of inputs variables operated by the researcher). To perform a heat vulnerability analysis, in this case, I would argue it is necessary to go back to each factor to review the composing weights and variables to then understand the overall influence of a particular variable over the final score. This process poses some additional analysis constrains compared to the CVA and AHP, making the process of extrapolating information simpler on the latter two rather than on the former.

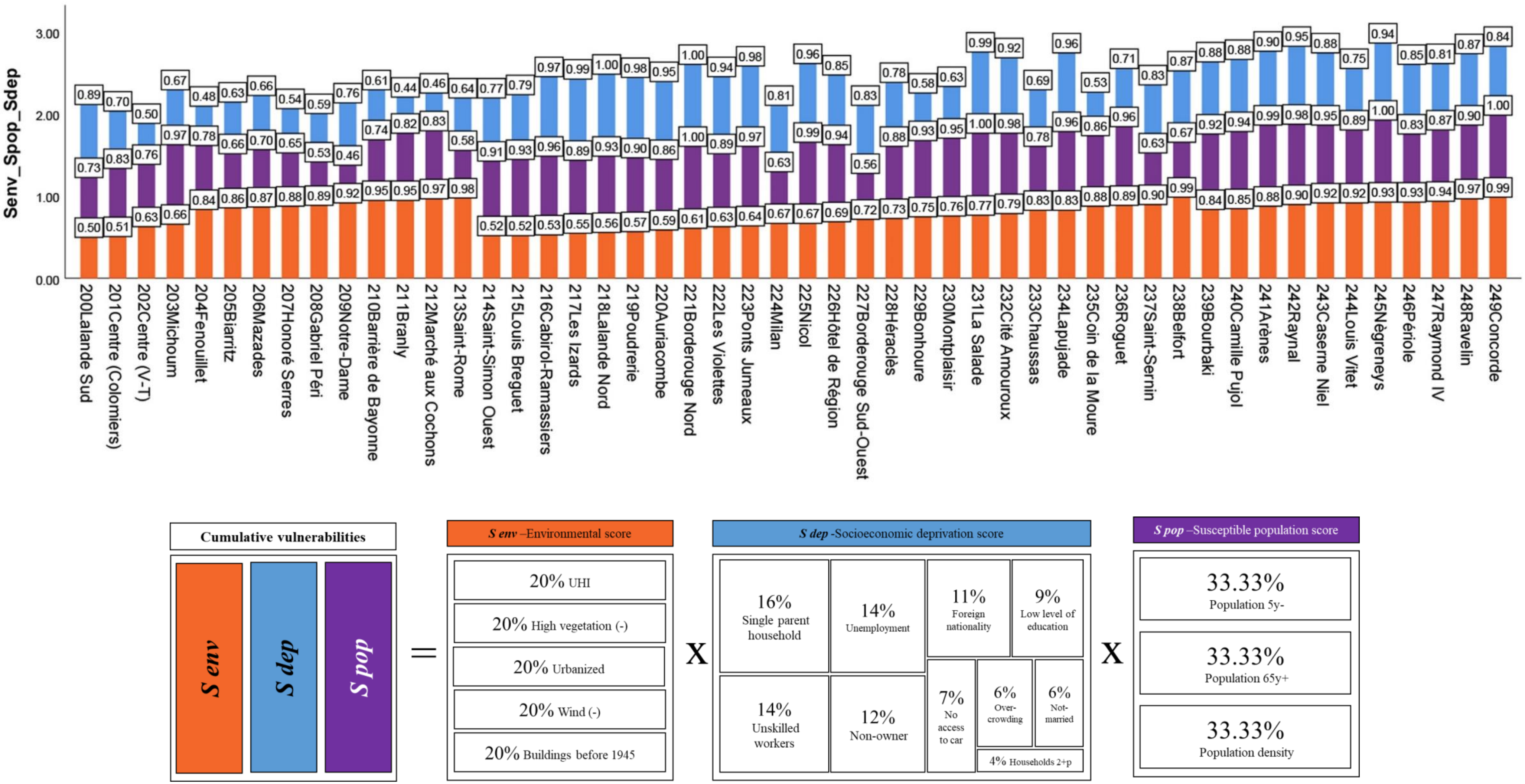


Figure 26. CVA highest quantile (IRIS 200-249) and CVA composite index structure. IRIS units are ranked from lowest to highest cumulative vulnerability class

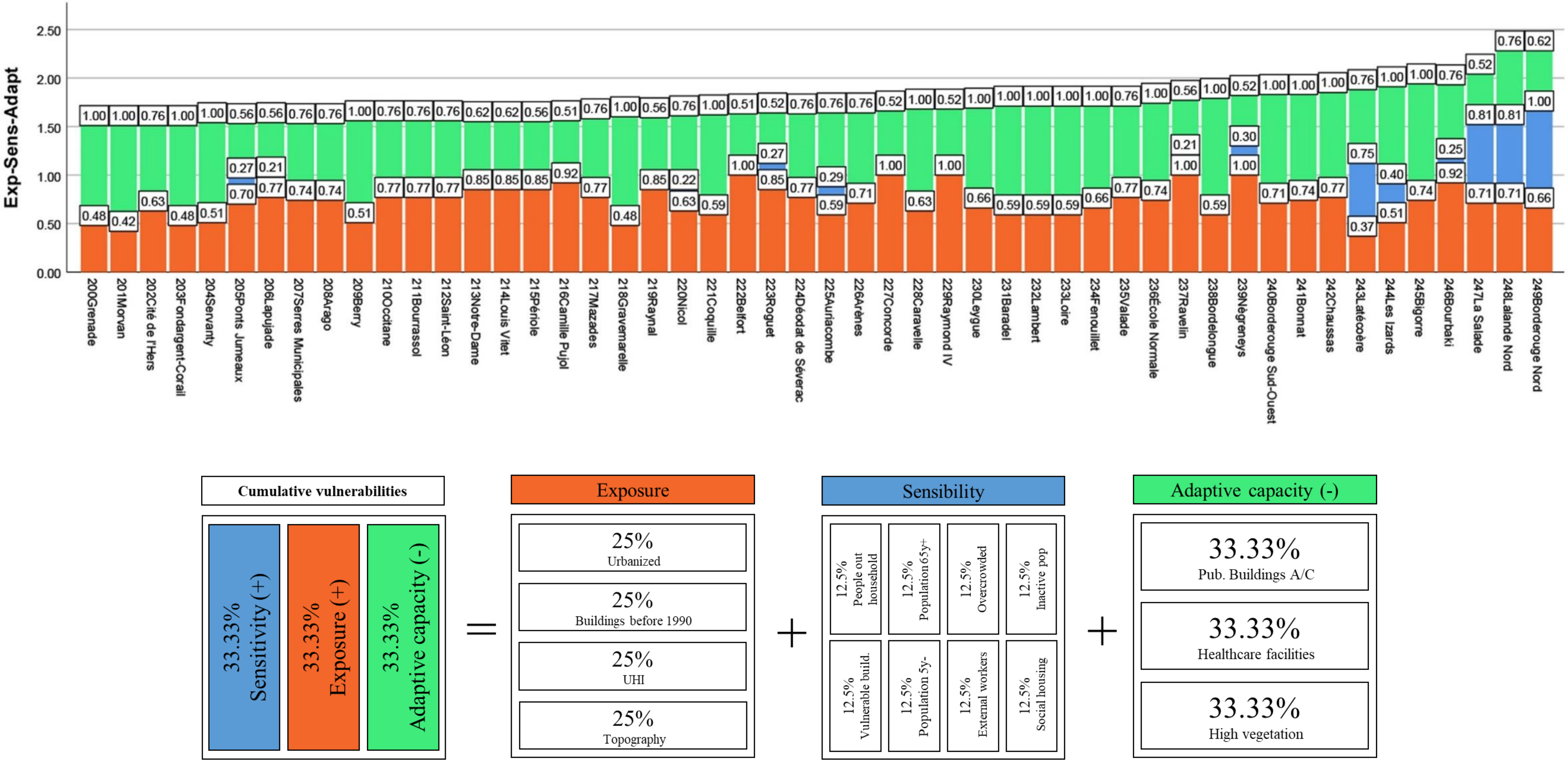


Figure 27. AHP highest quantile (IRIS 200-249) and AHP composite index structure. IRIS units are ranked from lowest to highest cumulative vulnerability class

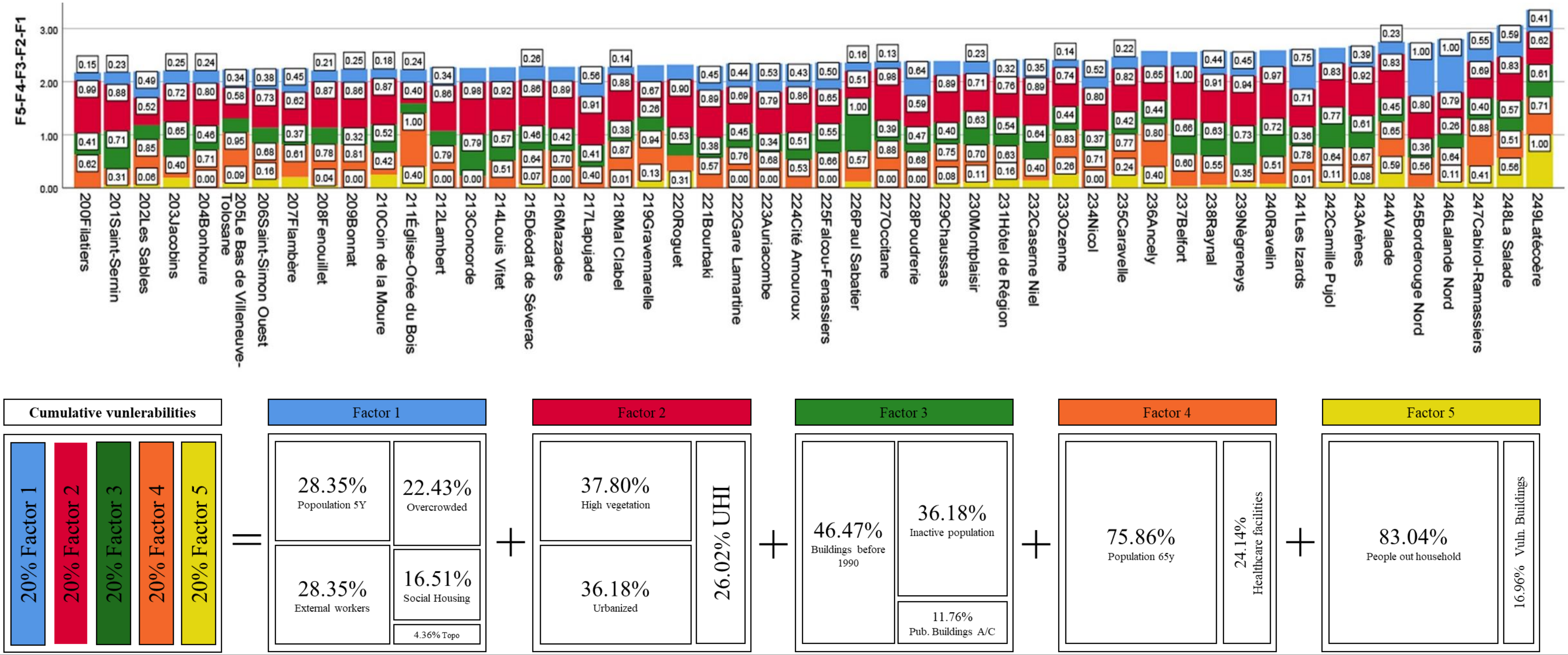


Figure 28. PCA highest quantile (IRIS 200-249) and PCA composite index structure. IRIS units are ranked from lowest to highest cumulative vulnerability class

5.3 Combined AHP-CVA-PCA composite index

Producing a composite index combining the results of AHP-CVA-PCA allows to spatially visualize the cumulative vulnerabilities tendency over the metropolitan region while taking into consideration the three different approaches. As a result, it is possible to identify those areas within the region that would require particular attention. The downside in this process is that, once the composite index is complete, the information describing the vulnerability factors is lost –similarly to what was described for the PCA factors. The combined index is able to communicate *where* to look but doesn't provide any information on *why* a particular spatial unit cumulates higher overall levels of vulnerability. To understand the *why* it is necessary to go back to the composing factors of the single indexes and/or eventually the original variables. While the global visualization can be a very useful tool in understanding where mitigation and adaptation strategies need to be implemented, the final composite index by itself it is not sufficient to support decision makers and practitioners in defining what type of intervention would be more appropriate over a specific area.

