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Comparison of Eastern and Western Europe spatial development of cities based on Remote Sensing data

Master thesis
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„...if you have seen one, you have seen them all...”
Tsenkova (2003)

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Abstract

Comparison of Eastern and Western Europe spatial development of cities based on Remote Sensing data

Urbanization is one of the most dynamic processes in the context of global change. In this study the challenge is to find similarities and differences in spatial urban growth and its settlement patterns of cities located in Eastern and Western parts of Europe. The hypothesis of the research study is that the spatial dynamics and its respective settlement patterns show significant differences in cities having undergone the transformation process from a socialistic to a capitalistic phase in comparison to purely capitalistic ones. For this study nine different cities are chosen (four cities for each zone, West and East, plus one city including both parts according to the special historical situation – Berlin).

Landsat satellite imagery enables a spatiotemporal analysis in four time steps for the years 1975, 1990, 2000 and 2010 with the corresponding time interval of about 10 years. Urban footprints as a crucial part of research are derived by object oriented classification techniques. Based on the classified urban patterns the dimensions of spatial growth are analyzed and compared in order to derive long-term trends and characteristics of cities under consideration. Beyond this, landscape metrics (e.g. Patch size) are applied for a quantitative analysis of the complex and various settlement patterns. Provided outcomes will be decisive while answering the following question: Is there any significant difference in the development of spatial patterns between Western and Eastern European cities? The study shows the diverse patterns of spatial urban development in Eastern and Western parts of Europe, as well as different magnitude of spatial growth of cities, especially due to the influence of socialistic and capitalistic systems.

Keywords: Remote Sensing, Urban Sprawl, Landscape Metrics, Urbanization, Change Detection, Western Europe, Eastern Europe, Capitalism, Socialism, Urban settlement patterns

Streszczenie

Porównanie rozwoju przestrzennego miast wschodniej i zachodniej Europy na podstawie zobrazowań satelitarnych.

Urbanizacja jest jednym z najbardziej dynamicznych procesów w kontekście zmian globalnych. Tematem niniejszej pracy jest porównanie różnic i podobieństw w przestrzennym rozwoju oraz sposobie rozlokowania terenów zurbanizowanych, w miastach zlokalizowanych we Wschodniej i Zachodniej części Europy. Głównym problemem badawczym poniższej pracy jest dynamika rozwoju przestrzennego, oraz jego układ wskazujący na znaczące różnice zachodzące w miastach, które przeszły procesy transformacji z systemu socjalistycznego do systemu kapitalistycznego, w porównaniu do miast czysto kapitalistycznych. Na potrzeby pracy wybrano dziewięć miast (cztery reprezentujące Wschód oraz cztery reprezentujące Zachód Europy). Dodatkowo wybrano jedno miasto (Berlin), jako jednostkę znajdującą się pomiędzy dwoma wybranymi grupami miast oraz sytuację historyczną.

Zobrazowania satelitarne programu Landsat pozwalają na czasowo-przestrzenne porównanie miast pod względem wybranych cech. Powyższa analiza została wykonana dla czterech punktów w czasie, reprezentowanych kolejno przez lata: 1975, 1990, 2000, 2010, z przedziałem czasowym około dziesięciu lat. Zurbanizowana klasa terenu jako kluczowa część pracy badawczej została wyodrębniona ze zdjęć satelitarnych za pomocą technik klasyfikacji obiektowej. Bazując na wyodrębnionych ze zdjęć satelitarnych klasach reprezentujących tereny zurbanizowane oraz ich wzorze, oszacowanyi porównany został wymiar rozwoju przestrzennego miast w celu wykazania trendów i cech charakterystyczneych wybranych miast w czasie. Dodatkowo zastosowano indeksy będące ilościowymi miarami rozmieszczenia elementów krajobrazu (*landscape metrics*) na przykład wielkość płatów (*Patch size*) w celu ilościowej analizy kompleksowego i zróżnicowanego układu terenów zurbanizowanych. Uzyskane wyniki będą decydujące podczas odpowiedzi na następujące pytanie: Czy istnieją jakiekolwiek różnice w rozwoju przestrzennym terenów zurbanizowanych oraz ich układzie pomiędzy miastami Zachodniej i Wschodniej Europy? Niniejsza praca wykazała różnorodny układ wzorów rozwoju przestrzennego miast Wschodniej i Zachodniej Europy, jak również odmienną wielkość zachodzących zmian w miastach. Różnice te związane są przede wszystkim z wpływem systemu socjalistycznego i kapitalistycznego na miasta ujęte w analizie.

Słowa klucze: Teledetekcja, Fotogrametria, Eksurbanizacja, Ilościowe miary rozmieszczenia elementów krajobrazu, Urbanizacja, Zmiany w czasie, Wschodnia Europa, Zachodnia Europa, Kapitalizm, Socjalizm, Układ terenów zurbanizowanych

Zusammenfassung

Vergleich der räumlichen Entwicklung ost- und westeuropäischer Städte basierend auf Erdbeobachtungsdaten

Im Kontext des Globalen Wandels stellt die Urbanisierung einen der dynamischsten Prozesse dar. Die Herausforderung dieser Arbeit besteht darin, Ähnlichkeiten und Unterschiede in Bezug auf Stadtwachstum und Siedlungsmuster ost- und westeuropäischer Städte aufzudecken. Dabei wird folgende Hypothese aufgestellt: Im Hinblick auf die räumliche Dynamik sowie die entsprechenden Siedlungsmuster weisen Städte, die den Transformationsprozess von einer sozialistischen zu einer kapitalistischen Phase vollzogen haben einen signifikanten Unterschied im Vergleich zu ausschließlich kapitalistisch geprägten Städten auf. Für diese Studie werden neun verschiedene Städte ausgewählt (je vier Städte für Ost- und Westeuropa und zusätzlich Berlin als eine Stadt, die aufgrund ihrer geschichtlichen Entwicklung beide Phasen beinhaltet).

Mit Hilfe von Landsat-Satellitenbildern ist es möglich, raum-zeitliche Analysen für vier Zeitschritte – 1975, 1990, 2000 und 2010 – mit entsprechenden Zeitintervallen von etwa 10 Jahren zu erzeugen. Den entscheidenden Teil dieser Forschungsarbeit bilden Urbane Fußabdrücke welche mit Hilfe objektorientierter Klassifikationsverfahren generiert werden. Auf Grundlage dieser klassifizierten urbanen Muster wird zum einen die Dimension des räumlichen Wachstums im Hinblick auf Langzeit-Trends analysiert, zum anderen stehen die individuellen Charakteristika der Städte im Fokus der Arbeit. Darüber hinaus werden zum Zweck einer quantitativen Analyse der komplexen und unterschiedlichen Siedlungsmuster sogenannte Landschaftsstrukturmaße angewandt. Mit Hilfe dieser kann folgende Frage beantwortet werden: Besteht ein signifikanter Unterschied in Bezug auf die räumliche Entwicklung von Siedlungsmustern ost- und westeuropäischer Städte? Die Arbeit zeigt Unterschiede bezüglich der räumlichen Siedlungsmuster in ost- und westeuropäischen Regionen auf. Ebenso werden unterschiedliche Größenordnungen des räumlichen Stadtwachstums deutlich, welche insbesondere durch die Einflüsse des sozialistischen und kapitalistischen Systems begründet werden können.

Schlagwörter: Fernerkundung, Urban Sprawl, Landschaftsstrukturmaße, Urbanisierung, Veränderungsanalysen, Westeuropa, Osteuropa, Europa, Kapitalismus, Sozialismus, Urbane Siedlungsmuster

Table of contents

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

AOI – Area of interest
CBD – Central Business District
CEE – Central and Eastern European Cities
COMECON - Council for Mutual Economic Assistance
DFD – German Remote Sensing Data Center
DLR – German Aerospace Center
DSM – Digital Surface Model
DTM – Digital Terrain Model
ESRI – Environmental Systems Research Institute
ETM+ - Enhanced Thematic Mapper
EU – European Union
GDP – Gross Domestic Product
GeoTIFF – Georeferenced Tagged Image File Format
GIS – Geographic Information System
GLOVIS – Global Visualization Viewer
GUI – Graphical User Interface
HR – High Resolution
JRC – Joint Research Center
LiDAR – Light Detection and Ranging
LDCM – Landsat Data Continuity Mission
LPI – Largest Patch Index
MR – Medium Resolution
MSS – Multispectral Scanner
NASA – National Aeronautics and Space Administration
NATO – North Atlantic Treaty Organization
NDVI – Normalized Difference Vegetation Index
OLI – Operational Land Imager
PAN –Panchromatic
PCA –Principal Components Analysis
RS – Remote Sensing
SAR – Synthetic Aperture Radar
SASMA - Spatially Adaptive Spectral Mixture Analysis
SAVI – Soil Adjusted Vegetation Index
SHP - Shapefile
SWIR – Short Wave Infra-Red
TCT – Tassel Cap Transformation
TIRS – Thermal Infrared Sensor
TM – Thematic Mapper
UF – Urban Footprint
USGS – United States Geological Survey
VHR – Very High Resolution

1. INTRODUCTION

Urbanization is one of the most significant driving forces when we are talking about change of land-use over time. The importance of this process is underlined in the United Nations publications (UN 2007, 2012) where estimations and projections of the total urban and rural World's population are given from the past (since the 1950s), throughout the nowadays and for the future (until 2050). Currently the world population equals 7 billion people, and is expected to rise within the next 40 years, reaching capacity of 9.3 billion in 2050 (UN, 2012) (see Fig. 1-1). Moreover this trend is not local, it is global. The World's urban population is changing from 3.6 billion in 2011 to 6.3 billion in 2050. Parallel the world rural population is constantly decreasing and expected to be 0.3 billion people less than nowadays (see Table 1-1).

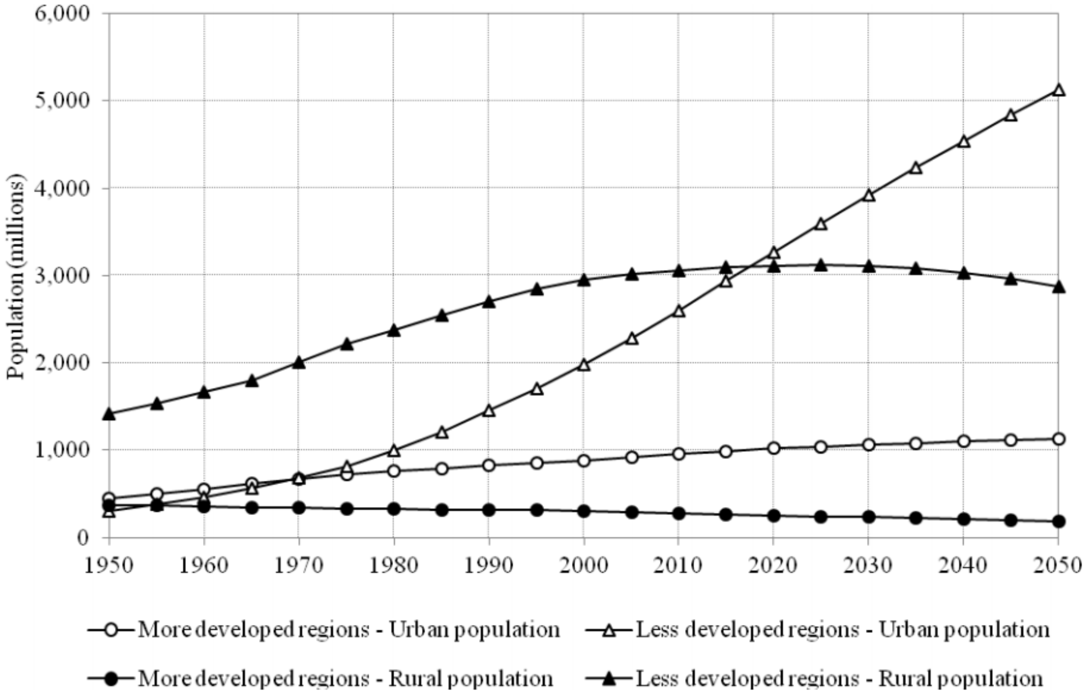

Fig. 1-1 Urban and rural populations by development group 1950 – 2050 (source: UN 2011)

	Population (billion)					*Average annual rate of change (percentage)*			
Development group	*1950*	*1970*	*2011*	*2030*	*2050*	*1950-1970*	*1970-2011*	*2011-2030*	*2030-2050*
Total population									
World	2.53	3.70	6.97	8.32	9.31	1.89	1.55	0.93	0.56
More developed regions	0.81	1.01	1.24	1.30	1.31	1.08	0.51	0.23	0.06
Less developed regions	1.72	2.69	5.73	7.03	7.99	2.23	1.85	1.07	0.65
Urban population									
World	0.75	1.35	3.63	4.98	6.25	2.98	2.41	1.66	1.13
More developed regions	0.44	0.67	0.96	1.06	1.13	2.09	0.89	0.52	0.29
Less developed regions	0.30	0.68	2.67	3.92	5.12	4.04	3.33	2.02	1.34
Rural population									
World	1.79	2.34	3.34	3.34	3.05	1.36	0.87	-0.01	-0.44
More developed regions	0.37	0.34	0.28	0.23	0.18	-0.48	-0.48	-0.92	-1.14
Less developed regions	1.42	2.01	3.07	3.11	2.87	1.74	1.03	0.07	-0.40

Tab. 1-1 Total urban and rural populations by development group, selected periods, 1950-2050 (source: UN, 2012)

Browsing given numbers we see that for the first time in human history the amount of urban residents has outreached the population living in rural areas. Additionally the number of megacities (cities with a number of inhabitants greater than 10 millions) is steadily growing. In 1975 we could point out 3 of them (New York, Tokyo, Mexico City). Today the amount of them already grown to 23 urban agglomerations and its expansion is foreseen to 37 in 2025 (UN, 2011).

These changes pushed forward many researchers to find comprehensive and efficient ways of defining, mapping, and finally measuring urban growth based on Earth observation data (e.g. Angel et al., 2007; EEA, 2006; Esch et al., 2012; Galster et al., 2001; Ji, 2008; Sudihra et al., 2003, Taubenböck et al., 2010; Yeh and Li, 2001). Growing availability of Earth observation data with higher spatial and temporal resolution, remote sensing techniques proofed as sufficient and comprehensive tools to capture, describe and quantify urbanization processes seen as spatiotemporal dynamics of urban growth (urban understood as impervious surfaces) taking place all over the World. Its' usefulness has been underlined in a wide range of studies on various scales – from global to regional and local level (Donney et al., 2001; Esch et al., 2010; Esch, et al., 2012; Taubenböck et al, 2012; Taubenböck and Kraff, 2013). The physical structure of vast, heterogeneous and continuously growing urban agglomerations has been shown in these studies.

In the following study the spatial focus is on the European continent which is one specific example among many affected by vast urbanization processes (EEA, 2006, Siedentop and Fina, 2012). The most interesting fact is that changes mentioned above have been arising with different magnitudes in both East and West European countries. Moreover they have been driven by different and various factors in time (Kovács, 1999, Ruoppila, 2004 Tsenkova, 2003, 2012).

By means of multi-temporal analysis of Landsat (MSS, TM, ETM+) satellite data, the goal is to map nine different European cities and their spatial growth over time.

The spatial growth is analyzed by measuring urban pattern by means of defined landscape metrics. The goal is to extract and present in quantitative manner similarities and differences in spatial development of selected West and East European cities. Additionally the higher-ranking goal is to underline the most important factors which could have been crucial with respect to urbanization processes taking place in Europe before the collapse of “Iron Curtain” and the following years.

1.1 Urbanization in Europe

Europe is the second smallest world continent (10,5 mld km^2) but on the other hand the most variable concerning countries. Europe's total population is estimated to 711 M inhabitants (UN, 2011). The spatial distribution of the population with respect to East and West in Europe equals 294,771 thousands in East and 189,052 thousands in West Europe (data for 2010 year, UN, 2011)). In addition approximately 75% of total Europe's population lives in urban areas (EEA, 2006).

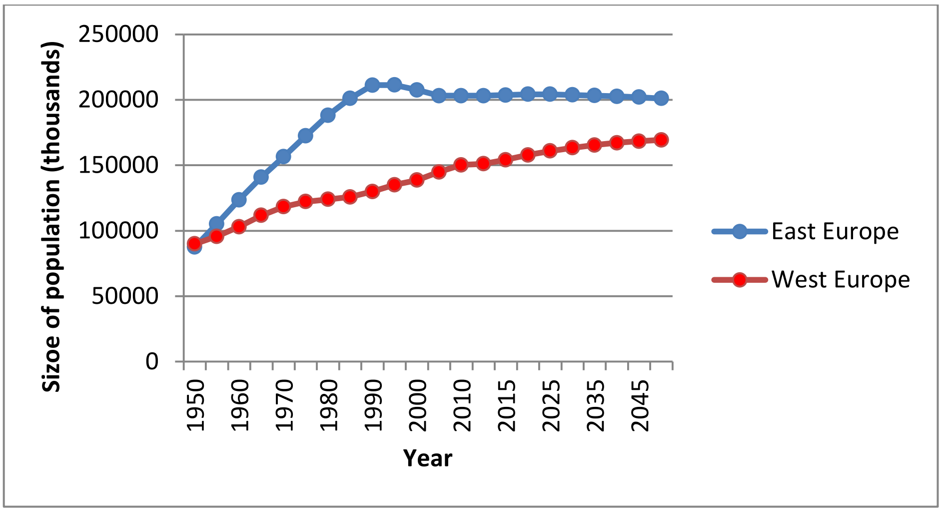

Fig. 1-2 Development of East and West European urban population (1950-2050), (UN 2011)

It is estimated that this trend will continue and by 2020 almost 80 % of the EU population will be living in urban areas (EEA, 2006); in several countries the proportion will be 90% or more. Ongoing changes have great and irreversible impact not only to people's life quality in big cities but also to land use. Nowadays around one fourth of Europe is affected by uptake of urban land. Though, it stands among the most urbanized regions on the globe. Another fact, however from the past is that the European cities were growing faster (in average 78%) than growing population (33%) so that undoubtedly the development of European towns was attended by urban sprawl. Since early 1950s we have seen densification processes ongoing in Europe but not equally distributed all over the continent. In general European cities become less compact (EEA, 2006).

