Translation of Urban Climate Analysis Output Using Chorematic Representation: Case of French Cities

Banu Melis Suher-Carthy

A thesis submitted for the Joint programme of
Master in Urban Climate & Sustainability

August 2021

GCU Glasgow Caledonian University
LAB University of Applied Sciences
uhu.es Universidad de Huelva
LISST UMR 5193 Laboratoire Interdisciplinaire Solidarités, Sociétés, Territoires
cnrs

<table>
<tr><td>Author
Last name: SUHER-CARTHY
First name: Banu Melis</td><td>Publication type
Thesis</td><td>Completion year
2021</td></tr>
<tr><td></td><td colspan="2">Number of pages: 67</td></tr>
<tr><td>Supervisor I
Dr. Julia Hidalgo Rodriguez</td><td colspan="2">Supervisor II
Najla Touati</td></tr>
<tr><td>Supervisor III
Prof. Dr. José-Enrique García-Ramos</td><td colspan="2">Supervisor IV
Benjamin Fisher</td></tr>
<tr><td colspan="3">Title
Translation of Urban Climate Analysis Output Using Chorematic Representation:
Case of French Cities</td></tr>
<tr><td colspan="3">Degree: Master in Urban Climate & Sustainability</td></tr>
</table>

Abstract

With the intention to support the integration of climatology into urban planning, this thesis explores an uncommon method for communication of microclimatic data to planners. The research aims to devise a methodology to conduct microclimatic analysis and deliver recommendations for 47 French cities. This approach builds on the chorematic representation technique as a form of graphic modelling that has been applied on Toulouse by the LISST Research Team. In this context, the urban climate data of 47 French cities is analysed with a focus on UHI effect.

Prior to the analysis of 47 cities' UHI input, the MésoNH-SURFEX simulation data was investigated and pre-processed in R Statistical Software. To categorise cities on UHI intensities, the analysis was conducted with a perspective of spatial pattern and form. At this stage spatial metrics were used through patch analysis in ArcGIS. Following patch analysis, cluster analysis was performed for the partitioning of cases.

Four clusters were obtained with different UHI intensity characteristics: Cluster 1-Concentrated High Intensity, Cluster 2-Limited Intensity, Cluster 3-Dispersed High Intensity, and Cluster 4-Dispersed Cool Zones. Toulouse, situated within Cluster 1, was found to be compatible with the other cities in the cluster. Thus, the application of the Toulouse chorematic model for Cluster 1 was validated. The reproduction of chorematic representation for other clusters was demonstrated on Cluster 3 due to the high UHI intensity characteristics it held. For Metz, as the representative city of Cluster 3, UHI analysis and recommendations chorematic models were prepared.

The research showed that clustering method coupled with the spatial metrics yielded the desired outcomes in grouping of similar cases. While it is easier to reproduce graphic models for clusters with lower irregularities, clusters with higher complexities might require further focus on peculiarities. It is concluded that this workflow contributes to communicating the urban climatic information of multiple cities to planners through a holistic and time-efficient approach.

Keywords

UHI, chorematic representation, graphic modelling, shape/spatial metrics, patch analysis, cluster analysis, French cities

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.	**Signature**

TABLE OF CONTENT

ACKNOWLEDGEMENTS

Throughout my research there has been many people I owe thanks to, without whom this thesis would not be a reality.

I would like to express my deep gratitude to my supervisor, **Dr. Julia Hidalgo Rodriguez** from LISST for giving me this opportunity to take part in this unique project and to experience the research environment in LISST. From the development of this research topic to technical details till completion, her guidance formed the milestones of this thesis work. Special thanks go to my co-supervisors from LISST; to **Najla Touati**, for her assistance with all kinds of technical aspects besides her generous help and support with the design stages of the representation; to **Laurent Jégou**, for his invaluable insights on the technique, conceptualisation, and feedback throughout my progress. I would like to thank my co-supervisors from MUrCS; **Prof. Dr. José Enrique García Ramos** for his encouragement, support and feedback throughout my progress, and **Ben Fisher** for his assistance and valuable comments at the milestones of the research.

My sincere thanks go to my Professors from MUrCS who granted me the chance to participate in this master's degree, which became one of the most unforgettable experiences of my life. My appreciations extend to our Programme Coordinators, to **Prof. Dr. Rohinton Emmanuel**, for his constant support and guidance both in theoretical and practical matters throughout the two years. I am thankful to our coordinators from LAB and UHU, **Eeva Aarrevaara** and **Dr. José Antonio Dueñas Díaz** for their support for the time we were accommodated in Finland and Spain. I would like to thank the administrative staff that offered their assistance during these semesters.

I am indebted to my family, my greatest luck, for their endless support; to my husband **Brian Carthy,** my rock and my source of motivation who provided his endless support and love always and by all means, helping me keep things in perspective, also providing feedback for the quality of the thesis; to my parents **Ayşe Suher**, my dear mom, the source of endless and selfless love, joy and support no matter what, **Murat Suher**, my dear dad, with his unconditional support and never-ending belief in me, my dear sister **İpek Suher Ekin**, for her encouragement at all times and always being there whenever I needed support, **Prof. Olcay Kırışoğlu**, my dear aunt, for always being a role-model and inspiration to me. Without their presence in my life, I would not be able to complete this thesis.

I would like to thank my dear friends, whom I am so lucky to have met, my dear best friends since my bachelor's, **Aydan Özkil**, **Buse Ceren Ener**, **Ezgi Armağan**, and **Nur Ceren Çakmak Dam** for providing all kinds of moral support and friendship; **Pelin Turan**, who was always available in my toughest times. Finally, I am thankful to all my friends from MUrCS (family), for their warmth and sincere friendship who made these two years much more enjoyable than I could imagine.

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1: INTRODUCTION

1.1.Rationale

Since the Earth Summit in 1992, as the first large scale organized step towards addressing climate change with UN's initiation (UN, 2019), there has been increasing effort to express and guide action towards climate change at global scale. The implications of climate change in relation to increasing urbanization have emerged in several forms of catastrophes over the globe throughout the last decades (UN, 2011). While they have been encountered as storms and flooding in tropical regions, drought and heat waves have been the prominent threat for public health that has become a norm after 2003 especially in Europe (Jougla *et al.*, 2019; Kwok *et al.*, 2019; UN, 2011). Thus, in an environment of growing concern for climatic issues, researchers have urged for special attention to be directed on cities (Masson, *et al.*, 2020). Beginning from Luke Howard's discovery of urban impact on microclimate in the 19^{th} century, Oke's contribution in the 1970s provided a major leap towards understanding urban climate dynamics. In association with Urban Heat Island (UHI) phenomenon the field has received wider attention in research throughout the last decade (Hidalgo *et al*., 2019).

Nevertheless, the climatic aspect of urbanization has rarely been conveyed in urban development and planning practices (Ren *et al.*, 2011). The narrow context of climatology in urban planning is explained by the lack of a systematic approach towards the city-planning-climate relationship and extensive climate sensitive design methods (Alcoforado & Matzarakis, 2014). Although there is a growing number of sources that take on the connection between global climate change and local modifications at urban scale, the outcomes are found to be diverse and adversary (Alcoforado & Matzarakis, 2014) which can also be shown as a challenge to structure a systematic method. While transfer of science into planning practice comes across as a decades long experience in limited regions of the world (Klimaatlas, German experience) (Hebbert, 2014), a big portion of global geography has been recently adapting to these concerns and associated techniques.

In this regard, it is essential to examine how practices of bridging climatology and planning have evolved and worked for the regions that invested in such applications up to now. As was pointed out by Eliasson (2000), maps have been instrumental for communication with decision makers (Hebbert, 2014). In relation, urban climate mapping has been applied for this purpose under different forms, such as, Urban Climate Maps (UCMaps), Urban Environmental Climate Maps (UECM), Urban Climate System (UCS), Air Ventilation Assessment System (AVAS), or Local Climate Zones (LCZ) (Hebbert, 2014). As one of the most commonly used type of urban climate mapping practices, UCMaps have been adapted to the national contexts of more than 15 countries (Ng & Ren, 2015; Ren *et al.*, 2012). UCMaps support the integration of climatic considerations into planning through their UC-ReMap component where recommendations for climate-oriented planning are provided (Ren *et al.*, 2011). LCZ maps which help classifying urban land use in different local climate zones have also been shown effective in transmission between climate scientists and planning practitioners (Hidalgo *et al.*, 2019). Following this step, the input needs to be passed on to the planning domain in the form of master plans, zoning and land use plans and related policy documents.

Although working on maps is intrinsic to the urban planning profession, planners still need the consultation of climatologists as the assessment entails expert know-how and qualitative interpretations (Ren *et al.*, 2011). In order to support this transition, innovative techniques and software have been facilitated and combined in climate data simulation, modelling (e.g. EnviMET, SURFEX, UrbClim, etc.), spatial analyses, geovisualization (GIS and remote sensing) and automation of these processes (Hebbert, 2014). Nevertheless, considering the urgence and scale of climate change from local to global level, the requirement for immediate action necessitates even further improvement and application of more practical approaches.

In order to improve the communication between climatology and planning, it is essential to consider the stratified and complex structure of planning processes. Urban planning and policy-making mechanisms function at different scales, levels and responsibilities. It intermediates between various sectors and actors (Ren *et al.*, 2011). In this regard, simpler representation techniques are sought that are easily communicable and capable of expressing the outcomes of analyses and recommendations in the clearest way possible (Mills *et al.*, 2010; Ren *et al.*, 2011).

Founding on these concerns, innovative approaches have been explored and proposed to make contribution in filling this gap. An approach in semiology of graphics and geographic visualisation with a focus on urban microclimatic analyses has been proposed by the research team of the Interdisciplinary Laboratory Solidarities, Societies, Territories (LISST) and French National Centre for Scientific Research (CNRS) (Hidalgo *et al.*, 2021; Jégou *et al.*, 2021; Yin *et al.*, 2021). This work was developed on the preceding research conducted through ANR-MApUCE Project (Applied Modeling and Urban Planning Law: Urban Climate and Energy), in collaboration with the Departments of the Environment and of the Urban Regulations of Toulouse Métropole (Hidalgo *et al.*, 2021; Jégou *et al.*, 2021). With the objective of producing data and developing methods to incorporate climatology into the context of urban policy making in France, the project had two major components. The first component was composed of producing an urban database on climate data of forty cities in France while the second investigated different methodologies to introduce this data into French regulatory framework (Hidalgo *et al.*, 2021). Related to the second component, the potential of the chorematic approach has been presented to the field and researched over the case of Toulouse city (Jégou *et al*, 2021). This approach has explored the potential of the "chorematic scheme" as a form of graphic modelling to translate urban climate output integrated with Urban Climate Analysis Maps (UC-AnMaps) and Recommendation Maps (UC-ReMaps). In this manner, schematic forms and graphic representations have been identified as supportive tools to address the gap in delivering urban climate data to urban planning and policy making processes (Hidalgo *et al.*, 2021; Jégou *et al.*, 2021).

1.2. Aims and Objectives

Building on the research that has been conducted throughout ANR MApUCE project, this thesis further explores an uncommon technique to respond to the need in communication of climatic requirements and simplification of technical input representation for planning and policy making processes. Through this research, it is aimed to devise a methodology that could support urban climate mapping in meeting and assisting the connection between climatology and planning. In this context, the chorematic representation technique implemented on Toulouse is applied to 47 French cities towards delivering urban climate analysis and recommendations.

In relation, main objectives are defined as below:

- To assess and showcase the capabilities of chorematic representation as a form of graphic modelling to complement the translation of urban climate data for urban professionals;
- To analyse urban climate data for 47 selected French cities;
- To develop a workflow that allows to handle, analyse, interpret and represent the urban climate information of multiple cities;
- To validate the Toulouse chorematic representation structure on 47 French cities;
- To demonstrate the chorematic representation of urban climate analysis and recommendations on representative cases.

With these motives, initially the state of the art of chorematic applications in research is explored throughout Chapter 2 - Literature Review. In Chapter 3 – Methodology section, the followed methods are elaborated and justified for the urban climate analysis and chorematic representation of 47 French cities. This includes the introduction of data and techniques utilised on the way to categorise the UHI data of cities and graphic modelling of the output. Following this section, Chapter 4 – Results and Discussion is presented in three sub-sections. Firstly, in the context of 'Results', the outcomes of the analyses are introduced and interpreted through the classification of 47 cities according to their UHI intensity characteristics. Secondly, in the 'Discussion' part, upon the validation of the Toulouse model on the rest of the cities, chorematic representation of climatic analysis and recommendations for selected cities is exercised. Finally, in the 'Conclusion' part, the execution of the workflow is evaluated. Accordingly, shortcomings, limitations and improvement points are detailed.

CHAPTER 2: LITERATURE REVIEW

2.1. Chorematic Schemes as a Graphic Modelling and Cartographic Representation Tool

Chorems (chorémes in French) were conceptualized by Brunet in 1980 and defined as elementary structures of spatial organisation (Brunet, 1980; Brunet, 1986). In this regard, they refer to elements that represent complex geospatial situations (Reimer, 2010) alongside spatial, temporal and logical relationships (Casanova Enault & Chatel, 2017; Reimer, 2010). For the scheme of chorems that define a geography with its most significant components through graphic figures, Brunet used the expression, "the alphabet of space" (Dhieb, 2020). Thus, this representation is illustrated as a way of communication, in a sense, a language for complex spatial processes. In relation, chorematics (chorématique in French) is an approach that combines geographic modelling with this symbolic language to depict spatial models (Reimer, 2010). Nonetheless, chorematism is not just a simulation and in spite of its simplifying notion, it requires more than simple skills for an accurate representation. On the contrary, it necessitates a broad and comprehensive knowledge to reveal "the hidden or unknown structures of the geographical space, its conceals, patterns and forms, whatever the space is and whatever the spatial structures are, by pointing their strengths and weaknesses" (Brunet, cited in Dhieb, 2020).

Although the chorematic representation method is not widely employed as a visual representation tool, it has been emphasized and utilised by many researchers for its strong potential in geovisualisation (Cherni, 2019; Del Fatto *et al.*, 2008; Fusco *et al.*, 2017; Laurini *et al.*, 2009; Reimer, 2010; Velut, 2001).

2.2. Chorems' Usage & Evolution in History

Up until chorems' conceptualisation by Brunet, it is possible to mention a history that dates back to the 19th century where different forms of cartographic representations were applied as visual summaries. Beginning from cartograms used in the 19th century (Cherni, 2019), as the oldest version of visual summaries, Waldo Tobler's computer generated models in the 1960s took the big leap for graphic models (Cherni, 2019; Del Fatto, 2009).

Similar usage of graphic models can also be found in urban geography theory. Von Thünen's economic rent model (19th century), Christaller's Central Place Theory (1933), alongside pioneering city models by Chicago School, namely, Burgess's 'Concentric Zone Model' (1925), Hoyt's 'Sector Model' (1939), Harris and Ullman's 'Multiple Nuclei Model' (1945) (Figure 1) are based on similar simplified conceptualisation of the economic impact on urban spatial configuration. Such abstractions, especially models developed in the research of Chicago School became an inspiration for Brunet (1980). Combined with influences of French structuralism and constructivism, situationism and Bertin's ideas on Semiology of Graphics

(1973), Brunet developed his scheme of chorems (Brunet, 1986; Reimer, 2010) (Table 1). Yet this scheme was subjected to changes by different researchers either in the context of developing the scheme or according to their own needs (Brocard, 1993; Cheylan, 2007; Ducruet, 2006; Fontanabona, 1994).

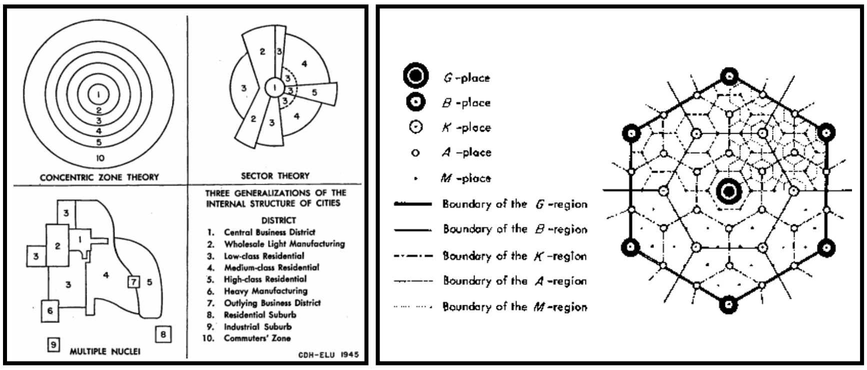


Figure 1 – Predecessor Applications of Graphic Models

On the left (1) Chicago School City Models by Burgess, Hoyt, Harris & Ullman; on the right (2), Christaller's Central Place Theory Model (1933)
Source: (1) (Harris & Ullman, 1945), (2) (Christaller, 1966)

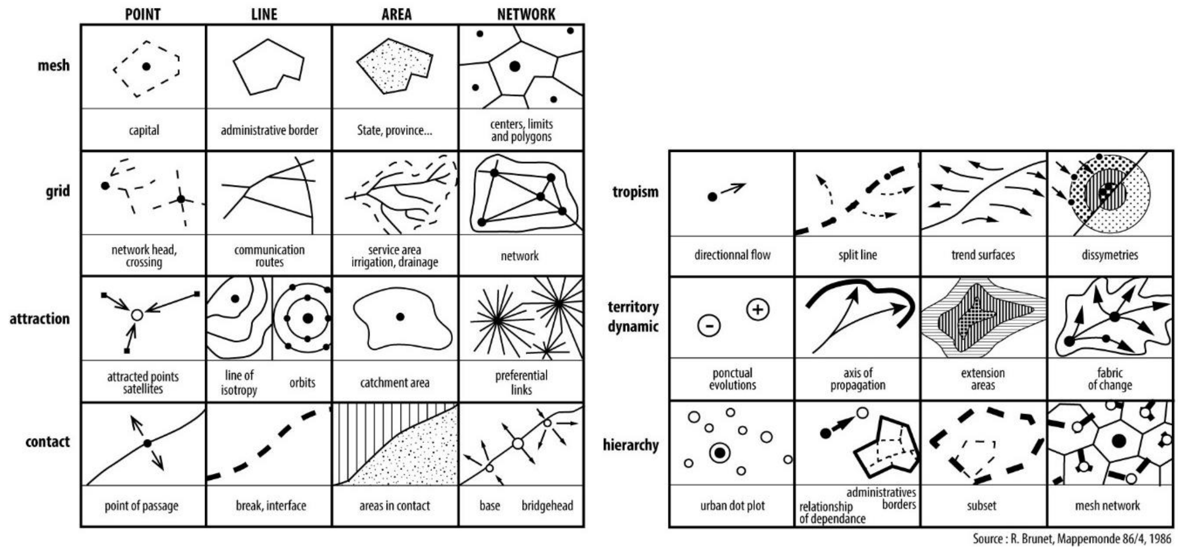


Table 1 – Brunet's Chorem Table (1986)

After their extensive application for the production of atlases and for teaching in middle and high school levels, the analysis of spatial organisation of cities and countries appear among the most common purposes that chorems were exercised. In this regard, one of the pioneering researches was presented by Théry for Brazil where he proposed a chorematic atlas (Arreghini, 1995; Brunet, 1986; Velut, 2001). With his research, Théry introduced the paleochorems and chronochorems which serve for tracing a geography's historical evolution in a graphic representation (Arreghini, 1995).

The use of chorems saw a wider application in academy beginning from the mid-90s. It is possible to come across chorematic representations in many different countries and contexts beginning from France where it was originated and used the most. More cases from Brazil, Bolivia, Argentina, Spain, Poland, Saudi Arabia, India, Thailand, Indonesia joined French predecessors in facilitating chorems to represent spatio-temporal dynamics (Arreghini, 1995; Brunet, 1986; Dhieb, 2020; Laurini *et al.*, 2009; Reimer, 2010; Velut, 2001).

On the 20th year of chorems' conceptualisation, Velut (2001) analysed the spatial organisation of 90s' Argentina with a method close to the one Théry used for Brazil (Velut, 2001) (Figure 2). In a similar manner, Rodier and colleagues (2010) used chrono-chorematics to investigate the evolution of Tours' spatial organisation in history. Arreghini's work (1995) on Bolivia also employed a historical research while comparing two different chorematic work, between J. P. Deler's and his own approach. The difference in graphic choices showed a distinctive result in analyses, leading him to recommend different graphic models for different contexts (Arreghini, 1995).

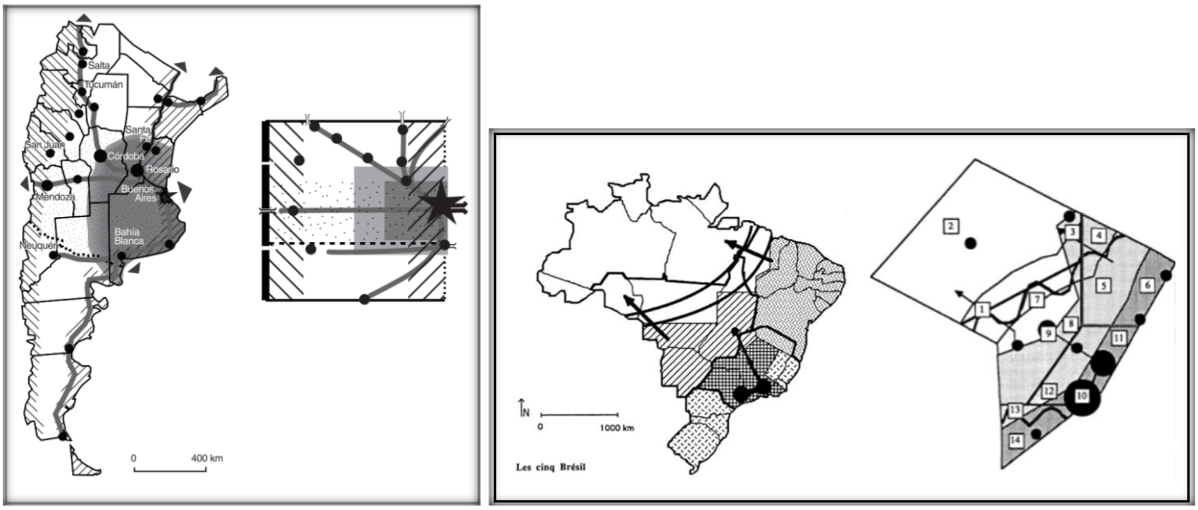


Figure 2 – Chorems' Implementation for Spatial Organisation

On the left, Velut's Graphic Model For Argentina (2001);
on the right, Thery's Graphic Model for Brasil (1988)

Chorems' capability to communicate the spatial dynamics were more commonly tested for agricultural research. Beginning from the 90s, initiated by Jean-Pierre Deffontaines, Jean-Paul Cheylan and Sylvie Lardon (1990) applied chorems for the analysis of territorial transitions in the context of graphic modelling and agronomy (Lardon & Houdart, 2017).

Several different research from various fields have proven the wide range of application and flexibility of chorematic schemes. Piveteau and Lardon (2002) made use of chorematic representation in education through the training process of engineering students on regional planning. They investigated the benefit of graphic models in territorial analyses and the communication of these dynamics in an academic platform (Piveteau & Lardon, 2002). Lafon (2005) made use of chorems to present the water problem in Brazil (Laurini *et al.*, 2009). Garmy, (2011) utilised chorematic schemes to explore the watercourse crossings and the reciprocal influence they have with the spatial organisation in French ancient towns (Garmy, 2011).

With the influence of globalisation and changing inter-territorial dynamics some researchers employed chorems to develop an understanding into restructuring spatial relationships. As an example, Ducruet (2006) used chorems to grasp the significance of supranational networking amid a globalising world. The achievements of partnerships in the context were discussed through comparison of two different cases, namely Normandie Métropole (France) and South Coast Metropole Partnership (England) with the support of chorematic representation (Ducruet, 2006) (Figure 3).

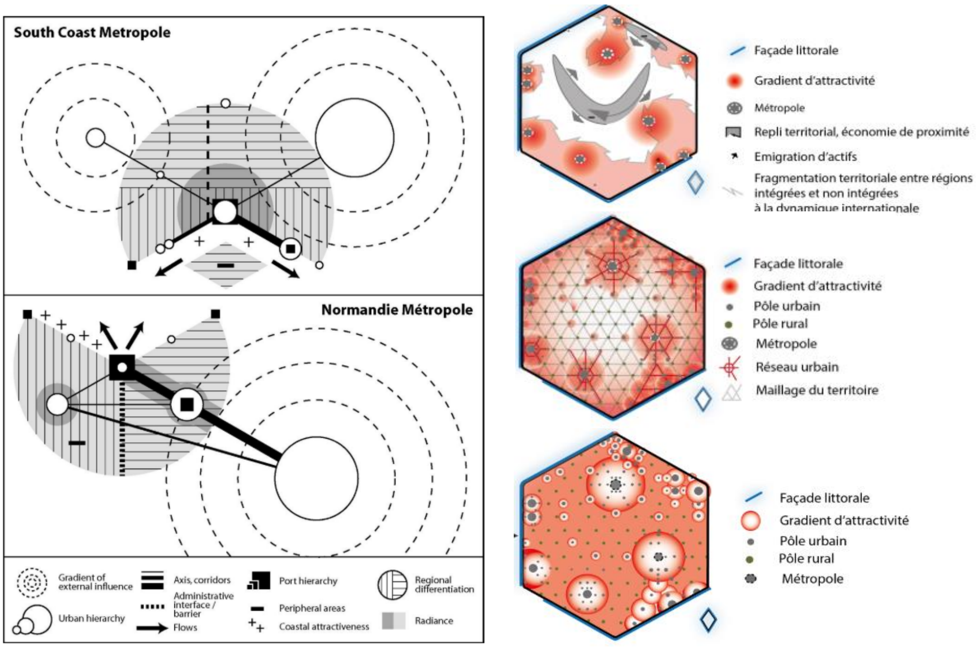


Figure 3 – Chorems' Application in the Context of Restructuring Inter-Territorial Interactions

On the left, comparison of Normandie Métropole (France) and South Coast Metropole Partnership (England) by Ducruet, 2006; on the right, three scenarios for Sustainable Development and Energy Program: Sustainable Territory 2030 by Casanova Enault & Chatel, 2017

In a parallel manner, Casanova Enault & Chatel (2017) demonstrated the use of chorems to project alternative futures. They put forth a conspicuous work where they analysed three scenarios presented by the Ministry of Ecology, Sustainable Development and Energy's program: Sustainable Territory 2030. They produced a scheme of spatio-temporal chorems to examine the dynamics of spatial change. The transition from France's 2010 status to its projected 2030 status was explored and the territorialization of the three scenarios were put under investigation through graphic modelling. In this case, the representation did not just focus on spatial compositions but the likely spatial dynamics to arise throughout territorial evolution (Casanova Enault & Chatel, 2017) (Figure 3).

Besides appearing in different visual platforms like maps, atlases, infographics, etc., advancements in quantitative techniques, modelling, geographic systems and information technologies made it possible to observe the combination of chorematic schemes with different methods.

Houdart and colleagues (2005) demonstrated this by combining chorems with GIS and multi-agent simulation (MSA) to test the impact of agricultural and rural land organisation on the spatial variability of the pollution load. They used the method to investigate the evolution of agricultural plots in 46 farms of Pelée along with their capacity for development and the polluting pressure they create (Houdart *et al.*, 2005).

Lardon and Capitaine (2008) supported chorematic representation with graphs through the collaboration of computer science and agronomy. Farms were compared by using spatial modelling to come up with feasible functioning modes. Chorematic schemes were explained through diagrams/graphs that helped code spatial and functional relations in agricultural fields. Graphs were used to relate and mark matching cases to form an organised system (Lardon & Capitaine, 2008).

Certain researchers took the method one step further with the objective to automate the chorem creation process. Automation of chorem generation and visual summary production for geodatabases were initiated by a research team from Lyon LIRIS INSA (Reimer, 2010). In order to overcome the limitations of manual creation process, these researchers introduced a computational component in the method (Cherni, 2019; De Chiara *et al.*, 2011; Del Fatto *et al.*, 2008; Laurini *et al.*, 2009). By proposing a new markup language for chorematic schemes, ChorML, they worked on automating the data extraction and visualisation processes (Del Fatto *et al.*, 2008; Laurini *et al.*, 2009). Throughout these operations, the researchers had to modify Brunet's chorems, yet they prioritised the simplification of a spatial database "both at semantic and geometric points of view" (Laurini *et al.*, 2009). Del Fatto and colleagues (2008) introduced the Chorem Editor to serve for importing, displaying, generating, modifying and exporting graphical representation (SVG) and a ChorML representation of chorems (Del Fatto *et al.*, 2008). Parallel to that, to simplify the data mining processes, Reimer (2010) proposed a taxonomy for chorems (Reimer, 2010).