5.4 Adoption of cumulative heat vulnerability composite index and map by local authorities

If a local authority, like *Toulouse Metropole*, would like to adopt this type of tool to contribute toward their climate plan (*Plan climat-air-énergie territorial* -PCAET), it would be important to consider what are the pros and limitations that comes with them. For instance, to identify recommendations to tackle heat vulnerability over a specific spatial unit, the final composite index by itself is not sufficient. As seen in the results' section, factors determining high levels of cumulative vulnerability –as well as the characteristics of each unit— can vary from IRIS to IRIS. To draft appropriate interventions, it is then necessary to review the determining factors for each spatial unit or group of similar units, as a *one-size fit all* type of initiative won't be very effective. A particular geographical unit can present high levels of vulnerability mostly influenced by the presence of elderly and very young population while another can present similar levels of cumulative vulnerabilities mostly influenced by the high level of exposure, urbanization, and lack of vegetation.

In the first type of IRIS, initiatives focusing on advocacy regarding protective behaviours, identifying and signalling cool shelters and places to go in case of extreme heat could be beneficial. In those IRIS units that have higher level of exposure and little place for vegetation, interventions could rather look at the built environment and strategies aiming at increasing roof albedo, shading devices, and buildings insulation. On the other hand, for units with high exposure and available space, initiatives aiming at increasing the high vegetation surface coverage could be implemented –in line for example with the "*Plan arbres*" of the city of Toulouse which aims to plant 10 000 threes in the city by 2030. To develop a set of tailored interventions to fit the needs of particular areas in the metropolitan region, it is also important to take into consideration a set of qualitative information collected from the field and aiming at gathering the inputs from habitants of the neighbourhood's objects of the interventions. This step is largely absent from the existing studies consulted.

In summary, the adoption of heat vulnerability indexes and maps can be an efficient way for local authorities to understand where to focus their attention on the implementation of urban heat mitigation and adaptation strategies. However, this needs to go in parallel with a detailed analysis of the areas to be tackled to have a comprehensive understanding of the dynamics and characteristics that influence heat vulnerability and therefore tackle them in the most efficient way. In addition to the analysis work conducted by the authorities' experts, it would also be important to involve other areas of expertise and roles. This translates in the need to conduct further investigations that involve actors present in the target areas, identifying those private and institutional stakeholders that can have an important role for heat mitigation and adaptation in neighbourhoods and cities. These could potentially include other local authorities (*mairies*), neighbourhoods' groups, schools, businesses, and citizens among others.

Another aspect that should be taken into consideration is related to the potential uses of heat vulnerability assessments and maps as communication and awareness raising tools, within local authorities, but also externally to target larger groups in the community. This approach has already been taken by cities such as Philadelphia, Phoenix and New York, that have made results of their heat vulnerability assessments as well as other heat relief related resources available for their citizens. Furthermore, the same resources have then be used to accompany heat adaptation and mitigation planning projects in an effort to clearly and coherently vehiculate information to the community building the link between scientific based assessments, operationalization choices and communication/awareness raising. It is my opinion that a similar approach could be taken by the metropolitan authority of Toulouse, shall they adopt heat vulnerability assessment and maps into their climate action plans.

5.5 Findings validation

As highlighted in Chapter 2, multiple studies approach heat vulnerability from the morbimortality perspective. Within this type of studies heat related deaths and/or heat related hospitalizations are central to the vulnerability description, quantification, and localization. These proxies are also employed to validate the findings following the approach higher vulnerability= higher deaths/hospitalizations. While theoretically this approach could be used to eventually validate the findings presented (disregarding the fact that mortality and morbidity data are not released at the IRIS scale in France), this study argues that heat impact on individuals goes beyond the number of reported deaths or sickness. Quality of life, capacity to perform work and other activities, social interaction and individuals' behaviours are severely impacted by extreme heat exposure without necessarily resulting in sickness of the loss of life.

To validate the statistically obtained findings, in line with the conceptual heat vulnerability approach taken by this study, it won't be accurate then to employ heat related death and sickness counts proxies. A validation of the heat vulnerability findings will need to pass through a field based qualitative information collection able to assess individuals heat vulnerability on the field and corroborate the information provided by the heat vulnerability assessment indexes.

5.6 Limitations of the study and future studies' recommendations

This study, as most heat vulnerability related studies consulted, doesn't incorporate qualitative information over the study area. As already noted, to better understand the results obtained through the statistical methods employed it would be important to complement the results with information collected from the field employing methods such as observations, interviews, focus groups, surveys, and secondary research. Incorporating this data into future studies can support the validation of statistically obtained information and enable a more accurate understanding of heat related dynamics. Furthermore, this information can support better understanding individuals' behaviours and perceptions linked with heat exposure, that could better inform the design of heat mitigation and adaptation strategies.

Although there isn't a common understanding on the concept of vulnerability across HV studies, several researchers agree on the *dynamic* nature of vulnerability. Over-simplifying, an individual might be considered vulnerable today but not in one week, one month or one year as their conditions (e.g., salary, health condition, place of residence, or other) might have changed based on the determinant factors employed to describe and measure vulnerability. This nature points out the temporal dimension limit of this study; meaning that the cross-sectional results of the study describe an overall vulnerability condition which is specific to a certain moment(s) in time. By combining data from different years and with some years gap between collection and publication, the final "picture" provided is then just an approximation. To somehow address this issue, studies could take a longitudinal approach rather than the cross-sectional one taken here.

As explained in the Methodology section, different input variables were employed for the CVA and the two other methods (AHP- PCA). For future inter-method studies aiming to combine results, employing the same input variables could enable a more robust comparison of the results and final composite index construction, also allowing a more precise evaluation of the classification consistency. Furthermore, considering the lack of a universally agreed definition and methodology to characterize and quantify (heat) vulnerability, exploring and refining the factors and variables' qualities through which assessments are performed remain a solid way to further improve HV assessments overall quality. Additional room for improvement in this regard could come from the exploration of diverse proxies to describe and quantify heat exposure. While this study used UHI intensity (nocturnal air temperature), urbanized surface percentage, high-vegetation surface coverage percentage, pre-1945 buildings presence, and average wind velocity, the combination of other variables could provide a more accurate description of the individual exposure component.

The CVA method employed in this study uses the socio-economic deprivation index known as French-EDI. While data employed in this study refers to the French version of the index, the EDI can be calculated for different European countries (Guillaume *et al*., 2015) making the CVA methodology applied to the heat vulnerability assessment context a suitable methodology for studies aiming at comparing heat vulnerability across different European cities. This could potentially signify that, granted that equivalent intercity components to describe and measure the Environmental and Susceptible population components are found for each of the study areas, a study covering diverse European metropolitan areas could be attempted. Furthermore, studies could be integrated with AHP and CVA assessments as conducted in this work.

5.6 Conclusions

This research aimed at contributing towards heat vulnerability assessing and mapping in the metropolitan region of Toulouse -France, by integrating urban heat maps with environmental, demographic and socio-economic data. Results of the study identified different clusters of heat vulnerable IRIS over the metropolitan region, with the highest concetration occuring with the limits of the *commune* of Toulouse. These results confirmed the expectations of encountering higher level of heat vulnerability in concomittance with the mostly urbanized areas of the metropolitan region. However, contrary to initial belief, results showed that high urban heat exposure levels not always correspond with the highest levels of vulnerability, suggesting that climate adaptation and mitigation efforts should carefuly take into consideration socioeconomic and demographic individuals conditions when planning climate adaptation and mitigation interventions aiming at tackleling urban heat related vulnerability.

The study found that composite indexes combining environmental, demographic and socio-economic data can be an effective tool to spatially visualize cumulative vulnerabilities tendency over a metropolitan region. While this global visualization can be a useful tool in understanding where metropolitan authorities could focus their urban heat related climate interventions, final composite indexes results by themselves are not sufficient to support decision makers and practitioners in defining the type of intervention that would be more appropriate over a specific area. Local authorities should pay attention to the indexes' composing determinants to plan and deliver tailored solutions according to the specific needs of clusters of geographical units with similar characteristics. This is particularly relevant for the metropolitan region of Toulouse as results suggest that spatial units with high vulnerability values can have different underlying determinants.

Furthermore, the study suggests that statistically obtained findings should be accompanied by qualitative field research to validate, complement, better characterize, and describe heat vulnerability tendencies identified over a study area. Results also points out the importance of considering the impact of urban heat on individuals from a perspective that considers its associations with quality of life, capacity to perform work and other activities, social interaction, and influence on individuals' behaviours in addition to the commonly addressed associations with morbidity and mortality. Of particular importance is also the adoption of longitudinal studies to better understand the dynamic component of heat vulnerability and its interaction with environmental, demographic, and socio-economic determinants linked with the processes of urban evolutions in the context of climate change.

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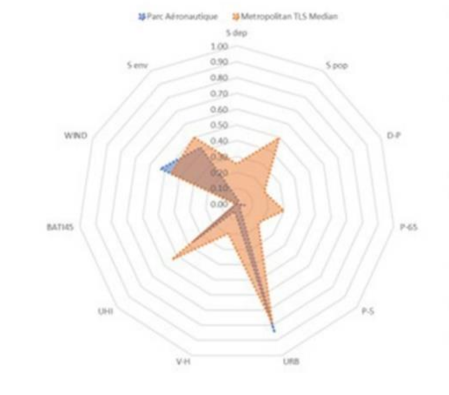
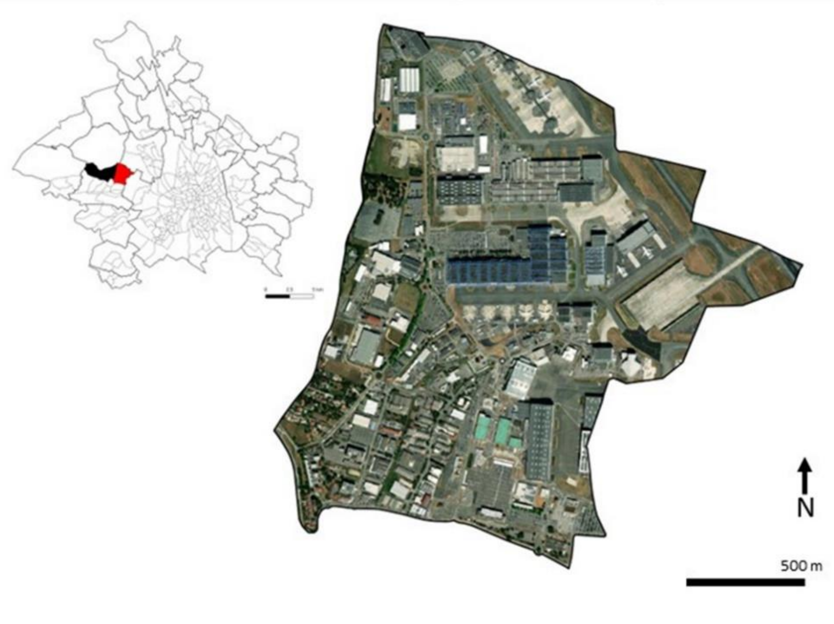
APPENDICES