Current development practices shows replacement of dense city structure by free standing buildings, hence the total area of one inhabitant was at least doubled. It has been found that within the last 20 years low density suburban development became a standard in Europe, hence European cities have been expanding more significantly than ever (EEA, 2006). On the other hand we should not forget about socio-economic driving forces which were fastened by one, common politics served by European Union's institutions as well as local governments – structural funds. Money transfer from common European budget to member states triggered sprawl of European cities, increased economic growth and cities rivalry (EEA, 2006). Following this trends necessary routes to link cities were developed. That pushed people forward to travelling. Thereby they could work in city. However attractive locations outside dense, urbanized areas become more accessible. Since that moment advantages of both living outside city as well as taking all advantages of being there have become in peoples sight (EEA, 2006).

According to UN HABITAT State of the World's Cities (2010/2011) two tipping points have to be underlined in connection with population development in Europe. We see that population became more urban than rural earlier in Western than Eastern Europe. Therefore as plotted below (Table 1-2) the amount of urban inhabitants in the Western part of Europe is greater and equals 77% in 2010, where in case of east Europe its 68.8%. Despite of relevant differences these numbers are expected to equalize within next 30 years.

Region	Tipping point before 2010 (year)	2010 urban (%)	Tipping point after 2010 (year)	2050 urban (%)
World		50.6		70
MORE DEVELOPED REGIONS	before 1950	75		86
Europe	before 1950	72.6		83.8
Eastern Europe	1963	68.8		80
Northern Europe	before 1950	84.4		90.7
Southern Europe	1960	67.5		81.2
Western Europe	before 1950	77		86.5

Tab. 1-2 Level of urbanization per region and tipping points urban vs. rural. Source: UN HABITAT, State of the World's Cities 2010/2011: Bridging the Urban Divide

Summing up Europe shows different dynamics concerning growth of urbanized areas especially comparing its Eastern and Western parts.

1.2 Former studies

Former studies related to ongoing World urbanization processes are either focused on one city (Aguirre, 2008; Diermayer et al., 2008, Heldens et al., 2008; Herold et al., 2003), few agglomerations located in one cultural area (EEA, 2006; Kasanko et al., 2006; Seto et al., 2005; Siedentop and Fina, 2012; Taubenböck et al., 2008a), or cities gathered at a higher hierarchical level, so called megacities (Taubenböck et al., 2010b). Authors of given studies underline the fact, that the framework of GIS and Remote Sensing especially with higher spatial resolutions is decisive for understanding spatial urbanization processes and their influence to land cover change. Nevertheless they complain about the lack of homogenous data and insufficient amount of investigations (only few studies on European level are based on GIS/RS approach).

Siedentop and Fina (2012) investigated 26 European cities across European countries and used 20 km cells as spatial level using geodata from the CORINE land cover dataset. They found substantial differences across countries and regions in terms of intensity of urbanization and the spatial pattern of land consumption. According to the topic raised within the scope of this study Siedentop and Fina admitted that in the majority of Eastern European countries the legacy of socialistic housing policies is still visible in the form of above-average urban densities and a concentration of urban functions. In addition they found that urban sprawl was taking place around a few concentrated islands and it is correlated with studies reporting huge regional disparities in income level and economic growth. On the other hand Western European countries have been described as those where suburbanization and counter urbanization processes resulted in more decentralized and land-consuming pattern of urban growth (Siedentop and Fina, 2012).

Another contribution around urban sprawl in Europe is the project MOLAND developing an urban model by the JRC (Joint Research Center), where the sprawl phenomenon was assessed from the 1950s to the year 2000 for 28 European countries. The main conclusion of that project is that growth of built-up area in Europe reached its peak in 1950s – 1960s.

However, the EEA (2006) study shows that within the period between 1990-2000 growth of urban areas was equal to 8 000 km^2. Although, urban sprawl has been linked only with places where urban growth was high already in 1970s and 1980s. It was also found urban footprint have been expanding more towards countryside.

Nevertheless with the focus on East European cities, transformation from state-socialistic to capitalistic ones is one of the key factors for urban change. How it happened, what the driving forces of changes were, which cities have been affected by transformation, how changes can be shown, what are the results of changes? Answers for these questions are a part of following scientific contributions (Bertaud, 2005; Bertaud and Renaud, 1995; Kovács, 1999; Ruoppila, 2004; Smith, 1996; Tsenkova, 2003, 2012; Turnock, 1998; Węcławowicz, 1979).

To strengthen understanding of changes that were triggered in the past, it is obligatory to give a comprehensive description of the pre-socialistic period and definition of “Socialistic” city from spatial point of view. Until early 90s countries such as: Latvia, Lithuania, Belarus, Ukraine, Romania, Hungary, former Czech-Slovakia, Poland and partially Germany have been under the influence of former Soviet Union and its socialistic political system. This “central” state level is characterized by: system of one political party, large stately owned companies that guarantee jobs as well as cheap housing market. The state sector is oriented towards gathering employees in trade unions and homogenous labor markets. Additionally the housing market policy is completely based on and controlled by the state. This has great influence to nonpublic housing sectors. In addition housing market is inefficient and based on high level subsidies provided by government. According to Ruoppila (2004) the state’s role in socialistic countries is also underlined in production (supplies of building materials produced only by state industry), ownership and the allocation of housing as well as land development, make practically all income groups dependent on publicly subsidized housing. Private housing market is reduced only to founding single family houses in rural areas (Kovács, 1999). In addition, it was believed that single-family housing was not under special policy focus in socialism (Ruoppila, 2004), although in general it depends on particular city policy. It results due to lack of real estate market. The consequence is that communistic cities are characterized by distinctive compact form of built-up areas with large, relatively homogeneous functionality (Kovács, 1999). Moreover Bertaud and Renaud (1995) reveal that the periphery of socialistic city is highly dense comparing to its center and mainly occupied by lower social classes – workers living in residential area. They can be found in districts on the edge of cities (Ruoppila, 2004), because their location is near to manufacturing sites. In addition Bertaud (2005) points out more features characterizing CEE (Central and Eastern European Cities) like: enormous amount of industrial land neighboring within the city center, lack of retail and service space in the city center, week means of transportation especially in compact city centers.

Summarizing, the decisive role of the central government unit is clearly visible as well as its huge influence to socio-economic life aspects and urbanization processes. Land use in socialistic cities is mainly divided to industrial and residential use.

Such a system is affecting the economy, the market, housing and socio economic sphere which was indoctrinated in the post Second World War times into the Eastern parts of Europe by the Soviet Union. To underline the physical and ideological border dividing Europe into two parts after the end of II World War term “Iron Curtain” was introduced. It was used first time in 5th of March 1946, by Great Britain’s Prime Minister – Winston Churchill in the context of Soviet Union domination in East Europe, which lasted until 1991. However, Bertaud (2005) argues that CEE cities have been under influence of the socialistic system for the time period varying from 45 to 75 years. Nevertheless, in 1989 the former European “iron curtain” collapsed and ignited long-lasting, tremendous changes in post-socialistic, Eastern European agglomerations. We can distinguish two driving forces that lead to new order, namely transformation of political and economic system.

Economic transformation of Eastern European countries starts with the collapse of the former COMECON (Council for Mutual Economic Assistance). It leads to liquidation of many companies especially in branches of heavy industry, where they were seen as cure to catch-up the West. It has to be reminded that in the socialistic system companies are large and owned by the state. It resulted with huge unemployment rates (layoffs) in Eastern Europe and subsequent work emigrations.

Political transformation implies re-establishment of political sovereignty in the individual countries; this was triggered by dissolution of the Warsaw Pact. The one party political system switches to a multi-party one. Since that moment free parliamentary elections are possible. Another crucial point is come back to self-governance (shift of control from central – state, to local) at community level, decentralization, devolution of power and privatization. Tsenkova (2003) admits that local governments have become the principal institutions responsible for urban planning and management. Although in case of the Czech Republic, Hungary and Slovakia, the number of them was far exceeded so that it resulted in governance fragmentation as well as inefficient coordination of projects.

In this situation western companies tried to “fill the gap” by bringing foreign capital investment and modern technology (Turnok 1998) as cure for an inefficient system. Since that moment Eastern market has been opened for investments of foreign companies, therefore money flows to East European countries, but in various proportions. As Kovács (1999) underlined when the Berlin Wall collapsed, approximately 500 billion US$ has been pumped to cure the market. In that time Hungary is seen as the most potential region for investments, however only 20 billion US$ has been located there. Since the Eastern European market has been opened, companies have undergone restructuration – from big nationally owned to small and more flexible ones. Also this development brings demand for qualified, multi skilled, young employees and marginalization of old workers. Subsequently various salaries are paid – more attractive from West investors, thus society stratification is well visible. Justification for such process was found by Ruoppila (2004) in many topic related contributions: “Nonetheless, a number of case studies have confirmed that residential differentiation, i.e. the uneven spatial distribution of social groups according to socio-economic criteria, continued to exist in socialist cities”. Tsenkova (2003) supports statement that social differentiation is getting bigger, however, some researchers believes that inequalities in urbanization decreased under era of socialism (Smith, 1996; Węcławowicz, 1979).

Privatization of companies plays a decisive role in changing cities. Eastern Europe is flooded by new investors - “New corporate headquarters, business and commercial centers, hotels and tourist facilities have flooded the city centers all around Eastern Europe” Smith (1996), especially in the field of trade, tourist, financial markets, and thereby new facilities like CBD* (Central Business District) has to be developed. It has to be reminded that socialistic cities were lack of services like: banking, insurance and real estate brokers – Bertaud, (2005). Cities revitalization is more focused on building stock of the city centers used for office and retail functions (Kovács, 1999), thus demand for non-residential space in inner part of cities is bigger than ever.

He also emphasizes direct connection between the labor and housing market which is very strong, therefore actions on the one end has feedback to another and vice versa. After 1989 ownership of state housing was transformed from central to local government in Eastern Europe. Its management since that moment is in charge of local communes. Kovács (1999) claims that after long decades of constant urbanization and a limited growth of suburbs (rural urbanization) one of the most striking phenomena of post-socialistic cities is suburbanization.

At first, the above mentioned process (immense city centers growth and suburbanization processes) affected East Germany, when in post-socialistic countries it's kind of new phenomena. Nevertheless these changes in the majority of cases undergo in Eastern capital cities, where smaller one falls into recession. According to Tsenkova (2003), capital cities and large urban centers have been privileged in that respect attracting a large scale of investment in banking, retail and information-based technologies (for instance, in 1997 Prague's GDP per capita is 85% of the EU average, while in northern Bohemia and northern Moravia, its half of that value).

The main pattern of housing construction in socialist cities within 1960s – 1980s time period is given by Ruoppila (2004) and supported by citations (Ciechocinska, 1987: 15, Tallin arvudes, 1992; Kovács, 1994: 1083; Sỳkora, 1999: 80) and state as follows: "Housing construction increased in socialistic cities in the 1960s, reaching its peak in 1970s, and decreasing again in the 1980s following the economic recession".

The entire process of transformation form socialistic city to capitalistic one is given in comprehensive manner by Kovács, (1994). He underlined the most important driving forces (Fig. 1-3) shaping former socialistic cities and pointed out as the most important political and economic transformation. These factors resulted in the end of a central planning, thus shift to market regulation. Since that moment labor and housing market could undergo transformation. These changes led to completely new spatial form of former socialistic cities.

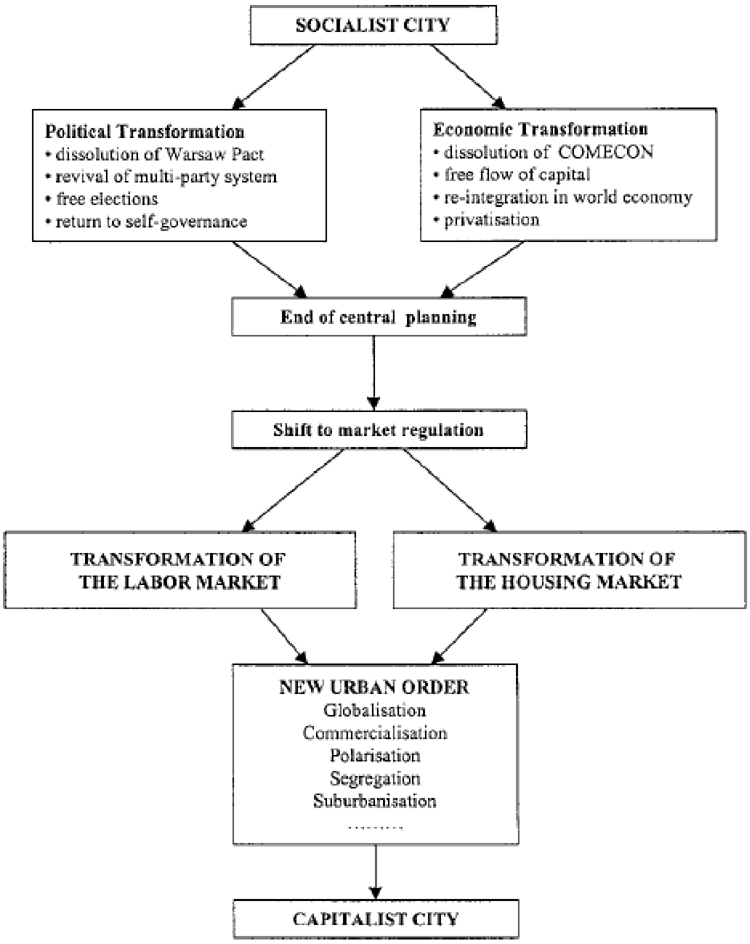

Fig. 1-3 Post-socialist urban transformation, Kovács, (1994)

Capitalism as a leading system was dominating in West European cities earlier than in East European cities. Especially industrial capitalism and it's arising in the late 18th century led to emergence of urban societies in Great Britain and North-West Europe (Peng et al., 2000). For instance, England by 1800 was 20% urban. Changes caused by industrialization pushed citizens to live in cities. Census data of England shows already 60% of citizens living in cities by the end of 1890 (Sanders, 2002). It has to be emphasized that there was no distinction between urban-rural populations before the industrial revolution. Hence industrialization is the main factor of shifting rural population to a more urban one. The direction of this process is well described by Peng et al., (2000) "And all countries, primarily in the West, that begun to industrialize rapidly after Great Britain became highly urbanized by the mid-twentieth century, which was followed by accelerated industrialization and the urbanization in the rest of the world through the last century and into the present". Since that moment people have started to think about land as a source of income. According to Sanders, (2002), it resulted in:

- assigning higher value to areas located closer to downtown, harbors or rivers as potentially associated with bigger economic activities
- emergence of industrial districts specialized in certain fields of production
- rise of a new upper social class

The most important driving forces of urbanization in capitalistic cities are: market competition, private property and high state of welfare. In contrast typical for socialistic countries are factors such as: central planning strategy, restricted settlement pattern and collective ownership of land and infrastructure (Van Kempen & Murie, 2009). The presence of the above mentioned driving factors in capitalistic cities indicate bigger housing freedom among citizens. In comparison, new settlements in East Europe depend on the central planning unit. Additionally new privately owned semi-detached houses are limited or held down by a centrally organized authority, which follows its own urbanization plan, reflecting the socialistic point of view. Another factor revealing distinct pattern of urban areas in West Europe is the presence of a real estate market. On the one hand it has influenced the spatial structure of capitalistic cities and provides free flow of money through the market, where on the other hand its lack in East European cities caused alterations in their development.
As written in chapter 1.2, the subsidized housing system and demand for workers pushed construction of housing estates to the periphery of East European cities. However massive housing estates which remain as a legacy of socialism have not been founded only there. Cities of Western Europe also used the same, prefabricated system to build subsidized houses in far suburbs. As Betraud (2005) writes "blocks of flats constitute as socialistic enclave in an otherwise capitalistic economy and represents only a minor fraction of totally founded buildings". The motivation behind was to mix population classes in the neighborhood (Van Kempen & Murie, 2009). In addition, Betraud (2005) admits that parameters like densities, site design and location of these massive blocks were not very different from their socialistic counterparts in the Central and Eastern European cities region. However, in Eastern Europe housing estates are persistent as dominating building form, reflecting the approach of a centralized, leading socialistic system. Another difference referring to Tsenkova (2003) is that in Western European cities less than 7% of the people live in housing estates and represent rather lower social classes, whereas in Eastern Europe this kind of settlement is mainly occupied by the lower and middle social class (Kovács, 2000). Notwithstanding these kinds of high density residential projects were founded in Western cities until the mid-60s, but no longer. In comparison this process lasted up to the early 90s in socialistic ones.
Having in mind factors underlined in the second paragraph, another distinctively differing pattern of development in Western countries is revealed as a tendency for growing residential densities. Generally it refers to more suburban development since dwellers prefer to found their own private houses. Such a tendency is well visible in capitalistic countries throughout

the last decades. Thus, the density of settlements is higher compared to the Eastern counterparts (Van Kempen and Murie, 2009).
Concerning industrial areas there is a trend of companies moving to the city peripheries because of lower land prices and well developed road infrastructure. However, Central Business Districts (CBDs) stay untouched as offices in the city center, with management and design role. Industrialized land in Western European cities usually was reconverted faster to other uses and therefore covers much less total built-up area. It has to be underlined that it was not matter of special urban planning restrictions but rather caused by rules of market (Betraud, 2005). Such actions were ignited by higher economic activity and led to mixed land use patterns. In contradiction to Western Europe, Eastern European cities are characterized by a slow rate of land use conversion. Mainly this was caused by missing market mechanisms. The value of real estate did not appear as assets in the accounts of industrial enterprises (Betraud, 2005). Betraud also underlines big disparities comparing the amount of built-up area against industrial land. Socialistic cities reveal land occupied by factories at least doubled and even more compared to residential built-up areas.
Overall evident disparities in spatial development exist between both data sets. Certainly, various factors could be pointed out concerning differences in urban pattern development. However the most crucial ones between capitalistic and socialistic systems are in the sphere of market and politics. Nevertheless, the process of industrialization in Great Britain should be treated as primary factor igniting transformations mentioned above.
To provide better insight into similarities and differences between both, socialistic and capitalistic systems a tabular comparison on various levels is given below (Table 1-3).

