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Analysis, modelling and visualisation of spatiotemporal data for urban studies

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Christian Kaiser

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D.E.S.S. Systèmes d'Information Géographique
Université du Québec à Montréal, Canada

Jury:

Président du colloque:	Prof. Jean-Luc Epard
Directeur de thèse:	Prof. Mikhail Kanevski
Directeur de thèse:	Prof. Antonio Da Cunha
Expert:	Prof. François Golay
Expert:	Dr. HDR Gilles Maignant

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Co-directeur de thèse	: M. le Professeur Mikhail **Kanevski**
Co-directeur de thèse	: M. le Professeur Antonio **Da Cunha**
Expert	: M. le Professeur François **Golay**
Expert	: M. le Docteur Gilles **Maignant**

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Professeur Jean-Luc **Epard**

Analyse, modélisation et visualisation de données spatio-temporelles pour les études urbaines

Résumé

La part de personnes vivant dans une région urbaine est plus élevé que jamais et continue à croître. L'étalement urbain et la dépendance automobile ont supplanté la ville compacte adaptée aux piétons. La pollution de l'air, le gaspillage du sol, le bruit, et des problèmes de santé pour les habitants en sont la conséquence. Les urbanistes doivent trouver, ensemble avec toute la société, des solutions à ces problèmes complexes. En même temps, il faut assurer la performance économique de la ville et de sa région. Actuellement, une quantité grandissante de données socio-économiques et environnementales est récoltée. Pour mieux comprendre les processus et phénomènes du système complexe "ville“, ces données doivent être traitées et analysées. Des nombreuses méthodes pour modéliser et simuler un tel système existent et sont continuellement en développement. Elles peuvent être exploitées par le géographe urbain pour améliorer sa connaissance du métabolisme urbain. Des techniques modernes et innovatrices de visualisation aident dans la communication des résultats de tels modèles et simulations.

Cette thèse décrit plusieurs méthodes permettant d'analyser, de modéliser, de simuler et de visualiser des phénomènes urbains. L'analyse de données socio-économiques à très haute dimension à l'aide de réseaux de neurones artificiels, notamment des cartes auto-organisatrices, est montré à travers deux exemples aux échelles différentes. Le problème de modélisation spatio-temporelle et de représentation des données est discuté et quelques ébauches de solutions esquissées. La simulation de la dynamique urbaine, et plus spécifiquement du trafic automobile engendré par les pendulaires est illustrée à l'aide d'une simulation multi-agents. Une section sur les méthodes de visualisation montre des cartes en anamorphoses permettant de transformer l'espace géographique en espace fonctionnel. Un autre type de carte, les cartes circulaires, est présenté. Ce type de carte est particulièrement utile pour les agglomérations urbaines. Quelques questions liées à l'importance de l'échelle dans l'analyse urbaine sont également discutées. Une nouvelle approche pour définir des clusters urbains à des échelles différentes est développée, et le lien avec la théorie de la percolation est établi. Des statistiques fractales, notamment la lacunarité, sont utilisées pour caractériser ces clusters urbains. L'évolution de la population est modélisée à l'aide d'un modèle proche du modèle gravitaire bien connu.

Le travail couvre une large panoplie de méthodes utiles en géographie urbaine. Toutefois, il est toujours nécessaire de développer plus loin ces méthodes et en même temps, elles doivent trouver leur chemin dans la vie quotidienne des urbanistes et planificateurs.

Analysis, modelling and visualisation of spatiotemporal data for urban development

Abstract

The proportion of population living in or around cities is more important than ever. Urban sprawl and car dependence have taken over the pedestrian-friendly compact city. Environmental problems like air pollution, land waste or noise, and health problems are the result of this still continuing process. The urban planners have to find solutions to these complex problems while keeping the economic performance of the city and its surroundings at the same level. At the same time, an increasing quantity of socio-economic and environmental data is acquired. In order to get a better understanding of the processes and phenomena taking place in the complex urban environment, these data should be analysed. Numerous methods for modelling and simulating such a system exist and are still under development and can be exploited by the urban geographers for improving our understanding of the urban metabolism. Modern and innovative visualisation techniques help in communicating the results of such models and simulations.

This thesis covers several methods for analysis, modelling, simulation and visualisation of problems related to urban geography. The analysis of high dimensional socio-economic data using artificial neural network techniques, especially self-organising maps, is showed using two examples at different scales. The problem of spatiotemporal modelling and data representation is treated and some possible solutions are shown. The simulation of urban dynamics and more specifically the traffic due to commuting to work is illustrated using multi-agent micro-simulation techniques. A section on visualisation methods presents cartograms for transforming the geographic space into a feature space, and the distance circle map, a centre-based map representation particularly useful for urban agglomerations is shown. Some issues on the importance of scale in urban analysis and clustering of urban phenomena are exposed. A new approach on how to define urban areas at different scales is developed, and the link with percolation theory established. Fractal statistics, especially the lacunarity measure, and scale laws are used for characterising urban clusters. In a last section, the population evolution is modelled using a model close to the well-established gravity model.

The work covers quite a wide range of methods useful in urban geography. Methods should still be developed further and at the same time find their way into the daily work and decision process of urban planners.

Acknowledgements

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Ein ganz spezielles Dankeschön möchte ich auch meiner ganzen Familie widmen. Ganz speziell natürlich Mama und Papa, die mich während den letzten Jahren viel zu wenig gesehen haben, und die trotzdem immer für mich da waren.

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Contents

Acronyms

ABM Agent Based Model ... 115
AI Artificial Intelligence ... 171
ANN Artificial Neural Network ... 6
ASSOM Adaptive Subspace Self-Organising Map ... 173
CA Cellular Automata ... 5
CCA City Clustering Algorithm ... 8
CNRS Centre National de la Recherche Scientifique ... 95
DAI Distributed Artificial Intelligence ... 86
DM Data Mining ... 127
ESDA Exploratory Spatial Data Analysis ... 8
EPFL Swiss Federal Institute of Technology in Lausanne ... 11
ESOM Emergent Self-Organising Map ... 173
ETHZ Swiss Federal Institute of Technology in Zurich ... 95
FIFO First-In First-Out ... 94
IPF Iterative Proportional Fitting ... 103
GIS Geographic Information System ... 8
GISc Geographic Information Science ... 30
GNG Growing Neural Gas ... 173
GNU GNU's Not Unix
GPL General Public Licence ... 205
GPS Global Positioning System ... 108
GRNN General Regression Neural Network ... 172
HAC Hierarchical Ascendant Classification ... 11
HSOM Hybrid Self-Organising Map ... 11
INS Inertial Navigation System ... 108
JSP Job-Shop Scheduling Problem ... 88

KDD	Knowledge Discovery in Databases	127
LiDAR	Light Detection And Ranging	107
MAS	Multi-Agent System	4
MATSim	Multi-Agent Traffic Simulation	84
MAUP	Modifiable Area Unit Problem	30
MDS	Multi-Dimensional Scaling	171
ML	Machine Learning	171
MLA	Machine Learning Algorithm	6
MLP	Multi Layer Perceptron	172
NP	Non-Deterministic Polynomial-Time	
OD	Origin-Destination	91
OPUS	Open Platform for Urban Simulation	84
QAP	Quadratic Assignment Problem	88
PC	Personal Computer	114
PDF	Probability Density Function	177
RBF	Radial Basis Function	172
SFSO	Swiss Federal Statistical Office	54
SOM	Self-Organising Map	3
SQSim	Stochastic Queue Based Agent Traffic Simulation	95
SVG	Scalable Vector Graphics	126
SVM	Support Vector Machine	172
TS	Traffic Simulation	91
TSP	Traveling Salesman Problem	88
TU	Technische Universität	95
VRP	Vehicle Routing Problem	88

Chapter 1

Introduction

1.1 Motivation

Urban agglomerations are the living place of more than half the world's population. Cities have emerged and grown over the last centuries. The population pattern has progressively changed from numerous smaller towns dispersed in space to highly centralised urban agglomerations with an important proportion of population and economic activity located in cities (Da Cunha & Both, 2004). Most developed countries have made an *"urban transition"* characterised by a transformation of the urban system with a high but stable urbanisation rate and growing occurring mostly in peripheral zones of the agglomerations. The *"metropolisation"* is the continuation of the concentration process in the most important agglomerations (Bochet, 2006; Bassand, 1997; Bassand, Kaufmann, & Joye, 2001). It can be considered as the set of dynamic processes transforming a city into a metropole (Derycke, 1999; Bochet, 2006). A metropole is an important urban agglomeration of international importance; the metropoles are connected together at the first level in the global network of cities.

Cities are the product of the territorial appropriation and organisation of human activities. The urban morphology and the spatial arrangement of cities are influenced by complex systems of actors, actions and features modifying continuously the urban structure. The *"urbanisation regime"* describes all the changes occurring in time modifying the urban structure and morphology.

The development scheme of the cities follows a set of opportunities varying in space and time by respecting dynamic human and environmental constraints. The current urbanisation regime leads to urban sprawl and spatial fragmentation, resulting in pollution of air, soil and water, noise and land use conflicts. Studies of urbanisation dynamics in Switzerland showed that the cities are growing by spatial extension (sprawl) and losing the connectivity to the agglomeration centre (Bassand, Joye, & Schuler, 1988; Da Cunha, 1993; Da Cunha & Both, 2004).

The urban structure influences strongly the environmental footprint of a city. Environmental impact and amount of traffic seem to be strongly correlated to the population density (Newman & Kenworthy, 1989; Fouchier, 1995, 2002). In this sense, the urban structure is a core factor in the framework of the sustainable urban development. The sustainable development aims for making the economic and social development compatible with the environment (Da Cunha, 2005). Different models for a more sustainable city have been discussed and analysed (see e.g. Lynch, 1981; Frey, 1999; Bochet, 2006). A compact city seems to be the solution for making the city more sustainable. Empirical studies suggest that a compact city can improve the use of public transports, reduce the frequency of journey's and limit the cost of equipments (Real Estate Research Corporation (RERC), 1974; Franck, 1989). However, the direct link between high density and low need for mobility has not been proved formally (e.g. Breheny, 1995; Knight, 1996; Fouchier, 1995). For example Breheny (1995) states that with a compact city, energy savings will only be minimal and that other forms might be more adapted. New modelling and simulation approaches are needed for testing the above hypotheses, and better understanding of the link between urban structure and ecological footprint is required. Maignant (2009) uses the urban morphology, and especially the constructal theory (Bejan, 2000) for finding optimal urban arrangements. This is an interesting approach as it combines the mathematical analysis of the morphology with spatial optimisation. There is no possible optimum for all criteria; the optimum is always a compromise solution (Maignant, 2009). For example, a compact city is not the optimal urban shape for air pollution (Maignant, 2005).

Classic urban theories are not adapted to the metropolisation process or the evaluation of the ecological footprint. Rapidly changing urban structures with the emergence polycentric cities, urban sprawl and modification of the accessibility of the city are dynamics unknown to classical urban models (Torrens, 2000). As Batty (2005) notes: *"urban systems are far-from-equilibrium systems, whose elements are changing at different rates and whose impact is diverse across different spatial scales and time spans"*. A new paradigm has been developed over the last two decades, based on the disequilibrium inherent to the urban system (Batty, 2008). For example Bak (1996) suggests that cities preserve their structure by self-organisation, in order to avoid radical changes in the system. Wilson (2008) develops the idea of phase transitions in urban evolution with the example of retail systems. There seem to be critical thresholds in the urban sub-systems; crossing these thresholds lead to a phase transition like for example the change *"from 'corner shop' food retailing to supermarkets in the late 1950s and early 1960s"* (Wilson & Oulton, 1983; Wilson, 2008).

The city has been analysed using new approaches and methods. The urban morphology has been studied using fractal geometry (Frankhauser, 1994; Batty & Longley, 1994). It has been recognised that urban systems are evolving with emerging structures from the bottom up (e.g. Batty, 2005, 2008). Urban agglomerations are treated in this bottom-up approach as emerging phenomena generated through a big number of decentralised decisions and actions. The urban system has been recognised as being complex, dynamic and non-linear. Concepts like fractal morphology, self-similarity, scaling laws, self-organisation or far-from-equilibrium states have been introduced from physics into quantitative urban geography. The constructal theory (Bejan, 2000) is another interesting concept; according to this constructal law, self-organising systems distribute the imperfections, generating the shape and structure of the system. Maignant (2009) shows how this theory, and optimisation in general, can be used in geography and especially in urban geography.

This thesis explores several novel ways in urban analysis, simulation and visualisation. Of course, it is not possible to draw a complete picture of the complex system "city", this would be far beyond the possibilities of a single thesis. However, it tries to make some bridges between urban geography and modern quantitative analysis and visualisation. It shows how new methods can be integrated into urban analysis and addresses some concrete problems in urban geography. One of these questions are the visualisation of spatial and spatio-temporal information in a way allowing a useful interpretation and better understanding of simple parameters in the urban systems. This type of approach can be found in the field of "visual analytics", which is the integration of interactive visualisation with analysis methods (see e.g. Yuan & Hornsby, 2007, for an example in geoscience). Providing advanced visualisation techniques that can be combined with analysis methods can help urban geographers and decision makers with useful information for planning or simply a better understanding of the complex urban system.

Another question is to define urban clusters, for example agglomerations, or also clusters of specialised services. This thesis provides some insights in how such spatial clusters can be defined using the percolation approach. A discussion about the scale of analysis accompanies these considerations. The exploratory data analysis using Self-Organising Map (SOM) is another interesting topic allowing the urban geographer defining similar groups of spatial units; it is another form of clustering, performed this time in the feature space and not in Euclidean space. This thesis provides also a simulation approach to the problem of traffic simulation in order to retrieve additional information about the mobility behaviour of the population. Such a simulation can help defining links between the urban morphology and the ecological footprint in the mobility behaviour.

1.2 Objectives and challenges of the thesis

The main challenge of this thesis is the building of a bridge between urban geography and advanced quantitative geography. Urban geographers are used to make simple models and apply qualitative analysis methods. In quantitative analysis, a number of new methods have been developed that can be used for exploring and modelling the city which is a complex social and economic system.

Urban systems can be analysed using a plethora of methods and techniques very different from each other. This thesis does not provide one coherent method for the questions outlined in the previous section. It will rather take several different methods for various tasks in order to provide some possibilities for the urban geographer to analyse and model the city using novel techniques. The problem is common to all the methods presented in this work: provide tools for better understanding of the complex system "city".

Chapter 2 gives some elements of quantitative urban geography, describing the scientific context of this thesis. Section 2.4 gives an overview of the scientific questions behind this work. Four different important issues are identified: the work with spatially continuous data to avoid zoning effects, scale, change of support for spatial datasets, and visualisation methods. These issues are discussed throughout the thesis from different perspectives.

Different techniques for dealing with urban and socio-economic data are discussed in the following chapters. Some advanced methods are shown for defining spatial clusters like the delimitation of the agglomeration itself, how high-dimensional socio-economic data can be clustered, and how simulations can contribute to the understanding of the urban system. Methods like the SOM or Multi-Agent System (MAS) are already known in some fields; in this thesis, feasibility studies have been undertaken in these cases to show their potential applicability in the field of urban geography. The percolation approach presented in chapter 3 is a novel technique that has been considerably extended in this work and applied to different socio-economic and demographic data. For all methods, a case study is presented to show a concrete application.

One of the focuses of this thesis is also to provide some examples of how socio-economic data in an urban agglomeration can be visualised. Chapter 5 is dedicated to different visualisation techniques. Section 5.4 shows finally some examples of maps for the agglomeration of Lausanne, along with some explications related to the observed phenomenon (even if the explications would probably better fit into chapter 2). These maps should give an idea in which direction modern visualisation of urban phenomena should go. Of course, interactive and dynamic systems could help in further improving the visual analysis. The rising field of GeoVisual Analytics tries to provide an easy access to analysis results of geographical data through a visual approach. Visual Analytics techniques allow to explore huge structured and unstructured high-dimensional datasets through a visual exploration approach. Applications to urban and socio-economic data would be very promising for the urban geographer.

1.3 Short review of techniques and data

This sections provides a very short review of some techniques used in quantitative urban geography. It is impossible to be exhaustive at this stage, only a very general overview will be provided. We will also present briefly the data that were available for doing the research throughout this thesis.

1.3.1 Techniques

The general description of the fractal geometry and its application to the characterisation of images and pattern allowed advances in the analysis of the urban morphology. Two books have been given important impulses in this field in the middle of the 90's (Frankhauser, 1994; Batty & Longley, 1994). Several studies on urban morphology using the fractal approach have been conducted (Frankhauser, 2004; Tannier & Pumain, 2005). If we consider the city as a far-from-equilibrium self-organised system, the fractal geometry is indeed an adequate approach. The theory of complex systems is able to provide a powerful framework for the analysis of the dynamic processes in urban agglomerations.

The city is a complex system. In such a system, we find emerging structures. The constituting elements are interdependent. Interdependence means that in such a system, the actions of the ones depend on the structure and the actions of the others (Torrens, 2000). The concepts of complexity and emergence are related. Emergence is a phenomenon created by a high number of small constituting elements of a system, creating an ordered structure out of a set of simple rules. These simple rules have in appearance no direct link to this structure. This means, it is not possible to predict the structure from the set of rules at the origin (Batty, 2005). Only the interaction between the constituting elements lets "emerge" this global structure. We can say that the complex system is more than just the sum of its constituting elements.

In geography, two different methods are used for modelling this bottom-up approach: Cellular Automatas (CAs) and MASs.

CAs are computational models where a set of ordered cells can take a categorical value and where these cells may change their value in time according to the state of the neighbours; the rules of these changes are defined globally for the hole CA. CAs are typically used in geography to model land use changes and are constraint by a more or less big set of rules based on spatial interactions or demographics (e.g. White & Engelen, 1993;

White, 1997; White & Engelen, 2000). The cells of a CA are typicially arranged in a regular grid, but they can also be arranged in any other way (e.g. Pinto & Antunes, 2005; Pinto, Antunes, & Roca, 2009; O'Sullivan, 2001).

MASs are systems composed of numerous simple, interacting elements known as agents. Each agent has its own characteristics and goals. It acts in an independent way, but is able to communicate with other agents and to adapt to a changing environment. If used in geography, an agent is aware of his location, and generally free to move. MASs have been applied successfully to traffic simulation problems (e.g. Klügl, Bazzan, & Ossowski, 2005; Balmer, 2007; Meister et al., 2009) and location choice problems (e.g. Marchal & Nagel, 2005). There are also applications to urban phenomena, mainly to residential dynamics and in combination with CA (e.g. Benenson, 1998; Benenson, Omer, & Hatna, 2002; Benenson & Torrens, 2004; Waddell & Ulfarsson, 2004; Waddell, Ševcíková, Socha, Miller, & Nagel, 2005).

Machine Learning Algorithms (MLAs) are powerful and adaptive algorithms based on a learning-from-data approach (Kanevski, Podznoukhov, & Timonin, 2009; Kanevski, Foresti, et al., 2009). They have been successfully used in many different cases, for example for analysis or classification of high-dimensional data sets. The resulting model can be non-linear in nature enabling the study of very complex phenomena. In this thesis, SOM are used for clustering of features. A SOM is a kind of Artificial Neural Network (ANN) and part of MLAs. SOMs have already been used successfully for different clustering problems in geography (e.g. Openshaw & Turton, 1996; Bação, Lobo, & Painho, 2008; Lourenço, Lobo, & Bação, 2005).

1.3.2 Data

All the methods presented above require a quite large amount of data to operate optimally. In Switzerland, the Swiss Federal Statistical Office provides high quality data with a good resolution. However, due to privacy issues, individual data are of course not available. The data used in this theses come mainly from the following data sources:

- *Population census 1990 and 2000.* The population censuses contain a high number of variables related to demographics and socio-economic characteristics. For the resident population, variables as age, education, socio-economic status, religion, civil status, working place and mean of transportation are known at the level of the municipality. Information about the households are also contained in the census. Large parts of the census are not only available at the level of the municipality, but also as a regular grid with a resolution of 100x100 metres (the hectometric data).

- *Buildings census 1990 and 2000.* The buildings census is conducted at the same time as the population census and contains information about the apartments and houses, including their age, size and energy source for heating. This information is also available at the level of the municipality or as a hectometric grid.

- *Firms census 1998 and 2001.* The firms census contains information about all the economic activities of the firms, and also their size. Additionally, it is known how many jobs in which sector are available for each municipality and also for the hectometric grid.

- *Micro-census on traffic behaviour 2005.* A population subset of roughly 30'000 people has been asked on their detailed mobility behaviour like for example the purpose of their daily trips, available transportation means etc. For this subset, the exact location for each person is known, as well as the coordinates of all destinations during the census period. These data can typically be used for calibrating a MAS, as it gives detailed global statistics on the mobility behaviour.

1.4 Outline of the thesis

As already mentioned above, this thesis explores different methods and techniques useful for urban geographers or planners, and which are most of the time little known or new in geography. Several different topics might appear disconnected from each other at the first sight, but they are related to each other through the same problem described in section 1.1 above. At the same time, the different topics are analysed through the same scientific questions outlined in chapter 2 and specifically in section 2.4. However, because of this apparent disconnection, each chapter has its own introduction and conclusion, and bibliographic references are presented separately. The different topics treated in this work are the following (see also figure 1.1):

- Chapter 2 presents some aspects of quantitative urban geography and gives an overview of the scientific background of this thesis. The research questions are outlined in section 2.4 of this chapter.

- The urban structures and dynamics are investigated in chapter 3. The percolation approach, useful for defining urban areas, is presented, but also other socio-economic and demographic spatial clusters. The population growth for the example of Switzerland is also modelled in this chapter.

- The use of MASs in a spatial context is conceptually straightforward. The MAS approach is well suited for complex problems in situations where insufficient data is available for analytical solutions using traditional Geographic Information System (GIS) techniques. Traffic simulation can be done using a MAS, and we show an example of traffic demand modelling over an urban agglomeration in chapter 4.

- Visualisation techniques are discussed in chapter 5. The main focus is on innovative mapping methods. Spatially continuous data representations are discussed in the first section. A second section deals with cartograms having some interesting properties for the urban geographer. A last theoretical section presents a centre-based mapping technique allowing the comparison of different urban areas or with a theoretical city model. At the end of the chapter, section 5.4 shows an example of cartographic visualisation, applied to socio-economic and demographic data of the agglomeration of Lausanne. Each map is commented to make a link with the problems related to urban geography discussed in section 1.1 and chapter 2.

- Chapter 6 deals with different aspects of Exploratory Spatial Data Analysis (ESDA) useful in an urban context, notably with spatial clustering techniques and exploration of a high-dimensional feature space using SOMs. This method is especially useful for complex socio-economic data.

- Finally, a general discussion (chapter 7) provides a short overview of the achievements of this thesis.

1.5 Contributions of the thesis

All chapters 3 to 4 present some innovative approach for the urban geographer and planner. The presented methods contribute to establishing some new bridges between urban geography and quantitative analysis, and can potentially improve the understanding of the complex urban systems. For each chapter, we list the particular contribution, as well as the publications and presentations related to these works.

1.5.1 Chapter 3: Analysis of urban structures and dynamics

The concept of the City Clustering Algorithm (CCA) initially proposed by Rozenfeld et al. (2008) is developed further into a more advanced percolation algorithm. The main modifications are the addition of two new parameters: a functional threshold and a minimum cluster size. Additionally, the algorithm has been applied to other socio-economic and demographic data leading to a generalisation of the algorithm into the concept of spatial percolation. A case study for delimiting the agglomerations in Switzerland

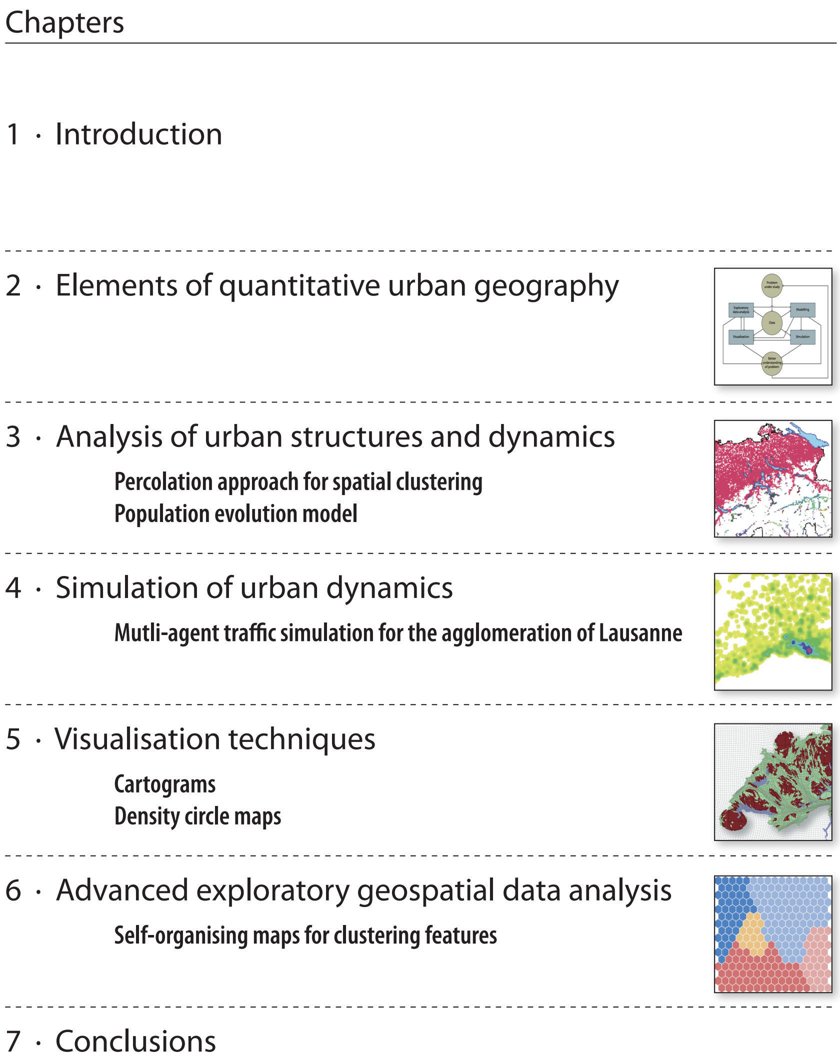

Figure 1.1: Outline of the thesis

showed an excellent and promising result, and the conditions to respect for Zipf's law of city size distribution being valid have been explored. The results of this analysis have been presented at two conferences and have been submitted to two different journals.

An attempt to model the population evolution in Switzerland over the last 150 years has been undertaken. The gravity model usually used for such a model has been compared to other slightly different models. It has been shown that the gravity model is roughly equivalent to a random evolution and does therefore not provide an interesting model for population evolution, at least in our case study.

Kaiser, C. and Tuia, D. (2007). Structuration hiérarchique autosimilaire des réseaux de service suisses: une caractérisation par les lois de puissance. In Da Cunha, A. and Matthey, L., editors, *La ville et l'urbain: des savoirs émergents*, pages 105–120. Presses polytechniques et universitaires romandes, Lausanne.

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Tuia, D., Kaiser, C., and Kanevski, M. (2008). Clustering in environmental monitoring networks: Dimensional resolutions and pattern detection. In Soares, A., Pereira, M. J., and Dimitrakopoulos, R., editors, *geoEnv VI - Geostatistics for environmental applications. Proceedings of the Sixth European Conference on Geostatistics for Environmental Applications*, volume 15 of *Quantitative Geology and Geostatistics*, pages 497–509, Rhodos, Greece. Springer.

1.5.2 Chapter 4: Simulation of urban dynamics

The main contribution of this chapter is a feasibility study of a multi-agent traffic simulation. The purpose of this simulation is the use of the result for further analysis. The motivation behind this analysis is the question of the link between the ecological footprint of the mobility behaviour and the urban morphology. How does the urban morphology change the mobility behaviour? Are there shapes and structures more suitable for sustainable development? This simulation approach is very demanding of computation power. It also requires high-resolution data on demographic and socio-economic characteristics of the population for the initial calibration. As shown in chapter 7, the calibration of the multi-agent simulation is a difficult and challenging problem.

Kaiser, C. and Kanevski, M. (2010). Population distribution modelling for calibration of multi-agent traffic simulation. In *13th AGILE International Conference on Geographic Information Science, 11-14 May*, Guimarães, Portugal.

1.5.3 Chapter 5: Visualisation techniques

The highlight of the visualisation techniques presented in this thesis are probably the cartograms with the development of the user-friendly, multi-platform application "ScapeToad", in collaboration with the Laboratoire Chôros of the Swiss Federal Institute of Technology in Lausanne (EPFL). ScapeToad is the first cartogram application able to deform several GIS layers simultaneously. At the same time, the algorithm is very efficient and with the upcoming version 1.2, multi-core processors will be supported for even faster computation times.

Another interesting contribution is the animated cartogram where the user can see both the topographic map and the cartogram. A prove-of-concept example can be found at www.clusterville.org/cartogram_morphing.

The distance circle maps are a novel way to represent centre-based maps, and is especially adapted for the study of urban agglomerations where a centre is clearly defined.

A particular contribution shortly mentioned in chapter 5 is the "Atlas interactif de la Roumanie" (interactive atlas of Romania).

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1.5.4 Chapter 6: Advanced exploratory geospatial data analysis

Chapter 6 provides an interesting tool for clustering geographic units into groups using high-dimensional socio-economic features. The clustering process uses a SOM for a non-linear transform of the data before separating the geographic units into different groups using classical Hierarchical Ascendant Classification (HAC). This method has the advantage to be close to tools already known in urban geography while providing highly adaptive non-linear transformation. Different case studies using this Hybrid Self-Organising Map (HSOM) approach have been presented in conferences and published in several papers and book chapters.

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Chapter 2

Elements of quantitative urban geography

Over the last two centuries, the world's population evolved in a spectacular way (figure 2.1). While in 1800, according to an estimation of the United Nations, population was roughly 1 billion; it was over 6 billion in 2000. For 2150, a population of nearly 10 billion is expected (United Nations Population Division, 1999). At the same time, the urban areas around the world increased rapidly. Today, more than half of the population is living in cities; huge agglomerations are the result. The hierarchical and spatial organisation of the inhabited places has been profoundly modified during the same period. In the case of Switzerland, the urban system has been transformed over the last two centuries (Both, 2005). Initially, the population was located in many smaller settlements all over the country. Since more than two centuries, population is concentrating more and more in the urban areas, and the surface occupied by agglomerations is increasing. These changes in the spatial distribution of the population went in parallel with economic and social changes. Industrialisation and the following shift to a tertiary sector based economy allowed and required a better transportation and communication infrastructure. These enhancements modified the mobility behaviour of the population by increasing the potential space where people could go within a given amount of time.

Today, the cities are essential for the economic development as they are important platforms for the exchange of ideas, innovations and trend. They play a key role in the spread of information. The emergence of the new communication technologies did not weaken the role of urban centres, we can even say that the opposite is true. In the network of human settlements all over the world, the cities play the role of hubs. Networks like the one used for innovation spread, or also for other diffusion processes like epidemics, have a structure based on the long-distance links between the big metropolitan areas, from where more local networks link smaller cities and so on.

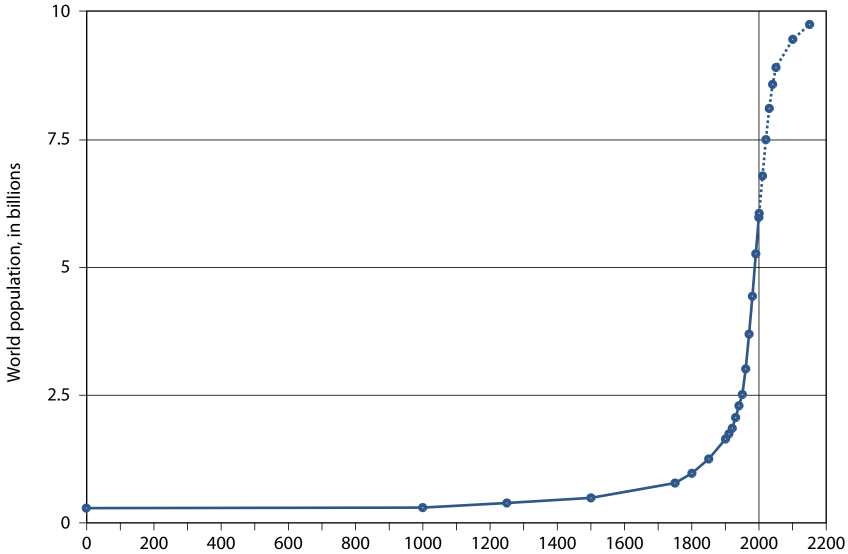

Figure 2.1: World population evolution between the year 0 and 2150, according to the United Nations Population Division (1999)

At the local level, the urban areas around the world are the living and working space of more than half the humans. Sometimes, cities are considered as a kind of anti-nature, the opposite of what is natural. Indeed, cities are sources of pollution – noise, air pollution, and soil pollution. Cities are associated to physical stress for a lot of people. In a city, we find social conflicts due to the social and economic differences in the population. Managing and solving all these problems is a huge challenge for the 21st century. Making cities an attractive and sustainable place is an important task for the next generation.

Over the last few decades, the access to mobility has increased for almost the whole population. Figure 2.2 shows the evolution of the number of cars per 1000 people for Switzerland. The increase goes from 212 cars in 1970 to 517 cars in 2008. In 2008, for the first time since 1970, the number of cars per 1000 people dropped very slightly from 519 in 2007. This increase in mobility leads to the possibility for the population to accept longer distances for going to work or for accessing to services. Services can optimise their location to the new accessibility, shopping centres at the border of highways is one of the consequences. Another consequence is the spread of the residential zones into more rural zones, as people prefer the lower land rates of remoter areas, as well as the relative proximity to "green zones" associated with less pollution and noise. The car dependence of the population is just the next step of this evolution, leading to saturation of the existing road network and traffic jams. Therefore, decision makers and urban planners should prevent

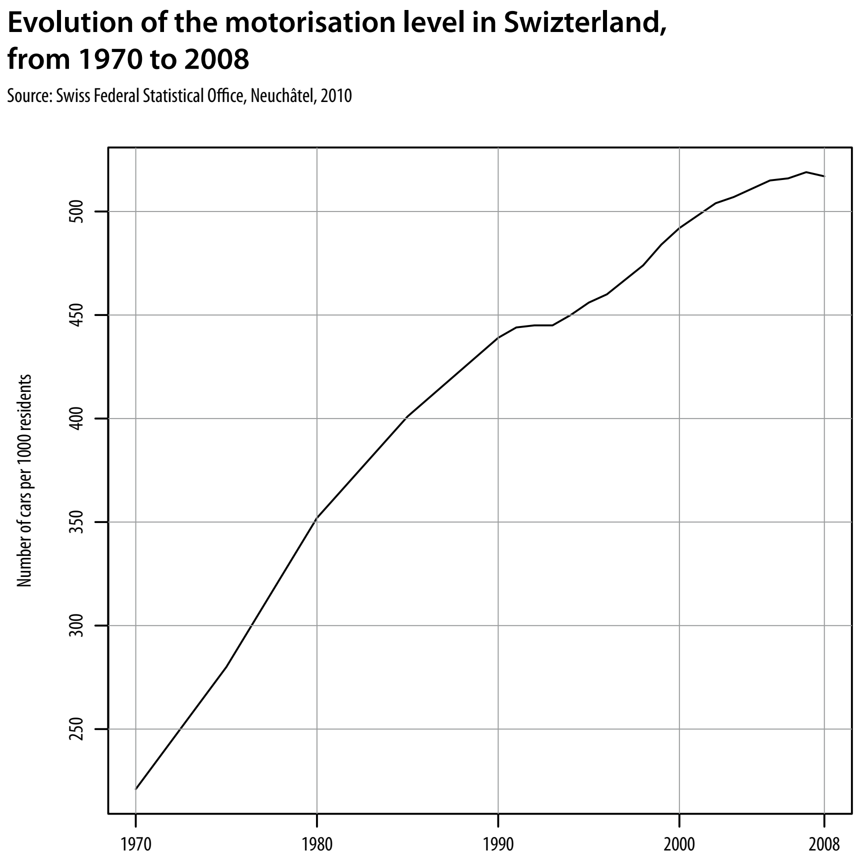

Figure 2.2: Evolution of motorisation level in Switzerland.

excessive developments and undertake the necessary step for providing a sustainable development of the urban areas.

In order to make the right decisions, decision makers should dispose of useful information about the processes taking place in a city, and the urban environment itself. As an urban system is complex, the task of providing this information is not easy. Analysis, modelling and simulation of an urban system attempt to understand the processes in order to provide the decision maker with useful information. This thesis tries to show some of the methods for analysing, modelling, simulating and visualising the data related to the city.

2.1 What is a city, and why does it exist?

Structurally, a city is an important cluster of buildings where humans live and work. A city is a human settlement of a given size, which distinguishes it from a village. Agriculture is much less present in a city than in a village of a rural area. A city is an 'urban area', in opposition to 'rural areas'.

Functionally, cities provide some important services to the humans living there, and to the regions surrounding the city. Historically, the role of protecting the population from attacks with a surrounding wall was very important; this wall gave also a very sharp limit between the urban and rural areas. Through its limited extension, the historic cities simplified and enhanced the exchange of information and goods between people. Access to the common knowledge became easier. According to Vicari (2007), cities have emerged due to climatic crises and allowed their inhabitants to exchange innovations which enabled them to adapt to the changing environmental factors.

Today, the big offer of different services and jobs is much more important than its protecting role. Cities have become much more diffuse, there isn't anymore a sharp limit between urban and rural zones. But economically, cities offer still an important advantage for service providers as the accessibility of the services increase with the number of persons living in a given area. The accessibility of a point i in space can be defined as follows:

$$Acc_i = \sum_j P_j {d_{ij}}^{-k} \qquad \text{for all } d_{ij} \leq d_{max} \tag{2.1}$$

where Acc_i is the accessibility at point i, P_j the number of people present at a point j, d_{ij} the distance separating the point i from point j and k is a scaling factor which depends on the distance measure. The distance measure can be the Euclidean distance between point i and j, but also another measure like the travel time between i and j. d_{max} is the maximum distance which we consider for estimating the accessibility.

The equation 2.1 makes clear that the accessibility depends solely on the number of people and some distance measure, typically time distance. The map in figure 2.3 shows the population within a distance of 3 kilometres for each point. This map shows clearly the urban areas of Switzerland.

The maximum distance in equation 2.1 might seem to be a somehow arbitrary value. However, it is probably useful to introduce some limit, as people won't use services too far away. Typically, the accessibility of a given service s_1 of type t is limited by the presence of other services s_n of the same type t at another location. Services of type t form a network where each service point has its own population basin. Of course, such a population basin is not static as people move in space. And there may be some overlap due to the fact that people do not always know the nearest service point, and there may also be some personal preferences. However, for sake of simplicity,

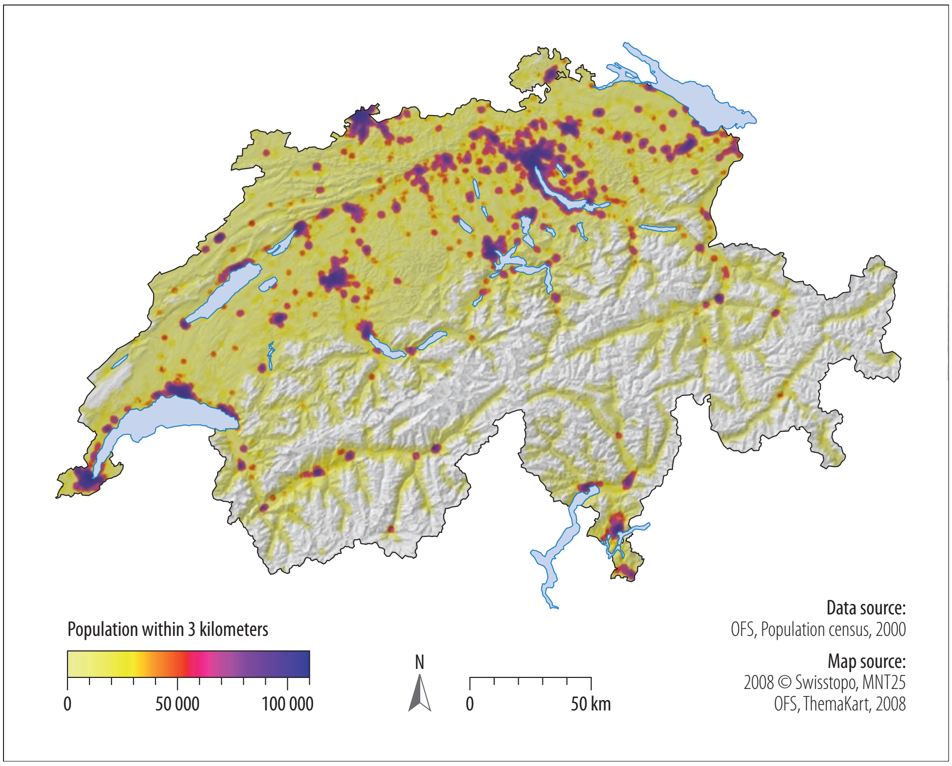

Figure 2.3: Population in Switzerland in 2000. The map shows for each point the number of people living in a circle of 3 kilometres around the centre point.

we shall consider here clearly defined population basins where people go always to the nearest service point. In this case, the Voronoi polygons (Boots, 1986) based on all the service points define these population basins. The Voronoi polygon V_i for the service facility i is defined as the set of points that are closer to i than to any other service point.

Services in urban areas have usually a larger population basin. This becomes clear if we consider the problem of choosing the location for p facilities like hospitals or supermarkets. The facilities are optimally distributed if the average distance to the nearest facility over the whole population is minimal. This is the so-called *p-median problem*, which is NP-hard and non-trivial to solve (Gastner & Newman, 2006). For p facilities and n points where we find potential customers, the number of possibilities to locate the p facilities is $\frac{n!}{p!(n-p)!}$.

As population is usually not distributed uniformly in space, it would be a bad idea to distribute the p facilities equally in space. It would be more adapted to choose a distribution proportional to the population. But this choice is also suboptimal, because in highly populated places, there would be a lot of facilities, and if we would remove one of them, the additional cost for people to going to another facility would be quite small. The optimal choice lies somewhere in between. It has been showed by Gastner and Newman (2006) that the density of facilities increases as the two-thirds power of population density:

$$D \propto \rho^{\frac{2}{3}} \tag{2.2}$$

where D is the facility density and ρ the population density. This result shows very clearly that there is an economic advantage for increasing the population density, and therefore for cities. By increasing the population density, the number of facilities for serving the whole population equally well can be diminished. If we consider that global costs go up with the number of facilities, it is reasonable to limit the number of facilities.

The size of the population basins (the area of the Voronoi polygons) increases for less common, more specialised services. However, equation 2.2 remains valid. We can consider the different types of services as a hierarchy, where more specialised services are higher in the hierarchy. This idea is similar to Christaller's central place theory describing such a hierarchical organisation of the space for a network of cities, according to the level of specialisation the city is offering (Christaller, 1933/1980). However, Christaller (1933/1980) based his theory on the assumption of a homogeneous space with equal population density everywhere. This assumption is clearly against the statement in equation 2.2.

Another important issue for the economy is the presence of sufficient and well-educated people. The immediate availability of human resources is one of the factors for economic growth, and it is more probable to find the necessary resources in a city, simply because there are more people in a city.

It is difficult to say whether modern cities exist only for economic reasons. But there are some very good economic reasons for the existence of cities.

2.2 Why do we need urban analysis?

A city is basically a big gathering of people. Each person has a set of activities making of the city a complex system of actions and interactions. These activities may enter in conflict with other activities and interfere with the environment. Modern cities are important sources of air pollution, noise, garbage, water and soil pollution. Health problems may be the consequence. There is also an increase of stress for the urban population due to the urban lifestyle in general and the daily course to growth of the globalised economy. Land consumption is the most immediate result of city growth.

The age pyramid in figure 2.4 does not show a higher life expectancy for the population living in rural zones, the contrary seem to be the case at first sight. But the age pyramid shows very clearly the preference of families with children for rural areas. This fact may underline the widespread opinion of a higher life quality in rural areas especially for children. It shows also that the young population is attracted by urban zones, probably due to economic reasons and studies. Migration between urban and rural zones, better access to health services in urban regions and eventually differences in life expectancy due to pollution or similar make the age pyramid itself a complex object to study. It is a typical example in urban geography where most of the time several contradictory mechanisms are present at the same time.

The city is a self-organised system where each individual tries to optimise his personal life. Part of this optimisation is the choice of the work or the place where to live. These choices depend on several factors. For example, the choice of the location of home will depend on the work, but also on other members in the same household, financial resources, personal preferences, the social network, the transportation network for going to work and for accessing other services and so on. Financial resources and mobility are important factors in such a choice. If the financial resources are limited, the choice where to live is smaller. Very often, people make a longer way to work for having a higher quality of home. This is possible because the prices for homes decrease with the distance to a city, and mobility is available at a reasonable price. In fact, mobility is only limited by time consumption and cost. In developed countries, the cost for a car is not very high. This offers to the individual a big flexibility in their location choices, with the downside of traffic jams in densely populated places, along with air pollution and noise. An increase in the cost for having a car would help to solve this problem. However, a general increase of living cost would be the result, and people

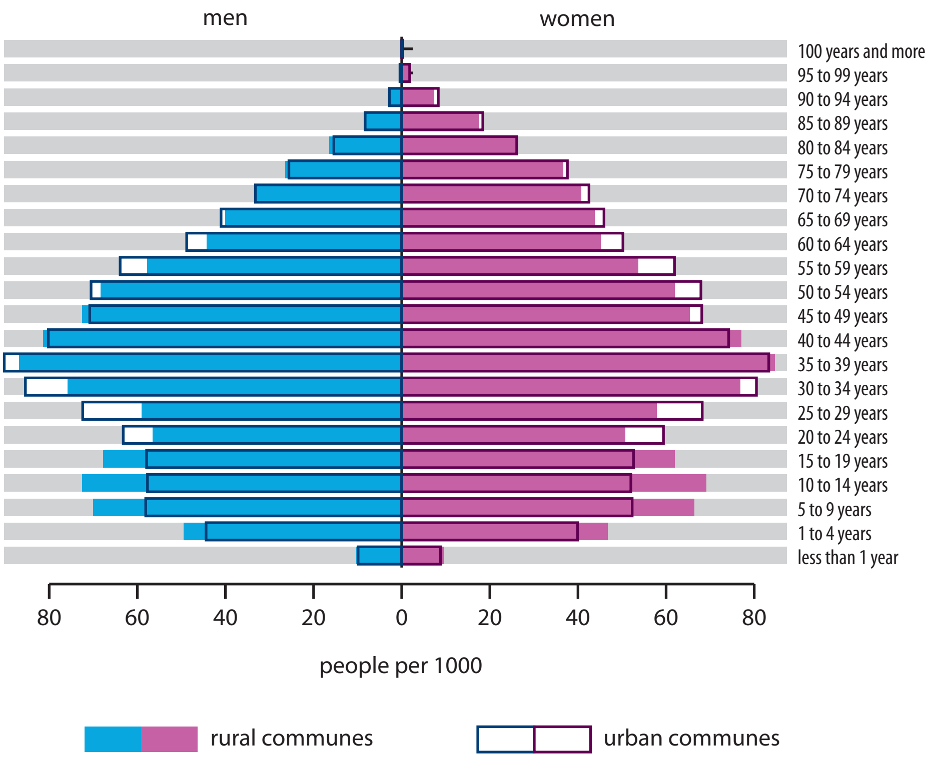

Figure 2.4: Age pyramid for rural and urban communes in Switzerland (2000).

with low financial resources would even have less money; social problems would be the result. For economy, a low cost for mobility is also interesting, as exchanging goods is essential for the functioning of each economic system.

The city is a complex system where the self-organisation does not lead to a sustainable state. A city cannot control itself. Planning and control are therefore needed. The urban analysis is the first step for understanding the processes at work in a city, and helps the urban planner and geographer in finding appropriate solutions for the urban development. The quantitative urban analysis tries to analyse data, to establish models and simulations for understanding the system and eventually to test effects of a plan. Urban infrastructure is very expensive. A careful planning is hence needed. Urban planners need reliable models and simulations for making their decisions. Urban analysis is very important in the context of the current environmental problems especially in metropolitan areas all over the world.

2.3 Quantitative urban analysis

The use of quantitative methods in urban geography has a long tradition, but it is also a challenging domain as the researcher is faced to a complex system with multiple interactions and many serious methodological problems (see e.g. Bernstein, Ferber, & Bernstein, 1973). From the first attempts for modelling the economic nature of cities to the simulation of complex urban phenomena, a lot of progress has been done and our understanding of the urban system has greatly improved. The emergent character of urban phenomena has been recognised as being an important key to the understanding of how cities are structured (see e.g. Pumain, 2006). However, despite the great progress achieved over the last decades, many processes and phenomena are still insufficiently understood.

This section gives a short overview of some interesting works in the field of quantitative urban analysis. Nearly two centuries ago, Von Thünen (1826/1986) developed a model of spatial economics connecting space and rents where he predicted a circular land use pattern determined by the ability of the actors to pay the rent and of the benefit they could obtain. His approach is remarkable as he developed the basis of the marginal productivity theory in a clear and rigorous way. He predicts the land rent R as follows:

$$R = Y(p - c) - YFm \tag{2.3}$$

where Y is the yield per unit of land, p the market price per unit of commodity, c the production expenses for the same unit of commodity, F the freight rate and m the distance to the market where the product is sold.

The urban field has been studies through the density gradient from centre to periphery as early as 1892 by Bleicher (1892) and later by Clark (1951).

The statistical analysis of the urban population shows different negative exponential density gradients from centre to periphery for different cities around the world (Clark, 1951). Only over 15 years later, Edmonston and Davies (1978) tried to find a statistical interpretation of this gradient as a measure of central tendency.

Other statistical observations involving urban areas comprise the structure of the system of cities, especially the hierarchy between the cities. A remarkable fact found in all countries of the world, independently of the culture or the epoch, is that the product of the population P of a city by its rank r in the hierarchy is constant:

$$P_i \cdot r_i = K \tag{2.4}$$

where P_i is the population of the i-th city, and r_i its rank. According to Pumain (2006), this relationship has been remarked as early as the 19th century and described formally by Auerbach (1913) nearly one century ago! Other authors describe also this law (Lotka, 1924, 1926, 1941; Goodrich, 1926) and links with statistical distributions are established (Singer, 1936; Gibrat, 1931). Today, this law is known as *rank-size rule* or *Zipf's law* according to the American linguist and philologist George K. Zipf (Zipf, 1941, 1949). Zipf worked initially on the frequency of words in a text (Zipf, 1935).

Another interesting quantitative study related to cities has been done by Gibrat (1931). He showed that a lognormal distribution of the city size can be explained by the independence of the population growth rate from the city size; this means that big cities do not grow faster than small ones. This "Gibrat's" law has been tested successfully in several cases (e.g. Robson, 1973; Pumain, 1982; Guérin-Pace, 1993; Clemente, Gonzáles-Val, & Olloqui, 2010). However, there is still some doubt about the validity of this "law", as in some cases, it could not be verified. Rozenfeld et al. (2008) show for different urban and regional systems (Great Britain, United States and Africa) that population growth deviates from Gibrat's law and that the growth rate decreases with population size.

Also in the 1930's, Christaller (1933/1980) elaborated his central place theory trying to explain the number, size and location of populated places in space. This theory explains the hierarchy in a system of cities (the central places), and is complementary to the city size distribution shown by Gibrat (1931) or later by Zipf (1949).

The functional differences between cities has been considered already in the 1920's by Aurousseau (1921) for American cities. The typology was based on qualitative descriptions, quantitative classifications have been used only later (e.g. Pumain & Saint-Julien, 1978). The functional diversity between cities integrates well with the hierarchy of cities and the concept of the system of cities (Pumain, 2006).

The urban hierarchy and the urban structure itself are emerging properties of a complex system with multiple interactions (Pumain, 2006; Batty, 2005). Such systems can typically be studied using a bottom-up approach: the small constituting elements are relatively simple, but a complex pattern can emerge through multiple interactions. Cellular automata have widely been used for studying the evolution of cities and land use (e.g. Tobler, 1979; Torrens, 2000; Batty, 2005; Benenson & Torrens, 2004; Benenson, Aronovich, & Noam, 2005; Marceau, Ménard, & Moreno, 2008; White, 1997; Holm & Sanders, 2001; Al-Kheder, Wang, & Shan, 2008; Pinto, Antunes, & Roca, 2009). Cellular automata have been used widely in urban geography since the 1990's, but the concept itself is much older; it has been developed in the 1940's by Stanislaw Ulam and John von Neumann. The work of Wolfram (2002) contains a very complete empirical and systematic study of computational systems such as cellular automata. However, despite the wide variety of models, the predictive capacity of cellular automata for urban systems seems to be limited.

The geometric structure of cities has been studies using fractal geometry (e.g. Frankhauser, 1994; Batty & Longley, 1994). It is known that urban systems have some self-similar properties.

Location theory, based on Von Thünen's work, allows to demonstrate how different kinds of industry can locate between the market and primary resources (Batty, 2005; Isard, 1956). The connection between location theory and Christaller's central place theory seem to provide the necessary framework for a more comprehensive understanding on how cities are structured and how they evolve. These deterministic models assumed that essentially every existing system, including cities, evolve toward a stable equilibrium. Nobody imagined that there could exist a dynamic system that is stable and unpredictable (chaotic)(Gleick, 2008). Either, a system is unstable and it evolves rapidly into a stable equilibrium, or it is already stable; this was the base of the deterministic view of the world until the 1960's. But: cities are not deterministic, and predicting the evolution of a city is not an easy matter.

Cities are complex, dynamic but organised systems. An urban theory not accounting for the city dynamics will just be descriptive and will not be of great help in the understanding of the processes reining the evolution of cities. Dealing with such highly non-linear complex and dynamic systems is just about a mathematical nightmare. And cities are 'far-from-equilibrium' systems, as all human systems (Batty, 2005); they are changing all the time. An additional difficulty in modelling cities is the availability (or non-availability) of data. If some data are available for a specific phenomenon, most of these data sources are available only at an aggregated level. The first problem would then be the disaggregation of these data, or the development of methods working with aggregated data. Both of them are non trivial problems.

Quantitative data analysis has a quite long tradition in physical geography, and there is a plethora of studies dealing with analysis and modelling of spatial environmental data. In the field of human geography in general and urban geography in particular, quantitative geography experienced a decline in popularity between the early 1980s and the mid-1990s (Johnston, 1997; Graham, 1997; Fotheringham, Brundson, & Charlton, 2000). The reasons for this decline are difficult to find, but the fact that human and urban geography is traditionally a social science played certainly a role. Social sciences, and hence also urban geography deal mainly with complex systems. Such systems are usually difficult to characterise and to model, and there may some chaotic behaviour involved. The traditional deterministic approach to modelling, where each system can be perfectly modelled if enough parameters are included, is not able to assess those complex systems. As a result, human geographers dismissed the quantitative approach for a more qualitative one, whereas physical geographers were not confronted to *'the madness of people'* [1] and continued integrating the quantitative models in their research. During the 1980s and 1990s, the knowledge and also the computation power to deal with such complex systems was not available. The upcoming of cheap and powerful personal computers opened the way for new simulation approaches. The domain of GIScience became more mature as the base functions were widely available in GIS software and the efforts could be put more and more into the methodology. Powerful software systems became available for analysing spatial datasets. With the spread of the World Wide Web, our understanding about complex networks and other complex systems did increase (see e.g. Barabási, 2003). This new achievements did open the way to new approaches in quantitative geography, but also in other research fields. The knowledge how to deal with non-linear complex and dynamic systems did increase and find its way into geographical analysis.

Another challenge in human and urban geography is the availability of data. Usually, only very limited data is available, and it is virtually impossible to design real world experiences. However, through new sensor technology and a world more and more linked to the Web, more data become available. New methods have to be designed for dealing with this new, sometimes very big quantity of data. Urban geography is currently evolving from a domain where reliable data were difficult to obtain to a domain where a wide variety of different data with different resolutions have to be treated. Spatial data mining provides techniques that will be used more and more for quantitative urban analysis.