Appendix 1. CVA IRIS units profiles - S *env*-S *pop*-S *dep* descriptors' tables

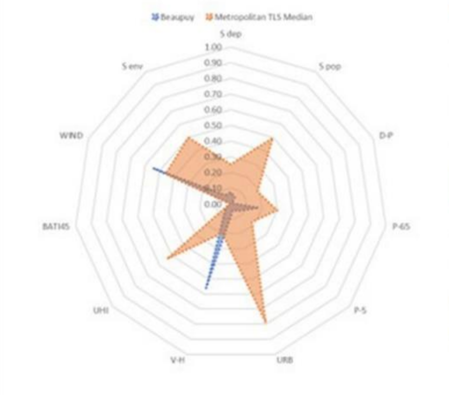
IRIS: Parc Aéreonautique



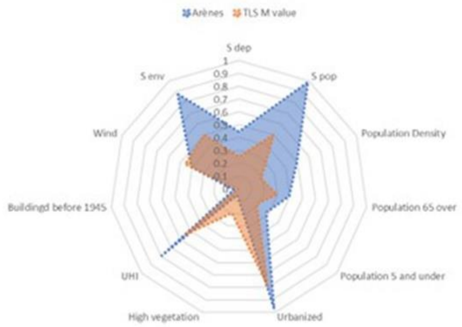
Score	Rank
S *env*	**106/249**
Urbanized	High
High vegetation	Very low
UHI	Low
Buildings before 1945	Very low
Wind	High
S *pop*	**6/249**
Population Density	Very low
Population over 65	Very low
Population 5 and under	Very low
S *dep*	**7/249**
Cumulative Vulnerabilities score	**3 (Low CV)**



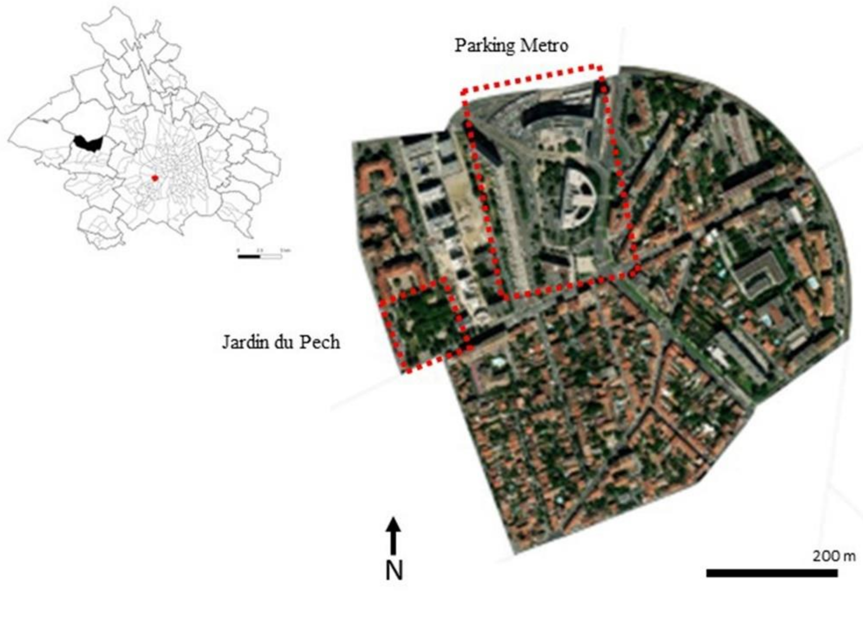
IRIS: Beaupuy

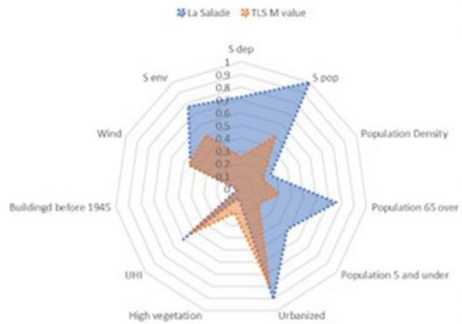


Score	Rank
S *env*	**17/249**
Urbanized	Very low
High vegetation	High
UHI	Very low
Buildings before 1945	Very low
Wind	High
S *pop*	**13/249**
Population Density	Very low
Population over 65	Low
Population 5 and under	Very low
S *dep*	**14/249**
Cumulative Vulnerabilities score	**1 (Low CV)**

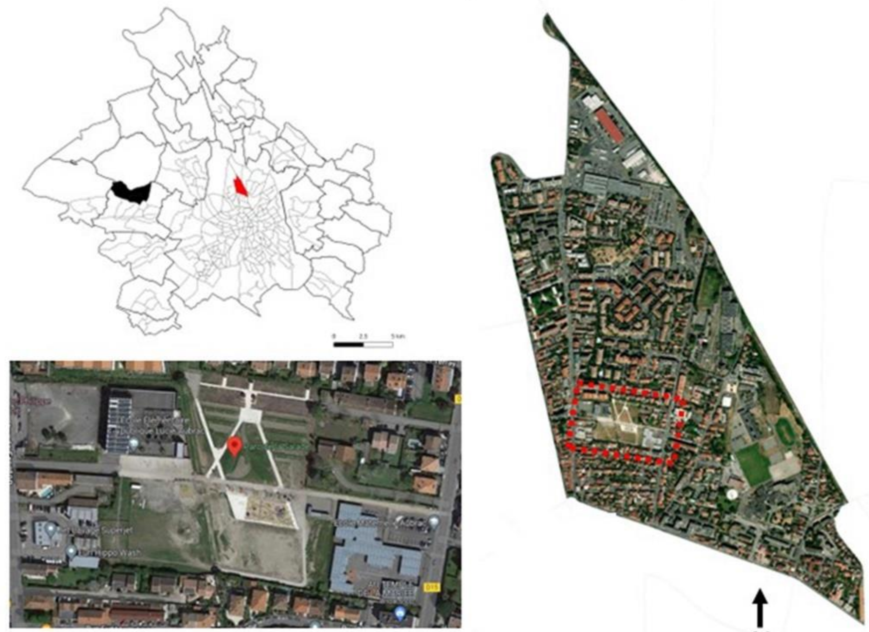


IRIS: Arènes	Score	Rank
	S *env*	**220/249**
	Urbanized	High
	High vegetation	Low (-)
	UHI	High
	Buildings before 1945	Low
	Wind	Medium
	S *pop*	**244/249**
	Population Density	Medium
	Population over 65	High
	Population 5 and under	High
	S *dep*	**224/249**
	Cumulative Vulnerabilities score	**96 (High CV)**



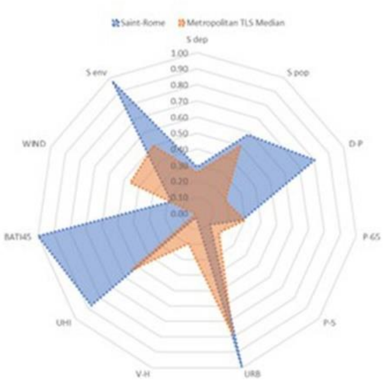


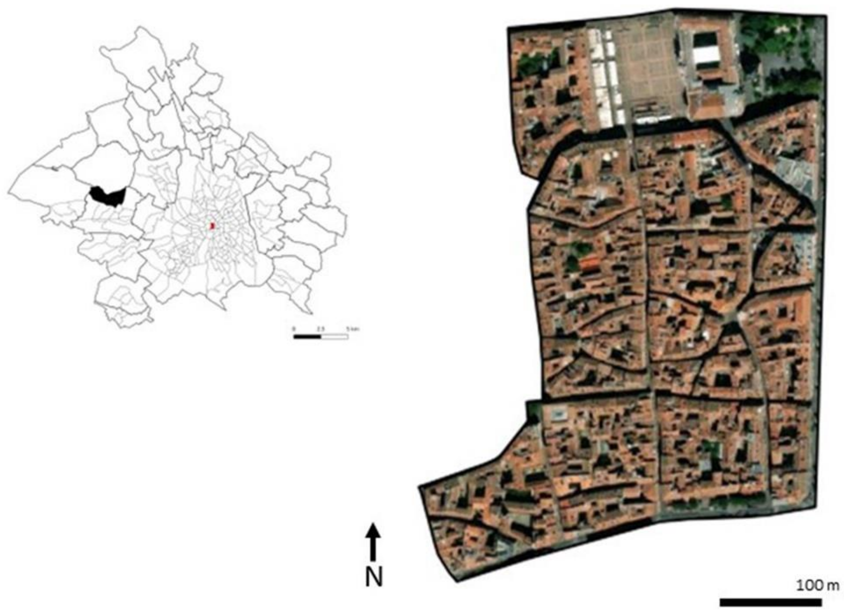
IRIS: ***La Salade***	Score	Rank
	S *env*	**193/249**
	Urbanized	Medium
	High vegetation	Low (-)
	UHI	Medium
	Buildings before 1945	High
	Wind	Medium
	S *pop*	**247/249**
	Population Density	Medium
	Population over 65	High
	Population 5 and under	High
	S *dep*	**246/249**
	Cumulative Vulnerabilities score	**80 (High CV)**



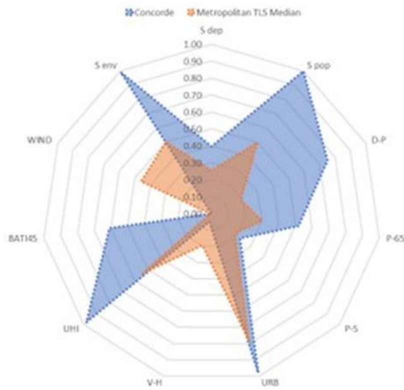
La Salade Park – Elementary School and Kindergarten

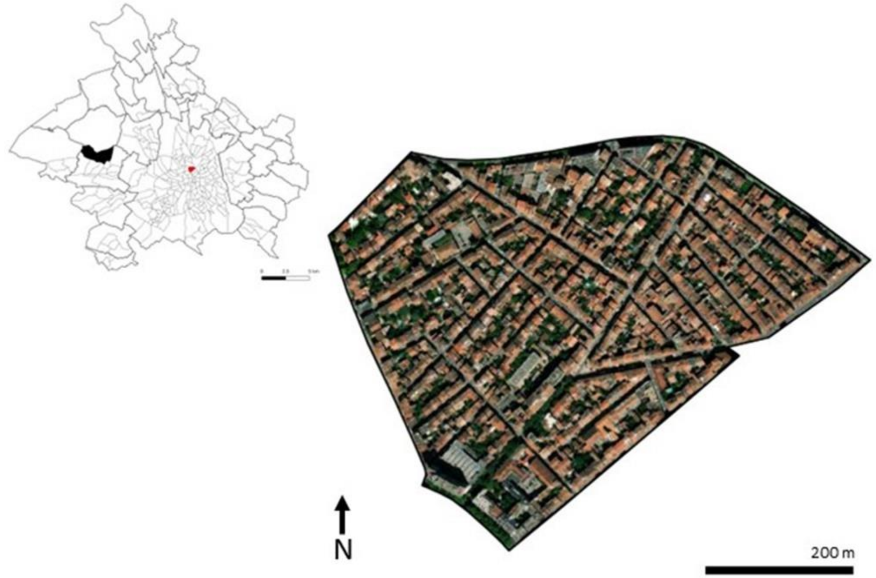
IRIS: Saint-Rome	Score	Rank
	S *env*	**243/249**
	Urbanized	Very high
	High vegetation	Very low
	UHI	Very high
	Buildings before 1945	Very high
	Wind	Very low
	S *pop*	**144/249**
	Population Density	Very high
	Population over 65	Medium
	Population 5 and under	Low
	S *dep*	**160/249**
	Cumulative Vulnerabilities score	**54 (Low CV)**