2.3. Criticisms & Limitations

From the beginning of their conceptualisation and usage, chorematic representations have received various criticisms. One of the most reactional viewpoints was presented by Lacoste (1995), expressing them as tools for manipulation with the aesthetic graphic representations they provide (Lardon & Capitaine, 2008). In addition, the subjectivity intrinsic to the method, especially at the stage of choice of elements is found by Lacoste against a rigorous scientific approach (Houdart *et al.*, 2005).

Meanwhile, applicational difficulties and limitations of the method were presented through the experience of researchers that applied graphic modelling method through chorematic representation. Houdart and colleagues mention that sole usage of chorems lead to controversy as they might give way to reductionism (Houdart *et al.*, 2005). This is a natural result of the simplification process which the user should be wary of when applying. Another restriction arises from the flexibility of the structure allowing for the re-creation of different chorematic representations by each user (Lardon & Capitaine, 2008). This stands in the way of coming up with a common language or standardisation intentions.

2.4. Chorematic Schemes to Represent Urban Climate Data

As can be observed from the existing research up to now, although utilised mostly in the agriculture field, chorematic schemes carry immense potential in various disciplines that involve geovisulisation processes. Especially for planning processes where applications need to consider and deal with unprecedented and emergent events and where resilience, risk mitigation and adaptation have become prior concerns for decision making, chorematic representations can be a key tool. In situations where policies build on uncertain geographic knowledge (that refer to imprecise, incomplete, fuzzy knowledge), representations like chorematic schemes pose great capacity with the way they refer to structures rather than actual data and the way they incorporate temporal processes (Fusco *et al.*, 2017). In this regard, chorematic representation arise as a powerful tool to be employed for professions shaping the future of geographies and to allow for the integration of climate considerations throughout relevant processes.

Applying chorems in such context unfolds several possibilities for their application at different stages of delivering climate data to planning:

- First, it can be used when communicating highly technical processes in a synthetic way.
- Second, it can be employed at the stage of strategy building where recommendations are proposed to take action against the current situation.
- Finally, it might be facilitated at the future projection stage. Through scenario building, while exploring different options similar to the approach Casanova Enault and Chatel (2017) conducted in their research, visualisation of alternatives can be enabled in a refined way, unmasked and free of redundance. This could involve the comparison of current state and projected state on how far the situation evolves and if the change is effective or efficient in the specific context.

Among the listed potentials, the first one constructs the focus of the research applied on Toulouse by the LISST research team with the objective to support the communication of urban climate data for urban professionals. Thus, it is presented for use in a pedagogical manner to allow for the representation of highly technical processes to non-specialist users in climatology (Jégou *et al.*, 2021). Within this framework, the case of Toulouse has been taken through an intensive groundwork up to the process of chorematic representation.

2.4.1. Chorematic Representation of Climate Analysis of Toulouse

The steps followed by the LISST research team for the chorematic representation of Toulouse climatic considerations were based on the structure of UC-Maps (Figure 4). The components of Analysis Map were represented individually to form a combined synthetic model and based on that, recommendations were represented as a separate graphic model to be provided to urban planners (Jégou *et al.*, 2021).

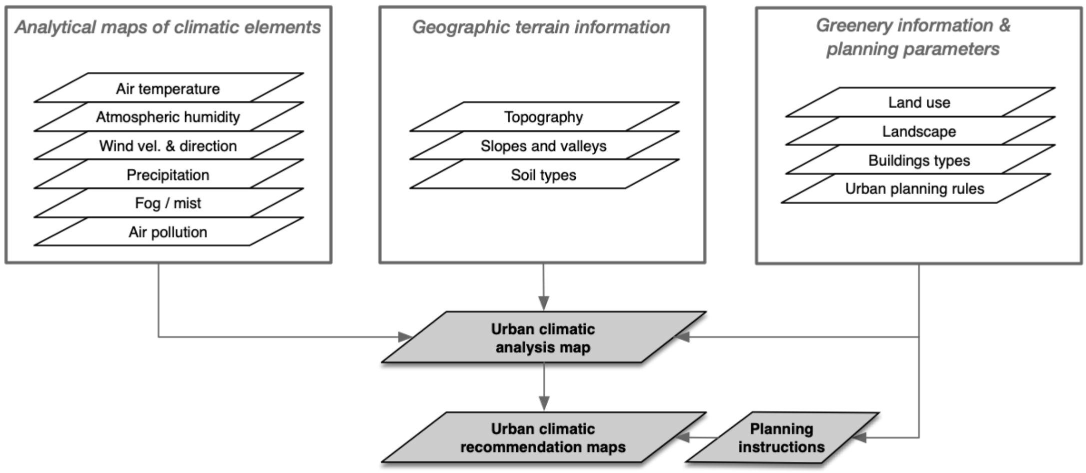


Figure 4 - The structure of UC-Maps (adapted from Ng et al., 2015 by Jégou et al., 2021)

Each chorematic representation termed as a "chorotype" or "chorematic map-model" indicated a process on its own (Jégou *et al.*, 2021). In this context, two separate processes were applied that led to the representation of urban climate recommendations through graphic modelling for the city. Combined with wind and topography data, UHI that represented the night-time situation and thermal comfort (UTCI) that represented the day-time situation were prepared as chorotypes.

The process of graphic modelling was based on H. Théry's modelling structure (Jégou *et al.*, 2021) (Figure 5). At this stage, a combination of Brunet and Cheylan's chorems were used by the authors for Toulouse case. Following the selection of chorems, a "basic model" is prepared according to Théry's structure. With the integration of modifiers into the basic model, a "theoretical model" is produced. After the territorial form is applied on the theoretical model, the "final graphic model" is achieved.

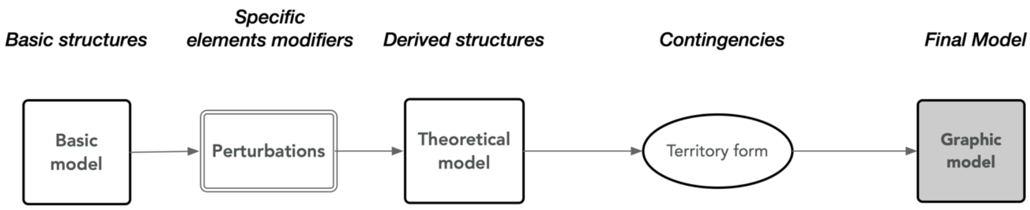


Figure 5 – Process of graphic modelling based on Théry's conceptualization. Source:(Jégou et.al., 2021)

The two graphic models representing the climate analysis for Toulouse in the specified structure are shown in Figures 6 and 7. The initial models were produced with a focus to detect and depict the current situation. These models emphasized the heat intensity, represented with a hierarchical structure between the core and the surrounding intensities in small cities, propagation and contact fronts created at tension areas, thermal comfort zones, and the river effect (Jégou *et al.*, 2021). On these analyses, recommendations were provided in the form of a graphic model (Figures 8 and 9).

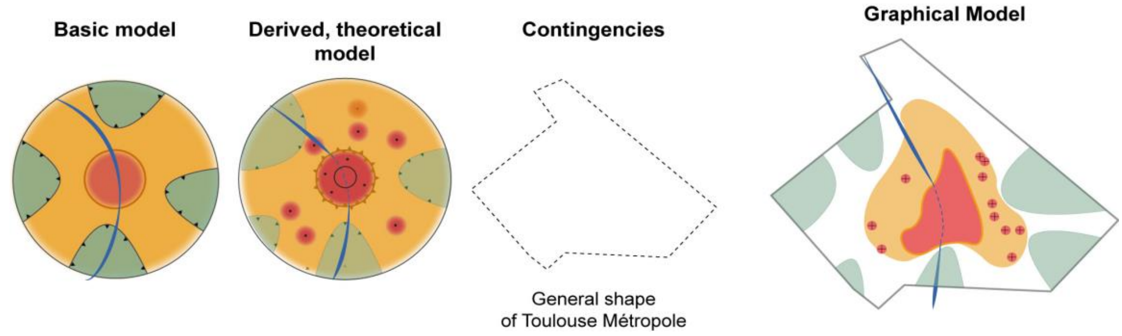


Figure 6 - Toulouse UHI final model, Source: (Jégou et al., 2021)

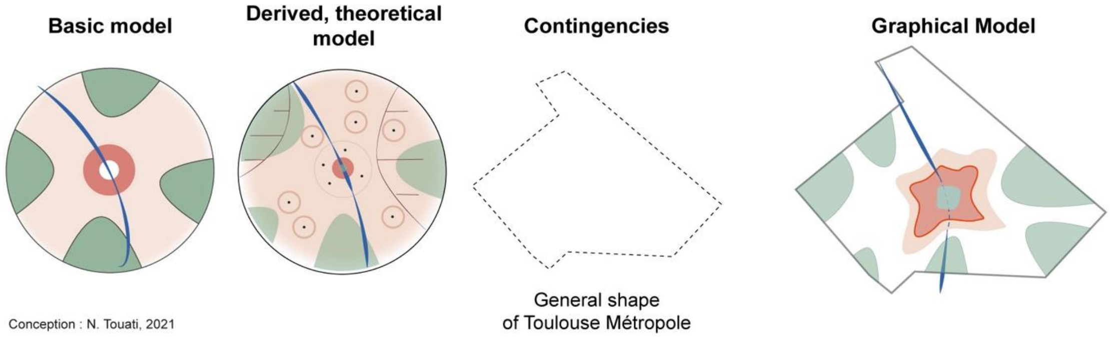


Figure 7 – Toulouse UTCI (Thermal Stress) final model, Source: (Jégou et al., 2021)

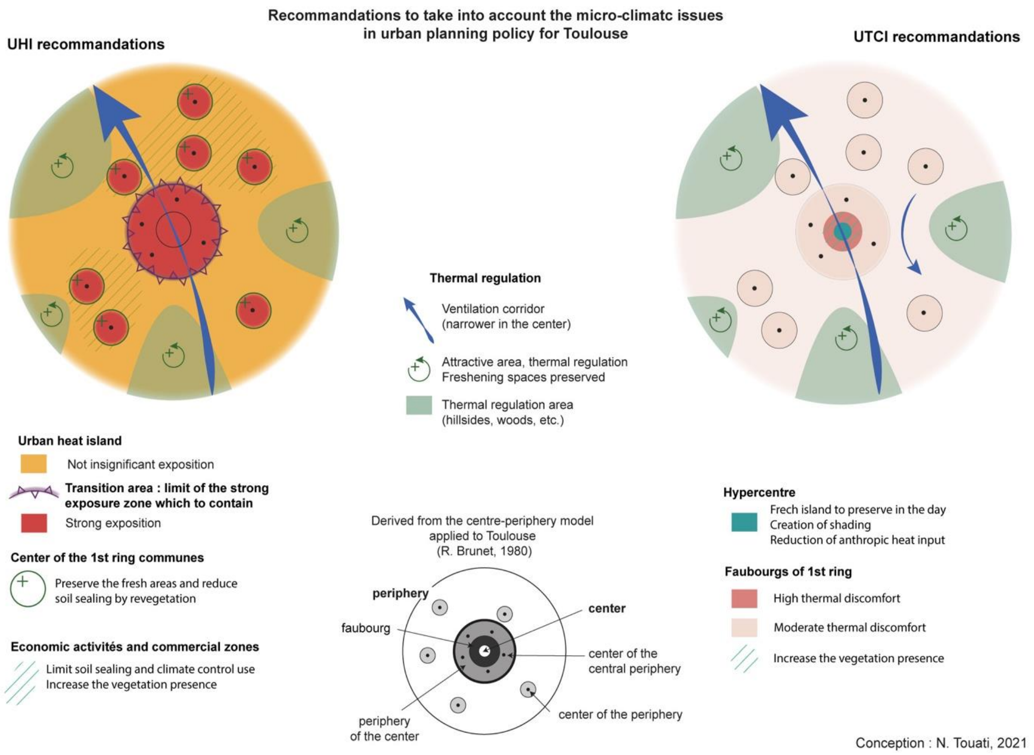


Figure 8 – Recommendations on Toulouse UHI and UTCI Models, Source: (Jégou et al., 2021)

The practicality of these models can be observed through the capability of representing not just a static structure but also the dynamics. Building on these dynamics and tendencies, focus areas were detected more easily which led to the proposal of recommendations. The recommendation models for Toulouse helped determine the zones that needed attention for policy making. Through this model (Figure 9), it was shown that the cool island effect during the day required preservation. The boundaries of strong UHI cores were pointed out to be managed by reducing thermal stress through introduction of natural ventilation and intervention in structure orientations. In the surrounding areas of small centres permeabilization in pavement and vegetation was suggested along with reduction of air conditioning. Finally, attractive zones with cooling effect and ventilation corridors to be preserved were emphasized.

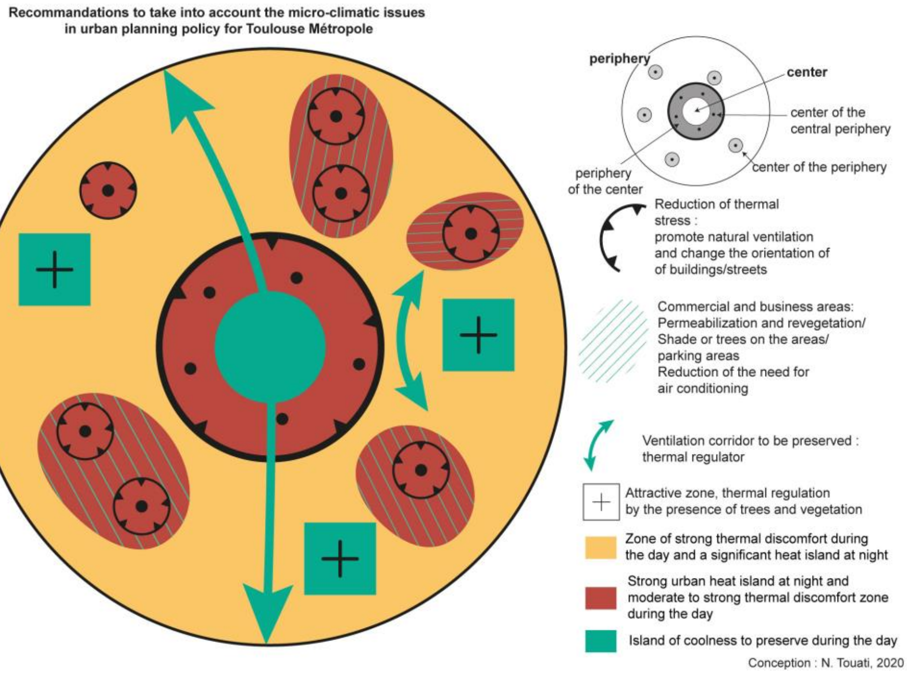


Figure 9 –Model of Strategies and Recommendations for Toulouse
Source: (Jégou et al., 2021)

As was observed from the work of Jégou and colleagues (2021), through chorematic representation, urban climate considerations were brought to an easily interpretable context. Thus, a supportive step was introduced in delivering the outputs of urban climate mapping to planners and urban policy makers. In the next section, this research will develop a methodology to validate this approach on 47 French cities following the steps of Jégou and colleagues.

CHAPTER 3: METHODOLOGY

On the way to represent 47 French cities' microclimatic data through chorematic schemes, the approach was shaped according to how the urban climate trends could be reflected by graphic modelling for multiple cities. In this context, the workflow was formulated around preparing the ground for collective analysis and interpretation of similar cases based on their microclimatic resemblances. To administer the complexities of the process, a stratified workflow was followed (Figure 10).

Throughout the workflow, quantitative research methods were applied in the data management and analysis steps. This involved data preparation and pre-processing of 47 French cities, spatial analysis of the processed data through raster analysis, patch analysis and cluster analysis which was then followed by statistical analyses to quantify, interpret and validate the results.

Upon the analysis of the UHI data, qualitative techniques were employed for the chorematic representation step. In this regard, a chorem table was prepared compiling suitable chorems from previous works by different authors to serve as a framework. This table was used to suggest chorematic elements for the communication of UHI analysis output as graphic models. This led to the reproduction of the method to other cases and to propose recommendations.

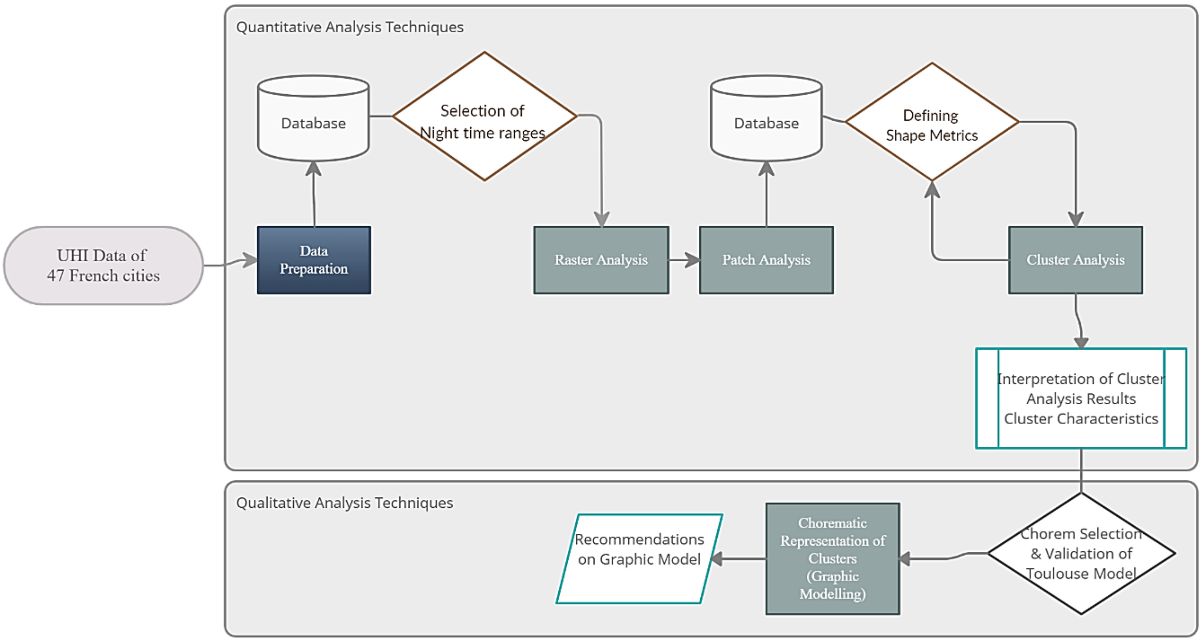


Figure 10 –The Workflow Followed Throughout the Research

3.1.Data Source

The chorematic representation of urban climate analysis is based on the Urban Heat Island (UHI) data for the case of French cities. The scope was determined by the availability of climate data for the cities. Since there was no UTCI indicator available for all of the cities, it could not be included in the context of the research.

The UHI data used in this research was produced by the National Center of Scientific Research (CNRS) during the MApUCE Project using the MésoNH-SURFEX atmospheric model. In MApUCE database, the UHI data is stored in the form of R binary data files. For each city there are two weather situations that were simulated according to the temperature values of 6 days of summer that ranges between the years 2000 and 2009. These weather situations are based on Local Weather Types (LWT) as were formulated by Hidalgo & Jougla (2018). They were defined according to daily values of temperature amplitude, specific humidity, precipitation, wind speed and wind direction (Hidalgo & Jougla, 2018; Jougla *et al.*, 2019).

The simulated UHI data has a horizontal resolution of 250mx250m. Thus, the binary files include grid points for each city that store the air temperature (in K) information at 2 meters height. The points provide the urban impact in terms of temperature difference between two scenarios of with and without urban pattern. They have a repository of 24-hour UHI data with constant values of latitude, longitude and surface height.

3.2.Data Preparation and Preprocessing

Initially, the data required to be validated and prepared for analysis. The binary files were converted into dataframes containing grid point constants and 24-hour values for each weather situation. As the extent of grid points covered much larger area than the analysis area for cities, the points were extracted according to Urban Unit (UU) boundaries for each city.

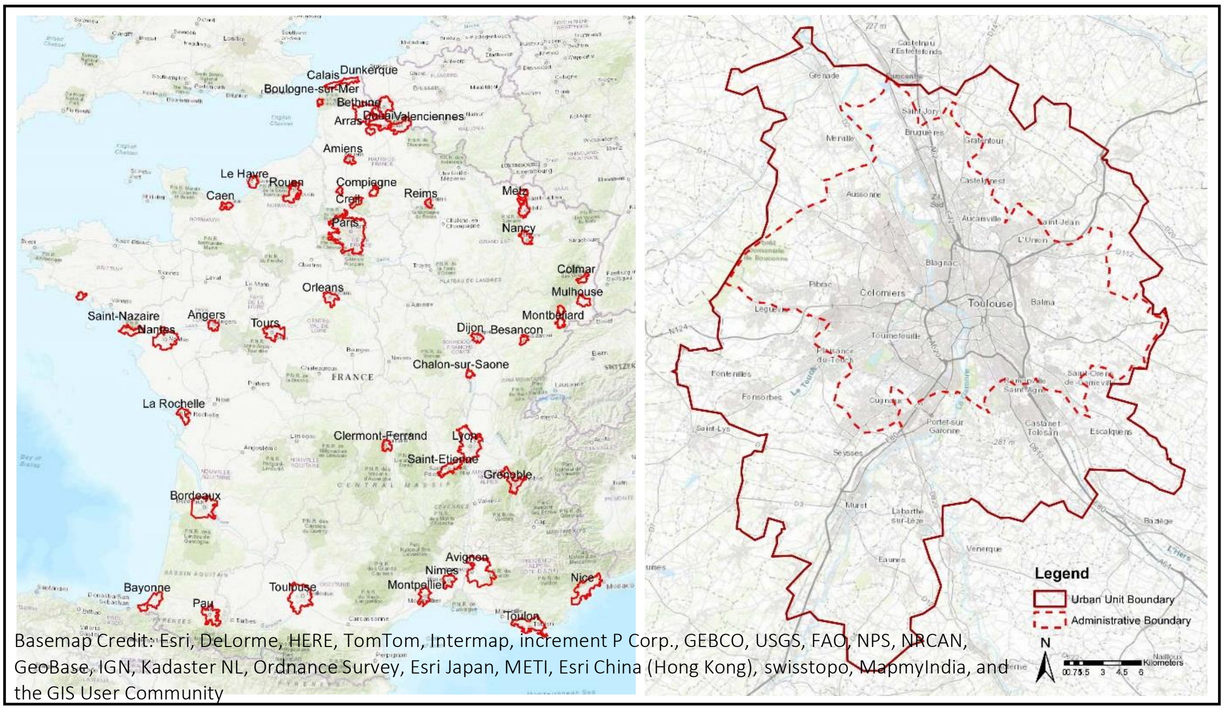


Figure 11 - Urban Units of Research Area
On the left: Urban Units in France. On the right: Urban Unit and Administrative Boundaries of Toulouse

The selection of Urban Unit as city extent was made according to the boundary used in MApUCE database (Figure 11). This Urban Unit definition was used according to the definition by the National Institute of Statistics and Economic Studies (INSEE) under the

France Ministry of Economy and Finance. Two criteria considered for this definition were the continuity of urban texture and the number of inhabitants. In this context, it was defined as, "a municipality or a set of municipalities with a continuous built-up area (no distance of more than 200 meters between two buildings) and has at least 2,000 inhabitants" (INSEE, 2020). In this context, the population and surface area information for 47 Urban Units are presented in Table 2.

General Information on 47 French Cities

City	Urban Unit Population 2018	Surface Area (km²)	City	Urban Unit Population 2018	Surface Area (km²)
Amiens	164,319	137.3	**Lille**	1,047,075	446.7
Angers	242,613	243.3	**Lorient**	121,843	149.4
Arras	87,745	105.6	**Lyon**	1,669,730	1141.4
Avignon	456,651	1364.4	**Metz**	285,930	308.8
Bayonne	254,519	513.7	**Montbeliard**	113,057	166.6
Beauvais	60,869	70.1	**Montpellier**	449,187	310.0
Belfort	79,364	106.8	**Mulhouse**	247,065	239.1
Besancon	138,691	134.9	**Nancy**	286,565	245.9
Bethune	355,994	760.3	**Nantes**	655,187	498.6
Bordeaux	969,897	1287.3	**Nice**	944,321	743.6
Boulogne sur Mer	84,676	62.8	**Nimes**	184,347	265.8
Caen	205,708	173.6	**Orleans**	282,904	289.5
Calais	97,789	105.2	**Paris**	10,816,803	2853.5
Chalon sur Saone	79,405	129.7	**Pau**	200,401	530.9
Clermont Ferrand	272,551	180.8	**Reims**	215,729	106.8
Colmar	94,960	134.4	**Rouen**	470,369	461.1
Compiegne	71,210	134.4	**Saint Etienne**	374,068	414.0
Creil	124,689	167.3	**Saint Nazaire**	186,760	472.2
Dijon	245,895	169.6	**Thionville**	134,104	137.4
Douai-Lens	504,281	485.2	**Toulon**	580,281	763.7
Dunkerque	165,123	148.7	**Toulouse**	1,019,460	957.5
Grenoble	451,096	358.1	**Tours**	359,992	684.9
La Rochelle	133,597	129.4	**Valenciennes**	335,262	440.0
Le Havre	234,945	194.9			

Table 2 - General Information on 47 French Cities
Source: INSEE, 2020

At the stage of data exploration, the temperature difference was plotted for each hour (Figure 12). This provided perspective on where the highest UHI intensities were concentrated. Parallel to that, maximum temperature difference values were obtained for each dataframe for each weather situation and city. The 24-hour dataframes were subsetted to night-time range and maximum values were calculated for each city on R. As the 24-hour data is in UTC time format, they were converted to local time of France (UTC+2). The time ranges representative of maximum UHI intensities for both weather situations are shown in Table 3.

Time Ranges Selected for Each Weather Situation for Each City

City	City Code	Time range WS1*	Time range WS2*	City	City Code	Time range WS1	Time range WS2
Amiens	ami	3-6 a.m.	0-3 a.m.	**Lille**	lil	0-3 a.m.	0-3 a.m.
Angers	ang	3-6 a.m.	0-3 a.m.	**Lorient**	lor	0-3 a.m.	0-3 a.m.
Arras	arr	0-3 a.m.	0-3 a.m.	**Lyon**	lyo	3-6 a.m.	0-3 a.m.
Avignon	avi	3-6 a.m.	3-6 a.m.	**Metz**	metz	0-3 a.m.	0-3 a.m.
Bayonne	bay	3-6 a.m.	0-3 a.m.	**Montbeliard**	montb	3-6 a.m.	0-3 a.m.
Beauvais	bea	0-3 a.m.	3-6 a.m.	**Montpellier**	montp	3-6 a.m.	3-6 a.m.
Belfort	bel	0-3 a.m.	3-6 a.m.	**Mulhouse**	mul	3-6 a.m.	0-3 a.m.
Besancon	bes	3-6 a.m.	0-3 a.m.	**Nancy**	ncy	0-3 a.m.	3-6 a.m.
Bethune	bet	0-3 a.m.	0-3 a.m.	**Nantes**	nant	3-6 a.m.	0-3 a.m.
Bordeaux	bord	0-3 a.m.	3-6 a.m.	**Nice**	nic	3-6 a.m.	0-3 a.m.
Boulogne sur Mer	bou	0-3 a.m.	3-6 a.m.	**Nimes**	nim	3-6 a.m.	3-6 a.m.
Caen	cae	3-6 a.m.	0-3 a.m.	**Orleans**	orl	0-3 a.m.	0-3 a.m.
Calais	cal	3-6 a.m.	0-3 a.m.	**Paris**	par	3-6 a.m.	0-3 a.m.
Chalon sur Saone	cha	0-3 a.m.	0-3 a.m.	**Pau**	pau	3-6 a.m.	0-3 a.m.
Clermont Ferrand	cle	3-6 a.m.	3-6 a.m.	**Reims**	rms	0-3 a.m.	0-3 a.m.
Colmar	col	3-6 a.m.	3-6 a.m.	**Rouen**	rou	3-6 a.m.	0-3 a.m.
Compiegne	com	3-6 a.m.	3-6 a.m.	**Saint Etienne**	stet	0-3 a.m.	0-3 a.m.
Creil	cre	3-6 a.m.	3-6 a.m.	**Saint Nazaire**	stnz	0-3 a.m.	0-3 a.m.
Dijon	dij	3-6 a.m.	3-6 a.m.	**Thionville**	thi	3-6 a.m.	3-6 a.m.
Douai-Lens	dou	0-3 a.m.	0-3 a.m.	**Toulon**	tou	3-6 a.m.	3-6 a.m.
Dunkerque	dun	0-3 a.m.	3-6 a.m.	**Toulouse**	touls	0-3 a.m.	3-6 a.m.
Grenoble	gre	3-6 a.m.	3-6 a.m.	**Tours**	trs	0-3 a.m.	3-6 a.m.
La Rochelle	lar	0-3 a.m.	3-6 a.m.	**Valenciennes**	val	0-3 a.m.	0-3 a.m.
Le Havre	leh	0-3 a.m.	3-6 a.m.				