Urban analysis can be done using qualitative and/or quantitative methods. Quantitative methods rely on data available at a given spatial level and at a given moment in time. Quantitative urban analysis is part of the more

[1] Newton once said that *'modelling the madness of people is more difficult than the motion of planets'* (Bouchaud, 2008)

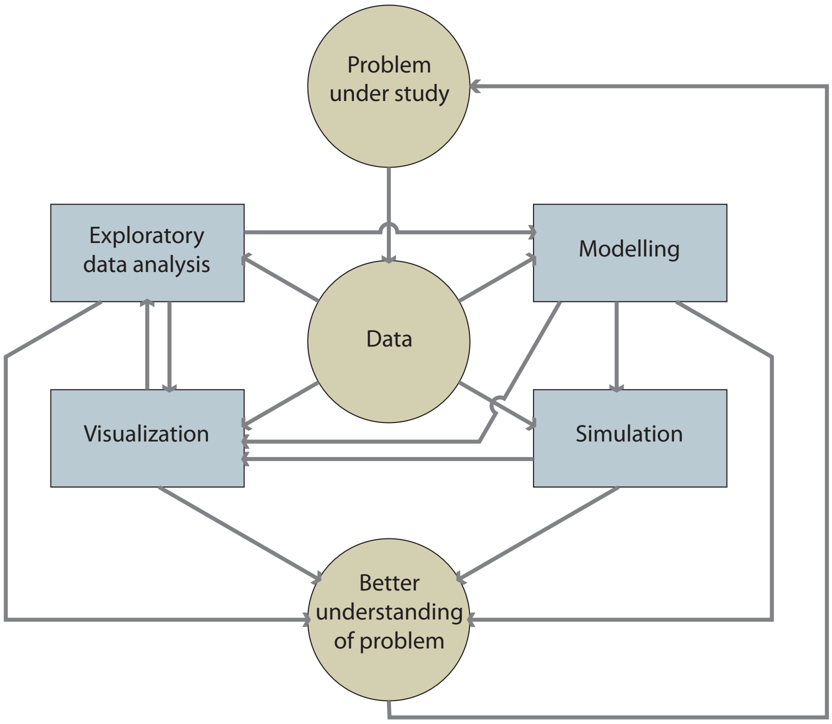

Figure 2.5: From problem to better understanding and back: the spatial data analysis workflow

general quantitative geography which consists, according to Fotheringham et al. (2000), *"of one or more of the following activities: the analysis of numerical spatial data; the development of spatial theory; and the construction and testing of mathematical models of spatial processes"*. One should probably include simulation of complex spatial systems, as they have gained in importance over the last decade.

Quantitative methods can be grouped as follows:

- *ESDA* is the first stage of an analysis. It enables the researcher to familiarise himself with the available dataset. The data is plotted and/or mapped, and tasks like feature selection, feature extraction and cluster analysis can be conducted.
- *Modelling* relies generally upon some theories and tries to simplify the reality in order to understand thoroughly this simplified model of the reality. Traditionally, modelling is a classical 'top-down' approach.
- *Simulation* tries to reproduce the reality as a sort of virtual reality,

generally using some iterative computational procedure. Usually, simulation is typically a 'bottom-up' approach.

- *Visualisation* is involved in all analysis steps and allows the representation of original data and of computed intermediary or final results. It can serve as the basis for descriptive tasks and for establishing new theories.

The current trend in Geographic Information Science (GISc) is towards an integration of all these topics into a system for interactive analysis and visualisation of spatial and spatio-temporal data; this is done in the field of geovisual analytics (Andrienko et al., 2007). User-friendly geovisual analytics systems can help decision makers directly in their daily work. Efficient methods for analysing high-dimensional spatio-temporal data are required for such a system. Machine learning algorithms can be very efficient in this context (see e.g. Kanevski & Maignan, 2004; Kanevski, 2008; Kanevski, Foresti, et al., 2009; Kanevski, Podznoukhov, & Timonin, 2009). It is important to have accurate results easy to interpret, with powerful visualisation methods. Prototype examples are the real-time topo-climatic mapping of Switzerland (`http://www.geokernels.org/services/meteo`) or the avalanche danger forecasting (Foresti et al., 2008).

2.4 Beyond the MAUP

The Modifiable Area Unit Problem (MAUP) is a potential source of bias in statistical analysis involving aggregated data. The issue has been first described by Gehlke and Biehl (1934); the authors observed variations in the correlation coefficient for different levels of aggregation. The geographic units become typically more correlated when they are aggregated. They observed also that different ways of grouping together the smaller units can have a considerable influence on the correlation coefficient.

The MAUP occurs in cases where spatial point data are aggregated into geographic regions. Consider for example the population in the agglomeration of Lausanne, with around 300'000 people reported in year 2000. Census data is typically aggregated to administrative levels, such as communes. Such administrative units are in every case somehow arbitrary delimitations and statistical and geographical analysis will be influenced by the way the units are defined. The MAUP can be decomposed into two issues: scale effects and zoning effects (Openshaw, 1984b; Ruddell & Wentz, 2009). Scale defines the number of aggregated units, while the zoning refers to the spatial delimitation of a given number of units. Figure 2.6 illustrates the effect of delimiting arbitrarily a geographic region on the mean and variance values. The depicted values could for example be the population density for each of

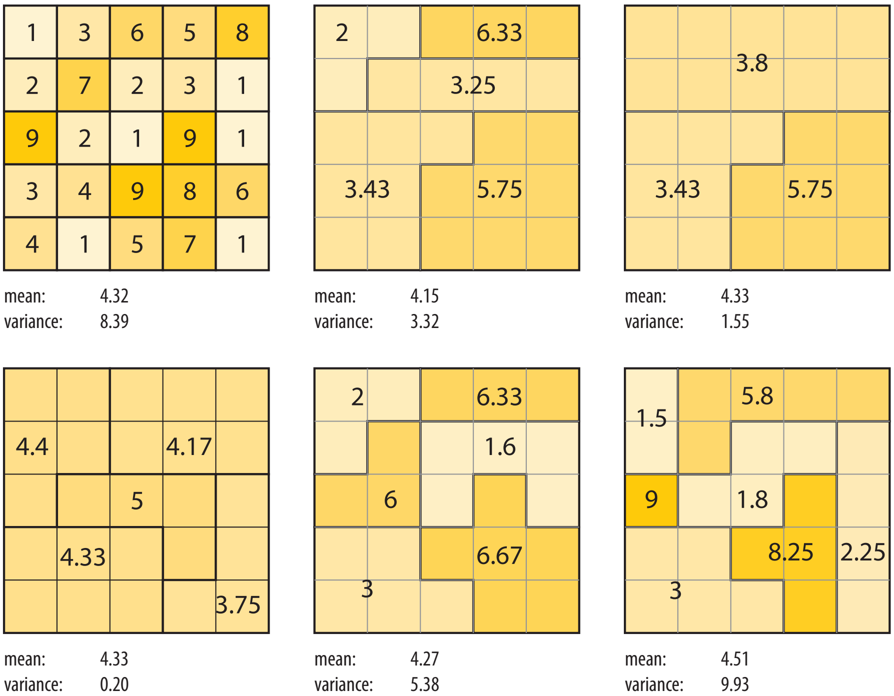

Figure 2.6: The effect of aggregating geographic data.

the geographic units. The colours show the effect of the MAUP on a choropleth map. Important differences can be seen in this simple example; the mean value varies between 4.15 and 4.51, while the variance ranges between 0.2 and 9.93. Openshaw and Taylor (1979) showed that it was possible to obtain almost any correlation coefficient between voting behaviour and age in Iowa by aggregating the counties in a different way. The definition of the geographic units is therefore an important factor to be taken into account.

The MAUP has been extensively discussed in the literature (e.g. Openshaw & Taylor, 1979, 1981; Openshaw, 1984b, 1984a; Fotheringham & Wong, 1991; Unwin, 1996; Reynolds, 1998; Nakaya, 2000). However, it is still an important issue in all studies related to space, and in practice, it is often neglected. In urban geography for instance, the existing administrative boundaries are generally considered for performing statistical analysis and comparison between regions. This is due to several factors:

- Census data are usually available at the level of the existing administrative units.

- Only few generic and practical methods for dealing with the MAUP exist, and they are often unknown to the urban geographer.

- Urban geographers are used to work with discrete units instead of continuous fields, simplifying considerably the complexity of the analysis.

Let's take the example of people having a higher eduction. It is impossible to count the number of such people at one specific point. Indeed, the probability to find such a person at one given exact point is extremely low. It is necessary to define some geographic region in which the wanted quantity can be counted. The most detailed data would be to dispose of a set of locations at which a person with higher education can be found (typically the centre of the house in which this person is living would then be given). However, such data is already aggregated to the level of the house in which several people having a higher education might live. And in most cases, data at such a detailed level is not available for privacy reasons. It is therefore necessary to consider the MAUP in studies implying the spatial dimension.

This thesis tries to show some methods applicable to urban geography for dealing with spatial and spatiotemporal data while taking into account scale and zoning effects. It considers namely the following questions:

1. Does the use of **spatially continuous data** allow a better analysis and representation of the information at hand? Continuous data is not aggregated to arbitrary spatial units but present rather an expected density of the phenomenon under study at a given point. Very often, socio-economic data is not available as continuous data and have to be estimated based on some aggregated data. Which methods can be used for making data continuous? What is the accuracy of such an estimation?

2. **Scale** is an important issue in geography and in urban studies. The analysis of a phenomenon may give different results if conducted at a different scale. Some information or relationships can only be detected at a given scale. However, there are currently no methods for finding the appropriate scale of analysis or representation, and only few methods exist for analysing a phenomenon at multiple scales. An important research question is therefore how to find a good scale for studying a given phenomenon. Can we detect automatically the best scale? Which methods allow conducting multi-scale analysis? Is it sufficient to find an appropriate scale and use classical methods, or are adapted methods needed?

3. The two previous questions on spatially continuous data and scale issues raise the question on the availability of sufficiently precise and high-resolution data. Modern simulation approaches, especially micro-simulation, need data at an individual level. However, usually, such data is not available. It is therefore important to consider issues related to **disaggregation of data**. Several variants of this issue are known.

It can concern the change of the spatial resolution. Very often, it is also a matter of downscaling of data. In geostatistics, this issue is known as **change of support**. In the context of urban geography, this problem has not been studied to a great extent. However, it is important to know if some given dataset can be used at a given scale. Can the spatial support of the dataset be changed without loosing the characteristics of the phenomenon under study? Can new information be detected after a change of support? These questions are very important as they give indications about how useful methods for analysing and visualising continuous and multi-scale data are.

4. **Visualisation** methods are crucial as they give an easy access to the result of an analysis. As such, they deserve special consideration. Spatio-temporal and multi-scale analysis need sophisticated and often interactive and dynamic visualisation tools. What kind of visualisation method is adapted to complex geographic information? How can different visualisation methods help in accessing the information extracted by different analysis methods? Are new visualisation techniques needed, or should existing methods be adapted?

These questions are fundamental in urban geography, and imply a wide variety of fields in quantitative geography. Of course, only some aspects can be treated in this thesis. However, as these questions are essential, it is important to analyse them from different perspectives. The following chapters try to find some answers to these questions; methods are described and studied for advanced analysis and visualisation of spatio-temporal and multi-scale data related to socio-economic and urban phenomena.

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Chapter 3

Analysis of urban structures and dynamics

An urban area is an area with a high density of structures created by humans, and is the opposite of a rural area. According to this simple definition, urban areas can be defined simply using the density of one or several parameters, e.g. population density or density of buildings. Generally, a settlement must have a minimal size in order to be accepted as an urban area; rural villages are then not considered as urban.

But urban geography is not only about densities. There are also the socio-economic structure of the population, the presence or absence of firms, flows of persons and goods, interactions and so on. Analysing an urban area is more complex than only mapping some densities. There are also well established theories and models which can, or should, be verified using quantitative methods. In this chapter, we are going to analyse three different aspects of urban areas:

1. The first analysis is an attempt to define the extent of the urban area. This is necessary as we need to have a clear and systemic definition in order to be able to study the 'content' of this delimited zone. Not only the urban area is delimited, but also socio-economic clusters.

2. The different zones are analysed using Zipf's law, and an application of fractal geometry to the urban clusters is shown.

3. In a last step, the urban dynamics are analysed. This includes changes in socio-economic clusters, population growth rate and population evolution over the last 150 years. Urban dynamics at a daily scale, i.e. commuters going to work, are analysed in chapter 4 on urban simulation.

3.1 A word about the importance of scale

Scale is an important concern in urban analysis. It is crucial to define a scale while analysing an urban phenomenon; in classic urban geography, these scales are traditionally referred to as 'at the scale of the agglomeration', 'at the scale of a town', 'at the scale of the city quarter' and so on. Very often, the scale of analysis is already fixed by the data at hand. But when using high resolution data, we can fix the scale in a different manner as we can define analysis windows of a given size in continuous space. It is not possible anymore to 'just' take the aggregated statistics for some more or less arbitrarily, most often historically, defined administrative area, for example municipalities. The researcher needs to fix himself a size for his analysis window, and he must determine at which scales the phenomenon under study can be analysed.

Figures 3.1 and 3.2 show both the population for the agglomeration of Lausanne (see also map 4 in section 5.4 of chapter 5). But people typically are not distributed equally inside a commune; they are usually concentrated in a quite small part of the territory. The city of Lausanne is an interesting case: almost half of the territory is not inhabited (in the north of the city), but the overall density of the city remains important. The population density map based on the administrative units is somewhat biased due to this fact (see also section 2.4 in chapter 2, especially figure 2.6). It is possible to represent these data in a spatially continuous field; section 5.1 in chapter 5 discusses this possibility. Such a representation accounts for a better independence between the representation and analysis scale.

The analysis of aggregated data sources is a well-known and long-standing problem in spatial analysis, also referred to as the 'modifiable areal unit problem' or the 'ecological fallacy' (Openshaw, 1984; Unwin, 1996; King, Rosen, & Tanner, 2004).

3.2 Defining the urban area

In urban geography, defining the area to analyse is the first step and not the most simple one. Urban agglomerations are not defined the same way at different places over the world. In order to have statistically comparable urban areas, it is important to have a systemic method that can be applied for a large region and in different contexts. The definition of the urban area will have a considerable effect on the results of a statistical or spatial analysis. Uchida and Nelson (2008) describe for example the problem of comparing the share of population living in urban areas over all countries of the world. The authors focus on the issues when working with cross-country data compiled by the United Nations and recognise as main problem how to measure urban concentration in a consistent and systemic way. The

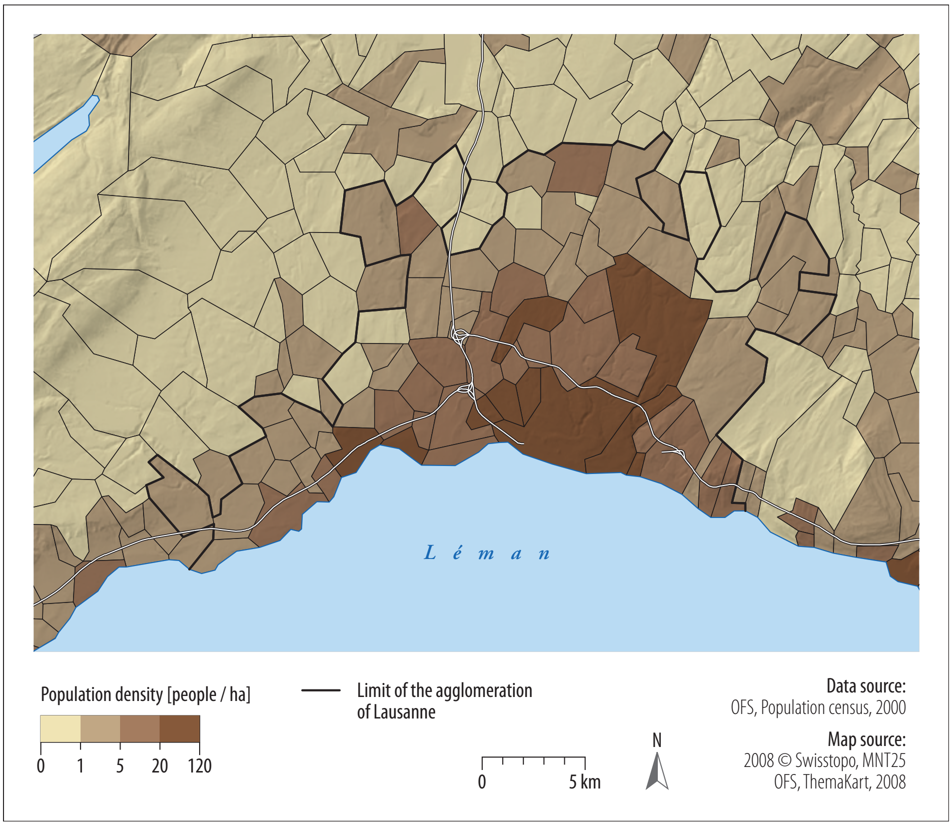

Figure 3.1: Population of the municipalities around Lausanne

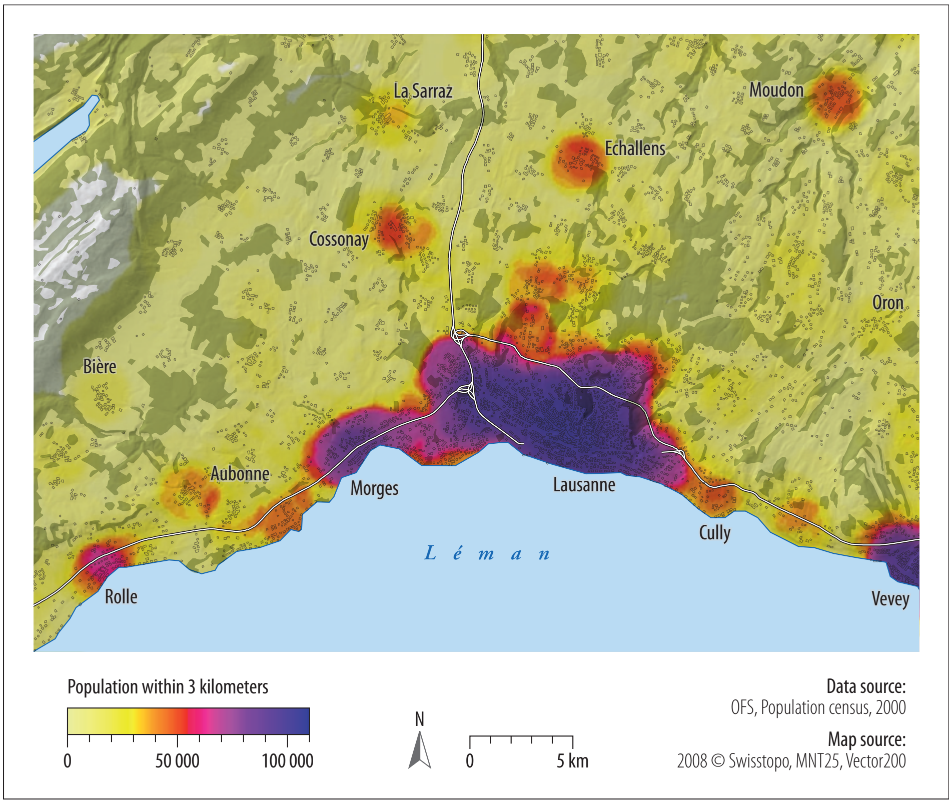

Figure 3.2: Population in the agglomeration of Lausanne

definition of what is urban and what is rural strongly influences the result; analysis of the resulting data is only of limited interest if there is no systemic way for defining urban areas. The agglomeration index proposed by Uchida and Nelson (2008) takes into account the population density, the size of the population in the central city of the agglomeration, and the travel time to the centre. However, it does not define what is an urban agglomeration *per se*. The main problem is how to define urban areas in a consistent and systemic way. Administrative units, like municipalities, are of little help in doing so, as they are more or less arbitrary (or rather historic) delimitations of space.

Traditionally, urban agglomerations are defined analytically using several statistical criteria, generally based on the smallest administrative units. Among different countries, the definition varies, and there are not necessarily all data available. As an example, in Switzerland, the statistical criteria are the following (Schuler, Dessemontet, & Joye, 2005):

- Agglomerations are continuous areas of several municipalities with a total of at least 20'000 inhabitants.
- Each agglomerations has a central zone consisting of a central city and optionally other municipalities. Each of these municipalities must have at least 2000 working places and at least 85 working places for 100 working inhabitants. They must also either have 1/6 of the working population commuting to the central city, or being connected to the central city through a continuously built zone, or being a neighbour.
- A municipality not belonging to the central zone is part of an agglomeration if:
  - at least 1/6 of the active population is working in the central city and
  - at least 3 of the following five criteria are met:
    1. Continuously built zone with the central city; the distance between two built zones (agriculture, forest) must not exceed 200 meters.
    2. The sum of inhabitants and working places per hectare (only inhabited and agricultural land without alpine pastures are considered) is bigger than 10.
    3. The population growth over the last 10 years is more than 10 percents greater than the mean of the whole country. This criterion is only valid for municipalities which do not yet belong to an agglomerations; for municipalities which already belong to an agglomeration, this criteria is always considered as being met.

4. At least 1/3 of the active population is working in the central city. Municipalities neighbouring two agglomerations fulfil this criterion also if at least 40% of the active population works in one of the two central cities and if for each of the two central cities, at least 1/6 of the active population is commuting to.
5. The share of the population working in agriculture does not exceed twice the share of the average for the whole country.

This definition, as other similar methods employed for the delimitation of urban areas, is based on the attempt to capture the notion of the city as a functional economic region, and some experience is used to establish the criteria. The definition is complex and is not suitable for automatic delimitation. Additionally, it is quite difficult to compute and needs a fair amount of time and data available. This availability may be guaranteed in countries like Switzerland, but are probably not in other contexts. And it is not sure whether this definition will produce satisfactory results in a completely different context. Another short-come is that it is based on the municipalities which is in our opinion not a suitable spatial delimitation. As some of the statistical data may not be available at some time intervals, it is also difficult to study the evolution of urban agglomerations in time.

Another well known problem in statistical analysis of aggregated data is the scale at which the data have been acquired. Considering a given phenomenon at an appropriate scale of information will allow the identification of processes at different locations; the level of detail is an important characteristic of a geographical description (Ruddell & Wentz, 2009). The statistical challenges related to the delineation of zones and the use of aggregated data are known for a long time (e.g. Gehlke & Biehl, 1934) and are referred to as the *"Modifiable Area Unit Problem"* (Openshaw, 1984).

3.2.1 The percolation algorithm

In recent years, a considerable amount of work has been done on how to define urban areas and how these different definitions affect the statistical distributions of urban activity (Rozenfeld et al., 2008; Gabaix, 1999; Gabaix & Ioannides, 2004).

The *"City Clustering Algorithm"* recently introduced in Rozenfeld et al. (2008) allows the delimitation of urban clusters in a simple and automatic way based solely on population distribution. The algorithm requires population data on a regular grid. An urban cluster is defined as a continuous area connected by nonzero population cells. The only parameter to be defined is the grid size.

Cities can be seen as clusters of population in space. If we cover the entire study region with a fine geographical grid with square cells, the cities

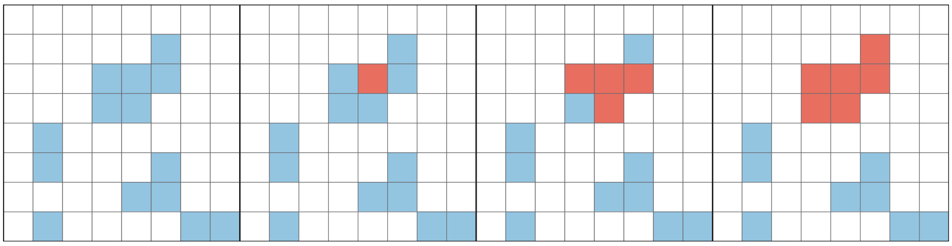

Figure 3.3: Illustration of the operation of the CCA. Populated cells are blue, unpopulated white. Red cells belong to the urban cluster being created. This process is repeated for every populated cell that is not already part of the cluster.

are zones of adjacent populated cells. We can see the region as a raster image as used frequently in GIS, where the value of the pixel cell is equal to the population located inside this cell. An urban cluster can be defined in such a population raster image as zones of connected cells with non-zero population values. The CCA is based on this simple definition of urban zones (Rozenfeld et al., 2008).

Figure 3.3 shows the way the CCA operates. The algorithm starts delimiting a new cluster at an arbitrary nonzero population cell (depicted in blue) and includes iteratively all nearest neighbours with nonzero population cells. The cluster (depicted in red) is defined if there are no more neighbouring nonzero cells. This procedure is repeated for all nonzero population cells which are not yet included in a cluster. This technique is also known as the 'burning algorithm' in forest fire dynamics (Stauffer & Aharony, 1992). The type of the neighbourhood can be defined in different ways. It is possible to use the *"Von Neumann neighbourhood"* that includes the *"nearest neighbours"* comprising the four cells sharing an edge with the central cell. Another option is to use the *"Moore neighbourhood"* that includes the *"next nearest neighbours"* comprising the eight cells sharing at least one common point with the central cell.

The population clusters can also be studied in the framework of percolation theory. A "city" would then be defined as a space where population can flow freely from one point to another. In practice, this would mean that a person can relocate to another point in this space without leaving a continuum. We could call this phenomenon *"urban percolation"*. For this reason, we will also use the term of percolation algorithm instead of City Clustering Algorithm.

Of course, the scale (the grid cell size) is an important issue in this context. When the cell size of the used grid becomes bigger, very big clusters can result from the algorithm. Mobility in space is limited by the time available and by the speed of the used mean of transportation. It would then be conceptually possible to define the scale for a given mean of transporta-

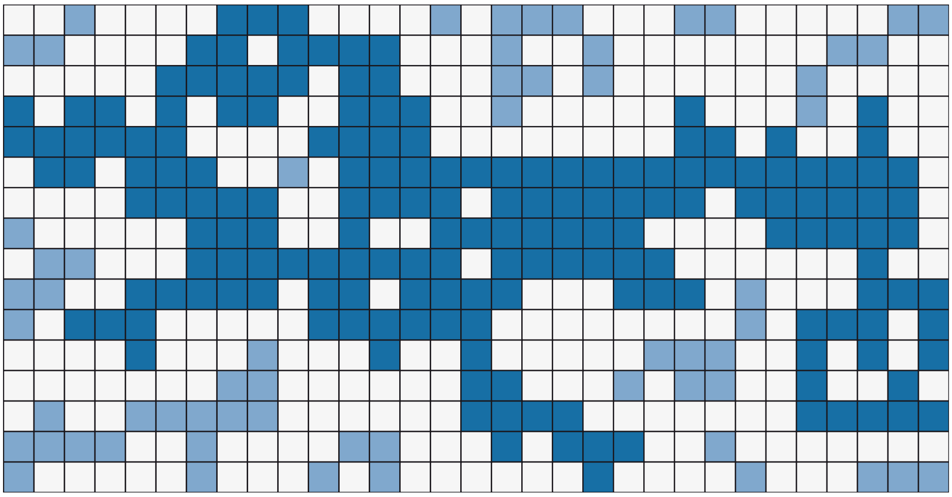

Figure 3.4: An example of a lattice for the study of the bond percolation. Occupied cells are depicted in blue. The dark blue cluster extends from left to right and top to left.

tion, and for a given type of mobility (mobility between home and work, accessibility to needed services, commercial contacts, etc.).

In a regular lattice like the one in figure 3.4, lets denote p the fraction of occupied (blue) cells. If there is a cluster extending from left to right and top to bottom of the lattice, we say that this cluster percolates through the system (like water percolates through a coffee machine) (Stauffer & Aharony, 1992); a continuous path of nearest neighbours exists from one side to another of the lattice. The critical fraction p_c where for the first time occurs a percolating cluster is called the *"percolation threshold"*. Percolation theory studies the clusters formed in a very large lattice where every cell (site) is occupied randomly with probability p, and the percolation threshold p_c is an important critical phenomenon.

The CCA aka percolation algorithm depends obviously on the cell size of the regular grid. This parameter allows the study of urban agglomerations at different scales. In reality, the minimum cell size will generally be defined by the availability of the original data on population. There is no maximum for the cell size, except of course the overall extent of the study region. When increasing the grid size, we get ultimately at a given moment a population cluster spanning the whole region. In analogy to the percolation theory, we could call this grid cell size corresponding to the scale of analysis the *"urban percolation threshold"*. Figure 3.7 shows three different scales for the urban clusters of Switzerland. The urban population threshold is reached at a scale of 500 metres.

Depending on the original population data, the percolation algorithm may yield many very small clusters with almost no population inside. These

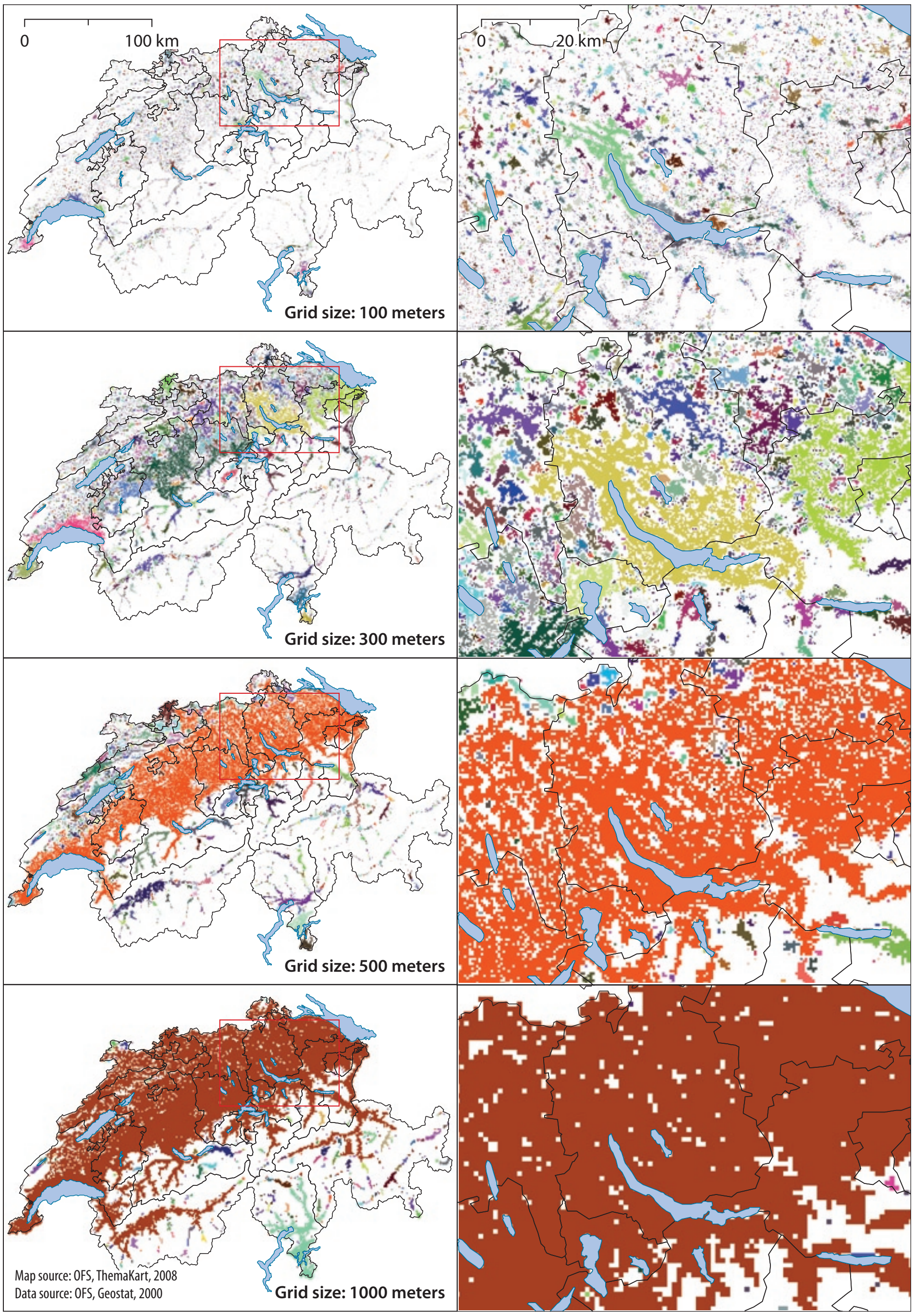

Figure 3.5: Urban clusters for Switzerland for four different grid cell sizes, at two different scales. The right image series is centred on Zurich (at the Northern end of the lake of Zurich).

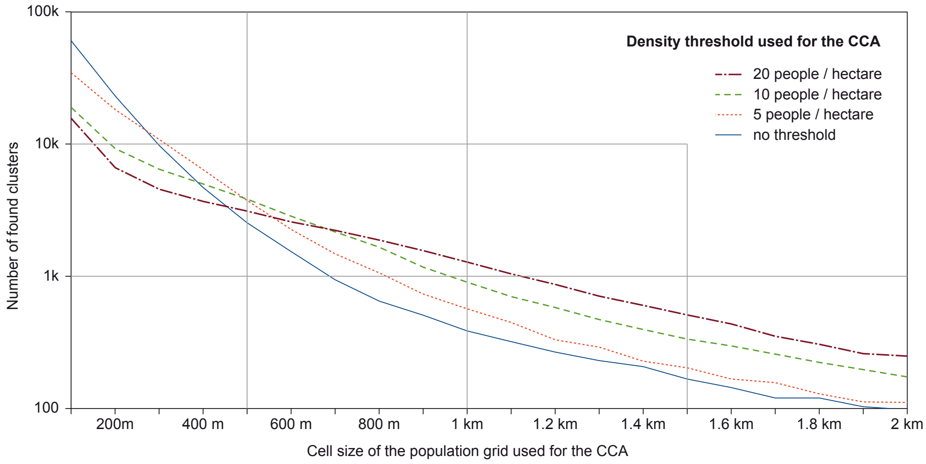

Figure 3.6: The impact of the cell size and the density threshold on the number of clusters found.

clusters may not be relevant and can be eliminated. Two different approaches are possible. The first consists of taking into account only population cells with a value higher than a given threshold, e.g. 5, 10 or 20 people per hectare; this approach is equal to require a minimal population density for a population cell. The second is to retain only clusters with a total population bigger than a given value, for example 10'000 people. These two parameters are optional parameters and are not part of the definition proposed by Rozenfeld et al. (2008). However, they have been presented in Kaiser, Kanevski, and Da Cunha (submitted) and Kaiser, Kanevski, Da Cunha, and Timonin (2009).

Figure 3.6 shows the relation between the number of resulting clusters and the population density threshold for population data in Switzerland. When using small cell sizes for the population grid, the number of clusters decreases significantly by defining a density threshold. As the cell size increases, more clusters are found when using a density threshold. This behaviour is due to the fact that without threshold, cells with low population value are able to make a "bridge" between two clusters and therefore the total number of clusters decreases.

The density threshold is a functional threshold as it require a minimum functional value for our data under study. We will therefore speak of *"functional percolation"* when applying a functional threshold in the percolation algorithm. This simply means that the phenomenon under study must reach a given intensity for percolation being able to take place. In social sciences, this is a reasonable approach as there might be some phenomena which are found only once a critical density threshold has been exceeded. For example, this may be true for social conflicts where a given density of poor population might be an important factor.

We suggest here the use of the CCA for other variables than just population data which is straightforward. We will discuss an example application later.

The second optional parameter of the CCA is the minimum size for the clusters. It simply cuts the number of clusters at the lower end. It is mainly intended for visualisation purposes for removing very small or non relevant clusters; this may enhance the readability of the resulting map.

Figure 3.7 shows three different scales for the percolation algorithm, with two different sets of parameters. The left column presents the original, unfiltered data for population in Switzerland. As already seen in figure 3.5, the percolation threshold is at a grid resolution of 500 metres in this case. The right column shows the clusters defined with a density threshold of 10 people / hectare and only clusters bigger than 10'000 people are shown (this corresponds to the somewhat arbitrary minimum size of a city in Switzerland). When using the original, unfiltered data, many very small clusters cover virtually the whole country; the space appears to be very segmented at an analysis scale of 300 metres. The introduction of a density threshold and a minimal cluster size filters out such small clusters; the urban cluster at the cell size of 300 metres is close to the statistical definition of the urban agglomerations (figure 3.8). The statistically defined agglomerations make use of the administrative boundaries and contain also non populated regions, whereas the CCA concentrates on the populated regions only. Hence, the agglomerations in figure 3.8 appear bigger than the urban clusters from the CCA.

In the case of the unfiltered data in figure 3.7, the whole Swiss Plateau including the Lake Geneva region are connected together at a cell size of 500 metres. The main economic activity of Switzerland is located in this region and the biggest cities, Zurich, Basel and Geneva, are part of this cluster. At this scale, Switzerland can be considered as a unique metropole (the *"Swiss metropole"*). It is possible to travel from one end of Switzerland to another without leaving the same cluster. Using the filtered data, the percolation threshold occurs with a slightly coarser grid, at 700 metres cell size (not shown). When increasing the grid cell size, the global behaviour of the result using the filtered data is similar to the one using unfiltered data, except that the cell sizes for the filtered data are always slightly bigger.

Rozenfeld et al. (2008) have defined the urban clusters in the United Kingdom using the CCA with a grid cell size of 2.2 kilometres, and the delimitation of the metropolitan area of London seems to match fairly well. When applying this same cell size to the population in Switzerland, all the country is only one cluster. Thus, we can consider Switzerland as one metropole in international comparison.

The number of urban clusters decreases very quickly when increasing the grid cell sizes, up to a resolution of about 800 meters in the case of

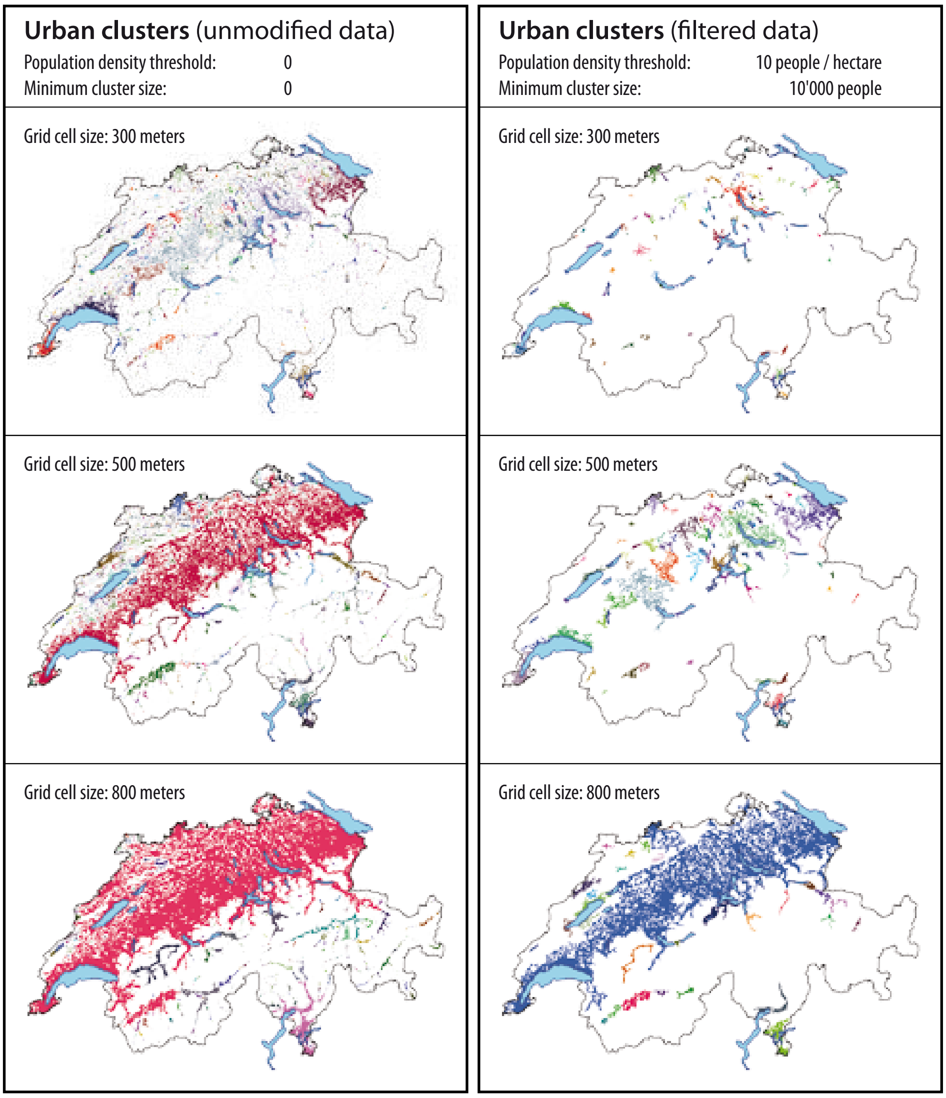

Figure 3.7: Population clusters for Switzerland with different grid cell sizes and two different sets of parameters for the population density and the minimal cluster size. Map source: SFSO, Geostat, 2000; Data source: SFSO, Geostat, Population census, 2000

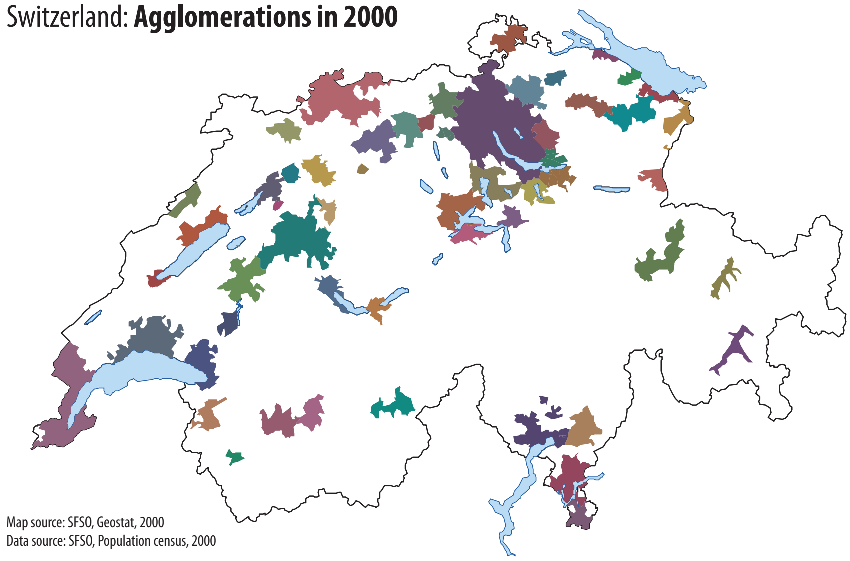

Figure 3.8: The agglomerations of Switzerland defined using the official statistical definition.

Switzerland (figure 3.9). As already seen, at the same scale, one big cluster (the *Swiss metropole*) emerges. The curve in figure 3.9 shows that this emergence starts already at a threshold of about 500 meters and the number of clusters is stable for cell sizes of more than 1000 meters. The number of clusters is very sensitive to scale below this threshold. The cell sizes of 300 to 500 meters, corresponding to the validity domain of the rank-size rule, are not specially marked in this plot.

3.2.2 Zipf's law for urban clusters of different scale

Zipf's law states that the size distributions of cities follow a power law with exponent -1. According to Soo (2005), it has been Auerbach (1913) who first proposed that the city size distribution follows a Pareto law of the type $y = Ax^{-\alpha}$, where x is the population size of a particular city, y the number of cities with populations greater than x, and A and α are constants ($\alpha > 0$). The contribution of Zipf (1949) was to propose that in the case of the city size distribution, the parameter α takes the value 1.

Zipf's law can be defined as follows for city sizes (Gabaix & Ioannides, 2004, p. 2344): let S_i denote the normalised size of city i (population of city i divided by the total urban population). City sizes satisfy Zipf's law if we have for large sizes S:

$$P(S_i > S) = \frac{a}{S^{\zeta}} \tag{3.1}$$

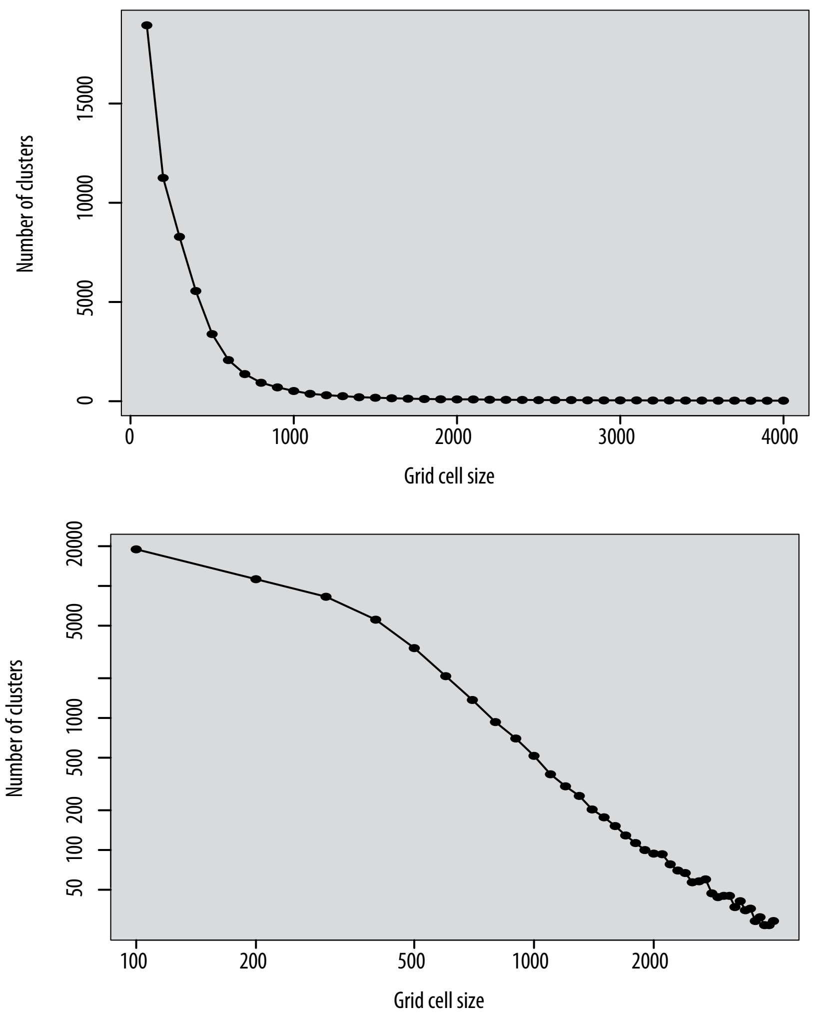

Figure 3.9: Number of clusters at different grid cell sizes (at bottom with log-log scale).

where a is a positive constant and $\zeta = 1$. Or, put in another way, the size of a city multiplied by the percentage of larger cites is constant. It has been shown by several authors that Zipf's law holds quite well for city sizes, at least for the upper tail of the distribution (Gabaix & Ioannides, 2004; Soo, 2005). Recent studies have shown that Zipf's law holds also for the lower tail of the city size distribution if the cities are correctly defined (Rozenfeld, Rybski, Gabaix, & Makse, 2009).

An approximation to Zipf's law is the rank-size rule. The rank of the biggest city is 1, for the second-largest city 2 and so on. It is then very easy to visualise the city size distribution by plotting the log of the rank against the log of the population. It is rather surprising to see a straight line with a slope of -1.

Figure 3.10 shows a rank-size plot for the Swiss agglomerations as defined by the official statistical definition and the urban clusters as defined by percolation with a grid cell size of 500 metres, a density threshold of 20 people/hectare and a minimum cluster size of 5'000 people. The resulting clusters are very similar to the urban clusters using the filtered data in figure 3.7. If we run a simple linear regression, we get a slope very close to -1, which is an expression of Zipf's law. The difference between the slopes of the two regressions is only minimal, but the fit for the small cities is better for the urban clusters issued from the CCA.

Figure 3.11 shows the rank-size plot for the urban clusters with four different grid cell sizes (using the same density threshold and minimum cluster size as for figure 3.10).

Figure 3.12 shows the slopes of the regression line for grid cell sizes between 100 and 1000 meters. Zipf's law can be verified only at cell sizes between 300 and 500 meters. For smaller cell sizes, the regression line slope is higher than -1, and with increasing cell size, it becomes smaller. This means that globally the hierarchical differences of the urban clusters are getting more pronounced with the increase of the grid cell size. However, the curve in figure 3.12 shows a break at a cell size of 700 to 800 meters. It is interesting to note that the resolution of 800 meters corresponds to the percolation threshold with the used values for the density threshold (20 people/hectare) and the minimum cluster size (5'000 people) (see also figure 3.7). The slope of the regression line drops at a cell size of 700 meters, just before percolation occurs. After percolation, the slope is only slightly different from the one for the cell size of 600 meters. However, due to percolation, one big cluster has emerged, and this cluster is an outlier in the rank-size plot (see figure 3.12).

3.2.3 Measuring the urban concentration using percolation

As already mentioned in the beginning of section 3.2, the definition of the urban area has a considerable effect on the results of statistical or spatial

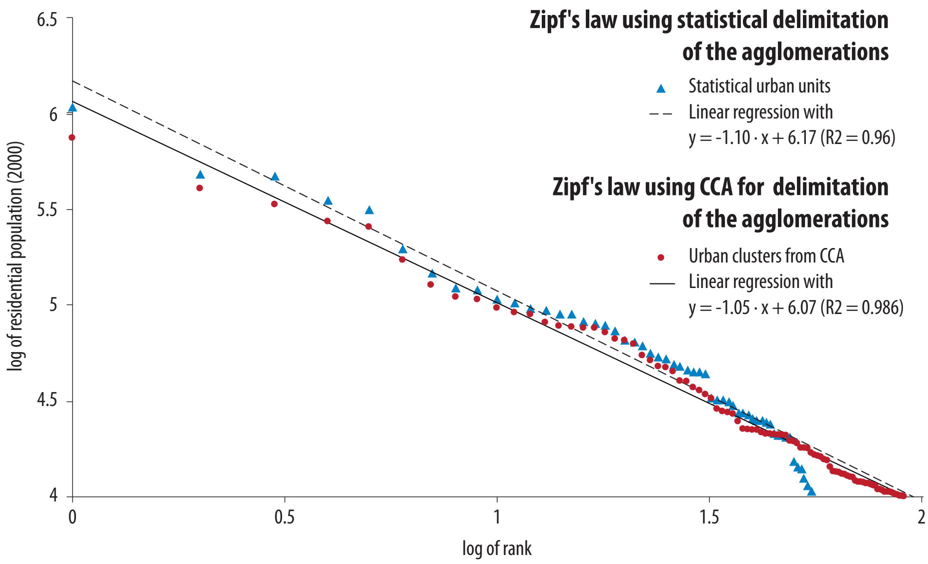

Figure 3.10: Zipf's law for the city sizes using the official statistical definition of Swiss agglomerations (blue triangles and dashed line), and using the percolation approach (red circles and solid line).
The part with the statistical delimitation comes from Da Cunha and Both (2004). The data source is the Population Census 2000 from the Swiss Federal Statistical Office (SFSO).

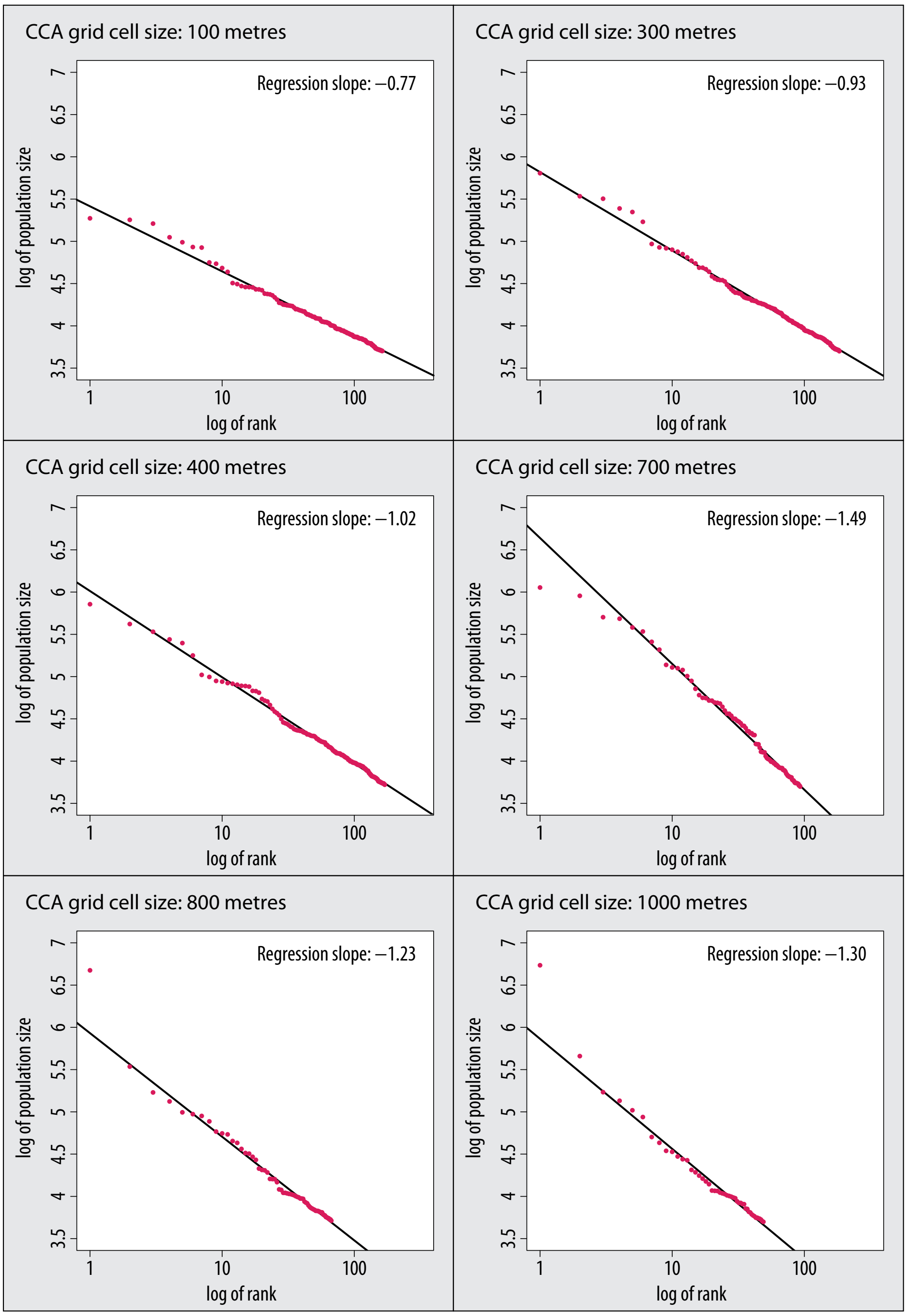

Figure 3.11: Rank-size plots for three different grid cell sizes for the percolation algorithm.

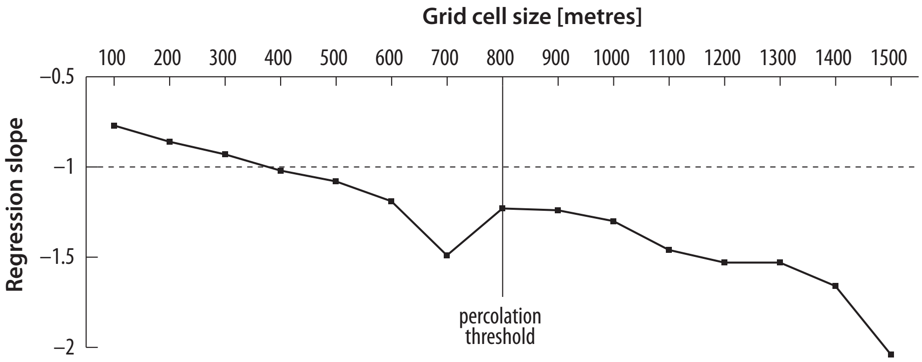

Figure 3.12: Slope of the regression line against the grid cell size for the percolation algorithm.

analysis. In this section, we will study the impact of the definition of the agglomerations using the percolation approach and the official definition of agglomerations for Switzerland.

The share of population living in an urban area is commonly used for analysing the urbanisation of a country. Urbanisation seems to be driven by economic growth (Da Cunha & Both, 2004; Satterthwaite, 2007). The proportion of the world's population living in an urban area has dramatically increased from 15% in 1900 to 50% in 2008. The definition of the urban area has been recognised to be one of the main challenges in analysing urbanisation. An *"agglomeration index"* has been proposed by Uchida and Nelson (2008) measuring the urban concentration of a nation using three parameters: the population density, the presence of a main urban centre and the travel time to this urban centre. This agglomeration index should remove discrepancies between the definitions of urban areas across different countries. The CCA as a simple but systemic definition for urban areas can also serve as a basis for measuring the urban concentration. It is straightforward to compute the ratio of population living in an urban area (figure 3.13). A population cartogram provides a way to map the spatial distribution of the urban areas in a country. As already seen, cartograms equalise the population density over a given region, the ratios between urban and rural population are therefore respected. In Switzerland, the share of population living in an urban area using the percolation algorithm is roughly 64%. Using the official census data with the agglomeration definition from the SFSO, over 73% of the population lives in an urban area. The fact that the official agglomeration definition includes also regions that are economically dependant from a centre in an urban area may explain this difference. However, this simple example illustrates the importance of a systemic definition of urban areas.