IRIS: Concorde	Score	Rank
	S *env*	**247/249**
	Urbanized	Very high
	High vegetation	Very low
	UHI	Very high
	Buildings before 1945	Very high
	Wind	Very low
	S *pop*	**247/249**
	Population Density	Very high
	Population over 65	Very high
	Population 5 and under	Very high
	S *dep*	**210/249**
	Cumulative Vulnerabilities score	**96 (Low CV)**





Appendix 2. Variables employed in the study conducted by Lagelouze (2022).

n.	Variable	Impact on vulnerability	Source
1	Number of unemployed in 2017	+	Insee
2	Number of inactive population in 2017	+	Insee
3	Number of CNAM beneficiaries in 2020	-	Insee
4	Number of people living in social housing in 2017	+	Insee
5	Poverty rate	+	Insee
6	Number of overcrowded housing units	+	Insee
7	Number of persons without fixed residence in 2017	+	Insee
8	Number of people 15+ without school education	+	Insee
9	Number of people 15+ without secondary or technical education	+	Insee
10	Number of foreign nationals in 2017	+	Insee
11	Number of immigrants in 2017	+	Insee
12	Number of people 65+ in 2017	+	Insee
13	Number of people 5- in 2017	+	Insee
14	Number of people female sex in 2017	+	Insee
15	Number of retired people in 2017	+	Insee
16	Number of outdoor workers	+	Insee
17	Number of vulnerable facilities in 2017	+	Insee
18	Population density in 2017	+	Insee-BD Topo-IGN
19	Number of people living alone in 2017	+	Insee
20	Number of health facilities in 2020	+	Insee
21	Number of air-conditioned facilities in 2020	-	Insee
22	Number of people renting	+	Insee
23	Percentage of high vegetation	-	CES - OSO - Cesbio
24	Number of buildings built before 1990 in 2017	+	Insee
25	Percentage of Urbanized area in 2020	+	CES - OSO - Cesbio
26	UHI in 2014	+	MApUCE - CNRM
27	Topography in 2021	-	IGN BD Alti 25m

Appendix 3. AHP-CVA-PCA Results table

INSEE_C(	NOM_COI	IRIS	CODE_IRI	NOM_IRIS	TYP_IRIS	N Sdep	N_Spop	N_Senv	CVA_Sco	CVA_CLA	N_class_(	CVA_RAN	AHP_Ada	AHP_Exp	AHP_Sen	AHP_Vuln	AHP_RAN	PCA_F1	PCA_F2	PCA_F3	PCA_F4	PCA_F5	PCA_FG	PCA_RANK P
31555	Toulouse	2004	31555200	10 Avril	H	0.52	0.44	0.71	30	E	0.31	160	0.38	0.4	0.08	0.29	59	0.24	0.67	0.38	0.44	0.01	0.36	77
31069	Blagnac	0110	31069011	Aéroport	A	0.02	0.01	0.19	2	B	0.01	22	1	0.2	0	0.46	125	0.04	0.61	0.02	0.64	0	0.2	17
31555	Toulouse	5902	31555590	Aérospatia	A	0.13	0.07	0.27	2	B	0.01	28	1	0.3	0	0.51	147	0.17	0.66	0.04	0.64	0	0.28	40
31157	Cugnaux	0102	31157010	Agora	H	0.84	0.87	0.31	32	E	0.33	169	0.76	0.25	0.17	0.45	124	0.37	0.58	0.3	0.84	0.03	0.52	188
31555	Toulouse	6002	31555600	Ancely	H	0.68	0.92	0.39	36	F	0.37	175	0.38	0.4	0.29	0.4	98	0.29	0.65	0.44	0.8	0.4	0.69	236
31555	Toulouse	5402	31555540	Antonio M	H	0.24	0.07	0.43	3	B	0.02	37	0.76	0.59	0.03	0.55	164	0.2	0.76	0.26	0.48	0.02	0.36	76
31555	Toulouse	2001	31555200	Arago	H	0.34	0.19	0.96	12	D	0.12	102	0.76	0.74	0.03	0.63	208	0.15	0.94	0.33	0.56	0	0.46	150
31557	Tournefeu	0103	31557010	Arc-En-Cie	H	0.09	0.13	0.14	1	A	0.00	13	0.76	0.25	0.03	0.38	86	0.12	0.52	0.21	0.82	0	0.34	65
31555	Toulouse	3301	31555330	Arènes	H	0.90	0.99	0.88	96	H	1.00	241	0.76	0.71	0.17	0.68	226	0.39	0.92	0.61	0.67	0.08	0.73	243
31555	Toulouse	5303	31555530	Auriacomt	H	0.95	0.86	0.59	64	G	0.66	225	0.76	0.59	0.29	0.68	225	0.53	0.79	0.34	0.68	0	0.6	223
31032	Aussonne	0000	31032000	Aussonne	Z	0.91	0.87	0.26	32	E	0.33	167	0.28	0.37	0.27	0.32	64	0.46	0.38	0.48	0.42	0.06	0.39	100
31555	Toulouse	2402	31555240	Avions	H	0.11	0.16	0.76	5	B	0.04	53	0.76	0.59	0	0.54	161	0.12	0.86	0.3	0.58	0	0.42	127
31069	Blagnac	0103	31069010	Baradel	H	0.69	0.41	0.64	24	E	0.24	150	1	0.59	0.12	0.72	231	0.37	0.8	0.22	0.65	0	0.49	169
31555	Toulouse	3503	31555350	Barrière de	H	0.61	0.74	0.95	54	F	0.56	212	0.62	0.77	0.03	0.57	177	0.23	0.95	0.38	0.36	0	0.43	129
31555	Toulouse	5601	31555560	Basso Car	H	0.60	0.09	0.36	9	C	0.08	85	1	0.34	0.05	0.56	171	0.27	0.67	0.17	0.71	0.16	0.46	146
31555	Toulouse	0702	31555070	Bazacle	H	0.72	0.66	0.44	27	E	0.27	156	0.62	0.4	0.08	0.41	101	0.25	0.39	0.36	0.79	0	0.39	101
31053	Beaupuy	0000	3.11E+08	Beaupuy	Z	0.05	0.05	0.06	1	A	0.00	7	0.38	0	0	0.05	2	0.05	0.13	0.14	0.58	0.13	0.09	3
31555	Toulouse	2801	31555280	Bécanne	H	0.32	0.39	0.94	24	E	0.24	152	0.62	0.59	0	0.47	132	0.22	0.92	0.3	0.32	0.08	0.41	121
31557	Tournefeu	0106	31557010	Belbèze	H	0.19	0.35	0.13	2	B	0.01	20	0.76	0.3	0.06	0.42	109	0.1	0.57	0.26	0.82	0	0.37	79
31555	Toulouse	1001	31555100	Belfort	H	0.87	0.67	0.99	72	G	0.75	232	0.51	1	0.12	0.68	222	0.27	1	0.66	0.6	0.03	0.69	237
31561	L'Union	0106	31561010	Belvèze	H	0.10	0.28	0.21	4	B	0.03	44	0.51	0.37	0.06	0.33	70	0.1	0.65	0.26	0.89	0	0.43	134
31069	Blagnac	0101	31069010	Berry	H	0.37	0.57	0.50	18	D	0.18	132	1	0.51	0.05	0.64	209	0.26	0.77	0.27	0.76	0.07	0.52	184
31555	Toulouse	3501	31555350	Biarritz	H	0.63	0.66	0.86	54	F	0.56	208	0.62	0.74	0.08	0.58	181	0.27	0.88	0.26	0.45	0	0.42	125
31555	Toulouse	2902	31555290	Bigorre	H	0.68	0.59	0.65	36	F	0.37	181	1	0.74	0.2	0.83	245	0.4	0.81	0.31	0.67	0	0.54	195
31555	Toulouse	4603	31555460	Bitet	H	0.17	0.52	0.29	6	C	0.05	61	0.38	0.37	0.05	0.26	45	0.16	0.57	0.26	0.58	0.04	0.32	60
31555	Toulouse	4602	31555460	Bois de Li	H	0.25	0.49	0.27	8	C	0.07	76	0.18	0.29	0.03	0.11	7	0.12	0.6	0.25	0.38	0.11	0.26	36
31555	Toulouse	2103	31555210	Bonhoure	H	0.58	0.93	0.75	60	G	0.62	216	0.76	0.59	0.05	0.56	175	0.24	0.8	0.46	0.71	0	0.55	204
31555	Toulouse	2404	31555240	Bonnat	H	0.36	0.42	0.74	20	E	0.20	136	1	0.74	0.09	0.78	241	0.25	0.86	0.32	0.81	0	0.56	209
31555	Toulouse	2903	31555290	Bordelong	H	0.71	0.48	0.58	24	E	0.24	148	1	0.59	0.2	0.76	238	0.43	0.8	0.23	0.73	0	0.54	197