Table 3 – Time Ranges Selected for Each City
**WS: Weather Situation*
City Codes represent the abbreviations used for cities in later graphs and figures

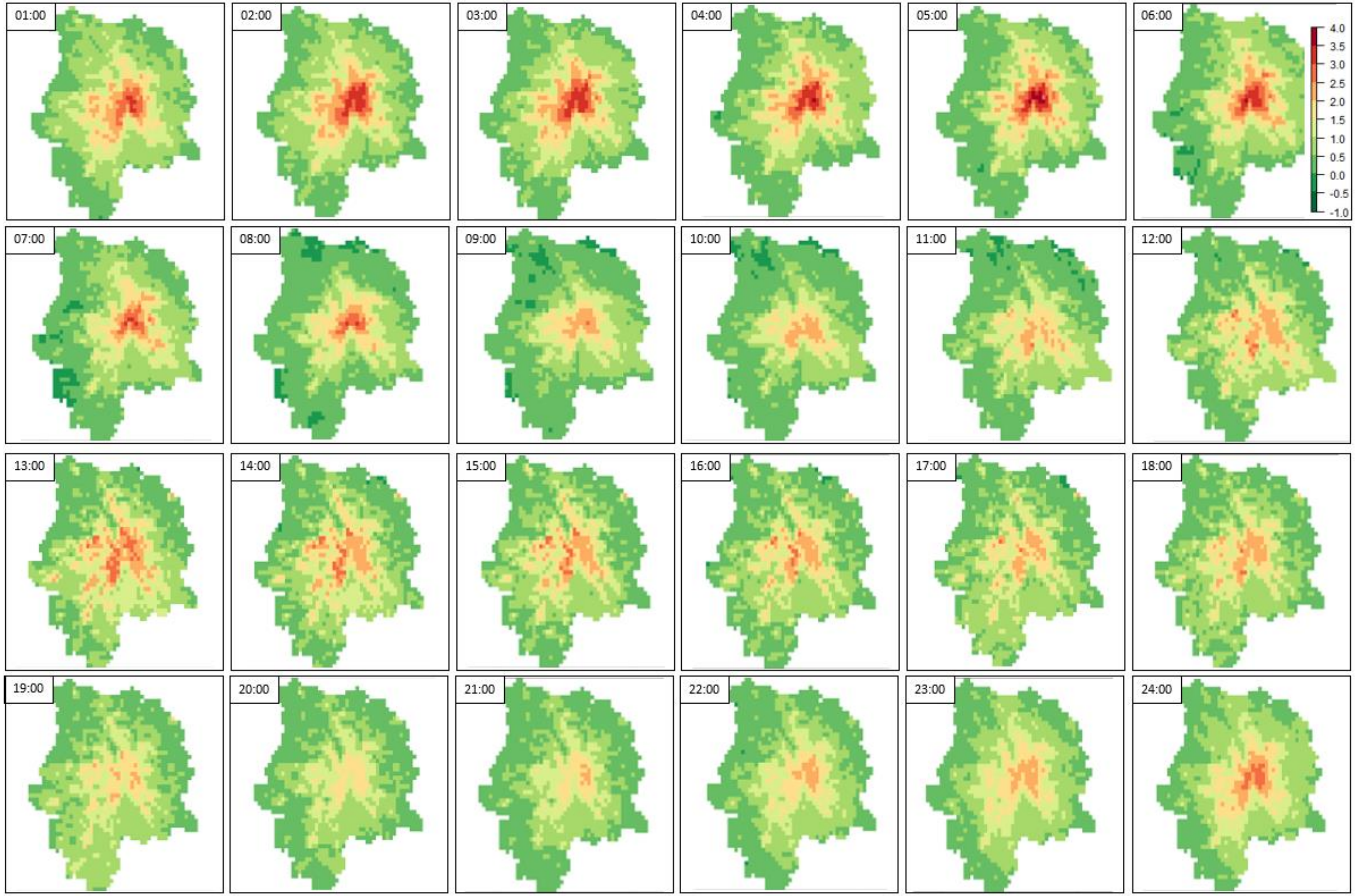


Figure 12 – 24 Hour UHI Intensity Distribution in Toulouse for Weather Situation 2

3.3.Raster Operations

Certain steps that involved spatial analysis were continued in GIS platform over raster format. There were two main reasons for the processing to be carried out on pixelated data. Since spatial metrics were going to be applied through Patch Analysis extension in ArcMap, the data format had to be made compatible with the software which could be either vector or raster format. In relation, regarding that the UHI data for cities was already in the form of grid points, the spatial analysis steps were decided to be continued in raster format.

Building on the time range analysis carried out in the previous step (see Table 3 and Figure 12), datasets were rasterised based on the mean value of 3-hour time ranges with maximum night-time temperature difference. During the conversion, few of the pixels were returned with null values for certain cities. At this stage, focal statistics were applied to manage the empty pixels and interpolate the values from neighbouring cells. In the next step, the raster files of each weather situation for cities were composited to reflect the highest exposure area of UHI intensity (Figure 13).

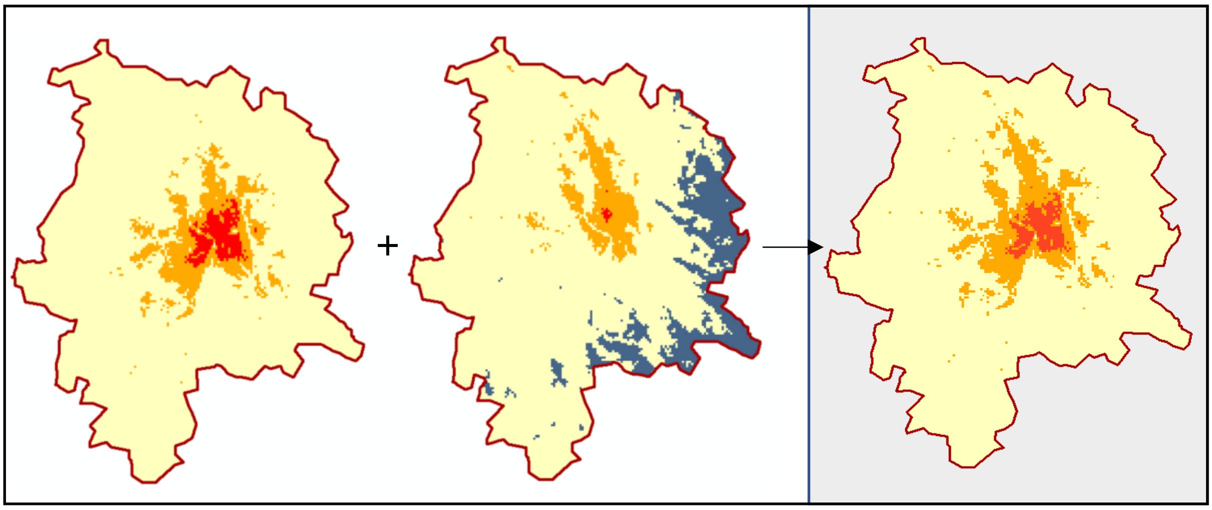


Figure 13 – Composition of Rasters with Two Weather Situations Into One Raster (Toulouse)

Following the raster processing operations, the outputs were reclassified into different UHI intensity classes as shown in Table 4.

Temperature Range	UHI Intensity Class
Below 0 °C	Cool zones
0 °C to 2 °C	Negligible exposure
2 °C to 3 °C	Significant exposure
3 °C to 6 °C	Strong exposure
Over 6 °C	Very strong exposure (only Paris)

Table 4 – UHI Intensity Classes' Definition

3.4. Patch Analysis

Patch analysis was fundamental to the investigation of UHI intensity trends for cities and to detecting similarities between them. This method allows to analyse the form and spatial distribution of UHI zones corresponding to the intensity classes. Thus, this step was crucial to first classify the cities into clusters and then to deduct specific features of these clusters towards their representation with chorems.

While conducting analysis that is based on spatial forms, the high variety of parameters that need to be considered based on extremely varying characteristics from geography to geography is a major challenge to overcome. Landscapes are composed of elements which exist in the form of a patch mosaic (Forman 1995, Urban *et al*. 1987, cited in McGarigal, 2015). The efforts to quantify complex urban form and landscape characteristics in research has brought about many different approaches and methods (Chelaru *et al.*, 2014). Besides zonal statistics, landscape/spatial/shape metrics employed in this research through patch analysis, have been used in different contexts to quantify and classify varying spatial forms. It is possible to encounter the use of these metrics, especially to analyse the degree of fragmentation in habitats and urban areas. Thus, its application ranges from biodiversity studies to urban form and sustainable development over land use change analyses (Fang *et al.*, 2017; Gherraz *et al.*, 2020; Lowry & Lowry, 2014; Schneider & Woodcock, 2008; Tsai, 2005). In relation, some researchers benefitted from shape metrics to investigate the influence of open and vegetated areas on UHI intensity (Gherraz *et al.*, 2020). This research takes the method a step further using shape metrics to depict typologies based on UHI intensity classes for graphic modelling purposes.

Various definitions and combinations of spatial metrics are present in research depending on the context through dimensions termed as compactness, centrality, complexity, density, porosity, accessibility, fragmentation and so forth (Fang *et al.*, 2017; Gherraz *et al.*, 2020; Lowry & Lowry, 2014; Schneider & Woodcock, 2008; Tsai, 2005). While these dimensions can be formed using specified formulas according to metrics of interest, pre-defined metrics can be used in the way they were provided by certain tools. FRAGSTATS Software is one of the tools that was established and used for examining the landscape ecology and pattern characteristics. Developed by McGarigal and Marks, the tool allows the analysis of spatial patterns of categorical maps (McGarigal, & Marks, 1994). Besides FRAGSTATS, it is possible to conduct this analysis with other software like QGIS, ArcGIS and LEAP II (Chelaru *et al.*, 2014). For this research ArcGIS was found suitable to apply patch analysis as it builds on FRAGSTATS metrics. Following the application of packages provided for ArcGIS (Patch Analyst) and QGIS (LecoS – Landscape Ecology Statistics by Martin Jung)[1], it was observed that Patch Analyst was a more suitable option for masked raster datasets with irregular shaped boundaries and extents. Patch Analyst allows for the processing of rasters through Patch Grid extension which will be elaborated on later.

[1] For more information on LecoS, see Jung, M., 2015. LecoS - A Python Plugin For Automated Landscape Ecology Analysis. *Ecological Informatics*. **31**. Available from: 10.1016/j.ecoinf.2015.11.006.

In this research, patches that were processed in Patch Analyst – Patch Grid were treated as constituents of Urban Heat Island Intensity patterns. This was instrumental to form typologies among cities. Three levels of analysis were addressed:

- **Urban Unit Level:** the level where different intensity classes form the whole city area in terms of urban units and where comparison with other cities is carried out;
- **Urban Heat Island Intensity Class Level:** the level where several patches with the same intensity value are found and where the Patch Analysis is based on;
- **Patch Level:** the level where individual patches are found.

These levels are shown in Table 5 with the terminology used in the extension that correspond to the levels of this research.

<table>
<tr><th>Patch Grid Extension Terminology</th><th colspan="2">Research Terminology</th></tr>
<tr><td>Landscape Level</td><td colspan="2">Urban Units</td></tr>
<tr><td rowspan="6">Class level</td><td>UHI Intensity Class Number</td><td>UHI Intensity Class</td></tr>
<tr><td>1</td><td>Cool zones</td></tr>
<tr><td>2</td><td>Negligible exposure</td></tr>
<tr><td>3</td><td>Significant exposure</td></tr>
<tr><td>4</td><td>Strong exposure</td></tr>
<tr><td>5</td><td>Very strong exposure (only Paris)</td></tr>
<tr><td colspan="3">Patch Level</td></tr>
</table>

Table 5 – Levels of Patch Analysis

The choice of spatial metrics for patch analysis was built on ArcMap Patch Analyst – Patch Grid metrics (see definitions in Table 6). Within this framework, dimensions were identified that would lay the foundation for cluster comparison in the next stages. The dimensions are defined as:

- **Homogeneity:** implies the purity of the Urban Unit to the degree of patchy and/or mosaiced structure it holds;
- **Complexity:** implies the shape irregularity based on individual patches;
- **Depth:** implies the breadth of individual patches referring to the dimensions of patch shape;
- **Fragmentation & Isolation:** implies the extent of dispersity of patches among intensity classes opposite to having a compact structure (see also Figure 14).

The definition of these dimensions through spatial metrics was an iterative process. According to the results obtained at the Cluster Analysis stage, the dimensions were revised, and the analysis was repeated. While doing so, the objective of chorematic representation was taken into consideration. It was ensured that the cities would reflect and be classified in terms of their similarities in the UHI intensity trends. This facilitated the handling of similar cases collectively and made it easier to select chorems in the next stages.

Research Dimension & Metric Definitions			
Dimensions	**Metric Type**	**Spatial Metric**	**Definition**
Homogeneity	**General Metrics**	Class Proportion (ZLAND)	Classes' proportion in total area (TLA = Urban Unit). (1)
		Number of Patches (NP)	Patch number in a UHI intensity class. (1)
		Mean Patch Size (MPS)	Average patch size. (1)
Depth	**Core Area Metrics**	Total Core Area Index (TCAI)	The total size of disjunct core area patches (hectares). (1)
Complexity	**Shape Metrics**	Area Weighted Mean Shape Index (AWMSI)	The sum of each patch's perimeter, divided by the square root of patch area (in hectares) for each Cluster, and adjusted for square standard (for rasters (grids)), divided by the patch number. It is weighted by patch area so that larger patches weigh more than smaller ones. (1)
		Edge Density (ED)	The amount of edge relative to the landscape area. (1)
Fragmentation & Isolation	**Diversity Metrics**	Mean Proximity Index (MPI)	Normalized by TLA. The spatial context of a patch is quantified with reference to its neighbours of the same class. The index distinguishes disperse distributions of small patches from complex clusters with larger patch configurations. (2)
		Mean Nearest Neighbour (MNN)	Normalized by TLA. The shortest distance to a similar patch (from edge to edge). The mean nearest neighbour distance gives the average of these distances (metres) for individual classes at the class level. (1)

Table 6 – Spatial Metrics' Definitions (Compiled from (1) ArcMap- Patch Analyst Help (Rempel et al., 2012) and (2) Landscape Ecology Lecture Notes (McGarigal, 2001))

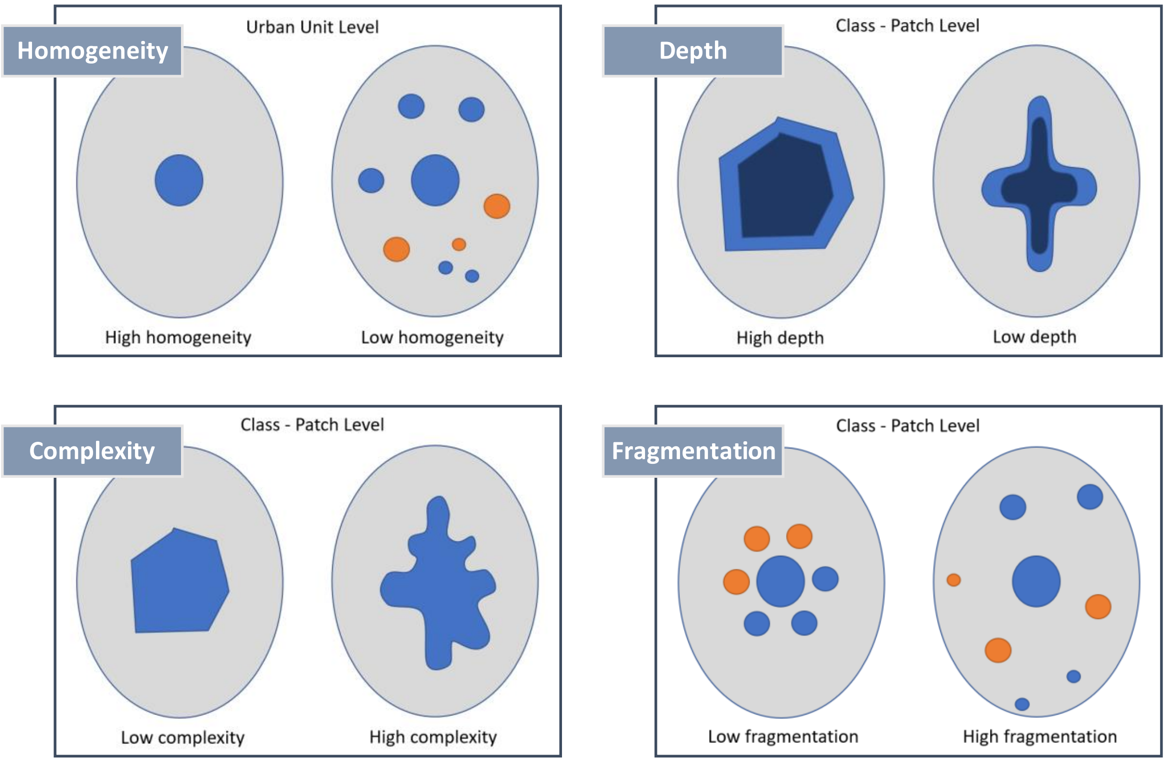


Figure 14 – Illustration of Dimensions

To reflect homogeneity some of the general metrics were taken into account. Total Landscape Area or urban unit area (TLA) and Class Area (CA) were not directly included as they were not determining to define chorematic elements but were used to normalize size related indicators to direct the clustering. Class Area Proportion (ZLAND) and Patch Number (NP) were considered selective to form clusters as main features of UHI intensity classes. They reflect homogeneity through the proportion of classes and patch numbers within urban units. In relation, Mean Patch Size, as a function of these two indicators (McGarigal & Marks, 1994) was included after being normalized by urban unit area (TLA).

As the second dimension, depth is measured through Core Area metrics. This group of metrics were considered essential regarding the correlation between centrality and exposure to strong UHI intensity. Core area reflects shape, area and edge depth effects. It has a direct relationship with area effect while having an indirect relationship with shape and edge-depth effects (McGarigal, 2001). What this metric implies for this research is the increasing likelihood of strong exposure areas to occur with more compact and deeper forms of significant exposure classes. With this in mind, Total Core Area Index (TCAI) was computed in the analysis. Taking edge as "an area of varying width" rather than a boundary, Core Area Index gives the edge-to-interior ratio (McGarigal, 2001). Thus, TCAI represents the total core area in the urban unit (Rempel *et al.*, 2012).

In terms of complexity, shape and edge metrics were used. Area Weighted Mean Shape Index (AWMSI) was implemented to calculate the degree of patch shape irregularity. AWMSI adjusts to patch size while calculating this index (Rempel *et al.*, 2012). In addition to shape metrics Edge Density (ED) was found complementary to the complexity of UHI intensity classes. The amount of edge is calculated relative to the Urban Unit area by dividing total edge by total urban unit area (Rempel *et al.*, 2012). In this context, the result represents the shape irregularity at class level as the value increases.

The last dimension that focuses on fragmentation and isolation benefitted from Diversity metrics. These indices represent the degree of diffusivity and sprawl of patches through calculation of patches' adjacency and proximity. In other words, it shows to what extent the different intensity classes are found adjacent to each other. Mean proximity Index (normalised by Urban Unit Area) gives the adjacency of patches from same classes (Rempel *et al.*, 2012). Thus, sparse distribution and fragmentation of small patches are quantified. Mean Nearest Neighbour (MNN) measures the shortest distance to a similar patch (Rempel *et al.*, 2012). In this regard, it quantifies the degree of isolation of similar patches from each other.

3.5. Cluster Analysis

To come up with a categorisation for the 47 cities according to their microclimatic properties, cluster analysis was determined as the optimal method. The aim was to be able to detect typologies between UHI intensity trends of different cities and to review similar cases collectively. Clustering techniques build on the spatial distribution of sample points (Lemenkova, 2019) and grouping of them according to similarities/dissimilarities that are represented in terms of distances. Thus, it can be applied to many fields and topics. Several studies are found in the field that conduct UHI analysis together with cluster analysis (Kamruzzaman *et al.*, 2018; Kim & Baik, 2004; Zhou *et al.*, 2013). Some of them also combined spatial metrics with cluster analysis and have been inspirational for this research (Huang *et al.*, 2007).

Since R was used at the data management stage of the research, cluster analysis was also performed on the same platform. In R it is possible to use the {cluster} and {factoextra} packages to conduct cluster analysis (Kassambara, 2017; Lemenkova, 2019). For this research, the {factoextra} package was preferred as it provides a practical way to implement the clustering and the visualisation of the results.

As the clustering method, the Partitioning Around Medoids – PAM algorithm that was developed by Kaufman & Rousseeuw (1990) was selected. The intention for the clustering to be based around real observations was the main reason behind this choice. PAM searches for k-number of representative medoids that are derived from data points. Following this set of k medoids, k clusters are formed by assigning each observation to the nearest medoid. This method focuses on the dissimilarities between observations and their closest representative object trying to minimize the dissimilarities (Kassambara, 2017). In this regard, Euclidean distance was used to measure the distance between object while calculating the dissimilarities between objects.

To prepare patch analysis results for clustering, it was checked that the dataset satisfied a number of conditions. Initially, to assemble the output in one matrix, data tables of cities were brought to the same size and structure. These tables were processed to have 4 UHI intensity classes as rows and indicators as columns. As a second condition, the analysis requires null values to be removed (Kassambara, 2017). Thus, cells with “na” values were interpolated. Another requirement for the analysis is the scaling of the dataset. Scaling is essential for algorithms that calculates distances between data as especially machine learning algorithms are sensitive to “relative scales of data” (Roy, 2020). With methods like K Nearest Neighbours, k means, PCA that use distance values to generate outputs, data scaling becomes critical (Roy, 2020). Especially datasets that have high range of mean and standard deviation values or columns with different units need to be scaled before clustering (Kassambara, 2017)

At the analysis stage, after a number of clustering attempts the number of cities was decreased to 46. It was decided to remove Paris from clustering considering its peculiarities. As one of the most influential cities in the global extent and as the biggest city and capital of France, it was concluded that it would not be easily comparable to other cities. This point showed itself on cluster plots where Paris was not clustered with any other city and its observation point was located much more remote from the rest (see Appendix 1). Therefore, as an outlier, and as a unique case, it was concluded that Paris should be represented through a separate review process. Following the partitioning of the 46 cities, clusters were examined in terms of the UHI intensity trends they show. They were compared with their medoid cities in relation to the footprint of UHI intensity classes on reclassified raster datasets and the patch analysis tables. For the general statistics, information like cluster size, medoid objects, average distance within and between clusters were calculated throughout the process and analysed. To check the quality of the partitioning, silhouette width values were reviewed (Kassambara, 2017).

3.6. Chorematic Representation

For the chorematic representation stage, the workflow applied for Toulouse in Jégou and colleagues’ work (2021) was followed. The process is integrated with urban climate mapping practices specifically with Urban Climate Analysis and Recommendation Maps. As was mentioned earlier at the Data Source section, due to the lack of information on thermal stress aspect for the 47 cities, it was not added to the representation. Thus, among the climatic elements of UC-AnMaps only one component, air temperature, was focused on through UHI effect to be represented by graphic modelling. In this context, only night-time intensities were investigated.

Based on the clusters formed at the Cluster Analysis stage, chorematic elements were suggested according to the characteristics they show and were compiled in a chorem table. This step went hand in hand with the validation of Toulouse model for other cities. At this step, the group that Toulouse was clustered in was reviewed together with Toulouse’s chorematic model. In the light of the outcomes achieved in the validation step, suggestions on chorematic representation were provided for other clusters. For graphic modelling, the clusters that were showing strong

UHI intensities were given priority. As was mentioned previously in the Literature Review chapter, the structure of Théry was used up to the theoretical model building stage. Based on the theoretical model, urban climate recommendations based on night-time situation were represented through chorematic representation which are elaborated in the next chapter.

CHAPTER 4: RESULTS AND DISCUSSION

4.1.Results

4.1.1. Data Structure & Analysis

Prior to the interpretation of Cluster Analysis results the data matrix was analysed. The matrix consisted of the observations (46 cities) in rows and 8 spatial metrics applied for each UHI intensity class in each city (32 metrics) in columns.

In order to identify the relationship between selected metrics a correlation matrix was generated based on Pearson's correlation coefficient (r) (Figure 15). Positive correlation was represented with shades of blue while negative correlation was shown by shades of red. Darker shades and larger radii indicated more extreme values.

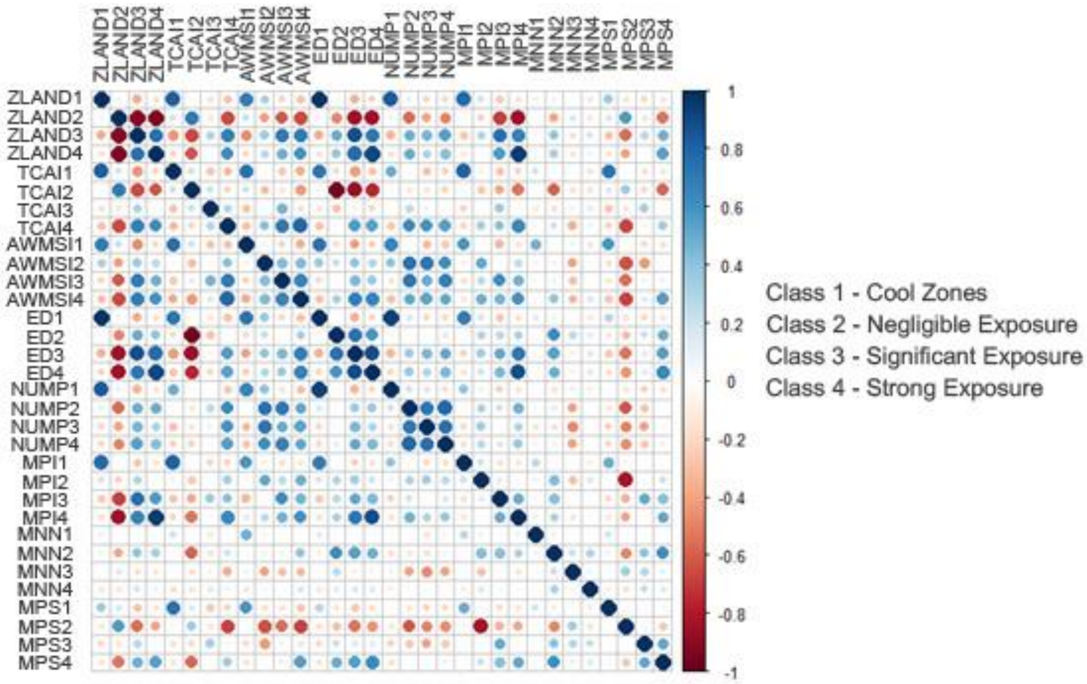


Figure 15 – Data Matrix – Correlation Between Spatial Metrics

When focused on the shape complexity of strong and significant exposure classes (3 and 4), it was found that they were affected comparatively more by class proportion (ZLAND) and number of patches (NP) metrics in classes 2, 3 and 4. It was detected that class 3 shape index (AWMSI3) was affected positively by the core area index of class 4 (TCAI4) even more than class 3 (TCAI3). This meant that growing extent of strong exposure classes impacted on the shape regularity of the significant exposure class. Mean Proximity Index of class 3 (MPI3) also had a positive high correlation with the shape complexity. In contrast, it was observed that it had high negative correlation with Mean Patch Size class 2 (MPS2). This is explained by the fact that class 2 decreased in size with increasing irregularities in class 3 due to direct contact. Edge Density for high intensity classes (ED3, ED4), as another metric for shape complexity, showed high correlation with class proportion, positive with classes 3 and 4 and negative for class 2. On the contrary, they displayed high negative correlation with TCAI2 similar to the case of mean patch size. They showed high positive correlation with shape index of class 4 (AWMSI4). In addition, proximity index of class 4 (MPI4) was detected to increase with growing complexity in both classes.