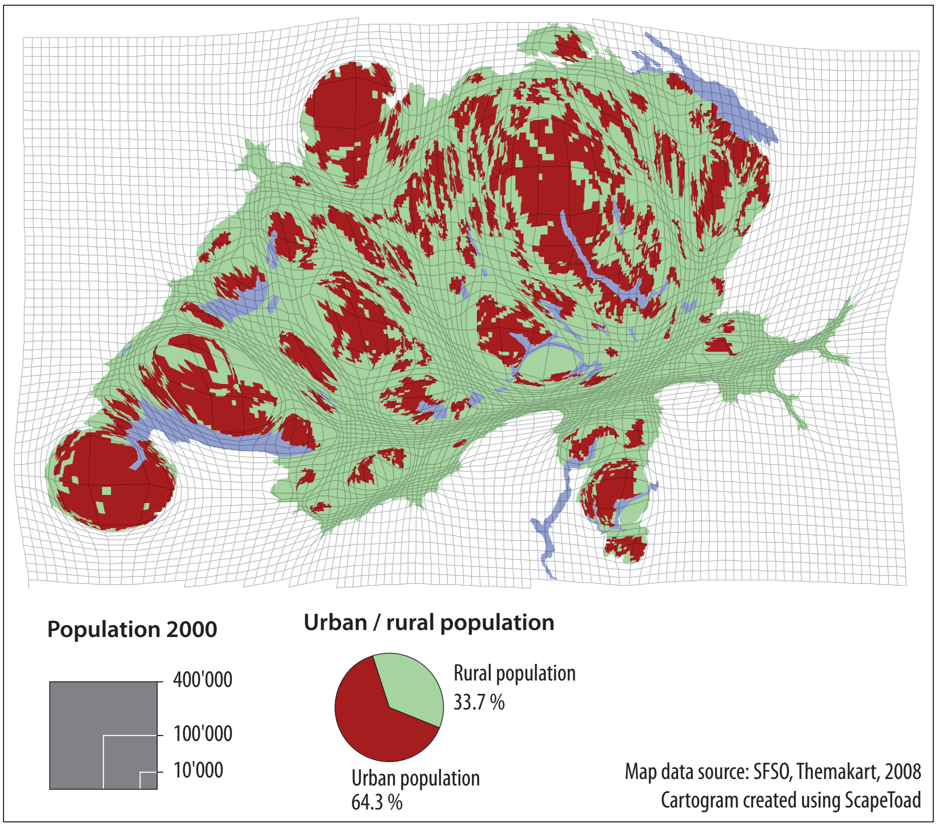

Figure 3.13: Population cartogram showing the distribution of urban and rural population in Switzerland.

3.2.4 Application of the percolation approach to socio-economic data

As already stated, it is easy to replace the population criteria of the percolation algorithm by any other statistical variable or indicator available at a sufficient spatial resolution. The Swiss Firms Census (Swiss Federal Statistical Office SFSO, 2005b) provides data at a hectare level for the number of firms active in a given sector. We have selected one service type: specialised services for firms, which is generally a service type typically found in a city centre. We have used a modified version of the service type classification established by Browning and Singelmann (1975). The following service industries are included in our specialised service type (with the classification code, see Swiss Federal Statistical Office SFSO (2002) for the details): bank, insurance and other financial services (65-67); real estate (70); computer and related activities (72); research and development (73); legal activities, business and management consultancy activities, architectural and engineering activities, miscellaneous business services (74).

Figure 3.14 shows the specialised service clusters for Switzerland. The clusters have been computed using a cell size of 1 kilometre and using a density threshold of 20 firms per hectare. Only clusters with at least 800 firms offering specialised services have been retained. The result shows roughly the same agglomerations as the population clusters at 500 metres resolution. However, the service clusters are as expected a little bit smaller and less numerous. It is interesting to note that the order of the most important service clusters is not exactly the same as for the population clusters: Zurich is clearly the most important city. However, in terms of specialised services, Basel is the second most important cluster, followed by Geneva, Berne and Lausanne. In terms of population, Geneva is second most important cluster, followed by Basel, Lausanne and Berne.

If we study the cluster size against their rank (figure 3.14 at bottom), a similar structure as for Zipf's law based on population can be observed. However, the dominant position of the biggest cluster (Zurich) becomes very clear, more than for the population clusters. This shows the predominant economic position of Zurich, even compared to Basel or Geneva.

If we compute the clusters for two different years, it is possible to study and compare the evolution of several urban areas. Figure 3.15 shows the evolution of the specialised service clusters between 1998 and 2001. It is possible to observe the geographic changes of the clusters (top) and to study the way the different urban areas have evolved (bottom). Three new clusters have emerged between 1998 and 2001. There is currently a trend in urban development to densify existing urban areas. By plotting the cluster area against the number of firms, we can identify the trend for a given urban area. The map and the plot can be created automatically for a series of different demographic and socio-economic variables.

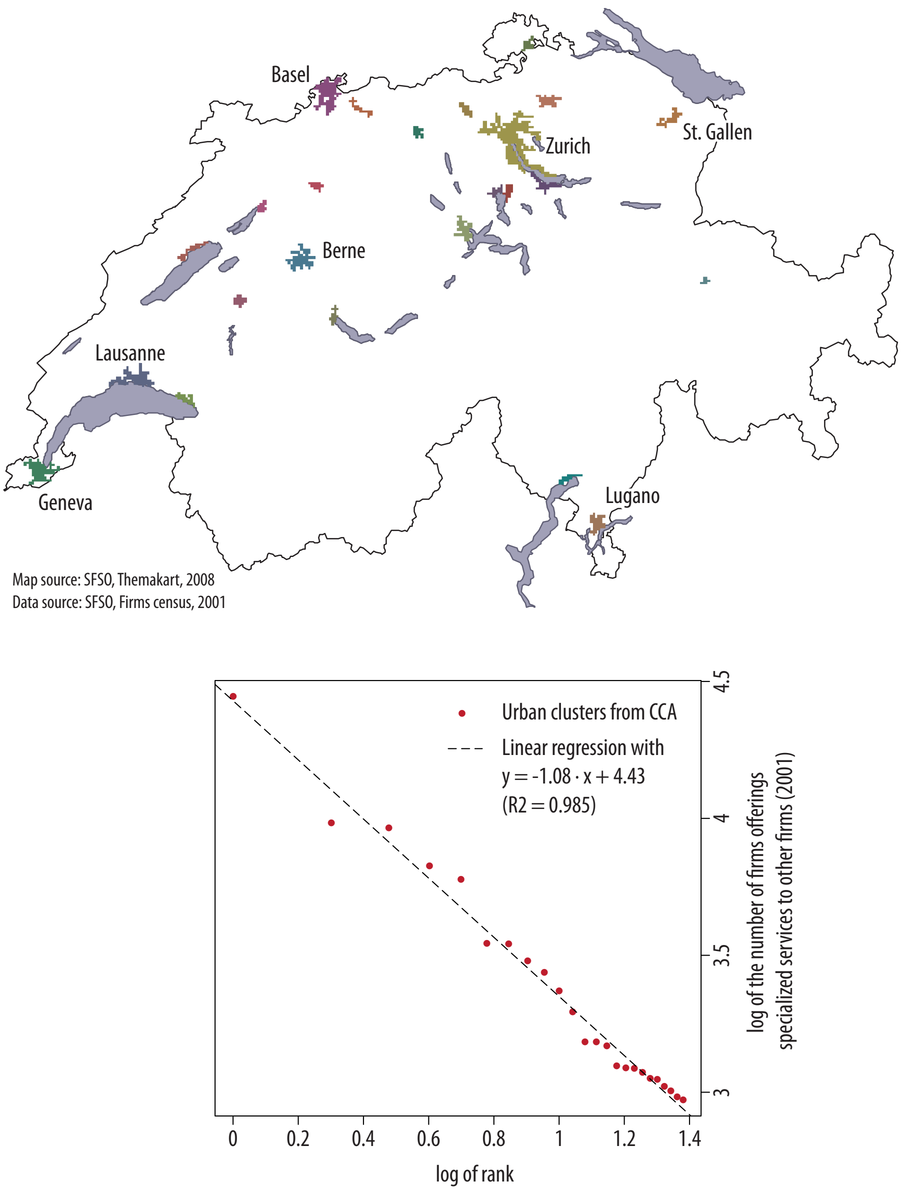

Figure 3.14: Clusters of specialised services and the corresponding ranking.

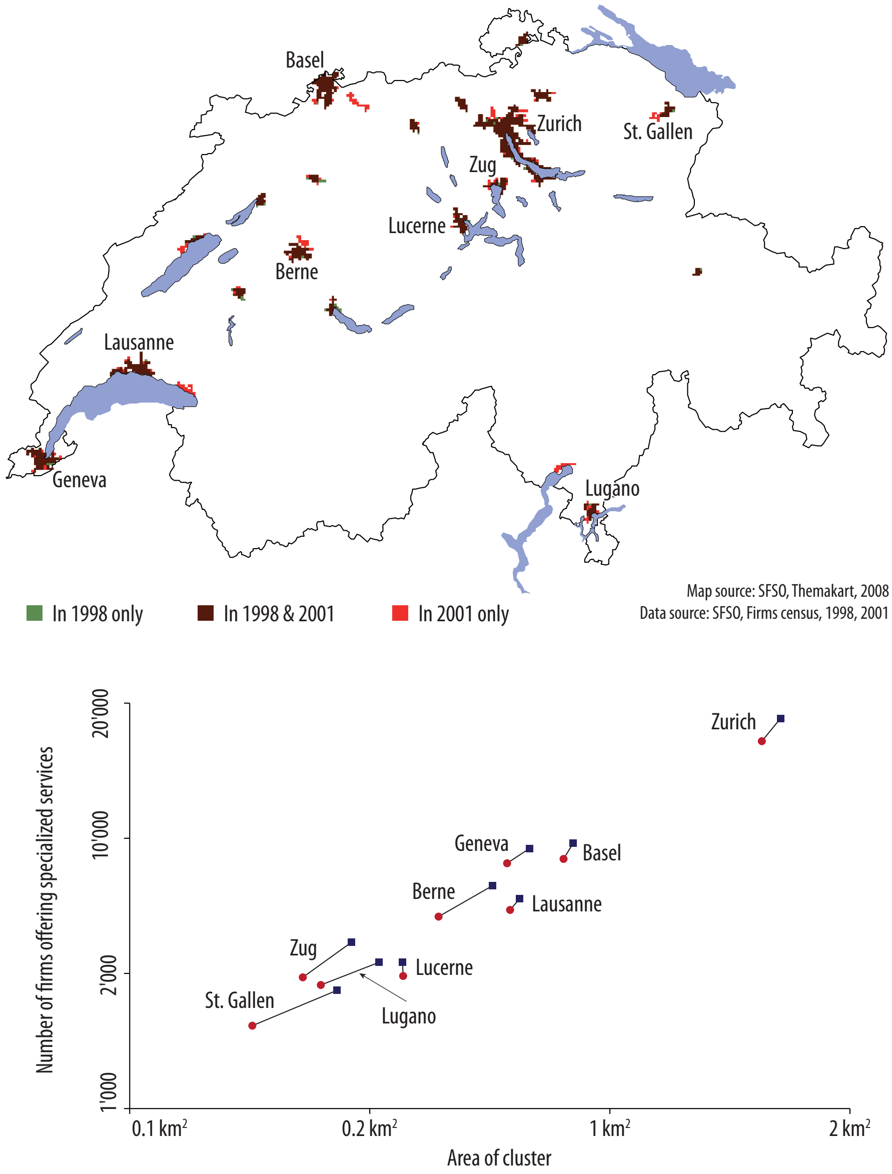

Figure 3.15: Clusters of specialised services in 1998 and 2001 and the evolution of the cluster area against the number of firms for the nine biggest clusters.

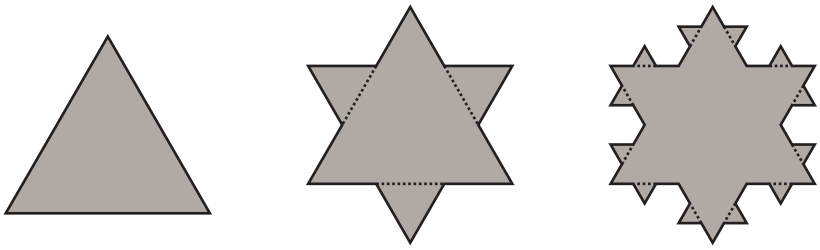

Figure 3.16: The first three iterations for creating the Koch snowflake.

3.3 Analysis of the urban structure using fractal geometry

The urban structure contains the built structure of the city – buildings, transportation infrastructure and other infrastructure – but also a socio-economic structure. In section 3.2, we have defined a way how to define spatial clusters using data of every kind available as a regular grid. The morphological patterns of a city can also be studied using the framework of fractal geometry which has become popular after the monograph of Mandelbrot (1983). A fractal object has some interesting properties and is typically difficult to study using traditional Euclidean geometry. Two of the main properties of a fractal object are its self-similarity and its scale invariance. Many geometric objects can be considered as *"statistically self-similar"* where each part can be considered as a reduced image of the whole (Mandelbrot, 1967).

A simple example of an abstract fractal object is the *"Koch snowflake"*. Figure 3.16 illustrates the first steps for creating a Koch snowflake. Start with an equilateral triangle. Then divide each side of the triangle in three parts. Replace each middle part with an equilateral triangle pointing outward. Then start again with each line of the snowflake and iterate endlessly. If we compute the perimeter L for the iteration n of the Koch snowflake, we get:

$$L_n = 3\left(\frac{4}{3}\right)^n l_0 \tag{3.2}$$

where l_0 is the length of the side of the initial triangle and N the number of iterations. It can easily be seen that

$$L_n \to \infty \qquad \text{for} \qquad n \to \infty \tag{3.3}$$

If we compute the area of Koch snowflake, we get:

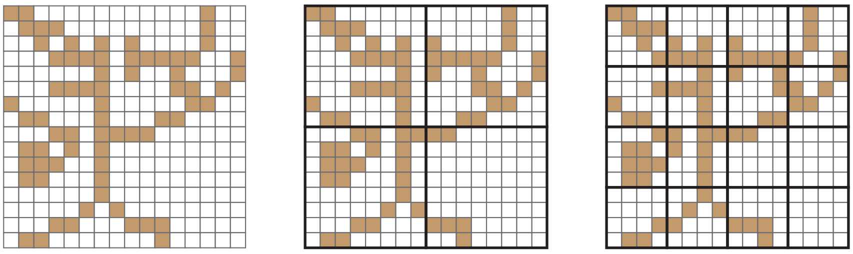

Figure 3.17: A fractal pattern (left) and the first steps of the box counting method for estimating the fractal dimension.

$$A_n = \frac{1}{4}A_0 + \frac{3}{4}A_0\left(1 + \frac{4}{9} + \left(\frac{4}{9}\right)^2 + \ldots + \left(\frac{4}{9}\right)^n\right) \tag{3.4}$$

where A_0 is the area of the initial triangle. The area is a geometric series with constant $c = \frac{4}{9}$ which means that for $n \to \infty$, the area A_n does not grow to infinity. In fact, we get:

$$A_\infty = \sqrt{3}\left(\frac{4}{5}\right)A_0 \tag{3.5}$$

This shows a very interesting property of the Koch snowflake. While the perimeter grows to infinity, the area stays limited (Frankhauser, 1994). We can also see that a part of the snowflake in iteration 3 (figure 3.16 at right) is a reduced version of a part of the snowflake in iteration 2. This is the property of self-similarity found in fractal objects.

In order to characterise such fractal object, the concept of *"fractal dimension"* has been introduced. The fractal dimension is not a integer number as the Euclidean dimension, but can take any value in between. In the next section, we present in more detail the concept of fractal dimension and one possibility how to compute it.

3.3.1 Fractal dimension

Several methods exist how the fractal dimension can be estimated. We will present here the box-counting method for computing the fractal dimension d_f (Falconer, 1990; Peitgen, Hartmut, & Saupe, 1992).

Let's take a binary geometric pattern on a regular grid like the one depicted in figure 3.17 (left). We cover the grid with one box of size L and the number of boxes $S(L)$ needed for covering all coloured cells in the grid is computed (this is of course 1 in the first step). The box size L is then iteratively decreased and the total number of boxes N increased accordingly; the number of filled boxes $S(L)$ is again computed. The box-counting operation is repeated until the box size L is equal to the grid cell

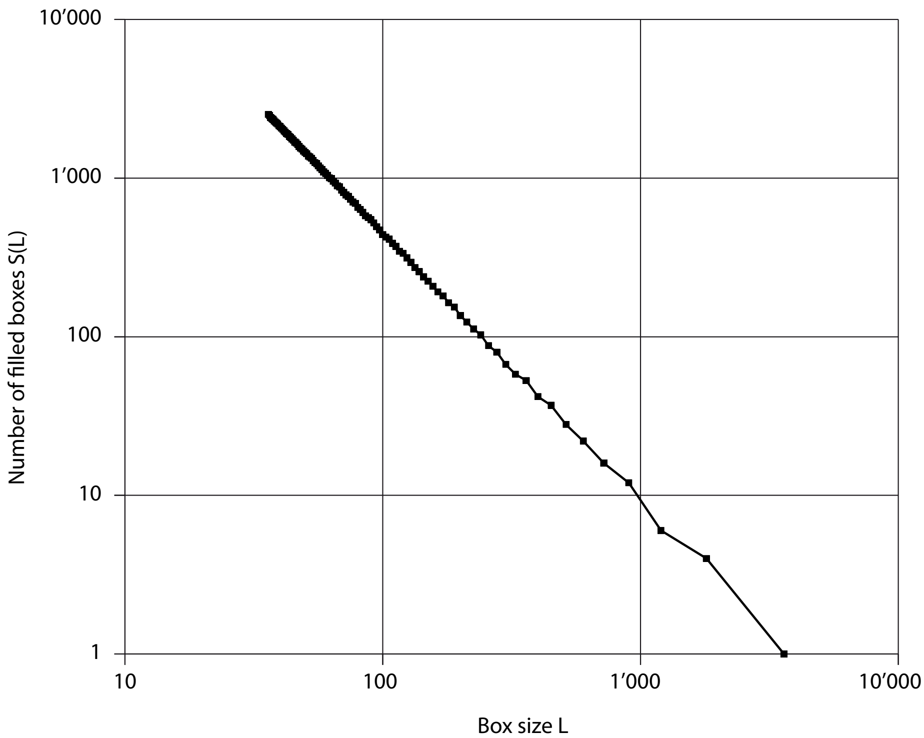

Figure 3.18: Example of a log-log plot with the result of a box-counting process.

size. For a fractal geometry, the number of boxes necessary to cover the filled cells in the geometric pattern follows a power law:

$$S(L) \propto L^{-d_f} \tag{3.6}$$

The fractal dimension of the pattern d_f can be computed as the slope of the regression line after log-transformation of both sides of equation 3.6. Figure 3.18 shows an example of such a log-log plot showing the result of a box-counting process on a grid with the population in Switzerland. The regression line has a slope of approximately -1.69. Hence, we estimate the fractal dimension $d_f \approx 1.69$.

For a pattern with an Euclidean dimension of 2, a value smaller than 2 shows that there is some clustering in the pattern.

It has to be noted that there exist also *"multifractal"* patterns. In a multifractal pattern, the fractal properties vary from one region to another (Stanley & Meakin, 1988). This type of pattern can for example occur in the case of heterogeneous phenomena responsible for the generation of the pattern.

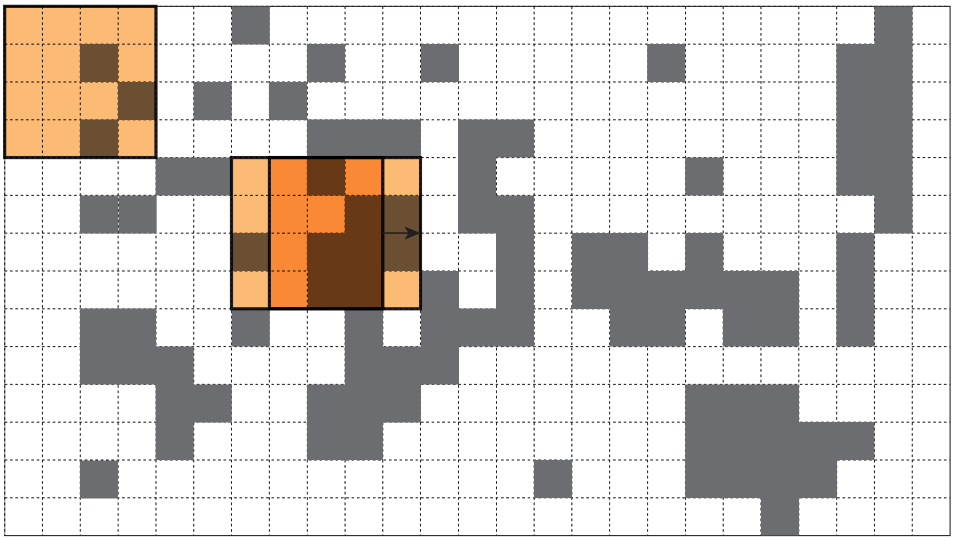

Figure 3.19: Principle of the gliding box algorithm for measuring the lacunarity of a pattern.

3.3.2 Lacunarity

Lacunarity is a complementary measure to the fractal dimension for characterising the structure of an object. It has been first described by Mandelbrot (1983). In fact, different fractal sets may have the same fractal dimension but very different textures (Mandelbrot, 1983, 1995; Voss, 1986; Myint & Lam, 2005; Tuia, Kaiser, & Kanevski, 2008). Lacunarity can be considered as a scale-dependant measure of heterogeneity or texture of an object, independently of its fractality (Allain & Cloitre, 1991; Plotnick, Gardner, Hargrove, Prestegaard, & Perlmutter, 1996). A higher lacunarity value indicates a more heterogeneous pattern, or a more complex spatial arrangement (it has a more variable structure). Or in other terms, lacunarity represents the distribution of gap sizes in a pattern (Myint & Lam, 2005). Lacunarity has initially been developed to describe a property of fractals. However, it is possible to extend this concept for describing the spatial distribution of real data sets, including, but not restricted to, those with fractal and multifractal distributions (Plotnick et al., 1996). Lacunarity can be interpreted as a deviation from, or lack of, translational and/or rotational invariance and can, of course, be a property of a non-fractal pattern (Gefen, Meir, Mandelbrot, & Aharony, 1983; Tuia & Kanevski, 2008). Translation invariance is obviously a scale-dependent measure; a pattern which seems to be heterogeneous at a small scale can be homogeneous at a larger scale.

Gliding box algorithm for binary images

Several algorithms have been proposed for computing the lacunarity measure and there is no general agreement about the best one to use. We describe here the 'gliding box‘ approach from Allain and Cloitre (1991), and as presented by Plotnick et al. (1996), Myint and Lam (2005) or Tuia and Kanevski (2008). This algorithm can be applied to binary images, and Plotnick et al. (1996) and Myint and Lam (2005) have also applied an extension to grey scale images. Figure 3.19 shows the principle of the gliding box. In our example, a grid of 25x14 cells covers the space, and a gliding box of size $r = 4$ is placed at the upper left corner. The number of filled cells within the box is counted (the box mass s). Then the box is moved by one cell to the right and the box mass counted again. Once the gliding box has reached the right end, it is placed one row below, again at the left end, until it reaches the lower right corner of the space. This repetition produces a frequency distribution of the box masses $n(s, r)$. This frequency distribution is then converted into a probability distribution $Q(s, r) = n(s, r)/N(r)$ where $N(r)$ is the number of boxes of size r. The first and second moments (mean and variance) of the probability distribution are then determined:

$$Z(1) = \sum sQ(s, r) \tag{3.7}$$

$$Z(2) = \sum s^2 Q(s, r) \tag{3.8}$$

The lacunarity for box size r is defined as:

$$\Lambda(r) = \frac{Z(2)}{[Z(1)]^2} \tag{3.9}$$

The lacunarity is a dimensionless measure that however depends on the box size r.

If we recall that

$$Z(1) = \overline{s}(r) \tag{3.10}$$

$$Z(2) = s_s^2(r) + \overline{s}^2(r) \tag{3.11}$$

where $\overline{s}(r)$ is the mean and $s_s^2(r)$ the variance of the number of occupied cells per gliding box, we can express the lacunarity as

$$\Lambda(r) = \frac{s_s^2(r)}{\overline{s}^2(r)} + 1 \tag{3.12}$$

which is a dimension-less representation of the variance to mean ratio and is closely related to a number of statistics like the Morisita index (Plotnick et al., 1996).

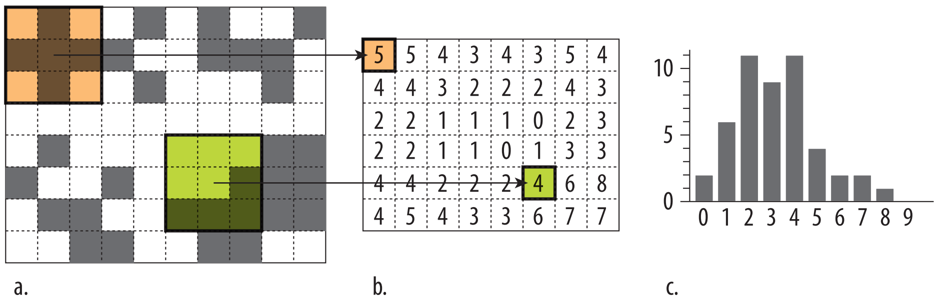

Figure 3.20: Determining the number of filled cells for each gliding box (b) of a spatial pattern (a) and its frequency distribution (c).

For easier understanding, we present the step-by-step computation of a small example. Figure 3.20 shows the binary spatial pattern with 10x8 cells. Filled cells are in grey, empty in white. We use a gliding box of size 3x3 cells. For each position of the gliding box, we count the number of filled cells which gives the matrix in b. This matrix has a size of 8x6 cells; it is smaller than the initial pattern because of the border effect due to the gliding box. The difference is the size of the gliding box minus 1 $(10 - (3 - 1) = 8)$. We can compute the mean and variance for this matrix which gives us 3.1875 for the mean and 3.26 for the variance. These two values correspond to the equations 3.10 and 3.11 which allows us to compute the lacunarity using equation 3.12: $(3.26/3.1875^2) + 1 = 1.321$.

If we want to determine the lacunarity using equation 3.9, we transform the frequency distribution in figure 3.20 (c) into a probability distribution by dividing each frequency by the sum of all frequencies, as illustrated in table 3.1 (probability column). Using equations 3.7 and 3.8, we compute the first and second moment which allows to estimate the lacunarity using equation 3.9.

Lacunarity case study: the Swiss urban agglomerations

In this case study, we use the definition of the urban agglomeration discussed in section 3.2 (page 40). We have estimated the lacunarity for different grid cell sizes of the City Clustering Algorithm (CCA), ranging from 100 meters (the resolution of the dataset) up to 2 kilometres. Figure 3.5 (page 47) shows four of these images. For the lacunarity analysis, we consider these images as binary patterns where populated cells get the value 1 and non-populated cells 0. The lacunarity is estimated using the gliding box approach presented above, for different gliding box sizes.

Figure 3.21 shows the result of the analysis. Larger boxes are generally more translation invariant than smaller boxes, except for highly clustered sets (Plotnick et al., 1996). If we recall the formula for the lacunarity (equa-

Number of cells in gliding box	Frequency	Probability	First moment	Second moment
0	2	0.04167	0.00000	0.00000
1	6	0.12500	0.12500	0.12500
2	11	0.22917	0.45833	0.91667
3	9	0.18750	0.56250	1.68750
4	11	0.22917	0.91667	3.66667
5	4	0.08333	0.41667	2.08333
6	2	0.04167	0.25000	1.50000
7	2	0.04167	0.29167	2.04167
8	1	0.02083	0.16667	1.33333
9	0	0.00000	0.00000	0.00000
Sum	48	1.00000	3.18750	13.3542

Table 3.1: Frequency and probability distribution for the number of cells in the gliding boxes.

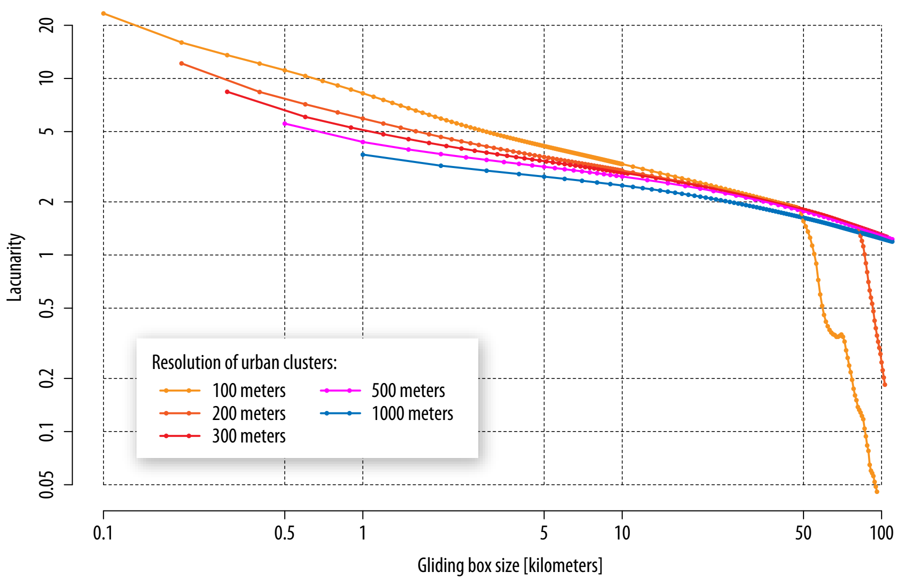

Figure 3.21: Lacunarity curves for different urban clusters as defined by the City Clustering Algorithm.

tion 3.9), it is the second moment divided by the square of the first moment. It seems to be intuitive that the second moment decreases relative to the first one when increasing the box size (variance goes down). A higher lacunarity value for a given gliding box size indicates higher clustering. There is no surprise that clustering diminishes as the urban cluster resolution (grid cell size of the City Clustering Algorithm) goes up. The curve for the urban cluster resolution of 100 meters present an abrupt change at a gliding box size of about 50 and 70 kilometres, whereas the curve for the resolution of 200 meters shows a break at about 80 kilometres. Higher resolutions don't show such an abrupt change in slope. Plotnick et al. (1996) has observed such breaks in clustered datasets where the break in the gliding box size corresponds to the the size of the clumps. For the dataset under study, the City Clustering Algorithm detects a percolation threshold of 500 meters (the resolution of CCA grid), while at a threshold of 300 meters, clusters becomes non-detectable. This would correspond to a near-percolation threshold, which is quite intuitive.

Another interesting observation is the nearly linear curve for resolutions higher than 200 meters, and even below for a gliding box size smaller than 50 kilometres. As described by Allain and Cloitre (1991), the lacunarity curve for self-similar monofractals should be a straight line with slope $D-E$, where D is the fractal dimension and E the Euclidean dimension. The fractal dimension for the urban cluster with resolution of 1 kilometre, computed using the box-counting method, is approximately 1.71. If $D-E$ holds, the curve would have a slope of $1.71 - 2 = -0.29$. A linear regression on the curve with 1000 meters resolution yields a slope of -0.27.

In conclusion, we can note that the first results of CCA and its developments presented above are very promising and stimulating. Further research and new case studies can be very interesting both from fundamental and applied points of view. For example data from the Swiss firms census 2005 and soon 2008 will be available for analysis.

3.4 Analysis of urban dynamics

3.4.1 Population growth

The population P at a given location i at time $t+1$ can be defined in formal terms as follows (Batty, 2005, p. 25):

$$P_i(t+1) = P_i(t) + \Delta P_i(t) = (1+\lambda)P_i(t) \tag{3.13}$$

where $\Delta P_i(t)$ is the population growth at location i at time t, and λ the population growth rate. Thus, the λ can be expressed as:

$$\lambda = \frac{P_i(t+1)}{P_i(t)} - 1 \tag{3.14}$$

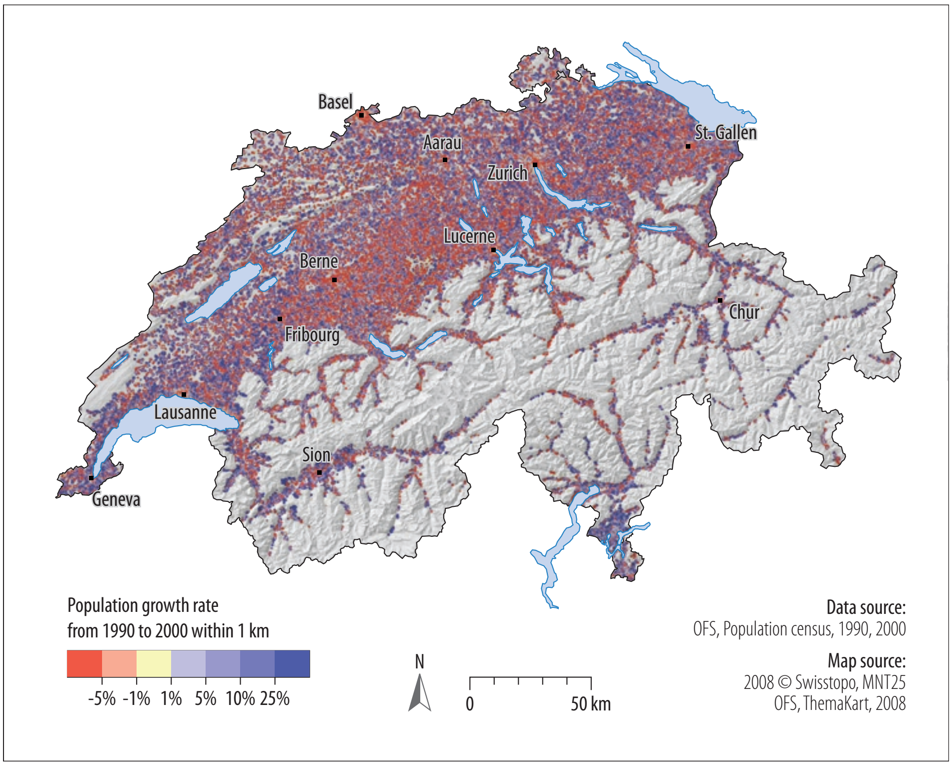

Figure 3.22: Population growth rate from 1990 to 2000 in Switzerland.

We can now determine the population growth rate at all locations i using empirical data from two population censuses at time t_1 and t_2. In case of Switzerland, population data is available for 1990 and 2000 at the hectare level (Swiss Federal Statistical Office SFSO, 2005a). At this scale, more or less arbitrary local variations are visible. Using the moving window technique, we can change the observation scale. At a scale of 1 km, the population growth rate is computed for a given point i inside a circle of 1 km diameter. Even at this scale, big local variations predominate; no pattern is visible (fig. 3.22). Only at a coarser scale, e.g. 10 km, a pattern becomes visible (fig. 3.23). This is one more example which proves the importance of scale in the analysis. Figure 3.24 shows the semi-variogram of the population growth. The local variations can be seen clearly at lag distances lower than 7 to 8 kilometres; the a prior variance is much lower than the variogram value. Only at higher distances, the variogram value stabilises at a lower value. This semi-variogram shows that the population growth rate has a negative spatial auto-correlation at short distances. When adapting an arbitrary delimitation such as administrative boundaries, it is more difficult to vary the scale, and the scale is not homogenous in space. Misinterpretations can be the result of a non-adapted mapping support.

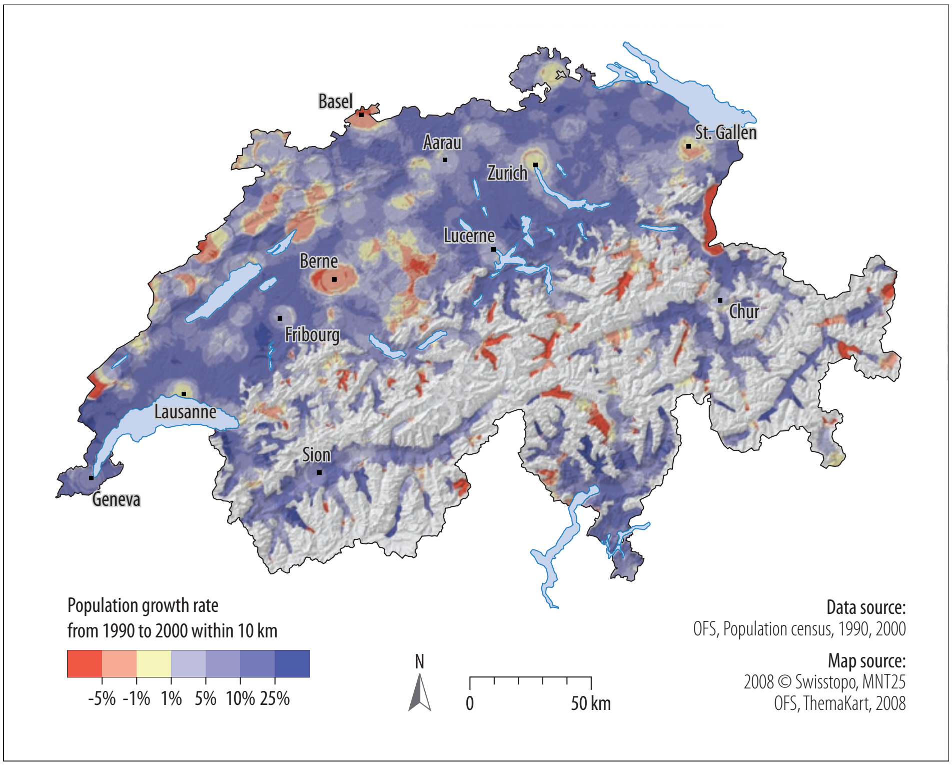

Figure 3.23: Population growth rate from 1990 to 2000 in Switzerland.

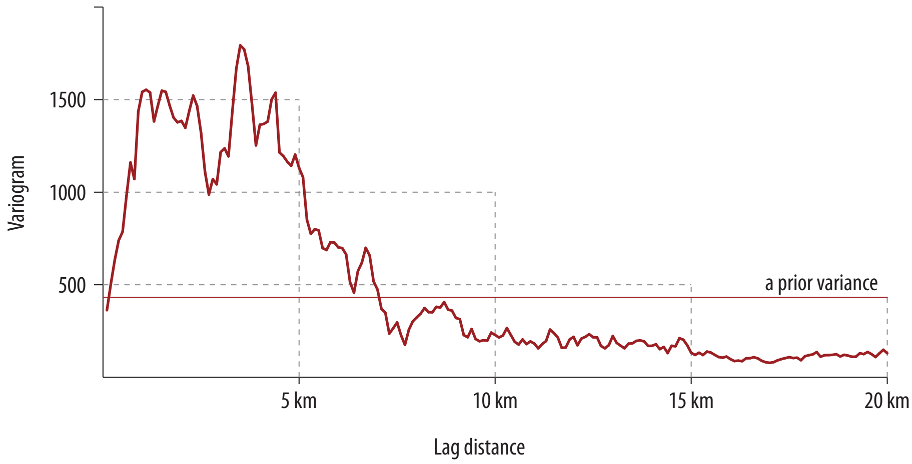

Figure 3.24: Semi-variogram for the population growth rate from 1990 to 2000 in Switzerland.

In urban geographic terms, the pattern of population growth rate between 1990 and 2000 has some interesting characteristics. Cities like Zurich, Basel, Lausanne, Berne and some more show no or a negative growth rate. A notable exception is Geneva. There are also a couple of remote alpine valleys that show negative population growth, together with regions like the Rhine valley around Sargans and Buchs, the Emmental between Berne and Lucerne or the region around St-Imier or Le Locle. The interstitial regions between the cities have known the highest growth rates. These regions are generally not too far from a city and are certainly the result of the ongoing urban sprawl.

3.4.2 Modelling the evolution of population

The gravity model is used in geography for estimating the degree of interaction between two places. It is derived from Newton's law of universal gravitation which states that the gravitational force between two objects is proportional to the masses of the objects and inversely proportional to the distance separating them. If the objects are considered as a point, this law can be written as:

$$F = G\frac{m_1 m_2}{r^2} \tag{3.15}$$

where F is the force of attraction (identical for both objects), G is the gravitational constant, m_1 the mass of the first object, m_2 the mass of the second object, and r the distance between the two objects.

In geography, the gravity model can be applied for the estimation of the migration between two places. The masses in Newton's law are then replaced by the population of the two places. This model is based on the hypotheses that the interactions between two places increase with their size, and that there is a distance decay in the quantity of the interactions. The distance decay effect states simply that the interaction between two places declines with distance.

The gravity model has been used widely in population flow modelling and also in estimating the overall population potential at a given place (see e.g. Calvo Palacios, Jover Galtier, Jover Yuste, Pueyo Campos, & Zúñiga Antón, 2008). The population potential at a given location i is the sum of the interactions with all possible locations:

$$Pot_i = P_i + \sum_{j=1}^{n} P_j r_{ij}^{-2} \tag{3.16}$$

where Pot_i is the population potential at location i, P_i the population at this same location, n the set of all possible locations except i, P_j the population at location $j \in n$, and r_{ij} the distance between i and j (Calvo Palacios et al., 2008). However, there is no formal prove of the shape of the distance decay function. In equation 3.16, this distance decay is a power function with exponent -2. This distance decay function could also be any other strictly monotonic decreasing function, for example an inverse exponential or any power function with a negative exponent. We can therefore rewrite equation 3.16 in a more general way:

$$Pot_i = P_i + \sum_{j=1}^{n} P_j f(r) \text{ with } \frac{d}{dr} f(r) < 0 \text{ for all } r \tag{3.17}$$

Reasonably, we should add the constraints that $f(r) \rightarrow 1$ if $r \rightarrow 0$, and $f(r) \rightarrow 0$ if $r \rightarrow \infty$. Distance r is by definition always positive.

As the population potential represents the sum of all possible interactions, it is a simple but reasonable hypothesis to say that there is some positive correlation between the population potential and the population growth. Using equation 3.13 from section 3.4.1 and by replacing the real but unknown population growth by the population potential, we can estimate the population at time $t+1$ using the population at time t:

$$P_i(t+1) = P_i(t) + \frac{Pot_i \Delta P(t)}{\sum_i Pot_i} \tag{3.18}$$

where $\Delta P(t)$ is the overall population growth at time t, and $\sum_i Pot_i$ the overall population potential. Of course, $\Delta P(t)$ may be negative in a case of an overall population loss. Equation 3.18 can be used for estimating the population at time $t+i$ given the population at time t, but also at time $t-1$, as the overall population growth can be negative. The only parameter to define is the function $f(r)$ in equation 3.17. This function defines how the population spreads in space during one time step; we will call it the *spread function*. The spread function is constrained between 1 and 0. The function $\gamma(r) = 1 - f(r)$ is then similar to a variogram model function as used e.g. in kriging. Figure 3.25 shows three different possible functions for $\gamma(r)$. These three functions have the following formulas:

1. Exponential: $\gamma_1(r) = 1 - e^{\frac{3r}{1.5}}$
2. Spherical: $\gamma_2(r) = \frac{3r}{2 \cdot 1.5} - \frac{x^3}{2 \cdot 1.5^3}$ if $r < 1.5$ and $\gamma_2(r) = 1$ if $r \geq 1.5$
3. Square power: $\gamma_3(r) = 1 - (x+1)^{-2}$
4. Gaussian: $\gamma_4(r) = 1 - e^{-\frac{3r^2}{1.5^2}}$

The exponential, gaussian and spherical functions are well known from geostatistics; these three functions as depicted in figure 3.25 have a *range* of 1.5. This range can be seen as a distance of influence for the population potential. Beyond this range, the effect of an occupied place is quite limited.

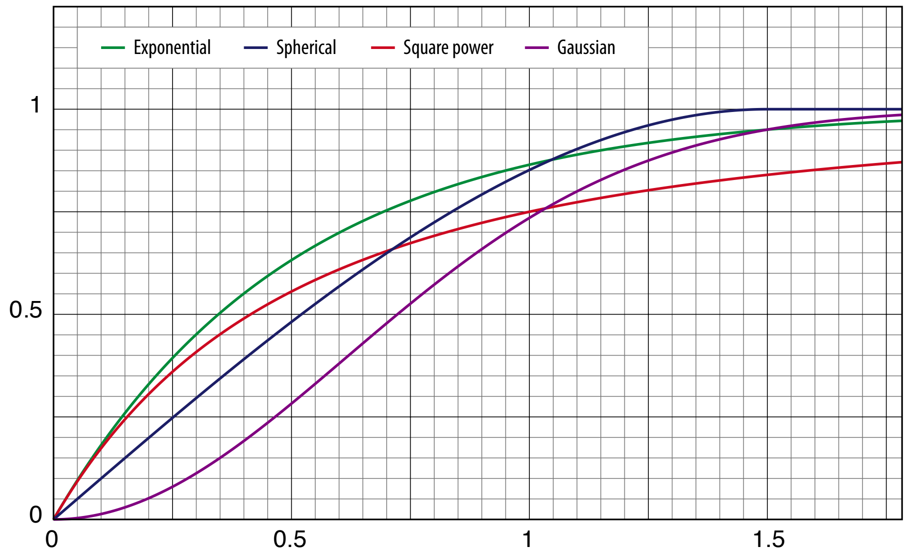

Figure 3.25: Possible functions for modelling the spread of the population potential.

The program `r.potential` which is part of the *SpatialTools* package (see addendum) allows the computation of the population potential based on a population raster file and an exponential, spherical, gaussian or power function. Figure 3.26 shows the population at the level of a hectare in 1990 and 2000 around the city of Lausanne, along with the population potential based on the 1990 population and computed using 4 different spread functions.

However, the choice of the spread function is not trivial. It depends on the population evolution process itself, and on the time period considered between two evolution steps. We have computed for a selection of spread functions the statistical pixel-by-pixel correlation between the population potential and the hectare population in Switzerland in 2000. The population potential has been computed using one of the spread functions based on the hectare population in Switzerland in 1990. Figure 3.27 shows this correlation factor for 12 different spread functions, and for comparison also the pixel-by-pixel correlation factor between the hectare population 1990 and 2000. The 'best' spread function for this particular case seems to be the exponential function with a range of 100 meters; the correlation factor is 0.773. The correlation factor between the population 1990 and 2000 is 0.718; this means if we would use simply the population 1990 as an estimator for the population 2000 instead of a computed population potential, the pixel-by-pixel correlation is already quite high. Only a few spread functions allow to obtain a slightly better correlation factor, and all of them have a range of 100 or 200 meters only. The square power function used in the gravity

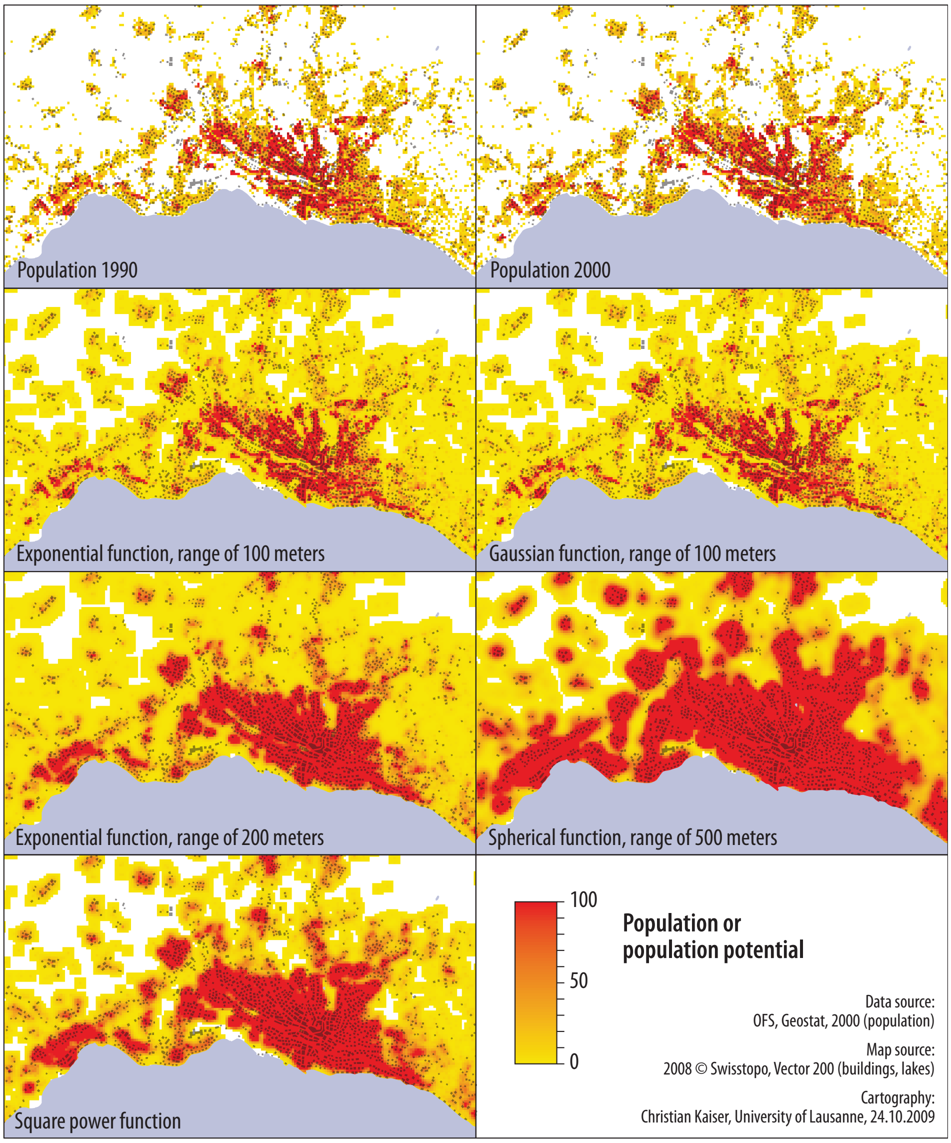

Figure 3.26: Population 1990 and 2000, and population potential using different spread functions computed based on the population 1990, for the city of Lausanne and surroundings.

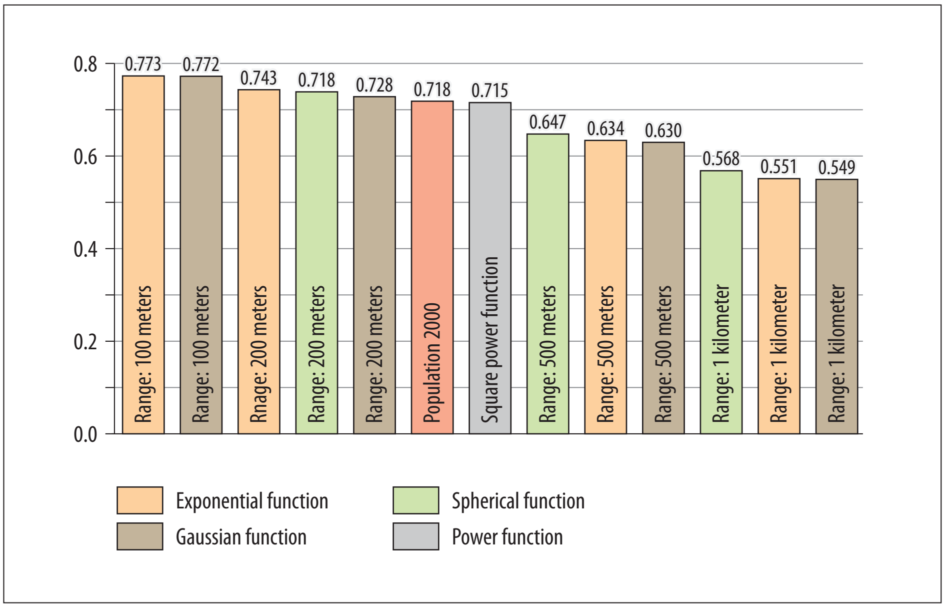

Figure 3.27: Pixel-by-pixel correlation factor between the Swiss population 2000 and the population potentials based on the population 1990 using different spread functions, and the correlation factor between the population 1990 and 2000.

model yields about the same correlation factor as the one for the population 1990/2000. The gravity model is in this particular case unable to provide an accurate estimation for the population potential. The small ranges in the 'best' spread functions suggest that population evolution between 1990 and 2000 in Switzerland is a very local process. According to the official population census, the overall population has increased from 6′873′687 in 1990 to 7′288′010 in 2000, which corresponds to a population growth rate of around 6% for this decade. The correlation factors for all spread functions are not very high compared to the one for the population 1990/2000. This shows the difficulty to model the population evolution at a local scale. The gravity model is very appealing because of its simplicity and has also proved its reliability at a smaller scale. However, for local scales, other factors seem to determine where the population increases or decreases. Another issue is the measurement of the accuracy of the population estimation. The simple pixel-by-pixel correlation factor cannot approximate regional matching between two maps.

Using the population potential for estimating the population evolution 1850-2007 in Switzerland

In this case study, we estimate the population evolution at the level of one hectare for whole Switzerland, from 1850 to 2007. The population is known from census data at the level of a municipality for the whole period at an interval of approximately 10 years. The population is also known at the level of one hectare for 1990 and 2000. Based on this data, we use the population potential of the year $t-1$ or $t+1$ from the year t, and then by removing or adding the difference of population for each municipality using a random function by respecting the population potential. The process is then repeated for the year $t-2$ (or $t+2$) based on the estimated population data for year $t-1$ (or $t+1$). Figure 3.28 shows different states of the evolution for the city of Lausanne and its surroundings. The estimation has been computed using an exponential function with a range of 100 meters as spread function.

If we compute the pixel-by-pixel correlation factor between the estimated population in 1990 and the real observed population in 1990, we get a value of 0.720. The population estimation is based on the population in 2000 and an intermediary map for each year has been computed. The result is correct at the level of a municipality. For a more local scale, the estimation shows a typical spread over all the region. This spread can also be observed in figure 3.26 in the different spread function; these functions cover an area bigger than the one used by the real population evolution. Additionally, the population evolution seems to be a process where already populated places tend to densify, followed by a subsequent expansion in space at adjacent places. This spatial expansion seems to follow non-random patterns, typically along already existing transportation axes. The population potential estimation does not integrate this two-step process or the spatial expansion patterns. Thus, the estimation of the population estimation should not be used for analysing differences inside one municipality. However, at smaller scales, it can be used to show the overall evolution. For example, it can be used inside a distance circle map at the scale of the agglomeration.

3.5 Discussion

This chapter has shown the importance of well defining the base assumptions in urban analysis. We have described a method for defining urban clusters and we have also shown some results that demonstrate the coherence of this approach. It is also important to be aware of the issues related to the scale of analysis and take them into account carefully. The urban phenomena vary in space and time, but also in scale. The percolation approach is basically a very simple tool, but at the same time, it is a very valuable one. It has the capacity to discover spatial clusters at different scales and at different

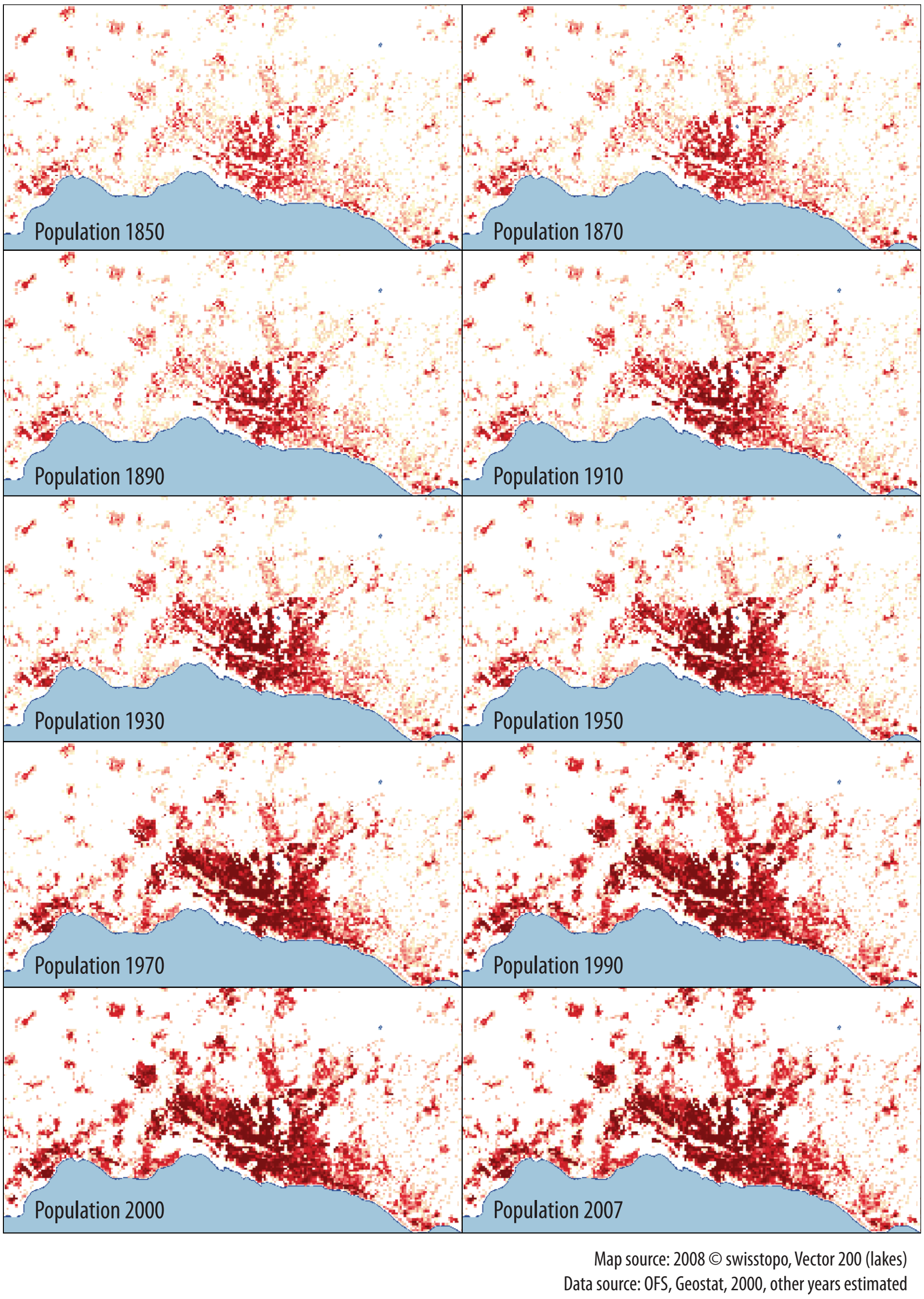

Figure 3.28: Estimation of the population evolution 1850-2007 for the city of Lausanne and surroundings.

functional levels. The percolation algorithm allows at the same time to get urban clusters at an explicit scale which is very important. However, the main requirement of such an analysis is the availability of the data on a regular grid at a sufficient resolution. Rozenfeld et al. (2008) were able to work on population data with a grid of only 7.74 kilometres of resolution, and the results seem to be consistent. The percolation algorithm seems to be a robust method, despite the requirement of data on a regular grid. Rozenfeld et al. (2009) have also worked on quite high-resolution data not lying on a regular grid; the results seem still to be consistent even if the issues of irregular data should be clarified further.