31555	Toulouse	4007	31555400	Borderoug	H	1.00	1.00	0.61	64	G	0.66	226	0.62	0.66	1	1	249	1	0.8	0.36	0.56	0.01	0.76	245
31555	Toulouse	4006	31555400	Borderoug	H	0.23	0.39	0.34	6	C	0.05	62	0.24	0.57	0.03	0.28	53	0.19	0.6	0.15	0.38	0.11	0.24	30
31555	Toulouse	4005	31555400	Borderoug	H	0.83	0.56	0.72	60	G	0.62	215	1	0.71	0.12	0.78	240	0.4	0.86	0.13	0.69	0	0.5	174
31555	Toulouse	1803	31555180	Bourbaki	H	0.88	0.92	0.84	96	H	1.00	239	0.76	0.92	0.25	0.83	246	0.45	0.89	0.38	0.57	0	0.59	221
31555	Toulouse	1603	31555160	Bourrasso	H	0.44	0.72	0.82	30	E	0.31	163	0.76	0.77	0.03	0.64	211	0.19	0.87	0.37	0.6	0	0.48	164
31555	Toulouse	1203	31555120	Branly	H	0.44	0.82	0.95	48	F	0.49	206	0.56	0.85	0.03	0.58	185	0.19	0.93	0.5	0.33	0.07	0.47	159
31091	Bruguières	0000	31091000	Bruguières	Z	0.86	0.85	0.15	16	D	0.16	109	0.18	0.37	0.25	0.26	43	0.38	0.32	0.41	0.6	0.11	0.4	108
31149	Colomiers	0601	31149060	Cabirol-Ra	H	0.97	0.96	0.53	64	G	0.66	221	0.38	0.25	0.59	0.47	131	0.55	0.69	0.4	0.88	0.41	0.83	247
31555	Toulouse	2101	31555210	Camille Pu	H	0.88	0.94	0.85	96	H	1.00	240	0.51	0.92	0.13	0.64	216	0.29	0.83	0.77	0.64	0.11	0.72	242
31506	Saint-Orer	0101	31506010	Cammas-(	H	0.30	0.41	0.51	16	D	0.16	114	0.62	0.48	0.06	0.44	120	0.15	0.71	0.25	0.53	0	0.33	63
31417	Pibrac	0103	31417010	Campagne	H	0.40	0.36	0.00	4	B	0.03	39	0.52	0.02	0.05	0.16	17	0.19	0	0.2	0.78	0.09	0.18	14
31555	Toulouse	2002	31555200	Caravelle	H	0.58	0.71	0.71	45	F	0.46	191	1	0.63	0.05	0.7	228	0.22	0.82	0.42	0.77	0.24	0.65	235
31555	Toulouse	3504	31555350	Cartouche	H	0.97	0.70	0.32	24	E	0.24	145	0.38	0.37	0.23	0.35	78	0.49	0.62	0.38	0.38	0.01	0.42	126
31555	Toulouse	2501	31555250	Caserne N	H	0.88	0.95	0.92	96	H	1.00	243	0.56	0.71	0.17	0.58	184	0.35	0.89	0.64	0.4	0.14	0.63	232
31506	Saint-Orer	0105	31506010	Catala-Ca	H	0.04	0.08	0.03	1	A	0.00	4	1	0.16	0.03	0.46	127	0.09	0.3	0.18	0.78	0.02	0.22	24
31149	Colomiers	0101	31149010	Centre	H	0.70	0.83	0.51	48	F	0.49	201	0.52	0.4	0.13	0.39	90	0.34	0.79	0.29	0.2	0.01	0.32	55
31588	Villeneuve	0101	31588010	Centre	H	0.50	0.76	0.63	48	F	0.49	202	0.62	0.4	0.08	0.41	106	0.24	0.8	0.27	0.57	0.07	0.45	145
31157	Cugnaux	0101	31157010	Centre	H	0.42	0.75	0.65	24	E	0.24	151	0.56	0.4	0.06	0.37	85	0.21	0.77	0.3	0.4	0	0.34	68
31116	Castelgine	0101	31116010	Centre	H	0.81	0.78	0.15	16	D	0.16	108	0.62	0.31	0.12	0.39	89	0.37	0.37	0.29	0.64	0.02	0.35	70
31069	Blagnac	0107	31069010	Centre	H	0.38	0.47	0.59	16	D	0.16	116	0.32	0.48	0.03	0.28	52	0.19	0.65	0.32	0.4	0.17	0.37	85
31561	L'Union	0101	31561010	Centre	H	0.07	0.33	0.49	6	C	0.05	69	0.38	0.51	0.06	0.34	76	0.06	0.73	0.24	0.69	0.12	0.41	123
31044	Balma	0101	31044010	Centre	H	0.06	0.31	0.16	2	B	0.01	21	0.51	0.13	0.06	0.21	26	0.06	0.51	0.23	0.87	0	0.34	66
31044	Balma	0103	31044010	Centre An	H	0.09	0.23	0.67	5	B	0.04	52	0.62	0.51	0.03	0.44	117	0.11	0.88	0.21	0.5	0	0.35	71
31557	Tournefeu	0101	31557010	Centre Vill	H	0.35	0.59	0.39	18	D	0.18	126	0.38	0.33	0.05	0.24	30	0.23	0.62	0.26	0.49	0.04	0.33	61
31555	Toulouse	0701	31555070	Chapou	H	0.43	0.21	0.56	8	C	0.07	79	0.18	0.63	0.08	0.31	63	0.11	0.54	0.48	0.35	0.24	0.36	74
31555	Toulouse	4804	31555480	Charbonni	H	0.31	0.15	0.45	6	C	0.05	67	0.76	0.48	0.03	0.5	141	0.16	0.66	0.33	0.59	0.01	0.37	88
31557	Tournefeu	0109	31557010	Château d	H	0.56	0.85	0.15	12	D	0.12	93	0.24	0.21	0.09	0.13	12	0.24	0.44	0.31	0.64	0.04	0.34	64
31555	Toulouse	1802	31555180	Chaussas	H	0.69	0.78	0.83	60	G	0.62	218	1	0.77	0.08	0.79	242	0.27	0.89	0.4	0.75	0.08	0.62	229
31555	Toulouse	4202	31555420	Cité Amou	H	0.92	0.98	0.79	80	G	0.83	237	0.62	0.71	0.14	0.6	195	0.43	0.86	0.51	0.53	0	0.6	224
31555	Toulouse	4501	31555450	Cité de l'H	H	0.58	0.73	0.65	36	F	0.37	182	0.76	0.63	0.12	0.62	202	0.31	0.81	0.35	0.6	0	0.49	171
31555	Toulouse	2202	31555220	Coin de la	H	0.53	0.86	0.88	72	G	0.75	229	0.56	0.77	0.13	0.59	191	0.18	0.87	0.52	0.42	0.25	0.56	210
31555	Toulouse	1102	31555110	Colombett	H	0.57	0.22	0.85	18	D	0.18	133	0.13	0.85	0.05	0.38	87	0.16	0.85	0.56	0.39	0.06	0.48	163
31069	Blagnac	0108	31069010	Compans	H	0.17	0.37	0.43	6	C	0.05	66	0.51	0.33	0.03	0.3	61	0.13	0.6	0.27	0.6	0.04	0.32	57
31555	Toulouse	0901	31555090	Concorde	H	0.84	1.00	0.99	96	H	1.00	249	0.52	1	0.14	0.69	227	0.27	0.98	0.79	0.22	0	0.57	213
31555	Toulouse	4402	31555440	Coquille	H	0.28	0.33	0.66	16	D	0.16	119	1	0.59	0.03	0.67	221	0.18	0.8	0.28	0.8	0.04	0.51	182
31150	Cornebarr	0000	31150000	Cornebarr	Z	0.90	0.85	0.08	16	D	0.16	106	0.18	0.23	0.27	0.2	25	0.44	0.26	0.43	0.58	0.1	0.39	99
31555	Toulouse	4805	31555480	Coteaux d	H	0.77	0.10	0.21	8	C	0.07	75	0.52	0.15	0.09	0.24	34	0.21	0.07	0.57	0.65	0.14	0.33	62
31555	Toulouse	2303	31555230	Courrège	H	0.31	0.62	0.83	30	E	0.31	164	0.76	0.55	0.03	0.53	156	0.13	0.88	0.41	0.62	0	0.49	170
31555	Toulouse	0401	31555040	Croix Bara	H	0.21	0.47	0.99	12	D	0.12	103	0.38	0.77	0.05	0.46	126	0.09	0.97	0.35	0.47	0.1	0.46	148
31555	Toulouse	0502	31555050	Dalbade	H	0.70	0.72	0.60	36	F	0.37	180	0.13	0.55	0.14	0.27	48	0.23	0.53	0.58	0.59	0.18	0.51	178
31555	Toulouse	2702	31555270	Daste	H	0.83	0.45	0.54	32	E	0.33	171	0.62	0.4	0.38	0.56	172	0.43	0.54	0.4	0.79	0	0.53	192
31555	Toulouse	2201	31555220	Deltour	H	0.13	0.43	0.74	10	C	0.09	88	0.76	0.7	0.03	0.61	196	0.1	0.85	0.37	0.62	0.04	0.46	147
31555	Toulouse	1502	31555150	Déodat de	H	0.69	0.67	0.82	45	F	0.46	194	0.76	0.77	0.1	0.68	224	0.26	0.86	0.46	0.64	0.07	0.58	215
31555	Toulouse	1101	31555110	Dupuy	H	0.47	0.63	0.80	30	E	0.31	162	0.38	0.71	0.03	0.42	111	0.17	0.74	0.52	0.38	0	0.4	110