	Capitalism	**Socialism**
Politic	Multiple political parties	One political party
Economy	Marked oriented (competition) Land has value	Egalitarian system (equal income)
	Privately owned companies	Promotion of state industry
	Multiple companies	Large stately owned companies
Labor market	More diverse, due to market regulations	Homogenous, controlled by government
Society	Higher state of welfare with social classes mixed each other	Divide to upper class living in city center and lower class in city periphery
Housing market	-	Subsidized by government
	-	Land management dependent on centralized unit
	Private property	Private housing market reduced to minimum
	Presence of real estate market	Lack of real estate market
Spatial aspects of cities		Compact form of core city
	Growing importance of residential densities (dispersed urban periphery)	Dense city periphery
	Lower significance of housing estates (however they occur as legacy of socialistic system)	Housing estates as dominating building form
	Diverse functionality of cities	Homogenous functionality of city
	Mixture of various land-use classes	Land use in city center occupied mainly by industrial areas
	Well-developed infrastructure	Week means of transportation

Tab. 1-3 Comparable table of main similarities and differences between Capitalism and Socialism system

1.3 Urban Remote Sensing

In the last decades constant growth of urban areas can be noticed. Changes in spatial extent of cities have been followed by number of urban citizens, however not equally. As written in chapter number 1, world's urban population has already outreached rural population and will continue to grow in the future (UN, 2011). Urban areas are characterized as centers of policy, economy, society and culture, as well as highly dynamic and infrastructure complex units (Esch et al., 2010). In the past link between socio-econimoc conditions or economic activities could not be reflected on city's spatial level. Thus Remote Sensing and GIS provide framework and play extensive role of acquiring knowledge about urban areas and make cities comparable among each other. This possibility pushed scientists to firstly: differentiate between data that can be used for urban structure analysis; secondly to invent new techniques and methodologies for better city cognition thus work on definition of urban sprawl.

The most consistent feature when we are talking about cities is that they are constantly changing. Therefore urban sprawl as a definition is inconsistent and complex phenomenon to measure and define. Ewing (1994, 1997) defines sprawl as: (1) *discontinuous pattern of* development, (2) *development of residential areas with low* densities, (3) *commercial strip* development, (4) *segregation of land* use, (5) *low accessibility and high dependency on vehicles.* Spatial dimension of city and its growth rate depends on location and it is caused in particular by: historical and political issues, construction methods, organizational concepts of society (Taubenböck et al, 2010). Many contributions have been done towards to find the most suitable practical solution for sprawl measurement and its definition (Angel et al, 2007; EEA, 2006; Galster et al, 2001.; McGarigal et al., 2002; Frenkel et al., 2008). Leitao et al., (2002) pointed out core set of landscape metrics which can be applied to measure phenomenon of urban sprawl. Taubenböck et al., (2010) use gradient analysis to provide insight into spatial pattern development from the urban core to the periphery. Analyzing list of landscape metrics suitable for urban sprawl identification (McGarigal et al., 2002, Galster et al., 2007) we can realize about complexity and ambiguity of this phenomenon. Although only certain part of them can accurate describe ongoing changes based on spatial extension of the city.

Today's cities are not the same as those 40 years ago concerning their spatial extent. As explained in chapter 1 we can notice significant and immense growth of many agglomerations such as megacities. From simple structures they become transformed into spatially heterogeneous urban objects (various composition of urbanized patches) with own spatial characteristic, dimension and specific type of built up area (Taubenböck, 2010).

As Donnay (2001) underlined, aerial photography was found as extensively used solution employed as a first, remote technique in urban analysis. Nowadays orthophotos with high spatial resolution up to 15 cm are significant data for city analysis. Next step was implemented by American's known as Landsat satellite mission. Since early 1970s Landsat sensors such as: Multispectral System, Thematic Mapper, Enhanced Thematic Mapper +, Landsat Data Continuity Mission have been providing, continuous and consistent information of the Earth. Therefore it's a great chance for analysis of changes in Earth's landscape as well as in context of urbanization processes that lead to change cities.

Since early beginnings Remote Sensing proved its usefulness as efficient and reliable source of physical characteristics of urban areas. It provides information like changes in land cover, size, shape orientation or growth rates of built-up area (Donnay et. al. 2001, Taubenböck et al, 2010). Thanks to increasing spatial resolution of satellite sensors from medium (MR: Landsat) through high (HR: SPOT) to very high resolution images less than 1 meter (VHR: Quickbird, Worldview 2, Ikonos) and increasing temporal resolution cognition of constantly growing urban areas was much strengthened.

The next satellite generation starts with SAR sensors (TerraSAR-X, Tan-DEM-X, RADARSAT-2 or ALOS-PALSAR) capable to acquire data at day and night, regardless to weather and environmental conditions, so that more reliable than optical sensors which generally are affected by atmosphere. Reliability also comes with finer resolution and more constant behavior of urban features detected by SAR sensors (Esch, et al. 2012, Taubenböck and Roth, 2008).

However, LiDAR (Light Detection and Ranging) technology is also a very popular tool deriving buildings height through extracted elevations (Digital Surface Model, Digital Terrain Model), useful for urban applications like: building morphology extraction (Wurm et al., 2009), assessment potential of district heat (Geiß et al, 2011), 3D visualization and growth analysis (Wurm et al., 2013), assessment of buildings vulnerability to flood, earthquake calamities (Mück et al., 2012, Taubenböck et al., 2011).

City pattern has been defined as ‘urban footprint’ or ‘urban mask’. This definition is associated with anthropogenic features through which water cannot infiltrate into the soil and represented by roads, driveways, sidewalks, parking lots, rooftops (Weng, 2011) and called as impervious surface. Taubenböck et al., (2012) defines term ‘urban footprint’ as the land directly occupied by a particular physical man made structure – built up area. Another definition can be taken from the Office for National Statistics of the UK (2001) which compares urban footprint to density (buildings or populations) or to so call functional area. Nevertheless it has to be underlined that impervious surface products derived from remotely sensed data are reliable inputs for analysis. Their accuracy grows with the usage of data of higher spatial resolution or integration with external data sources like street geometries (Geiss et al., 2011).

Classification of impervious surfaces is a complex task especially in urban environments which are heterogeneous and composed by different materials, thus displayed in various spectral responses (Liang et al., 2013). In addition spectral and spatial characteristics vary within and among cities.

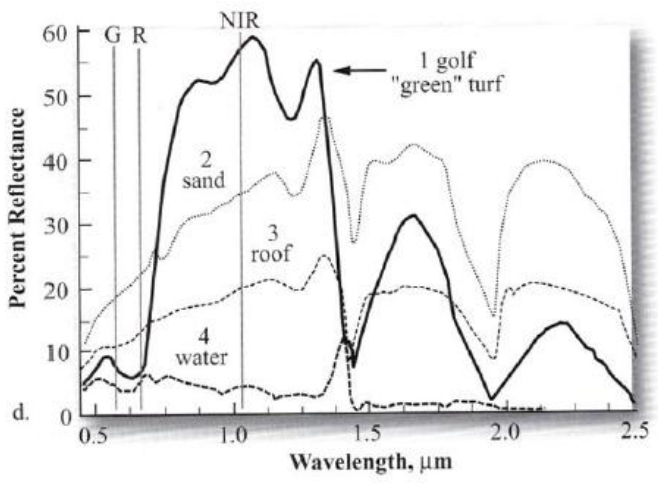

Fig. 1-5 Spectral signatures of land cover common classes. (source: Jensen, 2005)

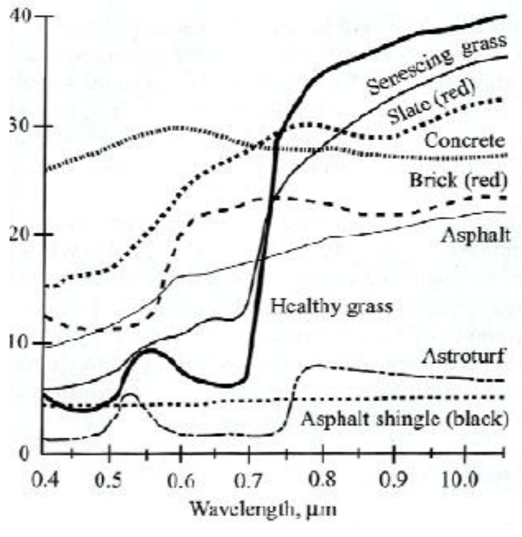

Fig. 1-4 Reflectance characteristics of common urban materials. (source: Jensen, 2007)

Another obstacle is coarse spatial resolution of Landsat ETM+, TM and MSS data, where several land-use land-cover types are contained in one pixel. Nevertheless many efforts have been undertaken to describe those complex land covers. Ridd (1995) illustrate urban land cover as a linear combination of three components: vegetation, impervious surface, and soil. The V-I-S model consist on urban and near urban features and tries to identify various land cover patterns that can be found in the city.

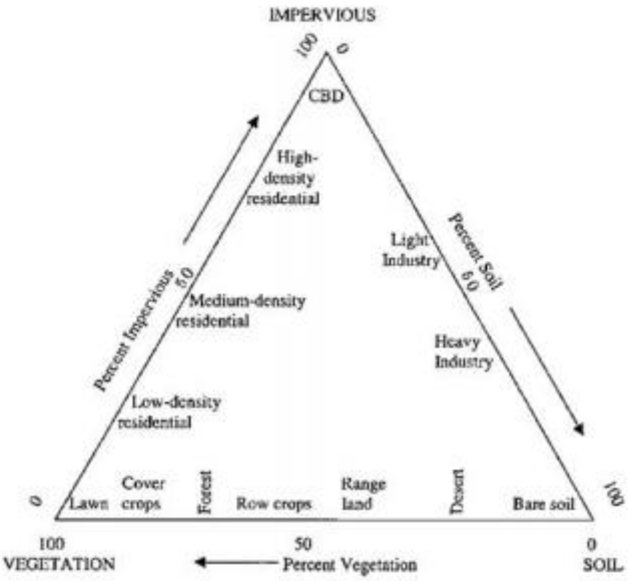

Fig. 1-6 The V-I-S (Vegetation-Impervious surface-Soil) model illustrating the characteristics of urban landscapes. (source: Ridd, 1995)

Until today many contributions have been done to derive the most accurate pattern or representation of urban footprint from both: optical and radar remotely sensed data (Esch, et al., 2012, Felbier et al., 2012, Taubenböck et al., 2012). Investigations based on TerraSAR-X and TanDEM-X missions resulted in fully automatic detection of Built-Up areas as well as ongoing extraction of GUF as world-wide catalogue of urban settlements (Esch, et al., 2012, Felbier et al., 2012, Marconcini et al., 2013). Example of classified urban areas is presented in figure 1-7.

Heldens et al., (2008) investigated potential of hyperspectral remote sensing to derive features characterizing urban structure.

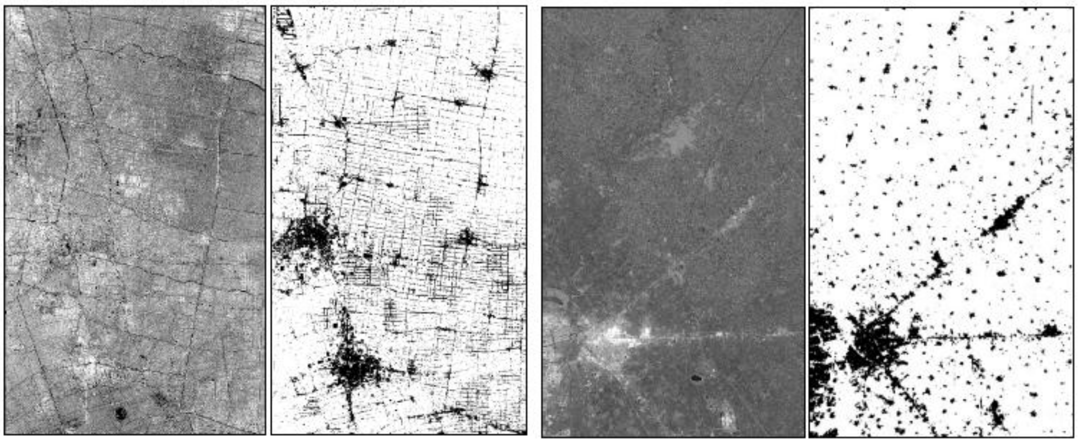

Fig. 1-7 Amplitude images (50 x 50 km) and derived urban footprint for regions Hai'an (China) and east Delhi (India). (source: Esch et al., 2012)

Concerning optical data sets, variety of approaches have been implemented to segment and classify remotely sensed data, thus obtain urban footprint. Marceau et al., (1990) tested texture indices. Deng and Wu (2013) tried to derive urban patterns via texture indices approach and they proposed SASMA (Spatially adaptive spectral mixture analysis) for estimating urban impervious surface distribution at sub-pixel level. Their efforts resulted in relatively high precision (root mean square error of 15.25% and R^2 0.701).

Although, for this study object oriented classification approach was found useful as easy applicable method for classification of medium resolution as well as very high resolution satellite data. In this study, hierarchically structured decision tree (Fig 3-3) was implemented via eCognition software (Definiens AG, 2013) and combined with GUI (graphical user interface) which helps the user to apply certain parameters and features manually. Advantages of GUI are described in following studies (Abelen, S., 2010, 2011).

Overall process comprises of firstly image segmentation and then, image classification as shown in figure 1-8. Segmentation deals with dividing entire satellite image into smaller segments (groups of pixels). Continuously, segmented image can be classified according to certain rules and criteria.

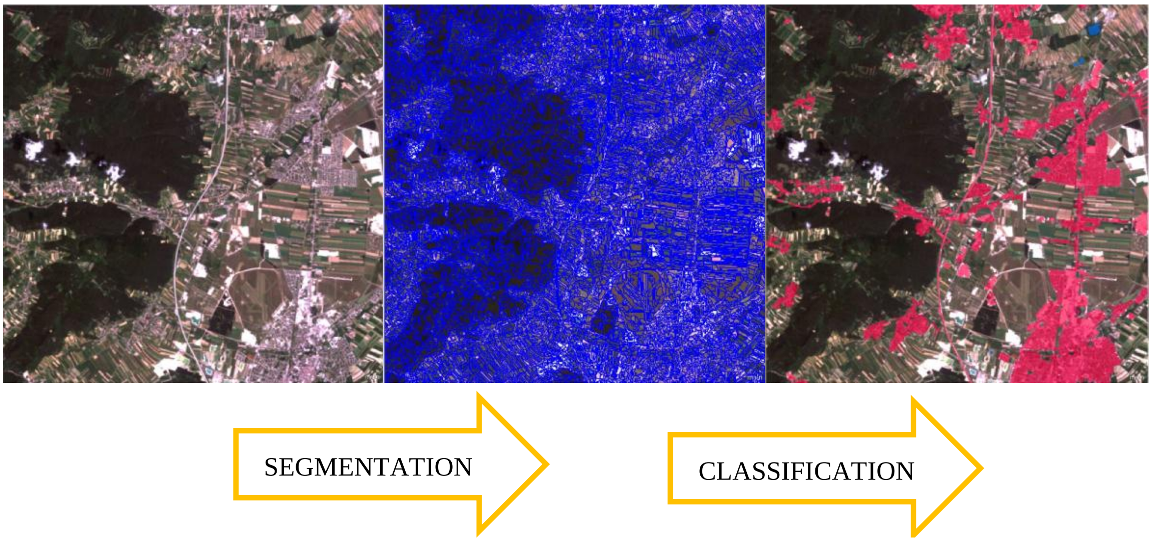

Fig. 1-8 Object oriented classification procedure. (source: Own)

Various algorithms can be used here, although comprehensive description of applied methods as well as algorithms is given in subchapter 3.1.2 and 3.1.3 as well as consequent publications (Abelen, 2010).

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1.4 Objective of the study

The main objective of this master thesis is the assessment and quantification of similarities and differences in spatial developments between Eastern and Western European cities since 1975. The analysis is based on nine representative cities comparable with respect to size and current population.

By means of remote sensing we are able to quantify changes related to physical patterns and their evolution over time. Multi-temporal analysis was performed for every city in four time steps beginning in 1975, hence 35 years of urbanization processes can be analyzed. Urban footprints as a basis for analysis have been created by the use of an object oriented, hierarchical classification algorithm implemented in the Definiens Software (Trimble, 2013). Despite of post classification comparison we incorporate landscape metrics (McGarigal et al., 2012) as external source of information about distribution and characteristics of urbanized patches (Herold et al., 2003). Comparison was performed on three spatially different levels:

- LEVEL I – the **entire** Area of Interest (AOI) (100 km by 100 km square with the fixed center point in particular downtown)
- LEVEL II – this level consists of an:
    - 1) **inner** area of the particular city (with a 13 km radius from the city center point)
    - 2) **peripheral** area (as a circle with the inner city area erased and a radius of 12 km)
    - 3) **hinterland** (representing the entire AOI with the inner as well as peripheral area erased).
    - 4) **administrative** area (defined by digitized administrative border)
- LEVEL III – a **chessboard** approach separating the entire AOI into a uniform grid of a 1 km edge length

In further steps we relate the built-up area to population development of the administrative spatial entity of the particular city. Having in mind all techniques and levels of analysis mentioned above, in this study we try to answer following questions:

1. Is there any significant difference in spatial development between Western and Eastern European cities?
2. What is the relation between ongoing spatial changes with respect to population development?

Overall analysis of spatial growth as well as distribution of spatial patterns among cities can be divided into three main stages. At first part called ‘spatial data’ has to be introduced as part dealing with acquisition of remotely sensed satellite data and their classification. Consequently, based on derived urban footprints representing unique location and distribution of spatial patterns for cities ‘spatial analysis’ has been applied. Here, investigation was done on three various spatial levels introduced above. Finally, based on results of spatial analysis, ‘spatial interpretation’ has been performed, with interpretation of urban dynamics for each city under consideration. A visual description of applied data and methods is to be found in figure 1-9.