In urban geography, the way to analysis methods not relying on the administrative units is open. Multi-scale methods and continuous modelling of urban phenomena are sufficiently powerful and methodologically well developed in order to be used by the urban geographer. After the decline of quantitative geography in the 1980s (Fotheringham, Brundson, & Charlton, 2000), the methods are now powerful enough for being used for a wide variety of real world problems. However, the field of urban geography will require more skills in statistical analysis, geomatics and modelling as it is currently the case.

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Chapter 4

Simulation of urban dynamics

Dynamics in a city are generated by top-down and bottom-up decisions at the same time. Top-down decisions consist of planning efforts and political discussions lead by the government, society and the administration. These efforts try to manage the evolution of the urban structure in order to optimise the spatial arrangement of the different services and facilities. Bottom-up decisions on the other hand are made by all the individual actors, often due to some constraints encountered in the daily life, e.g. for buying a specific good or for doing some activity. Decisions made by investors and other economical actors are also bottom-up decisions. Such bottom-up decisions are coming from independent actors taking a the decision on their own; they are free to do it or not and their decision is based on a utility function; an action is only executed if there is a positive utility.

Modelling the behaviour of all the actors in a city and to analyse all the bottom-up decisions is a major challenge in urban modelling. One of the reasons is the high complexity in these decisions, which can be accompanied with some irrational and subjective behaviour for some of the actors. Another reason is the lack of enough detailed data about the behaviour and the decisions made by all the different actors; the assessment of such data would be very difficult because of the high number of actors and different types of actors. In fact, everybody present in a city becomes such an actor, and modelling such behaviour becomes rapidly very complex as the amount of different possibilities is very big; the number of parameters to adjust in the system increases rapidly, and finding a realistic and stable solution becomes more difficult.

Cellular Automatas and Multi-Agent Systems have been used for modelling different aspects of urban dynamics, among which we cite two big categories of models: the first category includes models for urban sprawl and land-use change, and the second models for traffic simulation. These two categories of models can also be combined together. This has been done for example in the Open Platform for Urban Simulation (OPUS) (Waddell, Ševcíková, Socha, Miller, & Nagel, 2005) or in UrbanSim (`www.urbansim.org`) combined together with Multi-Agent Traffic Simulation (MATSim) (`www.matsim.org`). Portugali (2000) presents the concept of "free agents in a cellular space", which is a combination between MAS and CA.

In this chapter, we will provide a brief overview on cellular automata and multi-agent systems that are two popular simulation approaches, followed by a short introduction to urban simulation and a more detailed study on traffic simulation. A case study of traffic simulation for the agglomeration of Lausanne is presented; this study has been done for assessing the ecological impact of commuting and to study the relationship with the urban structure generating the commuting patterns. A particular focus is the calibration of the multi-agent based traffic simulation.

4.1 Cellular Automata

A Cellular Automata (CA) is a model based on a regular grid of *cells*. Each cell has a discrete state; the number of possible states is finite. The automaton evolves in time (which is also discrete), in an iterative process. The state of each cell is updated at each time step according to its neighbourhood. A neighbourhood function defines the rules of how the cell changes (or not) its state. Batty (2005, p. 67) defines the cellular automata in a similar manner:

> *'Cellular automata are computable objects existing in time and space whose characteristics, usually called states, change discretely and uniformly as a function of the states of neighbouring objects, those that are in their immediate vicinity. The objects are usually conceived as occupying spaces that are called cells, with processes for changing the state of each cell through time and space usually articulated as simple rules that control the influence of the neighbourhood on each cell.'*

According to Wolfram (2002, p. 876), the concept of CA has been introduced by John von Neumann. Von Neumann tried to develop an abstract model of self-reproduction in biology. In 1951, after discussion with his colleague Stanislaw Ulam, he constructed a 2D CA. This work has been completed together with Arthur Burks and published in 1966 (Von Neumann & Burks, 1966). In 1970, the 'Game of Life', a simple two-state CA created by John Conway, became famous after publication by Gardner (1970). This simple automaton is able to create complex patterns out of very simple rules, which makes it so appealing. The game of life is a 2D CA where each cell can take a value of 0 or 1 (or 'dead' and 'alive'). Two simple transition rules determine the state of the cell after the next iteration. These rules are based on the state of the eight neighbours of the cell:

- If a living cell has 2 or 3 living neighbours, it remains alive. In all other cases, it dies.
- If a dead cell has exactly 3 living neighbours, it is getting alive in the next iterations. Otherwise, it stays dead.

The Game of Life is a deterministic game not requiring any interaction with a human. The evolution of the game is determined through its initial pattern. Many different types of pattern occur in the Game of Life, among them static (still lives) and repeating patterns (oscillators), but also gliding or escaping patterns ('spaceships‘).

Formally, a cellular automaton can be divided into four different elements:

1. A regular *grid* composed by a finite number of cells. This grid space is typically two-dimensional, rectilinear and homogeneous, even if sometimes, these assumptions are dismissed for a more appropriate representation for a given problem at hand (White & Engelen, 2000).
2. A finite number of *cell states*. The state can represent virtually anything as long as it is discrete. Continuous variables can be transformed in classes in order to be represented in a cellular automaton.
3. A *neighbourhood* defining the spatial interactions inside the automaton. The two most common neighbourhoods are the Von Neumann neighbourhood (the four neighbours sharing a side with the cell) and the Moore neighbourhood (the eight neighbours sharing at least a common point). However, it is also possible to enlarge the neighbourhood and define any type of neighbourhood.
4. The *transition rules* define how the cellular automaton evolves in time. This is the heart of the automaton. They represent the logic of the state change for all cells during one time step. These rules can be very simple like in the Game of Life, or very complex with some sophisticated probability estimations.

Cellular Automata have been used widely for simulating urban dynamics such as urban sprawl or land use change. Sometimes, cellular automata have been used together with multi-agent systems (discussed later). According to White and Engelen (2000), Tobler (1979a) was the first to suggest the use of CA for geographical modelling. Subsequently, many researchers used a CA in a geographical context (e.g. Phipps, 1989, 1992; Couclelis, 1985, 1997; Phipps & Langlois, 1997; Cecchini & Viola, 1990). Integration of CA in GIS has also been considered (e.g. Itami, 1994; White & Engelen, 1994).

The concept of CAs has been extended by several authors by modifying the regular grid and the neighbourhood. For example, it is possible to use any shape with defined neighbourhood as support for the CA. It is possible for example to use administrative units (Pinto & Antunes, 2005; Pinto, Antunes, & Roca, 2009) or a graph (O'Sullivan, 2001), as in both cases the neighbourhood is well defined.

White and Engelen (2000) present a CA of the Netherlands with a 500 meter resolution for the simulation of the land-use dynamics. This macro-scale model is driven by economic development and planning projections. The economic development is translated into need for new infrastructures and thus a change in land-use. The CA attempts to locate this demand. However, a major concern in this case is the predictability of economic and demographic evolution and thus the future changes in land-use.

A similar CA has been constructed for the land-use change and urban growth in the canton of Vaud (Donzé, 2008; Crevoisier, 2009).

4.2 Multi-Agent Systems

A MAS has been defined by Durfee, Lesser, and Corkill (1989) as a loose network of entities acting together in order to solve problems beyond the capacities of the individual entity (Treuil, Mullon, Perrier, & Piron, 2001). It consists of an ensemble of concepts and techniques where heterogeneous entities ("agents") interact according to some defined rules. The relatively simple agents are built as autonomous units and enable a complex behaviour of the overall system through the interaction with other agents. The system itself is designed to solve some problem, to model a real world phenomenon or to simulate some scenario. As the system is capable of self-organisation with the sole definition of some simple rules, the domain of multi-agent systems is a Distributed Artificial Intelligence (DAI) technique.

MASs are often seen as a metaphor of a swarm of social insects (e.g. Bonabeau, Dorigo, & Theraulaz, 1999). Social insects, e.g. ants, bees or termites, are relatively simple animals but show very advanced problem solving capabilities. As Bonabeau et al. (1999) say, *the modelling of social insects [...] can help design artificial distributed problem-solving devices that self-organise to solve problems* and call such a system *swarm-intelligent system*. The difficulty in designing an "intelligent" MAS is to know exactly what behaviour each agent must have, and which are the interactions necessary for solving a given problem. One of the fundamental hypothesis comes from the domain of complex systems: the interactions between the small entities generate emergence and persistence of forms at a more global level (Holm & Sanders, 2001, p. 191). In geography, spatial interactions like flows of people, goods or information are the result of the resources and potentialities of each location. These interactions create differences in space, like centre-periphery gradients or segregation effects (Holm & Sanders, 2001).

Shoham (1993) defines an agent as *'an entity functioning in a continuous and autonomous way and which is located in an environment in which other processes happen and where other agents exist'*. This is a very large definition that may include a lot of systems that we are not going to consider in our context. Wooldridge (2002, p. 15) defines an agent as *'a computer system that is* situated *in some* environment*, and that is capable of* autonomous action *in this environment in order to meet its design objectives.'* He limits his definition to computer systems, which restricts the possible interpretations and limits clearly the domain. An agent can therefore be a software or hardware agent. The latter is heavily used in robotics. For spatial problems, agents are usually a piece of software.

Some of the characteristics of an agent are generally intelligence, autonomy, interaction with other agents, reactivity, adaptability, pro-activity, ability to communicate, to cooperate and to behave socially:

- *Autonomy* is probably the most important characteristic of an agent. According to Kiss (1992), an agent is a local process having its own private domain on which he is the only one to operate and which he does not share with another process. Such an agent can be represented very easily by an instance in a object-oriented programming environment. The private domain is translated by the private attributes for this type of object. An autonomous agent should also be capable of adaptation to a changing environment.

- *Reactivity* is the capacity of the agent for adapting in a timely fashion to the environment (Franklin & Graesser, 1997).

- The *adaptability* of an agent is its capacity to learn, that is to change its behaviour based on its previous experience.

- A *co-operative* and *social* agent is able to communicate with other agents, and to achieve goals important not only for himself, but also for others (the society).

- *Pro-activity* refers to the fact that an agent should be goal-oriented, and not just be reactive.

For programmers used to object-oriented programming, the difference between an object and an agent might not be obvious. In the object-oriented programming literature, we can even find comparisons with agents: *'Objects are not passive containers for state and behaviour, but are said to be the agents of a program's activity'* (NeXT Computer Inc., 1993). There are a lot of parallels between an agent and an object in object-oriented programming. An object has attributes and methods and is embedded in an object hierarchy. Agents have internal states (attributes) and can perceive and act upon their environments (through methods). An agent can be differentiated through its functioning, like asynchronous messaging, structuring of all the attributes and methods in modules with a generic function (memory, perception, action, communication...) (Treuil et al., 2001). The famous paper of Franklin and Graesser (1997) discussing the differences between agents and programs underlines the apparent difficulties to distinguish agents from objects or simple computer programs. Some programs, for example daemons on a Unix system, can be seen as agents. But there are some conceptual differences between an object and an agent. The most important difference is probably the fact that an agent is autonomous, this means he can decide on his own whether he wants to execute an action (a method) or not. In the case of an object, the object will execute a method unconditionally, if asked to do so. Agents should also be able to learn, this means to adapt their behaviour. This is not necessarily the case with an object. Agents and objects are somehow similar concepts, but they are not the same. Agents can be implemented through an object, but this is not necessarily the case.

4.2.1 Self-organisation with Multi-Agent Systems

A MAS is a bottom-up approach, where a high number of relatively simple entities interact to form a system capable of complex behaviour. Such systems organise themselves through the definition of the properties of the constituent entities. Analogies to colonies of social insects like ants, bees or termites, have given raise to some quite successful optimisation algorithms. For example Bonabeau et al. (1999) have reviewed the paradigms behind such "swarm intelligent" systems, and showed a couple of applications to different problems, e.g. the Traveling Salesman Problem (TSP), the Quadratic Assignment Problem (QAP), the Job-Shop Scheduling Problem (JSP) or the Vehicle Routing Problem (VRP).

In order to understand how such a swarm algorithm works, we consider in more detail the functioning of an ant colony. An insect colony is indeed a very puzzling structure: each individual seems to have its own task and its own agenda, and the colony seems to be perfectly organised at a global level, without some central, deciding instance. As Bonabeau et al. (1999) point out very correctly: *"An insect is a complex creature [...] [but] the complexity of an individual insect is still not sufficient to explain the complexity of what social insect colonies can do.*" Many of the activities of an ant colony, or a social insect colony in general, is *self-organised*. Theories of self-organisation which have been originally investigated especially by physicists and chemists, can also been applied to ant colonies. They show that complex collective behaviour can arise from the interactions among individuals that exhibit simple behaviour (Bonabeau et al., 1999; Haken, 1983; Nicolis & Prigogine, 1977; Deneubourg, Goss, Franks, & Pasteels, 1989). An ant colony must solve several important problems like finding food, building and repairing their nest, defend the nest to external invaders (other insects), divide the labour etc. What is surprising is the efficiency and robustness of the problem solving. For example if an exploratory ant has found a new food source, a pheromone trail is laid between the food source and the nest. Other ants will follow this trail and enforce the pheromone trail. Like this, many ants will start to exploit this food source, unless it is exhausted or if there is a nearer source. Pheromone is a chemical substance laid in different quantities by an ant and which evaporates slowly. So, if there are many ants passing on a given trail, the pheromones are very present and other ants will easily take this path. If there is another food source closer to the nest, the ants will return more quickly to the nest and can enhance the pheromone trail faster. More and more ants will visit the closer food source, while the number of visiting ants at the further source diminishes.

Bonabeau et al. (1999, pp.9–11) identify four basic ingredients on which self-organisation relies:

1. *Positive feedback (amplification).* This mechanism allows maintaining of currently successful behaviour. For example, the pheromone is an amplification mechanism, as it will encourage other ants to follow this path. It is used to reinforce the current structure.

2. *Negative feedback.* This mechanism is needed to counterbalance the positive feedback and helps stabilise the system. For example the pheromone evaporation is such a mechanism, as it will allow competition between different sources to take place. It also allows reducing crowding, as the ants will need more time if there are too many individuals at the food source and the frequency of ants passing on the pheromone trail will be limited in this way.

3. *Amplification of fluctuations.* A crucial mechanism in self-organising is some randomness and occurrence of errors. Random walks, errors made by the individuals and random task switching will allow the discovery of new solutions. For example, if an ant gets lost on a pheromone trail, it is possible to find a new, closer food source.

4. *Multiple interactions.* Each individual should be able to take advantage of its previous experience and the experience of all the other individuals.

Through the mechanisms at work in a self-organising system, the system is searching permanently the optimal equilibrium. If there is a perturbation changing the environment, a new optimal solution is found very quickly.

This continuous adaptation to the current conditions is an important characteristic of a self-organising system and allows the use of such a system in a wide range of applications.

4.2.2 Multi-agent simulation

Basically, if a multi-agent system is used for representing the reality, we call it a multi-agent simulation (Treuil et al., 2001, p. 221). More specifically, a multi-agent simulation is a micro-simulation approach based on a multi-agent system, where the overall behaviour of the system is formalised at microscopic level by defining the composing units. Generally, two levels are considered: the level of the individual, e.g. people, households, firms in social sciences, and the aggregated, global level, which corresponds in geography to the study region (Holm & Sanders, 2001).

The modelling of spatial dynamics through a multi-agent simulation comprises the following steps, according to Treuil et al. (2001):

- Identification, in the reality, of a finite set of types of entities and relations.
- Characterisation of these types of entities and relations through a finite number of attributes.
- Identification of the process types and the characterisation of their effects and mechanisms on an algorithmic level.
- Definition of a control schema controlling the temporal order of the process execution.
- The programming itself, respecting the defined structures of the entities, processes and their control.
- Creation of an "initial world" with instances of the different types of entities, relations and processes.
- Execution of the program producing different simulations according to different scenarii.

4.3 Traffic simulation

Traffic planning is an important issue in modern cities and agglomerations. Transportation is necessary for fulfilling the needs of each individual in the society, and also for goods needed at a given location in space. Traffic is essential for the economy, but has also some negative effects like noise, air pollution or injuries caused by accidents. Inefficient traffic, like the occurrence of traffic jams, increases these negatives effects and adds additional negative effects, particularly time loss for people involved. Individuals using the transportation system are not concerned about the system itself, but only about their own benefit. As transportation capacity on such a network is limited, competition for the use of this offer arises (Balmer, 2007). Transportation planning is therefore an important tool for offering an optimal network for the needs of the economy and the people by limiting the negative effects of traffic.

People generate traffic. But we should keep in mind that people generate traffic for accomplishing their activities, this means for some purpose. The traffic planning should ideally integrate the reasons for the transportation at an individual level. This would enable the planer to monitor each person and extract information about the time dependant traffic volumes, the modal split and the reasons for the modal choice, the human density at a given time or the activity chain (Balmer, 2007). Such detailed real world data does of course not exist because of privacy protection. In traffic planning, tools and techniques for dealing with incomplete data are therefore essential.

According to Balmer (2007), the traditional approach for transport planning is the *four step model* (see e.g. Sheffi, 1985; Ortúzar & Willumsen, 2001). In this approach, the study zone is divided into subzones. The traffic flow between the different zones is then determined (the demand), and an equilibrium solution for the flow of vehicles in the network is searched. The four steps are the *trip generation*, *trip distribution*, *modal choice* and the *route selection*. During trip generation, for each zone the incoming and outgoing trips are defined. The trip distribution creates the Origin-Destination (OD) matrix; in this step, the origins and destinations are connected together. The modal choice step defines the mean of transportation used for each trip. Finally, the route selection step assigns a path on the network for each trip (generally, this step is limited to trips done by car). However, the four-step model lacks differentiation at the level of an individual and temporal dynamics. The former allows links between transportation behaviour and demographic or social characteristics, while the latter is essential in an urban context with peak hours.

Micro-simulation is an important tool in Traffic Simulation (TS) (Balmer, 2007; Vovsha, Petersen, & Donnelly, 2002; Bowman, Bradley, Shiftan, Lawton, & Ben-Akiva, 1999; Bhat, Guo, Srinivasan, & Sivakumar, 2004). TS enables us to have a precise spatiotemporal image of the real traffic. Among the objectives are understanding of capacity problems (traffic jams) or optimisation of the road network through guidance systems (red lights, information systems). TS can also be used to understand interactions between the urban structure and the real traffic. It allows estimating more accurately the transportation duration with respect to different traffic situations during a day. And it can be used to simulate the car dependence for different populations by comparing the simulation transportation duration for private and public transportation means. Using such a micro-simulation approach, it is possible to integrate the individual decision-making process in the TS. This is important as people do generate traffic for a given purpose, and integrating elements leading to the choice can enhance the simulation itself. Such choices can include for example activity location choice (where to go?), activity time choice (when should I do a given activity?), activity chain choice (shopping before or after work?), modal choice (how to get there?) and so on.

In a micro-simulation approach, the following tasks must be accomplished:

1. Generation of a *statistically correct synthetic population*. This synthetic population is a virtual population that is one possible realisation of the true population. The synthetic population would give the same census results as the conducted censuses of the real population. Such a synthetic population is composed by households having well defined properties like spatial location, income, car ownership etc. (Beckman, Baggerly, & McKay, 1996; Balmer, 2007). The households are composed by a given number of individuals having some other properties like gender, age etc.

   It is a good practice to create several realisations of a statistically correct synthetic population; each realisation is different in some details. For each of these realisations, the traffic simulation should be run, and the results compared in order to estimate the sensitivity of our traffic simulation. However, creating such a synthetic population and running a traffic simulation are computationally intensive tasks and such a sensitivity analysis can not be conducted in each case.

2. Generation of a *daily activity agenda* for each individual. Individuals have different day activities: working, shopping, looking after the children, leisure, visiting friends, etc. An activity chain is a series of temporally ordered activities for a given individual. These activity chains have usually more or less known characteristics: most of the working people do so during day, visiting friends is rather done after work, etc. Censuses like the Swiss micro-census on traffic behaviour (Swiss Federal Statistical Office SFSO, 2005a) may help in defining and calibrating such activity agendas.

   Such an agenda contains the temporally ordered list of activities along with the location of each activity, and information about the begin and end of a given activity (Vaughn, Speckman, & Pas, 1997; Balmer, 2007).

3. *Modal choice* for each individual. For each trip an individual has to do between two activities not located at the same place, a mode of transportation should be chosen. This choice depends on characteristics

of the transportation offer available for the individual. Demographic characteristics can also play a role in this choice.

4. *Optimal path selection* through the simulation of the time-dependant traffic volume. The simulation of all the trips allows the choice of the optimal path to take for each trip. This simulation is usually an iterative process. After each simulation step, the individual may have the possibility to improve the path, change the activities, or the transportation mode.

5. *Validation* of the simulation. Once the simulation has found a stable simulation result, a validation should be done by checking some statistical characteristics of the simulation. This can be for example statistics on the length of the trips, number of trips by person etc. These statistics can be compared to census results. A subset of activity chains should be analysed manually in order to check their consistency; visual inspection tools are valuable tools for doing this. If possible, several simulations should be done and compared to check their sensitivity. If several synthetic populations are available, simulations between different populations should also be compared and checked for sensitivity.

Some of the above steps can vary in their order. For example, the transportation mode can be chosen before or after the activity location, or at the same time (see e.g. Lohse, Bachner, Dugge, & Teichert, 1997; Kutter, 1983; Balmer, 2007).

Each of the above steps have their own issues. The most crucial are the creation of the synthetic population, and the traffic simulation (optimal path selection) itself. The creation of the synthetic population is part of the calibration process of the traffic simulation and will be discussed in section 4.4 specifically for multi-agent simulations.

Different types of traffic simulations are known in the literature, e.g. cellular automata models, queue models or car following models. Each type of simulation has a different resolution and the need of computation power varies greatly between the models. Among all the models, we can find the following:

- *Cellular Automata model.* In a CA, time and space are divided into discrete units. In a traffic simulation CA, each cell contains zero or one vehicle or person. The state of a cell c at time t is defined by the state of its neighbouring cells at time $t-1$. A vehicle can move only to free neighbouring cells that are part of the network. Additionally, the vehicle will need some time to cross the cell it is currently on; this time depends on its speed. Speed may be limited like in real life traffic (there is a minimum time to cross the cell). A traffic simulation

CA is simple. As a lot of details can be included into the model, the simulation may be quite realistic. The drawback of this approach is the relatively slow computation speed; it is virtually impossible to run a large simulation using the CA model.

- Car following model. The car following model is based on the interactions between the different vehicles on the road. The model is based on four different states: free driving (no other car around), following a car (distance lower than a model dependent upper following distance but bigger than safety distance), approaching, and danger (safety distance not respected). The car following model describes the behaviour of a driver who wants to drive faster than the present speed of the preceeding vehicle; it can be combined with a lane-changing model for describing the behaviour of overtaking (Fellendorf-1994, 1994). Wiedemann (1974) developed a car following model based on perceptual thresholds and the physical spacing of vehicles; this model is called psycho-physical model (see e.g. Wiedemann, 1974; Fellendorf-1994, 1994; Fritzsche, 1994). The car following model allows very detailed simulation of car traffic, with individual characteristics for each vehicle and driver. Anticipation and cooperation, as we observe in reality, can be integrated into this model. The drawback of this approach is the computation speed that is far too slow for big simulations. The commercial software package *"VISSIM"* implements the car following model as described by Wiedemann (1974), together with a lane-changing model (see `http://www.ptvag.com` for more information on VISSIM).

- Queue model. The queue model divides, like the CA model, time and space into discrete units. Unlike the CA model, the queue model divides the edges (links) of a network into several pseudo-cells. Each street is one of these pseudo-cells. The model is agent based and allows very quick computation. The principle of the queue model is that vehicles on an edge drive with a defined maximum speed v_max until they encounter a queue. Each link is a First-In First-Out (FIFO) queue with three restrictions (Balmer, 2007):

    1. Each agent has to stay a minimum time amount on each link. This corresponds to the time needed to cross the link with free speed (maximum allowed speed on the link).
    2. Each link has a maximum capacity. This means the number of agents (vehicles) allowed on the link is fixed and usually proportional to its length times the number of lanes. If the maximum capacity is reached, no other agents can enter the link and have to wait on the previous link.
    3. The number of agents leaving a link during a given time is limited; this is the maximum capacity.

At intersections, there are no priority rules, but a flow defined by the capacity of each arriving edge. In the queue model, it is not possible to include some real, individual dynamic vehicle behaviour on each edge, as this would slow down the computation speed without improving considerably the model output.

The queue model is used in Stochastic Queue Based Agent Traffic Simulation (SQSim) (Balmer, 2007; Cetin, 2005; Gawron, 1998; Cetin, Burri, & Nagel, 2003). It gives rise, despite its simplicity, to a fairly realistic traffic simulation model and produces useful output for the purpose of transport planning (Balmer, 2007).

4.3.1 MATSim: a stochastic queue based agent traffic simulation package

MATSim (MATSim-T, 2009; Balmer, Meister, Rieser, Nagel, & Axhausen, 2008) is an open-source toolkit for transport simulation designed as a flexible developer platform for transport planning software (Balmer, 2007). The development of MATSim started in 1998 at the Swiss Federal Institute of Technology in Zurich (ETHZ) (Balmer et al., 2008). It builds on top of more than 30 years of experience in micro-simulation of travel demand (see e.g. Poeck & Zumkeller, 1967; Zumkeller, 1989; Axhausen & Herz, 1989; Balmer et al., 2008). The MATSim package is currently developed jointly by the ETHZ, the Technische Universität (TU) Berlin and the Centre National de la Recherche Scientifique (CNRS) Lyon.

The basic idea of the traffic simulation implemented in MATSim is a relaxation strategy where an initial travel demand is used for the flow simulation in the road network. After this first run, the result is used to update the activity chains and their timing, the location choice, the transportation mode and the route choice. This iterative step is done until a stable solution has been found and the improvement between two iterative update steps is not significant anymore (Balmer et al., 2008).

A traffic simulation as done by MATSim can be characterised by the initial conditions (boundary conditions) like for example the transport network, demographics, facility locations or the land use, and some parameters adapted during simulation. These adaptive parameters are typically used for making transportation related choices like the modal choice, activity time and location choice; these parameters are adapted in a *re-planning module*. MATSim is built in a modular way that allows to plug very specific user-defined re-planning modules into the standard simulator. The generation of the initial conditions is also done separately, which allows for a big flexibility in the simulation. This calibration step is indeed one of the main issues in multi-agent simulations in general, and therefore in agent based traffic simulations; the problems related to agent calibration is discussed in section 4.4.

4.3.2 Traffic simulation of the agglomeration of Lausanne using the MATSim package

The agglomeration of Lausanne consists of 70 municipalities with the central city of Lausanne counting roughly 125'000 inhabitants. The whole agglomeration counts around 300'000 people. Traffic jams are quite frequent, especially in the city centre and on the highway crossing the agglomeration. We have created a multi-agent traffic simulation for the commuting population using the car for going to work. Figure 4.1 shows the distribution of the number of working places against the number of working inhabitants for the agglomeration. The structure of the agglomeration of Lausanne is quite classical: the city centre has a high concentration of working places, typically in the service sector. There is another zone, west of the centre, around the highway junction, where working places are more important than residential areas; this is mainly due to its good accessibility for the individual motorised traffic. In this area, beside a high number of tertiary firms, we also find big shopping centres and industrial areas. Around the city centre, and especially towards east (where the protected zone of Lavaux lies between Lausanne and Vevey), we find mainly residential areas. This segregated structure between working places and residential zones leads to an important demand in mobility for commuting to work.

The traffic simulation for the agglomeration of Lausanne builds on the road network extracted from the Vector-25 dataset (Swisstopo, 2008), for the whole canton of Vaud. The road network was cleaned and attributes important for traffic simulation defined in a quite general manner; mainly the maximum speed, the number of lanes (for highways), and the capacity have been estimated. One-way or pedestrian roads could not been defined correctly based on the Vector-25 dataset.

The data for the calibration of the agents comes from public censuses conducted by the SFSO. The population census (Swiss Federal Statistical Office SFSO, 2005b) and the firms census (Swiss Federal Statistical Office SFSO, 2005c) are available at a hectare level which provides a good base for the calibration. Additionally, the micro-census of traffic behaviour (Swiss Federal Statistical Office SFSO, 2005a) gives a sample of roughly 30'000 people for which a big amount of details related to mobility and some socio-economic characteristics are known. For establishing the OD matrix for the commuting behaviour at the level of an agent, the population census provides an aggregated OD matrix at the level of the commune; this OD matrix is available for each different mode of transportation. For this traffic simulation, only commuters with a start and/or end point in the agglomeration of Lausanne and using the car have been considered. These data should allow a fairly good calibration of the virtual agent population. However, for sake of simplicity, no activity chains have been generated, and no other traffic than traffic to work included in the simulation. The traffic starts at

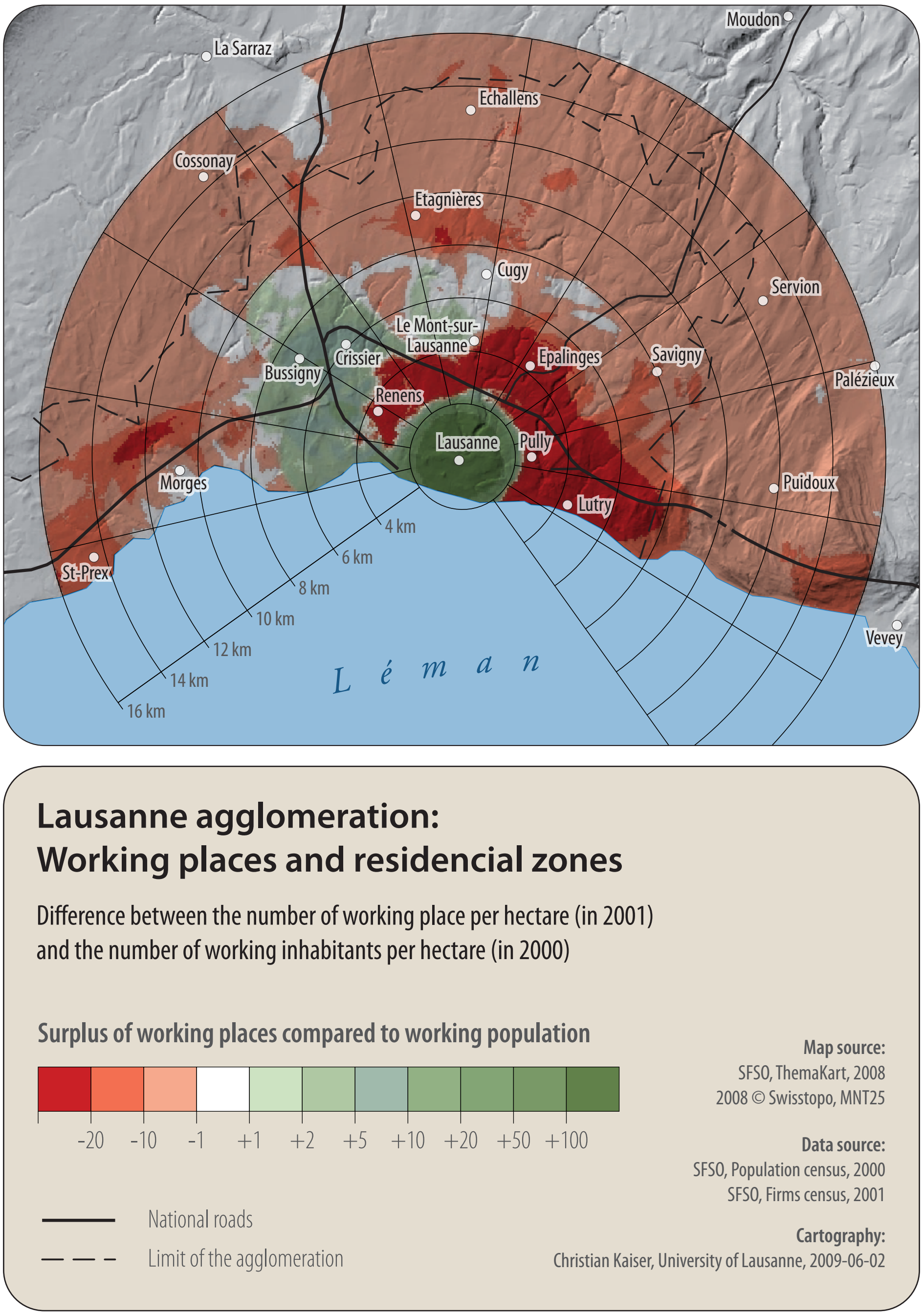

Figure 4.1: Difference between the working places and the working population for the agglomeration of Lausanne.

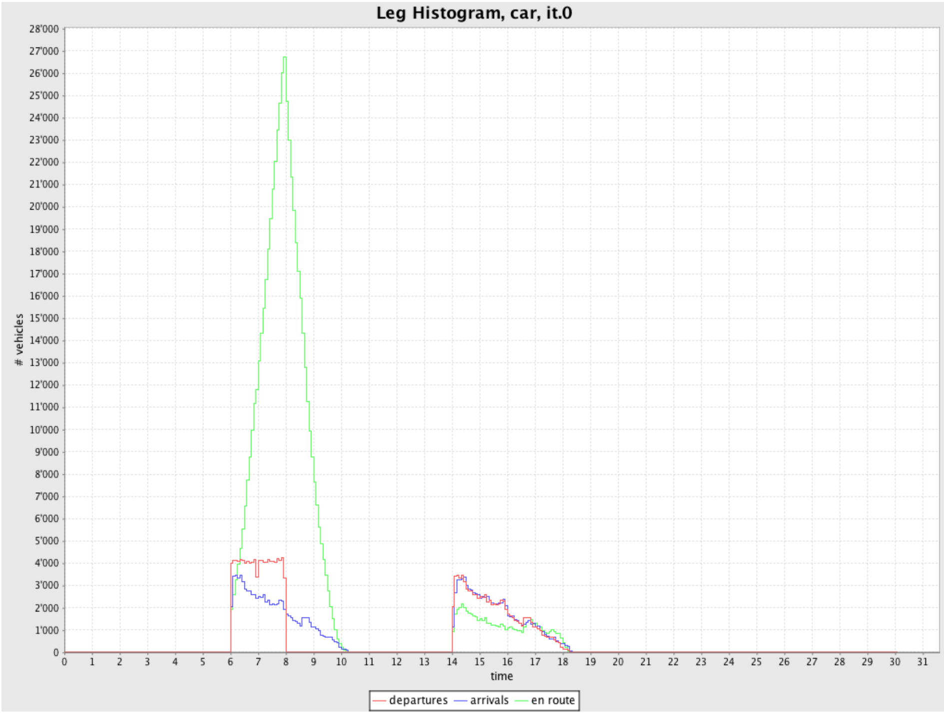

Figure 4.2: Number of vehicles on the road during the iteration 0, with starting and end time.

6 AM, agents stay typically around 8 hours at work, and return to home. This scenario creates two peak hours in the traffic: the first from 6 to 8 AM, and the second roughly between 2 and 4 PM; the traffic back to home takes place already in the early afternoon as a consequence of the simplicity of the simulation. However, as only commuters are considered in the simulation, this issue does not change the results.

The simulation has been done using the MATSim toolkit with the built-in re-planning unit. 50 iterations have been allowed for the optimisation process. At the first iteration (iteration 0), mean travel time was nearly 1 hour, more than 25'000 vehicles were on the way at 8 AM (see figure 4.2). Mean travel distance was about 12.5 kilometres. Figure 4.3 shows the number of cars on the road during the last iteration. At the maximum peak, "only" about 4200 cars were on the road. The mean travel time was about 10 minutes, which is less than reality. This is probably due to the absence of other traffic than commuter traffic and to the non-optimal road network where shortcuts across small roads are possible (no one-way or pedestrian only roads). The travel distance did not change significantly during the optimisation process.

For all the agents in our simulation, we know now exactly the distance between their home and their work. Figure 4.4 shows a map with the mean

Figure 4.3: Number of vehicles on the road during the iteration 50, with starting and end time.

distance to work for all the agents involved in the simulation. The statistic has been computed within a moving window of 1 kilometre. Note that the distance to work has been mapped at the place of residence of the agent. A comparison with figure 4.1 shows that the distance to work is smaller for the agents with a home in a zone with a surplus of working places. However, the shortest trips are for commuters living in the west of the Lausanne city centre. For the centre itself, the trips are slightly longer despite the fact that the city centre has the biggest surplus of working places; but they are still shorter than in average. Typical residential areas at the east and northeast of the agglomeration have longer trips to work. The map in figure 4.4 can be combined together with an estimation of the trip length using other means of transportation to an indicator of the economic impact of commuting.

Another statistic that can be retrieved from such a simulation is the evolution of the human density during a day. Figure 4.5 shows the human density between 6 and 8 AM for the traffic simulation. It shows a concentration process mainly from peripheral zones toward the centre of the agglomeration. However, this result is not comparable to figure 4.1, as it takes into account only the agents of the traffic simulation, that is the population commuting to work using the car.

Based on the simulation, it is possible to analyse further the resulting data and compare with other data coming from other sources. However, the simulation results must be analysed carefully and the sensitivity evaluated by running different simulations using several statistically correct virtual populations. Otherwise, issues similar to the ecological fallacy may occur. The ecological fallacy is an error in the interpretation of statistical data based on the assumption that individuals belonging to a group have average characteristics of this group, which is a wrong assumption if the group is heterogeneous. The ecological fallacy may occur if aggregated statistics are used, and is related to the MAUP (see e.g. Gehlke & Biehl, 1934; Openshaw, 1984; Pearce, 2000).

4.4 Calibration of a multi-agent simulation

The calibration of a multi-agent simulation defines the individual characteristics for each agent. In geography, these characteristics vary generally in space and time. We also need to place the agent at a precise point in the space-time continuum. A simulation is only viable if the calibration is done carefully and reflects the observed reality. It is therefore necessary to find the underlying spatiotemporal structures for each characteristic. If, for example, we observe a given age structure for the population in our study region, we have to reproduce this age structure at least approximatively. Generally, we don't have the disaggregated population data at each point in space. Usually, the public census, as for example the Swiss Population Cen-

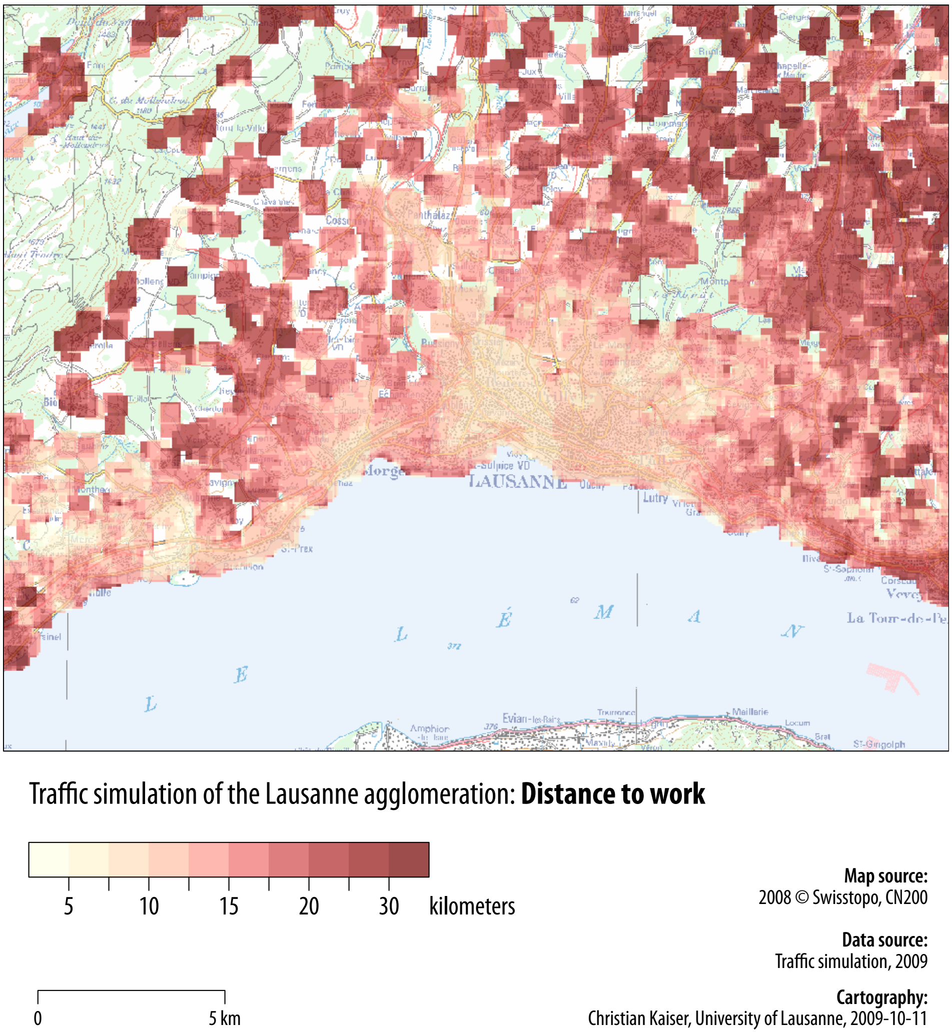

Figure 4.4: Distance to work for all the agents of the traffic simulation.

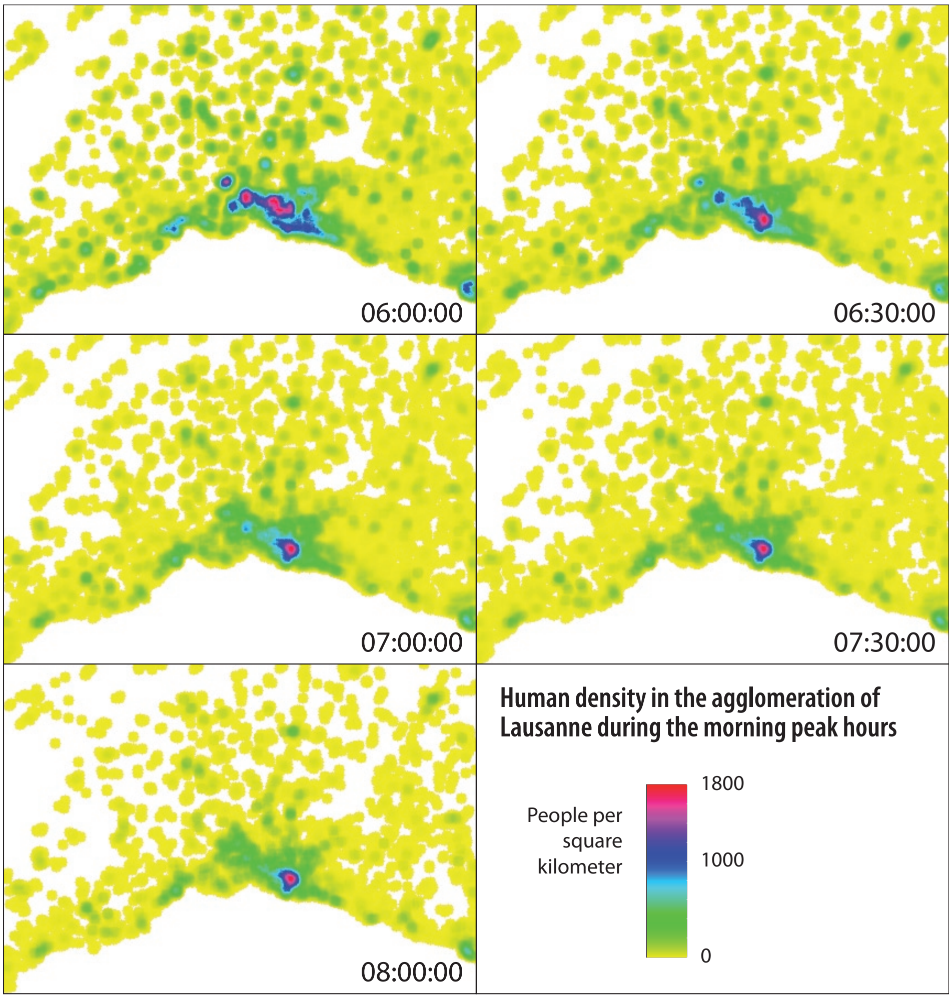

Figure 4.5: Human density during the morning peak hours in the traffic simulation.

sus (Office fédéral de la statistique OFS, 2000), provide only the marginal distribution for the most important population characteristics over an aggregated region, which may be communes or, for the Swiss Hectometric Census (Swiss Federal Statistical Office SFSO, 2005b), the hectare. It is therefore necessary to estimate, for each point in space (and time), the joint distributions. It is important to note that scale and boundaries of geographic features may considerably modify the results of a spatial analysis.

For the purpose of illustration, we will consider a practical example. In the area of travel simulation, we need to forecast the travel demand of the population. This forecast is typically done using activity-based microsimulation model systems providing robust behavioural frameworks in a wide variety of contexts (Ye, Konduri, Pendyala, Sana, & Waddel, 2009). In this type of simulation, each real person is represented by one agent. The calibration of such a simulation consists therefore in producing a virtual population with properties as close as possible to the real population. The agents should be preferably grouped into households and social networks (see e.g. Balmer et al., 2008; Hackney & Axhausen, 2006; Arentze & Timmermans, 2006; Axhausen, 2005).

The most widely used method for virtual population calibration is probably Iterative Proportional Fitting (IPF) (see e.g. Deming & Stephan, 1940; Papacostas & Prevedouros, 1993; Beckman et al., 1996; Anderson, 1997; Frick & Axhausen, 2004). The crucial step is the creation of a multidimensional table containing all the required attribute variables; the agents are then generated from this table. The IPF algorithm is demonstrated using a multiway table in 3 dimensions, but it can used for any number N of dimensions. It works as follows (as presented by Frick & Axhausen, 2004):

Let π be a 3 dimensional multiway table with unknown components but known marginal distributions $\{x_{ij\bullet},\ x_{i\bullet k},\ x_{\bullet jk}\}$, where a bullet represents the sum over that index. π_{ijk} represents the probability of co-occurrence of 3 different socio-economic categories i, j and k for an agent. The multiway table π should respect the following straightforward constraints:

$$n\pi_{ij\bullet} = x_{ij\bullet}, n\pi_{i\bullet k} = x_{i\bullet k}, n\pi_{\bullet jk} = x_{\bullet jk} \tag{4.1}$$

$$n = \pi_{\bullet\bullet\bullet} = x_{\bullet\bullet\bullet} \tag{4.2}$$

where n is the total sum of observations. The iteration process starts using an initial solution $\pi^{(0)}$ for π; this solution comes ideally from a known subset of the census. One iteration is done by executing the following equations in turn; the number of equations is equal to the number of dimensions:

$$\pi^{(1)} = \frac{x_{ij\bullet}\pi^{(0)}}{n\pi^{(0)}_{ij\bullet}} \tag{4.3}$$

$$\pi^{(2)} = \frac{x_{i\bullet k}\pi^{(1)}}{n\pi^{(1)}_{i\bullet k}} \tag{4.4}$$

$$\pi^{(3)} = \frac{x_{\bullet jk}\pi^{(2)}}{n\pi^{(2)}_{\bullet jk}} \tag{4.5}$$

The iterations continue until the change between two iterations becomes insignificant. According to Frick and Axhausen (2004), this algorithm converges sufficiently in about 20 iterations.

If a sample from the population is known, and the marginals of the multiway table are also known, the IPF gives a constrained maximum entropy estimate of the multiway table (Ireland & Kullback, 1968; Frick & Axhausen, 2004).

One problem that can be encountered with the IPF procedure is that the spatial variations of the population characteristics can be important in some cases if data are only available aggregated for larger areas. Aggregate data should be available at a rather fine resolution in order to not cause important distortions in the calibration result. If data are available at a municipality level, such problems can typically occur in bigger cities where the socio-economic differences are important in some cases between different residential areas and typically travel behaviour varies a lot. Spatial variations should then be included, for example using methods of area-to-point interpolation (see e.g. Tobler, 1979b; Kyriakidis, 2004, and also section 4.4.1).

Another issue that has to be addressed separately is the spatial distribution of the agents inside the aggregated zones for which data are available. This will be discussed in the next section.

4.4.1 Estimation of the spatial distribution of the agents

The methods for estimating the population distribution or the population density for a given area are numerous. We can estimate the number of people directly, or the population density: it is trivial to change from one measure to the other, using the study area for which we want to know the number of people or the density.

The simplest approach is to distribute the population uniformly for the whole extent of the geographic unit for which we know the population count. However, population is generally not distributed uniformly in space, and this method won't give a satisfactory result. If we take the case of a municipality – the smallest geographic unit for most censuses – population is generally concentrated into a small part of the whole territory that often includes agricultural land, forests, rivers etc. Figure 4.6 shows an example of a typical structure of a village.

Figure 4.6: Structure of a typical village.

Wu, Qiu, and Wang (2005) separate all the different approaches into two categories: the methods of area-to-point interpolation and the statistical models.

- *Area-to-point interpolation* allows solving the problem of area-to-area interpolation illustrated in figure 4.7 and the zone transformation problem where we have to estimate a variable known only for a set A of spatial units (the 2 polygons in figure 4.7) for another generally bigger-scaled set B of spatial units (the red square in figure 4.7). Such a transformation involves the estimation of the spatial distribution of the measured phenomenon.

- *Statistical models* try to apply urban geography theories in order to estimate the population distribution. These approaches try to establish a (statistical) link between the population and another variable (built area, land use, satellite imagery pixels, etc.).

Area-to-point interpolation allows the estimation of the population inside a spatial unit smaller than the one used by the census. We call *source zone* the set of units where we know the population, and *target zone* the set of usually (but not necessary) smaller units for which we want to estimate the population (Lam, 1983).

The methods with or without auxiliary data are numerous; some of them are briefly described here:

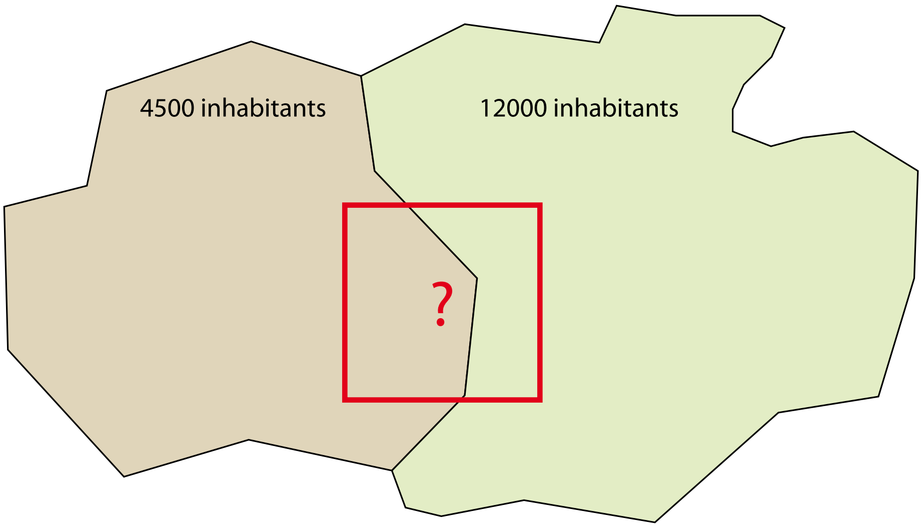

Figure 4.7: The problem of the area-to-area interpolation involves estimating the population in the red square with the population known only for the 2 polygons.

- Martin (1989) proposes a kernel-based interpolation method using the source zone centroid as a control point. He uses a distance weighting function for estimating the population for each node of a regular grid. This method supposes that each geographic unit is more or less symmetric, which is in reality rarely the case. This method, as other methods using the centroid as a control point, cannot guarantee that the total population is the same after interpolation, which is a big inconvenience (Wu et al., 2005).

- Tobler's pycnophylactic interpolation is a well-known area-to-point interpolation method (Tobler, 1979b). A smooth, continuous density function is computed in space that takes into account the neighbourhood and guarantees the respect of the total population after interpolation. The estimated surface approximates the neighbourhood mean.

- Kyriakidis (2004) presents a geostatistical approach for the area-to-point interpolation. His method is a generalisation of Tobler's pycnophylactic interpolation (Tobler, 1979b). His geostatistical framework allows the estimation of the value at each point in space using the area values and with respect to the total population. Kyriakidis (2004) considers the area-to-point interpolation as a special case of change of support and refers to Gotway and Young (2002). The proposed method is a special case of Kriging (Matheron, 1971), even if Kriging has more often been applied to classical point-to-point interpolation problems.

- Wright (1936) has developed the "dasymetric method" which uses auxiliary information for restricting the domain where the uniform distribution can be applied. Poulsen and Kennedy (2004) define this approach as follows: *"Dasymetric mapping involves estimating the distribution of aggregated data within the unit of analysis, by adding additional information that provides insights on how these data are potentially distributed."* The idea is to ignore regions without population, which is the same as to make a binary distinction between presence or absence of population. Using GIS, this approach has become very widespread and easy to implement. The method has also been applied to the non-binary case, for example by Maantay, Maroko, and Herrmann (2007) who uses a cadastral-based expert system, or by Langford, Maguire, and Unwin (1991) who use a regression analysis in order to refine the density in populated places. More case studies, some with variants to the dasymetric approach, are known in the literature, see e.g. Wu et al. (2005) for some of them. The advantage of the dasymetric interpolation is the ease of integration of several factors in order to get a probability map characterising the population distribution.

Example of population modelling in the Lausanne agglomeration using topographic maps, LIDAR elevation data and land management maps

In this example, we present a variant of dasymetric interpolation using the following auxiliary data:

- *Buildings.* The buildings can be extracted from a topographic map (see e.g. Tuia and Kaiser (2007)), from aerial photos or satellite imagery. The distribution will still be uniform, but only inside inhabited zones, which improves considerably the result. This approach is identical to the one of Wright (1936). Figure 4.8 illustrates the advantage of including this information comparing to figure 4.7 where such information was not considered.
- *Land use maps.* Some types of buildings, like factories or other industrial buildings, are not inhabited. A land management map for example can help in excluding inhabited buildings. This type of data allows to further restrain the zone where the population can be distributed uniformly.
- *Building heights.* With an easier access to the Light Detection And Ranging (LiDAR) technology, it has become possible to get the build-

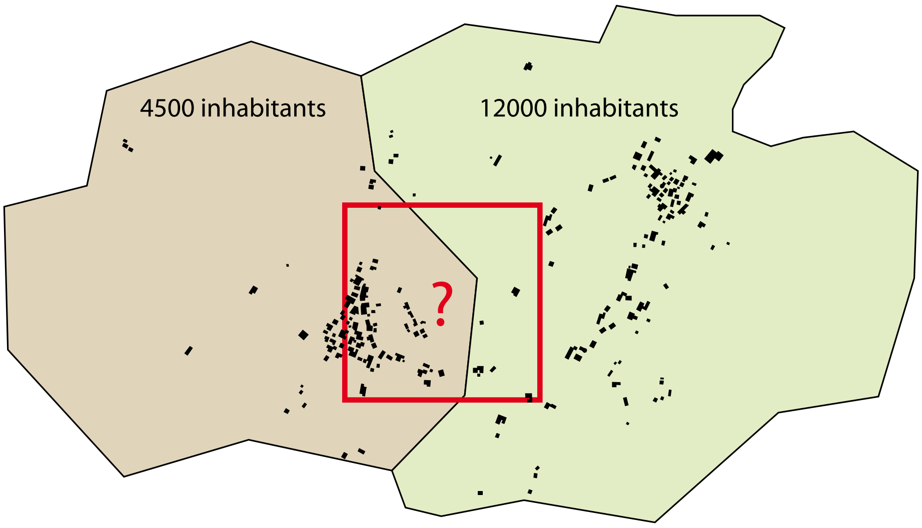

Figure 4.8: Auxiliary information alleges considerably the problem of the area-to-area interpolation.

ing heights for a whole, even quite large, study region. LiDAR allows determining the distance to an object using laser pulses. Deployed on a plane with Global Positioning System (GPS) and Inertial Navigation System (INS), it can be used for acquiring a digital elevation model with a resolution of only a few centimetres. The building heights allow the distribution of the population proportionally to the building volume instead of the area only. We are able to use 3D data; the third dimension can be seen as a probability map for the population distribution.