INSEE_C(	NOM_COI	IRIS	CODE_IRI	NOM_IRIS	TYP_IRIS	N Sdep	N_Spop	N_Senv	CVA_Scoi	CVA_CLA	N_class_(	CVA_RAN	AHP_Ada	AHP_Exp	AHP_Sen	AHP_Vulr	AHP_RAN	PCA_F1	PCA_F2	PCA_F3	PCA_F4	PCA_F5	PCA_FG	PCA_RANK P
31555	Toulouse	2502	31555250:	École Nori	H	0.18	0.26	0.94	12	D	0.12	101	1	0.74	0	0.73	236	0.13	0.94	0.29	0.67	0	0.48	165
31555	Toulouse	5301	31555530	Édouard E	H	0.82	0.83	0.33	32	E	0.33	170	0.12	0.48	0.17	0.25	40	0.41	0.5	0.43	0.36	0	0.35	73
31506	Saint-Orer	0106	31506010(	Église-Oré	H	0.59	0.45	0.08	6	C	0.05	57	0.76	0.05	0.27	0.4	100	0.24	0.4	0.19	1	0.4	0.56	211
31555	Toulouse	1701	31555170	Embouchu	H	0.79	0.80	0.47	48	F	0.49	199	0.38	0.43	0.25	0.39	92	0.42	0.47	0.39	0.54	0.1	0.44	136
31149	Colomiers	0701	31149070	En Jacca	A	0.03	0.03	0.11	1	A	0.00	10	0.76	0.16	0	0.32	65	0.04	0.55	0.05	0.48	0	0.13	9
31488	Saint-Jear	0103	31488010:	Est	H	0.63	0.68	0.09	9	C	0.08	83	0.24	0.19	0.09	0.12	11	0.22	0.47	0.24	0.59	0.04	0.3	50
31149	Colomiers	0201	31149020	Falcou-Fe	H	0.92	0.98	0.41	48	F	0.49	198	0.38	0.48	0.38	0.48	134	0.5	0.65	0.55	0.66	0	0.61	225
31557	Tournefeu	0107	31557010	Fanjeau	H	0.56	0.44	0.02	6	C	0.05	55	0.38	0.15	0.05	0.15	13	0.21	0.36	0.28	0.68	0.02	0.3	46
31555	Toulouse	3702	31555370:	Fenouillet	H	0.48	0.78	0.84	48	F	0.49	204	1	0.66	0.05	0.72	234	0.21	0.87	0.31	0.78	0.04	0.56	208
31182	Fenouillet	0000	31182000(	Fenouillet	Z	0.94	0.82	0.20	32	E	0.33	165	0	0.4	0.21	0.17	20	0.51	0.38	0.39	0.64	0.08	0.47	153
31555	Toulouse	5701	31555570	Ferdinand	H	0.80	0.61	0.42	36	F	0.37	176	0.76	0.51	0.17	0.58	183	0.39	0.75	0.28	0.62	0.03	0.49	172
31555	Toulouse	0501	31555050	Filatiers	H	0.40	0.50	1.00	24	E	0.24	154	0.38	0.85	0.05	0.5	140	0.15	0.99	0.41	0.62	0	0.54	200
31555	Toulouse	6001	31555600	Flambère	H	0.93	0.57	0.31	24	E	0.24	144	0.51	0.37	0.17	0.39	93	0.45	0.62	0.37	0.61	0.2	0.56	207
31555	Toulouse	5901	31555590	Fleurance	H	0.77	0.50	0.23	16	D	0.16	111	0.24	0.3	0.13	0.2	24	0.38	0.44	0.17	0.45	0.11	0.29	42
31184	Flourens	0000	31184000(	Flourens	Z	0.08	0.10	0.05	1	A	0.00	5	0.24	0	0.03	0	1	0.1	0.21	0.17	0.46	0.09	0.09	4
31186	Fonbeauzi	0000	31186000(	Fonbeauzi	Z	0.47	0.61	0.17	12	D	0.12	94	0.24	0.51	0.08	0.28	50	0.24	0.54	0.26	0.54	0	0.3	45
31506	Saint-Orer	0103	31506010:	Fondarger	H	0.07	0.18	0.27	2	B	0.01	27	1	0.48	0.03	0.62	203	0.08	0.68	0.19	0.82	0	0.38	97
31555	Toulouse	3701	31555370	Fondeyre	A	0.23	0.05	0.58	4	B	0.03	49	0.76	0.63	0	0.56	176	0.18	0.84	0.1	0.57	0.11	0.39	107
31555	Toulouse	3101	31555310	Fontaine L	H	0.46	0.45	0.75	20	E	0.20	137	0.62	0.63	0.03	0.5	139	0.21	0.84	0.36	0.55	0	0.45	142
31157	Cugnaux	0104	31157010	Francoy	H	0.40	0.79	0.46	24	E	0.24	146	0.62	0.4	0.09	0.42	113	0.21	0.75	0.27	0.6	0	0.4	114
31555	Toulouse	1805	31555180:	Frédéric E	H	0.42	0.55	0.90	36	F	0.37	184	0.62	0.77	0.03	0.57	179	0.22	0.9	0.31	0.36	0.01	0.39	105
31555	Toulouse	1103	31555110:	Gabriel Pé	H	0.59	0.53	0.89	54	F	0.56	211	0.13	0.85	0.08	0.39	94	0.17	0.87	0.53	0.39	0.04	0.47	156
31205	Gagnac-su	0000	31205000(	Gagnac-su	Z	0.39	0.27	0.10	4	B	0.03	40	0.56	0.31	0.08	0.34	72	0.26	0.21	0.19	0.73	0	0.23	26
31149	Colomiers	0501	31149050	Gare Lam	H	0.86	0.90	0.40	48	F	0.49	196	0.76	0.4	0.29	0.59	186	0.44	0.69	0.45	0.76	0	0.6	222
31555	Toulouse	3601	31555360	Ginestous	A	0.29	0.06	0.09	2	B	0.01	19	0.62	0.34	0.05	0.37	83	0.16	0.38	0.1	0.72	0.42	0.38	91
31555	Toulouse	5101	31555510	Gironis	H	0.90	0.57	0.35	36	F	0.37	173	0.32	0.37	0.18	0.3	62	0.52	0.64	0.28	0.24	0.08	0.37	86
31555	Toulouse	5204	31555520	Goya	H	0.85	0.62	0.38	36	F	0.37	174	0.76	0.45	0.23	0.58	182	0.45	0.69	0.3	0.75	0	0.54	198
31555	Toulouse	4101	31555410	Gramont	A	0.06	0.04	0.24	2	B	0.01	26	0.62	0.41	0.03	0.39	91	0.12	0.43	0.06	0.69	0.33	0.32	56
31069	Blagnac	0104	31069010	Grand Not	H	0.74	0.62	0.54	36	F	0.37	178	0.76	0.57	0.13	0.59	188	0.35	0.82	0.21	0.54	0.11	0.48	160
31555	Toulouse	4003	31555400:	Grand Sel	H	0.93	0.80	0.37	48	F	0.49	195	0.38	0.4	0.18	0.34	73	0.51	0.52	0.28	0.45	0	0.37	80
31230	Gratentoui	0000	31230000(	Gratentoui	Z	0.57	0.70	0.20	18	D	0.18	120	0.51	0.15	0.12	0.25	36	0.21	0.43	0.37	0.75	0.1	0.41	117
31116	Castelgine	0103	31116010:	Gravemar	H	0.74	0.90	0.30	24	E	0.24	143	1	0.48	0.12	0.66	218	0.31	0.67	0.26	0.94	0.13	0.59	219
31069	Blagnac	0105	31069010:	Grenade	H	0.28	0.26	0.33	12	D	0.12	96	1	0.48	0.03	0.62	200	0.18	0.66	0.23	0.77	0.06	0.42	124
31555	Toulouse	0802	31555080:	Héraclès	H	0.78	0.88	0.73	80	G	0.83	235	0.38	1	0.08	0.59	190	0.21	0.73	0.71	0.48	0	0.52	185
31555	Toulouse	4302	31555430:	Heredia	H	0.60	0.74	0.71	45	F	0.46	192	0.76	0.63	0.1	0.61	199	0.32	0.85	0.36	0.59	0	0.51	181
31555	Toulouse	3402	31555340:	Hippodron	H	0.89	0.87	0.40	48	F	0.49	197	0.32	0.4	0.4	0.42	110	0.5	0.63	0.4	0.32	0.22	0.5	175
31555	Toulouse	0902	31555090:	Honoré Se	H	0.54	0.65	0.88	54	F	0.56	210	0.28	0.85	0.05	0.45	121	0.17	0.85	0.52	0	0	0.29	43
31555	Toulouse	1303	31555130:	Hôtel de F	H	0.85	0.94	0.69	80	G	0.83	234	0.51	0.71	0.16	0.55	167	0.32	0.76	0.54	0.63	0.16	0.63	231
31555	Toulouse	2403	31555240:	Italie	H	0.14	0.48	0.91	12	D	0.12	100	0.62	0.63	0.03	0.5	142	0.12	0.91	0.33	0.56	0	0.44	138
31555	Toulouse	0101	31555010	Jacobins	H	0.76	0.24	0.79	20	E	0.20	139	0.24	0.63	0.09	0.34	74	0.25	0.72	0.65	0.4	0.19	0.55	203
31555	Toulouse	1202	31555120:	Jardin des	H	0.29	0.54	0.63	24	E	0.24	149	0.32	0.48	0.03	0.28	55	0.14	0.54	0.44	0.66	0.17	0.45	143
31555	Toulouse	2104	31555210	Jean Chau	H	0.16	0.29	0.81	10	C	0.09	90	0.76	0.48	0.03	0.5	143	0.09	0.83	0.29	0.58	0	0.39	106
31555	Toulouse	2601	31555260	Jules Julie	H	0.79	0.18	0.62	16	D	0.16	118	0.76	0.55	0.08	0.56	174	0.3	0.73	0.49	0.58	0.01	0.51	180
31555	Toulouse	2803	31555280:	La Digue	H	0.29	0.67	0.49	18	D	0.18	131	0.76	0.48	0.06	0.51	149	0.17	0.68	0.37	0.86	0.01	0.51	177
31555	Toulouse	2003	31555200:	La Gloire	H	0.52	0.22	0.75	15	D	0.15	105	1	0.43	0.05	0.6	193	0.18	0.73	0.39	0.73	0	0.48	161
31555	Toulouse	0602	31555060:	La Grave	H	0.35	0.11	0.77	10	C	0.09	89	0.76	0.55	0.03	0.53	154	0.16	0.77	0.33	0.43	0.01	0.35	72
31044	Balma	0102	31044010:	La Plaine	H	0.21	0.28	0.53	8	C	0.07	77	0.62	0.49	0.05	0.44	116	0.13	0.79	0.19	0.43	0.21	0.37	83
31555	Toulouse	2802	31555280:	La Pointe	H	0.30	0.31	0.79	20	E	0.20	140	0.52	0.59	0.03	0.43	115	0.18	0.83	0.27	0.09	0.07	0.25	33
31557	Tournefeu	0104	31557010	La Ramée	H	0.25	0.32	0.05	2	B	0.01	17	0.24	0.25	0.03	0.12	9	0.15	0.42	0.24	0.58	0	0.23	25
31555	Toulouse	3703	31555370:	La Salade	H	0.99	1.00	0.77	80	G	0.83	236	0.52	0.71	0.81	0.88	247	0.59	0.83	0.57	0.51	0.56	0.89	248
31555	Toulouse	3802	31555380:	Lalande N	H	1.00	0.93	0.56	64	G	0.66	223	0.76	0.71	0.81	1	248	1	0.79	0.26	0.64	0.11	0.78	246
31555	Toulouse	3803	31555380:	Lalande S	H	0.89	0.73	0.50	48	F	0.49	200	0.38	0.63	0.21	0.47	133	0.5	0.71	0.19	0.39	0.11	0.43	131
31555	Toulouse	3001	31555300	Lambert	H	0.71	0.25	0.73	15	D	0.15	104	1	0.59	0.12	0.72	232	0.34	0.86	0.28	0.79	0	0.57	212
31555	Toulouse	4001	31555400	Lapujade	H	0.96	0.96	0.83	80	G	0.83	238	0.56	0.77	0.21	0.63	206	0.56	0.91	0.41	0.4	0	0.58	217
31044	Balma	0106	31044010(	Lasbordes	H	0.26	0.12	0.29	4	B	0.03	47	0.76	0.11	0.05	0.32	66	0.22	0.42	0.21	0.61	0.09	0.3	49
31555	Toulouse	4702	31555470:	Latécoère	A	0.98	0.38	0.29	16	D	0.16	112	0.76	0.37	0.75	0.8	243	0.41	0.62	0.61	0.71	1	1	249
31588	Villeneuve	0102	31588010:	Le Bas de	H	0.72	0.81	0.25	24	E	0.24	142	1	0.3	0.12	0.57	180	0.34	0.58	0.27	0.95	0.09	0.55	205
31044	Balma	0104	31044010	Le Châtea	H	0.13	0.56	0.36	9	C	0.08	84	0.51	0.3	0.06	0.3	60	0.13	0.62	0.19	0.71	0.1	0.37	84
31588	Villeneuve	0103	31588010:	Le Haut de	H	0.16	0.41	0.22	4	B	0.03	46	0.76	0.23	0.06	0.39	96	0.12	0.53	0.32	0.8	0	0.37	89
31467	Saint-Alba	0102	31467010:	Le Mariel	H	0.42	0.61	0.41	18	D	0.18	128	0.76	0.51	0.06	0.53	153	0.21	0.74	0.27	0.78	0.02	0.47	152
31467	Saint-Alba	0101	31467010	Le Terroir	H	0.51	0.55	0.45	27	E	0.27	157	0.62	0.51	0.08	0.47	128	0.28	0.71	0.22	0.49	0.07	0.38	92
31282	Launaguet	0101	31282010	Le Village	H	0.45	0.54	0.04	6	C	0.05	56	0.24	0.34	0.05	0.18	22	0.24	0.25	0.27	0.56	0.02	0.21	20
31561	L'Union	0104	31561010	Les Acacia	H	0.18	0.46	0.60	8	C	0.07	81	0.76	0.51	0.06	0.53	159	0.12	0.85	0.25	0.76	0	0.46	151
31555	Toulouse	5802	31555580:	Les Capel	H	0.67	0.65	0.26	18	D	0.18	122	0.38	0.32	0.14	0.28	54	0.26	0.49	0.45	0.75	0.23	0.53	191
31506	Saint-Orer	0102	31506010:	Les Carme	H	0.22	0.40	0.07	2	B	0.01	18	0.18	0.33	0.06	0.15	16	0.12	0.46	0.3	0.55	0	0.25	34
31555	Toulouse	3502	31555350:	Les Fontai	H	0.27	0.48	0.60	16	D	0.16	117	0.62	0.74	0	0.54	160	0.15	0.69	0.28	0.78	0.1	0.47	155
31557	Tournefeu	0108	31557010:	Les Hauts	H	0.38	0.23	0.18	4	B	0.03	43	1	0.09	0.03	0.42	108	0.21	0.49	0.19	0.69	0.04	0.32	54
31555	Toulouse	3901	31555390	Les Izards	H	0.99	0.89	0.55	64	G	0.66	222	1	0.51	0.4	0.82	244	0.75	0.71	0.36	0.78	0.01	0.71	241
31555	Toulouse	4802	31555480:	Les Maraî	H	0.50	0.11	0.54	8	C	0.07	78	0.51	0.4	0.05	0.34	75	0.17	0.66	0.54	0.58	0.06	0.47	158
31282	Launaguet	0102	31282010:	Les Sable	H	0.92	0.81	0.29	32	E	0.33	168	0.76	0.4	0.21	0.55	162	0.49	0.52	0.27	0.85	0.06	0.55	202
31555	Toulouse	5401	31555540	Les Verge	H	0.62	0.59	0.32	18	D	0.18	124	0.76	0.45	0.25	0.59	189	0.41	0.67	0.31	0.79	0	0.54	196
31022	Aucamville	0102	31022010:	Les Violett	H	0.94	0.89	0.63	64	G	0.66	227	0.52	0.74	0.22	0.6	192	0.48	0.79	0.33	0.29	0.02	0.43	128
31293	Lespinass	0000	31293000(	Lespinass	Z	0.33	0.16	0.35	6	C	0.05	63	0.76	0.37	0.08	0.47	129	0.25	0.56	0.18	0.61	0	0.31	52
31555	Toulouse	2301	31555230	Lespinet	H	0.50	0.18	0.50	6	C	0.05	70	0.76	0.37	0.05	0.45	122	0.2	0.61	0.33	0.72	0.05	0.43	132