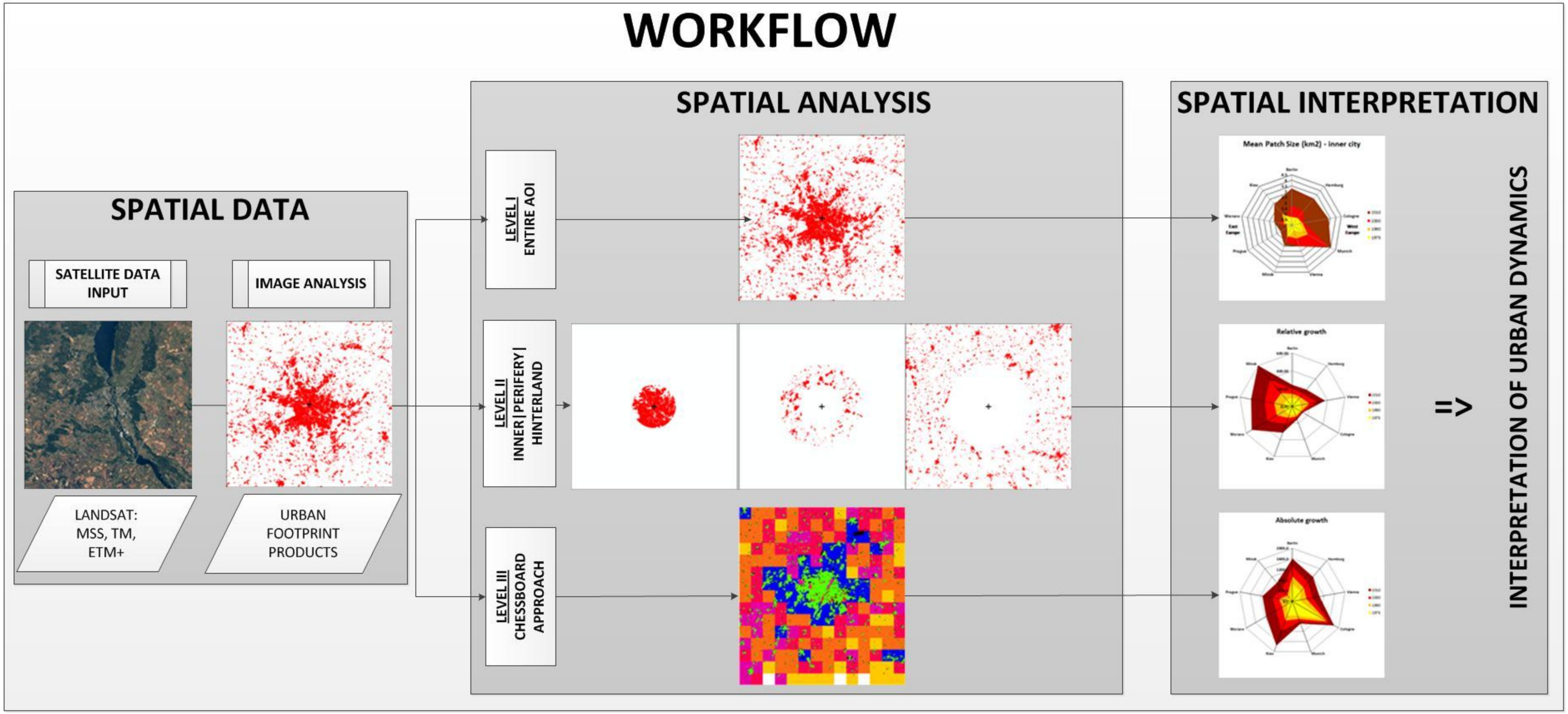


Fig. 1-9 Workflow representing the most important study stages

2. STUDY AREA AND DATA

Within this chapter descriptive information about the study areas as well as the sensors and respective remote sensing datasets are presented.

2.1 Study areas

For study purposes nine cities were selected among many in Europe according to division given below (Tab. 2-1). We chose cities similar in size (by occupied area) and population to approach a basically geographically comparable data set. Moreover the city of Berlin was chosen due to its specific character as a separated city until 1990. The following cities: Cologne, Munich, Hamburg, Berlin, Vienna, Kiev, Prague, Warsaw, Minsk have been selected for the study purpose. Location of all cities with former Europe border is presented on figure. 2-1. To give clear approach of applied division between cities of Eastern and Western Europe, two colors have been used: in red all cities under influence of socialistic system were colored; in blue all cities influenced by capitalistic system are colored; city influence by both systems (Berlin) was colored half blue, half red.

City name	Area (km^2)	Population (mio)	City name	Area (km^2)	Population (mio)
Hamburg	755,16	1,791,300	Kiev	839,00	2,797,553
Vienna	414,65	1,731,236	Warsaw	517,24	1,711,324
Cologne	405,17	1,007,119	Prague	496,00	1,262,106
Munich	310,43	1,378,176	Minsk	307,895	1,877,604
WESTERN			**EASTERN**		
Berlin	891,85	3,520,061			

Tab. 2-1 Descriptive information of selected cities (area, population)

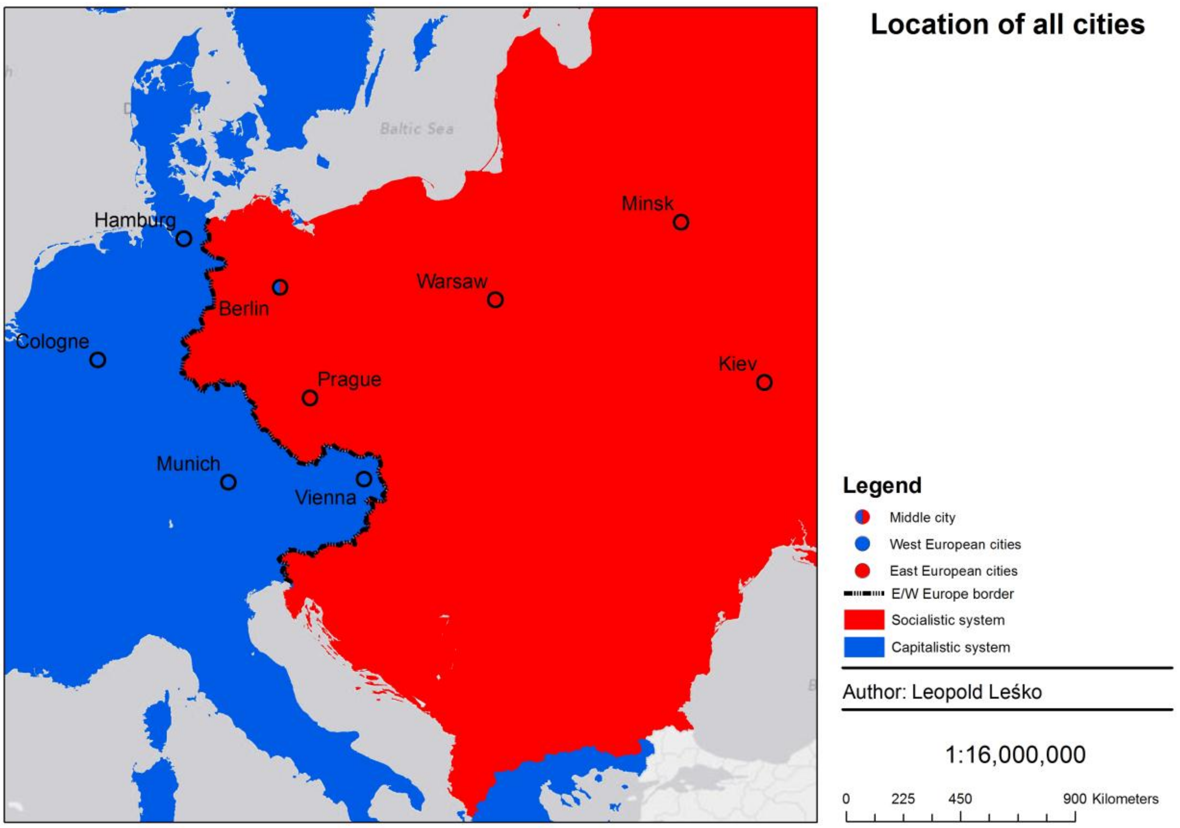


Fig. 2-1 Location of selected European cities with delineated former border between countries that existed until 1989

In this study we focus on comparison of spatial development between European cities because at first such diversity can be caused by geographical location. Secondly, taking a look back in history we know, that countries located in Europe were under influence of different political and economic systems, which we claim should show significantly influenced urban patterns of settlement within them. Generally we have to distinguish two terms, namely *capitalism* and *socialism*, describing political influences. We know that east European cities were under influence of the Soviet Union where socialism was dominating. On contrary Western counterparts have been influenced by NATO members and capitalism. As mentioned above, organizational schemes have had certain influence to spatial development of cities in time until 1989 when “Iron Curtain” collapsed. The role of the two political systems had huge influence on urbanization pattern and it is underlined in many studies (Bertaud, 2005; Bertaud and Renaud, 1995; Kovács, 1999; Ruoppila, 2004; Smith, D. M. 1996; Tsenkova, 2003, 2012; Turnock, 1998; Węcławowicz, 1979).

2.2 Data

The entire analysis is based on freely available Landsat data provided by the U.S. Geological Survey web site (USGS, http://www.usgs.gov/). What makes Landsat satellite data practical and useful for the following study is their multi-temporal existence in continuous manner. Despite of medium resolution all Landsat sensors incorporate similar spectral and geometrical resolution of sensors, thus high comparability of the results can be achieved (Klotz, 2010). Summarizing, the Landsat mission is an unprecedented data source for change detection of built up areas especially in relation to its time longevity.

The Landsat mission started with a sensor called (MSS) – Multispectral Scanner fully operated since July 1972, and used for the Landsat 1, 2 and 3 missions. With 79x57 meters original pixel size (now resampled to 60 meters) spatial resolution and 4 spectral bands on board MSS sensor was fully operated until October 1992. Its successor – the TM (Thematic Mapper) was founded in 1982 and contained seven spectral bands (bands 1-5 and 7) with 30 meters spatial resolution, band 6 - thermal (120 meters). 15th April 1999 NASA sent to space Landsat 7 with ETM+ sensor which consists of 7 spectral bands. The novelty is the application of a 15 meters panchromatic band. To ensure continuous acquisition and data availability on the 11th February 2013 NASA launched the next generation of Landsat satellite called as LDCM (Landsat Data Continuity Mission). This time, two sensors are on board, namely OLI (Operational Land Imager) and TIRS (Thermal Infrared Sensor). In comparison with Landsat 7 we the thermal infrared band is split into two separate bands, changes in the spectral range of bands are applied as well as band 9 for cirrus clouds detection is added. Capacity of all sensors can be found in table 2-2. However in this study we use only succeeding sensors: MSS, TM and ETM+. Application of Landsat 8 for urban pattern detection is a matter of next contributions.

Satellite	Spectral resolution (micrometers)	Band	Resolution (meters)
Landsat 1-3	Multispctral Scanner (**MSS**)		
	Band 4: 0.50-0.60	Green	57x79
	Band 5: 0.60-0.70	Red	57x79
	Band 6: 0.70-0.80	Near IR	57x79
	Band 7: 0.80-1.10	Near IR	57x79
Landsat 4-5	Multispctral Scanner (**MSS**)		
	Band 1: 0.50–0.60	Green	57x79
	Band 2: 0.60-0.70	Red	57x79
	Band 3: 0.70-0.80	Near IR	57x79
	Band 4: 0.80-1.10	Near IR	57x79
	Thematic Mapper (**TM**)		
	Band 1: 0.45-0.52	Blue	30
	Band 2: 0.52-0.60	Green	30
	Band 3: 0.63-0.69	Red	30
	Band 4: 0.76-0.90	NIR	30
	Band 5: 1.55-1.75	SWIR 1	30
	Band 6: 10.40-12.50	Thermal	120
	Band 7: 2.08-2.35	SWIR2	30
Landsat 7	Enhanced Thematic Mapper Plus **(ETM+)**		
	Band 1: 0.45-0.52	Blue	30
	Band 2: 0.52-0.60	Green	30
	Band 3: 0.63-0.69	Red	30
	Band 4: 0.77-0.90	Near IR	30
	Band 5: 1.55-1.75	SWIR 1	30
	Band 6: 10.40-12.50	Thermal	60
	Band 7: 2.09-2.35	SWIR 2	30
	Band 8: 0.52-0.92	PAN	15

Tab. 2-2 Technical details of Landsat Satellites and Sensors. Source http://landsat.usgs.gov/about_mission_history.php

3. METHODOLOGY

In following chapter the applied methodology is presented. Chapter 3.1 describes the data preprocessing techniques, the methodology of classifications for Landsat MSS, TM as well as the ETM+ sensors. Subsequently chapter 3.2 shows the succeeding steps to map spatial urban change, the identification of absolute spatial urban growth as well as the application of various landscape metrics for quantitative measuring and analyzing of urban patterns.

3.1 Land cover classification based on multi-sensoral and multi-temporal satellite data

3.1.1 Data preprocessing

Before starting with the spatiotemporal analysis of urban growth it is necessary to preprocess all data sets. The entire study is based on Landsat data. Therefore the imagery was downloaded via two services provided by USGS: GLOVIS (http://glovis.usgs.gov/) and Earth Explorer (http://earthexplorer.usgs.gov/). The selection of data sets was done on the highest priority on cloudless images to the intended particular time steps. Remotely sensed images have been downloaded according to four time steps: 1975, 1990, 2000 and 2010 year. When data were not available for particular time step, image from the neighboring years was acquired with emphasis to cloudless data sets.

Since the early beginnings of remote sensing the influence of the atmosphere to remotely sensed data is known as obstacle. Examples such as Rayleigh scattering or major atmospheric components (CO_2, O_2, O_3, H_2O absorption bands) can substantially affect data quality. Nonetheless, atmospheric correction was not applied due to huge amount of scenes to process (overall entire data set consist of 36 scenes). In addition classification process is semi-automatic with adjustment to all scenes, thus atmospheric correction has not been applied. Majority of data sets were in good quality where a few coming from early 70s were covered with stripes. Bands acquired for the study purposes were reordered, stacked and saved as GeoTiff files by use of ENVI 4.8 software.

The next step for data selection consists of area of interest extraction. In this case the goal was to have a uniform area of interest with an extent limited by rectangle (100 km x 100 km) with centroid in city center point. Figure 3-1 depicts example of extracted AOI for city of Kiev. All city central points were reprojected according to the coordinate system of the particular counter parting Landsat scene. By means of geoprocessing tools embedded in ArcMap 10.0 software, the final AOI was extracted. The number of scenes involved for spatial coverage of the final AOI depends on the city location, the time step and varies from one (Kiev) up to four scenes (Hamburg) per city. Regarding to city of Hamburg Landsat MSS scenes yield in 70s were shifted to referring TM and ETM+ scenes, hence we used georeferencing as appropriate tool to fix it.

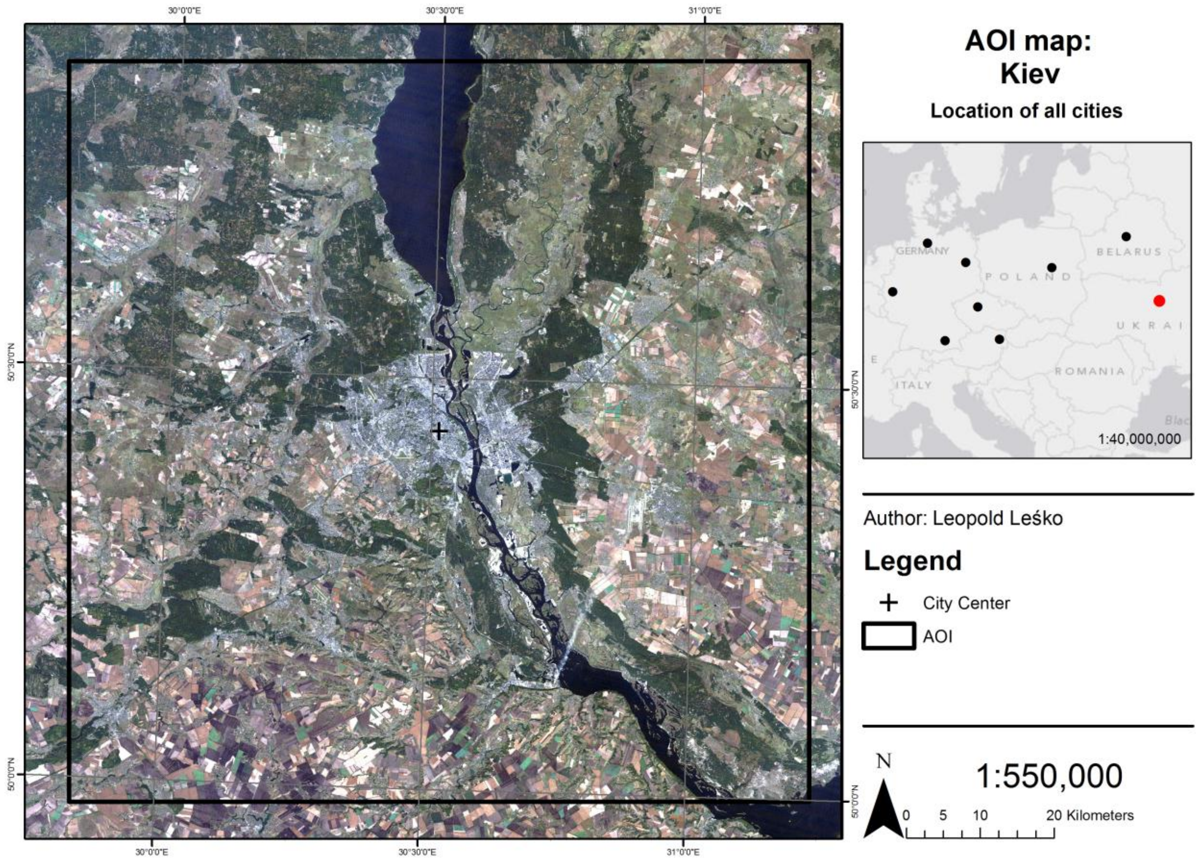


Fig. 3-1 Example of AOI overlaid on the Landsat scene

3.1.2 Classification of Landsat TM and ETM+ data

"In terms of semantic structure, a digital image is much like an analogue photograph. The general problem is hot to partition the digital image, and how to identify and segment its thematic categories." (Donney et al., 2001).

To extract an urban footprint from remotely sensed data algorithm based on decision tree with thresholds implemented in eCognition architect as GUI is applied. Generally it allows to semi-automatically detect urbanized patterns and to classify them. It is worth of mentioning that nowadays we can notice increasing importance of object oriented classification methods and its application to urban sciences (Abelen et al., 2011, Taubenböck et al., 2010a).

The entire process starts with segmentation as a first step of image analysis. Segmentation cuts the whole image into pieces (Definiens AG, 2013). The segmentation process depends on the scale parameter which has to be set up by the user before its start. Here the basic rule is as follows: the bigger value of scale parameter is, the bigger the created objects and vice versa. The variety of segmentation algorithms can be selected, among others (Top-down, Bottom-up segmentations); however, here we apply a multi-resolution segmentation algorithm. It's an

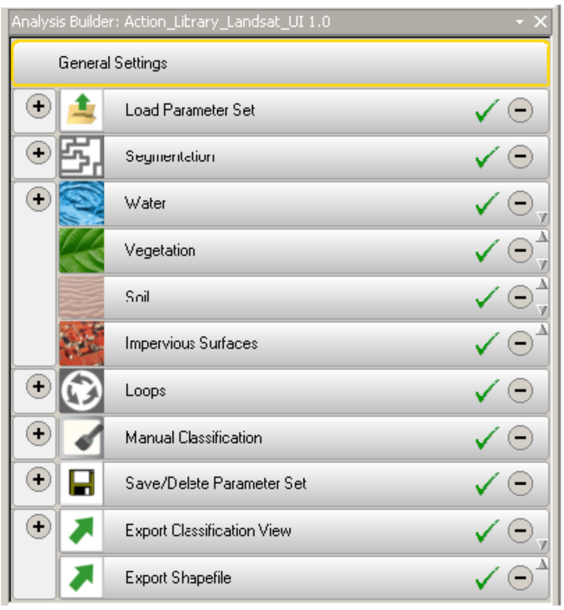


Fig. 3-2 Design of GUI. (source: Abelen, 2010)

optimization procedure which, for a given number of objects, minimizes the average heterogeneity of image objects and maximizes their respective homogeneity of color and shape (Definiens AG, 2013). Here homogeneity can be defined as a combination of spectral homogeneity and shape homogeneity. Therefore it is very applicable for detection of urban areas. In other words it identifies single image objects of one pixel in size and merges them with their neighbors based on homogeneity criteria, where the criterion is a combination of spectral and shape criteria (Benz, 2004). Image obtained in that way is used for further analysis.