Before the Cluster Analysis step, the clustering tendency of the data matrix with 46 cities and spatial metrics was visualised through a Matrix of Dissimilarity (Figure 16). Matrix of dissimilarity is based on the Euclidean distance between observations regarding disparities among them (Kassambara, 2017). The observations that have dissimilarity value approaching zero are located closely. As the grade of dissimilarity decreases, it gets more likely for the observations to be clustered. As can be inspected from the changing scale of colour in Figure 8, there are clear distinctions between certain groups. Shades of darker purple indicate a clearer distinction and it is possible to divide some groups where dissimilarity values reach 10. In this structure, while some cities showcased stronger link between each other (such as Dunkerque, Arras, Lorient in one group; Toulouse, Bordeaux, Nantes in one; Valenciennes, Douai-Lens and Bethune in another), others seem harder to cluster due to higher dissimilarity values (such as Reims, Lille, Lyon).

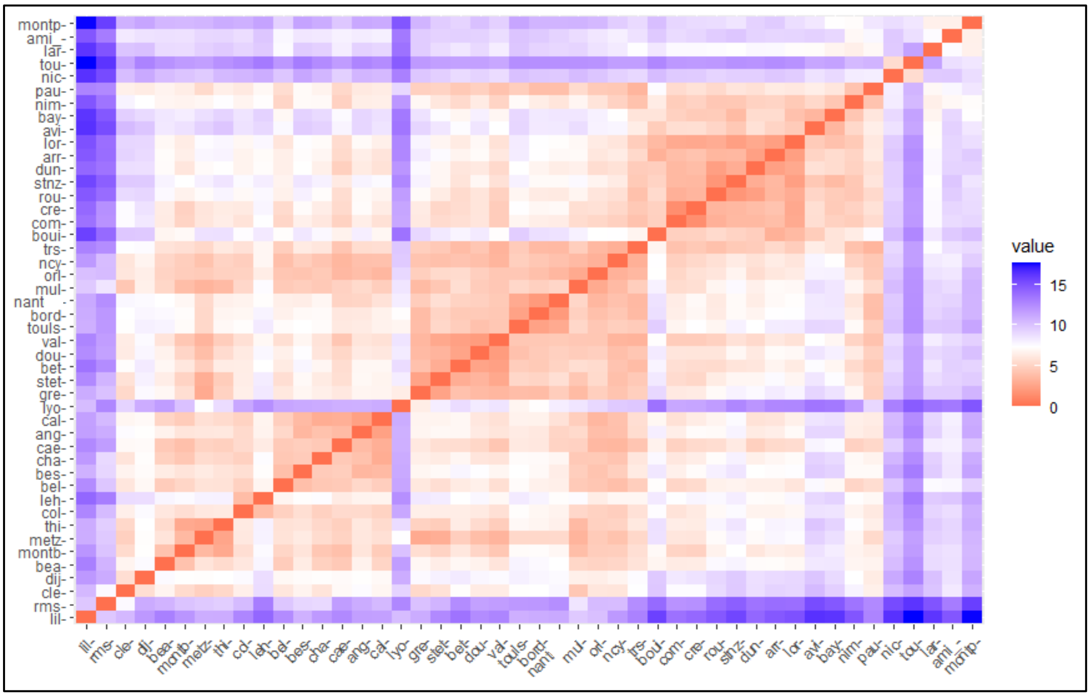


Figure 16 – Matrix of Dissimilarity

4.1.2. Cluster Analysis

At the clustering stage, one of the critical steps was to determine the number of clusters. In order to help with this decision, the optimal number of clusters (k number) was computed on R. As can be seen from Figure 17, three clusters seemed optimal. While it is possible to increase the clusters, the quality of clustering might decrease. As was mentioned previously, for the number of medoids (k), the practicality for chorematic representation stage was taken into consideration and k number was increased to 4 after experimenting from 3 to 7 (see Appendix 2 for results obtained with different values of k).

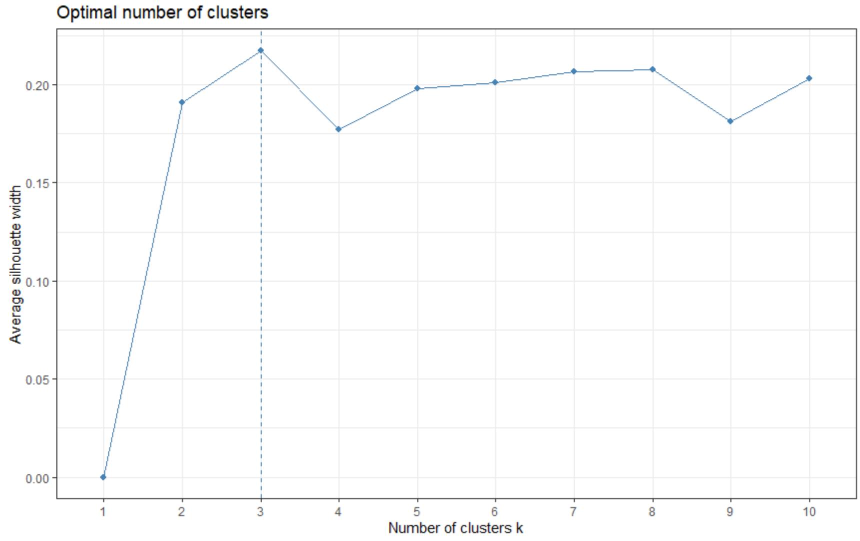


Figure 17 – Optimal Number of Clusters Plotted

During Cluster Analysis, four clusters were formed and grouped around the medoid cities, Orléans, Lorient, Metz and Toulon. In Figure 18, the partitioning among cities can be observed from different angles according to the dimensions selected to be displayed (For more details on the visualisation of dimensions see [Appendix 3](#)). Special attention must be given to the cities that lie between two clusters and are at similar distances from both medoids. In order to analyse the clustering accurately and to be able to make a comparison between cities, the distribution of values according to spatial metrics is examined in the next section.

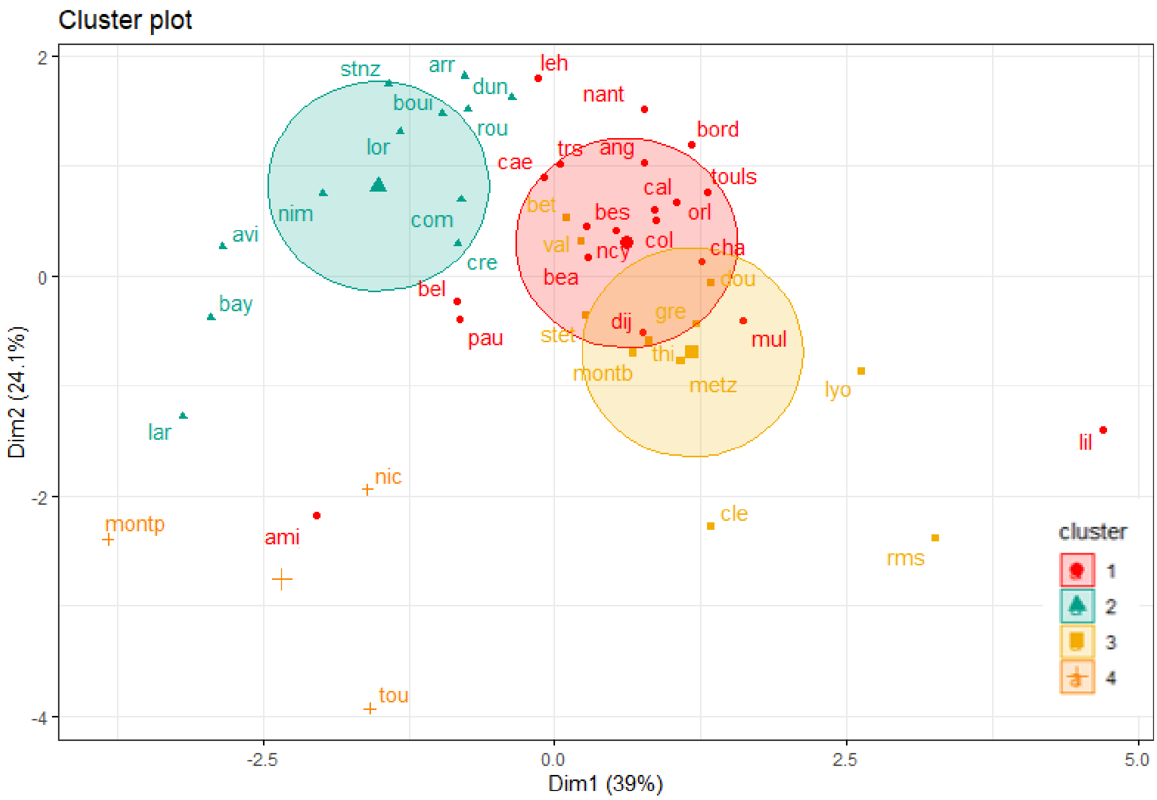


Figure 18 – Cluster Analysis Plot

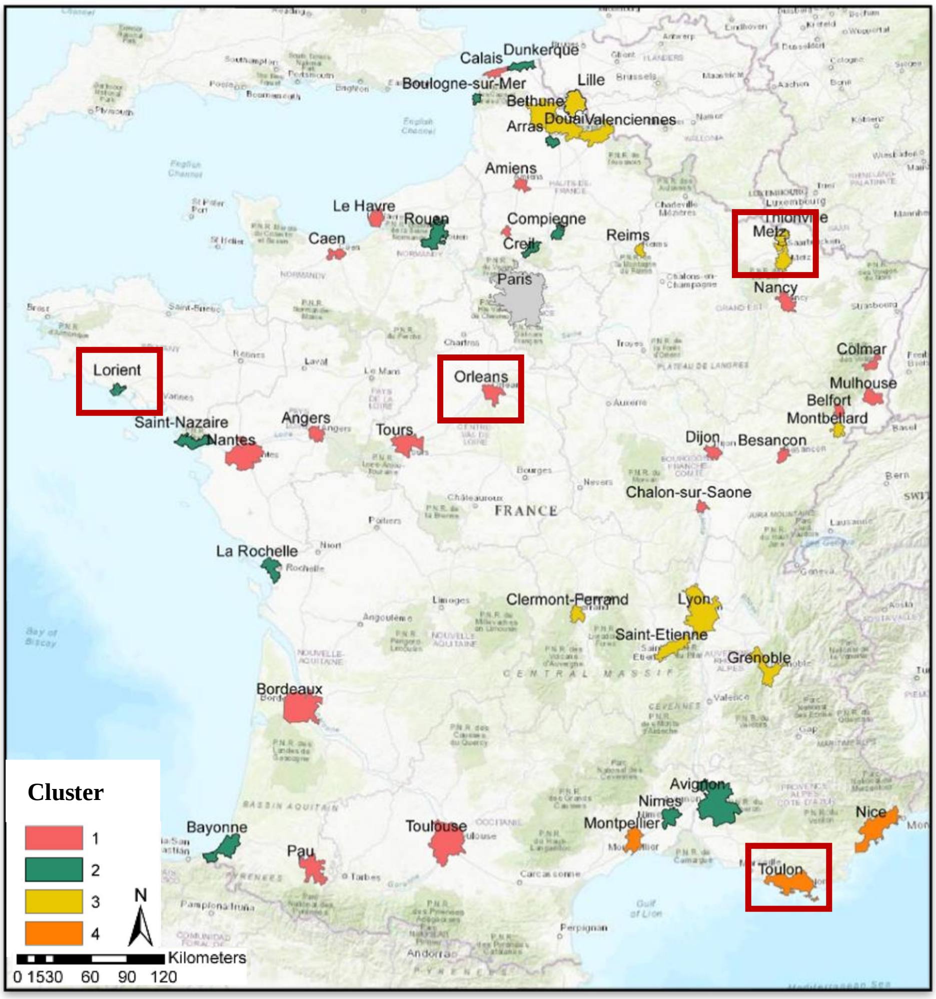


Figure 19 - Distribution of Clusters within France with Medoid Cities Marked

France, Basemap Source: Esri, DeLorme, HERE, TomTom, Intermap, increment P Corp., GEBCO, USGS, FAO, NPS, NRCAN, GeoBase, IGN, Kadaster NL, Ordnance Survey, Esri Japan, METI, Esri China (Hong Kong), swisstopo, MapmyIndia, and the GIS User Community

Cluster No	Cluster Name	Medoid City	Cluster Size
1	Concentrated High Intensity	Orléans	20
2	Limited Intensity	Lorient	12
3	Dispersed High Intensity	Metz	11
4	Dispersed Cool Zones	Toulon	3

Table 7 – General Information on Clusters

The general distribution of the clusters and the features they carried were analysed together with the UHI maps of urban units. From the results it was found out that the clustering satisfied the expectations to classify similar cases in associated clusters. Depending on the UHI intensity features they showed, the clusters were given titles to represent their main characteristics (see Table 7). The cities in clusters and their UHI intensity maps are presented in the next sub-sections.

4.1.2.1. Cluster 1 – Concentrated High Intensity

General Characteristics of Cluster 1
Strong exposure is concentrated at the urban cores
Strong exposure zones in highly compact forms are interrupted with water bodies passing through the cores of the cities

Medoid city - Orléans

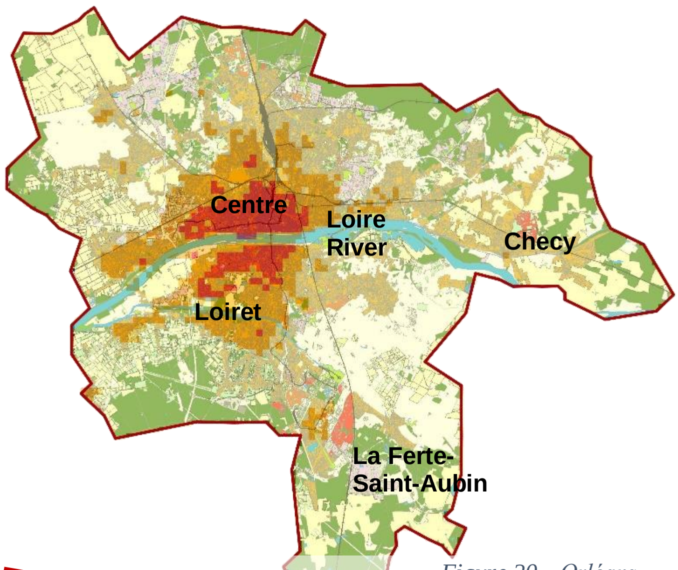


Figure 20 - Orléans
Orléans Basemap Source: Open Street Map & Geofabrik https://download.geofabrik.de/europe/france/centre.html

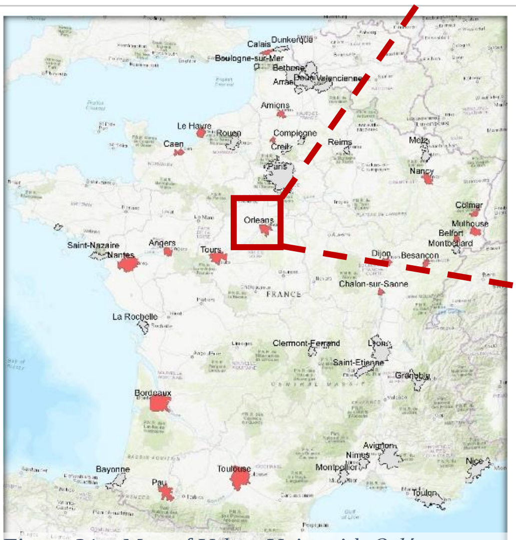
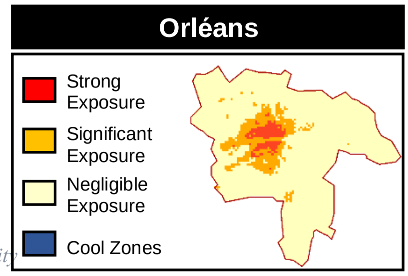


Figure 21 – Map of Urban Units with Orléans
France, Basemap Source: Esri, DeLorme, HERE, TomTom, Intermap, increment P Corp., GEBCO, USGS, FAO, NPS, NRCAN, GeoBase, IGN, Kadaster NL, Ordnance Survey, Esri Japan, METI, Esri China (Hong Kong), swisstopo, MapmyIndia, and the GIS User Community



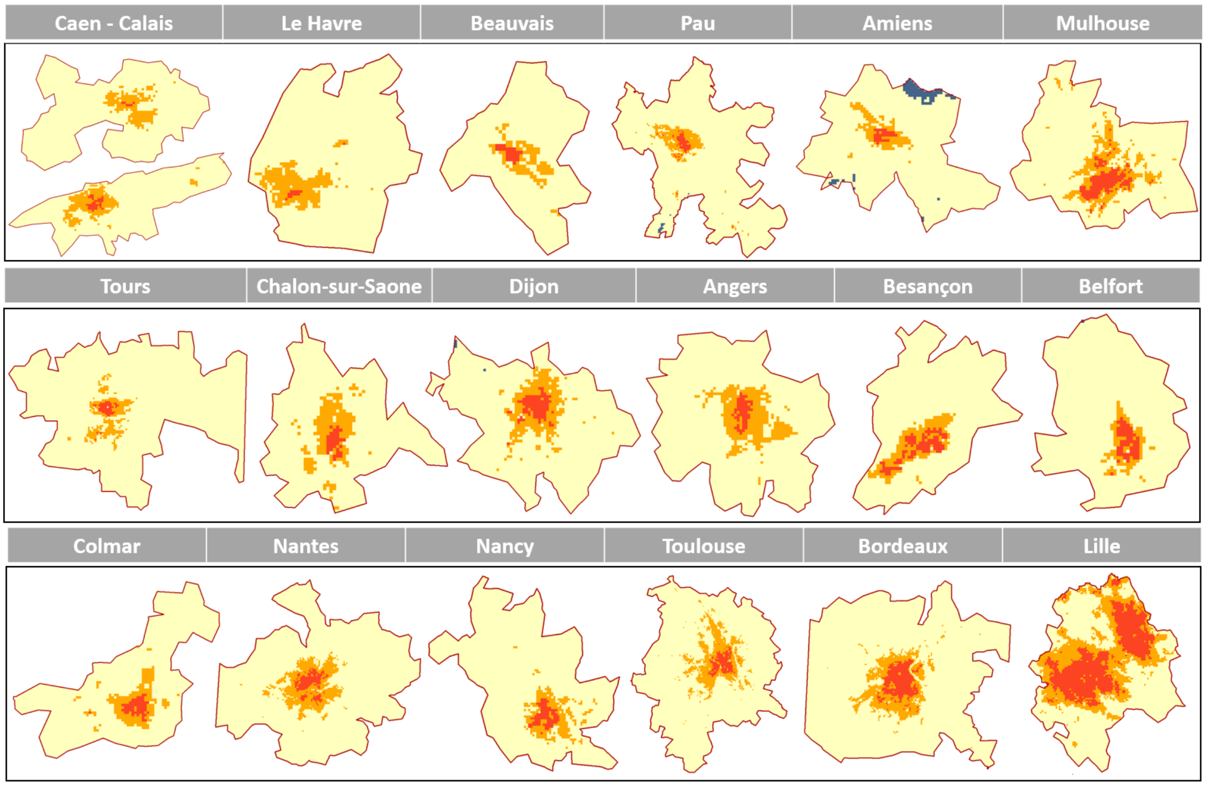


Table 8 – UHI Intensity Maps of Orléans and Remaining Cities in Cluster 1

4.1.2.2. Cluster 2 – Limited Intensity

General Characteristics of Cluster 2
Significant exposure shows limited expansion, sometimes they are observed in dispersed forms
Low patchiness in urban units

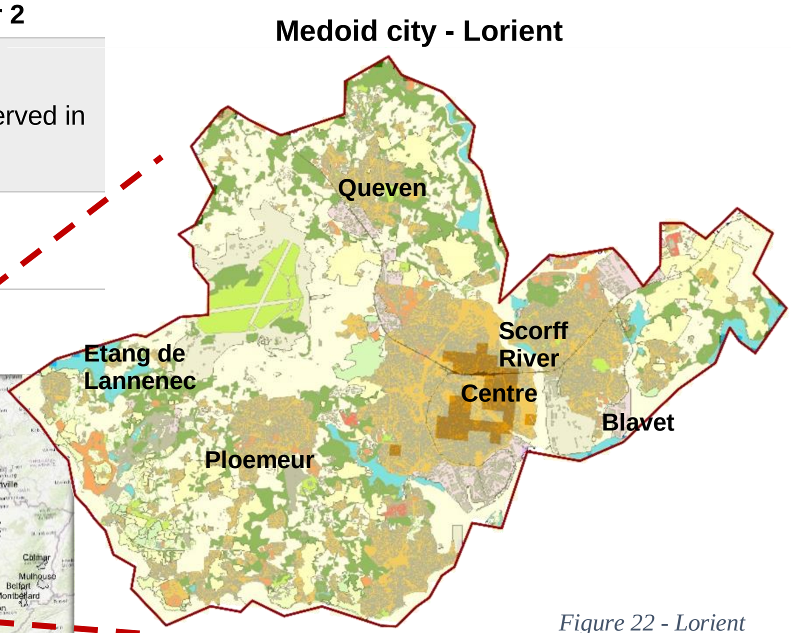
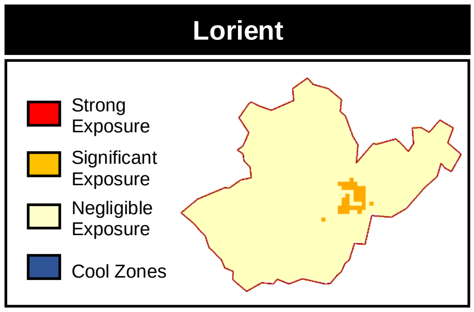


Figure 22 - Lorient
Lorient Basemap Source: Open Street Map & Geofabrik https://download.geofabrik.de/europe/france/bretagne.html

Figure 23 – Map of Urban Units with Lorient

France, Basemap Source: Esri, DeLorme, HERE, TomTom, Intermap, increment P Corp., GEBCO, USGS, FAO, NPS, NRCAN, GeoBase, IGN, Kadaster NL, Ordnance Survey, Esri Japan, METI, Esri China (Hong Kong), swisstopo, MapmyIndia, and the GIS User Community



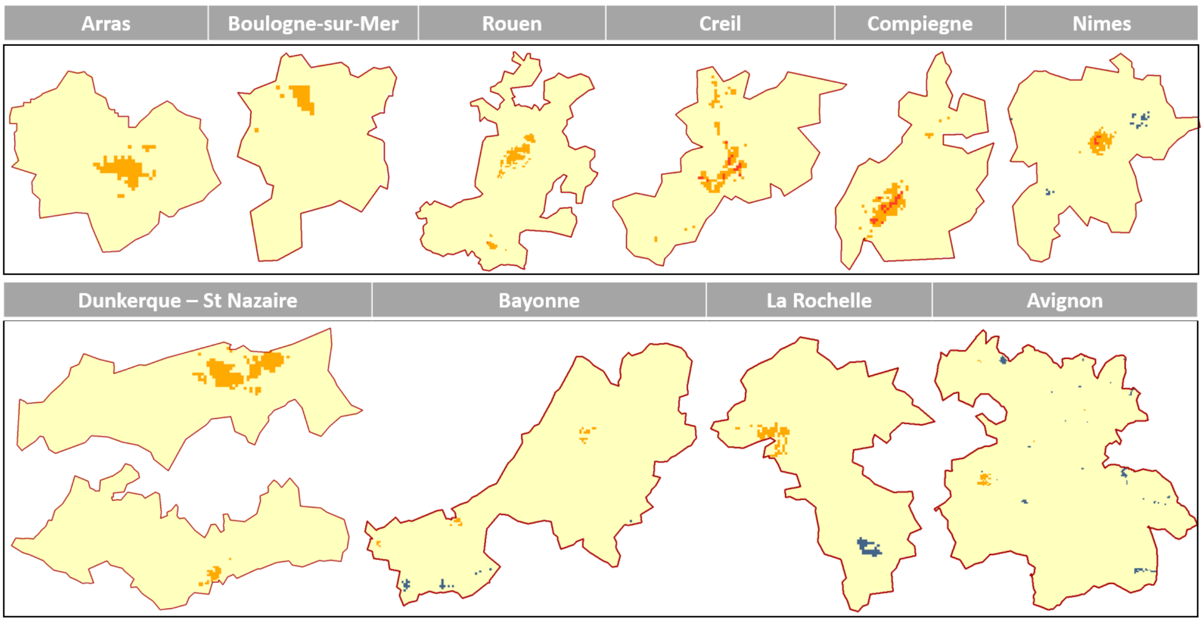


Table 9 - UHI Intensity Maps of Lorient and Remaining Cities in Cluster 2

4.1.2.3. Cluster 3 - Dispersed High Intensity

General Characteristics of Cluster 3
Strong exposure zones are highly dispersed and fragmented
Strong UHI exposure class is dominant and sprawled within significant exposure class

Figure 25 – Map of Urban Units with Metz

France, Basemap Source: Esri, DeLorme, HERE, TomTom, Intermap, increment P Corp., GEBCO, USGS, FAO, NPS, NRCAN, GeoBase, IGN, Kadaster NL, Ordnance Survey, Esri Japan, METI, Esri China (Hong Kong), swisstopo, MapmyIndia, and the GIS User Community

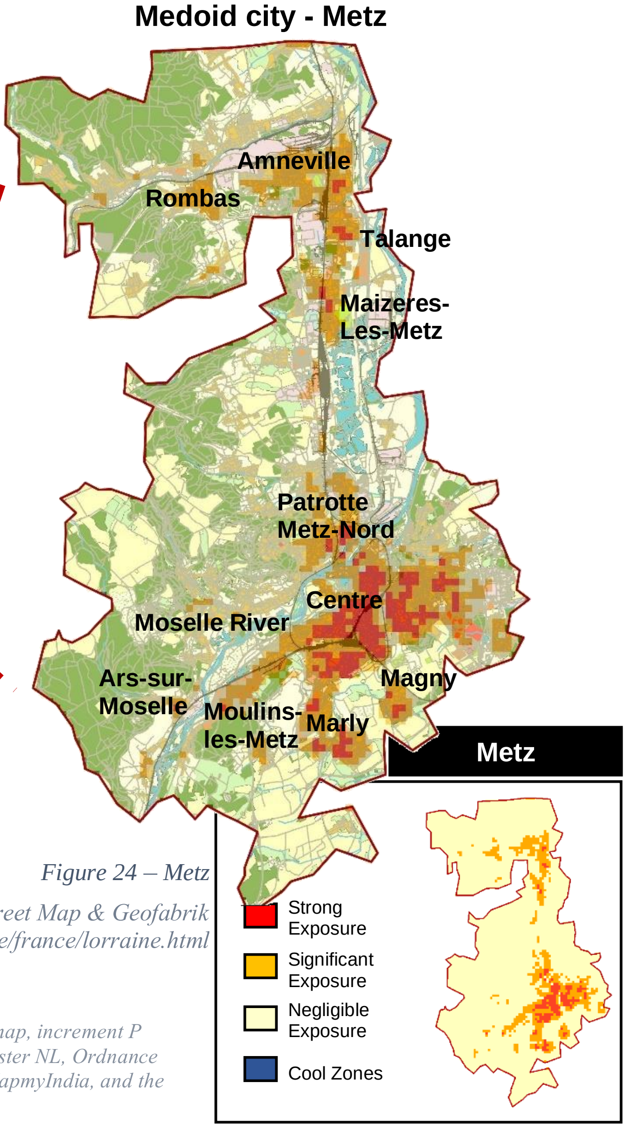


Figure 24 – Metz

Metz Basemap Source: Open Street Map & Geofabrik https://download.geofabrik.de/europe/france/lorraine.html

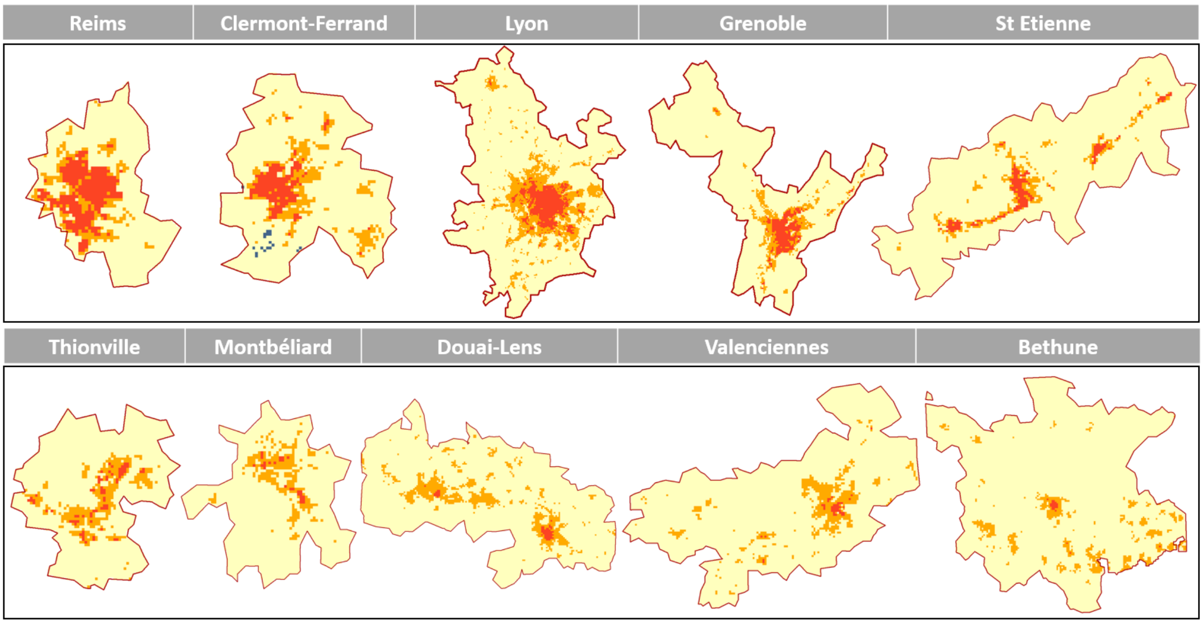


Table 10 - UHI Intensity Maps of Metz and Remaining Cities in Cluster 3

4.1.2.4. *Cluster 4 – Dispersed Cool Zones*

General Characteristics of Cluster 4
Cool zones' widespread presence causes high patchiness in Urban Units.
All cities are coastal cities in southern France.