For the population distribution estimation, we use essentially two elements: a *validity domain* where people may potentially live, and a *density layer* that allows estimating the population density at each point in space. In our case, the density layer contains the building heights, but it might also incorporate other information. Algorithm 1 outlines how we can find a location for each person respecting the validity domain and the density layer.

Algorithm 1 Distributing the population

Require: A bounding box *bbox* enclosing our region,
a polygon layer with our validity domain *vdom*,
a raster layer with the density probability p

```
Initialise an empty population array pop
repeat
  get a random location loc inside bbox
  if loc inside vdom then
    get a random probability value pval
    get p at location loc
    if pval ≤ p then
      add location loc to pop
    end if
  end if
until the whole population is located
```

The outlined procedure has been applied to the 70 communes composing the agglomeration of Lausanne. About 300'000 people live in the agglomeration. Population is distributed in a very unequal manner, with the city of Lausanne and its neighbouring communes having a much higher population density than surrounding areas. Generally, population is concentrated in the commune's centre. Figure 4.9 shows the density according to the population census 2000, with a resolution of one hectare (Swiss Federal Statistical Office SFSO, 2005b).

In this example, we will estimate the population distribution based on data at the level of the commune. Based on the estimated individual locations, we will aggregate the estimated population distribution according to the hectometric grid used in the population census; this enables us to validate the approach. Basically, we try simply to reproduce the same image as in figure 4.9.

Figure 4.10 shows the result of algorithm 1 at an individual level. Visually, the parallels between the model and the statistical reality are obvious. A validation using the hectometric data allows a quantitative measure of the estimation quality. The aggregation of the estimated individual data according to the hectometric grid (figure 4.11) allows comparing the estimation with the statistical reality. We have computed Person's correlation coefficient between the hectometric data from the population census and three different population estimation methods:

- *Method 1.* A uniform distribution inside of each commune, without validity domain or density layer.
- *Method 2.* A uniform distribution with the residential buildings as validity domain, but without density layer.

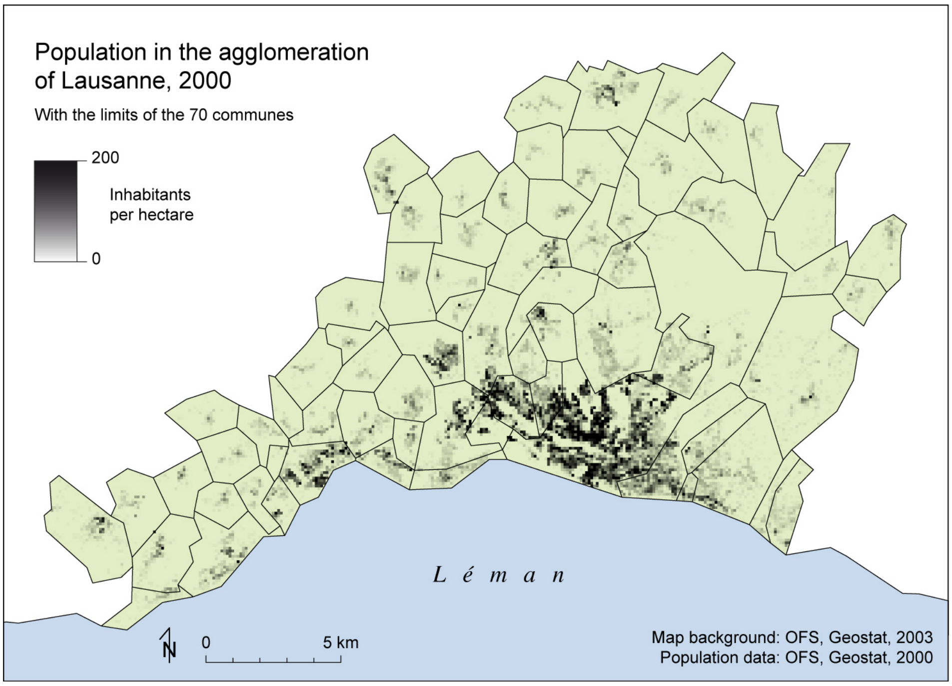

Figure 4.9: The population distribution in the Lausanne agglomeration.

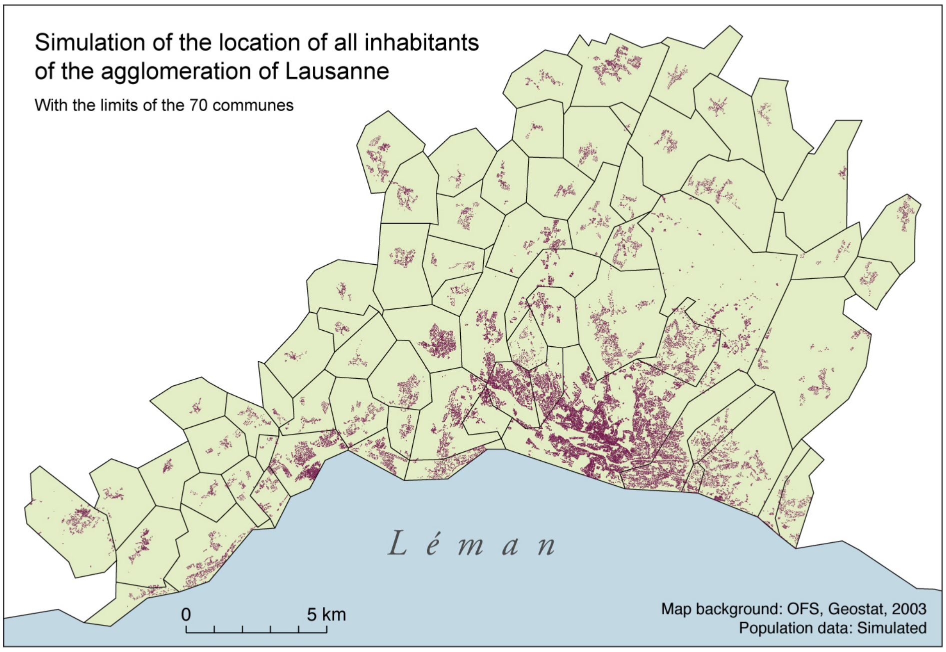

Figure 4.10: The result of the location estimation for about 300'000 people in the Lausanne agglomeration.

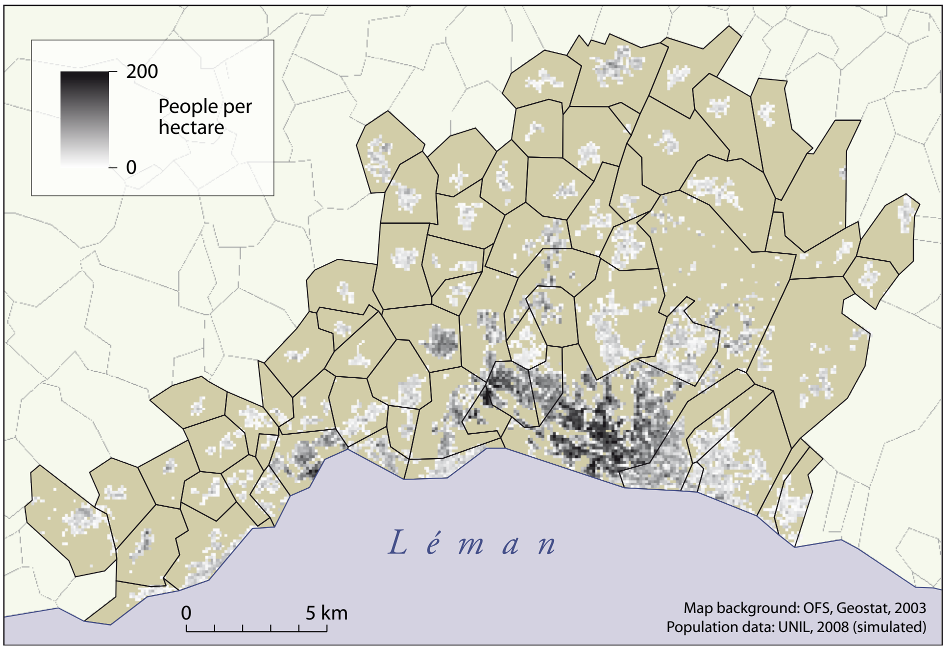

Figure 4.11: Random population distribution inside residential buildings and respecting the density layer containing the building heights.

- *Method 3.* The distribution computed using all available information, this is a uniform distribution with the residential buildings as validity domain, and the building heights as a density layer.

The comparison of these different methods allows the estimation of the contribution of each piece of information for the accuracy of the estimation. Table 4.1 shows the different correlation coefficients for the three methods. All coefficients are statistically significant. Comparing with the dasymetric interpolation using only a validity domain, the use of a density layer (method 3) improves appreciably the correlation coefficient. The simple uniform distribution (method 1) shows a clearly unsatisfactory result.

Note that these correlation coefficients are based on a pixel-by-pixel comparison. An eventual similarity or difference in the neighbourhood has not been assessed.

Even with a quite big number of included data in our estimation process, the resulting distribution does not correspond entirely to the reality. Figure 4.12 shows the areas with over- or under-estimation of the population. A qualitative analysis of this map allows the conclusion that we have a slight over-estimation of the population for large zones. These zones are often residential districts with a relatively low density. These districts, probably with a richer population, have a building volume per person higher than the overall mean. This results in an over-estimation of the population in these

	Method 1 Uniform distribution	Method 2 Uniform distribution with validity domain	Method 3 Uniform distribution with validity domain and probability density layer
Pearson's correlation coefficient	0.374	0.561	0.603
Confidence interval 95%	0.367 0.378	0.557 0.565	0.599 0.606

Table 4.1: Correlation coefficients between the real population values and each of the simulated population values.

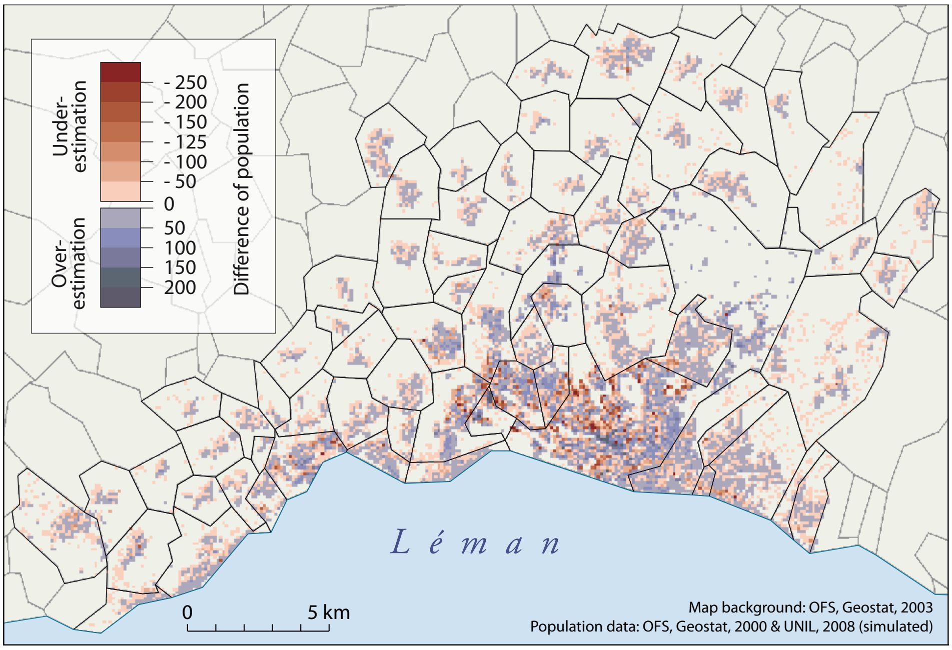

Figure 4.12: Difference between the simulated population distribution (as in figure 4.11) and the real population distribution (as in figure 4.9).

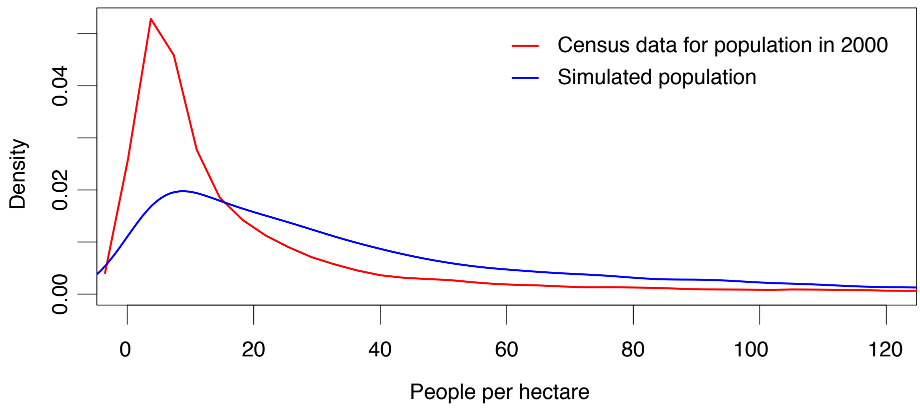

Figure 4.13: Density curves for the real population distribution (as in figure 4.9), in red, and the simulated population distribution (as in figure 4.11) .

zones. We have also an over-estimation in Lausanne's city centre, which is due to the presence of a high number of offices, commercial activities and other, e.g. administrative buildings being partly residential. Under-estimated zones are present mainly in the western periphery of the city of Lausanne. These are residential districts with slightly poorer population classes where the population density per volume is higher than expected.

The density curves of the estimated distribution and the real population distribution (figure 4.13) show also a slight difference. The real distribution has clearly more cells (hectares) with only very few people (typically 3 or less), and some cells with a very high number of people, the maximum being 1842. The algorithm generating the estimated distribution is not able to reproduce this characteristic. A much less pronounced and smoother density distribution is the result. We can explain this effect with the use of a uniform distribution inside the constraints defined by the validity domain and the density layer. This behaviour seems normal and can be expected. At the same time, this analysis shows the fact that the population distribution is clearly not uniform, even within quite restrictive constraints; we have emergence of clusters. Figure 4.12 can be used in this context as a population cluster map.

The major difference of the presented population density estimation method with classical mapping such as dasymetric mapping is the random component in the algorithm. Thus, the result of the density estimation varies from one run to another. However, each estimation is one possible realisation of the population distribution, and they are all correct at the aggregated level. This procedure allows estimating the variations between different runs and estimating the stability of the resulting population dis-

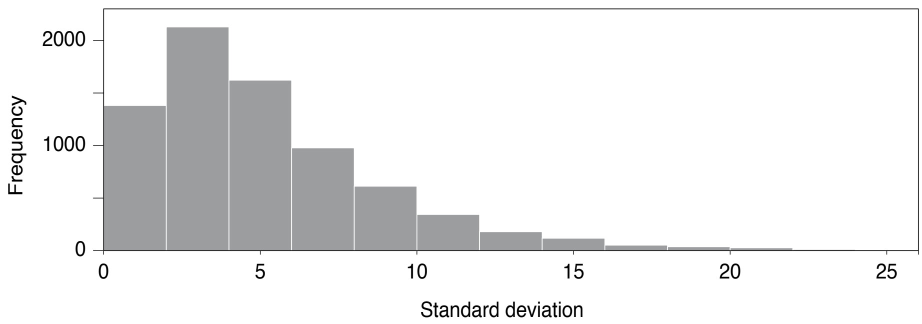

Figure 4.14: Histogram for the standard deviation for each hectare between different runs of the population distribution estimation
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tribution (Kaiser & Kanevski, 2010). We have run 100 estimations and computed the standard deviation for each hectare. The mean value for all standard deviations inside the validity domain is 5.1. Figure 4.14 shows the density histogram of the standard deviations. In this particular case, the variations between different runs seem to be quite low. This analysis can be done without knowledge of the real distribution and should therefore be performed for each population distribution estimation as a proxy for the estimation stability.

As a conclusion, we can say that this analysis has clearly shown the necessity to use auxiliary information for a more or less realistic population distribution. This is confirmed by Langford, Higgs, Radcliffe, and White (2008) who have studied the impact of the urban population distribution modelling on service accessibility: *"...it has been shown that the choice of population distribution model [...] can exert a significant influence on outcomes."* Even with the most sophisticated model, it is important to be careful and perform a sensibility analysis for the model used. The use of population density models issued from urban geography may improve the result. A lot of researchers have noted a decrease of the population density from the city centre towards the suburbs. Clark (1951) has described this relation mathematically (Wu et al., 2005). However, this simple concentric model does not consider functional differences between the city districts.

4.5 Discussion

MASs can provide an interesting and very powerful framework for simulating a complex system like the urban dynamics. It is a bottom-up approach and self-organised. Computer simulations try to make a virtual copy of the reality. With the increasing capacity of modern Personal Computers (PCs), such simulations become increasingly available to the researcher in urban geography. Testing changes in a simulated real world model becomes possible and can constitute a very valuable tool for researchers and planners. The most important issue for working with a micro-simulation model is the calibration of the agents. Generally, statistical data are only available at an aggregate level, and a MAS needs quite a big amount of detailed data. The agents have generally to be calibrated using some approximations, and validation of the simulation becomes an important issue. The sensitivity of the model has to be assessed by running several simulations and compare the variability of the result.

In order to get a reasonably good calibration of the agents, as much data sources as possible should be used and combined together. The spatio-temporal relationships of the data have to be analysed and modelled. These relationships can be very complex; they can be linear or non-linear, and they can be continuous or showing breaks in space and/or time. Some more research effort is needed in this field. Correct modelling of the data and incorporating some real world logic into the data model is a first step necessary for developing further the data integration using advanced statistical methods.

Another important issue in Agent Based Models (ABMs) is the existence of finite size effects. Alfi, Cristelli, Pietronero, and Zaccaria (2009) have showed that some characteristics of an ABM exist only within well defined limits for the number of agents involved. If the number of agents is too small or too big, these effects may disappear. This means that there is a critical point for obtaining the self-organising behaviour of a system. Alfi et al. (2009) have showed that in their minimal ABM for financial markets, the results are not coherent with real world behaviour and that the number of agents was an intrinsic parameter of the system. It has to be explored whether such effects are also present in other socio-economic systems; currently, there is no evidence that this is not the case.

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Chapter 5

Visualisation techniques

Visualisation of spatio-temporal data is essential for all researchers and practitioners using some kind of geographical data. It allows rapid understanding of a phenomenon. Thematic maps are the spatial counterpart of charts. A good thematic (statistical) map should allow to identify in a few seconds the spatial pattern of the mapped phenomenon. Recent advances in GIS, GPS and Web technology leaded to an increased use of cartographic representations. The new web mapping tools available freely on the Web are an example of this evolution; we can cite the Google Maps (maps.google.com) or Bing Maps (from Microsoft, www.bing.com/maps) as typical interfaces of the new generation with even the integration of 3D visualisation (Google StreetMap). The launch of Google Earth (earth.google.com) had also a big impact in the domain of GIS and cartography. This fast evolution allows new representation types, especially for the dynamic mapping. However, as more non-cartographers start making maps, errors occur more frequently and the theory on how to represent spatial data is mostly not known or ignored.

Interactive maps offer new possibilities in the field of geovisualisation. Many interactive atlases are available on the Web. Some of the most advanced are based on Geoclip (www.geoclip.fr) which is a statistical mapping solution based on the Adobe Flash plug-in. One such example is the Atlas of Romania (mesoscaphe.unil.ch/atlas/roumanie, available in French only; figure 5). It is possible to select several themes separately, to navigate in the map, query the polygons and display additional information.

Another interesting example for interactive mapping is the real-time temperature map of Switzerland (www.geokernels.org/services/meteo/spatial_meteo.html; figure 5) where dynamic data are included in a model and updated automatically at a regular time interval. The thematic map can be queried using the mouse, and it is possible to zoom and pan very easily. The interesting point in this map is the combination of an automatic modelling approach and interactive mapping. The application is based on the Google

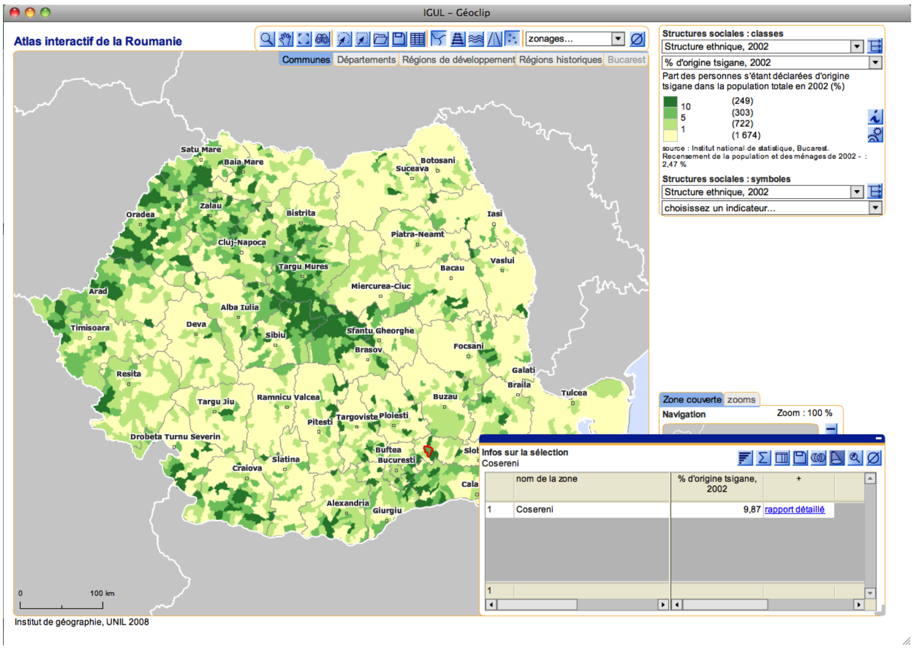


Figure 5.1: Screenshot of the Interactive Atlas of Romania

Maps framework, with the possibility to export the map to Google Earth.

Google Maps is a very popular framework for mapping as it is easy to use, it contains already a huge amount of maps and aerial and satellite imagery, and it is very flexible and powerful. Another similar framework, less known but open-source, is the OpenLayers framework (www.openlayers.org).

An interesting option for thematic mapping is the very recent library *"Cartographer"* (cartographer.visualmotive.com). As it is in an early development state, it lacks some important features for interactive mapping. However, it also contains some very interesting ideas. One such idea is the *"point clusters"* (see e.g. cartographer.visualmotive.com/cluster.html). This is basically a map of proportional circles; each circle is located at a precise location, a statistical value is associated and the circle drawn proportionally to this value. However, when zooming out, the individual circles are clustered together in order to reduce the number of displayed circles. This is interesting especially in the context of a map that can be zoomed from the level of the whole world down to a few square metres.

Another example also dealing with different representation scales has been developed at the Institute of geography of the University of Lausanne by Pascal Briod and myself (mesoscaphe.unil.ch/atlas/gmaps; figure 5). It is an experimental choropleth map of Switzerland with some toy data. At small scale, the geographic units are the 26 Swiss cantons, and when zooming into the map, the administrative units are switched automatically to the

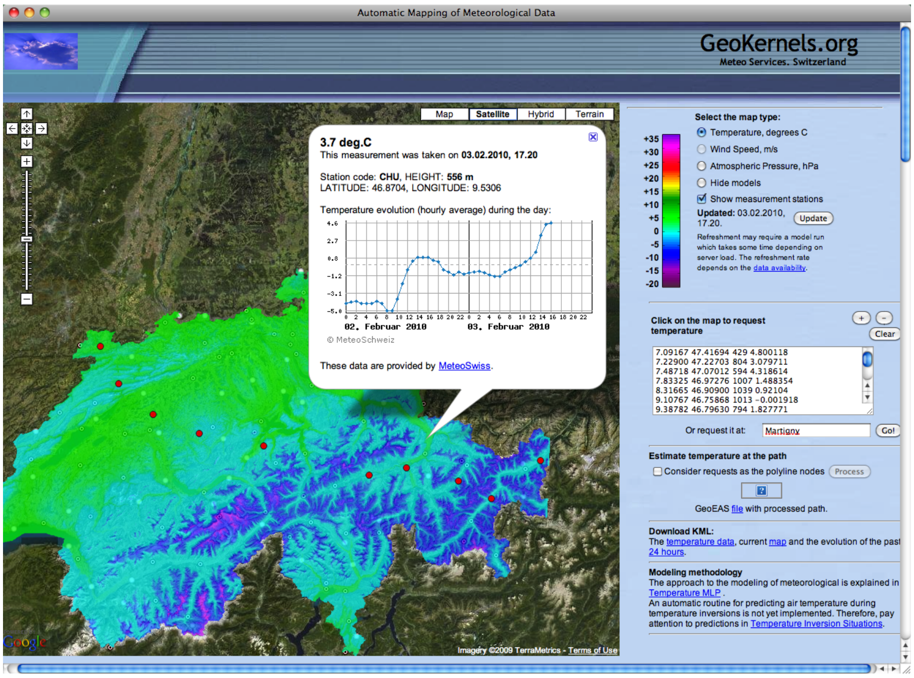


Figure 5.2: Interactive mapping of the real-time temperature of Switzerland

communes (around 2900 for the whole country). An interesting feature is also that only the visible polygons are loaded in the map accelerating considerably the speed for showing the map. Even if some major problems persist, notably with the complex polygons, it shows the power of the new interactive maps on the Web. Of course, some more administrative levels should be integrated and a legend integrated. It would also be interesting to cluster together automatically statistically and spatially coherent regions when zooming out, and display always an optimal number of polygons.

Interactive maps also allow animation of map elements. One possibility is to move one or several elements on the map. I have created a small toy example for testing the animation of points on a Google Map (`http://www.clusterville.org/gmaps_pt_anim`). The example draws just 50 dots at random in a pre-defined rectangle. And on a simple event, the dots can then be moved to a new location; in our example, the dots move to a new random location after a click on a link. The movement of the dots is not linearly, but sinusoidal. This means the point "accelerate" at the beginning smoothly, and at the end, it "slows down" smoothly. This example is entirely written in JavaScript and can be run on virtually every modern browser. One of the purposes of this example is to test the number of points that can be moved simultaneously using this technique. With 50 points, the animation is still quite smooth, but it is not possible to animate hundreds or

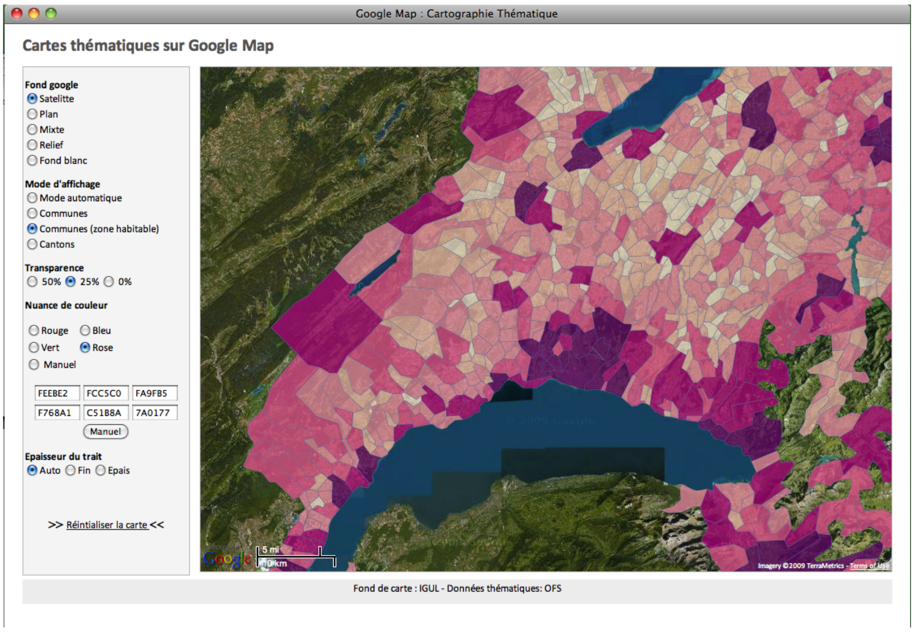


Figure 5.3: Experimental interactive choropleth map based on the GoogleMaps API (by Pascal Briod).

even thousands of points. It could for example be used for vehicle tracking, showing the progress of a bicycle or sailing race, or visualisation of bird's migration.

The evolution in time of a phenomenon could also be animated in an interactive map. This would mean to simply animate the elements in a thematic map, for example the colours in a choropleth map, or the symbol size in a proportional symbol map. Several examples can be found on the Web, even if they are not frequent or usual. One example is the USA hospital atlas[1] which is an example application for Geoclip. It shows an animated choropleth map for the number of visits to hospital emergency per 1000 inhabitants between 1999 and 2006.

For cartograms (presented in section 5.2), it is also possible to apply the polygon morphing technique for transforming a regular polygon layer to a cartogram. This technique can help the user to read cartograms which is not always straightforward (we will discuss this issue also in section 5.2). I have created a simple example for the 70 municipalities of the agglomeration of Lausanne using the Scalable Vector Graphics (SVG) technology. The example is available at the address http://www.clusterville.org/

[1] http://www.geostat.ca/realisation/sqlusa/carto.php?lang=en&nivgeos=state&curCodeDom=d01&curCodeTheme=hosp&typind=C&curCodeInd=emergency&curserie=2006

`cartogram_morphing`. However, as the animation feature in SVG is only implemented in Safari, Chrome and Opera, one of these browsers is needed for viewing this example.

In future, the interactive mapping techniques will more and more get associated with statistical or spatial analysis of real-time data in order to provide the user with useful information for decision making (e.g. Yuan & Hornsby, 2007; Guo, 2007). This very fashionable field is called "visual analytics". Methods of the areas of Knowledge Discovery in Databases (KDD) and Data Mining (DM) for geospatial databases are combined with interactive visualisation. Such a system can be very useful for conducting spatio-temporal analysis (see e.g. Peuquet, 2009; N. Andrienko, Andrienko, & Gatalski, 2003). If the analysis tools are combined with techniques from GISc, the "visual analytics" becomes "geovisual analytics" (G. Andrienko et al., 2007); such a system can be very useful for example for urban planners. In future, it will also be possible to combine the data analysis or simulations with virtual landscapes for 3D visualisation of the results.

In the next two sections, we will discuss two innovative map types, cartograms and density circle maps. Cartograms have recently gained more attention in the media and are becoming more popular. We will present the issues around the cartograms, and the new implementation of a cartogram algorithm into the user-friendly application ScapeToad. Density circle maps are a new map type useful for visualisation of centre based spatial data.

5.1 Spatially continuous data representation

In the field of thematic mapping, we can distinguish spatially discrete from continuous maps. Choropleth and proportional symbol maps are examples of discrete representation. Spatially aggregated data are used for this type of maps. Typically, official population census data are usually published using some aggregation according to administrative boundaries. However, most real world phenomena do not present clear breaks at the administrative border, even if such examples may be found in some cases. Typically socio-economic phenomena inside an urban agglomeration do not present clear limits at the commune's borders. Sometimes, the difference inside one commune is even bigger than between two neighbouring communes. Or in some cases, aggregated data may be misleading. One such example is the population density in the agglomeration of Lausanne where the northern part of the central commune of Lausanne has virtually no population (see figures 3.1 and 3.2 and map 4 in chapter 1). If the population density is then computed at the aggregate commune level, the communes of Renens or Prilly present a higher density which is misleading as the density is in reality higher in some parts of Lausanne. In this case, a continuous data representation is more adapted, or the density should be computed using a *"validity* *domain"*. A validity domain is a spatial region where the phenomena under study has the possibility to occur. In the case of the population density, this would be the zone where the population can potentially live. In practice, one possibility would be to delimit the built zone using a topographic map or remote sensing, and then to compute the population density based on this validity domain instead of the simple polygon surface. It would also be possible to use an areal interpolation technique for spatial disaggregation of the data. Areal interpolation is a variant of the more general change of support problem (see e.g. Gotway & Young, 2002) with the source and target values both being areas, but of different extent. One of these methods it the smooth pycnophylactic interpolation of Tobler (1979), or the more general geostatistic framework for area-to-point interpolation presented by Kyriakidis (2004) based on the works of Matheron (1971) and Journel and Hujbregts (1978). This geostatistical approach could also be extended to include a validity domain.

With the increasing availability of more and more detailed data, the problem is shifting from a situation where data were very sparse to a situation where very detailed data is available. In this case, methods for filtering out local variations have to be used for visualisation. Methods for averaging the data in a given neighbourhood can be used for this; the moving window approach and the kernel density estimation are two candidates for this task.

5.1.1 The method of the moving windows

The principle the moving windows is to define a circle or sometimes a square of a given size, to compute the sum or average of the points lying inside this geometry, and to associate this value with the centre of the shape. This window is then moved all over the study area to provide at each location the sum or average. Figure 5.4 shows the principle of these moving windows used for analysis in continuous space. It is of course possible to compute other statistics than the sum or average inside the moving window, like the median, minimum, maximum or variance. The moving window approach is a method for computing local statistics; all the points lying inside the selected window have the same weight. The size of the moving window defines the scale of analysis, while the raster cell size only defines the resolution of the resulting image. The moving window is implemented in all major GIS software packages. It is applied to raster data, where each raster cell will be the centre of the moving window. The size of the window can then be expressed in number of cells and has to be an odd number as the centre would not lie inside one cell in the other case.

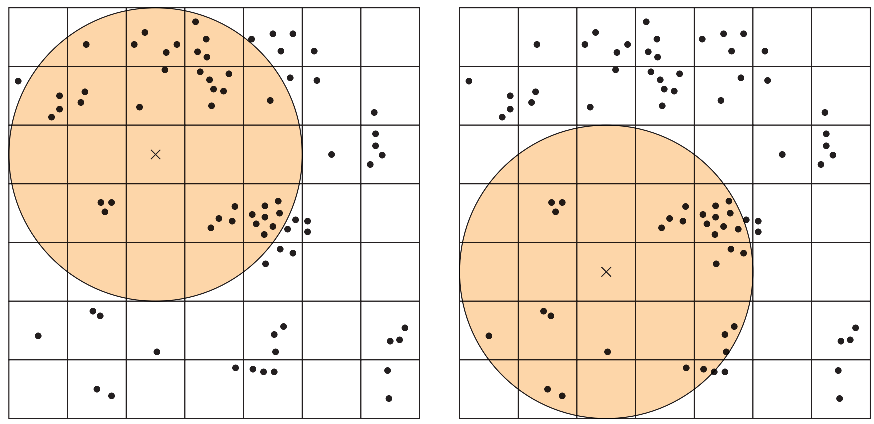


Figure 5.4: The moving window principle. The raster cell at the centre of the window contains the number of elements inside the window.

5.1.2 Kernel density maps

Instead of simply computing unweighted local statistics as with the moving window approach, we can use a kernel for weighting the points according to the distance from the centre. This kernel can be bounded (size of the window is limited) or unbounded. The most frequent kernel is the normal distribution function (Gaussian kernel), which is a bell-shaped curve going to infinity on each side (see e.g. De Smith, Goodchild, & Longley, 2009). Other functions can of course also be used instead of the normal distribution function. An important issue is the selection of the bandwidth, this is the size of the bell-shaped curve in the case of the Gaussian function. In the case of the normal distribution, it can be associated to the standard deviation and is frequently denoted as σ. The bandwidth defines the amount of "smoothness" of the resulting kernel density map. Fotheringham, Brundson, and Charlton (2000, p.149) suggest the following estimation for the bandwidth in the case of a variable that is normally distributed:

$$h_{opt} = \left(\frac{2}{3n}\right)^{\frac{1}{4}} \sigma \tag{5.1}$$

where h_{opt} is the optimal bandwidth, n the number of points and σ the spatial spread of the points to estimate, e.g. the standard deviation of the geographic coordinates in the case of two dimensions. This estimate gives rather a too large bandwidth resulting in over-smoothing of the phenomenon.

Most of the maps in section 5.4 use the kernel density to provide a smooth view of the original gridded data. However, the bandwidth has usually been defined manually to find the best representation of the phenomenon. The kernel density map has the advantage over the moving window approach to present more local details as the nearer points have much more importance in the local statistic procedure.

Kernel density maps can be created using some GIS software, or using statistical software. For example, the *"spatstat"* module of the statistical software R or the scientific tools library SciPy for Python provide algorithms for computing the kernel density. The maps in section 5.4 have been computed using our own Python-based module for the open-source GIS software GRASS.

5.2 Cartograms

Traditionally, proportional symbols are used in thematic maps for representing size values. As an example, population maps as the one in figure 5.5 are widely used. This type of map presents some visual problems. One problem are the overlapping circles that might reduce the 'visual size' of one of the circles and therefore modify the perception of the phenomenon. Another problem is that aggregation of several smaller entities may form a big entity; the perception of the phenomenon is again modified (see e.g. Slocum, McMaster, Kessler, & Howard, 2009, p.89). Finally, care must be taken to scale the symbols properly using *perceptual scaling*. If the area of the symbols are scaled mathematically proportional to the statistical value, the human reader will underestimate large symbols (e.g. Monmonier, 1993; Slocum et al., 2009). A perceptual correction is needed. Several empirical studies have been conducted and different formulas for correcting the symbols have been found (e.g. Slocum et al., 2009; Flannery, 1971; Crawford, 1973). And as in every thematic map, optic illusions may also occur with proportional symbols. However, proportional symbols remain very useful for thematic maps, and really better alternatives do not exist.

One alternative is the cartogram. A cartogram is a thematic map where the polygon of a geographical entity does not correspond to its physical shape, but where its area is proportional to a given quantitative number describing the entity. Therefore, a distortion of the geometrical shape is necessary. Figure 5.6 shows an example of a cartogram; it represents the same values as the proportional symbols map in figure 5.5.

The creation of the cartogram involves the computation of this transformation. As no exact or unique solution exist to the cartogram creation problem, several different algorithms have been proposed since the early 1960's (see Tobler, 2004). All algorithms have in common that they need a considerable amount of computer capacity, even if modern PCs are able to do the necessary computations in a very reasonable time.

A cartogram is a distorted (or projected) map where the polygons are

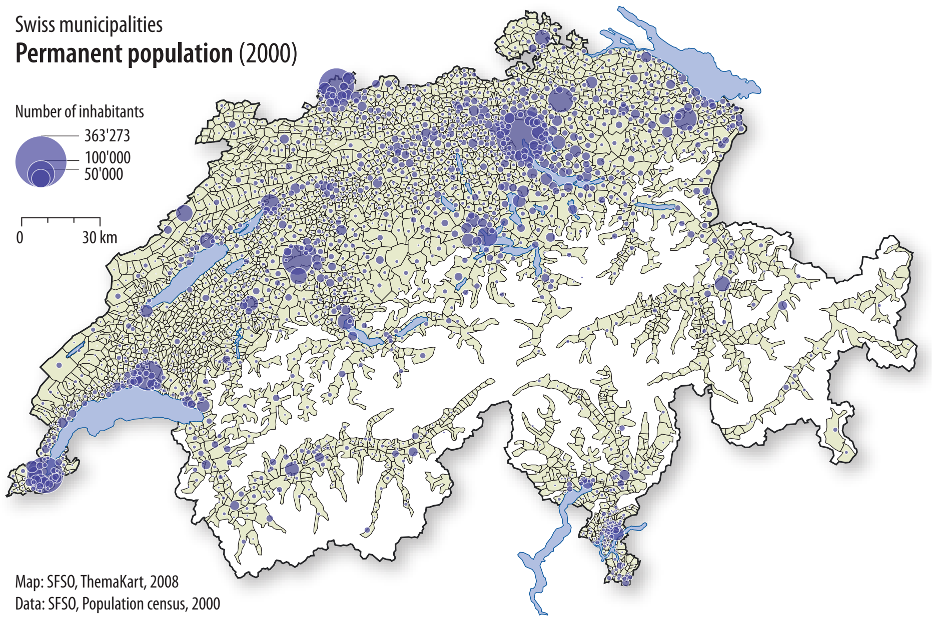


Figure 5.5: Example of a traditional proportional symbols thematic map.

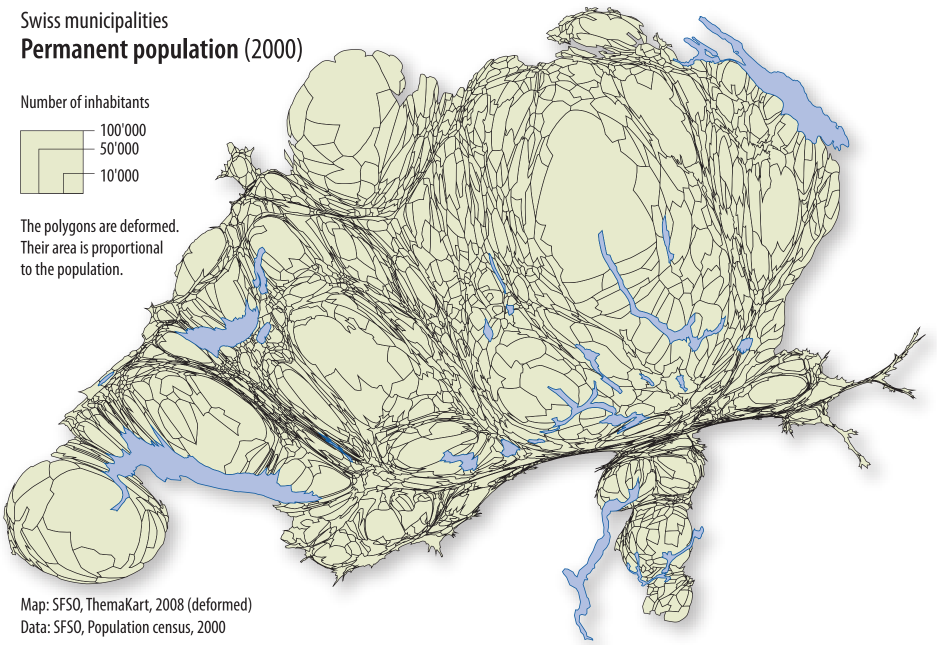


Figure 5.6: Example of a population cartogram.

resized according to a given statistical parameter, and where the main visual properties like shape, orientation and contiguity are respected as much as possible (Keim, North, & Panse, 2005). Mathematically, the creation of a cartogram in the plane involves finding a transformation (projection) $r \to T(r)$, this is from one plane into another plane. We are looking for a transformation where the Jacobian $\delta(T_x, T_y))/\delta(x, y)$ is proportional to the density $\rho(r)$ of the statistical value we want to map (Gastner & Newman, 2004).[2] In order to preserve the total area before and after transformation, a normalisation with the mean density $\overline{\rho}$ should be made:

$$\frac{\delta(T_x, T_y)}{\delta(x, y)} = \frac{\rho(r)}{\overline{\rho}} \tag{5.2}$$

Equation 5.2 does not define the cartogram projection in a unique way. Other constraints are needed for doing so. Typically, the limitation of the shape deformation is a good candidate for such constraints. We can see the cartogram creation problem also as finding a function that minimises the area and shape errors (Keim et al., 2005):

$$f(\overline{S}, \overline{A}) \to min \tag{5.3}$$

where $\overline{S}$ and $\overline{A}$ are the shape and area error respectively.

In the next section, we give an overview of some of the existing cartogram algorithms. Then, we will discuss the problems which are related to the creation of cartograms. Finally, we will discuss our approach that is implemented in the ScapeToad application and describe how we try to solve some of the problems.

5.2.1 Cartogram algorithms

In *Dorling's circle cartogram*, each geographical entity is represented by a proportional circle (Dorling, 1996). The circle's size is proportional to the variable value. At the beginning, the centre of the circle is placed on the centroid of the polygon. In an iterative procedure, overlapping circles are pushed away while circles without direct neighbour are approached to the nearest circle. This algorithm is implemented in the Mapresso application (Herzog, 2005). There is also a demo of the algorithm on the Mapresso homepage (`http://www.mapresso.com`). This algorithm has the advantage of being simple and quick. However, it is not possible to apply the deformation to polygons. Figure 5.7 shows an example of a circle cartogram for the population in the 70 municipalities of the Lausanne agglomeration.

The *algorithm of Dougenik, Nicholas, Chrisman, and Niemeyer (1985)* is probably the most frequent algorithm implemented in a program or a

[2] For sake of simplicity, we will consider only population cartograms from here on, but of course, every other raw number could be used.

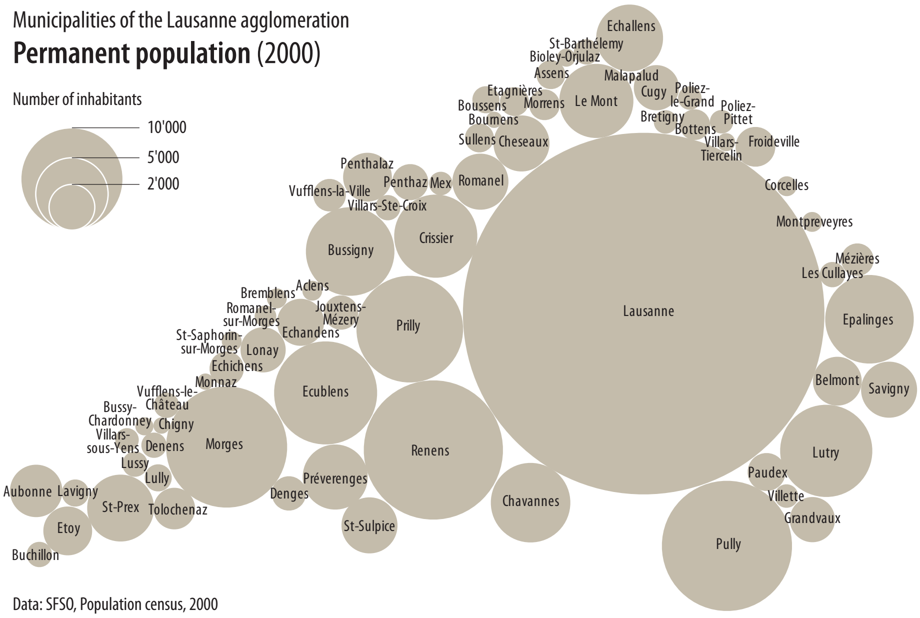


Figure 5.7: Example of a Dorling's circle cartogram for the agglomeration of Lausanne.

script. It is already known since 25 years, which has surely contributed to its popularity. The algorithm enables the deformation of polygons. For each vertex of each polygon, a force is computed directed from the centre or to the centre depending on whether the shape's size has to increase or shrink. The algorithm is running iteratively and converges to the result. The number of necessary iterations depends on the strength of the forces. Too big forces can produce errors in the polygon topology. This algorithm is implemented in the Java program Mapresso (Herzog, 2005), in a Avenue script for ArcView 3 (Du & Liu, 1999; Jackel, 1997) and in a VisualBasic script for ArcGIS 9 (CartogramCreator, Wolf, 2005). The algorithm is quite simple in its conception but needs some computation power especially for maps with a big number of polygons. For creating a cartogram with the about 30'000 municipalities of France using the CartogramCreator script, a computation time of several days is needed. The topology is not always guaranteed, intersecting polygons or holes between two previously adjacent polygons may occur.

The *diffusion algorithm of Gastner and Newman (2004)* is based on the physical process of gas diffusion. A regular grid is laid on the original map and for each grid point, the density is computed. The grid deformation can be computed analytically with the knowledge of the physical laws of gas diffusion. At the end, the grid deformation is applied to the polygon layer. Michael Gastner and Mark Newman have each implemented this algorithm in a freely available C program with source code (`www.santafe.edu/~mgastner/` and `www-personal.umich.edu/~mejn/cart/`, last checked 2008-05-22), and Frank Hardisty has created a Java version with a graphical interface (`people.cas.sc.edu/hardistf/cartograms/`, last checked 2008-05-22). There is also an add-on for MapInfo (`www.griddle-gidata-analysis.com`, last checked 2008-05-22). We have used this algorithm also for the implementation in ScapeToad. The algorithm shows an acceptable performance and the topology remains generally quite intact. The grid size is limited by the amount of available computer power.

The *algorithm of Keim et al. (2005)* moves in an iterative process all vertices of all polygons on a basis of a polygon skeleton (the medial axis). The cartograms produced with this algorithm have a good quality, and the algorithm is reasonably fast. The authors have implemented this algorithm in their CartoDraw program, which is freely available as a Unix binary (`http://infovis.uni-konstanz.de/~panse/CartoDraw/CartoDrawIndex.php`, last checked 2009-12-06). However, the source code is not available and the algorithm is, at least partially, covered by a US patent owned by AT&T.

There are some other algorithms described in the literature. Gusein-Zade and Tikunov (1993) use a continuous displacement field for every point on the map. Areas of high density produce a repulsive force. The result is computed using a differential equation for the displacement field. The cartograms produced with this algorithm are quite attractive. Kocmoud (1997) has developed a constraint-based approach in his thesis. Appel, Stein, and Evangelisti (1983) and Dorling (1996) have developed a cartogram algorithm based on a CA. Henriques (2005) suggests a cartogram algorithm based on SOM. Some more general non-linear magnification methods are described in the literature and can also be applied for creating cartograms (Keahey, 1997, 1999; Langlois, 2003).

5.2.2 Problems of cartogram creation

One of the main concerns in cartogram creation is the *conservation of topology*. In GIS, the topology is mainly about the perfect contiguity of adjacent polygons, and there must be no self-intersecting polygon as well. During the cartogram creation process, the original geometrical shapes are sometimes heavily deformed. Besides the self-intersection problem, there can be gaps and overlaps between polygons (see figure 5.8). During the cartogram creation process, we have to ensure that the topology is conserved correctly, in spite of the eventually important transformation.

For solving this problem, we have introduced in ScapeToad the use of a regular grid for the deformation instead of the irregular polygons. Indeed, it is much easier to check the topology of a "simple" grid. However, the introduction of such a regular grid implies the estimation of the density for

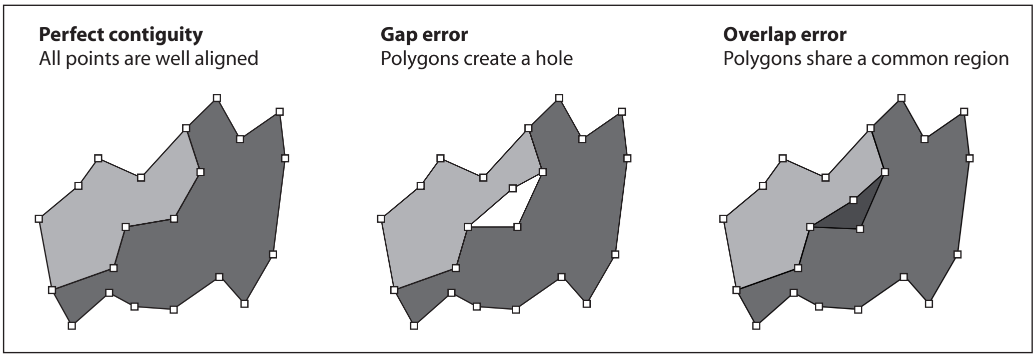


Figure 5.8: Topology concerns for cartograms

each grid cell based on the polygons. This is a typical example of areal interpolation (Wu, Qiu, & Wang, 2005; Lam, 1983) or change of support (Gotway & Young, 2002, 2005). In ScapeToad, it is currently admitted that the population is distributed uniformly in each polygon; the change of support is done proportional to the polygon areas in each cell. This weakness may be corrected in future, even if it is not clear whether there will be a noticeable difference in the resulting cartogram.

Once the deformation of the regular grid computed using one of the cartogram algorithms, we can use this grid for the projection of one or several layers from the geographic into the cartogram space. Figure 5.9 shows an example of such a deformed grid. The projection of the geographic (metric) space into the cartogram space, and vice-versa, can be defined using a continuous function in space, just like each other projection. However, it is easier to work with a discrete approximation, this means our regular but continuous grid. This grid is regular in the geographic space, and deformed in the cartogram space. It can be use for projecting each point from the geographic space into the cartogram space (see figure 5.10).

Another current problem for the cartogram creation is the *speed of computation*. Tobler (2004) thinks that the computational complexity of a cartogram should be the same as for any map projection and expects it to be polynomial in nature, even if there seems to be no empirical results in this direction. Keim et al. (2005) consider the cartogram problem as an optimisation problem as stated in equation 5.3. They mention that a simpler variant of the cartogram called "integer cartogram" is NP-hard.

Some well known implementations may take very long in order to achieve the computation process. As already stated, the algorithm of Dougenik et al. (1985) may take very long, especially in its implementation as a script (e.g. Wolf, 2005). This is also the case of the algorithms based on a CA (e.g. Dorling, 1996). The algorithm of Gastner and Newman (2004) however is

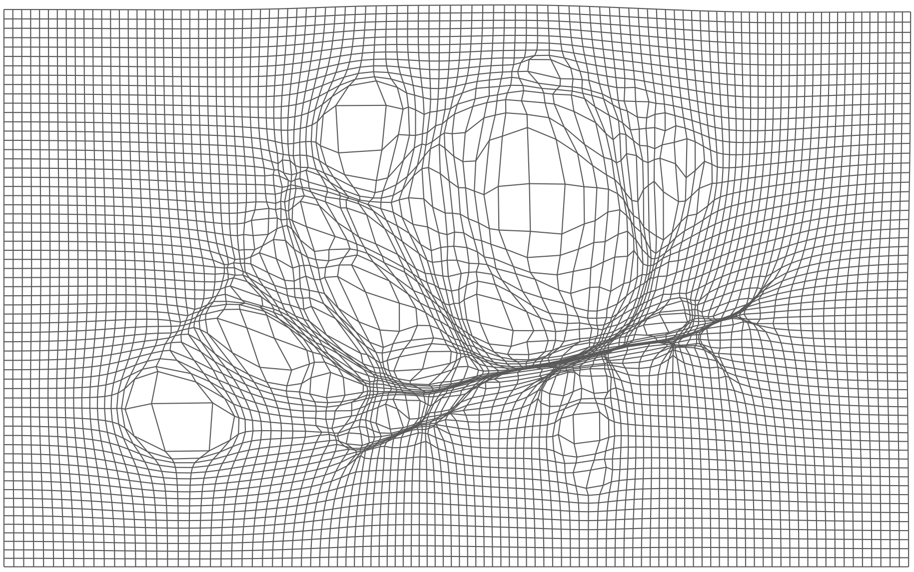


Figure 5.9: An example of a deformed cartogram grid.

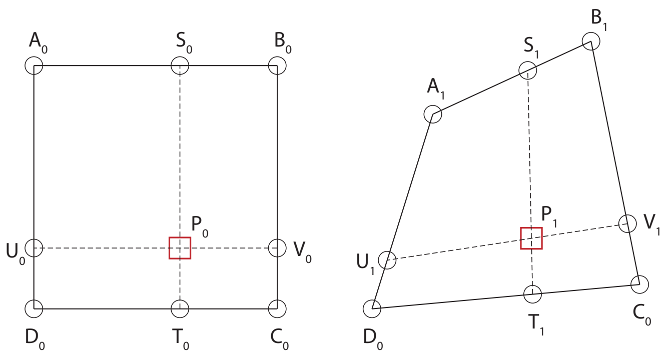


Figure 5.10: The principle of the deformation grid.

reasonably fast; computationally the most heavy part is the Fourier transform and back-transform. In ScapeToad, this part has been parallelised and allows therefore the use of multiple processors.

Another problem in current implementations of cartogram algorithms is that is is difficult or impossible to apply the computed transformation to several layers (also non-polygon layers). This may be a problem in some situation where we want to present more than just the spatial importance of a given variable. Figure 3.13 (page 57) shows an example of such a case. The cartogram deformation is based on the population; the urban areas have been drawn on top of the population cartogram in order to represent the share of population living in urban areas. In this cartogram, the urban areas have been defined using the "City Clustering Algorithm" (Rozenfeld et al., 2008). The cartogram contains also the deformed lakes which are necessary for a map of Switzerland. It would also be possible to overlay a road- or railway-network, or the river network. The simultaneous transformation of accessory layers might thus be useful and helpful for map readability. We have integrated this feature into ScapeToad, as it simply needs the application of the computed projection grid to several layers. The projection grid is chosen nearly twice the size of the base polygon layer to ensure that secondary layers can be transformed without problem.

5.2.3 Are cartograms useful?

Cartograms are often used in media because of their impact; the reader will be intrigued of the strange shape of the map. Slocum et al. (2009) argue that an area cartogram should not be used if the cartogram is not sufficiently deformed as this will destroy their dramatic impact. One of the problems of cartograms is the difficulty to identify some of the shapes and to represent the mapped phenomenon in a useful manner. Cartograms should therefore ideally be accompanied by a non-deformed map for improving the orientation in the map. In a interactive map, it is possible to query the cartogram using the mouse and make a dynamic link with the non-deformed map, and vice-versa. Another possibility is to include an animation where the user can switch from the deformed to the non-deformed map (see `http://www.clusterville.org/cartogram_morphing` for an example).