The next step consists of image classification where single classes are assigned to segments (objects) according to their attributes such as: the spectral information and customized features like: Normalized Differenced Vegetation Index (NDVI) and the Soil Adjusted Vegetation Index (SAVI). Image objects created in previous step are classified on behalf of their features, by use of individual thresholds and membership functions that can be adjusted manually by user. Classes as mentioned before are identified hierarchically in a sequence, starting with classes of significant separability, towards to those with lower (Abelen, 2010). According to figure 3-4, algorithm is able to detect four classes in hierarchical manner. At first 'water' class is detected as the easiest to classify. Consequently, 'vegetation' and 'soil' class is classified. At the very end classification of 'impervious surfaces' is done as this class is the most challenging to detect. This specific sequence prevents that at the beginning many objects are misclassified, which can later not be assigned to the correct class any more (Abelen, 2010) (see Fig. 3-2 and 3-4). Each class is identified by means of certain parameters, membership functions as well as thresholds. However, after classification procedure certain pixels can stay as unclassified. To deal with this problem loop which uses objects topological information is implemented. Given solution provides that all pixels neighboring with impervious surface class are assigned into that class. The same procedure is done for remaining classes in iterative steps. Although all pixels have already been assigned to certain class, it is quite possible that some remains misclassified. Here user has an opportunity to re-classify them manually. Visual description of classification procedure is shown as figure 3-6.

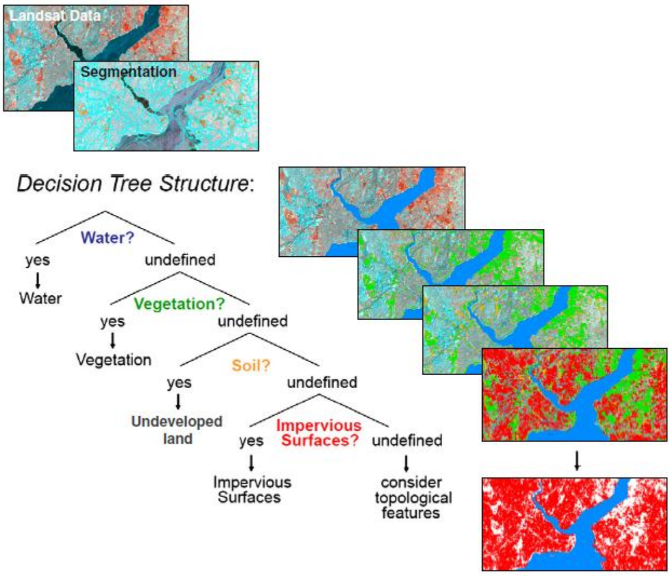


Fig. 3-3 Visual structure of applied decision tree (source: Taubenböck et al., 2011)

Decision tree (Fig. 3-4) is combined with graphical user interface (Fig. 3-2) via the Architect extension of the eCognition Developer 8.8. Entire solution is divided into two parts (Fig. 3-3): first, the process tree with decision nodes (classification procedure containing segmentation algorithms and the decision rules); second, class hierarchy, where user can apply certain parameters and features manually, via graphical user interface. Here user can decide whether to include or exclude certain parameters from classification.

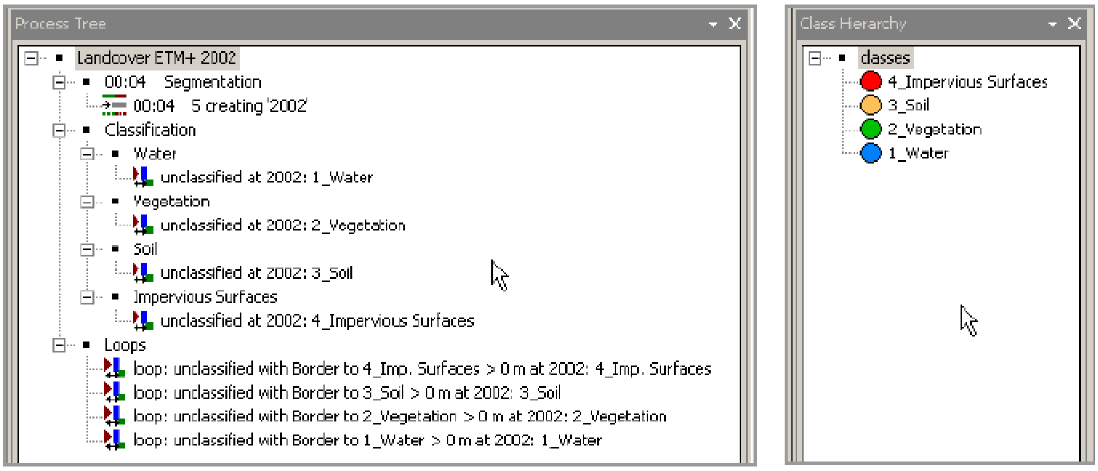


Fig. 3-4 Process tree and succeeding Class Hierarchy (source: Abelen, 2010)

In addition, single features are linked by AND, IF operators: an image object has to fulfill all rules which are specified in the particular class description to be assigned to the class (Klotz, 2010). Every image object has to fulfill implemented rules included as "description: of single class. Here hard classification has been used to assure that each object created in the image is assigned only to one class, where soft classification uses membership functions. Membership functions use fuzzy logic to a class description. The degree of membership is defined by all values located between true and false (0 and 1). As a result of functions specification each particular segment is assigned to the class with the most convenient result (Definiens, AG 2013).

The complete decision tree consists of the thematic classes 'Water', 'Vegetation', 'Soil', 'Impervious surfaces'. According to Abelen (2010), the class extraction is based on the spectral bands and customized features such as: (**Water:** SWIR 2, SAVI, **Vegetation:** NDVI, Blue, **Soil:** Blue, Red, NDVI, **Impervious surfaces:** Blue, Red, SAVI). The features can be applied with lower and / or upper thresholds for the particular classes via interface (Fig. 3-5).

Because of numerous data sets in this contribution attention is put to class 'impervious surface' detection as the most important one. However for visualization purposes the water class was extracted too.

In that way urban footprints of the most recent time step were obtained. In the following they have been converted to shp-format (shape file) and loaded as thematic layer for classification of next scenes in chronologically decreasing manner. Following this idea the same solution was conducted for pairs of remaining scenes (2000/1990, 1990/1975). The template of the more recent time step is used here to restrict classification of urban growth to areas occupied by the UF in it. In other words built-up area is only classified in patches that have already been classified as urbanized previously. Such a treatment was used to restrict former urban growth to the area chronologically following urban footprint, so that eliminate a removal of built-up areas and spatial reduction of the urban footprint during time.

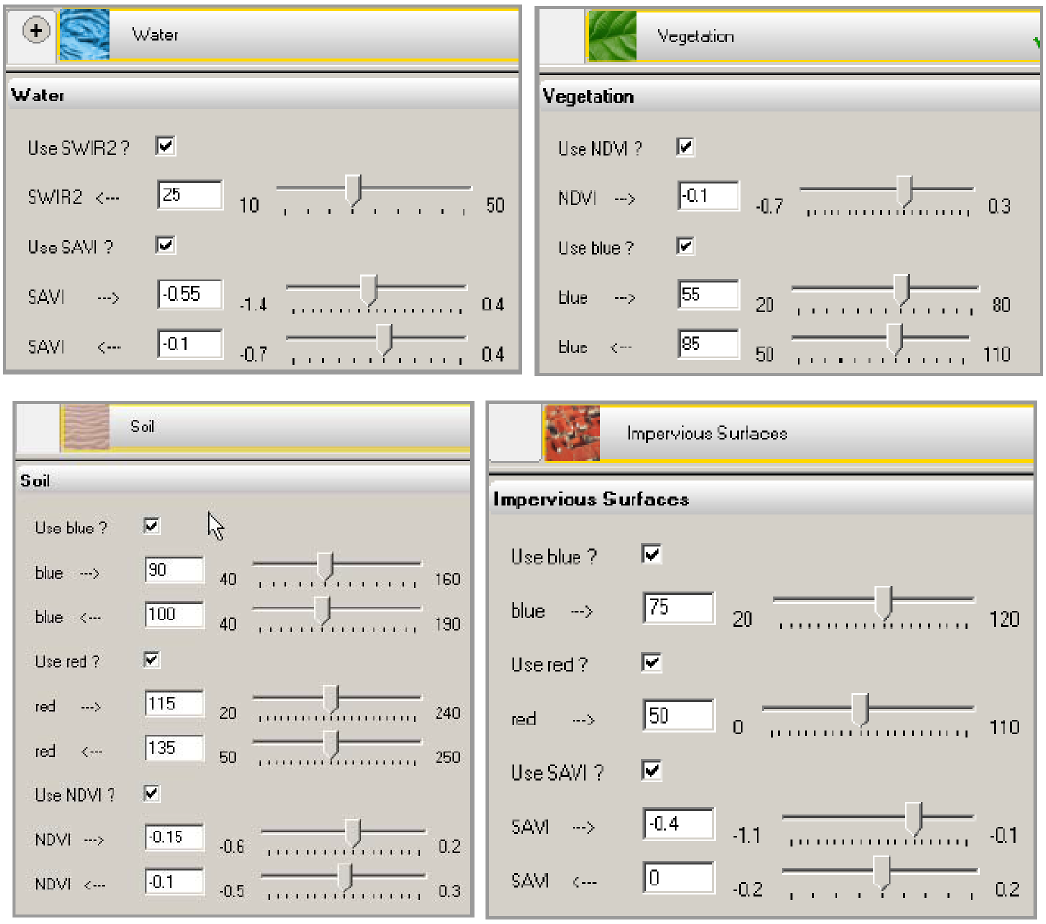


Fig. 3-5 Design of classification controllers (source: Abelen, 2010)

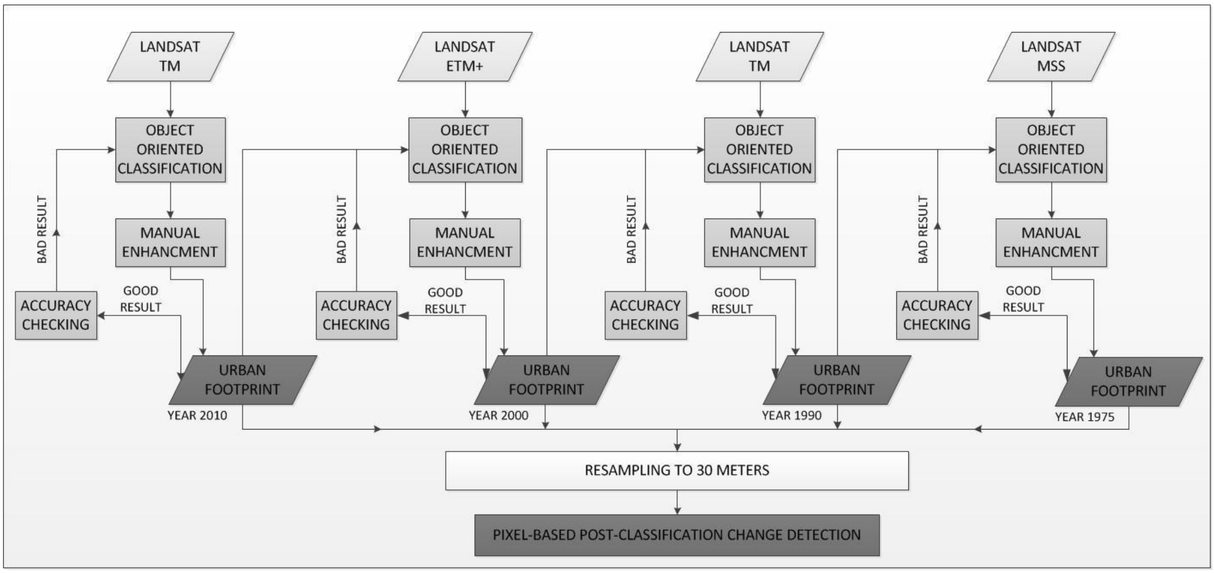


Fig. 3-6 Workflow presenting multi-temporal change detection based on multi-sensoral satellite data

3.1.3 Classification of Landsat MSS data

With Landsat MSS data the overall procedure is almost the same, nonetheless, some exceptions exist. Due to the coarse spatial resolution of Landsat MSS data image enhancement methods like Principal Component Analysis and Tassel Cap Transformation were applied. This treatment helps to reduce data redundancy when bands appear similar (highly correlated) thus convey the same information, as well as increases computational efficiency of classification process (Lillesand et al. 2008). We apply PCA to enhance images visually as well as extract the most important information form first Landsat sensor (MSS), so that better classification of urbanized area can be derived. In this study only the first two principal components were calculated as these characterized by the highest eigenvalues. After all, data is compressed from four to two bands conveying the majority of information (PCA1 and PCA2). On the other hand Tassel Cap Transformation (TCT) is known as “vegetation component” computed by linear transformation of Landsat MSS bands to provide image enhancement for better agricultural crop monitoring (Lillesand et al. 2008). In the process of MSS bands linear transformation four new components have been created: brightness, greenness, yellowness, non-such. In this case greenness component indicates places with lack of vegetation, therefore is a good indicator of imperviousness.

The analysis of MSS scenes was performed as a second and is based on one layer stack containing 11 bands:

- band stack of MSS scenes (4 bands)
- PCA (Principal Component Analysis) product (2 bands)
  - PCA1
  - PCA2
- TCT (Tassel Cap Transformation) product (4 bands)
  - Soil Brightness Index
  - Green Veg Index
  - Yellow Stuff Index
  - Non such Index
- urban footprint thematic layer as binary raster (1 band)

The coarse spectral resolution of Landsat MSS data makes classification process more challenging. At first among the bands, the UF mask from the classification of the Landsat TM data (1990 time step) was loaded as binary mask – 1 urban and 2 non-urban. Then segmentation process was applied as contrast split algorithm. It is an example of Top-down Segmentation. The succeeding algorithm divides segments into dark and bright image objects based on a threshold value that maximizes the contrast between them. Initially, it executes a chessboard segmentation of variable scale and then performs the split on each square, in case the pixel level is selected in the image object domain (Definiens AG, 2013).

For segmentation purpose scale parameter with scale value = 100000 was chosen, using the urban footprint as a thematic layer. In that way level number one was created. The second level was produced by use of segmentation with scale value equals 5. Subsequently we transferred urban footprint of level one into level two using classification as well as existence of super objects. Continuously, classification of impervious surfaces was performed with latter manual enhancement. Urban footprint of 1975 time step was classified only within the area limited by urban footprint from 1990s. In that way negative growth of built-up area was eliminated.

All image enhancement methods have been employed in ENVI 4.8. To be consistent all MSS scenes were resampled to 30 m resolution.

3.1.4 Post classification processing

Finally, the results of the object oriented-classification comprises two classes: water and urban classes. Raster files have been catalogued according to city name and appropriate time step of classification. Both land surface classes have been extracted in ArcMap 10.0 by means of model builder to single files. Consequently they were mosaicked to receive one raster file representing one time step. Summarizing 36 tiff files depicturing an entire data set have been created and stored. Before starting with the structural analysis of urban patterns it has to be reminded that roads were erased from the urban class. The reason behind this is their influence to the calculation of Shannon's entropy. Simplifying the aim is to avoid detect urban sprawl due to the roads and at a same time focus only on land fragmentation/compactness limited solely to urban patches.

3.1.5 Accuracy assessment of classification

One says that a classification is not complete until its accuracy is assessed (Lillesand et al., 2008); therefore the first important step after classification is the assessment of its exactness. Usually classifications accuracy is evaluated by comparison of the classification with ground truth data, often these are points collected in a field survey. Because of the size of each particular classified city areas (10 000 km^2 each**)** and the variety of landscape locations that was not feasible. Since ground truth data were missing straight-forward solution has been applied. As reliable reference data we applied visual comparison with Bing maps available in ArcMap 10.0 Esri software as base map. Accuracy assessment was conducted for the most recent classified time step (2010) in case of all nine cities (see Appendix A).

By means of the ArcGis tool, 100 points were distributed within every class located in area of interest. The classification is based on urbanized areas, therefore 100 points were distributed randomly within the built-up class, whereas another 100 points were randomly distributed in areas not classified as urban – the non built-up class. Finally comparison of randomly distributed points against Bing maps was performed. The results of the visual comparison with reference data were saved as zeros (for non built-up) and ones (for built-up) areas inside randomly distributed points as shape file. The accuracy assessment of the additional class 'water' was done separately.

Outcomes of such a binary comparison are presented as confusion matrix where relationship between known reference data and corresponding results of classification can be investigated (Lillesand et al., 2008). The matrix has a shape of a square and consists in this case of two classes under examination, namely built-up and non-built-up. The sum of the columns in the confusion matrix represents the number of control points per class. Consequently, the sum of the lines shows the number of points that have been assigned to a specific class during classification procedure. The matrix diagonal signifies points that have been classified correctly. Based on the following categorization we are able to calculate several characteristics (Lillesand et al., 2008), which indicate how well the classification was performed (see Appendix A).

- **Overall accuracy** – total accuracy of classified points in percentage
- **Producer's accuracy** – probability that a sampled point of the class has been assigned to the correct class
- **User's accuracy** – probability that sampled point assigned to certain class belongs to it
- **Error of omission** – represents points belonging to the class of interest which have been omitted during classification

- **Error of commission** – represents points of other classes that have been incorrectly assigned to class of interest
- **Kappa Index** – measure that the test if two data sets have a statistically different accuracies. Index varying from 0 to 1 where 0 indicates lack of agreement and 1 corresponds to total agreement between classification results and the reference image.