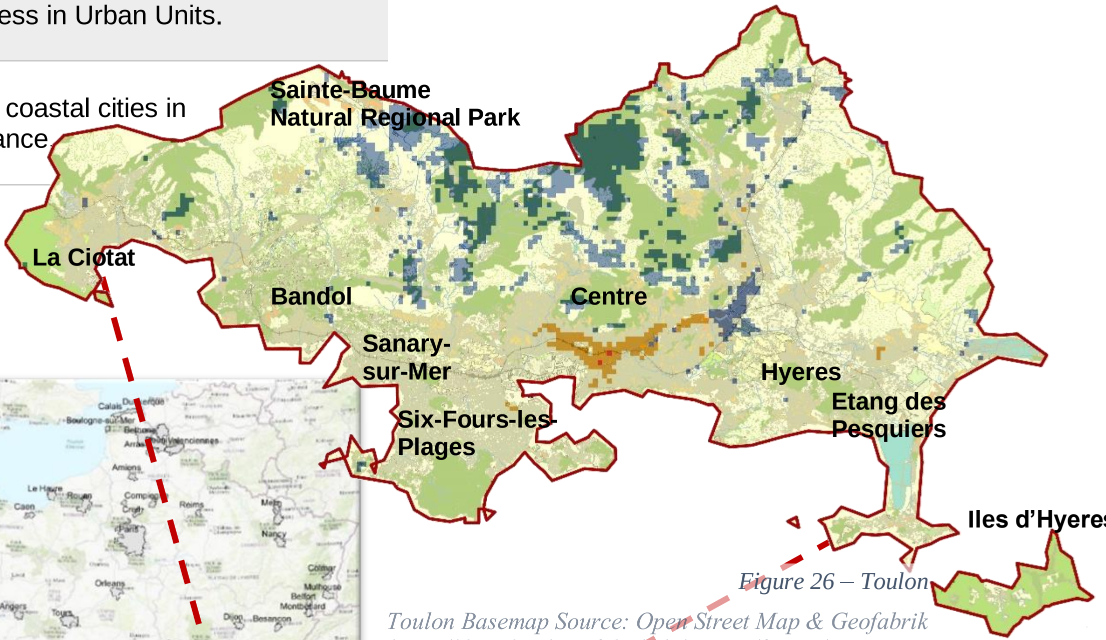


Figure 26 – Toulon

Toulon Basemap Source: Open Street Map & Geofabrik https://download.geofabrik.de/europe/france/ provence-alpes-cote-d-azur.html

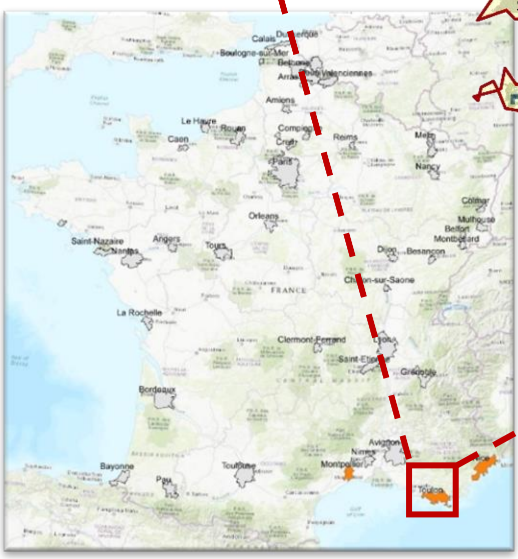
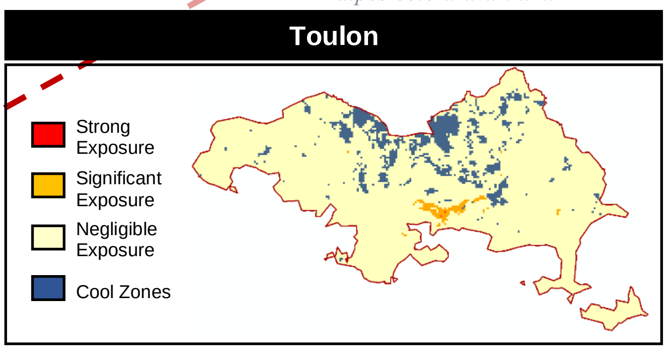


Figure 27 – Map of Urban Units with Toulon

France, Basemap Source: Esri, DeLorme, HERE, TomTom, Intermap, increment P Corp., GEBCO, USGS, FAO, NPS, NRCAN, GeoBase, IGN, Kadaster NL, Ordnance Survey, Esri Japan, METI, Esri China (Hong Kong), swisstopo, MapmyIndia, and the GIS User Community



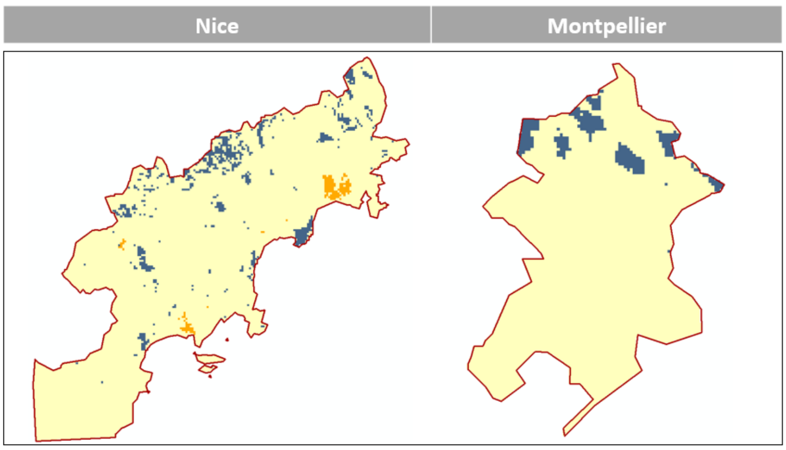


Table 11 - UHI Intensity Maps of Toulon and Remaining Cities in Cluster 4

4.1.3. Comparison Between Clusters

While comparing different clusters in terms of spatial metrics, variations in Significant Exposure Class and Strong Exposure Class were targeted as the main concern of the research (Figure 28). This selection was indicative of the characteristics displayed by strong heat island exposure patterns of different clusters.

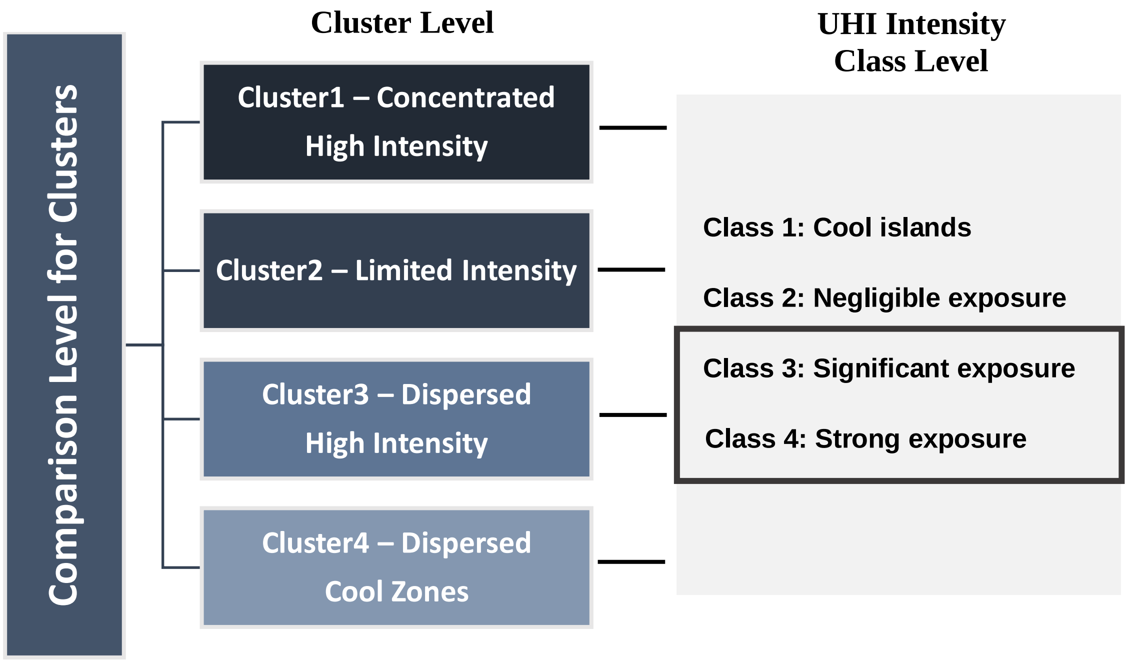


Figure 28 - Comparison Level for Clusters

In this context, value distributions among clusters were represented by box plots through focus on high intensity showing classes. The box size illustrates the degree of variety among values while the grey line in the middle of a box is the median. Outliers are represented by dots outside the boxes that were calculated according to the 25th and 75th percentiles.

For the homogeneity dimension, initially general metrics were analysed followed by size metrics. Homogeneity of the cities depended on how diffusive and extensive various classes were in the urban unit. In this regard, Class Proportion (ZLAND) and Patch Number (NP) value distributions were compared (Figure 29).

Although Clusters 1 and 2 showed similar features regarding significant and strong exposure class proportions, there was a considerable difference in terms of patch number between the clusters. For Cluster 1, Lille stood out as a constant outlier for both exposure classes. This is explained by the fact that the urban unit area of Lille is very dense, and it includes the commune of Roubaix in its agglomeration. Therefore, the extension of two intensive centres influenced the calculation which explains the high difference in values from other cities. In terms of patch number, Toulouse and Bordeaux joined Lille showing differences from other cities. In Cluster 2, Creil, Compiegne and Nimes diverged from the rest as they were the only cities that displayed strong exposure despite being very limited in extent. Yet, in patch number Nimes was separated from the outliers as strong exposure was observed over only one patch. For

Cluster 3, while Reims showed a high difference in class proportion, Lyon appeared as an outlier in number of patches.

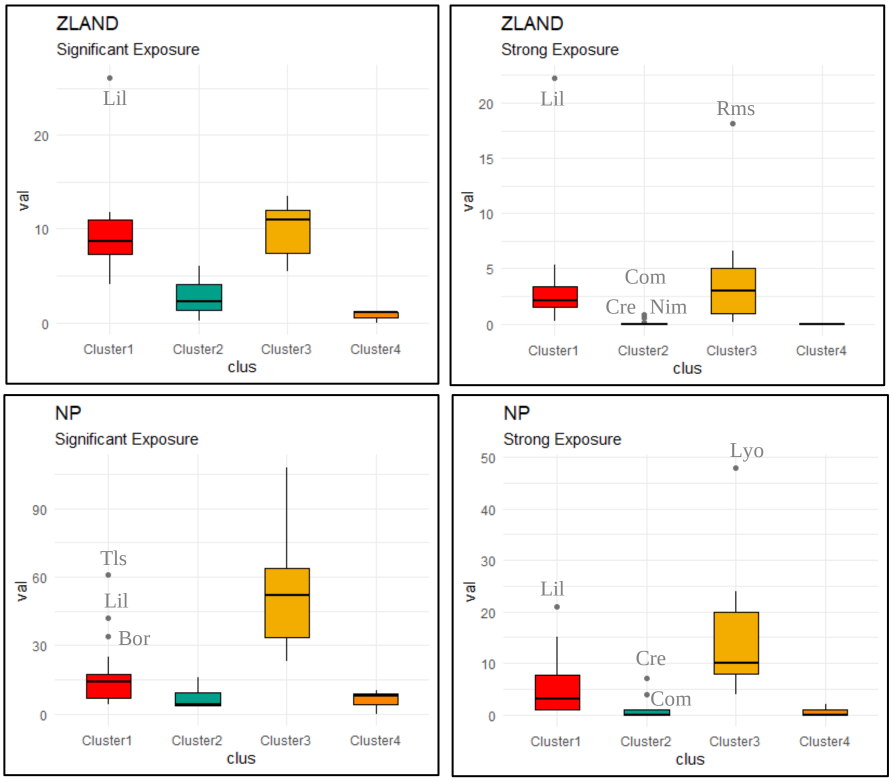


Figure 29 – Class Proportion (ZLAND) and Number of Patches (NP) Box Plots for Significant and Strong Exposure Classes

In terms of size metrics, it is important to note that indicators that involved areal measurements were normalized by the Urban Unit Area to make the metric less reliant on size. The purpose was to make cities of different sizes that ranged between medium and big cities as the subject of this research more comparable to each other.

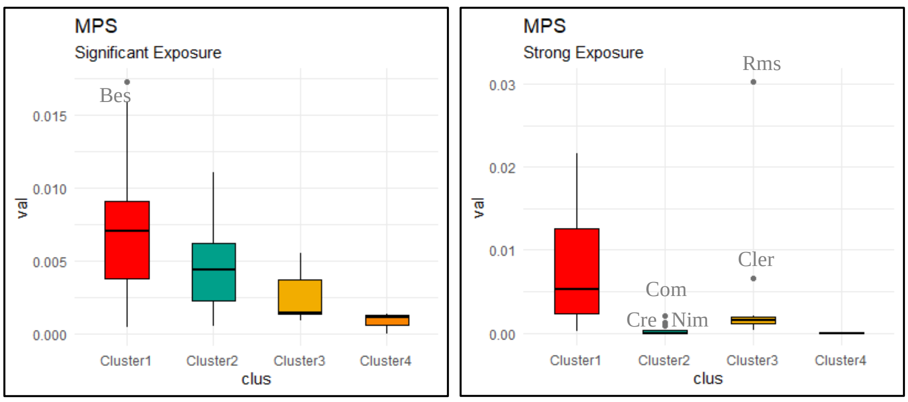


Figure 30 – Mean Patch Size (MPS) Box Plots for Significant and Strong Exposure Classes

During the analysis of Mean Patch Size (MPS) (Figure 30), it was found out that while significant and strong exposure classes showed similar range of value distribution for Cluster 1, the difference was much more dramatic for other clusters. Whereas Besancon staoot out this time as an outlier for Cluster 1- significant exposure class, Compiegne, Creil and Nimes remained for Cluster 2 as anticipated, and Clermont joined Reims as an outlier for Cluster 3 – strong exposure class.

Regarding the depth dimension, core area metrics were analysed (Figure 31).

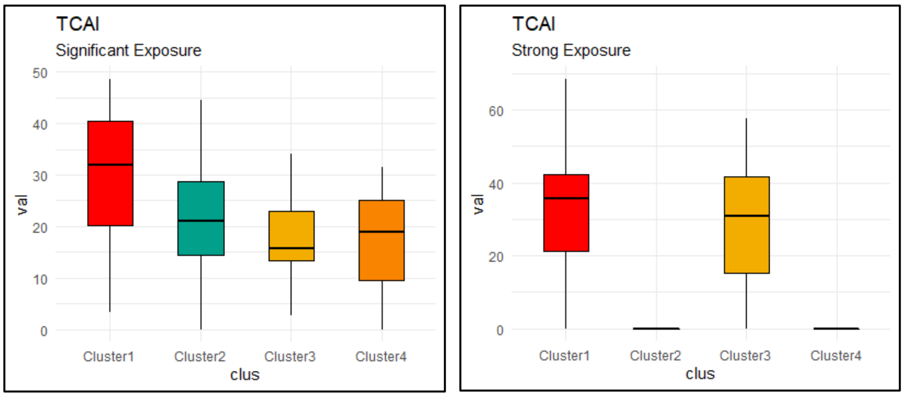


Figure 31 – Total Core Area Index (TCAI) Box Plots for Significant and Strong Exposure Classes

While for Cluster 1 Total Core Area Index (TCAI) did not show much difference in data distribution for both exposure classes, an increase in distribution was observed for strong exposure of Cluster 3 compared to the significant exposure class. Cluster 2 and 4 were absent in strong exposure as a result of low or zero intensity. Overall, although having high variation, Cluster 1 stood out with higher depth in the significant exposure class compared to others. In terms of strong exposure, Cluster 1 and 3 showed similar characteristics. Overall, when the median values of the two clusters were compared, it was concluded that significant and strong exposures were much more balanced in Cluster 1 whereas for Cluster 3, strong exposure had more dominance over significant exposure. This illustrated the strong UHI intensity pattern difference between two clusters that showed similar intensity characteristics in size and extent.

From the angle of complexity, shape metrics along with edge metrics were examined (Figure 32).

Area Weighted Mean Shape Index (AWMSI) was found to have greater difference between clusters in terms of significant exposure variability. While Cluster 1 was observed to have higher irregularity levels than other clusters in significant intensity, Cluster 3 showed similar irregularity for both exposure levels. Furthermore, Cluster 3 presented higher irregularity values in strong exposure than other clusters. As the outliers in significant exposure level, Lille stood out for Cluster 1 and Lyon for Cluster 3. When analysed together with intensity patterns over maps, the outcome was not surprising as both cities were highly dispersed and much more irregular in comparison to their peers. This was also the case for Toulouse in strong exposure that appeared as the outlier for Cluster 1.

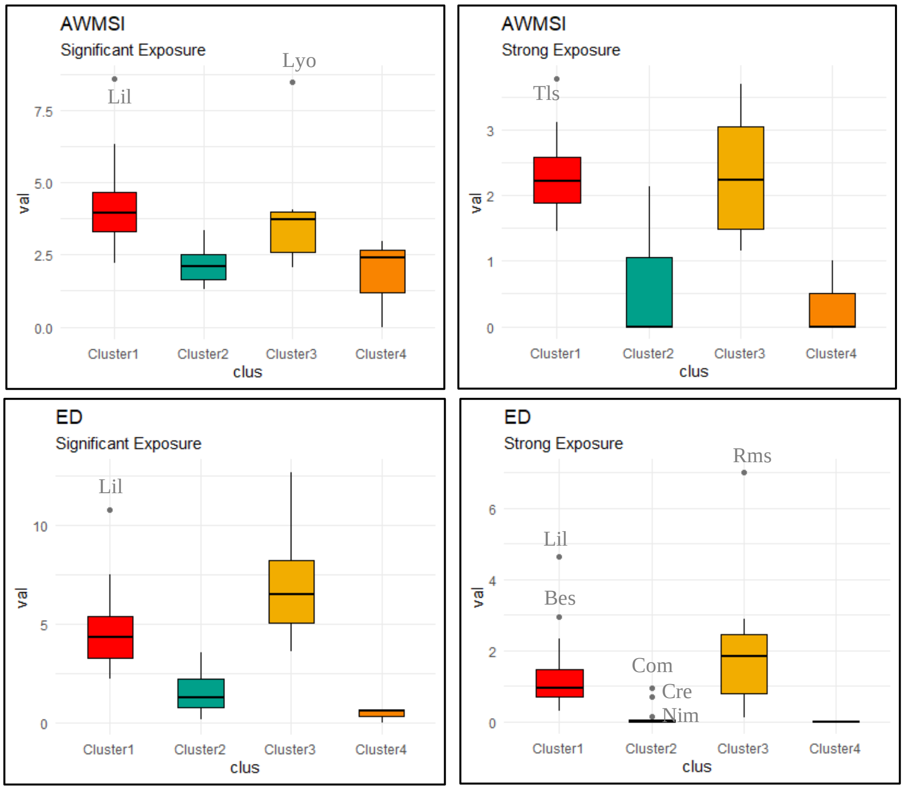


Figure 32 – Area Weighted Mean Shape Index (AWMSI) and Edge Density (ED) Box Plots for Significant and Strong Exposure Classes

Edge density value distribution illustrated that Cluster 3 carried the highest irregularity and complexity values both in significant and strong exposure. For Cluster 1 Lille was the outlier in both classes to which Besancon was added in strong exposure level. For Cluster 2 and 4 low complexity was detected for both classes. Similar to previous metrics Compiegne, Creil and Nimes appeared as outliers as they showed strong intensity.

In terms of fragmentation and isolation, diversity metrics were examined. As was the case for Mean Patch Size, Mean Proximity Index (MPI) and Mean Nearest Neighbour (MNN) were included in the analysis after being normalized by urban unit area (Figure 33).

MPI showing higher median values in significant exposure than strong exposure for Cluster 1 indicated that the sparse patches were more isolated in comparison to Cluster 3. This implied that Cluster 1 was likely to show rather polycentric structure while Cluster 3 was more dispersed with continuity when interpreted together with previously analysed metrics. For Cluster 1, Lille appeared as the outlier in both classes. While Dunkerque was observed as an outlier for Cluster 2 in the significant exposure class, Compiegne and Creil remained constant for the strong exposure class. What differentiated Dunkerque from other cities was its considerably higher extension in significant exposure. In relation, the reason why it did not appear in the Mean Patch Size metric was likely to be the number of small individual patches that decreased the average for the city. Meanwhile, it was not surprising that Lyon was detected as an outlier for significant exposure and Reims for strong exposure within Cluster 3 considering their widespread form.

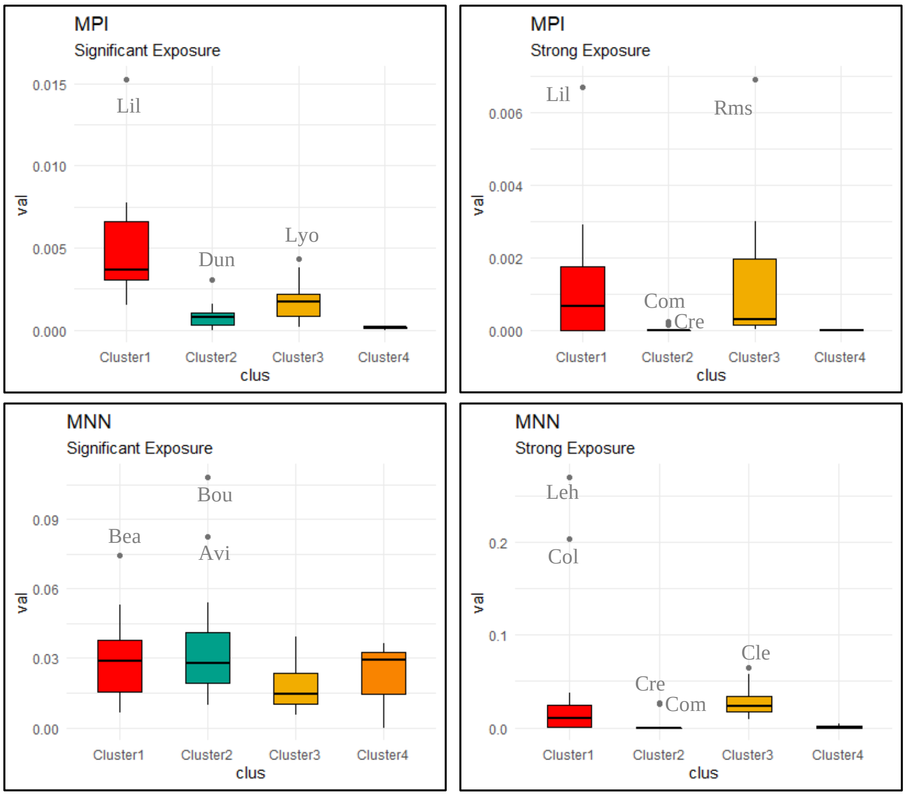


Figure 33 – Mean Proximity Index (MPI) and Mean Nearest Neighbour (MNN) Box Plots for Significant and Strong Exposure Classes

Regarding Mean Nearest Neighbour (MNN), while the median values were close to each other among clusters in significant exposure level, in strong exposure the values were found higher for Cluster 3 than Cluster 1. Emergence of outliers for Cluster 1 implids the presence of another patch in the form of a second centre in considerable distance from the main exposure concentrated at the core. This caused a rise in MNN value which was the case for Beauvais in significant exposure class and Le Havre and Colmar for strong exposure class. For Cluster 2, Boulogne-sur-Mer and Avignon showed higher distances between dispersed patches in significant exposure. While Creil and Compiegne were expected as the outliers in strong exposure, Nimes, as the other city with strong exposure presence, did not stand out since it carried only one patch in that class.

As a result, dimensions of clusters were compared with a focus on high intensity classes (strong and significant exposures) (Figure 34). It was shown that Cluster 1 had the highest depth features with high complexity and homogeneity values. Showing similarities in shape complexity with Cluster 3, the main distinction between Clusters 1 and 3 seemed to be the difference in fragmentation which was significantly lower for Cluster 1. This also showed in the values of homogeneity and depth. Meanwhile, Clusters 2 and 4 had similarities with a clear distinction in homogeneity where Cluster 4 was far more patchy with a wide distribution of cool zones within the Urban Unit.

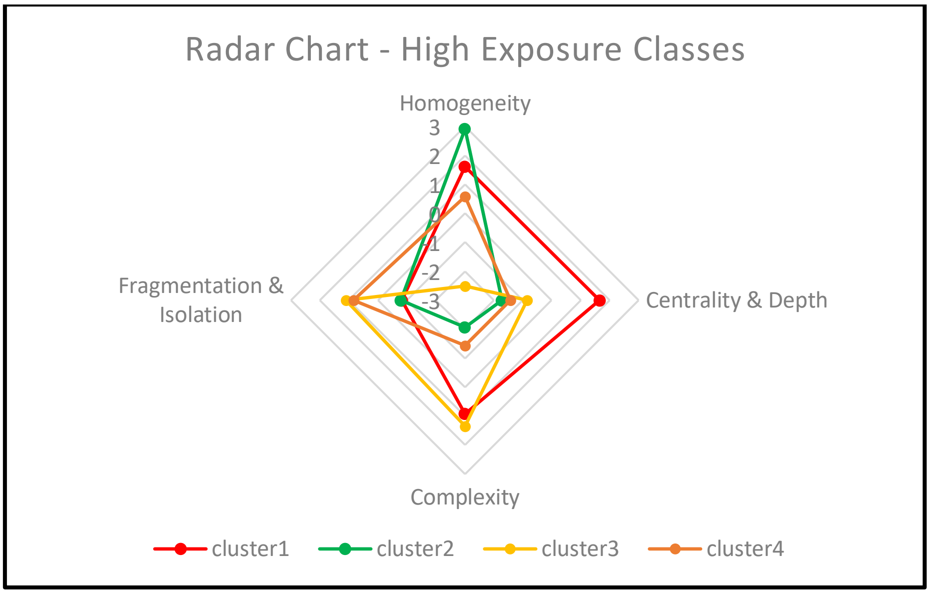


Figure 34 – Radar Chart for Dimensional Values of Clusters

The main distinctions between clusters that define their main characteristics are summarised in Table 13.