INSEE_C(	NOM_COI	IRIS	CODE_IRI	NOM_IRIS	TYP_IRIS	N Sdep	N_Spop	N_Senv	CVA_Sco	CVA_CLA	N_class_(	CVA_RAN	AHP_Ada	AHP_Exp	AHP_Sen	AHP_Vulr	AHP_RAN	PCA_F1	PCA_F2	PCA_F3	PCA_F4	PCA_F5	PCA_FG	PCA_RANK P
31555	Toulouse	5201	31555520	Lestang	H	0.36	0.13	0.47	6	C	0.05	68	1	0.42	0.06	0.6	194	0.28	0.72	0.18	0.74	0	0.44	137
31555	Toulouse	2203	31555220:	Leygue	H	0.08	0.29	0.85	12	D	0.12	99	1	0.66	0.03	0.71	230	0.07	0.91	0.28	0.79	0.08	0.52	186
31022	Aucamville	0101	31022010	L'Hers	H	0.43	0.53	0.23	12	D	0.12	95	0.76	0.48	0.05	0.51	145	0.27	0.55	0.23	0.81	0	0.41	116
31116	Castelgine	0102	31116010:	L'Hers	H	0.12	0.28	0.38	6	C	0.05	64	0.32	0.48	0.03	0.28	49	0.16	0.65	0.23	0.27	0.04	0.21	19
31555	Toulouse	3202	31555320:	Loire	H	0.65	0.52	0.70	45	F	0.46	190	1	0.59	0.12	0.72	233	0.33	0.85	0.23	0.76	0	0.53	190
31555	Toulouse	4703	31555470:	Louis Breg	H	0.79	0.93	0.52	64	G	0.66	220	0.38	0.63	0.29	0.51	152	0.42	0.71	0.4	0.61	0	0.53	194
31555	Toulouse	4301	31555430	Louis Plan	H	0.21	0.25	0.62	4	B	0.03	51	0.62	0.51	0.03	0.44	119	0.13	0.81	0.33	0.53	0.03	0.4	113
31555	Toulouse	2204	31555220	Louis Vitet	H	0.75	0.89	0.92	96	H	1.00	244	0.62	0.85	0.08	0.64	214	0.27	0.92	0.57	0.51	0	0.57	214
31555	Toulouse	4601	31555460	Mal Clabe	H	0.35	0.77	0.67	40	F	0.41	188	0.76	0.55	0.06	0.55	169	0.14	0.88	0.38	0.87	0.01	0.58	218
31561	L'Union	0105	31561010	Malbou	H	0.34	0.70	0.36	18	D	0.18	125	0.51	0.4	0.06	0.35	77	0.17	0.62	0.3	0.84	0	0.44	135
31555	Toulouse	4701	31555470	Marcaisso	A	0.67	0.14	0.04	3	B	0.02	34	0.18	0.23	0.1	0.12	10	0.31	0.29	0.21	0.29	0.29	0.23	28
31555	Toulouse	1804	31555180	Marché au	H	0.46	0.83	0.97	48	F	0.49	207	0.56	0.77	0.05	0.55	168	0.19	0.96	0.41	0.24	0.04	0.41	122
31555	Toulouse	2401	31555240	Marvig	H	0.53	0.30	0.39	18	D	0.18	127	0.62	0.4	0.08	0.41	104	0.26	0.62	0.39	0.71	0	0.46	149
31157	Cugnaux	0103	31157010:	Maurens	H	0.49	0.79	0.17	16	D	0.16	110	0.51	0.15	0.12	0.25	41	0.28	0.47	0.29	0.69	0.04	0.38	98
31555	Toulouse	1806	31555180	Mazades	H	0.66	0.70	0.87	54	F	0.56	209	0.76	0.77	0.05	0.65	217	0.27	0.89	0.42	0.7	0	0.58	216
31555	Toulouse	2304	31555230	Mendès Fr	H	0.27	0.35	0.70	20	E	0.20	135	0.51	0.59	0.05	0.44	118	0.18	0.8	0.23	0.63	0	0.4	112
31555	Toulouse	3002	31555300:	Mermoz	H	0.75	0.67	0.44	36	F	0.37	177	0.38	0.48	0.23	0.41	102	0.41	0.69	0.33	0.36	0	0.39	103
31555	Toulouse	4203	31555420:	Michoum	H	0.67	0.97	0.66	48	F	0.49	203	0.52	0.63	0.14	0.51	151	0.31	0.78	0.5	0.35	0.08	0.48	167
31555	Toulouse	5102	31555510:	Milan	H	0.81	0.63	0.67	60	G	0.62	214	0.62	0.59	0.12	0.53	155	0.39	0.84	0.24	0.32	0	0.38	93
31351	Mondonvil	0000	31351000	Mondonvil	Z	0.73	0.50	0.13	6	C	0.05	59	0.28	0.06	0.12	0.09	4	0.32	0.07	0.21	0.6	0.02	0.17	11
31352	Mondouzil	0000	31352000	Mondouzil	Z	0.01	0.01	0.00	1	A	0.00	1	0.62	0	0	0.17	18	0	0.14	0.03	0.64	0	0	1
31355	Mons	0000	31355000	Mons	Z	0.05	0.07	0.01	1	A	0.00	3	0.62	0	0	0.17	19	0.06	0.19	0.12	0.77	0.04	0.15	10
31557	Tournefeu	0102	31557010:	Montjoie	H	0.10	0.24	0.55	4	B	0.03	48	0.76	0.48	0.03	0.5	138	0.11	0.77	0.19	0.63	0	0.35	69
31555	Toulouse	1201	31555120	Montplaisi	H	0.63	0.95	0.76	60	G	0.62	217	0.51	0.71	0.12	0.53	158	0.23	0.71	0.63	0.7	0.11	0.62	230
31389	Montrabé	0000	31389000	Montrabé	Z	0.46	0.76	0.06	8	C	0.07	73	0.24	0.19	0.09	0.12	8	0.21	0.32	0.29	0.59	0.02	0.25	31
31555	Toulouse	3201	31555320	Morvan	H	0.54	0.31	0.69	30	E	0.31	159	1	0.42	0.09	0.62	201	0.29	0.81	0.18	0.68	0	0.45	140
31149	Colomiers	0401	31149040	Naurouze	H	0.64	0.59	0.30	18	D	0.18	123	0.28	0.37	0.1	0.24	33	0.33	0.64	0.42	0.14	0.04	0.3	47
31149	Colomiers	0402	31149040:	Naurouze	H	0.51	0.43	0.56	24	E	0.24	147	0.62	0.4	0.2	0.47	130	0.35	0.73	0.31	0.38	0	0.37	81
31555	Toulouse	1807	31555180	Nègreneys	H	0.94	1.00	0.93	96	H	1.00	245	0.52	1	0.3	0.77	239	0.45	0.94	0.73	0.35	0.09	0.69	239
31555	Toulouse	4004	31555400	Nicol	H	0.96	0.99	0.67	80	G	0.83	233	0.76	0.63	0.22	0.67	220	0.52	0.8	0.37	0.71	0	0.63	234
31056	Beauzelle	0101	31056010	Nord	H	0.55	0.76	0.10	12	D	0.12	92	0.18	0.23	0.09	0.11	6	0.23	0.37	0.29	0.48	0.11	0.27	37
31488	Saint-Jear	0102	31488010:	Nord	H	0.12	0.20	0.07	1	A	0.00	8	0.62	0.11	0.03	0.24	35	0.12	0.36	0.2	0.76	0	0.25	35
31555	Toulouse	1301	31555130	Notre-Dan	H	0.76	0.46	0.92	48	F	0.49	205	0.62	0.85	0.08	0.64	213	0.23	0.9	0.54	0.43	0.03	0.53	193
31417	Pibrac	0102	31417010:	Nouveaux	H	0.10	0.39	0.21	4	B	0.03	45	0.51	0.21	0.06	0.25	42	0.08	0.54	0.28	0.82	0.1	0.4	115
31555	Toulouse	2005	31555200	Observato	H	0.37	0.15	0.67	8	C	0.07	82	0.62	0.33	0.03	0.35	79	0.18	0.7	0.27	0.75	0.06	0.45	144
31555	Toulouse	0301	31555030	Occitane	H	0.27	0.59	0.98	36	F	0.37	187	0.76	0.77	0.03	0.64	210	0.13	0.98	0.39	0.88	0	0.62	227
31488	Saint-Jear	0101	31488010	Ouest	H	0.26	0.49	0.10	4	B	0.03	41	0.24	0.09	0.06	0.06	3	0.14	0.36	0.19	0.6	0	0.19	16
31555	Toulouse	0402	31555040:	Ozenne	H	0.31	0.77	0.78	40	F	0.41	189	0.62	0.63	0.05	0.51	150	0.14	0.74	0.44	0.83	0.26	0.63	233
31149	Colomiers	1001	3.11E+08	Parc Aéro	A	0.02	0.02	0.42	3	B	0.02	36	1	0.45	0	0.59	187	0.07	0.75	0.05	0.66	0.04	0.3	48
31555	Toulouse	4303	31555430:	Patinoire c	H	0.55	0.20	0.03	3	B	0.02	33	0.38	0.4	0.08	0.29	56	0.29	0.47	0.21	0.37	0.03	0.22	23
31555	Toulouse	4801	31555480	Paul Saba	H	0.96	0.06	0.21	8	C	0.07	74	0.62	0.45	0.31	0.55	166	0.16	0.51	1	0.57	0.12	0.61	226
31149	Colomiers	0802	31149080:	Perget Est	H	0.20	0.13	0.15	1	A	0.00	14	0.51	0.26	0	0.25	37	0.16	0.61	0.13	0.49	0.1	0.27	38
31149	Colomiers	0803	31149080:	Perget Ou	H	0.54	0.15	0.02	3	B	0.02	31	0.38	0.15	0.05	0.15	15	0.24	0.41	0.12	0.57	0.03	0.22	22
31555	Toulouse	1902	31555190:	Périole	H	0.85	0.83	0.93	96	H	1.00	246	0.56	0.85	0.14	0.64	215	0.37	0.92	0.51	0.27	0.06	0.52	187
31418	Pin-Balma	0000	31418000	Pin-Balma	Z	0.03	0.04	0.01	1	A	0.00	2	0.62	0.14	0	0.24	29	0.04	0.13	0.08	0.76	0.11	0.12	7
31069	Blagnac	0111	31069011	Pinot	A	0.65	0.17	0.02	3	B	0.02	32	0.38	0.19	0.05	0.17	21	0.3	0.37	0.08	0.55	0.03	0.21	21
31555	Toulouse	1801	31555180	Ponts Jum	H	0.98	0.97	0.64	64	G	0.66	228	0.56	0.7	0.27	0.63	205	0.57	0.78	0.45	0.37	0	0.53	189
31555	Toulouse	2701	31555270	Poudrerie	H	0.98	0.90	0.57	64	G	0.66	224	0.38	0.4	0.45	0.48	135	0.64	0.59	0.47	0.68	0	0.62	228
31555	Toulouse	5302	31555530:	Poulenc	H	0.75	0.42	0.33	16	D	0.16	113	0.76	0.45	0.08	0.51	148	0.35	0.68	0.27	0.7	0	0.47	157
31555	Toulouse	4901	31555490	Pouvourvil	H	0.73	0.27	0.12	6	C	0.05	58	0.52	0.05	0.13	0.21	27	0.23	0.09	0.33	0.81	0.12	0.31	53
31149	Colomiers	0301	31149030	Prat-Coud	H	0.38	0.35	0.52	16	D	0.16	115	0.51	0.25	0.05	0.27	46	0.18	0.62	0.27	0.72	0.07	0.41	118
31555	Toulouse	2102	31555210:	Providenc	H	0.33	0.58	0.91	36	F	0.37	185	0.76	0.7	0.03	0.61	198	0.13	0.88	0.41	0.6	0	0.48	166
31157	Cugnaux	0105	31157010	Quartier P	H	0.82	0.63	0.18	24	E	0.24	141	0.51	0.11	0.14	0.24	31	0.35	0.39	0.28	0.71	0.04	0.38	90
31445	Quint-Fon:	0000	31445000	Quint-Fon:	Z	0.78	0.83	0.11	16	D	0.16	107	0.28	0.23	0.42	0.33	68	0.27	0.34	0.42	0.71	0.26	0.47	154
31555	Toulouse	5702	31555570:	Ramelet M	H	0.60	0.72	0.58	36	F	0.37	179	0.76	0.63	0.1	0.61	197	0.27	0.78	0.36	0.72	0.06	0.54	199
31555	Toulouse	1401	31555140	Ramier	H	0.17	0.04	0.27	2	B	0.01	29	0.56	0.25	0	0.27	47	0.1	0.23	0.28	0.64	0.05	0.19	15
31555	Toulouse	1602	31555160:	Ravelin	H	0.87	0.90	0.97	96	H	1.00	248	0.56	1	0.21	0.75	237	0.31	0.97	0.72	0.51	0.08	0.7	240
31555	Toulouse	1002	31555100:	Raymond	H	0.81	0.87	0.94	96	H	1.00	247	0.52	1	0.16	0.7	229	0.24	0.93	0.64	0.21	0.01	0.48	162
31555	Toulouse	1901	31555190	Raynal	H	0.95	0.98	0.90	96	H	1.00	242	0.56	0.85	0.18	0.66	219	0.44	0.91	0.63	0.55	0.05	0.69	238
31555	Toulouse	4201	31555420	Réservoir	H	0.14	0.24	0.86	6	C	0.05	71	0.56	0.59	0.03	0.45	123	0.12	0.86	0.24	0.31	0	0.28	41
31069	Blagnac	0102	31069010:	Ritouret	H	0.06	0.14	0.28	2	B	0.01	30	0.38	0.37	0.03	0.25	39	0.07	0.63	0.2	0.42	0.01	0.2	18
31555	Toulouse	1601	31555160	Roguet	H	0.71	0.96	0.89	72	G	0.75	230	0.52	0.85	0.27	0.68	223	0.28	0.9	0.53	0.3	0.31	0.59	220
31555	Toulouse	4502	31555450:	Roucoule	H	0.56	0.65	0.25	18	D	0.18	121	0.38	0.33	0.08	0.26	44	0.26	0.54	0.28	0.69	0	0.37	82
31561	L'Union	0102	31561010:	Saint-Capı	H	0.08	0.20	0.23	2	B	0.01	24	0.76	0.48	0.03	0.5	144	0.09	0.62	0.2	0.86	0	0.38	96
31044	Balma	0105	31044010	Saint-Clair	H	0.19	0.52	0.19	6	C	0.05	60	0.62	0.16	0.06	0.28	51	0.12	0.5	0.18	0.86	0	0.34	67
31555	Toulouse	4503	31555450:	Sainte-Cla	H	0.41	0.54	0.48	18	D	0.18	130	0.38	0.29	0.03	0.21	28	0.13	0.61	0.35	0.54	0	0.32	59
31555	Toulouse	1501	31555150	Sainte-Luc	H	0.49	0.74	0.87	36	F	0.37	183	0.56	0.77	0.05	0.55	163	0.22	0.88	0.41	0.29	0.09	0.43	130
31555	Toulouse	2302	31555230:	Saint-Exup	H	0.15	0.26	0.73	10	C	0.09	87	0.51	0.59	0	0.41	103	0.17	0.79	0.27	0.59	0	0.4	111
31490	Saint-Jory	0000	31490000	Saint-Jory	Z	0.91	0.80	0.25	32	E	0.33	166	0.51	0.37	0.22	0.41	105	0.47	0.36	0.4	0.76	0.03	0.48	168
31555	Toulouse	1302	31555130:	Saint-Léor	H	0.61	0.39	0.96	36	F	0.37	186	0.76	0.77	0.03	0.64	212	0.21	0.94	0.45	0.5	0	0.51	179
31555	Toulouse	0102	3.16E+08	Saint-Rom	H	0.64	0.58	0.98	54	F	0.56	213	0.04	1	0.08	0.42	112	0.19	0.96	0.53	0.03	0.04	0.37	87
31555	Toulouse	0202	31555020:	Saint-Serr	H	0.83	0.63	0.90	72	G	0.75	231	0.32	1	0.08	0.56	173	0.23	0.88	0.71	0.31	0.05	0.54	201
31555	Toulouse	5502	31555550:	Saint-Simo	H	0.80	0.75	0.35	36	F	0.37	172	0.62	0.23	0.14	0.36	82	0.41	0.63	0.2	0.52	0.1	0.41	119
31555	Toulouse	5503	31555550:	Saint-Simo	H	0.77	0.91	0.52	64	G	0.66	219	0.62	0.29	0.21	0.42	107	0.38	0.73	0.29	0.68	0.16	0.56	206