3.2 Detection of urban change

In the following chapter the overall procedure concerning the detection of spatial urban change is described. As a main tool post classification comparison of urban footprints is applied as independent results of classification performed in eCognition software (Trimble Gmbh) are available for multiple time steps. The main parameter used here is built-up area calculated for every city and presented on maps (Appendix B). It allows identification, localization and quantification of urban pattern over time (Taubenböck et al., 2011). Moreover different landscape metrics are applied. They are appropriate spatial tools to identify and show trends of urban change over data time. However, in geography the scale of analysis is a common problem. For the detailed detection of possible disparities among cities landscape indices have been calculated on three different spatial levels. Hence the focus is more on trends in urbanization processes which were verified and compared.

3.2.1 Mapping of urban change

Mapping of urban change over time is based on comparison of urban footprints that were extracted for every city under consideration. In case of every city and particular time step urban footprint is represented as area classified as built-up or impervious surface. Classification of impervious surfaces for particular time step was limited by area that has already been classified as urban in chronologically time frame. Hence, following this methodology negative growth that could occur as a result of misclassification of Landsat scenes is neglected (as it is assumed that the cities under consideration are spatially shrinking). Nevertheless, certain condition in ArcMap (ESRI) raster calculator was employed to provide functionality of assumption given above. Maps of classifications were found as a sufficient and comprehensive tool depicting changes ongoing in time (see Appendix B). Every map consists of urban footprint described by built-up area for ≈1975, ≈1990, ≈2000 and ≈2010 time step.

3.2.2 Identification of absolute growth of cities

The calculation of absolute urban growth of all cities was based on previously derived urban footprints as raster file format. The same files have been used for application of landscape metrics in the software FRAGSTAT. Nevertheless we juxtapose absolute urban growth with population development inside the area delineated by administrative borders. Necessary data for all cities were achieved from the World Urbanization prospect provided by (United Nations, 2012).

3.2.3 Levels of mapping

As underlined in previous chapters and contributions (Ewing 1994, 1997; Angel et al., 2007; Esch et al., 2012; Galster et al., 2001; Ji, 2008; Yeh and Li, 2001) the definition of urban sprawl has not been clarified yet and is hard to determine. Lack of its clear definition as well as missing border between urban and rural areas (Taubenböck et al., 2011) causes problems with selection of appropriate geometric extent (scale) for analysis. Therefore it varies from author, chosen approach as well as available data. However border definition is one of the most crucial points of analysis.

In publications and conference papers generally we can distinguish local (one or few cities within one country) and global (cities among countries and continents) levels under investigation. When comparing 26 European cities Siedentop & Fina (2012) selected country and 20km cells as appropriate solution to differentiate changes in spatial development. Taubenböck et al., (2010) used complete urban footprints of the city region as well as ring-shaped zones with constant radius around the main urban core. Wurm et al., (2013) found for monitoring development of urban morphology administrative boundaries useful. On the contrary, Angel et al., (2007) delimited areas of analysis according to percentage of built-up pixels in surrounding neighborhoods.

Having in mind the problem of spatial units of analysis, in this study a fusion of all approaches has been applied, namely the approach tries to quantify spatial development of cities with regard to five levels: 1) the administrative unit, 2) the core city, 3) the periphery, 4) the hinterland and 5) the entire extent.

The application of different levels of analysis give better and spatially more detailed insights to ongoing spatial changes. Hence diversification of spatial development can be investigated more carefully. However, when using landscape metrics for city comparison the following spatial units were selected: core city, periphery, hinterland and entire extent, plus additionally a chessboard level.

1) Entire extent

In following example the entire extent level is presented as 100x100 km width square. In that way we can focus on changes and dependencies between patches in general. Fig 3-7 presents AOI related to city center point, which is defined as the downtown area of the city.

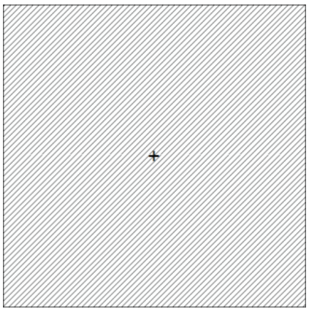


Fig. 3-7 Entire level of mapping

2) Inner/outer part of the city

As a second spatial level of analysis the large entire area of interest is divided to following subgroups:

a) Core area

The core city area (Fig. 3-8) was extracted based on 13 km radius around the particular city center. The radius value was derived using all nine administrative units. To allow for comparable and not artificial units the areas of the administrative units were added and their sum divided by nine. This resulting area is transformed into an equal area of a circle from which the 13 km radius for the core areas has been calculated. The following approach gives better understanding of changes which come around inside each city.

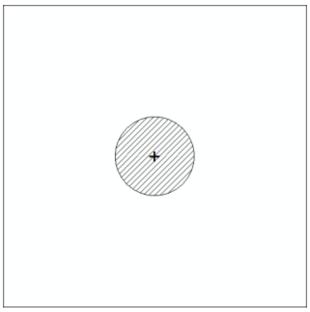


Fig. 3-8 Core area level of mapping

b) Periphery

The periphery (Fig. 3-9) is the area retrieved by erasing the core city area from an area represented by a circle with 25 km radius around the urban center. In this spatial level the idea is to analyze the change over from urban to rural landscapes and their changes and differences in spatial development to core city neighborhood.

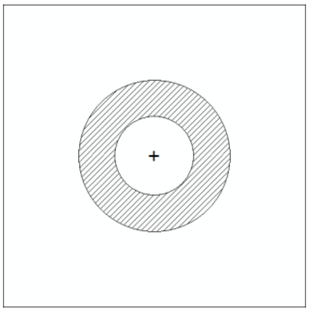


Fig. 3-9 Periphery level of mapping

c) Hinterland

The hinterland is representing the remaining area of the entire landscape (entire AOI diminished by circle with 25 km radius). The hinterland level is illustrated in figure 3-10.

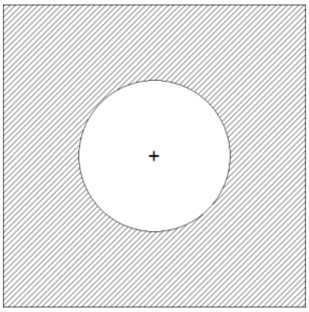


Fig. 3-10 Hinterland level of mapping

d) Administrative borders

The administrative borders are the digitized artificial spatial outline of administrative boundary around every city. Presented below figure 3-11, shows the example of Berlin, Germany.

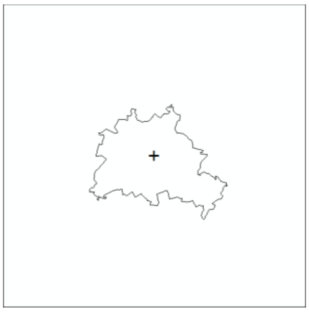


Fig. 3-11 Administrative border level of mapping (example of Berlin)

e) Chessboard approach

The application of the chessboard units (or grid) allows having a look at urban sprawl from another, spatially more explicit perspective. Generally this solution enables calculation of indices such as the Shannon’s entropy and its assignment to the fishnet with sizes defined by user – here a chessboard with 5x5 and 1x1 km cell size have been tested. Thus each cell represents value of the computed index. Figure 3-12 shows example of chessboard level.

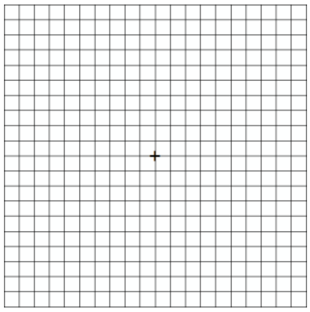


Fig. 3-12 Chesseboard level of mapping

Nevertheless we apply population to area ratio and growth of built up area inside administrative borders of each city.

3.2.4 Landscape metrics

The term: “Landscape metrics” refers to algorithms that quantify specific spatial characteristics of patches, classes of patches, or entire landscape (McGarigal et al., 2012). Generally those indices can be divided into two main categories namely metrics quantifying composition of map without reference to spatial attributes and ones that quantify spatial configuration of the map, requiring spatial information for their calculation (McGarigal and Marks, 1995). In following study the focus is on spatial configuration metrics. Another structuring is done according to aspect of landscape pattern that is measured: *Area and edge metrics, Shape metrics, Core area metrics, Contrast metrics, Aggregation metrics, Diversity metrics.* It has been proven that landscape pattern can be evaluated extensively by means of landscape metrics (Herold, et al., 2005; Ji, 2008; Lv, et al., 2012; Taubenböck et al., 2008a). Metrics originated from science of ecology play extensive method of understanding forms of urban cities which vary from continents, countries and cities. Using other words, urban footprints (as a landscape part) consists of patches which are characterized by: patch type, area, edge, neighbor type etc. Metrics describe these basic patch properties, therefore indices applied in ecology can be easily used for sprawl detection too. However, Leitao et al., (2002) pointed out that sprawl can be measured on two metric levels regarding to landscape composition and landscape configuration related metrics. Additionally Leitao et al., (2002) as well as Terzi and Kaya, (2008) admitted that metrics are good but not ultimate solution for characterization of the urban sprawl.

Metrics implemented in FRAGSTAT (McGarigal et al., 2012) can be calculated for each patch type on three different levels namely *patch, class* and *landscape* level. Class indices represent spatial distribution of and pattern of patches within a landscape of a single patch type (McGarigal et al., 2012). Therefore the class level was selected as emphasis is put on patches containing areas classified as “built-up” or “urbanized”. Measures at this level were calculated respectively to compute amount and spatial configuration and distribution statistics of the built-up class (see table 3-1).

The very last index (Shannon’s Entropy) has been applied by means of scripting in R (R Core Team, 2013) statistical software on cheseboard level. The program uses entropy (Hausser and Strimmer, 2012), raster (Hijmans and Etten, 2012), rgdal (Keitt et al., 2013), and SDMTools (VanDerWal et al., 2012) packages and simply is based on moving window/focal statistics concept (Fig. 3-13). The developed tool performs a neighborhood operation that computes an output raster where the value for each output cell is a function of the values of all the input cells that are in specified neighborhood around that location (ArcGIS Resource Center, 2011).

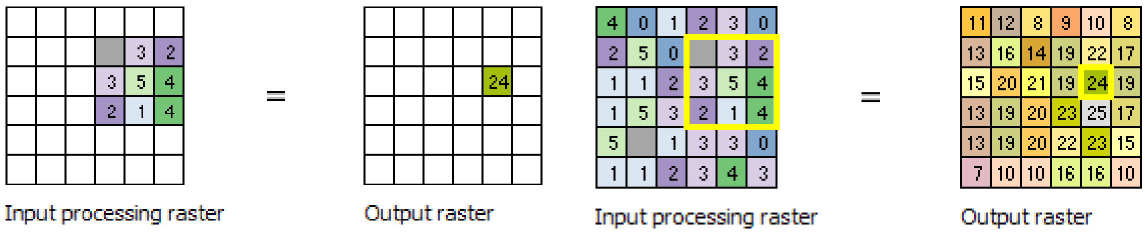


Fig. 3-13 Focal statistics calculation on single cell as well as all inpit cells (Source: ArcGIS Resource Center, 2011: Desktop 10)

As input the previously classified urban footprints with erased roads as binary raster files are used. Formula of Shannon's entropy landscape metric have been applied in appropriate functions and implemented in focal statistics window scoring mean value of cells falling in the fixed size of moving window. Outputs are available as raster files with its format depending on user preferences. Values received in that way have been aggregated into 1km x 1km and 5km x 5 km raster resolution by means of aggregate function in ArcMap and depicted as five classes. In the following study only results available as 1km x 1km Shannon's entropy maps have been integrated (see appendix D).

A comprehensive description of applied indices as well as all equations is given below.

3.2.4.1 Class area (CA)

Measures of landscape composition with emphasis to the area of the landscape comprised of particular patches (McGarigal et al., 2012) refer to class area metrics. The result is expressed in hectares and varies from 0 to without limits. CA equals 0 when the patch type becomes rare in the landscape. If the entire landscape consists of one patch, then value of CA equals TA (total area).

3.2.4.2 Mean Patch Size (AREA_MN)

The mean patch size is a measure that relates the number of patches in the class to the total class area. It has to be underlined that it does not convey information about patch quantity. Hence for interpretation purposes it is better to analyze it with class area and patch density. The mean patch size describes mean size of urbanized patches depending on particular spatial level.

3.2.4.3 Patch size coefficient of variation (AREA_CV)

The patch size coefficient of variation is an index measuring the relative variability about the mean (like variability as percentage of the mean), but not absolute variability (McGarigal et al., 2012). The following measure has to be interpreted with number of patches and patch density. Otherwise its values can be misleading. AREA_CV assumes normal distribution about the mean. In relation to urbanized patches the Patch size coefficient of variation can reveal information for instance about growing patches dispersion.

3.2.4.4 Largest Patch Index (LPI)

The LPI equals the percentage of the landscape comprised by the largest patch in percentage. The LPI equals 100 when the entire landscape consists of one single patch. Conversely, the LPI is approaching zero when the largest patch in the landscape is increasingly small. In relation to urbanization processes it can be used as a measure describing either polycentrism or monocentrism of urban pattern.

3.2.4.5 LPI (1-5)$_{land}$

This is a specification of the LPI. It is calculated for the biggest 5 patches within the particular AOI. With this measure the idea is to detect cities growing in the neighborhood of main city core as larger cities basically show large patches as core areas. It has to be reminded that this index is calculated only for the entire extent level.

3.2.4.6 LPI (1-5)$_{urb}$

Another modification of the LPI is presented as index related to total class area (in this case total built-up area). This slight modification gives insight to spatial changes of the biggest patches that are neighboring with the biggest patch of particular city. In addition to underline the significance of distinctively smaller patches (patch 2 to 5) we subtract area of the biggest one from total urbanized area and recalculate LPI values for remaining ones.

3.2.4.7 Patch Density (PD)

The patch density is expressed as number of patches belonging to certain patch type and divided to total landscape area. It describes the density of built-up area according to spatial level.

3.2.4.8 Euclidian nearest neighbor (ENN)

The Euclidian nearest neighbor is an index assessing distance in meters to the nearest neighboring patch of the same type, based on the shortest edge-to-edge distance (from cell center to cell center). The closer to 0, the shortest the distance to the nearest neighbor. The following metric reveals information about degree of densification processes depending on city.

3.2.4.9 Shannon's Entropy (H_n)

The Shannon's Entropy is described as index which measures the degree of spatial concentration or dispersion of a geographical variable *x (e.g. built-up area)* among *n* zones (Yeh and Li, 2001) and it is a convenient tool to measure urban sprawl. It can be calculated by the succeeding equation:

$$H_n = \sum_i^n p_i \log(\tfrac{1}{p_i})$$

where p_i is the probability of a phenomenon occurring in the ith zone given by:

$$p_i = x_i / \sum_i^n x_i$$

where x_i is the area of built up at the ith unit. The values of Entropy range from 0 representing concentrated pattern, and maximum of log n - describing dispersed distribution (Verzosa., Gonzalez., 2010). Increasing entropy indicates continuous dispersion of built-up areas. If this is highly occurring, it is associated with urban sprawl. Decreasing values imply that the area is less fragmented and homogenously covered. However the change in entropy can be used to identify whether land development is toward a more dispersed (sprawl) or compact pattern (Yeh and Li, 2001).

All introduced spatial metrics are presented in mathematical details in the table 3-2 and 3-3. In addition table 3-1 presents selected landscape metrics and their application to various spatial levels.

x_{ij} – value of patch metric for patch ij

Metric	Formula	Description
Mean (MN)	$MN = \frac{\sum_{j=1}^{n} x_{ij}}{n_i}$	MN (mean) equals the sum of all patches in one patch type divided to the number of them. The mean is given for the same units as adequate patch metric.
Standard deviation (SD)	$SD = \sqrt{\frac{\sum_{j=1}^{n}\left[x_{ij} - \left(\frac{\sum_{j=1}^{n} x_{ij}}{n_i}\right)\right]^2}{n_i}}$	SD (standard deviation) equals the square root of the sum of the squared deviations of each patch metric value from mean metric value of the corresponding patch type, divided by the number of patches of the same type; that is, the root mean squared error (deviation from the mean) in the corresponding patch metric. This is population standard deviation.
Coefficient of variation (CV)	$CV = \frac{SD}{MN}(100)$	CV (coefficient of variation) equals the standard deviation divided by the mean, multiplied by 100 to convert to a percentage, for the corresponding patch metric.

Tab. 3-1 Class Distribution Statistics used in the study (source: McGarigal et al., 2012)

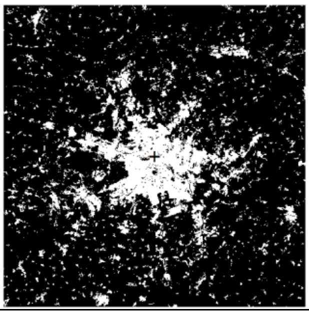
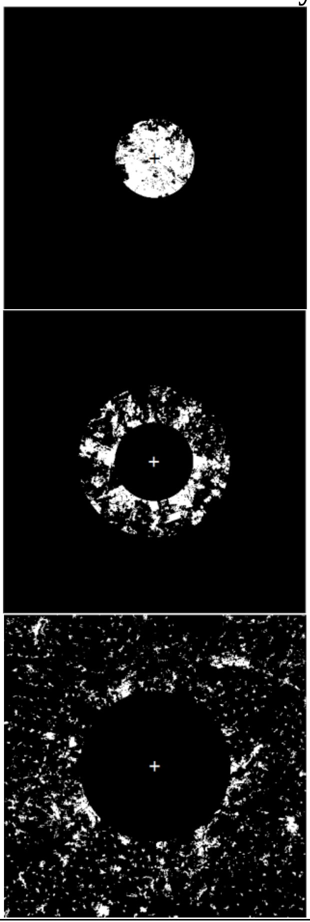
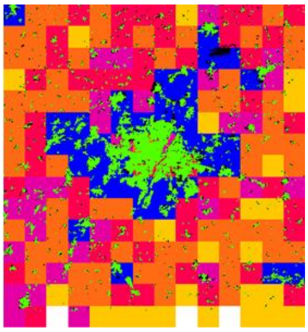
a_{ij} = area (m^2) of patch ij; **A** – total landscape area (m^2); **n_i** = number of patches in the landscape of patch type (class) i; **h_{ij}** = distance (m) from patch ij to nearest neighboring patch of the same type (class), based on patch edge-to-edge distance, computed from cell center to cell center; **SD** – standard deviation

Subject	Metric	Formula	Units	Range
Area and Edge Metrics	Class area (CA)	$CA = \sum_{j=1}^{n} a_{ij}\left(\frac{1}{10000}\right)$	hectares	CA > 0, without limit
	Mean Patch Size (AREA_MN)	$AREA\_MN = \frac{\sum_{j=1}^{n} a_{ij}}{n_i} * \left(\frac{1}{10000}\right)$	hectares	MPS≥0, without limit
	Patch size coefficient of variation (AREA_CV)	$AREA\_CV = \frac{SD}{MN} * (100)$	percent	PSCV≥0, without limit
	Largest Patch Index (LPI)	$LPI = \frac{\overset{n}{\max}(a_{ij})_{j=1}}{A} * (100)$	percent	0 <LPI≤100
	LPI (1-5)$_{land}$	$LPI = \frac{\overset{n=1-5}{\max}(a_{ij})_{j=1}}{A_{land}} * (100)$	percent	0 <LPI≤100

	LPI (1-5)$_{urb}$	$LPI = \frac{\max\limits_{j=1}^{n=1-5}(a_{ij})}{A_{urb}} * (100)$	percent	0 <LPI≤100
Aggregation Metrics	Patch Density (PD)	$PD = \frac{n_i}{A}$*(10000)*(100)	Number per 100 hectares	PD>0, without limit
	Number of Patches (NP)	$NP = n_i$	Number of the corresponding patch type (class)	NP≥1, without limit NP=1 when the class consists of a single patch
	Euclidian nearest neighbor distance mean (ENN_MN)	$ENN\_MN = \frac{\sum_{j=1}^{n} h_{ij}}{n_i}$	meters	ENN >0, without limit
	Euclidian nearest neighbor distance coefficient of variation (ENN_CV)	$ENN\_CV = \frac{SD}{MN}(100)$	percent	ENN_CV≥0, without limit

Tab. 3-2 Spatial metrics used in following study (source: McGarigal et al., 2012)

$\mathbf{H_n}$ – Shannon's Entropy; **Frac** – Fractal dimension; $_{(t)}$ – calculation throughout all time steps; **LPI (1-5)**$_{\mathbf{land}}$, **LPI (1-5)**$_{\mathbf{urb}}$ – modified LPI (Largest Patch Indexes).