	Class 1 Cool zones	**Class 2 Negligible exposure**	**Class 3 Significant exposure**	**Class 4 Strong exposure**	**Outliers**
Cluster 1 – Concentrated High Intensity	- (Exception Amiens)	Medium Homogeneity	High complexity, medium-low fragmentation Circumscribing strong exposure	Compact & concentrated at the core	Lille
Cluster 2 – Limited Intensity	Limited presence in some cities	High Homogeneity	Low complexity	Limited presence in outliers	Nimes, Compiegne, Creil
Cluster 3 – Dispersed High Intensity	- (Exception Clermont)	Medium -Low Homogeneity	Highly complex and fragmented	Highly fragmented, widespread in significant exposure class within urban unit	Lyon, Reims, Clermont
Cluster 4 – Dispersed Cool Zones	Highly decentralized, fragmented	Low Homogeneity	Medium-low complexity	Very limited presence in Toulon	

Table 12 – Comparison of Clusters in terms of Dimensional Characteristics

Before moving on to the next step, the quality of the partitioning was checked. In addition to the detection of outliers based on the comparison of spatial metrics, silhouette width values were reviewed for cities within clusters (Figure 35). Cities with negative values implied that their clustering could be flawed. These cities required more attention to investigate whether a revision in the clustering was needed or not.

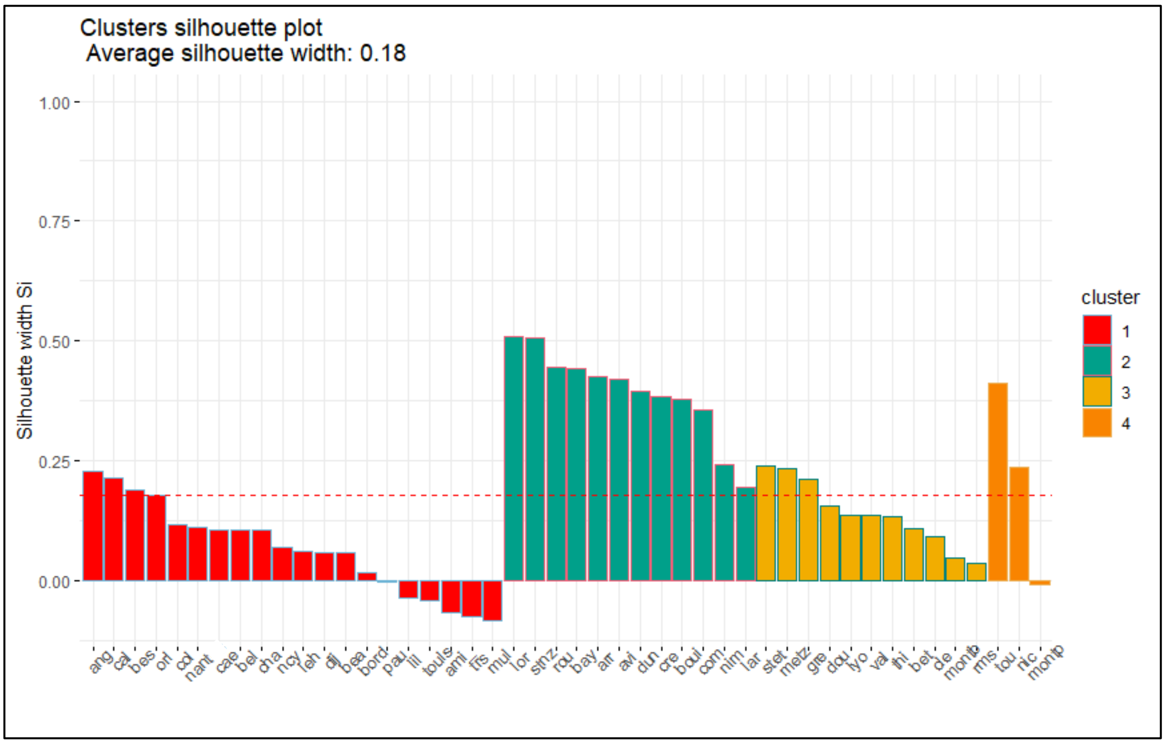


Figure 35 – Silhouette Widths of Cities in Clusters

As the cities with negative silhouette widths, Lille, Toulouse, Amiens, Tours and Mulhouse in Cluster 1 and Montpellier in Cluster 4 emerged as cases to be reviewed. Firstly, as Montpellier and Pau had very low negative values that approached zero, they were disregarded. It is important to note that, the spatial patterns of UHI intensities showed a continuous sequence among cities. This made some cities a possible fit for more than one cluster. At this stage, priority was given to the characteristics they showed in strong and significant UHI intensities.

Among cities with negative silhouette widths, Lille was an expected outcome due to its peculiarities like including another commune in the agglomeration, its high density, and the effects of commercial zones. With these factors in mind, it was decided that Lille should be considered separately. As another city in the margins, Amiens, with considerable presence of cool zones, showed characteristics that could suit Cluster 4. However, the patterns of strong and significant UHI intensities it held made it more compatible with Cluster 1 rather than Cluster 4. Toulouse and Mulhouse, showing more sprawl in significant exposure in comparison to their peers, were additional cities with negative values. Although Cluster 3 could be an alternative for them, since they did not show high irregularities as other cases in Cluster 3 and had quite compact strong exposure classes, they were better suited for Cluster 1. For Tours, it was the limited intensity of significant and strong exposure that could make it a good fit for Cluster 2. However, once again the compact strong exposure pattern concentrated at the core made it a better match for Cluster 1.

In light of these factors, outliers were revisited that had been detected at the stage of spatial metrics comparison and did not appear at the silhouette width calculation. Creil, Compiegne and Nimes as the outliers for Cluster 2 represented the characteristics of it. Therefore, they were not considered to be reclustered. In Cluster 4, Lyon appeared to be a fit for Cluster 1 as well. However, the way its strong exposure intensity class was sprawled throughout the significant exposure zones and the proportion of it within significant exposure area made Cluster 4 a suitable cluster for Lyon. This was also valid for Clermont and Reims. Although their strong exposure class areas seemed to be denser and more concentrated compared to the other cities of the cluster, they were more dispersed and irregular for Cluster 1. Thus, the clusters of these two cities were also decided to leave unchanged.

4.2.Discussion

Based on the findings of the Cluster Analysis, the discussion evolved around the following questions:

- Is the chorematic representation structure proposed for Toulouse suitable for application on Cluster 1 – Concentrated High Intensity?
- Considering Toulouse case, what type of graphic modelling structures can be proposed for other clusters?
- Based on these models what are the recommendations for cases with high exposure situation and how can this be represented through graphic modelling?

Before delving into the suitability of the chorems that were chosen for Toulouse for other cities in the cluster, it is essential to briefly explain the structure of the theoretical model of Toulouse developed by Jégou and colleagues (2021).

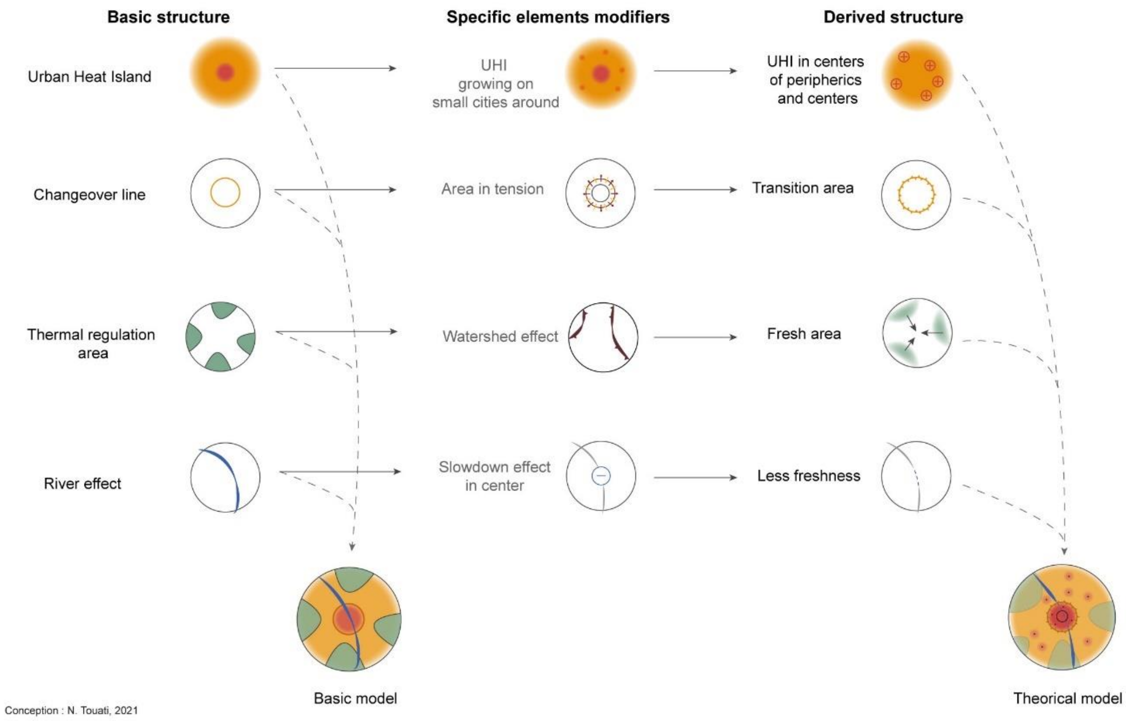


Figure 36 – Theoretical Model of Toulouse
Conception: N. Touati, 2021 in Jégou et al., 2021

For the representation of Toulouse, the chorems were chosen from a combination of Brunet (1986), Casanova-Chatel (2017) and Cheylan's (2007) tables. In the beginning, four elements were used to form the basic structure (Figure 36). The concentration of the UHI intensity at the core, the changeover line that represented the surrounding area of the high intensity, the cooling components that served as thermal regulation areas and the element of the Garonne River effect constituted the basic model. Next, modifier elements were introduced that had a transforming effect as dynamic processes. Hereby, surrounding town centres emerged as UHI attraction nodes in peripheries. Areas in tension that stood out as contact areas of different UHI intensities formed the transition areas. Watershed effect added on thermal regulation areas brought out the fresh zones. With the influence of topography and the city centre, the river effect underwent a slowdown. In the end, the derived structures combined formed the theoretical model for Toulouse (Jégou *et al.*, 2021).

4.2.1. Validation of the Toulouse Model

Regarding the graphic model structure proposed for Toulouse, Cluster 1 with Concentrated High Intensity was investigated to decide on the suitability of the suggested elements and models. The most straightforward way for it was to make a qualitative judgement over spatial patterns of UHI in combination with specific geographical characteristics. With the model structure in mind, one of the most definitive aspects was the composition of strong UHI intensity concentrated at the core. In relation, a hierarchical structure of centre-periphery was sought. The second critical aspect was the river effect that was created with a water body passing through the city. Thus, firstly Orléans as the medoid city of Cluster 1 was checked followed by the remaining cities in the cluster for these two conditions.

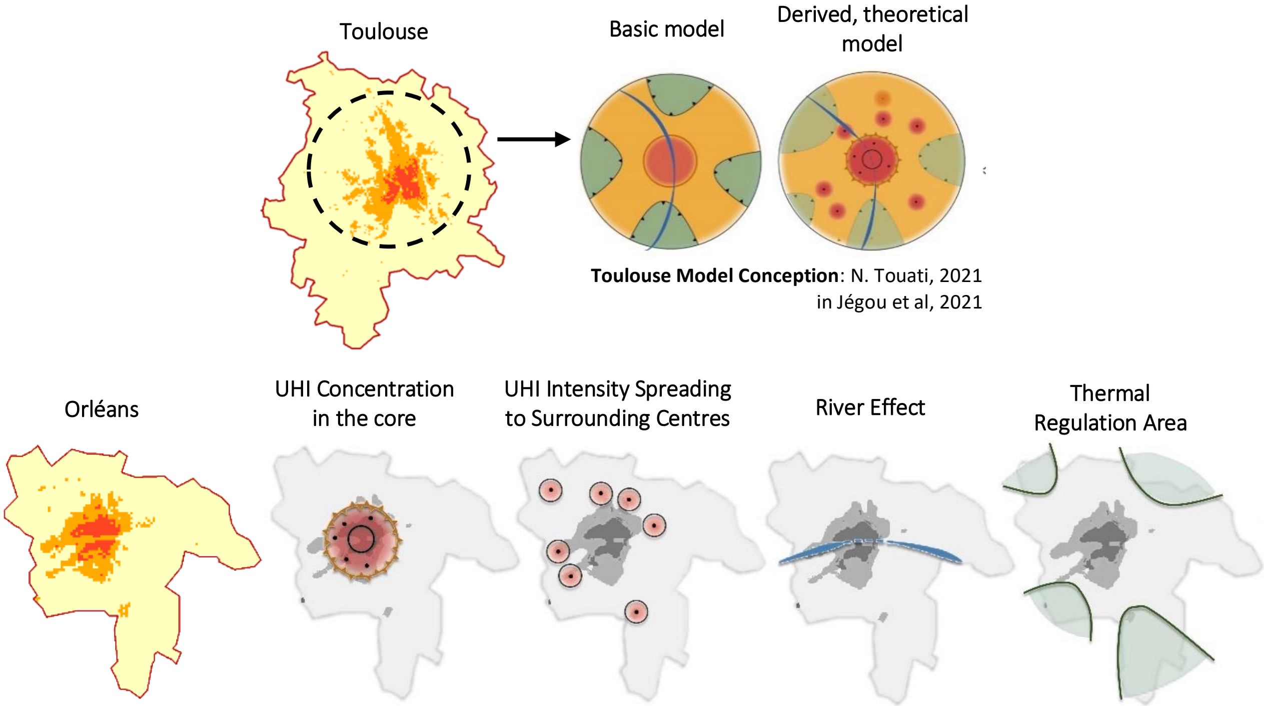


Figure 37 – Reproduction of Toulouse Chorematic Representation Model on Orléans

Compatibility of Cluster 1 with the Toulouse model was determined resulting from the application of the structure on Orléans (Figure 37). For Orléans, it is visible from the UHI intensity map that there was a concentration of strong UHI intensity at the centre. Formations of significant exposure zones around surrounding communal centres, like Ormes and Ingré in the northwest, Checy and Mardié in the east, and La Source where the Orléans University campus is located in the south, complemented the polycentric structure and the hierarchy between centres and peripheral intensity zones. A significant characteristic of the Toulouse model was also present in Orléans and other cities in Cluster 1 which is the disruption of strong UHI exposure by a water body. For Orléans this was observed through the River Loire in the mid part and by the Loiret, a tributary, in the south. Furthermore, forests and agricultural area in the south that limited the development created a thermal regulation area in addition to the forests in the northeast and northwest. Similarly, the cities in Cluster 1 were also found to exhibit the main characteristics that were detected in Toulouse and Orléans. In other words, it was concluded that this model could be easily applied and reproduced on the other cities.

4.2.2. Proposal of Chorems for Clusters

Following the validation of the Toulouse model for Cluster 1, a chorem table was formed regarding the main characteristics of the clusters (Table 14). In addition to the elements employed in Jégou and colleagues' work (2021) additional elements from Brunet (1986), Casanova-Chatel (2017), Cheylan (2007) and Helle's (1995) tables were used (see Appendix 5). Elements that were found suitable for the representation were classified in four categories according to the way they were termed by the authors mentioned above. The first category represents the quality and structure of UHI intensity classes. The quality is reflected through the presence of high UHI intensity. Regarding the structure of zones with high UHI intensity, the dimensions of depth and fragmentation/isolation were complementary to their distribution within urban units. The second category represents hierarchy and orientation aspects. In this section, all the dimensions that were constructed by the spatial metrics were represented. Hereby, a combination of Brunet's centre-periphery model and Casanova-Chatel's dissemination/concentration elements were used. The remaining two categories are complementary to each other; territorial dynamics and fronts of contact. While propagation and barriers make disruptions and create additional fronts, transition areas become critical to manage and restrain the intensity and expansion. In this category spatial metrics that measure adjacency and edge metrics were influential.

In addition to the elements identified for Cluster 1, the spatial organisation of cases with higher complexity was a major factor to be addressed. In this sense, 'orbital alignment' around major intensity centres and 'links' between centres were preferred. Since UHI intensity has a strong association with urban development, elements of urban organisation used by the authors mentioned previously were found suitable to represent heat exposures. For the cases with no principal centre of concentrated structure but rather several fragmented intensity nodes, 'disseminated orientation' element was employed. According to the quality of the interaction among intensity zones, 'nodal influence' and 'zonal interaction' elements were suggested. For situations where intensity cores were split, 'disrupted zone/node' was introduced. In relation, Brunet's split and propagation elements were employed as limiters. Finally, for the fronts between different exposures, Cheylan's 'contact front' element was chosen (Table 14).

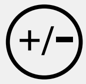
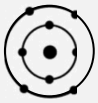
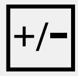
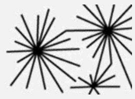
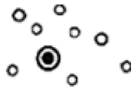
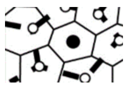
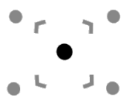
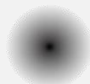
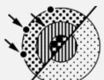
Chorematic Categories	Dimensions Reflected by the Categories		Chorems	
Quality (Attraction/ Repulsion) **Alignment (Grid)**	***High Intensity Pattern*** Presence and configuration of Strong Exposure Class - **Depth -** Extent of high exposure class - **Fragmentation/Isolation –** Spatial alignment of Strong and Significant Exposure Classes		 Attractive/repulsive centre[1]  Orbital alignment[3]	 Attractive/repulsive zone[2]  Links[1]
Hierarchy **Structure**	***Overall Spatial Organisation*** - **Homogeneity** – Mosaiced/ Patchy structure of UU - **Complexity –** irregularity of exposure classes - **Fragmentation/Isolation** Adjacency of Strong and Significant Exposure Classes - **Depth** of Strong Exposure Classes in UU	Center-periphery Structure	 Main-peripheral centres [1]  Concentrated structure[4]	 Network[1]  Disseminated structure[4]
Territorial Dynamics **Tropism**	***Territorial interaction*** Presence of Limiter elements within exposure classes - **Complexity** caused by limiters - **Depth** - high intensity classes interrupted	Influence - Interaction Split-separation Propagation, Limiter	 Nodal influence[2]  Disrupted node/zone[2]  Axis of propagation[1]	 Zonal interaction[2]  Dissymmetry[1]  Split element[1]
Contact	***Transition and Fronts*** - **Fragmentation/Isolation - Adjacency** of Strong and Significant Exposure Classes	Contact Areas - Fronts		 Contact front[5]

Table 13 – Chorem Table
Elements compiled from: (1)Brunet, 1986 – (2)Casanova-Enault & Chatel, 2017 - (3)Brunet, 1985; Helle, 1995 – (4)Maby, 2002 cited in Casanova-Enault & Chatel, 2017 - (5)Cheylan, 2007

4.2.3. Chorematic Model Reproduction for Cluster 3 with Dispersed High Intensity

For the reproduction of the chorematic model, Cluster 3 with Dispersed High Intensity was given priority regarding the criticality of the UHI intensity trends it showed. In this context, a graphic model was produced for the medoid city, Metz, as the representative case of the cluster.

H. Théry's modelling structure (Jégou *et al.*, 2021), as elaborated earlier on, was followed for the graphic modelling process (Figure 38). In this context, firstly, a basic model of Metz UHI structure that is composed of static components was prepared. The major element was the disseminated intensity cores of the UHI and their spatial configuration throughout the Urban Unit. To represent the organisation of the pattern, dissemination/concentration element and networking element that were used in Casanova-Chatel's work (2017) were used. The orbital alignment and links were important to show the interrelation between disseminated cores which stood out in multimodal structures. As a second element, influence zones were introduced as the continuity of UHI intensity cores with lower degree of intensity. This indicated the areas in contact with high intensity zones. At the next step thermal regulation areas and water bodies were introduced that were influential on the form of the UHI intensity. These elements combined formed the basic model.

On the basic model, the effect of modifying structures that would transform the basic elements were conceptualised. Initially, the intensity cores were represented with the territorial interactions in the form of radial connections and orbital alignments. In relation, following the interaction between nodes the tendency to sprawl and unite around the intensity cores was depicted through influence zones. Thermal regulation areas were illustrated with their limiting impact on the sprawl of the intensity in the western and eastern parts of the Urban Unit. This was also represented with a slowdown in the connection of influence zones between the core and the satellite centers in the north (Maizières-lès-Metz, Talange, Hagondange, Rombas). Finally, while perturbing the UHI intensity at the cores, water bodies' cooling effect slowed down with the density of activities and development in the urban core. As a result of the combination of these transforming effects with the basic model, the theoretical model of Metz was obtained. This theoretical model was defining for the propositions provided for the management of UHI effect in the city and to reduce its severity.

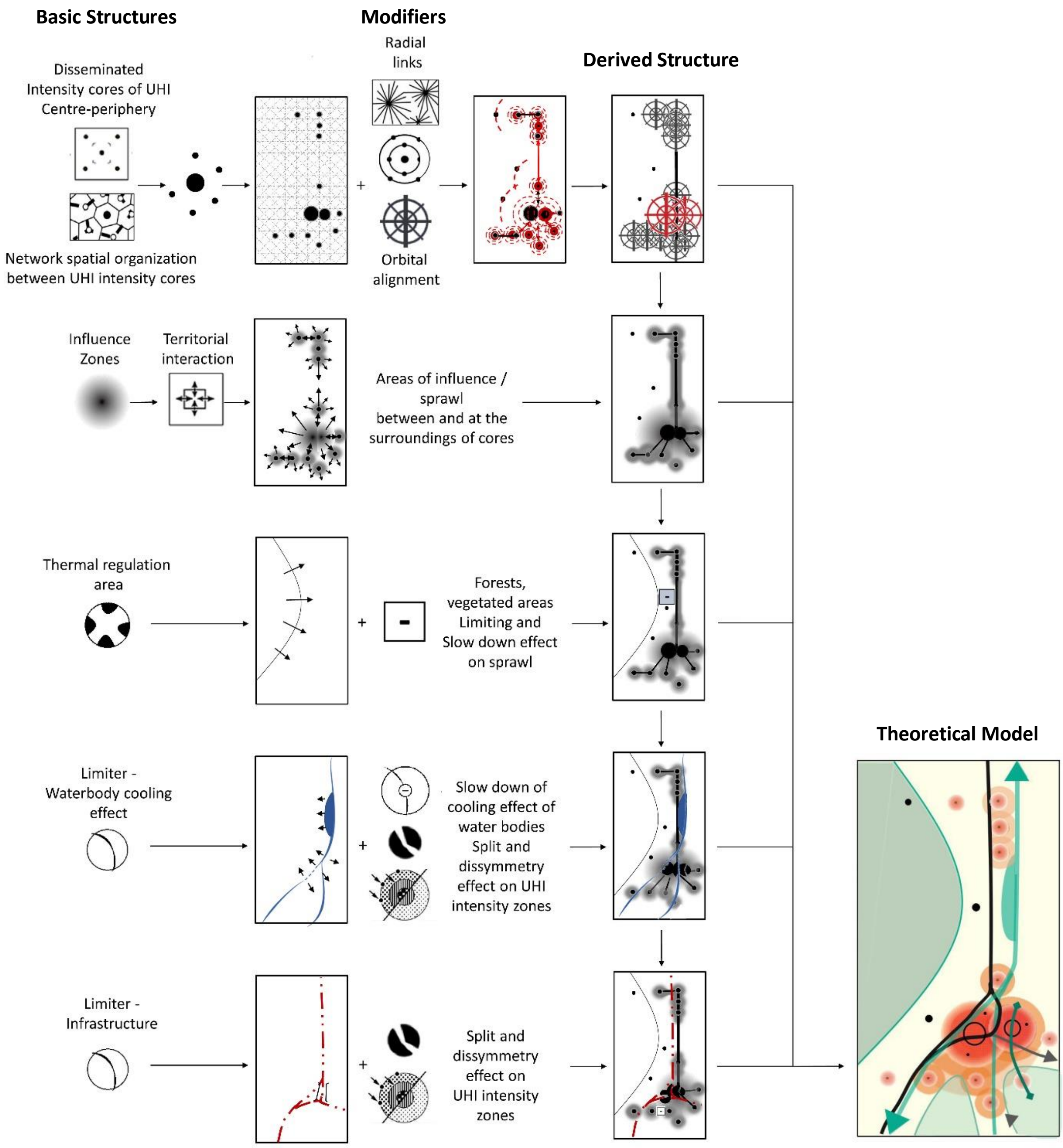


Figure 38 – Theoretical Model of Current UHI Situation for Metz

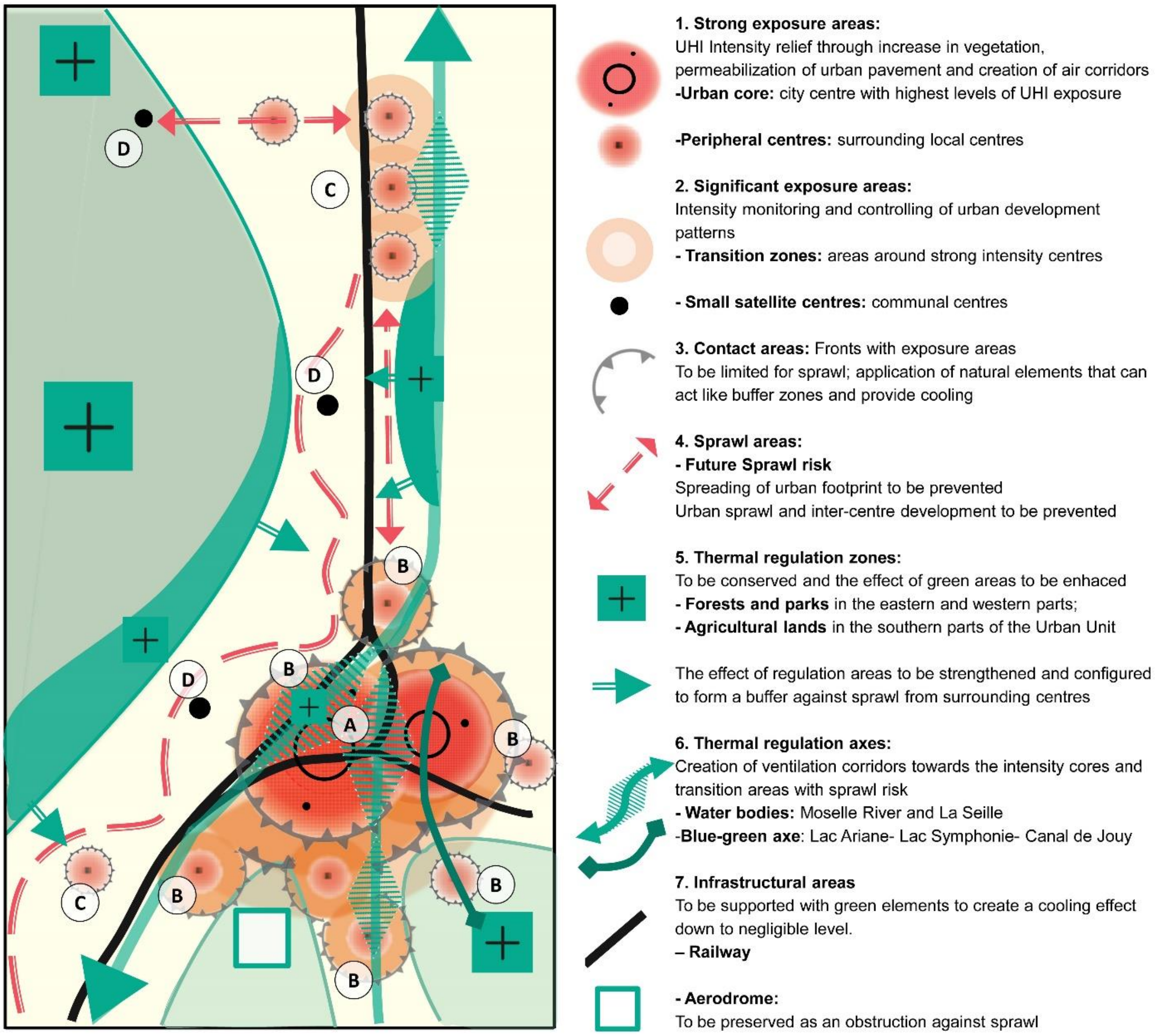
4.2.4. Recommendation Model for Cluster 3 with Dispersed High Intensity

Based on the theoretical model, certain focus areas were emphasised to decrease the impact of UHI intensity within Metz. Recommendations were proposed in the scheme of a graphic model (Figure 39) with the use of elements employed for the representation of the current situation in the previous step. In this context, the focus areas are:

1. **Strong exposure areas:** The most critical areas that show high UHI intensity require measures to support the reduction of UHI impact. These are mostly residential areas concentrated around commercial activities. Considering the already built structure,

complementary policies on increasing vegetation through the introduction of green areas, permeabilisation of urban pavement and providing ventilation corridors where possible are crucial. Strong exposure areas emerge mainly as the city core (A) and the peripheral centres that are located at the suburbs and outskirts (B).