Currently, there seems to be no study on the perception of cartograms by the users. It is difficult to say whether cartograms are a better representation than proportional symbols. Probably, they should be used in a complementary way. In some cases, it might also be useful to map the density instead of the raw values (see e.g. figure 2.3 on page 21).

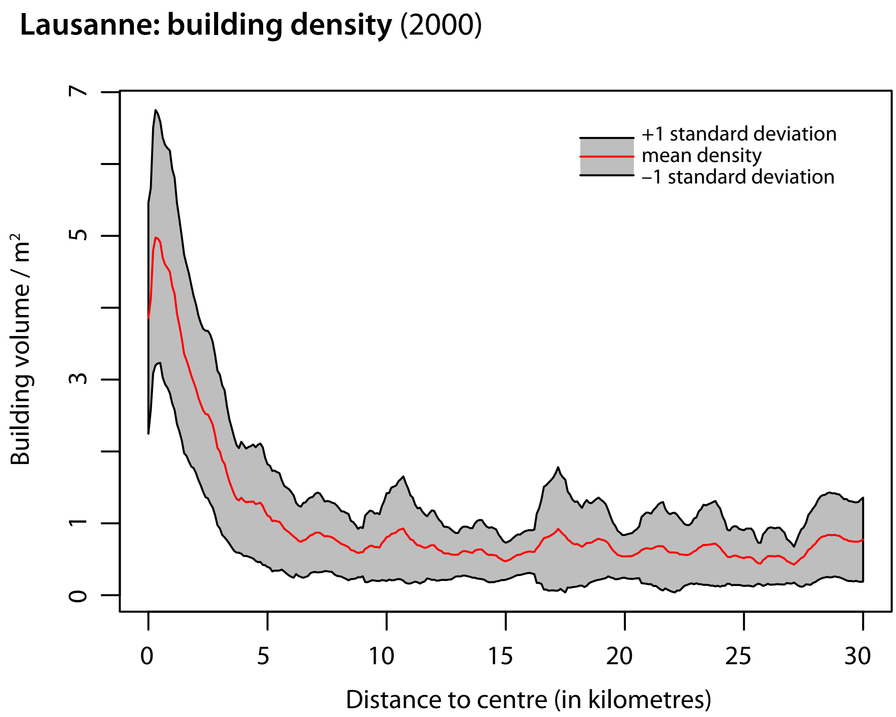


Figure 5.11: Gradient of the building density around Lausanne.

5.3 Distance circle map

In urban geography, it can be interesting to study the differences of some densities, for example population or jobs, from the city centre to the periphery. Figure 5.11 shows the gradient in building density between the centre of Lausanne to the periphery, at a maximum distance of 30 kilometres. This figure shows clearly the range of the city centre itself, and there can also be seen a number of secondary centres. The base data of this plot are the building heights on a raster image (resolution of 1 metre). For each pixel, the distance is computed to the centre. This gives a point plot of the building height against the distance to the centre. Then, for a regular distance interval and within a small distance window, the sum of the building heights is computed and the average value plotted. This method is something like a circular moving window starting at the centre and then growing.

In the plot in figure 5.11, no difference is made according to the direction; it is an omni-directional plot. However, the development of cities is usually not concentric, but rather organised in sectors. It is straightforward to make a sectorial map of the same data; figure 5.12 shows an example of such a plot. This plot gives more detailed information on the distribution of the

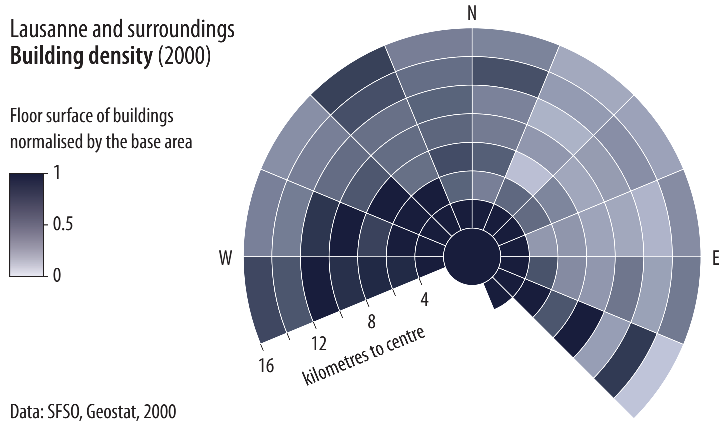


Figure 5.12: Sectorial building density around Lausanne.

buildings around the city centre. In this plot can be seen, that the city of Lausanne develops itself rather in western direction, which is due mainly to topographic reasons. We will call this type of map *"distance circle map"*. Such a distance circle map is a centre-based, map-like, exploratory data visualisation technique.

Instead of dividing the map into sectors, it is also possible to make a continuous image. Figure 5.13 shows an example of such a continuous map. Basically, it is a choropleth map with a centre, where the data is presented in an aggregated manner according to the characteristics of the circle. The continuous distance circle map shows for each point on the map the mean of the values in a defined neighbourhood around this point, whereas the sectorial distance circle map divides the circle in sectors and each sector gets the mean of the values inside. The representation as colours of the mean values can be done using a discrete or continuous colour scale; this topic is the same as for choropleth maps.

A distance circle map has of course, like every other map, a scale and an orientation. It also has a centre which we should mention on the map. We can also link the distance circle to another representation of the same space, e.g. a topographic map or a map of administrative units (fig. 5.14).

The original data source of a distance circle map should be a set of points for which we associate a statistical value. If the data source is not available as a point data set, a change of support is required and the appropriate techniques should be applied.

The creation of a continuous density circle map implies the estimation of the values at a given number of locations, typically for each pixel of a raster image grid. Figure 5.15 shows the principle of this estimation; the value should be estimated at the location z_i. Basically, the value at z_i is

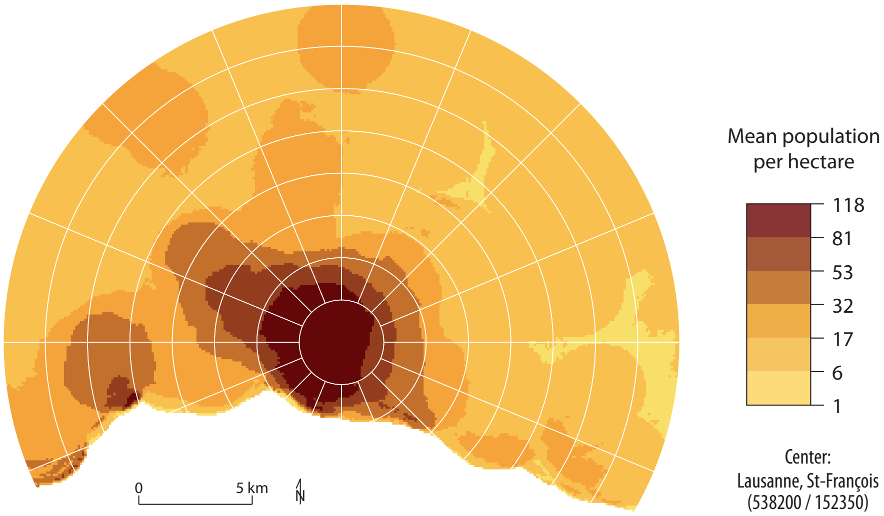


Figure 5.13: Distance circle map showing the population density around Lausanne (2000)

the average of the values of all points in a given neighbourhood of z_i. This neighbourhood is defined based on a parameter s defining the maximum distance of the points to consider from z_i. This is the principle of the moving window. However, a directional parameter is also considered; an angle ρ defines the sectorial wideness from the centre. And there is also a maximum distance d_{max} beyond which points are not considered anymore.

A distance circle map can be an additional visualisation technique useful for the urban geographer who wants to visualise the sectorial differences in a city where the centre is known. In these cases, it is an interesting tool as it focuses on the centre-based aspect of the phenomenon. At the same time, it is close to the moving window technique, at least if the angle ρ is sufficiently big. The distance based character of the map allows also comparisons between different cities.

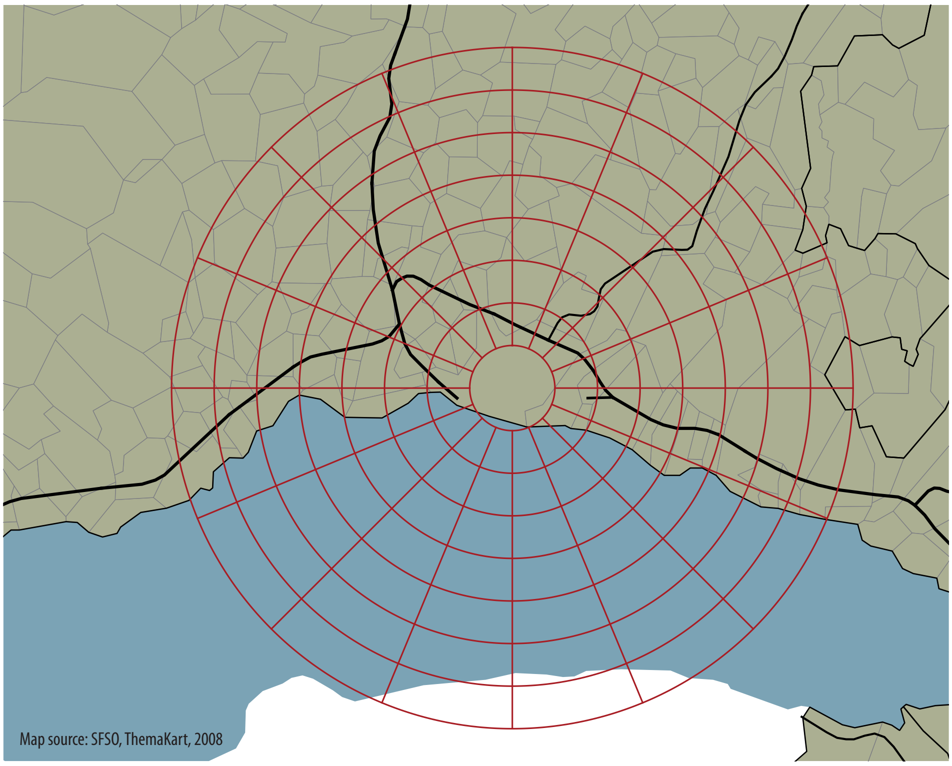


Figure 5.14: Distance circle drawn on a map of administrative units (municipalities and canton), together with the major roads. The circle is centred on the city of Lausanne with a distance step of 2 kilometres.

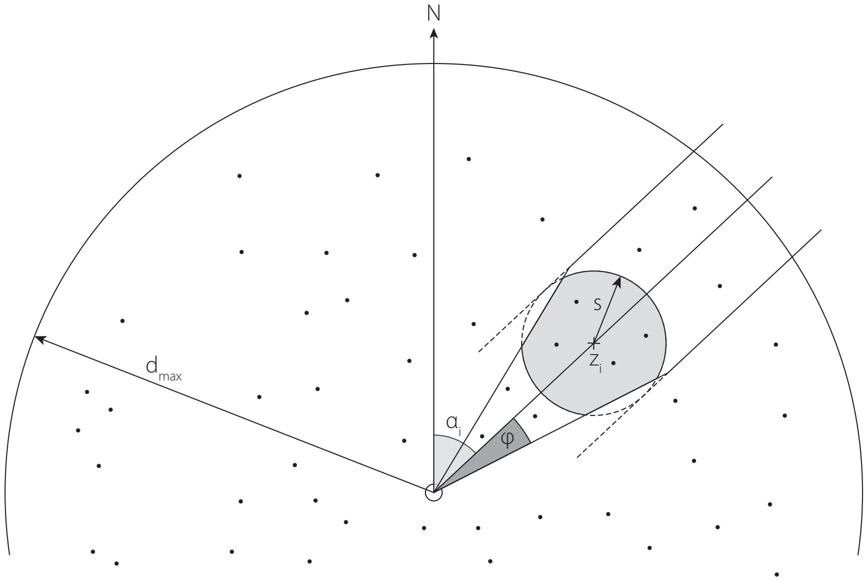


Figure 5.15: Principle of the continuous distance circle map and estimation of value z_i

5.4 Cartoscopy of Lausanne

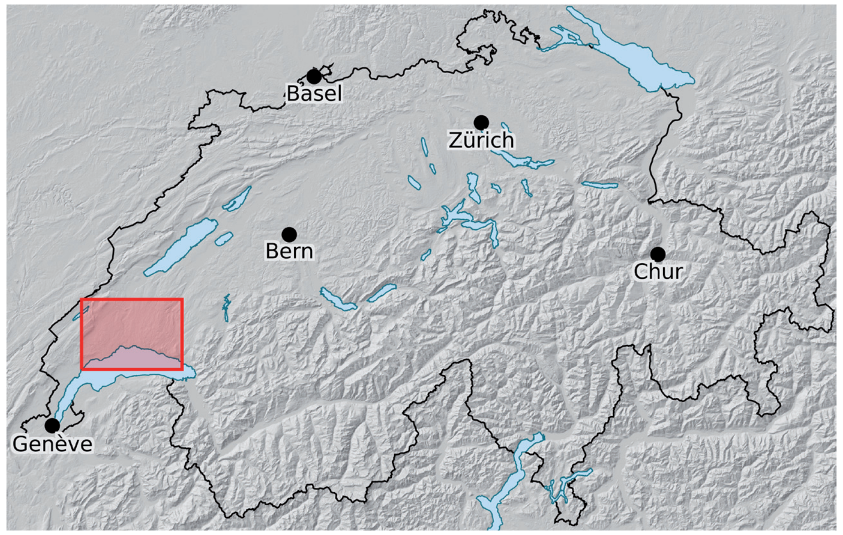
After a review of some advanced mapping methods, we make a cartographic trip to Lausanne, at the lake of Geneva, in Switzerland. Through a series of maps, we explore this urban agglomeration and show at the same time some examples of visualisation techniques.

The urban geographer studies the city and its agglomeration for understanding the development processes and provides the knowledge for planning the city in a sustainable and efficient way. An urban area is a place where people live and work. The network of cities form the economic backbone of a country, as most economic activities occur in or around the big agglomerations. Planning the development of a city is an optimisation process for providing the population with high quality living space and the economy with the necessary communication infrastructure for being efficient. At the same time, the environmental resources have to be respected. A city is a complex system and understanding all the ongoing processes is not an easy task. Providing the urban planner with relevant information needs the use of powerful analysis, modelling, simulation and visualisation techniques. Quantitative geography provides a good base framework that has emerged over the last decades. Today, more and more georeferenced data are available, due to the GPS and progress in computer and communication technology. A new challenge for the quantitative geography is to process efficiently this data flood. New techniques have to be developed for integrating different data sources.

The following maps should provide an overview of what kind of analysis and visualisation is possible and useful for the urban geographer. It is not exhaustive, but should illustrate some proposals we will discuss throughout this work.

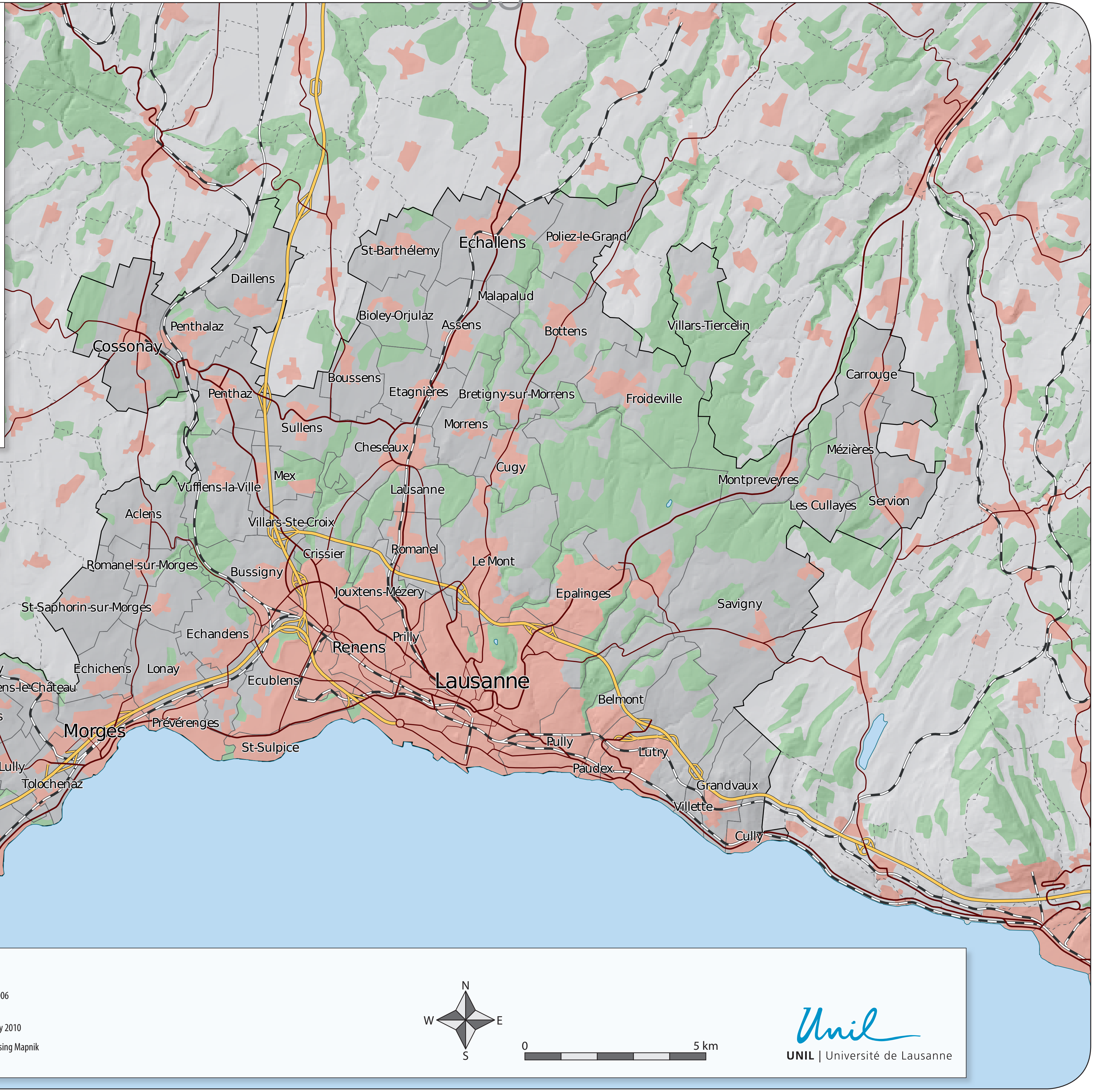
map 1 _ **The 70 communes of the agglomeration** _ 2000

agglomeration of lausanne



The agglomeration of Lausanne is located in the Western part of Switzerland, at the border of the lake of Geneva. It has a little more than 300'000 inhabitants and is the fifth agglomeration of the country, after Zurich, Basel, Geneva and Berne. It has a very good transportation infrastructure with fast train connections to the main Swiss cities and highspeed train connection to Paris. The highway network guarantees a good accessibility by the road, with the A1 going to Geneva and Yverdon-Berne, and the A9 to the Valais and further to Italy.

The city of Lausanne is the olympic capital, the International Olympic Comitee and several international sport organisations have there headquarter in this city. There is also a strong presence of multi-national firms in the region offering high qualified job opportunities. The École Polytechnique Fédérale (EPFL) and the Univserity of Lausanne make of the agglomeration an important place for research and studying.

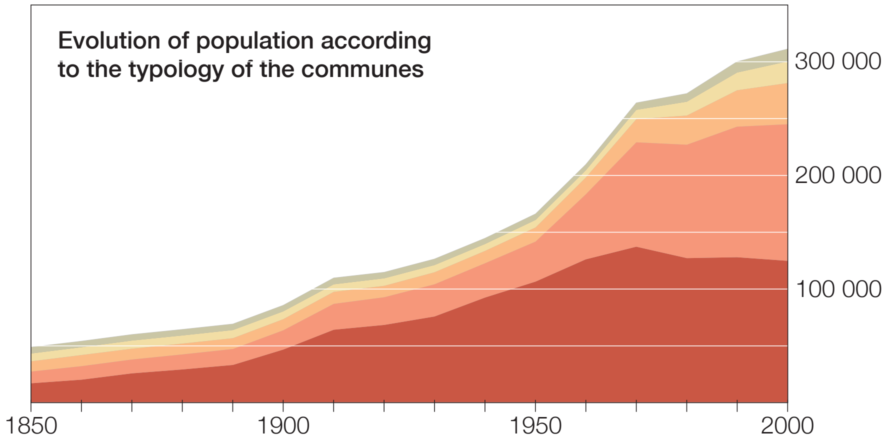


The 70 communes of the agglomeration _ 2000

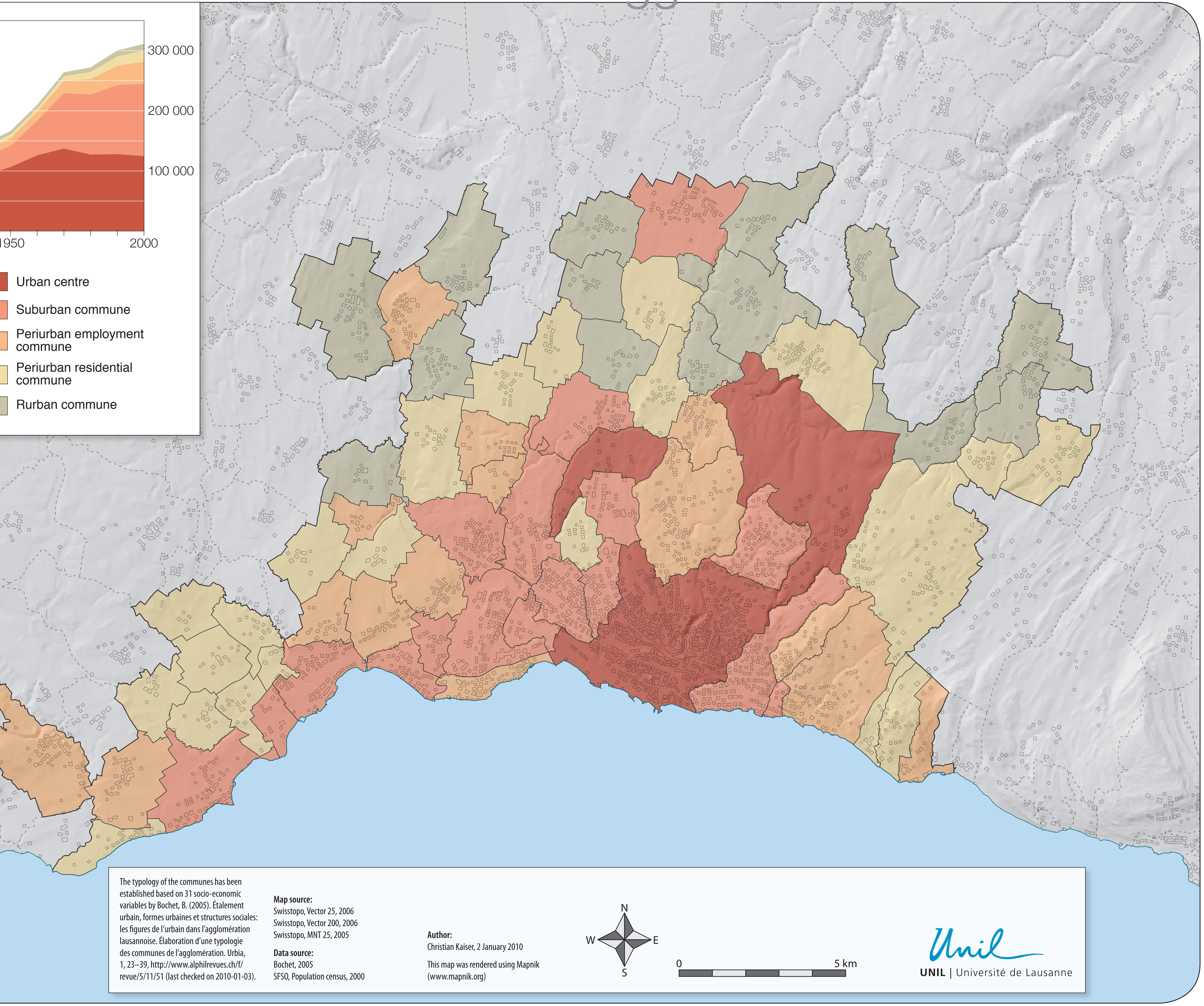
map 1
agglomeration of lausanne

map 2 _ **Typology of the communes** _ 2000

agglomeration of lausanne



Over the last 150 years, the agglomeration of Lausanne has known a huge evolution with a population growing from roughly 50 000 people to over 300 000 in 2000. The city of Lausanne is the centre of the agglomeration, with around 125 000 inhabitants. Since the 1970s, the population of the centre is stable, while the development of the agglomeration occurred mainly in suburban communes, and later also in periurban communes. The agglomeration is organised in several more or less concentric zones. The growth is going from inside and then progressively to the neighbouring concentric rings. The newly urbanised regions are less densely populated as the increase in mobility due to cars and an efficient road network allow to go further using the same amount of time. This decrease in density is called «urban sprawl» and is accompanied by a car dependance.



The typology of the communes has been established based on 31 socio-economic variables by Bochet, B. (2005). Étalement urbain, formes urbaines et structures sociales: les figures de l'urbain dans l'agglomération lausannoise. Élaboration d'une typologie des communes de l'agglomération. Urbia, 1, 23–39, http://www.alphilrevues.ch/f/revue/5/11/51 (last checked on 2010-01-03).

Map source:
Swisstopo, Vector 25, 2006
Swisstopo, Vector 200, 2006
Swisstopo, MNT 25, 2005

Data source:
Bochet, 2005
SFSO, Population census, 2000

Author:
Christian Kaiser, 2 January 2010

This map was rendered using Mapnik (www.mapnik.org)

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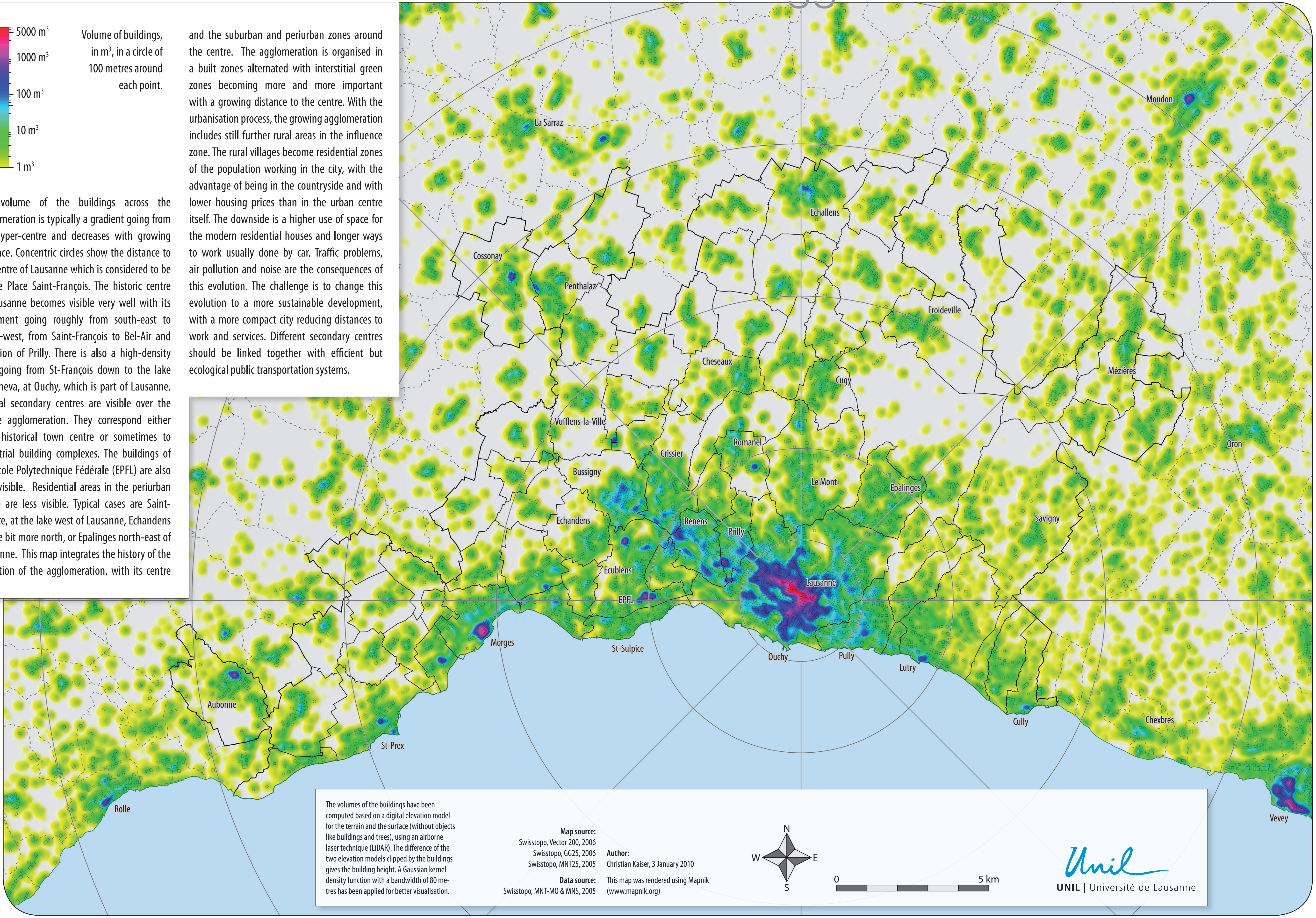
Typology of the communes _ 2000

map 2
agglomeration of lausanne

map 3 _ **Volume of buildings** _ 2005

Volume of buildings, in m³, in a circle of 100 metres around each point.

The volume of the buildings across the agglomeration is typically a gradient going from the hyper-centre and decreases with growing distance. Concentric circles show the distance to the centre of Lausanne which is considered to be at the Place Saint-François. The historic centre of Lausanne becomes visible very well with its alignment going roughly from south-east to north-west, from Saint-François to Bel-Air and direction of Prilly. There is also a high-density area going from St-François down to the lake of Geneva, at Ouchy, which is part of Lausanne. Several secondary centres are visible over the whole agglomeration. They correspond either to a historical town centre or sometimes to industrial building complexes. The buildings of the École Polytechnique Fédérale (EPFL) are also very visible. Residential areas in the periurban fringe are less visible. Typical cases are Saint-Sulpice, at the lake west of Lausanne, Echandens a little bit more north, or Epalinges north-east of Lausanne. This map integrates the history of the evolution of the agglomeration, with its centre and the suburban and periurban zones around the centre. The agglomeration is organised in a built zones alternated with interstitial green zones becoming more and more important with a growing distance to the centre. With the urbanisation process, the growing agglomeration includes still further rural areas in the influence zone. The rural villages become residential zones of the population working in the city, with the advantage of being in the countryside and with lower housing prices than in the urban centre itself. The downside is a higher use of space for the modern residential houses and longer ways to work usually done by car. Traffic problems, air pollution and noise are the consequences of this evolution. The challenge is to change this evolution to a more sustainable development, with a more compact city reducing distances to work and services. Different secondary centres should be linked together with efficient but ecological public transportation systems.



The volumes of the buildings have been computed based on a digital elevation model for the terrain and the surface (without objects like buildings and trees), using an airborne laser technique (LiDAR). The difference of the two elevation models clipped by the buildings gives the building height. A Gaussian kernel density function with a bandwidth of 80 metres has been applied for better visualisation.

Map source:
Swisstopo, Vector 200, 2006
Swisstopo, GG25, 2006
Swisstopo, MNT25, 2005

Data source:
Swisstopo, MNT-MO & MNS, 2005

Author:
Christian Kaiser, 3 January 2010

This map was rendered using Mapnik (www.mapnik.org)

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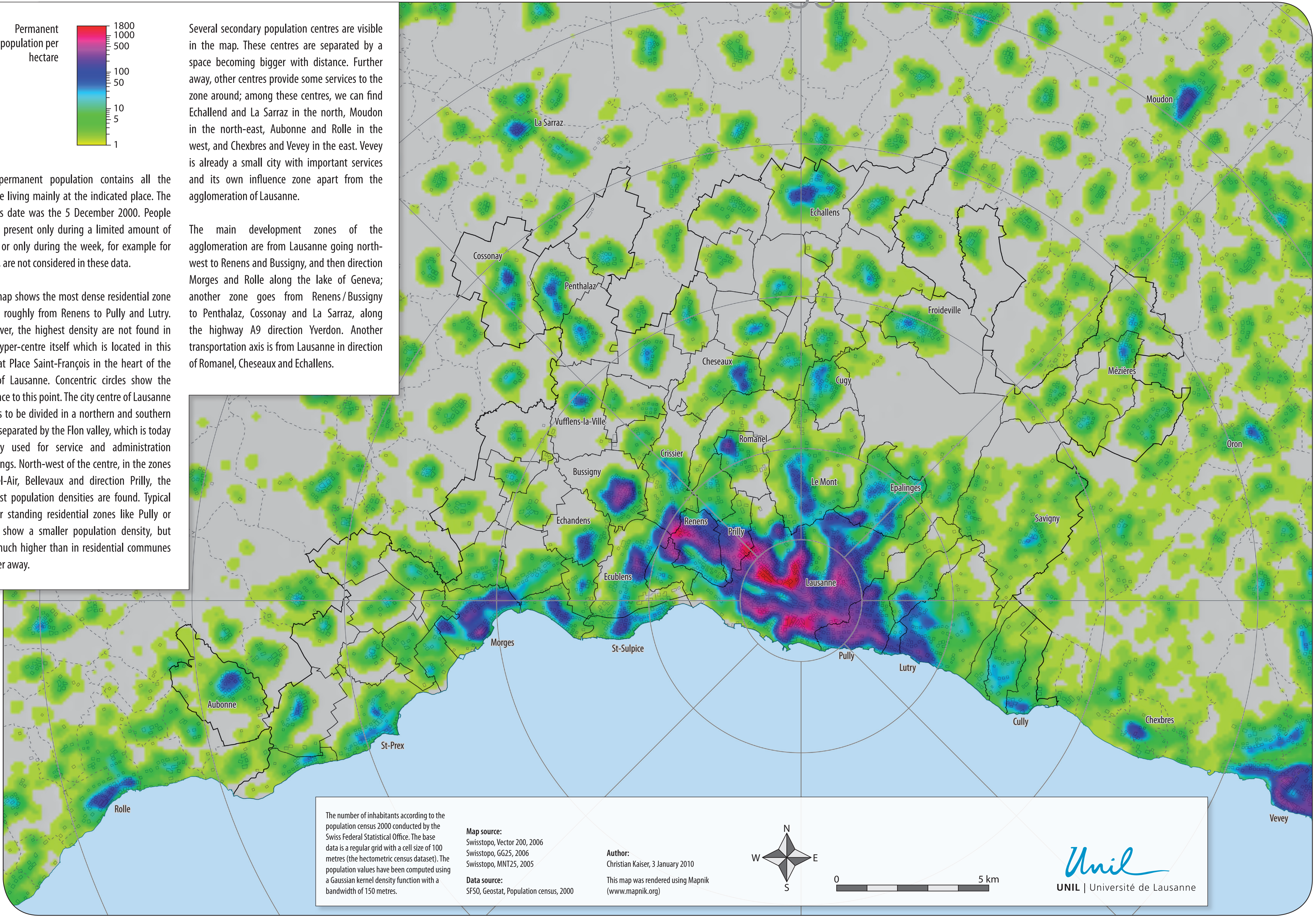
Volume of buildings _ 2000

map 3
agglomeration of lausanne

map 4 _ **Population** _ 2000

agglomeration of lausanne



The permanent population contains all the people living mainly at the indicated place. The census date was the 5 December 2000. People being present only during a limited amount of time, or only during the week, for example for study, are not considered in these data.

The map shows the most dense residential zone going roughly from Renens to Pully and Lutry. However, the highest density are not found in the hyper-centre itself which is located in this case at Place Saint-François in the heart of the city of Lausanne. Concentric circles show the distance to this point. The city centre of Lausanne seems to be divided in a northern and southern part, separated by the Flon valley, which is today mainly used for service and administration buildings. North-west of the centre, in the zones of Bel-Air, Bellevaux and direction Prilly, the highest population densities are found. Typical higher standing residential zones like Pully or Lutry show a smaller population density, but still much higher than in residential communes further away.

Several secondary population centres are visible in the map. These centres are separated by a space becoming bigger with distance. Further away, other centres provide some services to the zone around; among these centres, we can find Echallend and La Sarraz in the north, Moudon in the north-east, Aubonne and Rolle in the west, and Chexbres and Vevey in the east. Vevey is already a small city with important services and its own influence zone apart from the agglomeration of Lausanne.

The main development zones of the agglomeration are from Lausanne going north-west to Renens and Bussigny, and then direction Morges and Rolle along the lake of Geneva; another zone goes from Renens / Bussigny to Penthalaz, Cossonay and La Sarraz, along the highway A9 direction Yverdon. Another transportation axis is from Lausanne in direction of Romanel, Cheseaux and Echallens.

The number of inhabitants according to the population census 2000 conducted by the Swiss Federal Statistical Office. The base data is a regular grid with a cell size of 100 metres (the hectometric census dataset). The population values have been computed using a Gaussian kernel density function with a bandwidth of 150 metres.

Map source:
Swisstopo, Vector 200, 2006
Swisstopo, GG25, 2006
Swisstopo, MNT25, 2005

Data source:
SFSO, Geostat, Population census, 2000

Author:
Christian Kaiser, 3 January 2010

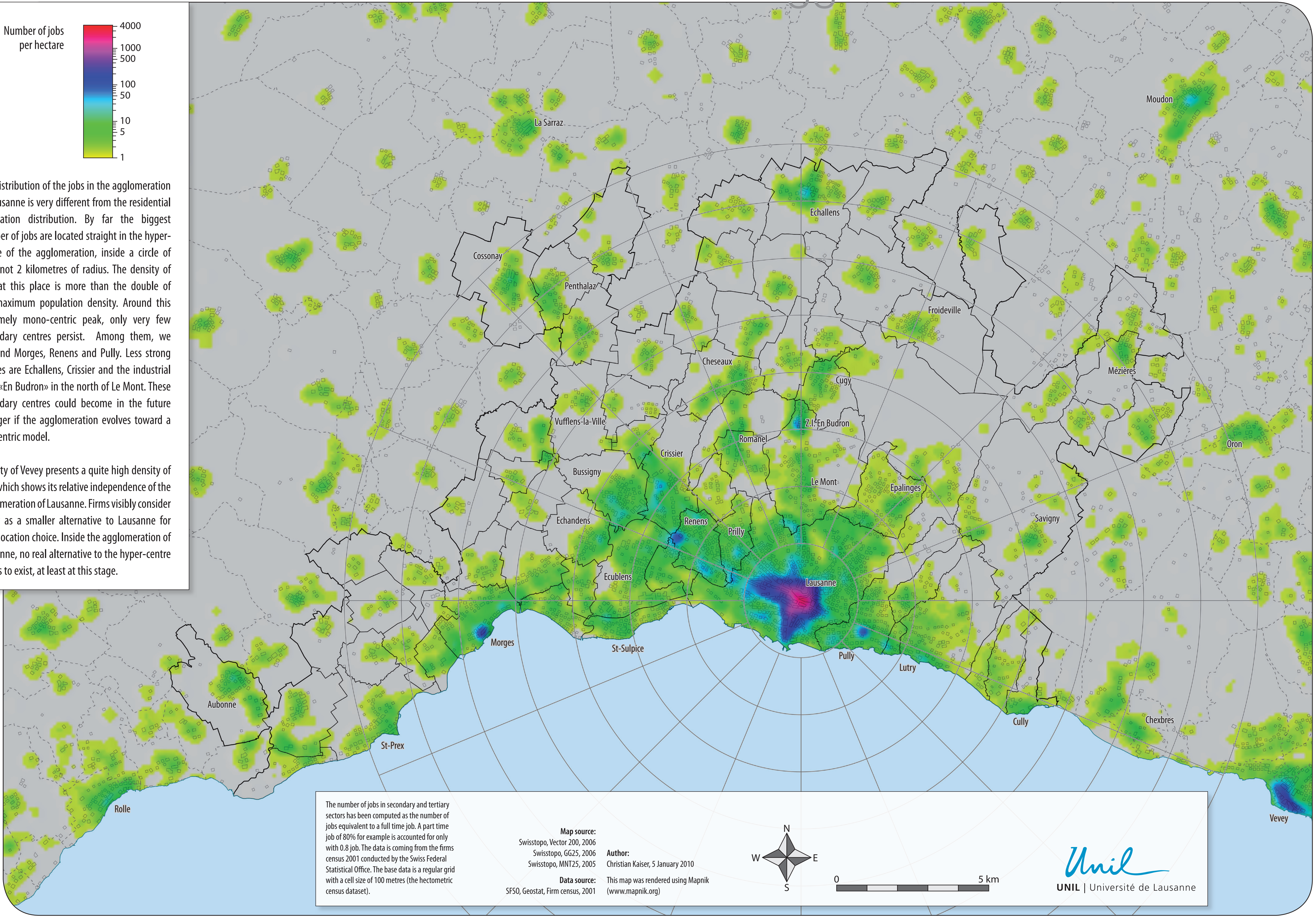
This map was rendered using Mapnik (www.mapnik.org)

Population _ 2000

map 4
agglomeration of lausanne

map 5 _ **Jobs in secondary and tertiary sectors** _ 2001

agglomeration of lausanne



The distribution of the jobs in the agglomeration of Lausanne is very different from the residential population distribution. By far the biggest number of jobs are located straight in the hyper-centre of the agglomeration, inside a circle of even not 2 kilometres of radius. The density of jobs at this place is more than the double of the maximum population density. Around this extremely mono-centric peak, only very few secondary centres persist. Among them, we can find Morges, Renens and Pully. Less strong centres are Echallens, Crissier and the industrial zone «En Budron» in the north of Le Mont. These secondary centres could become in the future stronger if the agglomeration evolves toward a polycentric model.

The city of Vevey presents a quite high density of jobs which shows its relative independence of the agglomeration of Lausanne. Firms visibly consider Vevey as a smaller alternative to Lausanne for their location choice. Inside the agglomeration of Lausanne, no real alternative to the hyper-centre seems to exist, at least at this stage.

The number of jobs in secondary and tertiary sectors has been computed as the number of jobs equivalent to a full time job. A part time job of 80% for example is accounted for only with 0.8 job. The data is coming from the firms census 2001 conducted by the Swiss Federal Statistical Office. The base data is a regular grid with a cell size of 100 metres (the hectometric census dataset).

Map source:
Swisstopo, Vector 200, 2006
Swisstopo, GG25, 2006
Swisstopo, MNT25, 2005

Data source:
SFSO, Geostat, Firm census, 2001

Author:
Christian Kaiser, 5 January 2010

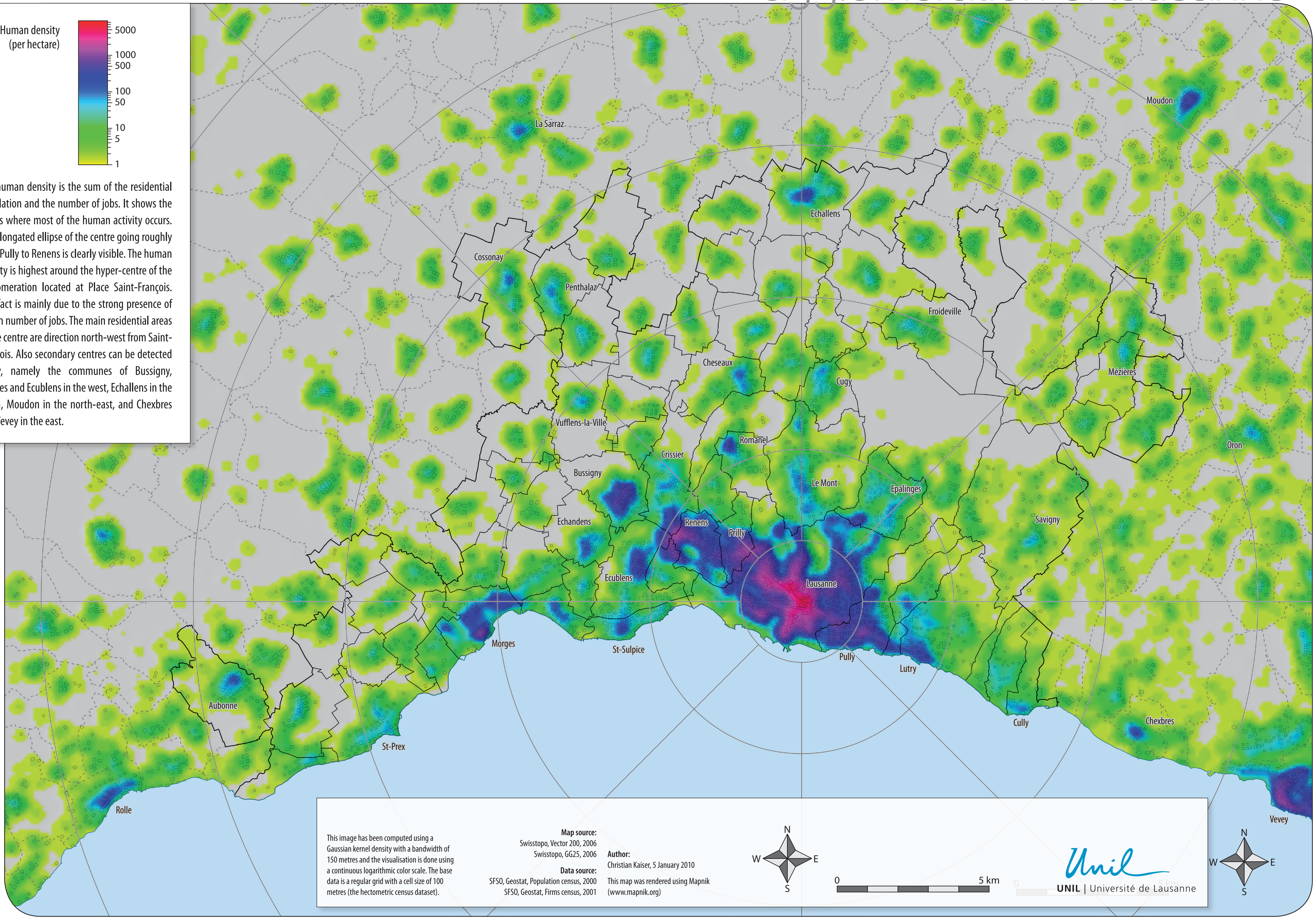
This map was rendered using Mapnik (www.mapnik.org)

Jobs in secondary and tertiary sectors _ 2001

map 5
agglomeration of lausanne

map 6 _ **Human density** _ 2000

agglomeration of lausanne



The human density is the sum of the residential population and the number of jobs. It shows the places where most of the human activity occurs. The elongated ellipse of the centre going roughly from Pully to Renens is clearly visible. The human density is highest around the hyper-centre of the agglomeration located at Place Saint-François. This fact is mainly due to the strong presence of a high number of jobs. The main residential areas in the centre are direction north-west from Saint-François. Also secondary centres can be detected easily, namely the communes of Bussigny, Morges and Ecublens in the west, Echallens in the north, Moudon in the north-east, and Chexbres and Vevey in the east.

This image has been computed using a Gaussian kernel density with a bandwidth of 150 metres and the visualisation is done using a continuous logarithmic color scale. The base data is a regular grid with a cell size of 100 metres (the hectometric census dataset).

Map source:
Swisstopo, Vector 200, 2006
Swisstopo, GG25, 2006

Data source:
SFSO, Geostat, Population census, 2000
SFSO, Geostat, Firms census, 2001

Author:
Christian Kaiser, 5 January 2010

This map was rendered using Mapnik
(www.mapnik.org)

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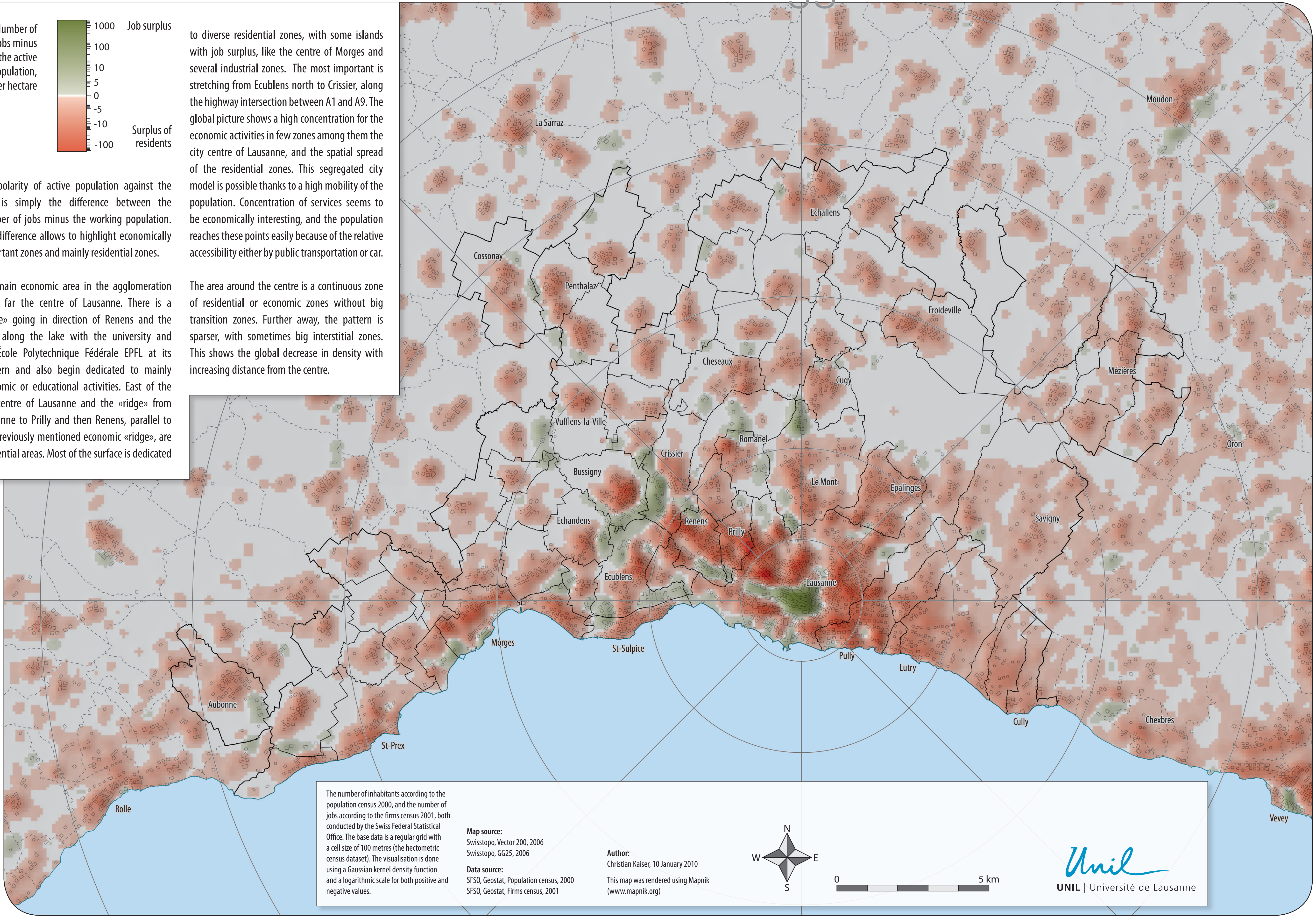
Human density _ 2000

map 6
agglomeration of lausanne

map 7 _ **Polarity of active population against jobs** _ 2000

agglomeration of lausanne



The polarity of active population against the jobs is simply the difference between the number of jobs minus the working population. This difference allows to highlight economically important zones and mainly residential zones.

The main economic area in the agglomeration is by far the centre of Lausanne. There is a «ridge» going in direction of Renens and the zone along the lake with the university and the École Polytechnique Fédérale EPFL at its western and also begin dedicated to mainly economic or educational activities. East of the city centre of Lausanne and the «ridge» from Lausanne to Prilly and then Renens, parallel to the previously mentioned economic «ridge», are residential areas. Most of the surface is dedicated to diverse residential zones, with some islands with job surplus, like the centre of Morges and several industrial zones. The most important is stretching from Ecublens north to Crissier, along the highway intersection between A1 and A9. The global picture shows a high concentration for the economic activities in few zones among them the city centre of Lausanne, and the spatial spread of the residential zones. This segregated city model is possible thanks to a high mobility of the population. Concentration of services seems to be economically interesting, and the population reaches these points easily because of the relative accessibility either by public transportation or car.

The area around the centre is a continuous zone of residential or economic zones without big transition zones. Further away, the pattern is sparser, with sometimes big interstitial zones. This shows the global decrease in density with increasing distance from the centre.

The number of inhabitants according to the population census 2000, and the number of jobs according to the firms census 2001, both conducted by the Swiss Federal Statistical Office. The base data is a regular grid with a cell size of 100 metres (the hectometric census dataset). The visualisation is done using a Gaussian kernel density function and a logarithmic scale for both positive and negative values.

Map source:
Swisstopo, Vector 200, 2006
Swisstopo, GG25, 2006

Data source:
SFSO, Geostat, Population census, 2000
SFSO, Geostat, Firms census, 2001

Author:
Christian Kaiser, 10 January 2010

This map was rendered using Mapnik (www.mapnik.org)

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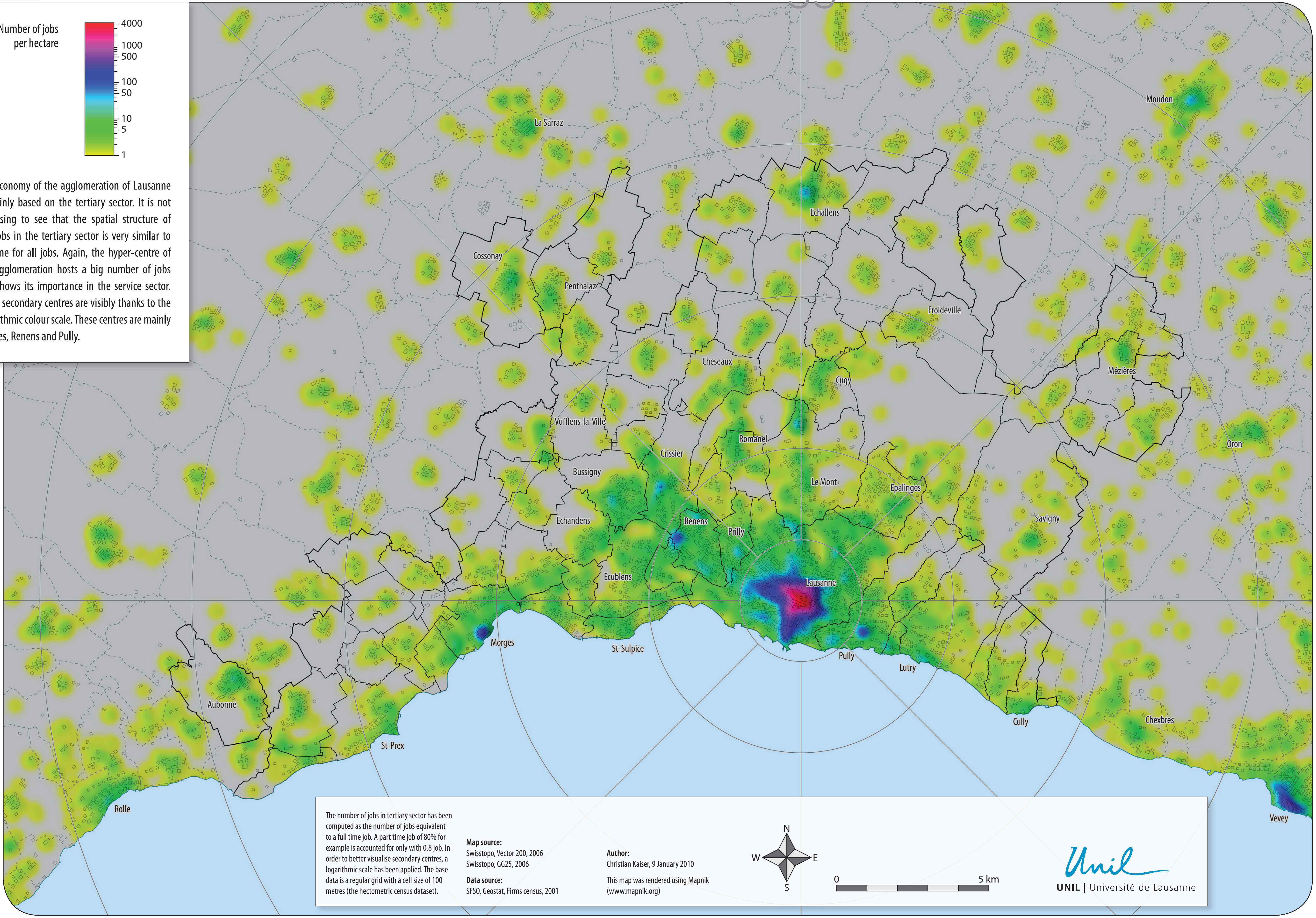
Polarity of active population against jobs _ 2000

map 7
agglomeration of lausanne

map 8 _ **Jobs in tertiary sector** _ 2001

agglomeration of lausanne



The economy of the agglomeration of Lausanne is mainly based on the tertiary sector. It is not surprising to see that the spatial structure of the jobs in the tertiary sector is very similar to the one for all jobs. Again, the hyper-centre of the agglomeration hosts a big number of jobs and shows its importance in the service sector. Some secondary centres are visibly thanks to the logarithmic colour scale. These centres are mainly Morges, Renens and Pully.