	SIZE	**PATTERN**	**POPULATION/ AREA**	**LANDUSE**
Entire extent 	$CA_{(t)}$	LPI (1-5)$_{land}$ LPI (1-5)$_{urb}$ $NP_{(t)}$ $PD_{(t)}$ $AREA\_MN_{(t)}$ $AREA\_CV_{(t)}$ $ENN_{(t)}$ $ENN\_CV_{(t)}$		
Inner/outer area of city 	$CA_{(t)}$	LPI (1-5)$_{land}$ LPI (1-5)$_{urb}$ $NP_{(t)}$ $PD_{(t)}$ $AREA\_MN_{(t)}$ $AREA\_CV_{(t)}$ $ENN_{(t)}$ $ENN\_CV_{(t)}$		Application of administrative borders.
Chessboard 	$CA_{(t)}$	$H_{(nt)}$		

Tab. 3-3 Types of landscape metrics that have been used for the study with levels of their application.

4 ANALYSIS AND RESULTS

In this chapter an overview is presented of all methods that have been applied for urban sprawl assessment in selected cities. Starting with results of the accuracy assessment data reliability for analysis is shown. Secondly comparison of absolute values of built-up area at different time steps is introduced. Subsequently, juxtaposition of built up area within administrative borders with city population growth since 1975 is given. At the very end the analysis of landscape metrics computed for spatially different levels is presented.

4.1 Accuracy assessment

As written above in chapter 1.3 *"Urban Remote Sensing"* Landsat ETM+, TM and MSS data are characterized by a relatively coarse spatial resolution, where in addition several land-use land-cover types can be contained in one pixel. Therefore, these are limiting factors for accuracy assessment results. Despite of that, the overall accuracy assessment in case of all classified satellite images varies from 79.0% to 91.5%. It means that for final analysis highly reliable data are retrieved. Regarding to Kappa index values the results are as follows: 0.58 – 0.83. Summing up, conducted accuracy assessment of built-up area gives high results despite of limitation in spatial resolution of satellite data. The highest accuracy was obtained for classification of Vienna - 91.5% (Tab. C-5), where the lowest was scored for Kiev - 79.0% (Tab. C-6). Results of accuracy assessment are shown in Appendix C.

4.2 Spatiotemporal analysis of selected European cities

In the following the results of the spatiotemporal comparison are presented. In a first stage the focus is on absolute spatial urban growth.

The comparison of built-up area and absolute two-dimensional growth over different time steps is the most straight-forward way to show differences and similarities in spatial development.

In the following urbanized areas limited by administrative borders are compared and set in correlation to the population of the particular cities – data obtained from the United Nations (UN, 2012). Its spatial growth (km^2/year) is exemplified in table 4-1. The following table shows in clear manner annual spatial growth rates calculated for administrative border unit with higher values in Eastern European cities.

	Cologne	Munich	Hamburg	Vienna	Berlin	Kiev	Prague	Warsaw	Minsk
1975-1990	5.3	9.5	28.1	47.0	60.7	32.8	49.0	59.7	36.8
1990-2000	6.4	6.8	66.0	27.1	64.6	31.6	26.0	53.3	38.4
2000-2010	8.2	0.9	54.4	27.7	45.4	33.4	60.5	78.9	41.4

Tab. 4-1 Annual spatial growth rate calculate for administrative border extent (km^2/year)

To show visually increasing values in spatial growth for entire extent level example of change detection map for Berlin (Germany) is introduced as figure 4-1. Here outcomes of classification procedure applied in chapter () are presents as: urban footprints derived for all four time steps and extracted water class. For better visual interpretation four different colors are applied to make differences in spatial development "easy to get". Therefore the succeeding time steps are presented as: 1975 – yellow, 1990 – orange, 2000 – red, 2010 – brown color. In that way, spatial growth of cities among the years can be detected easier. Visual inspection of provided map shows that city of Berlin has been spatially growing in time. Remaining change detection maps are available as Appendix B.

Table 4-2 introduces results of accuracy assessment obtained for classification of Berlin. The following table underlines that high values of accuracy assessment indexes have been scored.

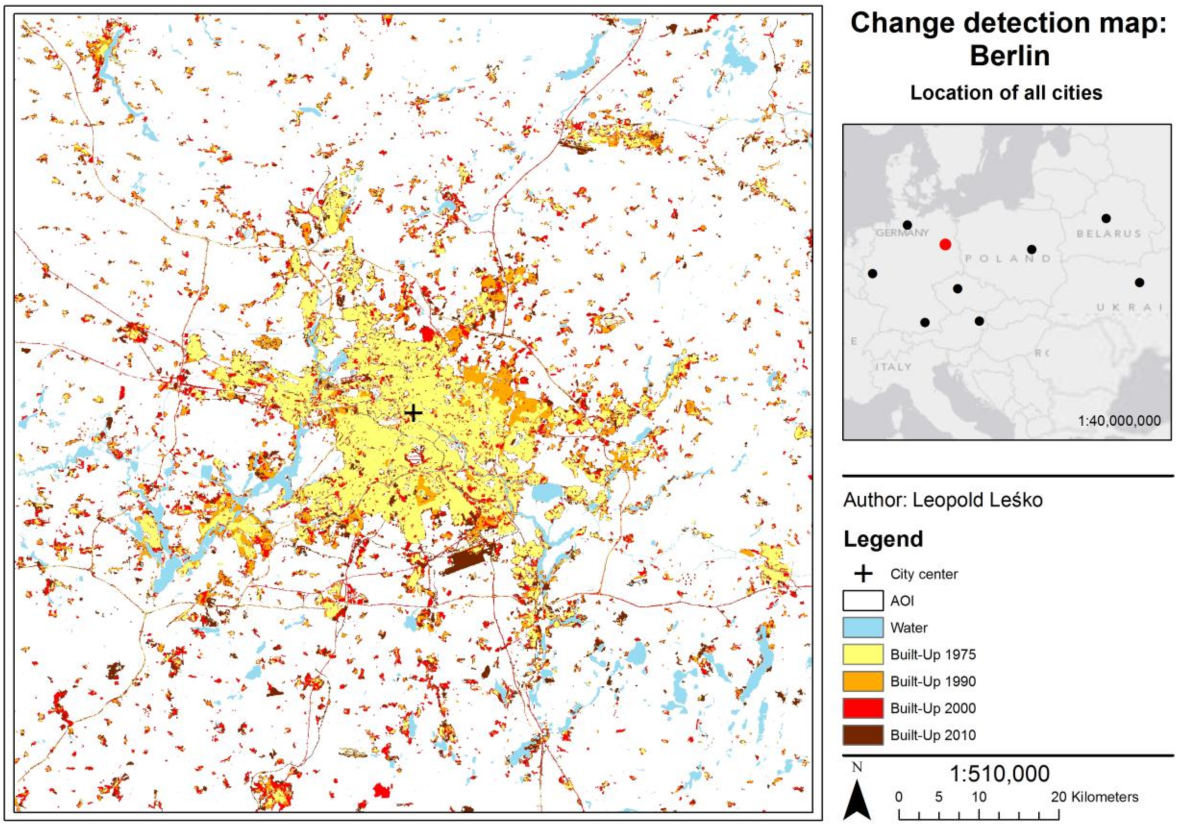


Fig. 4-1 Example of change detection map (Berlin)

Berlin 2010	**Built-Up**	**Non Built-Up**	
Built-Up	74	26	100
Non Built-Up	7	93	100
	81	119	200
Overall Accuracy	83.50%		
User's Accuracy			**Commision**
Non Built-Up	93.00%		7.00%
Built-Up	74.00%		26.00%
Producer's Accuracy			**Ommision**
Non Built-Up	78.15%		21.85%
Built-Up	91.36%		8.64%
Kappa	67.00%		

Tab. 4-2 Accuracy assessment table with all parameters (Berlin, 2010)

4.2.1 Spatial growth: Comparison on spatially different levels

The concept of having five spatially different levels allows determining spatially explicit differences and analogies with respect to space and time. In particular, levels such as: administrative border, core city, periphery, hinterland and entire extent have been used. The following areas have been created as shape files. Continuously they were used as a mask to in ESRI's ArcMap 10.0 to extract part of the UF derived through object-oriented classification process. Based on extracted urban footprints ultimate comparison of spatial growth as well as analysis of spatial pattern and distribution was performed. Comprehensive description regarding all spatial levels can be found in chapter 3.2.3. The classification process and extraction of UF is described in chapter 3.1.2 and 3.1.3. In addition built-up area masked by administrative unit was compared with population growth in case of every city.

4.2.1.1 Administrative unit

The idea is to relate population to spatial urban extension on the administrative level to allow for an assessment of density. This analysis needs to be on the spatial unit of administrative borders as no other reliable population data exist.

According to table 4-5 and figure 4-2 to 4-11 and 4.13 significant difference in spatial growth can be noticed between Eastern and Western European cities. Eastern European cities have been growing spatially much faster than their Western counterparts. Regarding the development of population conclusion is that Eastern cities are characterized by positive and faster growth of population, where in case of Western European cities small changes in citizen's number can be seen (Tab. 4-5). Detailed comparison of cities within each data set is given below.

Results reveal that Eastern European cities undergone spatial explosion. Following Eastern European cities grew adequately: Prague (210%), Minsk (224%) and Warsaw (241%) comparing to their size in 1975 year. Although, city of Kiev shows the slowest growth rate – 43%. Nevertheless, they are characterized by constant and significant growth of built-up area, thus densification processes occurred in strict city center. Since 1975 area of cities enlarged as follows: Kiev (97.7 km^2), Prague (135.5 km^2), Warsaw (191.9 km^2), Minsk (116.7 km^2), (Tab. 4-3). Relating to population development we see immense growth in Kiev, Warsaw, and Minsk especially between 1975 and 1990 which can associated with population boom.

On contrary, comparison of four Western European cities shows their growth spatially insignificant – from 9% (Munich), through 11% (Cologne), Hamburg (62%) to a maximum of 73% (Vienna) comparing to the particular area occupied in 1975. Overall, small variations of built-up area inside administrative unit can be noticed in case of Cologne and Munich - respectively (19.9 km^2 and 17.2 km^2) (table 4-3, 4-4) and charts (4-2 to 4-10 and 4-12). Two remaining Western European cities - Hamburg and Vienna exhibit unlikely bigger spatial growth. Since 1975 year Hamburg grew by 148.6 km^2, where Vienna has enlarged by 101.8 km^2. Hamburg is known as huge shipping city. Its growth can be linked with harbor development and business districts that have been created for management and shipping purposes. The population of Western European cities grew insignificantly.

It has to be underlined that among all cities under consideration Warsaw is the fastest growing one (from 135.7 km^2 in 1975, to 327.7 km^2 in 2010). However, Berlin (capital of Germany) is the biggest city within data set with its spatial extent equal to 591.9 km^2 (Tab. 4-5).

According to literature Kovács (2000) argues that the rise of Eastern city centers is especially well documented in the papers of Sỳkora on Prague and Tasan on Warsaw. In addition Kovács (2000) reveals in his paper an obvious connection between revitalization of inner city neighborhoods and the growing integration of these places to the world economy known as expansion of the global market – globalization.

	Cologne	Munich	Hamburg	Vienna	Berlin	Kiev	Prague	Warsaw	Minsk
≈1990	5.3	9.5	28.1	47.0	60.7	32.8	49.0	59.7	36.8
≈2000	6.4	6.8	66.0	27.1	64.6	31.6	26.0	53.3	38.4
≈2010	8.2	0.9	54.4	27.7	45.4	33.4	60.5	78.9	41.4
sum	19.9	17.3	148.6	101.8	170.7	97.8	135.5	191.9	116.7

Tab. 4-3 Annual spatial growth rate calculated for area limited by administrative borders (km^2/year)

4.2.1.2 Core city

The spatial growth of built-up areas within the city cores (fig. 4-12) reveals similar relations. We see centers of Eastern European cities growing faster especially since the year 1990. The core city areas of Minsk, Prague and Warsaw grew appropriately: Minsk from 94.85 km^2 to 266.66 km^2, Prague from 120.71 km^2 to 253.55 km^2 and Warsaw from 142.58 km^2 to 347.65 km^2 which is about 2-2.5 times comparing to area occupied by particular city in 1975. Noteworthy is the fact that the area occupied by western European cities is much bigger in 1975 than their Eastern counterparts. Eastern cities seem to be less spatially developed in 1975 and not as dense regarding to built-up area as their Western equivalents.

4.2.1.3 Periphery

On the spatial level ‘periphery’ we see Eastern cities growing significantly faster (fig. 4-15). Here immense increment has started in 1975; however the biggest spatial growth can be noticed beginning with the decadal interval between 1990 and 2000. Among Western cities on following level Berlin stays spatially as the biggest one over the entire monitoring period (467.21 km^2). On contrary in data set of Eastern European cities the biggest city is represented by Warsaw (349.74 km^2). On contrary the fastest spatially growing city among Western ones is Vienna (from 32.08 km^2 in 1975 to 40.43 km^2 in 2010) which is 6 times more comparing to its area in 1975. Concerning Eastern Europe cities the fastest spatially increasing is Minsk (from 11.05 km^2 in 1975 to 209.15 km^2 in 2010) and is represented as the highest (19 times) spatial growth in relation to its size in 1975.

4.2.1.4 Hinterland

Western European cities on level of the hinterland are much larger spatially (fig. 2-21); Here in Western data set the biggest is Cologne (1235.4 km^2 in 2010), where among Eastern cities the largest is Kiev (1083.2 km^2 in 2010); nevertheless we found the fastest growth rates in the hinterland level in East European cities (tab. 4-5). The fastest growing in Western Europe is Vienna (from 88.07 km^2 in 1975 to 557.19 km^2 in 2010) and it is compared to 6 times growth. Browsing Eastern European cities, Warsaw has to be underlined (spatial growth from 23.65 km^2 in 1975 to 437.51 km^2 in 2010) and stays for immense 18.5 times growth.

4.2.1.5 Entire extent

For comparison relative spatial growth was calculated. Calculation of relative spatial growth was related to the particular built-up area of each city in 1975. Analyzing the entire extent (100km x 100 km) we see immense spatial growth in East European cities; at the same time spatial development of west European cities is significantly slower and more constant. These relations are clearly visible on chart (4-13 to 4-16). In average at following level Western European cities grew 1.8 times where their Western counterparts grew 4.8 times comparing to size occupied by a particular city in 1975.

The fastest growing city among Western Europe on entire extent level is Vienna (four times its spatial extent than 1975 in 2010) comparing to its size in 1975. Second place in growth dynamics is taken parallel by Berlin and Hamburg (two and half times). Regarding Eastern European cities we can notice intensively increasing spatial growth rates especially since 1990. Here Minsk (six times), Warsaw (five times) and Prague (five times) are among fastest growing cities (See fig. 4-13).

	Cologne	Munich	Hamburg	Vienna	Berlin	Kiev	Prague	Warsaw	Minsk
Administrative unit	11%	9%	62%	73%	41%	43%	210%	241%	224%
Core city	13%	11%	51%	84%	36%	47%	218%	244%	281%
Periphery	21%	33%	351%	589%	224%	400%	710%	720%	1894%
Hinterland	47%	212%	318%	633%	482%	437%	730%	1850%	962%
Entire extent	37%	56%	247%	374%	242%	315%	472%	528%	602%

Tab. 4-4 Growth of built-up area relative to occupied area in 1975. Calculation for all levels of interest.