INSEE_C	NOM_CO	IRIS	CODE_IRI	NOM_IRIS	TYP_IRIS	N Sdep	N_Spop	N_Senv	CVA_Sco	CVA_CLA	N_class_	CVA_RAN	AHP_Ada	AHP_Exp	AHP_Sen	AHP_Vuln	AHP_RAN	PCA_F1	PCA_F2	PCA_F3	PCA_F4	PCA_F5	PCA_FG	PCA_RANK P
31555	Toulouse	4803	31555480	Salade Po	H	0.19	0.11	0.60	4	B	0.03	50	0.76	0.48	0	0.48	136	0.11	0.79	0.36	0.5	0	0.38	95
31069	Blagnac	0106	31069010	Saoulous	H	0.04	0.09	0.34	3	B	0.02	35	0.51	0.48	0.03	0.37	84	0.08	0.51	0.18	0.63	0	0.24	29
31555	Toulouse	5801	31555580	Sauvegrai	H	0.66	0.69	0.46	27	E	0.27	158	0.62	0.55	0.12	0.51	146	0.26	0.76	0.39	0.53	0.2	0.52	183
31555	Toulouse	0801	31555080	Sébastopo	H	0.65	0.33	0.48	18	D	0.18	129	0.38	0.45	0.1	0.33	69	0.26	0.62	0.37	0.52	0	0.38	94
31541	Seilh	0000	31541000	Seilh	Z	0.32	0.16	0.04	2	B	0.01	16	0.38	0.16	0.03	0.15	14	0.2	0.26	0.15	0.54	0.08	0.17	12
31555	Toulouse	2405	31555240	Serres Mu	H	0.22	0.22	0.80	5	B	0.04	54	0.76	0.74	0.03	0.63	207	0.14	0.88	0.31	0.62	0.11	0.49	173
31069	Blagnac	0109	31069010	Servanty	H	0.15	0.27	0.57	8	C	0.07	80	1	0.51	0.03	0.63	204	0.12	0.77	0.26	0.91	0.04	0.51	176
31488	Saint-Jear	0104	31488010	Sud	H	0.23	0.38	0.38	6	C	0.05	65	0.76	0.19	0.03	0.35	80	0.15	0.61	0.17	0.8	0	0.36	78
31056	Beauzelle	0102	31056010	Sud	H	0.41	0.36	0.12	4	B	0.03	42	0.38	0.3	0.08	0.24	32	0.26	0.41	0.28	0.56	0	0.28	39
31555	Toulouse	4401	31555440	Surcouf	H	0.24	0.34	0.72	10	C	0.09	86	0.76	0.59	0.03	0.55	170	0.22	0.85	0.24	0.58	0	0.43	133
31555	Toulouse	0201	31555020	Taur	H	0.39	0.37	0.98	24	E	0.24	153	0.18	0.77	0.08	0.38	88	0.14	0.99	0.38	0.27	0.04	0.4	109
31555	Toulouse	0601	31555060	Teinturiers	H	0.45	0.41	0.69	20	E	0.20	134	0.24	0.63	0.05	0.32	67	0.18	0.66	0.35	0.35	0.07	0.32	58
31555	Toulouse	5202	31555520	Tel Aviv	H	0.44	0.34	0.42	12	D	0.12	97	0.76	0.45	0.05	0.49	137	0.3	0.72	0.2	0.7	0.04	0.45	139
31555	Toulouse	3401	31555340	Tellier	H	0.62	0.30	0.78	30	E	0.31	161	0.76	0.59	0.06	0.57	178	0.29	0.88	0.3	0.49	0	0.45	141
31555	Toulouse	2901	31555290	Touraine	H	0.33	0.37	0.77	20	E	0.20	138	0.76	0.59	0.03	0.55	165	0.19	0.86	0.26	0.55	0	0.41	120
31555	Toulouse	1702	31555170	Troènes	H	0.52	0.51	0.43	27	E	0.27	155	0.51	0.51	0.03	0.39	95	0.2	0.59	0.39	0.63	0	0.39	104
31555	Toulouse	0203	31555020	Valade	H	0.48	0.12	0.81	10	C	0.09	91	0.76	0.77	0.18	0.72	235	0.23	0.83	0.45	0.65	0.59	0.76	244
31555	Toulouse	5203	31555520	Van Gogh	H	0.48	0.50	0.48	12	D	0.12	98	0.51	0.45	0.03	0.36	81	0.24	0.72	0.24	0.48	0.04	0.36	75
31555	Toulouse	3203	31555320	Vestrepair	H	0.73	0.68	0.81	45	F	0.46	193	0.62	0.59	0.13	0.53	157	0.3	0.92	0.23	0.35	0	0.39	102
31417	Pibrac	0101	31417010	Vieux Villa	H	0.11	0.09	0.17	1	A	0.00	15	0.24	0.19	0.03	0.09	5	0.11	0.35	0.21	0.47	0.01	0.13	8
31557	Tournefeu	0105	31557010	Vitarelles	H	0.25	0.21	0.07	1	A	0.00	9	0.38	0.25	0.03	0.19	23	0.17	0.42	0.21	0.54	0.1	0.25	32
31555	Toulouse	0302	31555030	Wilson	H	0.15	0.16	0.96	6	C	0.05	72	0.08	0.77	0	0.29	58	0.08	0.98	0.25	0.22	0.03	0.3	51
31506	Saint-Orer	0104	31506010	Zone d'Ac	A	0.00	0.00	0.46	3	B	0.02	38	0.62	0.45	0	0.4	99	0.03	0.68	0	0.25	0	0.06	2
31561	L'Union	0103	31561010	Zone d'Ac	A	0.02	0.02	0.24	2	B	0.01	25	0.76	0.37	0	0.43	114	0.05	0.5	0.04	0.65	0	0.17	13
31561	L'Union	0107	31561010	Zone d'Ac	A	0.00	0.00	0.14	1	A	0.00	12	0.56	0.3	0	0.29	57	0.03	0.42	0.01	0.62	0.01	0.11	6
31044	Balma	0108	31044010	Zone d'Ac	A	0.20	0.08	0.19	2	B	0.01	23	0.76	0.31	0	0.4	97	0.17	0.36	0.05	0.7	0.1	0.23	27
31044	Balma	0107	31044010	Zone d'Ac	A	0.01	0.02	0.06	1	A	0.00	6	0.62	0.16	0	0.25	38	0.04	0.3	0.02	0.64	0.09	0.11	5
31555	Toulouse	5001	31555500	Zones d'A	A	0.04	0.03	0.13	1	A	0.00	11	0.62	0.23	0.09	0.33	71	0.07	0.46	0.05	0.61	0.36	0.29	44