The number of jobs in tertiary sector has been computed as the number of jobs equivalent to a full time job. A part time job of 80% for example is accounted for only with 0.8 job. In order to better visualise secondary centres, a logarithmic scale has been applied. The base data is a regular grid with a cell size of 100 metres (the hectometric census dataset).

Map source:
Swisstopo, Vector 200, 2006
Swisstopo, GG25, 2006

Data source:
SFSO, Geostat, Firms census, 2001

Author:
Christian Kaiser, 9 January 2010

This map was rendered using Mapnik (www.mapnik.org)

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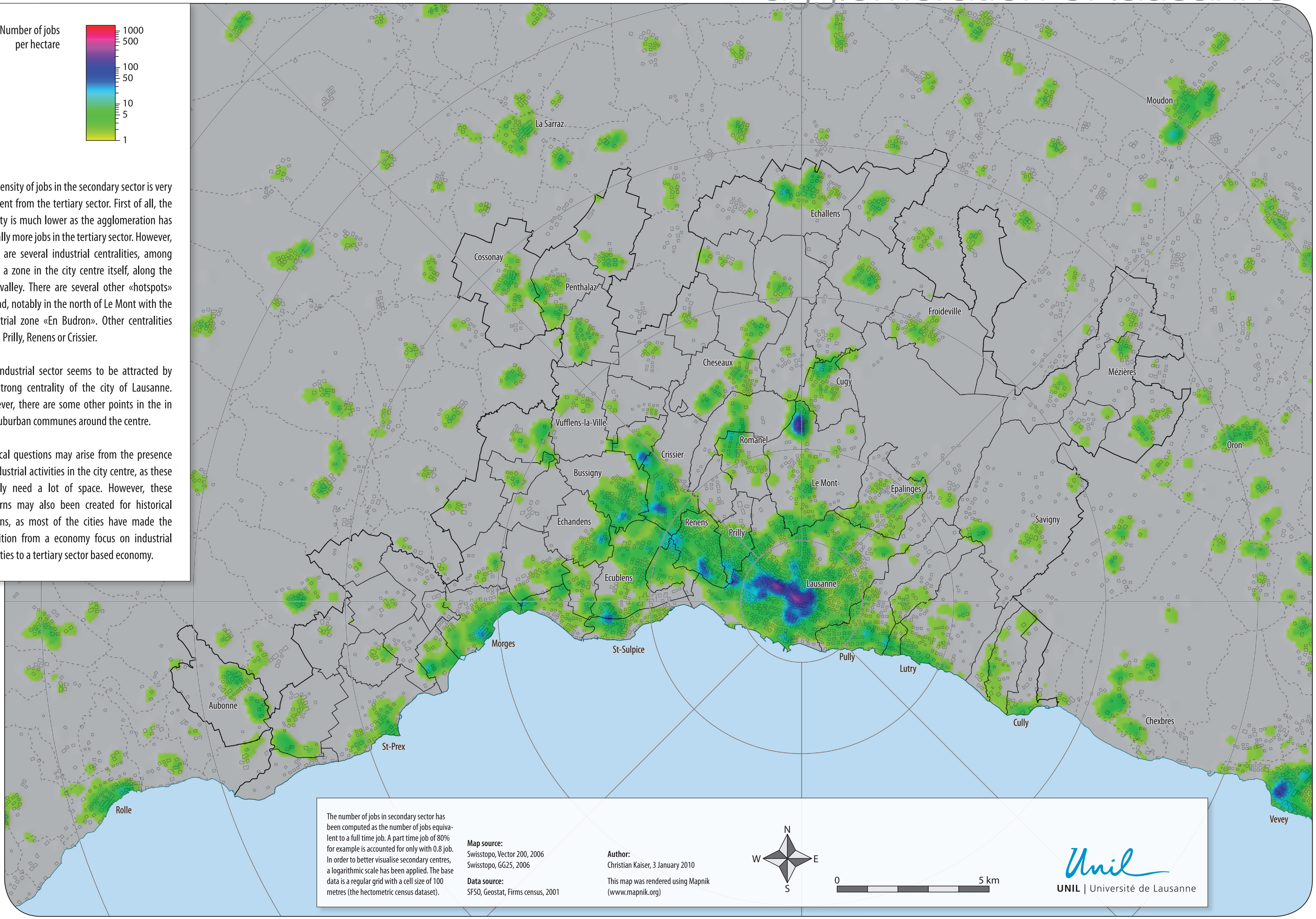
map 8
agglomeration of lausanne

Jobs in tertiary sector _ 2001

map 9 _ **Jobs in secondary sector** _ 2001

agglomeration of lausanne



The density of jobs in the secondary sector is very different from the tertiary sector. First of all, the density is much lower as the agglomeration has globally more jobs in the tertiary sector. However, there are several industrial centralities, among them a zone in the city centre itself, along the Flon valley. There are several other «hotspots» around, notably in the north of Le Mont with the industrial zone «En Budron». Other centralities are in Prilly, Renens or Crissier.

The industrial sector seems to be attracted by the strong centrality of the city of Lausanne. However, there are some other points in the in the suburban communes around the centre.

Political questions may arise from the presence of industrial activities in the city centre, as these usually need a lot of space. However, these patterns may also been created for historical reasons, as most of the cities have made the transition from a economy focus on industrial activities to a tertiary sector based economy.

The number of jobs in secondary sector has been computed as the number of jobs equivalent to a full time job. A part time job of 80% for example is accounted for only with 0.8 job. In order to better visualise secondary centres, a logarithmic scale has been applied. The base data is a regular grid with a cell size of 100 metres (the hectometric census dataset).

Map source:
Swisstopo, Vector 200, 2006
Swisstopo, GG25, 2006

Data source:
SFSO, Geostat, Firms census, 2001

Author:
Christian Kaiser, 3 January 2010

This map was rendered using Mapnik (www.mapnik.org)

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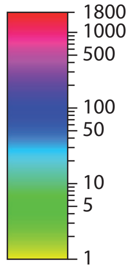
Jobs in secondary sector _ 2001

map 9
agglomeration of lausanne

map 10 _ **Population evolution** _ 1860–1920

agglomeration of lausanne

Permanent population per hectare



The evolution of population density estimated for the period of 1860 to 1920 for the agglomeration. The development of the population during this period is important mainly in the centre of the agglomeration. The population «ridge» between Lausanne and Renens is developing during this period, due to industrial activities in this sector. While the town east of Lausanne, Pully, Lutry, Cully or Chexbres, evolve only in a limited manner, the secondary centrality of Bussigny is already emerging during the first years of the 20th century. This evolution pattern shows that the spatial population structure was already present 150 years ago, and that evolution goes from the centre to the periphery by a more or less complex expansion process.

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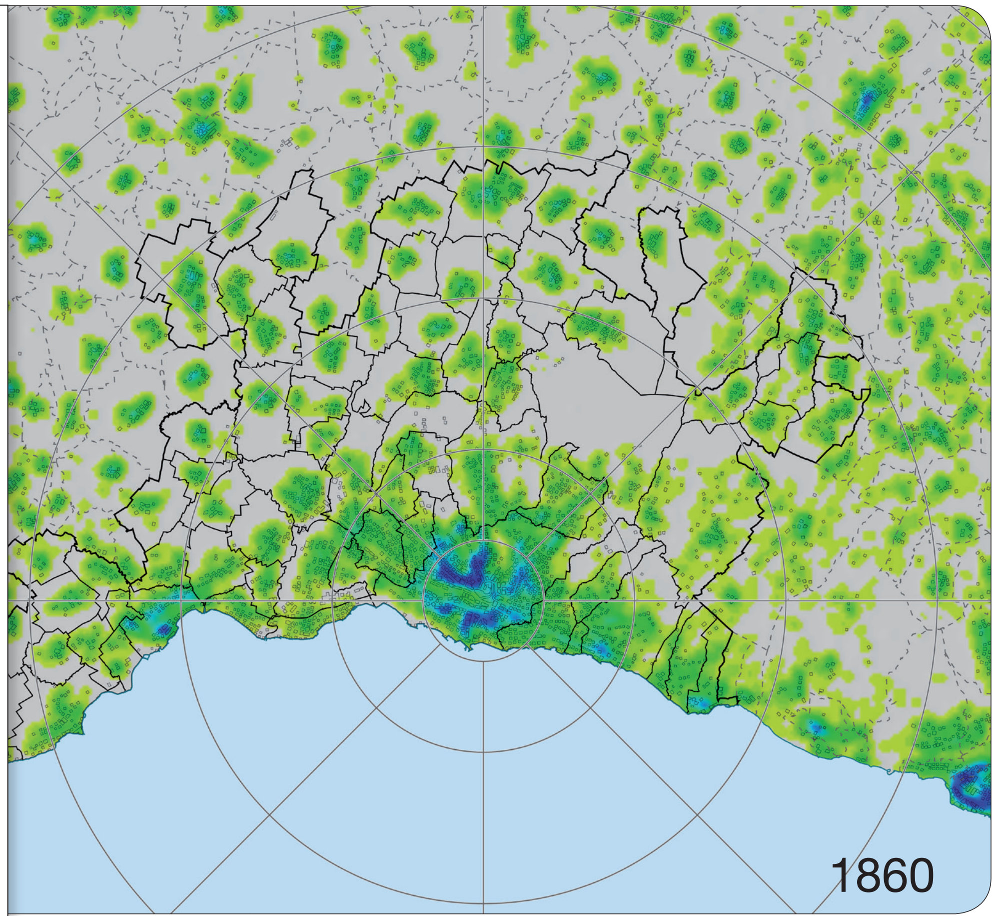
The population evolution has been estimated using a downsampling algorithm for simulating the population distribution at the hectare level. The census data provide the population for each year at the commune level only. A kernel density function has been applied, and visualisation is done using a logarithmic scale. The base data is a regular grid with a cell size of 100 metres (the hectometric census dataset).

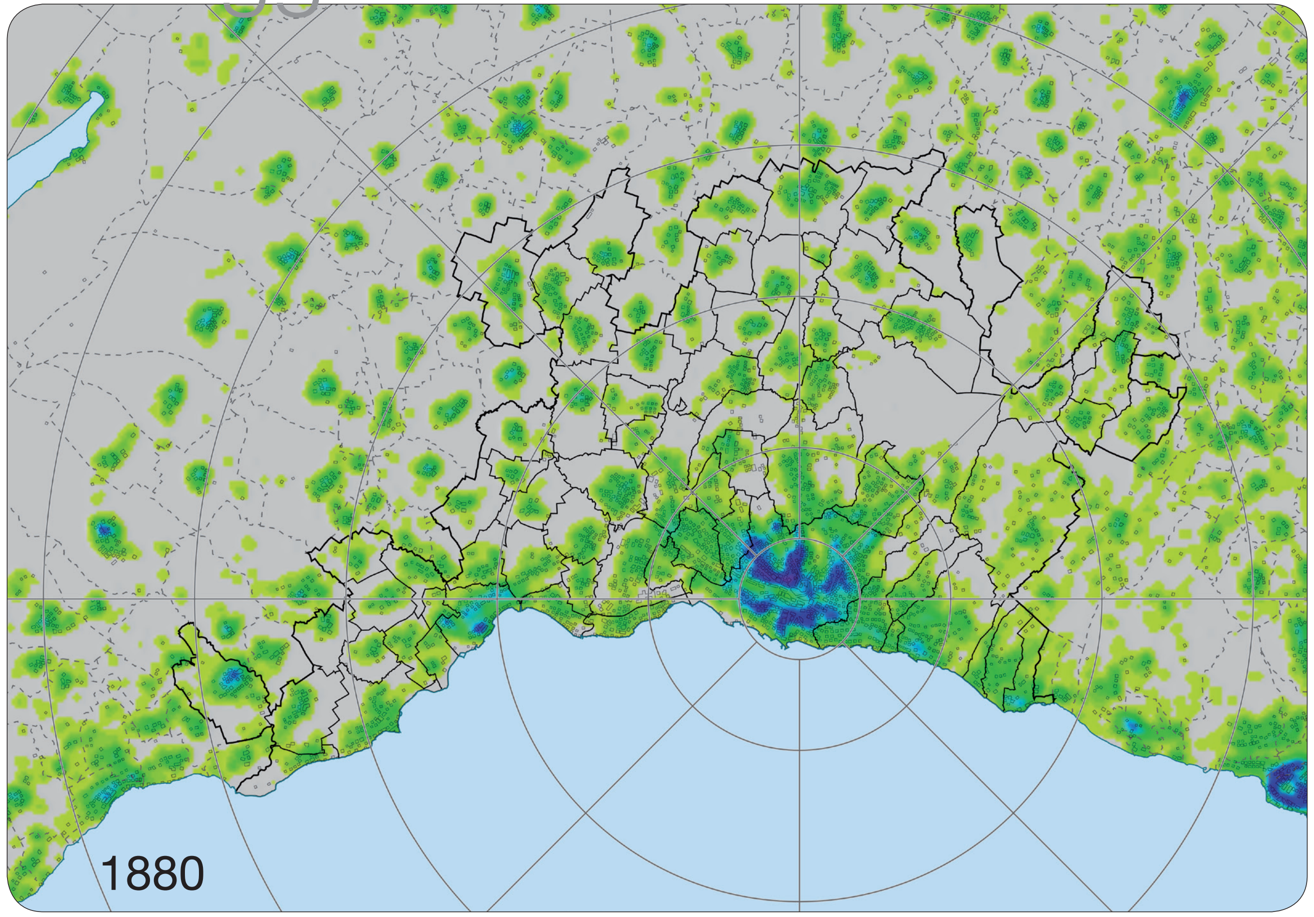
Map source:
Swisstopo, Vector 200, 2006
Swisstopo, GG25, 2006

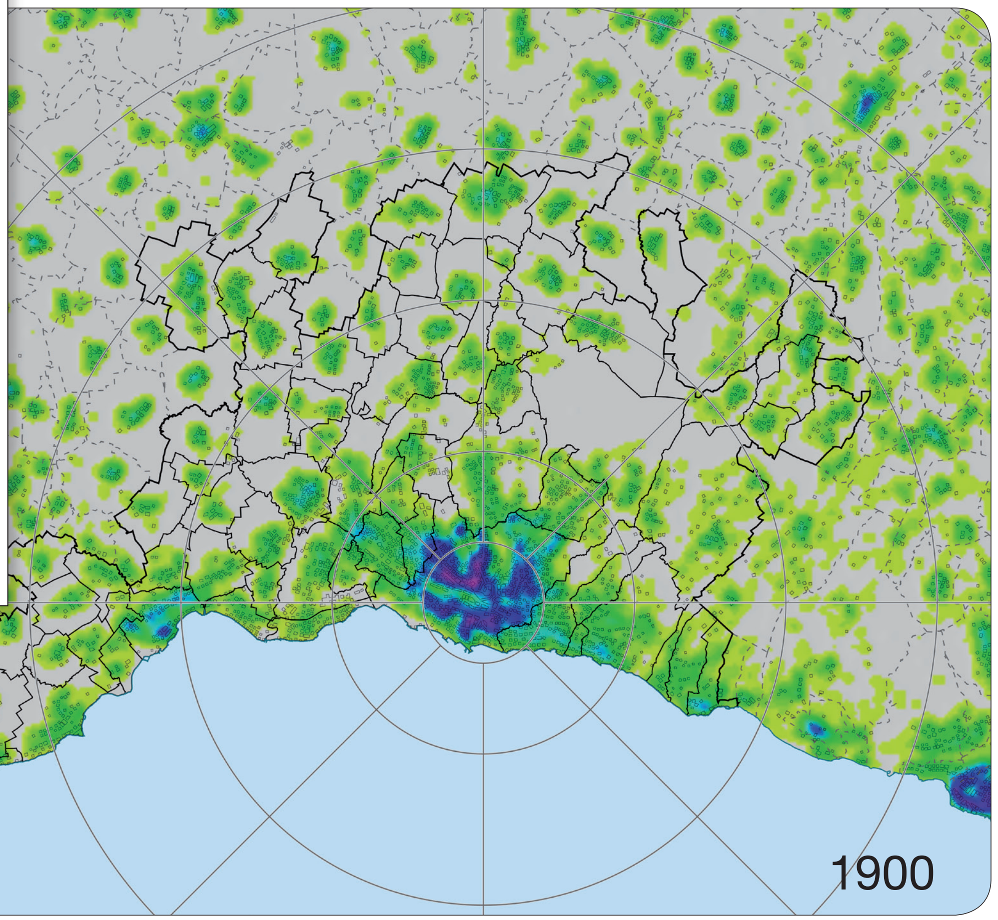
Data source:
SFSO, Geostat,
Population census, 2000
University of Lausanne
(downscaling)

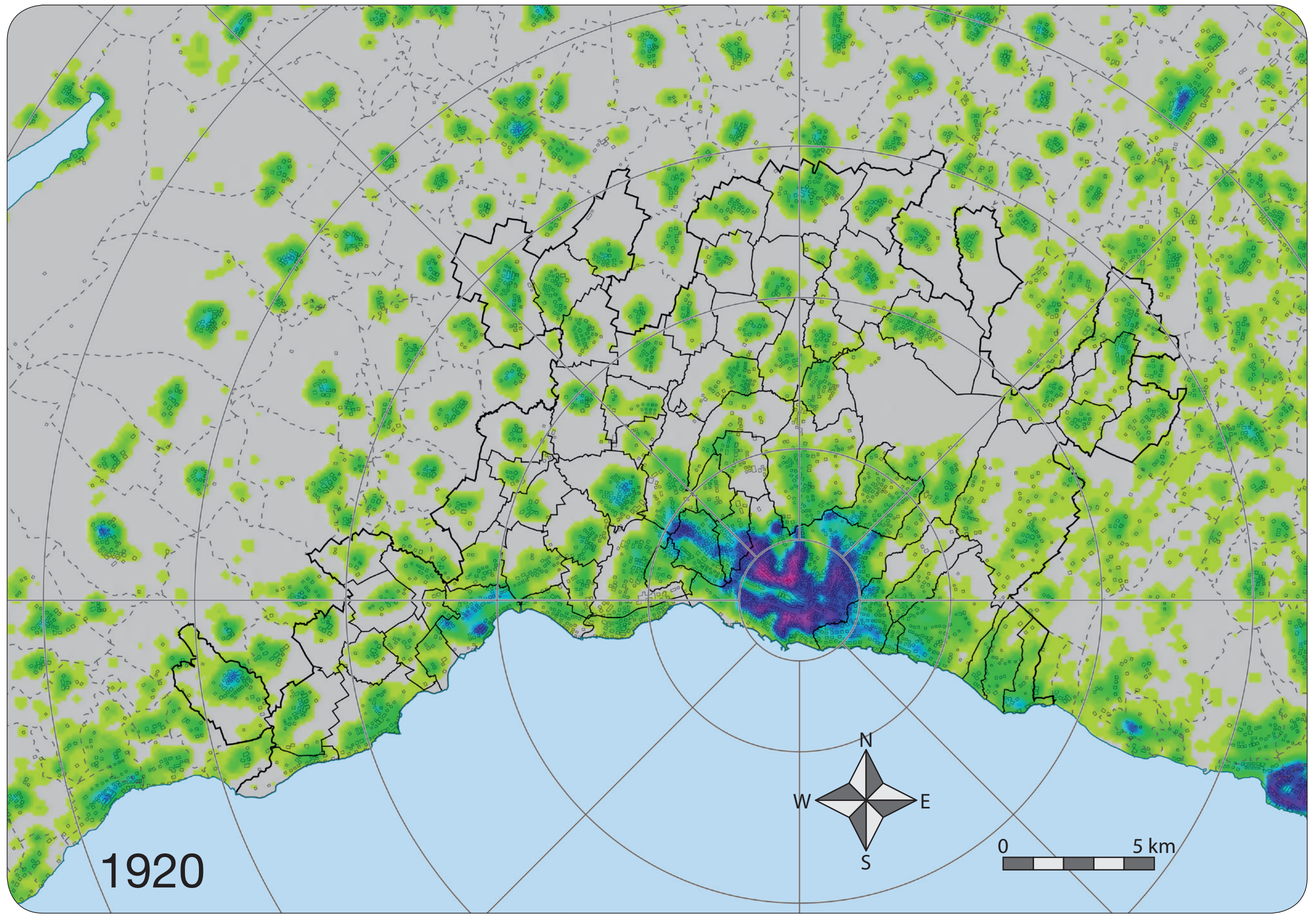
Author:
Christian Kaiser,
10 January 2010

This map was rendered using Mapnik (www.mapnik.org)







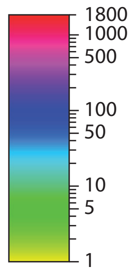


map 10
agglomeration of lausanne

Population evolution _ 1860–1920

map 11 _ **Population evolution** _ 1940–2000

agglomeration of lausanne



This map shows the continuation of map 10. It shows a rapidly growing agglomeration centre and the way this growth impact on the surrounding towns that still where rural in 1940. From 1960 on, the space between Lausanne and Morges gets filled progressively with population, and expansion direction north (Romanel, Cheseaux) starts after 1960. This expansive evolution reaches also further communes between 1980 and 2000, notably Echallens which is quickly growing in this period. While the development until 1940 is mainly concentrated inside the agglomeration centre located roughly from Lutry / Pully to Lausanne and Prilly / Renens, the development takes place a little bit further after 1960. This urban sprawl process is mainly due to the increase of mobility of the population.

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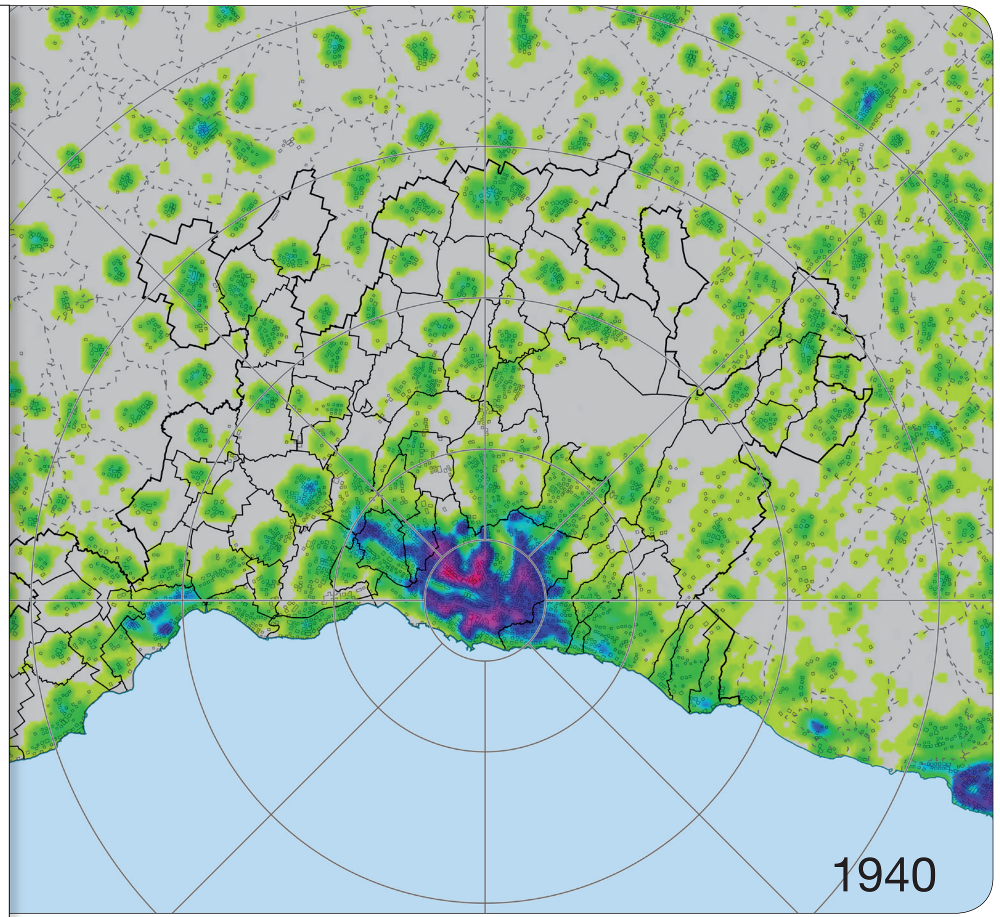
The population evolution has been estimated using a downsampling algorithm for simulating the population distribution at the hectare level. The census data provide the population for each year at the commune level only. A kernel density function has been applied, and visualisation is done using a logarithmic scale. The base data is a regular grid with a cell size of 100 metres (the hectometric census dataset).

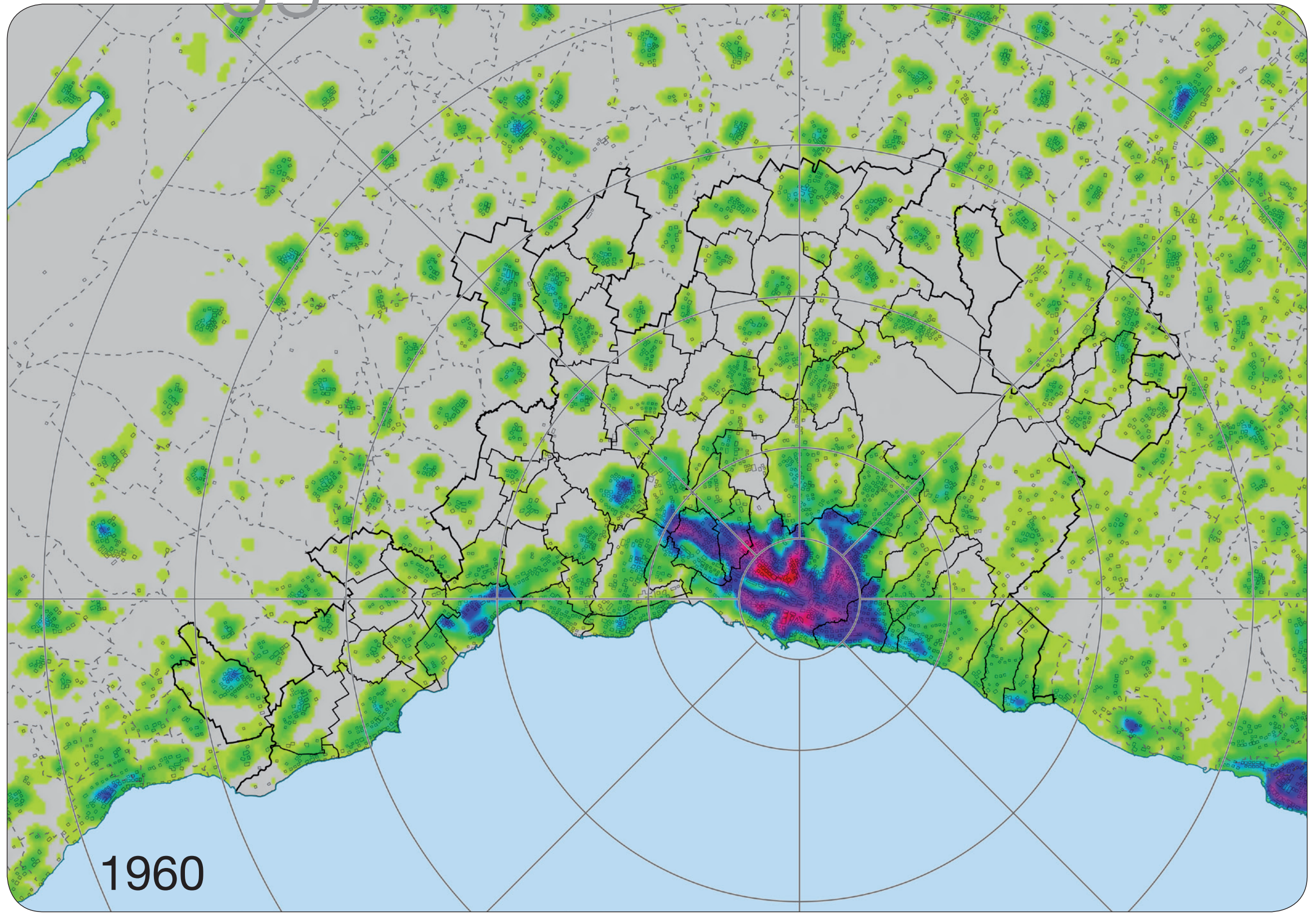
Map source:
Swisstopo, Vector 200, 2006
Swisstopo, GG25, 2006

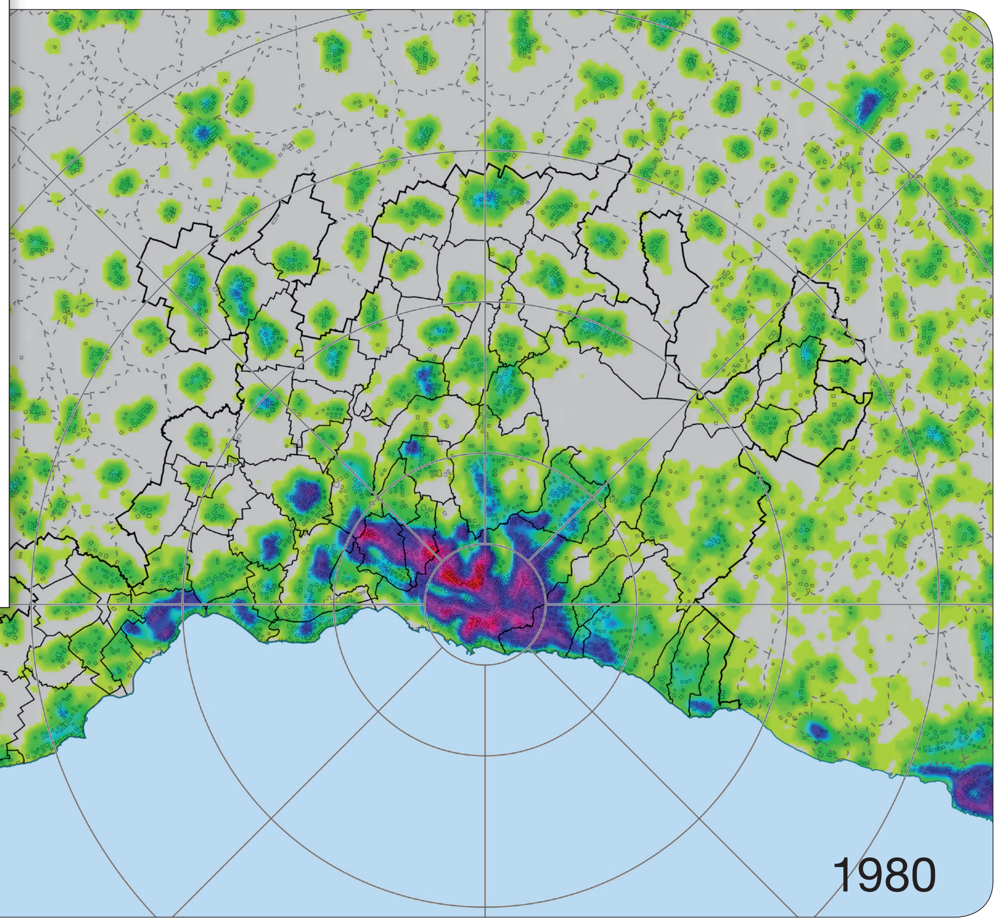
Data source:
SFSO, Geostat,
Population census, 2000
University of Lausanne (downscaling)

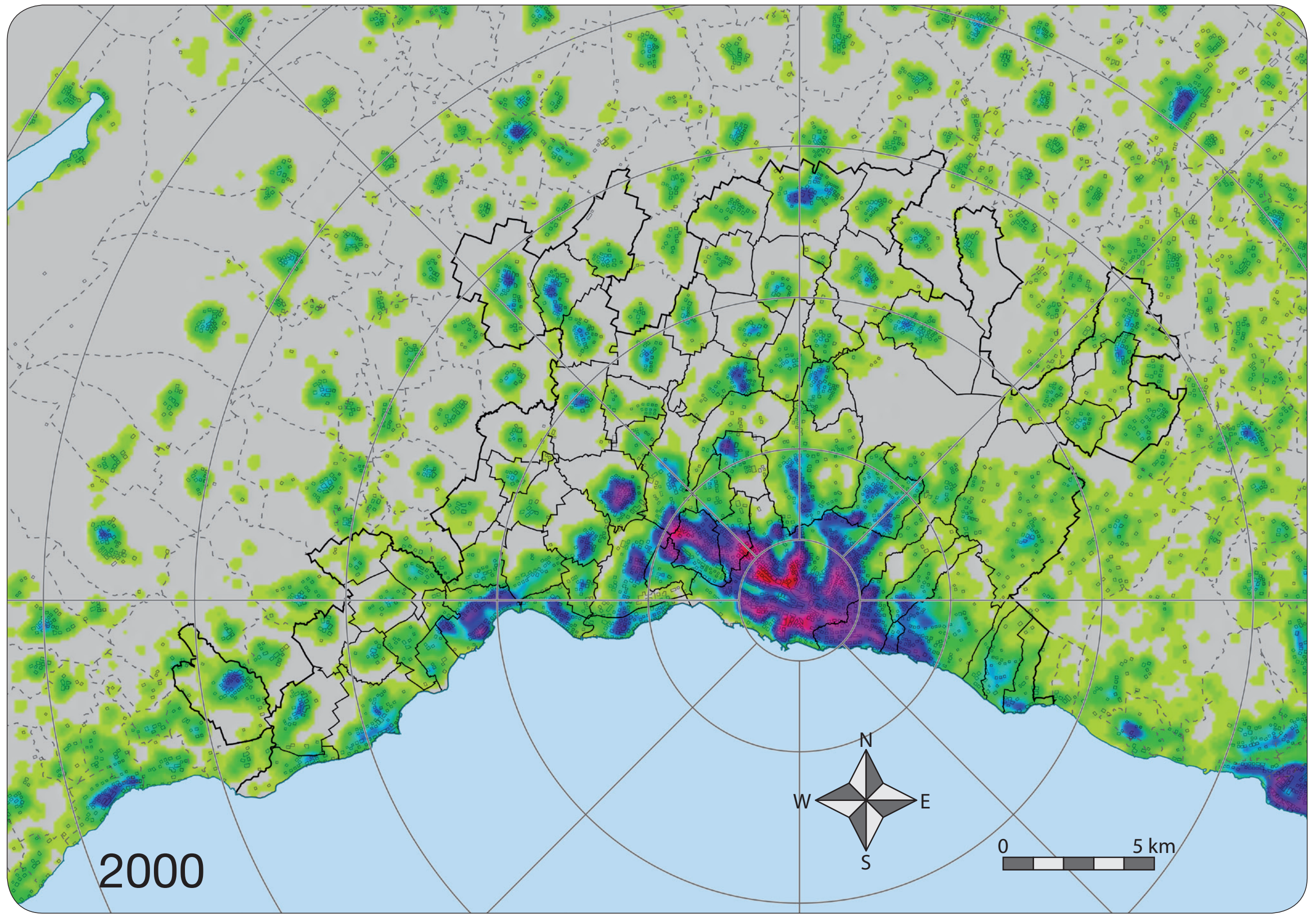
Author:
Christian Kaiser,
10 January 2010

This map was rendered using Mapnik (www.mapnik.org)









Population evolution _ 1940–2000

map 11
agglomeration of lausanne

5.5 Discussion

The visualisation of spatial and spatio-temporal data is important in geography. Recently, there has been a lot of activity in this field, with some progress mainly in the domain of interactive mapping, but also in the representation techniques. This is mainly due to the the rise of the Web, the progress of the animation technology, and also the availability of computation power and modern GIS software. However, the downside of this rapid development is the lack of professionalism in choosing the way how to represent the spatial data. The result are maps difficult to read or even with misleading information. More effort should be put in future in the discussion on how to represent spatial and spatio-temporal data in interactive and dynamic maps. The technological evolution raises some theoretical challenges for the professional cartographer. This progress should also be accompanied by some methodological research on how to represent the data. In a world where more and more spatial data is available, algorithms for feature selection will be important and should be integrated into interactive visualisation devices. There are also still challenges related to the scale of representation, and the dynamic aggregation of data. The scale-dependent representation of data is especially important when the user is able to zoom easily into the map, as this is the case for example with the Google Maps.

Another issue in spatial data visualisation is also the documentation of the maps. Very often, the legend is not enough precise, and explications concerning the content of the map not available. The reader of the map can then misinterpret the content. It is known that "an image says more than 1000 words“. This shows the importance of making the image right and to accompany the reader of the map by providing the relevant elements for the interpretation of the map. Each cartographer should also bear in mind that the content of a map should be assessed in only a few seconds.

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Chapter 6

Advanced exploratory geospatial data analysis

A pattern is a characteristic of the spatial arrangement of objects given by their spacing in relation to each other (Unwin, 1996). The space might consist of real surfaces, but also of of statistical surfaces where the statistical variables make the dimensions. The latter is called the 'feature space'. Patterns might consist of points distributed more regularly or more grouped than random, trends or anomalies. As Unwin (1996) points out, patterns come and go according to how we project the data. Statistics try to look for the right number of (orthogonal) dimensions with the factor analysis techniques. There are also other computer-based techniques known as 'projection pursuit' which try to reduce the dimensionality of high dimensional data (Friedman, 1987; Friedman & Tukey, 1974). Unwin (1996) mentions also the projection given by an area cartogram used by Dorling (1992, 1994) to show detailed variations in the social geography of Britain or studies by Gatrell (1979, 1983, 1991) using Multi-Dimensional Scaling (MDS).

6.1 Machine learning

Machine Learning (ML) is a subfield of Artificial Intelligence (AI) that is concerned with the design, development and application of algorithms and techniques that allow computers to learn from data (Kanevski, Foresti, et al., 2009), that is to adapt to the data presented to the algorithm. The focus of ML algorithms is mainly to model complex patterns in a generalised fashion, and to recognise a pattern. ML algorithms are generally applied to regression or classification problems. ML is strongly related to statistics and computer science.

ML algorithms have the ability to learn from data. They have the ability to handle complex pattern and can show a very good performance. However, they need generally a quite high amount of data for the learning process.

The fact that the algorithm can learn directly from the data is very useful for insufficiently known and/or complex phenomena. This is typically the case with socio-economic phenomena.

We can distinguish between *supervised* and *unsupervised* algorithms. A supervised technique requires labelled training data, this means for some of the data points, the desired result must be known. The algorithm creates then a mapping function between the input and output points by minimising the discrepancy between the two. An unsupervised algorithm does not require a labelled training data set; it is based only on the structural differences inside the provided data set. It is typically used for data clustering. A combination of the two types is the *semi-supervised* algorithm where labelled and unlabelled training data points are used for learning.

Different ML techniques like ANNs or Support Vector Machines (SVMs) are very popular. They have been used in a wide variety of different applications. Among the successful applications are also geography, geosciences and environmental problems (e.g. Kanevski & Maignan, 2004; Kanevski, Podznoukhov, & Timonin, 2009; Agarwal & Skupin, 2008; Bação, Lobo, & Painho, 2004b; Demyanov, Gilardi, Kanevski, Maignan, & Polishchuck, 1999). The ANN comprises several types of techniques, among them, we can cite the Multi Layer Perceptron (MLP), Radial Basis Function (RBF), General Regression Neural Network (GRNN) or SOM. In the next section, we describe in more detail the SOM, as this is a ML technique that suits very well socio-economic problems where we generally need an unsupervised method. The other mentioned ANN techniques are supervised methods and need therefore a labelled data set.

6.2 Self-organising map

A SOM is an artificial neural network for unsupervised classification and dimensionality reduction. It is basically, at least in its standard form, an unsupervised neural network with competitive learning and no hidden layers. Self-organising maps are also called Kohonen map, after the Finnish professor Teuvo Kohonen who has invented the concept.

The principle of *competitive learning* is based on the competition between the different output neurones when a data sample is presented. The best matching neurone is activated; it is called the *winner-takes-all neurone* (Haykin, 1999). In order to get a competition between the neurones, the winner adjusts himself to reduce his distance to the training data sample and the neighbouring neurones are inhibited by drawing them nearer to the winner. According to Haykin (1999), this idea has been first proposes by Rosenblatt (1958).

The objective of a SOM is to represent in a organised manner a number n of entities characterised by m features (variables) in a space of m' dimensions, where $m' \leq m$. Most of the time, $m' = 2$ which allows an easy graphic representation of the SOM result. The fact that a SOM is able to pass from m to m' dimensions allows its use for dimensionality reduction, and the fact of organising the data allows the classification of the input entities.

A high number of variants of the base algorithm exist for a lot of different problems; among them we also find algorithms adapted for specific spatial problems. The base SOM algorithm was conceived by Teuvo Kohonen in 1982 (Kohonen, 2001, p. 106) and is always the most widespread SOM algorithm. We will shortly describe this base algorithm, even if there are numerous other descriptions around, among them the excellent monograph from Kohonen itself (Kohonen, 2001).

A SOM converts the nonlinear statistical relationships between high-dimensional input data into simple geometric relationships in a low-dimensional space (Kohonen, 2001, p. 106). In the case of a 2D SOM, the SOM can be considered as a nonlinear projection of the probability density function of the high-dimensional input data onto the two-dimensional display (Kohonen, Hynninen, Kangas, & Laaksonen, 1995). And still Kohonen (2001, p. 106): *"The SOM may be described formally as a nonlinear, ordered, smooth mapping of high-dimensional input data manifolds onto the elements of a regular, low-dimensional array."* A SOM is composed by a given number of neurones organised according to a defined neighbourhood in a space of m' dimensions. The two most frequent topologies are the rectangular and hexagonal grid in two dimensions (fig. 6.1), where each cell represents a neurone. A vector of m dimensions is associated to each neurone. This vector has therefore the same dimension as the input data. During the training phase of the SOM, the competitive learning tunes the neurones in a way that they get arranged in an ordered fashion in respect to each other and corresponding to the statistical properties of the training data set.

The size of the SOM has a big impact on the result. There is the possibility to build a big or very big map where the number of neurones is much bigger than the number of input patterns (Ultsch & Siemon, 1990; Ultsch & Li, 1993; Bação, Lobo, & Painho, 2008). The so-called Emergent Self-Organising Map (ESOM) uses huge maps in order to detect emergent phenomena (Ultsch, 1999). A second option is to build a medium sized SOM, but big enough to represent all clusters present in the data (Kohonen, 2001; Bação et al., 2008). The last option is to use a small sized SOM, with only one neurone for each expected cluster (Bação, Lobo, & Painho, 2004a; Bação et al., 2008).

In a SOM, the number of neurones and their topology must be defined at the start. This inflexibility is not always wanted. Several variations of the original algorithm exist and try to relax one of the constraints of the original SOM. The Growing Neural Gas (GNG) allows to add or remove neurones during training; the problem of the rigid topology is solved (Fritzke, 1994). In the case of the Adaptive Subspace Self-Organising Map (ASSOM)

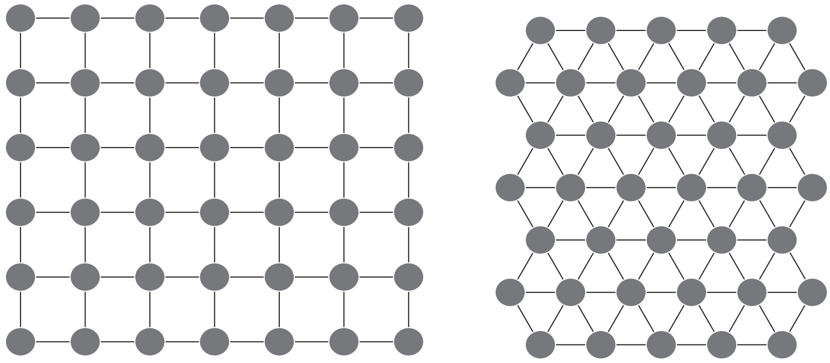

Figure 6.1: Rectangular and hexagonal topologies of a SOM in 2D. The small grey circles are the neurones of the neural network.

described by Kohonen (2001), the vectors associated to each neurone don't have the same dimension as the input units, but a smaller one. In this case, only the distance measure between the input vectors and the neurones is different. The 'Growing SOM' allows the growth of the SOM into a cube of n dimensions in order to take into account the intrinsic dimension of the data (Bauer & Villmann, 1997).

The construction of a SOM can be schematised as follows:

1. In the first step, all the neurones laying on the intersections of the lattice (see figure 6.1 for an example) are initialised, associating to each of them a data vector of the same dimension m as the input data vectors. This initialisation can be done randomly, or based on some criteria. The initialisation has an impact on the final orientation of the SOM.

2. The second step is the ordering phase. Each training data sample is compared to all the neurones and mapped to the most similar one (the winner or best matching unit). The data vector of this activated neurone is then updated in order to match better the training data vector. Using some defined neighbourhood rule, the neighbours of the winner are also updated to correspond better to the winning neurone. The neighbourhood role is a distance decay function for the importance of the update. This step is then repeated iteratively, in order to map completely the probability density function of the high dimensional training data to the output space. The rate of the update of the neurones (the learning rate) decreases during the learning process.

3. The third and final step, the convergence phase, is basically the same as

the second step, except that the neighbourhood role includes a smaller number of neighbours (the distance decay function is steeper). The learning rate is smaller, but the number of iterations higher. After the second step, the neurones should be already quite well ordered. The third step is only for refinement of the neurone's vectors to better represent the training data vectors.

6.2.1 U-Matrix and P-Matrix

The U-Matrix is the canonical display of a SOM (Ultsch, 1992). The distance relationship between the neurones in the high-dimensional input space are displayed as a height value, thus creating a 3D visualisation of the high-dimensional space (Ultsch & Mörchen, 2005). "Mountain ranges" on a U-Matrix point to cluster boundaries while "valley" indicate cluster centres. While the U-Matrix is a distance-based visualisation, the P-Matrix (Ultsch, 2003) is a density-based visualisation showing the local density measures using the Pareto Density Estimation (Ultsch, 2005).

6.2.2 Choice of the grid topology

SOMs use a neighbourhood function and are therefore able to preserve the topological properties of the feature space. This property makes a SOM useful for the visualisation of a high-dimensional feature space in a low-dimensional (typically 2D) representation space. The shape of the SOM grid restricts the possible topological arrangements. It is therefore important to make a reasonable choice for the grid shape. However, there are several decisions to take. First, the number of neurones in each dimension will define the overall shape of the SOM grid. Second, the grid topology can be rectangular (four nearest neighbours) or hexagonal (six nearest neighbours). Finally, a 2D grid can be planar or toroid. In a planar grid, the number of neighbours decreases at the borders of the grid and border effects may occur. In order to avoid border effects, it is possible to use a finite but border-less map topology (Ultsch & Mörchen, 2005). One possibility is to connect the left map border to the right and the upper to the lower border in order to form a toroid map space. Such a toroid allows easy representation in two dimensions. Figure 6.2 shows three possible grid topologies. Note that the toroid grid can also have four or six neighbours.

The choice of a good SOM grid topology is not straightforward. Kohonen et al. (1995) enumerate some advice for constructing stable maps:

1. A hexagonal grid is to be preferred on rectangular ones for visual inspection. However, as in GIS the use of (rectangular) raster data is widespread, it can be observed that for geographic applications, the rectangular grid is used more often. This choice may be suboptimal.

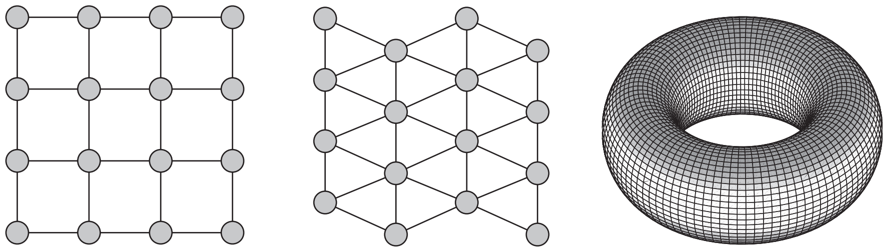

Figure 6.2: Three different grid topologies. A square SOM grid (left), a hexagonal one (centre), and a toroid grid where each cell has four neighbours (right).

2. The overall grid should be rather rectangular than square. In an optimal SOM, the probability density function $p(x)$ of the input data vectors x is mapped in the most 'faithful' fashion, trying to preserve at least local structures of $p(x)$. The 'elastic network' of neurones has to be oriented along with the $p(x)$ to stabilise the learning process. In a circular or square grid design, no stable orientation exists. The grid size should roughly correspond to the major dimensions of the probability density function. One might do a visual inspection of the rough form of $p(x)$ for example using Sammon's mapping (Sammon Jr., 1969) or MDS.

Figure 6.3 shows the quantisation error for the same dataset by just varying the number of neurones in each direction, for the two different grid topologies (rectangular and hexagonal grid). The dataset represents 75 socio-economic variables for 427 municipalities in Western Switzerland (see 6.3.1 for more details concerning the dataset). All SOMs have 400 neurones in total. Figure 6.4 presents the Sammon mapping of the initial dataset; the resulting map is nearly square in this particular case. A grid of 1 x 400 neurones has a less compact neighbourhood than a grid of 20 x 20 neurones; there are less constraints coming from neighbouring neurones for the 1-row grid and consequently, the quantisation error is lower. The figure 6.3 illustrates well the fact that the neighbourhood plays a crucial role for the quantisation error and the 'stiffness' of the map. It is therefore logical that the hexagonal grid yields higher quantisation errors. We should also note that the comparison of the quantisation errors across different grid sizes does not help in the choice of the grid size itself; it only shows the constraints occurring in the map during the self-organisation process. A higher quantisation error also means a higher generalisation or smoothing effect of the input data; the probability density function is represented in a somewhat simplified manner in such a case.

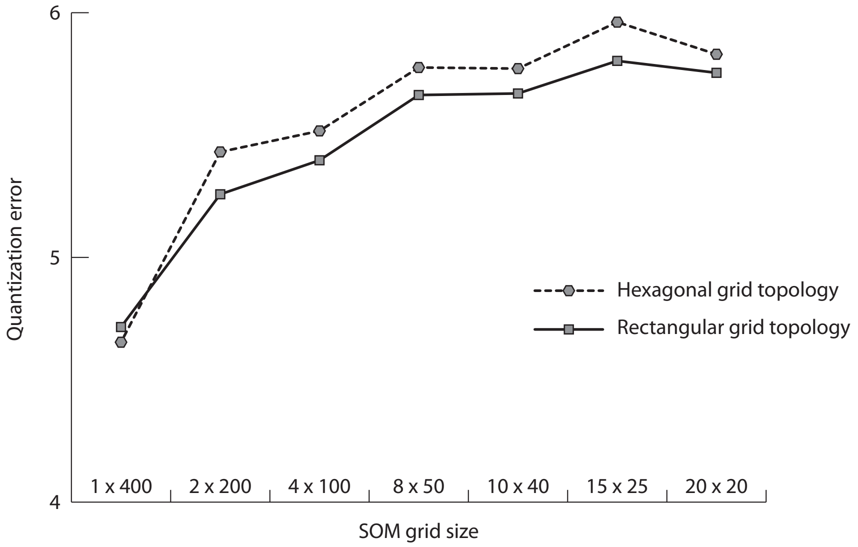

Figure 6.3: Quantisation error for different number of neurones in each of the two dimensions of the SOM. The total number of neurones is constant.

This discussion gives us some indications for the choice of the SOM grid size. The choice of the grid size depends on the use of the SOM one wishes to make. If one want to retrieve the full information for visualisation or visual classification, one should use sufficiently big grids, as mentioned by Ultsch and Mörchen (2005) in their 'Emergent SOM' approach. If however, we want to achieve some generalisation and smoothing of the data along with the topological ordering, the grid size can be smaller. However, if the SOM is used for clustering, the number of neurones should never be the same as the number of clusters. For example, if looking for 6 clusters in a data set, the SOM should not have only 6 neurones; this would be almost equivalent to traditional k-means clustering (Ultsch & Mörchen, 2005). If an appropriate grid size is chosen, the SOM can be used just for non-linear data transformation, for example in combination with a traditional linear analysis method.

If the grid cells are hexagonal, more neighbourhood constraints are occurring in the SOM. The shape of the grid cells can therefore be used to increase or decrease the constraints and therefore the generalisation effect. If one wants the complete unfolding of the input data in the SOM, a grid with hexagonal cells should be bigger than one with square cells.

The overall grid shape should generally be slightly rectangular. Sammon's mapping or multidimensional scaling can give indications on the shape of the Probability Density Function (PDF). The rectangular shape allows the SOM to adapt itself to the PDF. However, in some cases, a square grid

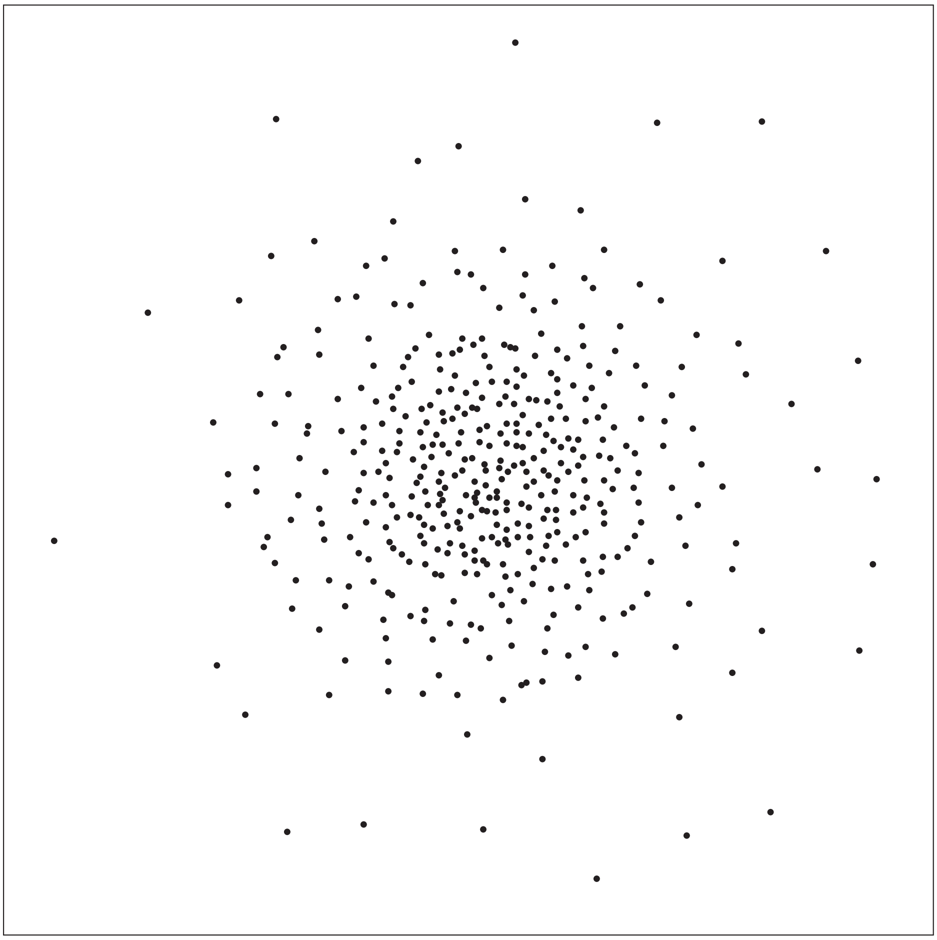

Figure 6.4: Sammon mapping of the 75 socio-economic variables for 427 municipalities in Western Switzerland.

can also be used, but the SOM must be given more time for finding a stable solution.

6.3 Case studies for urban analysis

In this section, we present two different applications of exploratory data analysis using a SOM for the field of urban geography. In the first case, a SOM is coupled with the HAC method for clustering the municipalities of the cantons of Vaud and Geneva in Western Switzerland according to their socio-economic structure. In the second case study, all municipalities of Switzerland are clustered according to a similar data set, but using an ESOM instead of a smaller grid; the grid topology is also changed and a border-less grid is used.

6.3.1 Socio-economic status of municipalities of Vaud and Geneva cantons

The metropolisation process (see e.g. Da Cunha & Both, 2004; Da Cunha, 1996; Schuler & Bassand, 1985; Bassand, 1997) changes the urban patterns and organizes the socio-economic urban landscape. Increased mobility has led to peri-urbanisation and sub-urbanisation. The relationship between the city and the countryside has been deeply modified, and the socio-economic structure has been changed. This evolution is complex and often subtle as it is a 'creeping' process. New analysis methods can help improve the understanding of what is going on and provide urban planners and politicians with valuable information for their decisions.