2. **Significant exposure areas:** These are the areas that show considerable but lower UHI intensity compared to the strong exposure zones. They require intensity monitoring and controlling of urban development tendencies. They are found as transition zones surrounding the high intensity areas at the city centre and small communal centres.



A Centre	B Residential areas around dense commercial activities		C Peripheral centres	D Small Satellite centres
- Metz Centre -Ancienne Ville -Nouvelle Ville	**East** -Plantieres Queuleu -Borny -Saint-Pierre **South** - Le Sablon -Augny, Marly	**North-west** - Patrotte Metz-Nord - Devant les Ponts - Le Ban-Saint-Martin - Maison Neuves	**North** - Vieil Amneville - Rombas - Talange - Maizeres-les-Metz **South-west** - Ars-sur-Moselle	**North** - Moyeuvre-Grande **West- eastwest** - Saulny - Lorry les-Metz - Plappeville

Figure 39 – Recommendation Model for Metz

3. **Contact areas:** The contact areas surrounding the core and circumscribing significant exposure areas require controlling for sprawl towards the eastern part of the urban core.

4. **Sprawl areas:** In relation with the contact areas, the connection zones between high exposure zones and centres should be considered for UHI intensity prevention through avoiding the sprawl of strong exposures in the area. It is proposed to introduce vegetated areas that can acts as obstructions or buffer zones for potential sprawl areas.

5. **Thermal regulation zones:** The natural and vegetated areas that create a thermal regulation effect ought to be conserved. In association with the measures proposed for peripheral centres, the effect of forests and parks is recommended to be enhanced at the west and east sides of the Urban Unit. Furthermore, the agricultural lands in the south of the urban unit that create an obstruction against urban development should be preserved to avoid spreading of UHI effect.

6. **Thermal regulation axes:** It is observed that the high exposure zones are interrupted with water bodies at certain parts. It is recommended to enhance these axes especially at the urban core and high exposure locations through provision of additional ventilation corridors that could penetrate into the concentrated intensity areas.

7. **Infrastructural areas:** The railway footprint that creates disruption within strong exposure should be turned into an advantage through the addition of green elements and to create a cooling effect. This will also be influential for the side of the railways showing strong exposure.

4.3. Conclusion

Based on the graphic modelling work conducted by the LISST research team on Toulouse for urban climate analysis and recommendation purposes, this thesis aimed to provide a practical approach that could be applied to 47 French cities. Patch analysis and cluster analysis stages were crucial for this approach to be validated and reproduced on other cities.

Depending on the results obtained, it was concluded that the clustering was in alignment with the chorematic representation requirements. Through the partitioning of the cities, it was first ensured that cases with critical UHI intensity levels were separated from the rest. Following this step, they were grouped according to the spatial characteristics of UHI intensity patterns. This allowed for the steps of chorem selection and representation to be reduced and applied simultaneously to multiple cases. This point is one of the main implications of this research. The other major implication in relation to the research aim is the introduction of the practicality offered by the chorematic representation method for the translation of urban climate information. This functionality was assessed over two steps. Firstly, a check was done through the application of the Toulouse graphical model on Cluster 1 with Concentrated High Intensity. On this cluster with less complex cases, it was demonstrated that the Toulouse model was easily applicable and reproducible to represent the microclimatic situation. The second step was made through the reproduction of graphic modelling for Cluster 3 with Dispersed High Intensity through the chorems proposed for Toulouse. Alongside the elements used for the Toulouse model, supportive chorematic elements were added to meet the peculiarities of this cluster. This process led to the generation of analysis and recommendation models of Metz where suggestions were provided on areas to pay attention to and the types of measures to be followed. The representation of the medoid city - Metz showed that, besides the practicality offered by the pre-determined chorems, clusters with complex cases are more likely to require further focus on individual cases while applying the medoid model to the rest of the cluster.

In the end, the whole process illustrated to what extent the chorematic map-models can be supportive for the transfer of microclimatic analysis and recommendations to planners and urban policy makers. Nonetheless, certain points need attention for future applications and the reproduction of the method proposed in this research.

4.3.1. Shortcomings, Limitations & Improvement Areas

To begin with, as was mentioned in the Methodology Chapter, due to the lack of weather data for the 47 French cities, the UHI analysis was based on the SURFEX simulation model output. When using simulation data for analyses, there is the risk of not being able to accurately represent the real situation and to amplify inaccuracies and errors in calculations. Although data validation was conducted through expert views in this research, application with real data or comparing the results with real data will improve accuracy for future applications and will provide a more robust approach.

Another shortcoming arises at the stage of spatial pattern and form analysis. When the peculiarities of each city based on several parameters are considered, clustering them on shape and patterns is a challenging task. This research used raster format to build the Patch Analysis on as the UHI data was generated in the form of grid points. Nevertheless, using vector format data might increase the precision and could lead to reveal additional focus areas. Furthermore, the definition of indicators is a significant aspect of this stage of analysis. Throughout this research, FRAGSTATS metrics were used to build the cluster analysis. Particular attention was paid to reducing the dimensionality of the data matrix for the cluster analysis stage. The term dimensionality here refers to the proportion of the number of variables (indicators) to the number of observations. Since the indicators were applied to each of the four different UHI intensity classes one by one, this increased the number of indicators, thus the dimensionality. A way to improve this aspect can be to create new formulas for indicators where the relationship of the intensity classes between each other is reflected. This could increase the practicality of the method and allow the addition of more parameters for the clustering.

Among the limitations the treatment of the outlier cases stands out. In this regard, as anticipated with its highly different and peculiar features, Paris was removed from the partitioning due to the disability to cluster it with any other city. Another case was Lille that needed to be regarded separately. This shows the methodology’s restrictions for cases with high numbers of outliers.

The last note is on shortcomings at the chorematic representation stage. The application on Toulouse included both daytime and night-time conditions through graphic modelling of UHI and UTCI effects. However, in this research due to the lack of data on UTCI for other cities, only the night-time condition could be represented, which led the recommendations to be solely based on UHI effect. Another point to consider is that, although clustering is convenient for the representation process and enables practicality for the handling of multiple cases, during the graphic modelling of each city and especially for clusters with high complexity, cases should be considered critically along with complementary information like land use, density, wind, and other influential factors.

4.3.2. Final Remarks

The method of chorematic representation as a form of graphic modelling has been applied in several different fields in research that include geovisualisation. Jégou and colleagues' work showed that it could additionally serve as a practical method to provide urban climate information into planning context. Through representation of highly technical climatological input in simpler forms, graphic models offer a significant step in bridging climatology and planning. The flexibility of these models allows for application in various levels and contexts through coupling with different research methods. In this regard, this research aimed to take the chorematic representation technique one step further to devise a methodology for its application in a collective and time efficient manner. At a time of need for urgent climate action, it shows great potential to speed up the processes of strategy making and putting policies into execution. Nevertheless, this research showed that human input and the artistic interpretation is still needed complementary to the collective analysis. For future developments in the field of geovisualisation, the automated generation of chorems should be explored further to expedite the timely production of easily interpretable urban climate information. The achievements in this field will extensively support enabling communication between climatology and urban planning.

REFERENCES

ALCOFORADO, M.J. & MATZARAKIS, A. (2014). Planning with Urban Climate in Different Climatic Zones. *Geographicalia* [online]. 57. Available from: 10.26754/ojs_geoph/geoph.201057808. [Accessed 09 February 2021].

ARREGHINI, L. (1995). La Modélisation Graphique Dans La Réalisation des Atlas Pour Le Développement [online]. Available from: http://www.cartographie.ird.fr/publi/geo95/communications/Arreghini.pdf. [Accessed 25 January 2021].

BROCARD, M. (1993). À Propos de Chorèmes. *Géographes Associés* [online]. 13(1), pp. 17-22. Available from: https://doi.org/10.3406/geoas.1993.1850. [Accessed 25 January 2021].

BRUNET, R. (1986). La Carte-Modèle et Les Chorèmes. *Mappemonde* [online]. (4), pp. 2-6. Available from: https://doaj.org/article/d763f79fc529416d874d0178deeb74bf. [Accessed 25 January 2021].

BRUNET, R. (1980). La Composition des Modèles dans L'analyse Spatiale Espace Géographique. 9(4), pp. 253-65.

CASANOVA ENAULT, L. & CHATEL, C. (2017). Une Grille Chorématique des Dynamiques Spatiales Pour Expliquer l'évolution des Territoires. *Mappemonde* [online]. 119. Available from: http://journals.openedition.org/mappemonde/2189. [Accessed 25 January 2021].

CHELARU, D., OISTE, A., MIHAI, F. C. (2014). Quantifying The Changes in Landscape Configuration Using Open Source GIS Case Study: Bistrita Subcarpathian Valley, Romania. *14th International Multidisciplinary Scientific GeoConference on ECOLOGY', ECONOMICS, EDUCATION AND LEGISLATION SGEM*. Sofia, 2014. (1):1314–2704Available from: 10.5593/sgem2014/b51/s20.076. [Accessed 14 March 2021].

CHERNI, I. (2019). *Discovery of Chorems by Spatial Data Mining.* PhD Thesis. University of Tunisia & INSA Lyon. Available from: https://hal.archives-ouvertes.fr/tel-02000009. [Accessed 08 February 2021].

CHEYLAN, J. P. (2007). Les Processus Spatio-Temporels: Quelques Notions et Concepts Préalables À Leur Représentation. *Mappemonde* [online]. 87. Available from: https://doaj.org/article/fd5eabb035ab4047bc27474bc3a4132c. [Accessed 25 January 2021].

CHRISTALLER, W. (1966). *Central Places in Southern Germany*. Englewood Cliffs, NJ: Prentice-Hall.

DE CHIARA, D., DEL FATTO, V., LAURINI, R., SEBILLO, M. & VITIELLO, G. (2011). A Chorem-Based Approach for Visually Analyzing Spatial Data. *Journal of Visual Languages and Computing* [online]. 22(3), pp.173-193. Available from: 10.1016/j.jvlc.2011.02.001. [Accessed 26 February 2021].

DEL FATTO, V. (2009). *Visual Summaries of Geographic Databases.* PhD Thesis. University of Salerno & INSA Lyon. Available from: https://liris.cnrs.fr/Documents/Liris-4346.pdf. [Accessed 08 February 2021].

DEL FATTO, V., LAURINI, R., LOPEZ, K., SEBILLO, M. & VITIELLO, G. (2008). A Chorem-based Method for Visualizing Evolutionary Scenarios. *Information Visualization Journal* [online]. 7(3). Available from: http://geoanalytics.net/GeoVis08/a11.pdf. [Accessed 08 February 2021].

DHIEB, M. (2020). Using Chorems in Graphical Modeling: The Case of the Kingdom of Saudi Arabia. *Current Urban Studies* [online]. 8(2), pp.265-283. Available from: 10.4236/cus.2020.82015. [Accessed 08 February 2021].

DUCRUET, C. (2006). Benchmarking Urban Networking Strategies in Europe. *The Korea Spatial Planning Review* [online]. 49(1), pp.3-24. Available from: https://halshs.archives-ouvertes.fr/halshs-00459041. [Accessed 25 January 2021].

FANG, S., ZHAO, Y., HAN, L. & MA, C. (2017). Analysis of Landscape Patterns of Arid Valleys in China, Based on Grain Size Effect. *Sustainability (Basel, Switzerland)* [online]. 9(12), pp.2263. Available from: 10.3390/su9122263. [Accessed 25 June 2021].

FONTANABONA, J. (1994). Ébauche d'une Grille de Concepts Spatiaux Utilisables Lors de L'analyse et de la Construction de Cartes. *Mappemonde* [online]. 94(1), pp. 1-5. Available from: https://doaj.org/article/a15c076da0ed42b38f7524b749d17193. [Accessed 25 January 2021].

FUSCO, G., CAGLIONI, M., EMSELLEM, K., MERAD, M., MORENO, D. & VOIRON-CANICIO, C. (2017). Questions of Uncertainty in Geography. *Environment and Planning* [online]. 49(10), pp.2261-2280. Available from: 10.1177/0308518X17718838. [Accessed 9 February 2021].

GARMY, P. (2011). Le pont et la ville. Questions d'urbanisme et d'environnement. In: Guy Barruol, Jean-Luc Fiches and Pierre Garmy eds., *Les ponts routiers en Gaule romaine*. Association de la Revue archéologique de Narbonnaise, pp. 573-588. Available from: https://halshs.archives-ouvertes.fr/halshs-00626606. [Accessed 25 January 2021].

GHERRAZ, H., GUECHI, I. & ALKAMA, D. (2020). Quantifying the Effects of Spatial Patterns of Green Spaces on Urban Climate and Urban Heat Island in A Semi-Arid Climate. *Bulletin De La Société Royale Des Sciences De Liège* [online]. 89. Available from: 10.25518/0037-9565.9821. [Accessed 18 June 2021].

HARRIS, C.D. & ULLMAN, E.L. (1945). The Nature of Cities. *The Annals of the American Academy of Political and Social Science* [online]. 242, pp.7-17. Available from: 10.1177/000271624524200103. [Accessed 10 March 2021].

HEBBERT, M. (2014). Climatology for City Planning in Historical Perspective. *Urban Climate* [online]. 10, pp.204-215. Available from: 10.1016/j.uclim.2014.07.001. [Accessed 9 February 2021].

HELLE C. (1995). Villes et Organisation de l'espace Vauclusien. *Mappemonde* [online]. 37, pp.14-7. Available from: https://doaj.org/article/14e11ca41ad74c4d9bf387447aa3b1e0. [Accessed 25 January 2021].

HIDALGO, J. & JOUGLA, R. (2018). On the use of Local Weather Types Classification to Improve Climate Understanding: An Application on The Urban Climate of Toulouse. *PloS One* [online]. 13(12). Available from: 10.1371/journal.pone.0208138. [Accessed 19 January 2021].

HIDALGO, J., LEMONSU, A. & MASSON, V. (2019). Between Progress and Obstacles in Urban Climate Interdisciplinary Studies and Knowledge Transfer to Society. *Annals of the New York Academy of Sciences* [online]. 1436(1), pp.5-18. Available from: 10.1111/nyas.13986. [Accessed 19 January 2021].

HIDALGO, J., TOUATI, N., JÉGOU, L., HAOUÈS-JOUVE, S., BAHOKEN, F., BRONNER, A.C., LE CAMPION, G., JOUGLA, R., MAINSONHOBE, M., PIERSON, J. & PISSOAT, O. (2021). Mapping the Local Climate for Urban Planning Purposes. Submitted Paper.

HOUDART, M., BONIN, M., LE PAGE, C., FORT, M. & SAUDUBRAY, F. (2005). SIG, Chorèmes et Systèmes Multi-Agents. *Revue Internationale De Géomatique* [online]. 15(3), pp.339-356. Available from: https://www.academia.edu/25558052/SIG_chorèmes_et_systèmes_multi_agent_Evolution_dun_système_rural_martiniquais_et_pression_polluante. [Accessed 25 January 2021].

HUANG, J., LU, X.X. & SELLERS, J.M. (2007). A Global Comparative Analysis of Urban Form: Applying Spatial Metrics and Remote Sensing. *Landscape and Urban Planning* [online]. 82(4), pp.184-197. Available from: 10.1016/j.landurbplan.2007.02.010. [Accessed 12 July 2021].

INSEE. (2020). *Urban Unit*. Available from: https://www.insee.fr/en/metadonnees/definition/c1501. [Accessed 6 May 2021].

INSEE. (2020). *Territory Comparator*. Available from: https://www.insee.fr/fr/statistiques/zones/1405599. [Accessed 6 May 2021].

JÉGOU, L., TOUATI, N. & HIDALGO, J. (2021). Proposals for the Use of Graphical Models in Urban Climatic Maps. Submitted Paper.

JOUGLA, R., HIDALGO, J. & POUPONNEAU, B. (2019). Identification of Local Meteorological Situations for Around Fifty French Cities. *La Méterologie*. 106, pp.1-10.

KAMRUZZAMAN, M., DEILAMI, K. & YIGITCANLAR, T. (2018). Investigating the Urban Heat Island Effect of Transit Oriented Development in Brisbane. *Journal of Transport Geography* [online]. 66, pp.116-124. Available from: 10.1016/j.jtrangeo.2017.11.016. [Accessed 12 July 2021].

KASSAMBARA, A. (2017). *Practical guide to cluster analysis in R - Unsupervised Machine Learning*. 1st Ed. STHDA.

KIM, Y. & BAIK, J. (2004). Daily Maximum Urban Heat Island Intensity in Large Cities of Korea. *Theoretical and Applied Climatology* [online]. 79(3), pp.151-164. Available from: 10.1007/s00704-004-0070-7. [Accessed 9 February 2021].

KWOK, Y.T., SCHOETTER, R., LAU, K.K., HIDALGO, J., REN, C., PIGEON, G. & MASSON, V.V. (2019). How Well Does the Local Climate Zone Scheme Discern the Thermal Environment of Toulouse (France)? An Analysis Using Numerical Simulation Data. *International Journal of Climatology* [online]. 39, pp. 5292–5315. Available from: 10.1002/joc.6140. [Accessed 19 January 2021].

LARDON, S., CAPITAINE, M. (2008). Chorèmes et Graphes. *Revue D'anthropologie des Connaissances* [online]. 2(2):195-217. Available from: 10.3917/rac.004.0195. [Accessed 25 January 2021].

LARDON, S. & HOUDART, M. (2017). Les Chorèmes facing the evolution of research themes and practices, in agronomy and land use planning. *Mappemonde* [online]. 121. Available from: http://mappemonde.mgm.fr/122as5/. [Accessed 25 January 2021].

LAURINI, R., SEBILLO, M., VITIELLO, G., SOL-MARTINEZ, D., RAFFORT, F. & GADAL, S. (2009). Computer-generated Visual Summaries of Spatial Databases: Chorems or not Chorems?. *Surveys and Perspectives Integrating Environment and Society* [online]. 2(2), pp.1-8. Available from: https://journals.openedition.org/sapiens/795. [Accessed 08 February 2021].

LEMENKOVA, P. (2019). K-means Clustering in R Libraries {cluster} and {factoextra} for Grouping Oceanographic Data. *International Journal of Informatics and Applied Mathematics* [online]. 2(1), pp.1-26. Available from: 10.6084/m9.figshare.9891203. [Accessed 18 June 2021].

LOWRY, J.H. & LOWRY, M.B. (2014). Comparing Spatial Metrics That Quantify Urban Form. *Computers, Environment and Urban Systems* [online]. 44, pp.59-67. Available from: 10.1016/j.compenvurbsys.2013.11.005. [Accessed 18 June 2021].

MASSON, V., LEMONSU, A., HIDALGO, J. & VOOGT, J., (2020). Urban Climate and Climate Change. *Annual Review of Environment and Resources Urban Climates and Climate Change* [online]. 45, pp. 411-444. Available from: https://doi.org/10.1146/annurev-environ-012320- 083623. [Accessed 26 February 2021].

MCGARIGAL, K. (2015). *FRAGSTATS Help*. Available from: http://www.umass.edu/landeco/research/fragstats/documents/fragstats.help.4.2.pdf. [Accessed 10 March 2021].

MCGARIGAL, K. (2001). Landscape Metrics for Categorical Map Patterns – Landscape Ecology [lecture]. Available from: http://www.umass.edu/landeco/teaching/landscape_ecology/schedule/chapter9_metrics.pdf. [Accessed 10 March 2021].

MCGARIGAL, K. & MARKS, B.J. (1994). Fragstats Spatial Pattern Analysis Program for Quantifying Landscape Structure Version 2.0 [computer program]. Available from: https://www.umass.edu/landeco/research/fragstats/fragstats.html

MILLS, G., CLEUGH, H., EMMANUEL, R., ENDLICHER, W., ERELL, E., MCGRANAHAN, G., NG, E., NICKSON, A., ROSENTHAL, J. & STEEMER, K. (2010). Climate Information for Improved Planning and Management of Mega Cities (Needs Perspective). *Procedia Environmental Sciences* [online]. 1, pp.228-246. Available from: 10.1016/j.proenv.2010.09.015. [Accessed 9 February 2021].

NG, E. & REN, C. (2015). *The Urban Climatic Map.* 1st Ed. London: Routledge.

PIVETEAU, V. & LARDON S. (2002). Chorèmes et Diagnostics de Territoire : Une Expérience de Formation. *Mappemonde* [online]. 68, pp. 1-6. Available from: https://doaj.org/article/f4e3eb9336584eb09560b63252d46370. [Accessed 25 January 2021].

REIMER, A.W. (2010). Understanding Chorematic Diagrams: Towards a Taxonomy. *Cartographic Journal* [online]. 47(4), pp.330-350. Available from: 10.1179/000870410X12825500202896. [Accessed 08 February 2021].

REMPEL, R.S., KAUKINEN, D. and CARR, A.P. (2012). Patch Analyst and Patch Grid [computer program]. Ontario Ministry of Natural Resources. Centre for Northern Forest Ecosystem Research, Thunder Bay, Ontario.

REN, C., NG, E.Y. & KATZSCHNER, L. (2011). Urban climatic map studies: a review. *International Journal of Climatology* [online]. 31(15), pp.2213-2233. Available from: 10.1002/joc.2237. [Accessed 9 February 2021].

REN, C., SPIT, T., LENZHOLZER, S., YIM, H.L.S., HEUSINKVELD, B., VAN HOVE, B., CHEN, L., KUPSKI, S., BURGHARDT, R. & KATZSCHNER, L. (2012). Urban Climate Map System for Dutch Spatial Planning. *ITC Journal* [online]. 18, pp.207-221. Available from: 10.1016/j.jag.2012.01.026. [Accessed 9 February 2021].

ROY, B. (2020). All about Feature Scaling. Available from: https://towardsdatascience.com/all-about-feature-scaling-bcc0ad75cb35. [Accessed 20 April 2021].

SCHNEIDER, A. & WOODCOCK, C.E. (2008). Compact, Dispersed, Fragmented, Extensive? A Comparison of Urban Growth in Twenty-five Global Cities using Remotely Sensed Data, Pattern Metrics and Census Information. *Urban Studies (Edinburgh, Scotland)* [online]. 45(3), pp.659-692. Available from: 10.1177/0042098007087340. [Accessed 12 July 2021].

TSAI, Y. (2005). Quantifying Urban Form: Compactness versus 'Sprawl'. *Urban Studies (Edinburgh, Scotland)* [online]. 42(1), pp.141-161. Available from: 10.1080/0042098042000309748. [Accessed 12 July 2021].

UN. (2019). *Climate Change.* Available from: https://www.un.org/en/sections/issues-depth/climate-change/. [Accessed 23 February 2021].

UN. (2011). *Cities and Climate Change: Policy Directions: Global Report on Human Settlements 2011 / United Nations Human Settlements Programme.* UN-HABITAT. Washington, D.C: Earthscan. Available from: https://unhabitat.org/global-report-on-human-settlements-2011-cities-and-climate-change. [Accessed 12 July 2021].

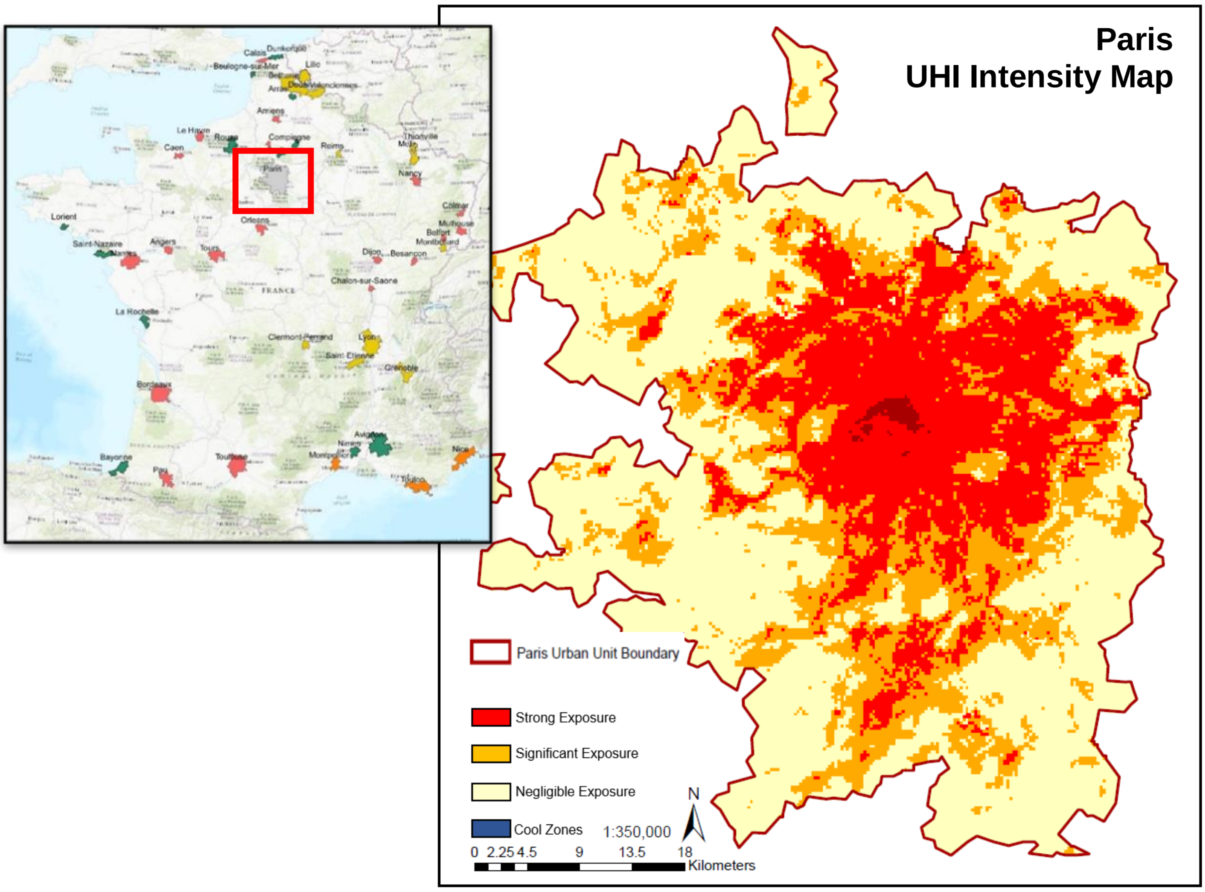
VELUT, S. (2001). Argentine, Modèle À Monter. *Espace géographique* [online]. 30(3), pp. 231-44. Available from: 10.3917/eg.303.0231. [Accessed 25 January 2021].

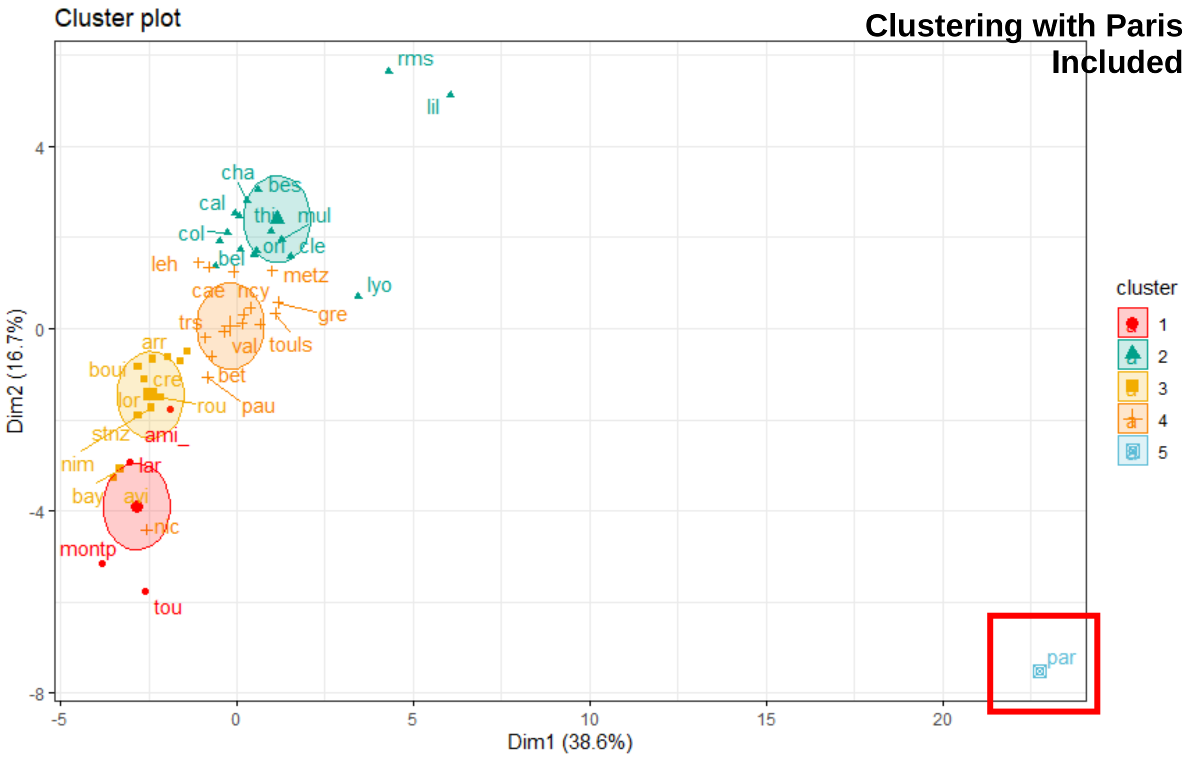
YIN, S., REN, C., ZHANG, X., HIDALGO, J., SCHOETTER, R., KWOK, Y.T. & LAU, K.K. (2021). Potential of Synthetizing Climatopes and Local Climate Zones for Urban Climatic Planning Recommendations: A Case Study in Toulouse, France. Submitted Paper.

ZHOU, B., RYBSKI, D. & KROPP, J.P. (2013). On the Statistics of Urban Heat Island Intensity. *Geophysical Research Letters* [online]. 40(20), pp.5486-5491. Available from: 10.1002/2013GL057320. [Accessed 18 June 2021].

APPENDIX

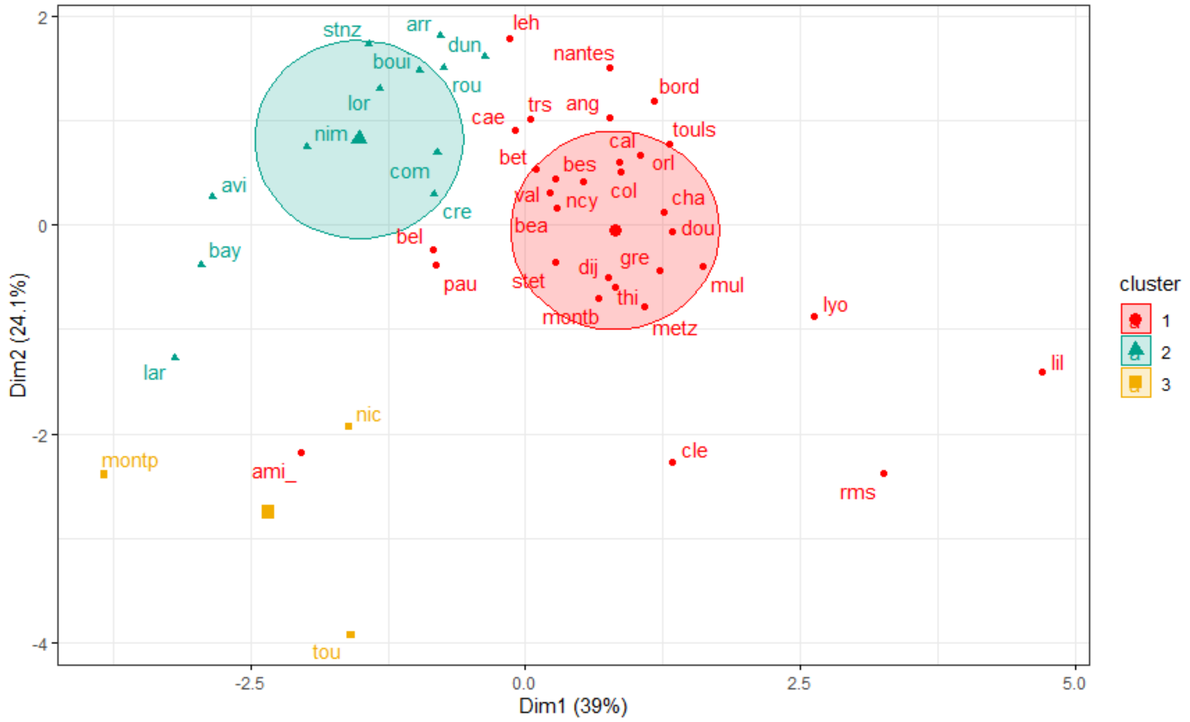
Appendix 1 – Clustering with Paris



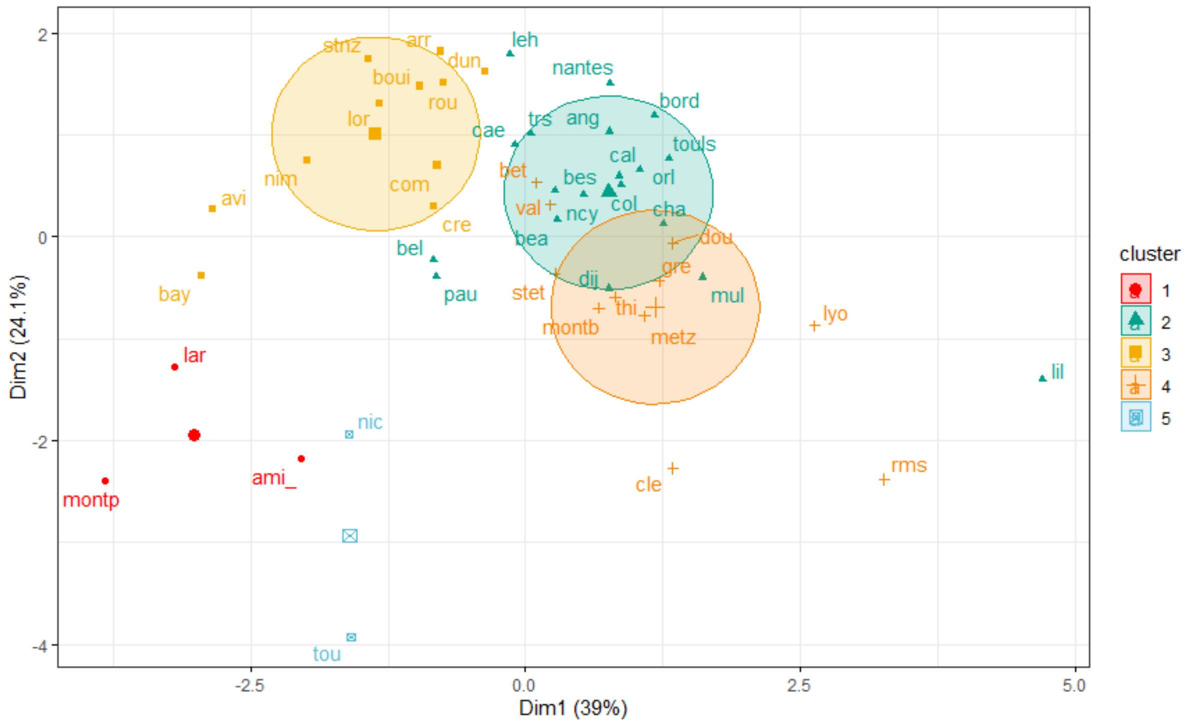


Appendix 2 – Clusters with Different k-numbers

Cluster Plot with k=3

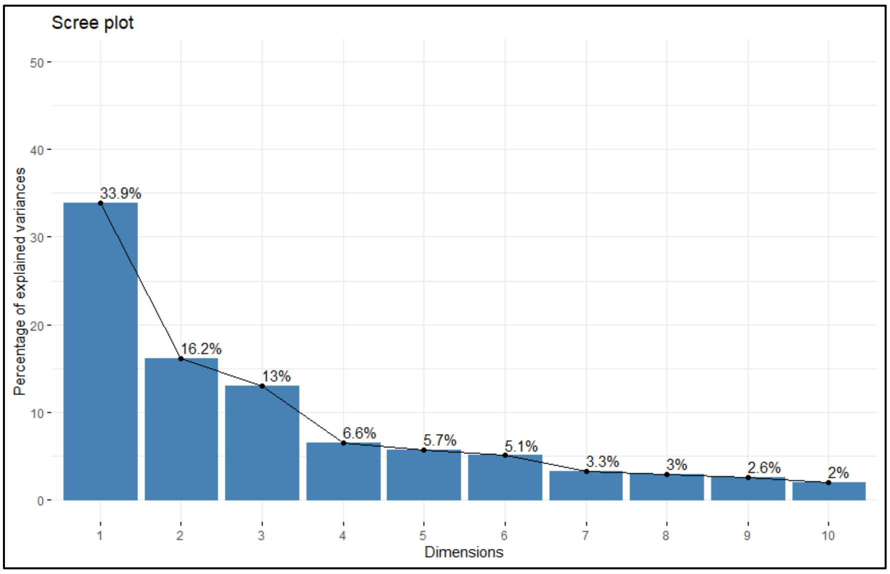


Cluster Plot with k=5

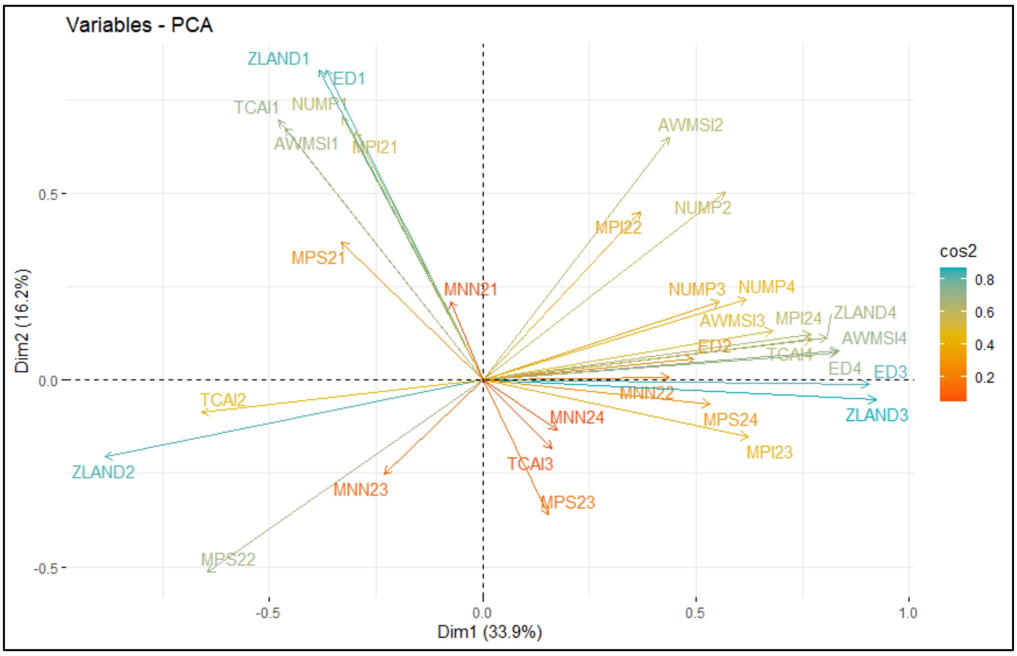


Appendix 3 – Cluster Visualisation

During visualisation, {factoextra} package uses Principal Component Analysis (PCA). The default visualisation is based on first 2 dimensions. Hereby, the term "dimensions" is used to indicate the axes of the plot and should not be confused with the dimensions term used throughout the research that stands for the classification of spatial metrics (homogeneity, complexity, depth, and fragmentation). In the figure below, the percentage of variance for represented metrics (termed as "variables" in the operation) are shown for dimensions (axes) of the plot.



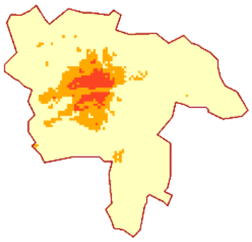
In the graph below, the representation of metrics (variables) in visualisation are shown. From blue to red, the weight in representation of the metrics (variables) decrease.



Appendix 4 – Medoid Cities & Paris

Tables with full shape metric values calculated throughout Patch Analysis for Medoid Cities:

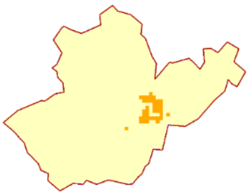
Orleans



Class	CACV1	ZLAND	CA	CACOV	MCA	CASD	TCA	TCAI	CAD	IJI	MPI
2	173.21	85.79	26481.25	0	22518.75	0	22518.75	85.04	0	2.36	1404.26
3	400	10.79	3331.25	316.23	105.11	332.4	1156.25	34.71	0.04	87.37	208.69
4	185.17	3.42	1056.25	94.77	137.5	130.3	412.5	39.05	0.01	4.96	48.01

MNN	AWMSI	MSI	MPFD	AWMPFD	CWED	TE	ED	MPS	NUMP	PSCOV	PSSD	TLA
475.35	3.46	1.66	1.04	1.13	1	229500	7.43	6620.31	4	172.93	11448.68	30868.75
972.43	4.94	1.47	1.03	1.18	1	153500	4.97	195.96	17	357.16	699.87	30868.75
692.97	2.05	1.38	1.04	1.09	1	45000	1.46	150.89	7	154.26	232.76	30868.75

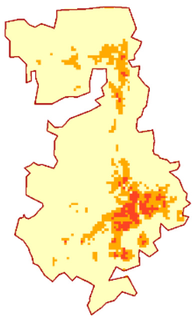
Lorient



Class	CACV1	ZLAND	CA	CACOV	MCA	CASD	TCA	TCAI	CAD	IJI	MPI
2	0	97.86	11425	0	9937.5	0	9937.5	86.98	0.01	1	0
3	141.42	2.14	250	100	18.75	18.75	37.5	15	0.02	1	14.31

MNN	AWMSI	MSI	MPFD	AWMPFD	CWED	TE	ED	MPS	NUMP	PSCOV	PSSD	TLA
1	2.07	2.07	1.08	1.08	1	88500	7.58	11425	1	0	0	11675
430.19	2.05	1.37	1.03	1.1	1	15000	1.28	83.33	3	130.81	109.01	11675

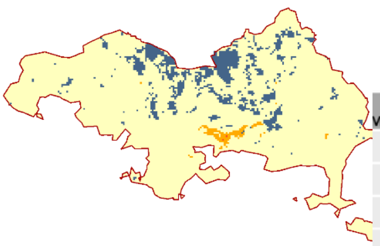
Metz



Class	CACV1	ZLAND	CA	CACOV	MCA	CASD	TCA	TCAI	CAD	IJI	MPI
2	316.23	85.55	30637.5	244.95	3459.82	8474.8	24218.75	79.05	0.02	24.66	3710.62
3	289.34	11.45	4100	268.33	22.99	61.69	643.75	15.7	0.08	81.51	70.42
4	328.18	3	1075	198.9	22.66	45.06	181.25	16.86	0.02	50.67	17.2

MNN	AWMSI	MSI	MPFD	AWMPFD	CWED	TE	ED	MPS	NUMP	PSCOV	PSSD	TLA
282.14	5.17	1.41	1.02	1.17	1	375000	10.47	2785.23	11	315.09	8776.04	35812.5
615.29	3.98	1.57	1.05	1.16	1	261000	7.29	128.12	32	237.74	304.6	35812.5
603.42	2.23	1.31	1.03	1.1	1	73500	2.05	56.58	19	213.07	120.55	35812.5

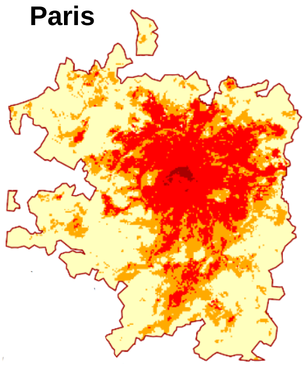
Toulon



Class	CACV1	ZLAND	CA	CACOV	MCA	CASD	TCA	TCAI	CAD	IJI	MPI
1	487.19	9.35	7531.25	278.03	61.46	170.87	2212.5	29.38	0.04	2.73	40.14
2	292.93	89.53	72143.75	403.06	3259.03	13135.77	58662.5	81.31	0.02	30.77	6871.33
3	300	1.11	893.75	173.21	42.19	73.07	168.75	18.88	0	28.71	15.79
4	0	0.02	12.5	0	0	0	0	0	0	0	0.5

MNN	AWMSI	MSI	MPFD	AWMPFD	CWED	TE	ED	MPS	NUMP	PSCOV	PSSD	TLA
743.38	2.36	1.34	1.04	1.1	1	438000	5.44	73.84	102	280.73	207.28	80581.25
450	6.65	1.9	1.05	1.18	1	773000	9.59	7214.38	10	290.74	20974.79	80581.25
2929.43	2.96	1.38	1.03	1.13	1	54000	0.67	89.38	10	233.63	208.81	80581.25
353.55	1	1	1	1	1	2000	0.02	6.25	2	0	0	80581.25

Paris



Class	CACV1	ZLAND	CA	CACOV	MCA	CASD	TCA	TCAI	CAD	IJI	MPI
2	490.95	53.14	131356.3	374.39	1460.91	5469.54	97881.25	74.52	0.03	14.82	1765.07
3	1068.97	23.78	58775	898.05	93.81	842.43	20731.25	35.27	0.09	62.53	772.12
4	1023.26	22.71	56131.25	783.19	521.92	4087.64	36012.5	64.16	0.03	28.55	1894.78
5	237	0.38	943.75	94.37	221.88	209.38	443.75	47.02	0	0	38.58

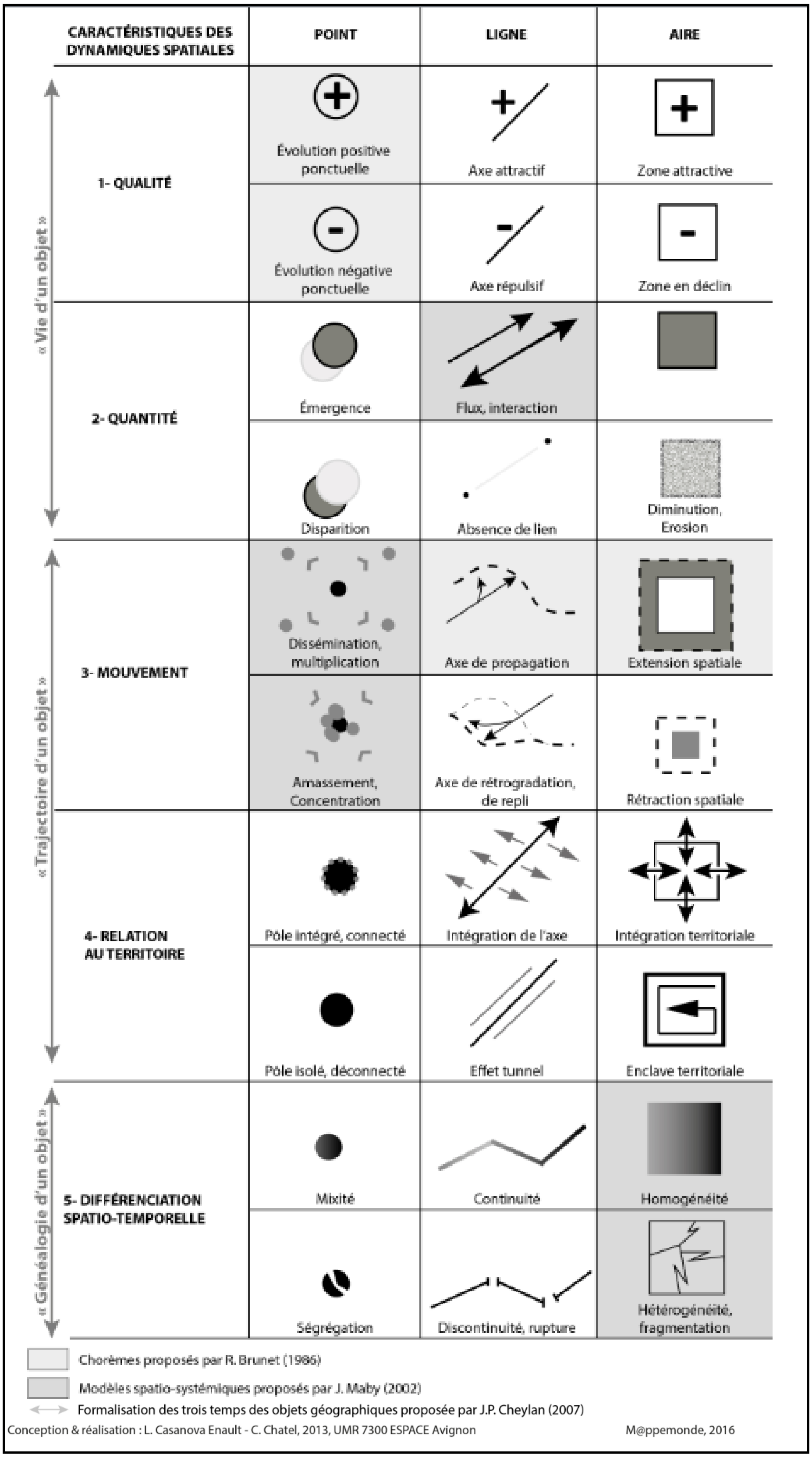
MNN	AWMSI	MSI	MPFD	AWMPFD	CWED	TE	ED	MPS	NUMP	PSCOV	PSSD	TLA
496.01	5.65	1.45	1.04	1.17	1	2105000	8.52	1172.82	112	476.78	5591.73	247206.3
426.65	9.29	1.41	1.03	1.21	1	2776500	11.23	188.38	312	851.89	1604.8	247206.3
710.35	9.03	1.35	1.03	1.22	1	1324000	5.36	479.75	117	940.6	4512.55	247206.3
517.75	1.92	1.34	1.04	1.08	1	37000	0.15	134.82	7	200	269.65	247206.3

Abbreviations of Spatial Metrics:

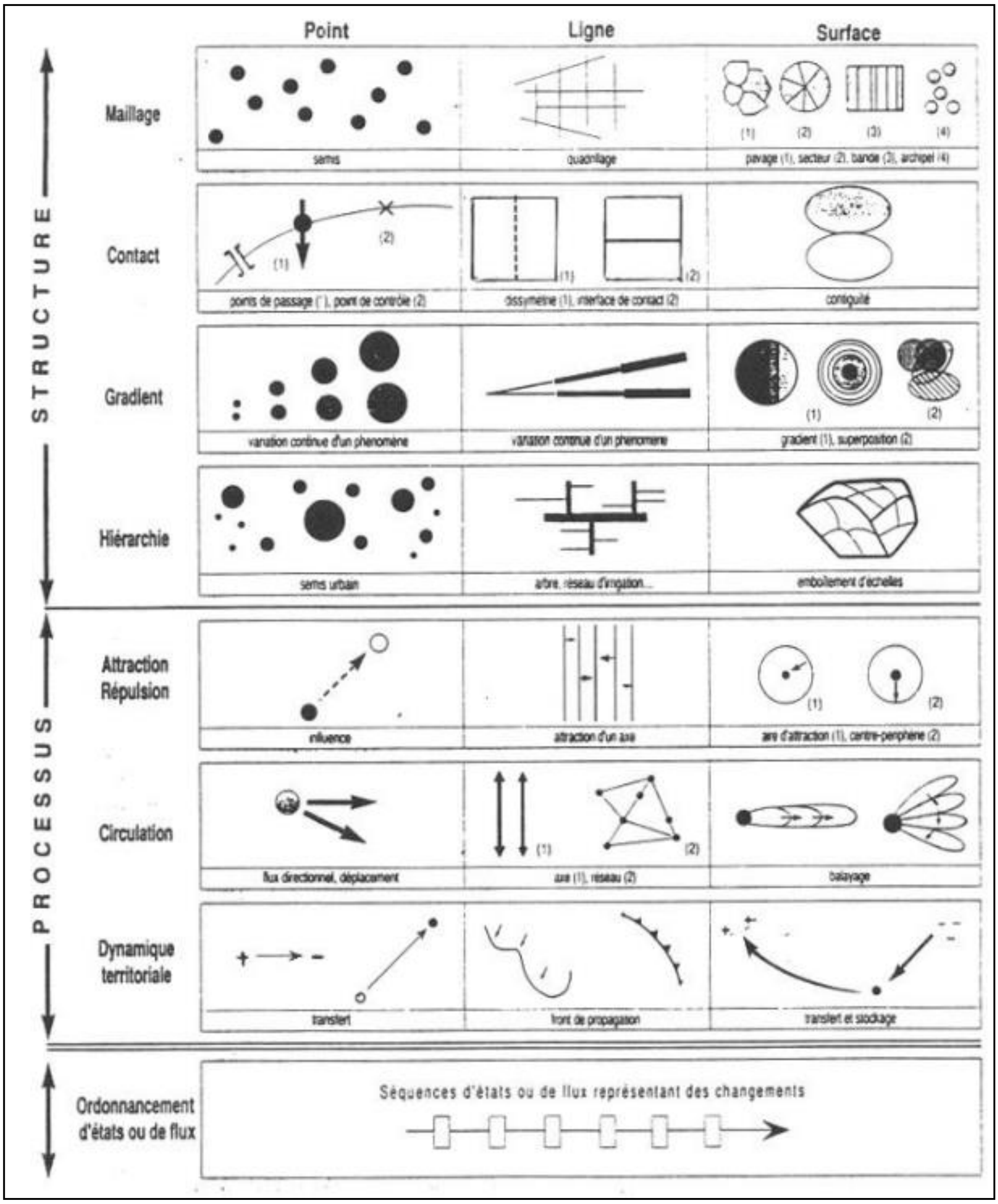
ABBREVIATION	SPATIAL METRIC
CACV	Patch Core Area Coefficient of Variation
ZLAND	Class Area Proportion
CA	Class Area
CACOV	Core Area Coefficient of Variation
MCA	Mean Core Area
CASD	Core Area Standard Deviation
TCA	Total Core Area
TCAI	Total Core Area Index
CAD	Core Area Density
IJI	Interspersion Juxtaposition Index
MPI	Mean Proximity Index
MNN	Mean Nearest Neighbour
AWMSI	Area Weighted Mean Shape Index
MSI	Mean Shape Index
MPFD	Mean Patch Fractal Dimension
AWMPFD	Area Weighted Mean Patch Fractal Dimension
CWED	Contrast Weighted Edge Density
TE	Total Edge
ED	Edge Density
MPS	Mean Patch Size
NUMP	Number of Patches
PSCOV	Patch Size Coefficient of Variance
PSSD	Patch Size Standard Deviation
TLA	Total Landscape Area

Appendix 5 – Chorems Used from Mentioned Authors' Tables

Chatel & Casanova, 2015



Cheylan, 1996



Helle, 1995