Understanding such a system in terms of socio-economic features is the analysis of their distribution in space. Socio-economic features are not equally spread over the territory and form generally groups of several spatial entities; in our case, we will base our study on the municipalities. Therefore, it makes sense to group similar units together, depending on their socio-economic profile in feature (variable) space. This feature space is complex and high-dimensional, the classification into a limited number of groups can be very effective for the understanding of the spatial structure and the functional relationships between the different entities. Ideally, the number of classes would lie somewhere between 4 and 8 for a visualisation of the result and for the interpretation of the classes. Classification of such data is a typical unsupervised problem, also called clustering, as the number of classes is not known in advance and examples to train the model are not available (there are no predefined classes). Several clustering models exist for such problems. The hierarchical methods aggregate the observations depending on their similarity in the feature space by optimising an objective function, e.g. the HAC (Ward, 1963). Hard partitionment methods, e.g. the k-Means

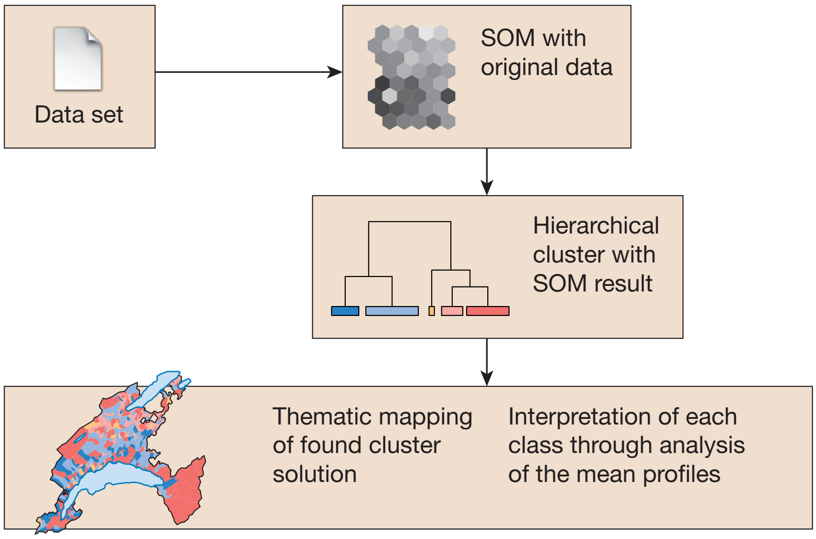

Figure 6.5: Schema of the Hybrid SOM algorithm

(Jain & Dubes, 1988) or SOM, cut the feature space into distinct regions, based on the maximisation of some similarity measure.

For the study of the socio-economic status, we use a HSOM, where the SOM is post-processed using a HAC. In this case, the SOM is used for classification; the visualisation is only a by-product. One of problems of the SOM algorithm is the unknown optimal number of neurones. If the number of neurones is very small, i.e. equal to the number of final clusters (4-8), the SOM algorithm produces virtually the same result as the k-Means algorithm (Ultsch & Mörchen, 2005). Large SOM are better able to represent the input data structure. As Ultsch and Mörchen (2005) point out, emergent phenomena involve by definition a large number of individuals. They think of *'at least a few thousands'* for the number of neurones, and call this type of large SOM *"Emergent Self-Organising Map"*. It has been showed that using a large SOM (an ESOM) is a significantly different process from using k-Means (Ultsch & Mörchen, 2005; Ultsch, 1995).

The algorithm of the HSOM can be schematised as follows (see also figure 6.5 and Kaiser and Kanevski (2007); Tuia, Kaiser, Da Cunha, and Kanevski (2009); Tuia, Kaiser, Kanevski, and Da Cunha (2009); Tuia, Kaiser, Da Cunha, and Kanevski (2008)):

1. Pre-processing of the socio-economic data using the SOM. This step corresponds to a non-linear transformation and a generalisation of the data. The degree of generalisation is determined by the size of the SOM. A small grid will generalise more than a bigger one. On the

other hand, as already stated, a too small grid is not a wanted solution neither.

2. Classification of the neurones of the SOM using a traditional HAC. The advantage of this step is the possibility to determine the number of classes with standard methods, for example the analysis of the dendrogram.

3. The original data are mapped onto the classified neurones of the SOM. Each data sample is assigned to one neurone that in turn has been assigned to one of the classes. Finally, a thematic map of the spatial distribution of the groups is drawn. The analysis of the class profiles enables labelling and interpretation of each group, which is a valuable tool for the urban planner.

In this case study, the HSOM has been applied to the 427 municipalities of the cantons of Geneva and Vaud, in Western Switzerland. The socio-economic structure is described in 75 variables; 54 variables contain information about the number of employments per economic domain in 2000, 20 variables are about the age structure in 2000, and 1 variable represents the percentage of foreigners. The economic domains are defined through the General Classification of Economic Activities (NOGA: **no**menclature **g**énérale des **a**ctivités économiques) of the SFSO (Swiss Federal Statistical Office SFSO, 2002). For all variables, the percentage and the standard scores have been computed for each municipality.

A planar grid of size of 16 x 16 cells has been chosen; the cells are square and have 4 nearest neighbours. The SOM has therefore 256 neurones for 427 municipalities, this is a ratio of 1.65. The neurones have been initialised with random values. The ordering phase has been done with 1000 iterations and an initial learning rate of 0.1. The convergence phase has taken 10'000 iterations with an initial learning rate of 0.01. The Gaussian function has been used for the neighbourhood function, with a radius of 8 cells (half of the grid) for the first phase, and 2 for the second.

The ordered code vectors resulting from the SOM have been classified using HAC. The obtained dendrogram suggests the creation of 5 classes (figure 6.6, left). The HAC enables us to visualise the classified SOM (figure 6.6, right).

In order to assign one of the 5 classes to each of the 427 municipalities, we determine the best fitting code vector in the SOM for which the class is known. With the class known for each of the municipalities, we are able to compute the mean profile for each class (fig. 6.7). These profiles allow finding an interpretation and a meaning for each class. They also show that the classification is able to highlight different characteristics of the municipalities. As the variables are z-scores, the unit of the y-axis is the

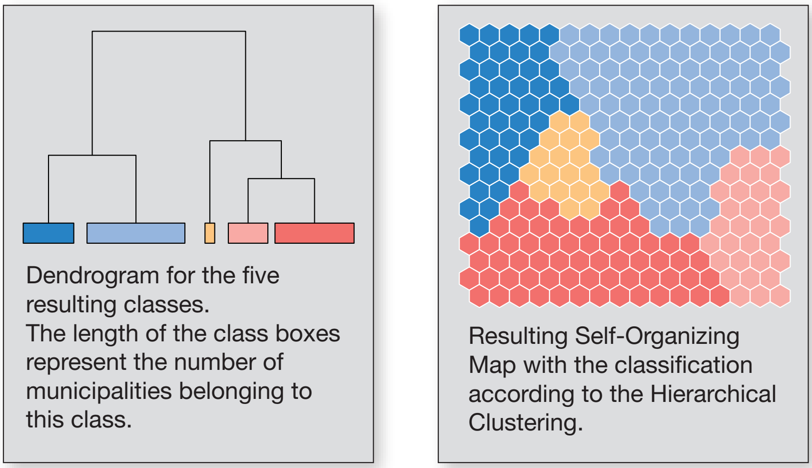

Figure 6.6: The resulting dendrogram from the HSOM process and the classified SOM.

standard deviation, and 0 the global mean value. A positive value shows the presence of a specific characteristic.

The HSOM classification map is shown in figure 6.8. As the socio-economic status is linked with the population, a bivariate map showing the population values and the socio-economic classification may be more appropriate (figure 6.9).

Typical spatial structures of the region can be seen on the map. The first class, in dark blue on the map, represents municipalities characterised by the working class and commuters, with an percentage of foreigners higher than the global mean. Such municipalities are typically in the attraction radius of the cities of the region and represent mostly workers that can afford living out of the cities in peri-urban areas and at the same time make profit from the urban amenities.

The second class, in light blue on the map, represents municipalities classified as residential. These are typically small municipalities with only low population, but they are quite numerous lying around the cities. These places are generally not along the main transportation networks and allow typically families to dispose of enough space for an affordable price while enjoying the tranquillity of the countryside, which makes them a good place for children.

The third class, in orange on the map, comprises only a few municipalities and is associated to some industrial particularities of the region: the regions of Vallorbe, Vallée de Joux, Moudon or Payerne are characterised by strong employment related to particular industries. For instance, the Vallée

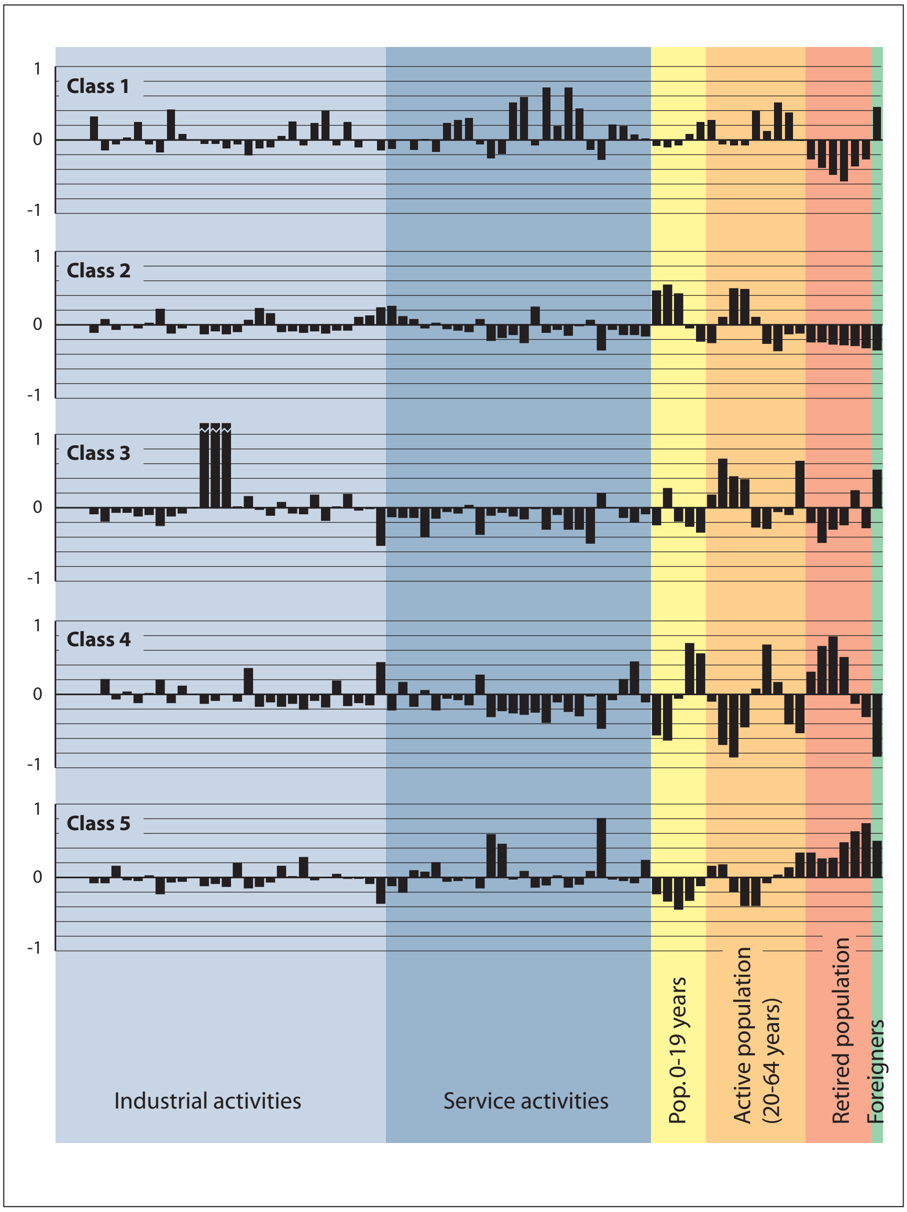

Figure 6.7: The mean profile for each class allows the analysis of what variables are represented in each class.

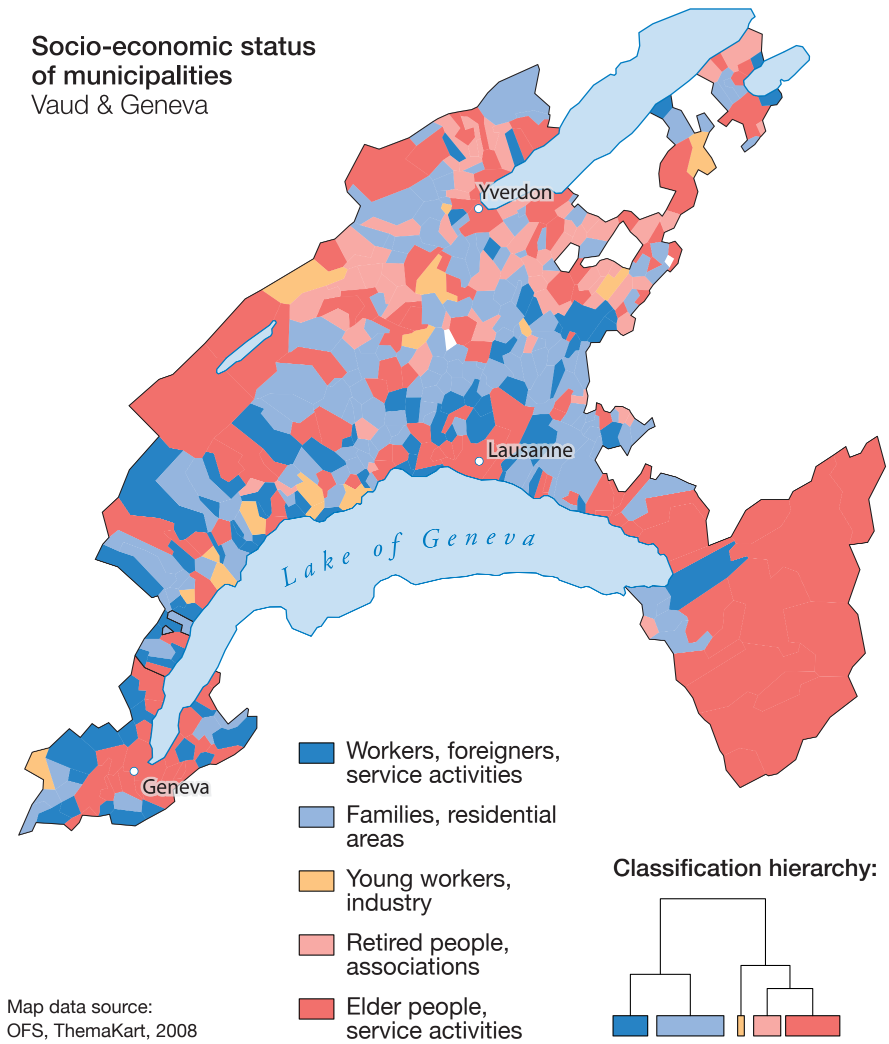

Figure 6.8: Thematic map for the resulting classification.

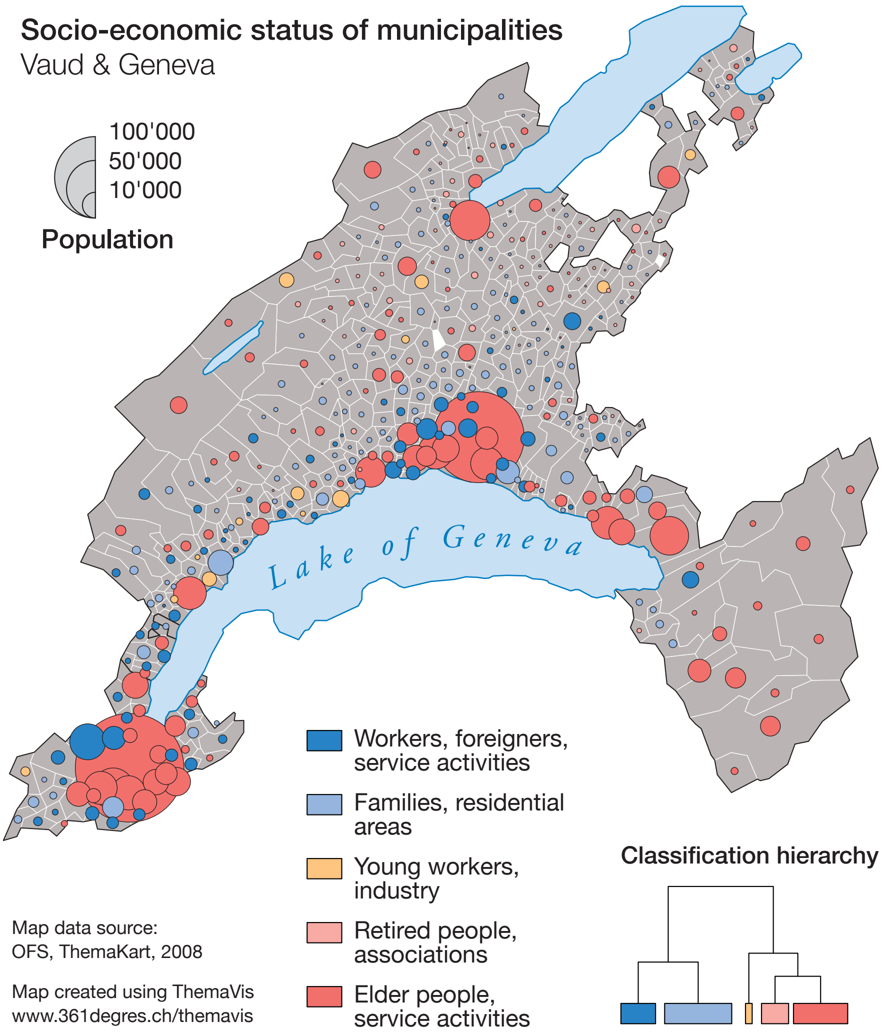

Figure 6.9: Bivariate thematic map with the population and the socio-economic classification resulting from the HSOM.

de Joux is well known for its clock industry. Consequently, the profile of these municipalities is somewhat atypical in the socio-economic landscape, and they are grouped together in a separate class.

The fourth class, in light red on the map, is more difficult to interpret and seems to group together mainly rural municipalities associated to retired people.

The last class, in dark red on the map, contains service-related municipalities, like the cities of Lausanne, Geneva, Yverdon or Montreux. The higher number of employments in some sectors of services is the common denominator of these cities. Another common characteristic is the over-representation of elderly people. It is well known that this population group has the tendency to move into the city where the facilities are usually closer and where good public transportation is available. However, there are also rural regions in the Eastern part of the canton of Vaud in this group; this is the most mountainous area of the region. The over-representation of elderly people can in some cases also be explained by the fact that younger people have to move for finding some work.

As a conclusion, we can say that a SOM can be used in a conventional analysis process as an additional step. In this case, it takes the role of a non-linear data transformation engine. The generalisation effect of the SOM leads generally to a quite robust classification. The size of the grid should be adapted to the number of entities present, but should not be smaller than half the number of entities in order to get acceptable results. However, the assessment of the classification quality is not trivial as the most methods rely on linear indicators. In our case, we were able to reduce the dimensionality of the space from 75 original variables to a unique map consisting of 5 groups. The SOM allows to embed nonlinearly the original data set into a lower dimensional feature space by taking into account the non-linear relationships learned by the self-organisation algorithm. The coupling of the HAC with the SOM allows an easy decision of the number of classes to retain. An interpretation of the classes is possible by constructing the mean profiles. Note that these mean profile can be built either from the initial data, or from the code vectors resulting from the SOM. The SOM is a useful method for the unsupervised classification of socio-economic profiles and has showed its potential in this small case study.

6.3.2 Socio-economic landscape of Switzerland

This case study is similar to the one presented in 6.3.1 in the sense that it also tries to classify municipalities according to some socio-economic criteria. The study area however comprises all the 2896 municipalities of Switzerland. The used approach is still the Hybrid Self-Organising Map combining SOM and HAC. But an ESOM is used, this means the number of neurones in the map is quite big. Additionally, a border-less topology has been used for avoiding border-effects.

A SOM is useful for visualisation of multivariate data, but can also be used for classification. In the case of classification, two different approaches can be found. The first are SOMs where each neurone corresponds to a cluster which has been shown to be almost identical to a k-means clustering (Ultsch & Mörchen, 2005). The second are SOMs where the map space is used as a tool for characterising high-dimensional data (Ultsch, 2003). In the latter, the SOM is composed by several thousand neurones describing the feature structure; this type of SOM is called Emergent SOM by Ultsch and Mörchen (2005), as it explicitly allows the structure to emerge. Since the difference between SOM and ESOM is basically just the size of the network, we will continue to use the terminology SOM in this study case.

Large SOMs are able to represent quite good the input data structure, but there is a need to group together similar neurones in the SOM. This can be done by visual inspection of the U-Matrix, or alternatively by the P-Matrix. Another possibility is to use another clustering technique for grouping together the similar neurones; this is the approach of the HSOM. A comparison between the HSOM result and the U- and P-Matrix is therefore possible.

The data of this case study contain 56 socio-economic variables, composed by 32 economic variables regarding employment per economic sector and position and 24 demographic variables about the age structure for both genders. All the data values come from the Swiss population census 2000. For all variables, the percentage for each municipality has been computed and the values have been reduced to standard scores. When the distribution of the features was skewed, a log transform has been applied. Extreme values have been discarded.

In order to enable emergence of the data structures, a sufficiently big grid of 100x60 cells has been chosen with square cells (4 neighbours). For avoiding border effects, a toroid grid topology has been selected (see figure 6.2, right). 6000 neurones are use for about 3000 municipalities. The learning rate decreases from initially 0.5 to 0.1 at the end by using a linear cooling rate. The Gaussian function has been used for the neighbourhood function, with a starting value of 24 neurones for the radius and a final value of 1.

The resulting SOM is a series of connected neurones representing the input space embedded into a 2-dimensional grid. Figure 6.10 shows 4 of the 56 input variables in the SOM. Note that the SOM is border-less, this means the lower edge is connected to the upper one, and the left edge to the right.

The code vectors of the resulting SOM are then classified using classical HAC. The dendrogram (figure 6.13, in the upper left corner) suggests the creation of 5 classes. Applied to the SOM, this classification gives a partition of the embedded space as shown in figure 6.11a. The classification result can be compared to the U-Matrix and P-Matrix that could have been used

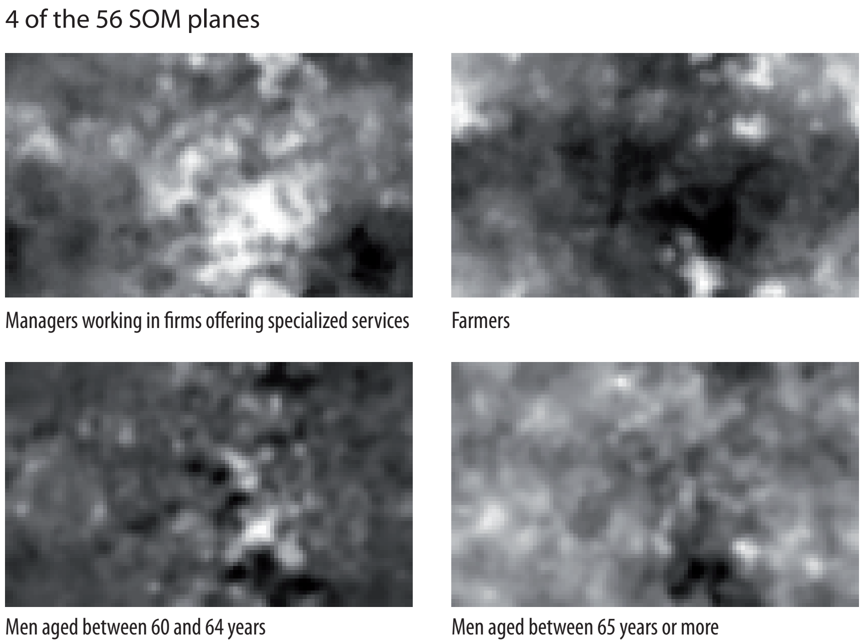

Figure 6.10: SOM representation of 4 of the 56 input variables. Dark zones correspond to higher percentage of occurrence.

for visual classification. These two matrices give additional details on the different classes issued from HAC. For example, the cluster E, in dark blue on the map, is located in a zone with high values in both U- and P-Matrix. This indicates that this class contains features with a higher variability than some of the other classes.

As the SOM geometry is based on a border-less toroid, upper and lower ends of the grid are connected. Thus, it is possible to represent the SOM by exploiting the coherent regions highlighted by the HAC. In this case, the neurones belonging to the same group are represented side by side, and the global grid shape becomes irregular. Figure 6.11 and 6.12 represent the same information. In the latter, the grid is reorganized by using the HAC cluster limits. The same transformation has been applied to the U-Matrix and the P-Matrix, which become a U-Map and a P-Map respectively (Ultsch & Mörchen, 2005). The classification map could be visualised in 3D using the U-Map as elevation data (figure 6.14, see also (Ultsch, 2003) for another example).

The thematic map resulting from the HSOM process (figure 6.13) partitions the socio-economic landscape of Switzerland into 5 distinct classes. Again, like in the case study presented in 6.3.1, typical spatial structures of the country can be detected.

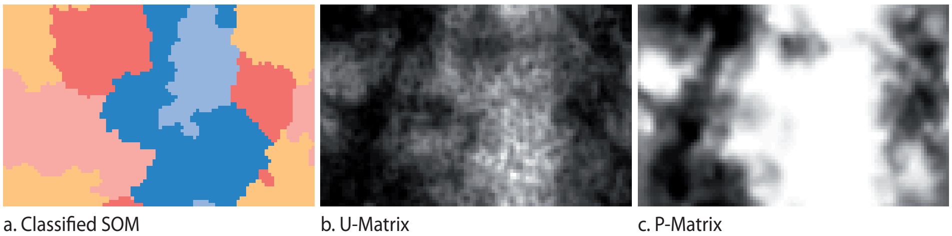

Figure 6.11: The classified SOM (left), the U-Matrix (centre) and P-Matrix (right).

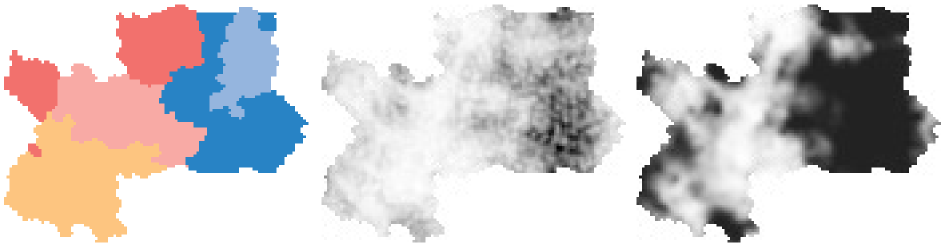

Figure 6.12: The reshaped versions of the SOM (left), the U-Matrix (centre) and the P-Matrix (right).

Cluster A, in orange on the map in figure 6.13, mainly represents municipalities with firms active in production services and that attract a young population. The main urban agglomerations of Switzerland belong to this category, with all the main cities and some touristic regions. Surprisingly, workers in specialised services are not particularly present in this group. An explanation to that may be the overall strength of these services in the country whereas production services are mainly present in urban areas only.

Cluster B, in dark red on the map, is marked by a strong presence of retired people (more than 65 years).

Cluster C, in light red on the map, is characterised mainly by managers and a population aged roughly between 50 and 64 years. Municipalities belonging to cluster C are mainly located in peri-urban areas. Clusters A to C form together the main economic regions of Switzerland.

Clusters D (in light blue on the map) and E (in dark blue) comprise more agricultural municipalities. Cluster E presents however a quite big variety.

It is noteworthy that the cluster boundaries from HAC correspond roughly to the visual clusters from the SOM. However, there is no perfect match, which reminds us the complexity of socio-economic data. However, the method highlights in a very clear way the main urban areas, and the main economic regions are correctly detected.

The results presented give an insight into the socio-economic landscape of the country. Such cartography allows simplifying interpretation about

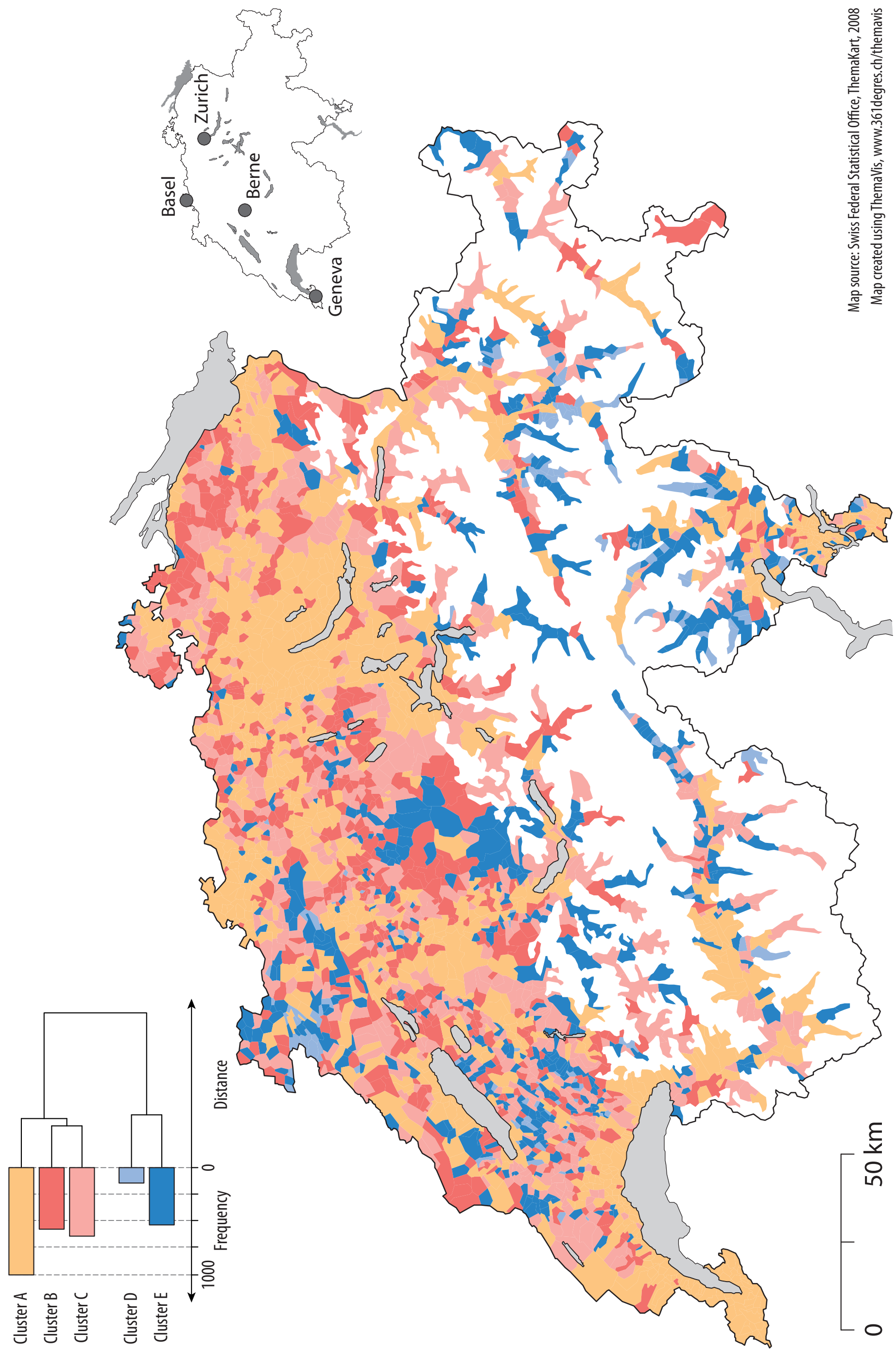

Figure 6.13: Thematic map for the resulting classification.

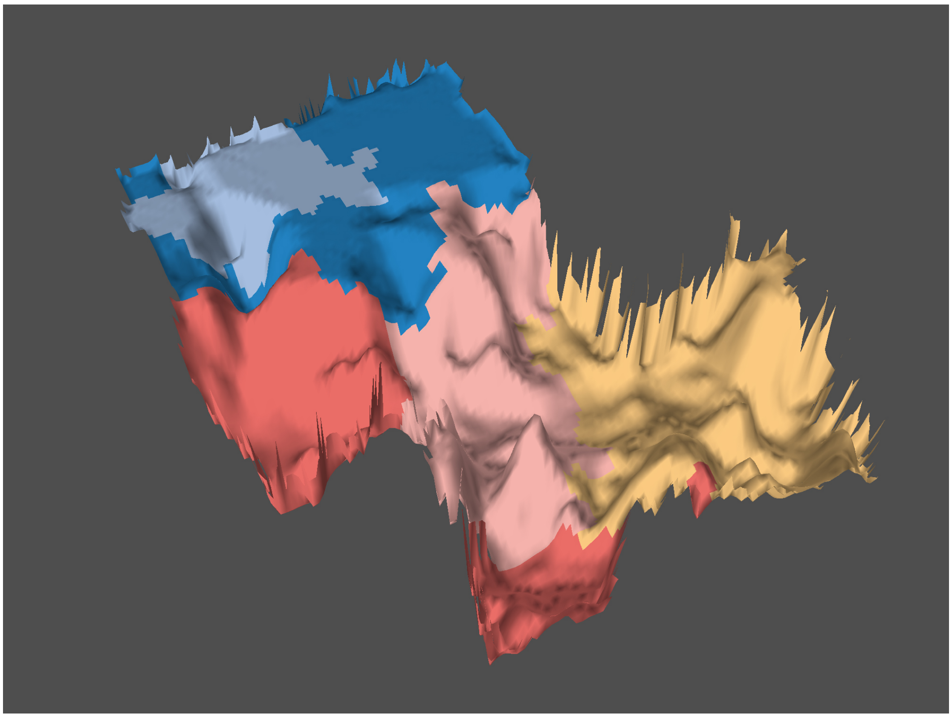

Figure 6.14: 3-dimensional view of the classified SOM with the P-Map as third dimension.

local and regional specificities. The dimensionality of the feature space has been reduced from 56 original variables to a unique map consisting of 5 groups only. The SOM has been used as a non-linear transformation step during the clustering process, as in the previous case study.

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Chapter 7

Conclusions

7.1 Contributions of the thesis

Each chapter of this thesis presents a specific aspect of the problem outlined in the introduction. This can be the development of a method, or simply a feasibility study. In this section, a short overview is given of the particular contributions of this thesis to the field of GISc:

- Chapter 3 presents the percolation approach for socio-economic and demographic data. The scale dependent study of the phenomenon was considered for the first time. The intensity of the phenomenon was studied using the functional threshold. This approach provides a promising tool for a wide variety of applications, including the definition of spatial clusters, and the study of the statistical characteristics of these clusters in function of the scale and intensity. One such example is the Zipf's law for the city size distribution, clearly demonstrated for the case of Switzerland.

  Some command line tools written in C for making analysis using the percolation approach are available inside the SpatialTools toolbox `http://www.clusterville.org/spatialtools`. The percolation algorithm is also used in the user-friendly Windows application "GeoPercolation" `http://www.clusterville.org/geopercolation`.

- The population dynamics are also studied in chapter 3. The difficulties of modelling the population evolution is clearly shown. Command line tools written in C are available also for estimating the population evolution `http://www.clusterville.org/spatialtools`.

- Chapter 4 contains a feasibility study for a multi-agent traffic simulation of the agglomeration of Lausanne. It shows the problems and challenges of the simulation approach for urban phenomena.

The data for the traffic simulation are held in a PostGIS database with one row for each agent (person). The algorithms for calibration are written in Objective-C using a specific library (SpatialAgents) incorporating many GIS algorithms for raster and vector data. The library itself could also be developed further towards an object-oriented GIS and simulation software. For the traffic simulation, the MATSim toolkit (`http://www.matsim.org`) has been used; this toolkit is written in Java and uses XML files for input and output. The conversion algorithms from PostGIS to XML and back have been written in Shell scripts, PHP code and Python scripts, using GRASS GIS for some tasks.

- Chapter 5 shows the principle of area cartograms. The user-friendly application ScapeToad was developed in Java using the GIS frameworks JTS (`http://www.vividsolutions.com/jts`) and JUMP (`http://www.vividsolutions.com/jump`). It allows the easy creation of multi-layer cartograms.

- Chapter 5 describes also the distance circle maps, a novel way of representing centre-based data. This is especially useful for urban geography, as an urban agglomeration has usually a quite well defined centre. A command line tool written in C has been developed for creating distance circle maps.

- Chapter 5 contains some references to other projects and experiences as well. The dynamic mapping of meteorological data on the GeoKernels web site is an interesting example as it combines the visualisation using GoogleMaps with dynamically updated models. While the GoogleMap API uses JavaScript, the interface with the dynamic mapping is written in PHP, and the modelling tools are written in C and C++ mainly for performance reasons.

- Section 5.4 in chapter 5 shows examples of the agglomeration of Lausanne and how demographic and socio-economic variables can be represented using spatially continuous maps. It opens also the door to a cartography where the representation scale of the data is more explicit, and the same over all the mapped region. All the maps have been created using GRASS GIS, using also some newly developed modules, and the rendering library Mapnik (`http://www.mapnik.org`).

  Another research project is the creation of thematic maps based on the GoogleMaps API, and the use of animated elements in the same environment.

  The Interactive Atlas of Romania was another project of interactive web mapping. This project is using the Geoclip environment (`http://www.geoclip.fr`), built on top of Flash.

The animation of the cartogram representation in SVG, where switching from the topographic representation to the cartogram view is possible is another interesting example.

- Chapter 6 shows an innovative clustering method for high-dimensional socio-economic data using SOM and HAC. The SOM acts as a non-linear transform of the socio-economic data.

7.2 New methods and techniques for dealing with complex spatial systems

In section 2.4 of chapter 2, we have outlined some important scientific questions in quantitative urban geography. A discussion on the contribution of this thesis to these different and difficult questions is given in this section.

- ***Question 1.*** *Does the use of spatially continuous data allow a better analysis and representation of the information at hand? Which methods can be used for making data continuous? What is the accuracy of such an estimation?*

  It seems to be clear that the visual representation of continuous data is more accurate and promising than aggregated data. Interpretation is easier and the spatial distribution of the intensity of the represented phenomenon is better visible. However, the analysis of such data is not easy, as it implies dealing with continuous spatial fields. Especially classification is not easy in such a case; using a regular grid is probably the best solution. However, the problem of choosing the grid resolution (the scale of analysis) is then occurring. Better ways for dealing with scale are definitely needed.

  Methods for change of support exist. However, it is difficult to evaluate the accuracy of such a procedure. It depends mainly on the source zones (e.g. administrative units) and the scale of the target zones. A big difference gives not very accurate information, and a seemingly good resolution can be misleading. If possible, additional information on the distribution of the studied phenomenon has to be included in the change of support procedure. Some more research is clearly needed in this field. It is surprising to see that such techniques that are a very common problem in geography are not more advanced. This is partly due to the difficulty to deal with this problem.

- ***Question 2.*** *Scale is an important issue in geography and in urban studies. The analysis of a phenomenon may give different results if conducted at a different scale. Some information or relationships can only be detected at a given scale. However, there are currently no* *methods for finding the appropriate scale of analysis or representation, and only few methods exist for analysing a phenomenon at multiple scales. An important research question is therefore how to find a good scale studying a given phenomenon. Can we detect automatically the best scale? Which methods allow conducting multi-scale analysis? Is it sufficient to find an appropriate scale and use classical methods, or are adapted methods needed?*

The percolation analysis of the urban clusters in Switzerland how it is possible to deal with several scales at the same time, and how the scale of analysis affects the result. However, the question about the best scale cannot be answered in a global manner. For each research question and phenomenon, the scale can vary. The only way to deal with this issue is to use methods that allow "scanning" of a range of different scales and to analyse the results simultaneously. Classical methods can probably in some cases be integrated into a new "scale-aware" method. And the use of fractal geometry allows to account for some additional scaling properties of a given spatial pattern. This thesis shows that the scale has to be integrated into the analysis methods, and it shows also some approaches on how to do it.

- ***Question 3.*** *Can the spatial support of the dataset be changed without loosing the characteristics of the phenomenon under study? Can new information be detected after a change of support? These questions are very important as they give indications about how useful methods for analysing and visualising continuous and multi-scale data are.*

  Change of support methods should more widely be used in urban geography and further developed to integrate for example the concept of validity domain. All additional information related to the phenomenon under study should be integrated into a downscaling process. In cases where data has to be aggregated, care should be taken to the scale of aggregation. Additional research is clearly necessary in this field.

- ***Question 3.*** *Visualisation methods are crucial as they give an easy access to the result of an analysis. As such, they deserve special consideration. Spatio-temporal and multi-scale analysis need sophisticated and often interactive and dynamic visualisation tools. What kind of visualisation method is adapted to complex geographic information? How can different visualisation methods help in accessing the information extracted by different analysis methods? Are new visualisation techniques needed, or should existing methods be adapted?*

  Visualisation methods should become more interactive and dynamic. Complex systems such as the city need sophisticated visualisation methods together with advanced analysis methods for extracting the information. Additional, easy to understand methods of mapping the spatial information should be found. This thesis shows some approaches, but the presented methods are far from being exhaustive. The field of (geo-)visual analytics will become more important in the next few years and will address these questions. However, a lot of research is still needed in this field. Existing visualisation methods are only the starting point for a new kind of science.

7.3 General discussion and future research

This theses shows some applications of quantitative methods to urban geography. It includes simple examples of spatially continuous mapping for demographic and socio-economic variables. But it shows also how to treat complex high-dimensional data in an efficient way. It is a fact that the fields of quantitative and urban geography are currently evolving very fast. This is mainly due to the availability of more detailed data and the increasing availability of computational resources. Therefore, it is important to develop methods to analyse and visualise complex data sets.

The chapter on visualisation shows some interesting approaches that could lead to automatic mapping systems. The field of visual analytics linking the analysis of phenomena using for example different clustering techniques with the interactive visualisation is a very fashionable topic. There are many candidate methods for automatic analysis. The presented clustering technique using a SOM is one of them. The percolation approach is another. The cartogram creation process is now sufficiently efficient to be implemented in user-friendly, interactive mapping systems where the user can switch from one representation to the other.

Let us remind that the percolation approach is very powerful and flexible; it allows the assessment of the concept of "continuous space" in a straightforward manner. A continuous space is in this case the space where a given phenomenon has at least a given strength; this minimum intensity is defined by the functional threshold. This continuous space – a spatial cluster – can be considered for a given feature (e.g. population) for a given scale (resolution, cell size) and associated to a functional threshold defining whether flowing (continuity) occurs or not. Thanks to the simplicity of the percolation approach, it is possible to build an automated analysis system, where the user – an urban geographer or planner – can explore the space interactively.

However, the percolation approach should be explored further. It is possible to extend the concept to other supports than a regular grid. One could also use another regular geometry shape to form a lattice (see e.g. Stauffer & Aharony, 1992, p.16). It would even be imaginable to use an arbitrary graph linking two neighbouring objects and assigning a weight or distance to the link. Two neighbouring objects are then connected if the distance does not exceed a given threshold. There is also the concept of "directed percolation" where the percolation process has to "choose" a preferential direction for flowing (Maignant, 2009). Directed percolation can occur in time or space, or both. One example is a forest fire where the spread has to be considered in space and time. In this case, the diffusion process occurs only in one direction, and is generally not reversal. Processes occurring in the urban agglomerations can be analysed using this flexible percolation approach.

Urban simulation is a powerful technique, but requires a big amount of data for calibration and important resources of computation power. Additionally, a validation is needed to assess the reliability of the result. However, if an accurate simulation can be conducted, it becomes a very valuable tool for decision makers. In order to be widely used widely, advances in the automation of such models should be made. There is a high potential for distributing on many computers such a model, but practical questions on the implementation have to be solved first. Cloud computing systems will probably used in the future to host and run complex simulations on a big number of computers.

It would then be possible to implement the simulation models in a distributed computer system and constantly update and re-calibrate the agents according to newly arriving data. These data can come from very different data sources. The user is then able to "program" a simulation for a scenario and test some hypotheses for future development. The urban planner will be able to simulate the effects of a particular project. However, a lot of research has still to be done to achieve such a system in production use.

One open question in urban simulation in general and in MASs and CAs in particular is the calibration and validation of the simulations. Machine learning algorithms are a promising way to investigate further this question. In the case of MAS, the question on what an agent should represent is not completely clear. In our traffic simulation, it seems straightforward to consider one person as one agent. However, Alfi, Pietronero, and Zaccaria (2008) have showed that the number of agents is an important factor in agent-based models. Further research should be done in this direction, as we don't have a clear idea on the effect of the number of agents on the behaviour of the model. It is also clear that a very high number of agents, as it is typically the case in individual-based simulations, is very demanding in computation power. A too individualistic model may destroy the generalisation capacities of the model.

More generally, the complex urban system should be further analysed by combining current methods with optimisation techniques. Maignant (2009) develops the idea of optimisation and shows how the constructual theory (Bejan, 2000) may help designing more sustainable cities. The optimum is close to a critical point in a dynamic system, and it is not always the objective to achieve if a more stable situation is needed. However, the question about the optimum should be integrated in geographic models and simulations. It could be, for example, very helpful for calibrating or validating simulations.

The city is a complex system difficult to analyse and to model. A lot of actors play a role, and there are numerous conflicting interests. New methods should be tried out for improving dynamic models and simulations. Machine learning algorithms may be helpful in these cases to model socio-economic variables in space and time. Kanevski, Podznoukhov, and Timonin (2009) explain some advanced machine learning algorithms that could be applied also for socio-economic problems in urban systems.

The goal of this work was not to provide a complete picture of the complex urban system, but rather to add a few elements to a global picture. Many doors are wide open for future research. A better understanding of the city will help urban geographers in developing new strategies for making the city more sustainable and to improve the quality of life for the citizens.

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Chapter 8

Addendum: Spatial Tools

Spatial Tools are a collection of simple command line programs written in C and available under the GNU General Public Licence (GPL) (see `http://www.gnu.org/licenses/gpl.html` for more details). The programs allow to achieve some very basic tasks that are difficult to achieve using common GIS software. The source code of all programs is available at `http://www.clusterville.org/spatialtools`.

r.clusters.stats

Purpose

Computes statistics for different clusters. The clusters are defined in a raster file where the value corresponds to the cluster ID. The statistics are computed for the statistic raster file according to the spatial clusters defined in the cluster raster file. The statistics include the sum, number of cells, average, minimum and maximum.

Synopsis

```
r.clusters.stats [--help] [--nodata 0] --clusters
clusters_raster --values statistics_raster --output output_text_file
```

Description

The following options are available:

`-h,--help` :
: Shows the usage note.

`-n,--nodata` :
: Indicates which values in the clusters raster file should be considered as no data.

`-c clusters_raster,--clusters clusters_raster` :
: The raster file containing the clusters. It should contain the IDs of each cluster. The raster file should contain integer values. Only the first band of the file is considered.

`-v statistics_raster,--values statistics_raster` :
: The raster for which we should compute the cluster statistics. Only the first band of the raster is considered. Both clusters and values raster file must have the same dimensions.

`-o output_text_file,--output output_text_file` :
: The path to the output text file which will contain the cluter statistics.

r.comparison.plot

Purpose

Creates a text file with two columns, the first containing the values of raster 1, and the second the values of raster 2. Only values different from NULL are considered. This file can be used for creating a comparison plot between two different raster files.

Synopsis

```
r.comparison.plot [--help] --raster1 raster1
--raster2 raster2 [--band1 band1] [--band2 band2]
[--null1 nullValue1] [--null2 nullValue2]
[--output output_text_path]
```

Description

The following options are available:

`-h,--help` :
: Shows the usage note.

`--raster1 raster1` :
: The path to the raster 1 file used for the comparison plot.

`--raster2 raster2` :
: The path to the raster 2 file used for the comparison plot.

`--band1 band1` :
: The band of raster 1 to use. Default value is 1.

`--band2 band2` :
: The band of raster 2 to use. Default value is 1.

`--null1 nullValue1` :
The NULL value for the raster 1. If both rasters have a NULL value at a given location, the values are not printed out. Default value is -DBL_MAX.

`--null2 nullValue2` :
The NULL value for the raster 2. If both rasters have a NULL value at a given location, the values are not printed out. Default value is -DBL_MAX.

`-o output_text_path,--output output_text_path` :
The path to the output text file. If you don't provide an output file, the result is written to the standard output.

r.downscale

Purpose

Takes aggregated values and distributes them according to a provided spatial probability distribution inside the spatial units according to which the values have been aggregated. This is useful for downsampling data from an administrative level to a larger scale pixel level.

Synopsis

```
r.downscale [-h] [-f format] [-p prior_raster]
[-v validity_domain_raster] aggregated_stats.txt
aggregate_raster probability_raster output_raster
```

Description

All raster files must cover the same region and have the same resolution. The following options are available:

`-h` :
Shows the usage note.

`-p prior_raster` :
Raster which contains the prior distribution. This must be an integer raster dataset.

`-v validity_domain_raster` :
Raster which contains 0 and 1 values. Regions of value 0 are excluded from the downscaling process.

`-f format` :
Format for the output raster file. Default is HFA. The following formats are supported: GTiff (GeoTIFF), HFA (Erdas Imagine (.img)), AAIGrid (Arc/Info ASCII Grid), PNG (Portable Network Graphics), JPEG (JPEG image), GIF (Graphics Interchange Format), PCIDSK (PCIDSK Database File), PCRaster (PCRaster Raster File), GMT (GMT NetCDF Grid Format), JPEG2000 (JPEG-2000), RST (Idrisi Raster A.1), ENVI (ENVI .hdr Labelled).

`aggregated_stats.txt` :
Text file containing the aggregated statistics. It is a tab-separated file with 2 columns. The first column contains the feature id, the second the aggregated statistical value (a sum, which must be an integer). The first line should contain a header, it is ignored.

`aggregate_raster` :
A raster file containing the spatial locations of the features. It is simply a raster containing the feature id's per pixel. Feature id's must be integer values.

`probability_raster` :
Raster which indicates the spatial probability distribution. This raster may contain double values.

`output_raster` :
The output raster containing the downscaled statistics. It is an integer raster dataset.

r.fdim.boxcount

Purpose

Estimates the fractal dimension using the boxcounting method.

Synopsis

```
r.fdim.boxcount [--help] [--band raster_band] [--minbox 1]
[--maxbox 20] [--vdom raster] [--plot output_plot]
--raster input_raster
```

Description

Computes the fractal dimension for a given raster file. The following options are available:

`-h,--help` :
Shows this information and quits.

`-b raster_band,--band raster_band` :
: The raster band number for which we should estimate the fractal dimension. Default is 1.

`--minbox integer_value` :
: The minimum number of boxes to use for the box counting. Default is 1.

`--maxbox integer_value` :
: The maximum number of boxes (in 1 dimension) to use for the box counting. Default is 20.

`-v validity_domain_raster,--vdom validity_domain_raster` :
: A raster file where 0 values are outside the allowed region. If present, a corrected fractal dimension is also computed.

`-p output_plot,--plot output_plot` :
: Path to an output SVG file containing the fractal dimension output plot.

`-r input_raster,--raster input_raster` :
: Raster for which we should estimate the fractal dimension. Values of 0 are considered as no occurence values, all others as occurences.

r.groupcells

Purpose

Groups several cells of a raster together; this is a special case of resampling, or a sort of spatial group by.

Synopsis

```
r.groupcells -r value [-f format] [-s statistic] input_raster
output_raster
```

Description

The following options are available:

`-r value` :
: The number of cells to group into one cell.

`-s statistic` :
: Statistic to use for grouping the cells together. Following options are available: sum, min, max, mean. Default is mean.

`-f format` :
Format for the output raster file. Default is GTiff.

r.lacunarity

Purpose

Computes the lacunarity for a raster.

Synopsis

```
r.lacunarity [--help] [--spatial] [--3d] --input input_raster
[--band input_band] [--binary] [--binaryThreshold 1] [--mwin 5]
[--gbox 3] [--gboxMin 3] [--gboxMax 30] [--gboxStep 1]
[--output output_raster_path] [--format format]
```

Description

The following options are available:

`-h,--help` :
Shows this usage note.

`-s,--spatial` :
Produces a spatial image of lacunarity using a moving window technique. If this flag is selected, an output image raster (–output) must be provided. This flag is not compatible with the gboxMin, gboxMax and gboxStep options. You may want to provide the moving window size using teh mwin option, and an output raster format using the format option.

`--3d` :
For non binary images, considers the gliding box in three dimensions. This flag is therefore not compatible with the binary flag. Preference will be given to the binary flag. If selected, the image is considered as being 3D instead of the layered analysis approach.

`-i input_raster,--input input_raster` :
The raster for which we should compute the lacunarity.

`-b band,--band band` :
The raster band for which we should compute the lacunarity. Default is 1.

`--binary` :
The input raster should be treated as a binary image instead of grayscale.

`--binaryThreshold` :
: The pixel value used as a threshold for binary images. Pixels smaller than this value are converted to 0, pixels greater or equal than the the threshold are converted to 1. This option is ignored if the binary flag is not set. Default value is 1.

`-m moving_window_size,--mwin moving_window_size` :
: The size of the moving window. If you specify a value for this, you must also choose the spatial flag, otherwise this value will be ignored. The default value for this option is 5.

`-g gliding_box_size,--gbox gliding_box_size` :
: The size of the gliding box used for estimate the lacunarity.

`--gboxMin gliding_box_minimum_size` :
: The minimum gliding box size if you want to compute the lacunarity for more than one gliding box size. This option is not compatible with the gbox option and with the spatial option as it is not possible to compute the spatial lacunarity for several gliding boxes.

`--gboxMax gliding_box_maximum_size` :
: The maximum gliding box size if you want to compute the lacunarity for more than one gliding box size. This option is not compatible with the gbox option and with the spatial option.

`--gboxStep gliding_box_step_size` :
: If you give a value for the gboxMin and gboxMax options, you can specify a step size for the gliding box size. Default is 1.

`-o output_raster_path,--output output_raster_path` :
: The path to the output raster file. You need to select the spatial flag in order to make something useful.

`-f format` :
: Format for the output raster file. Default is HFA.

r.percolation

Purpose

Computes the spatial clusters in a raster map based on percolation.

Synopsis

```
r.percolation [-x] [-s stat] [-b value] [-m value] [-f format]
input_raster output_raster [output_statistics]
```

Description

The following options are available:

`-x` :
Use extended neighborhood (next nearest neighbors instead of nearest neighbors)

`-s stat` :
Use the statistical value in the output raster rather than the cluster number. The following options are available: id (default), mean, sum, min, max. Note that id is a 32 bits integer, while the other statistics are double float (64 bits). Not all output formats may support these data types.

`-b band` :
The raster band to be considered. First band has number 1. Default is 1.

`-m value` :
Bias value. This is the minimum raster value which is considered as being part of a cluster. Default is 0.

`-c value` :
Cluster value. This is the minimum value (sum) for a cluster for being retained. Default is 0.

`-f format` :
Format for the output raster file. Default is HFA as it supports all needed data types.

`input_raster` :
Input raster file.

`output_raster` :
Output raster file.

`output_statistics` :
Statistics for the clusters are computed and stored in a text file.

r.potential

Purpose

Computes a potential surface based on an input raster and a spatial variogram.

Synopsis

```
r.potential [-m model] [-r range] [-s sill] [-n nugget]
[-p power] [-f format] [-b band] input_raster output_raster
```

Description

The following options are available:

`-m model` :
: The model type to use for the variogram. Possible options are: exp (exponential), spher (spherical), gauss (gaussian), power.

`-r range` :
: The range is measured in number of pixels (a range of 5 means 5 pixels, with a resolution of 100 meters per pixel, this is 500 meters.

`-s sill` :
: The sill should be 1 for the computation of the potential. (The potential is 1 - y, where y is the variogram value).

`-n nugget` :
: You may want to include some noise. E.g. if you have a nugget of 0.2, the potential at distance 0 is weightet with 0.8 instead of 1.

`-p power` :
: For power model only, where is replaces the nugget. Default is 2.

`-f format` :
: Format for the output raster file. Default is HFA as it supports all needed data types.

`-b band` :
: The band to be considered for the potential estimation. Default is 1.

`input_raster` :
: The input raster file.

`output_raster` :
: The output raster is a 64-bits floating point raster.

r.to.geoeas

Purpose

Writes a raster file into a GeoEAS text file.

Synopsis

`r.to.geoeas [-h] [-n value] input_raster output_eas`

Description

Converts the input raster file into a GeoEAS text file. The following options are available:

`-h` :
  Shows this information and quits.

`-b 1` :
  The band to convert. Default is 1.

`-n 0` :
  No data value which is not written to the output file.

`input_raster` :
  Raster file to convert.

`output_eas` :
  The output GeoEAS file.