	Cologne	Munich	Hamburg	Berlin	Vienna	Kiev	Prague	Warsaw	Minsk
Built-up area (km2)	475.7	319.4	713.9	941.5	758.8	97.7	899.5	920.0	757.1
Cities population (thousands)	94.0	54.0	65.0	320.0	125.0	879.0	139.0	274.0	727.0

Tab. 4-5 Range (difference between maximum and minimum value calculated for each city on entire extent level), built- up area and population

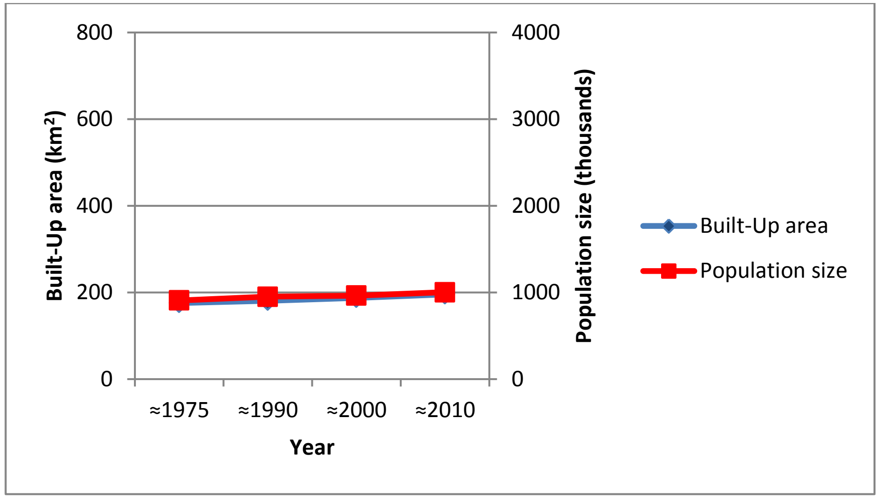


Fig. 4-2 Change of built-up area and population, Cologne (1975-2010)

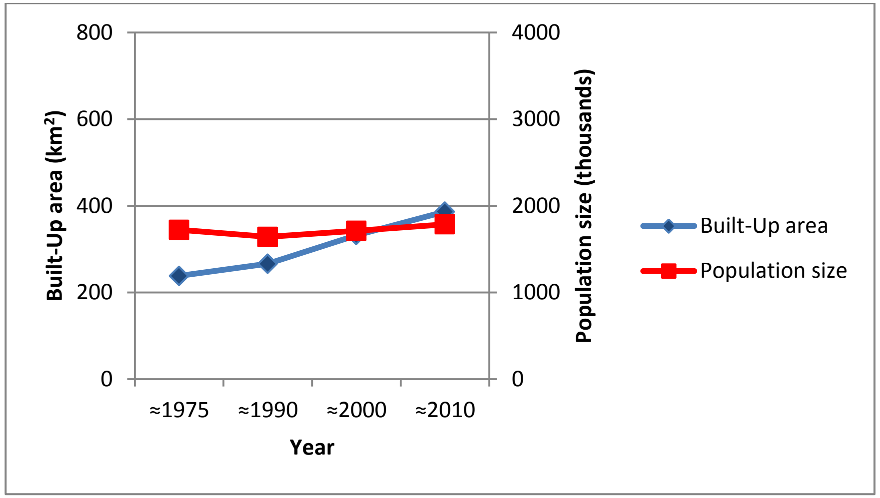


Fig. 4-4 Change of built-up area and population, Hamburg (1975-2010)

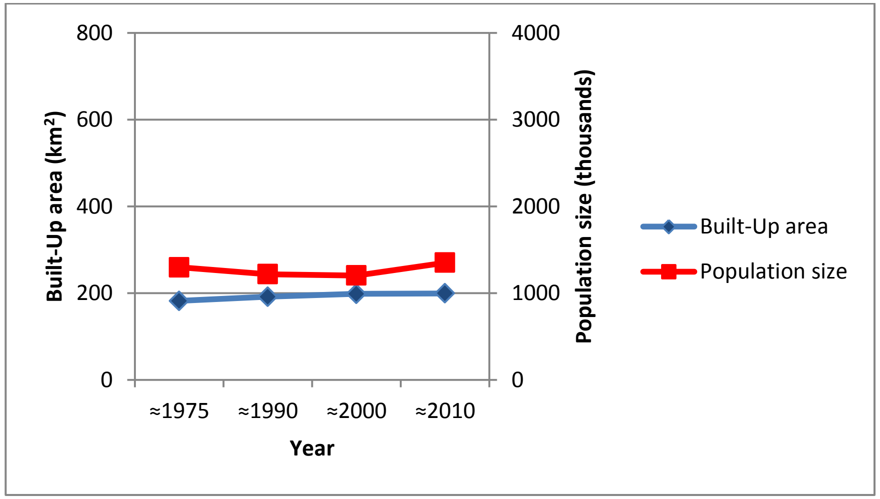


Fig. 4-3 Change of built-up area and population, Munich (1975-2010)

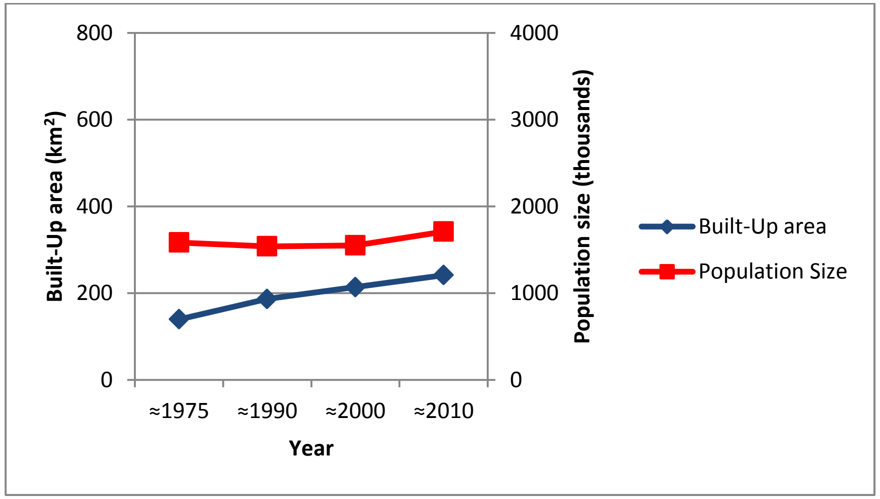


Fig. 4-5 Change of built-up area and population, Vienna (1975-2010)

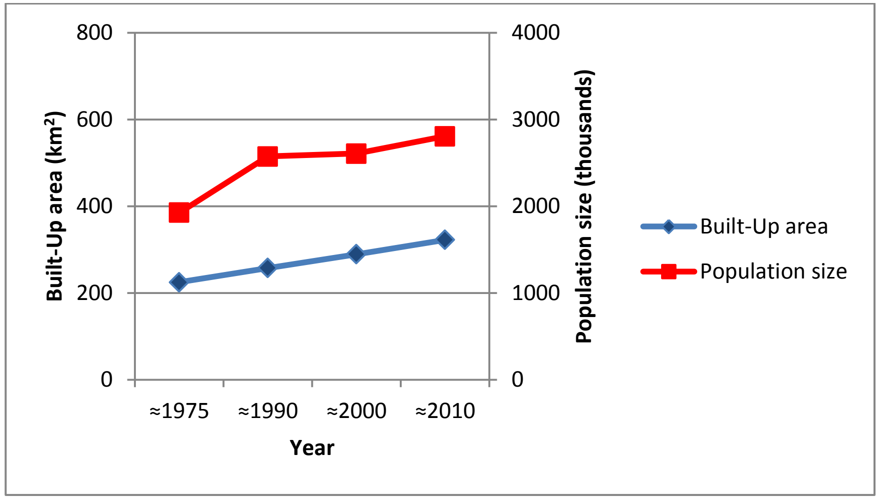


Fig. 4-6 Change of built-up area and population, Kiev (1975-2010)

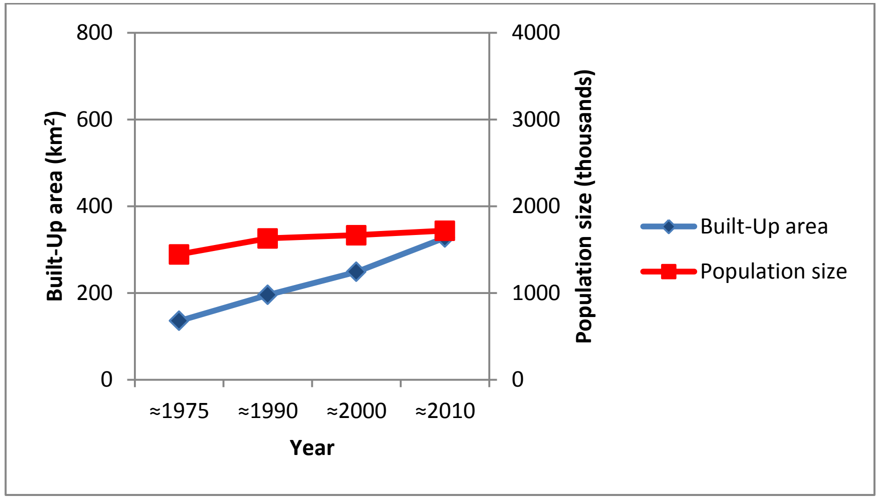


Fig. 4-8 Change of built-up area and population, Warsaw (1975-2010)

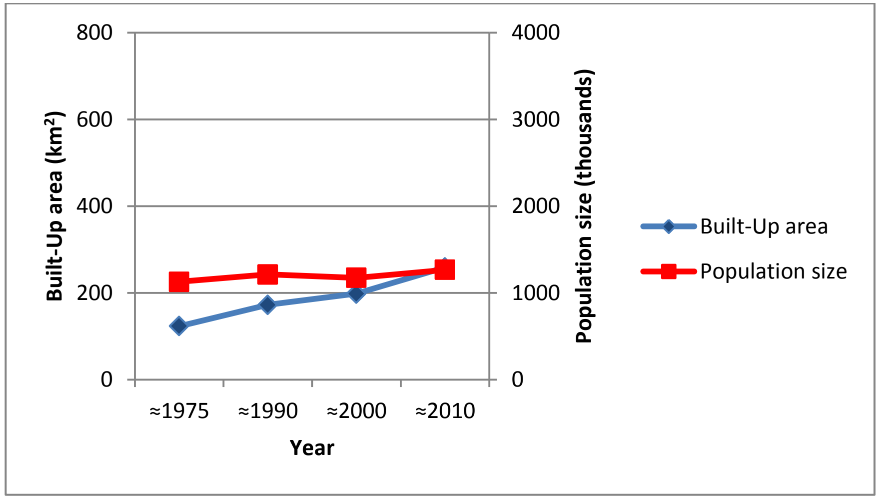


Fig. 4-7 Change of built-up area and population, Prague (1975-2010)

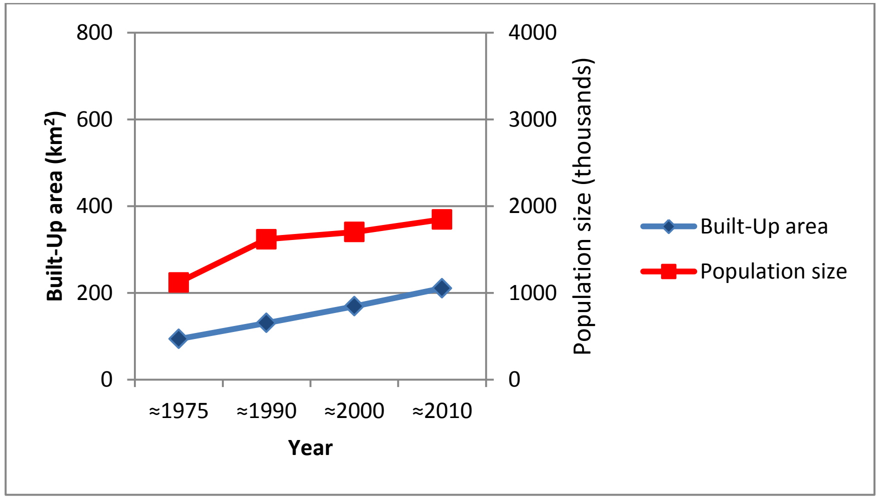


Fig. 4-9 Change of built-up area and population, Minsk (1975-2010)

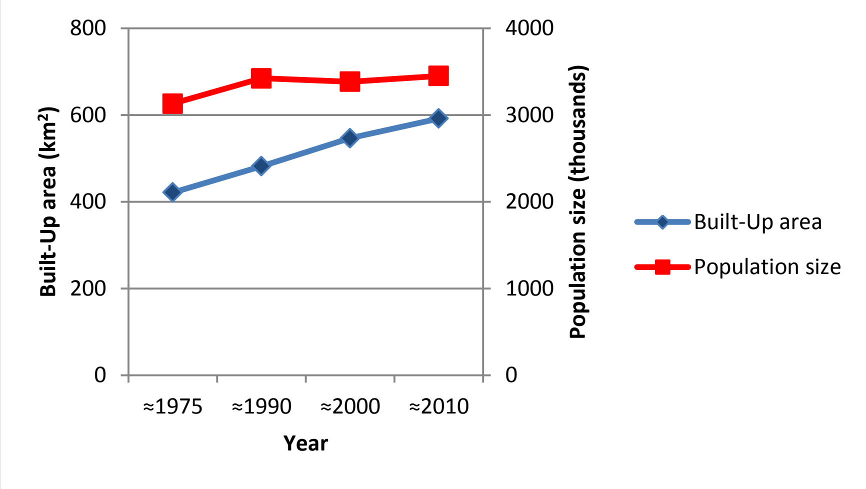


Fig. 4-10 Change of built-up area and population, Berlin (1975-2010)

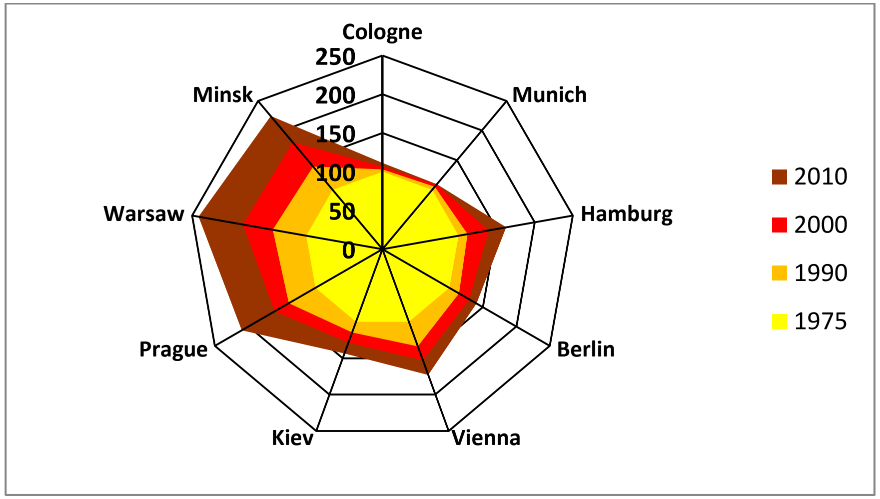


Fig. 4-12 Change of built-up area among cities within core area (1975-2010)

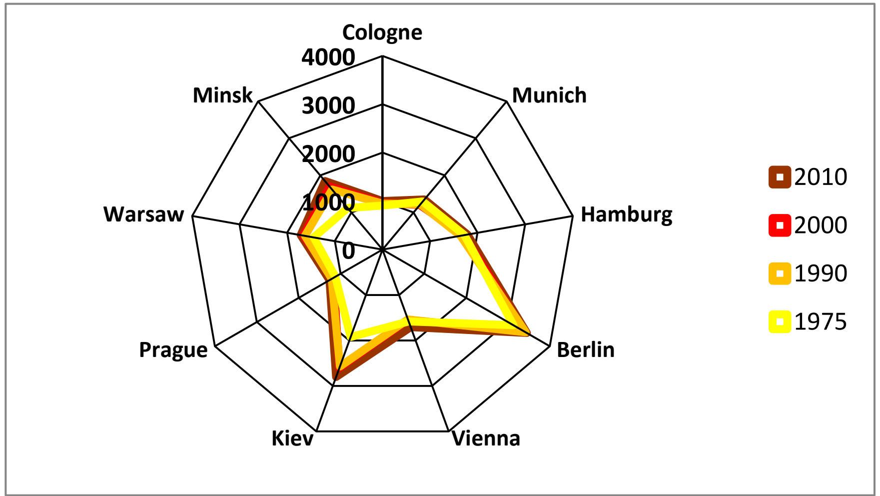


Fig. 4-11 Population development in selected European cities in thousands (1975-2010)

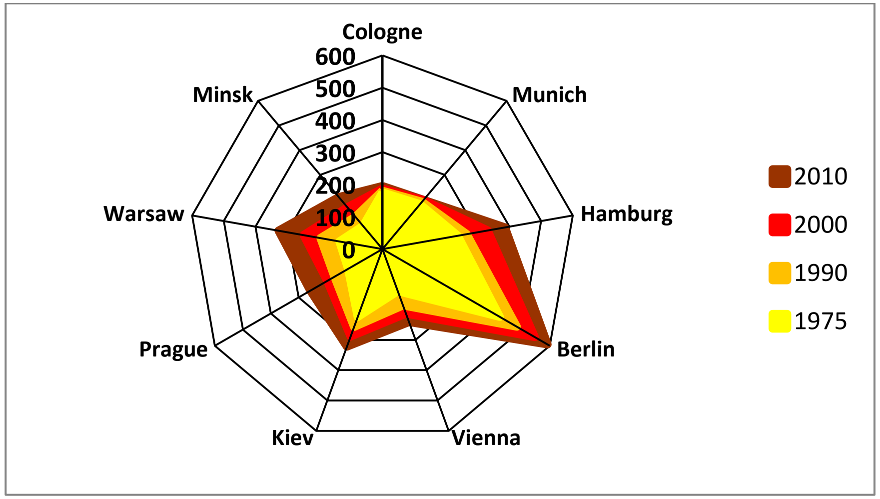


Fig. 4-13 Development of built-up area among cities within administrative border in km^2 (1975-2010)

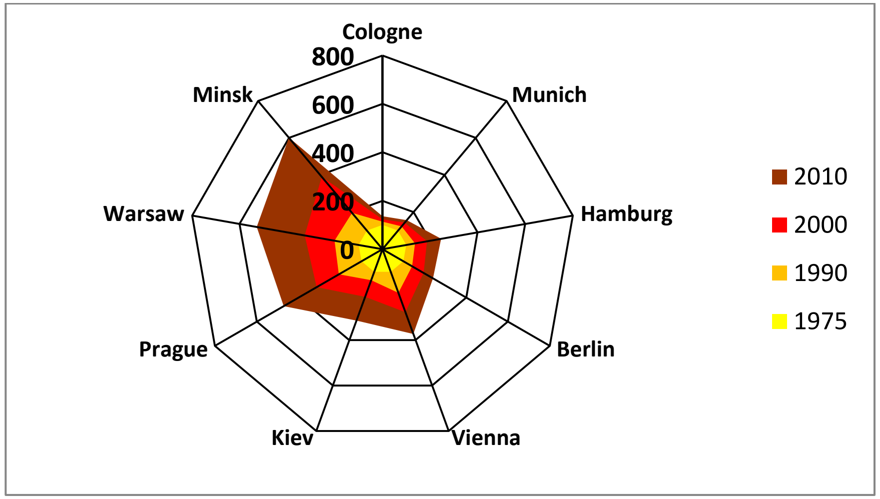


Fig. 4-14 Growth (in percent) of built-up area relative to its size in 1975, (entire extent)

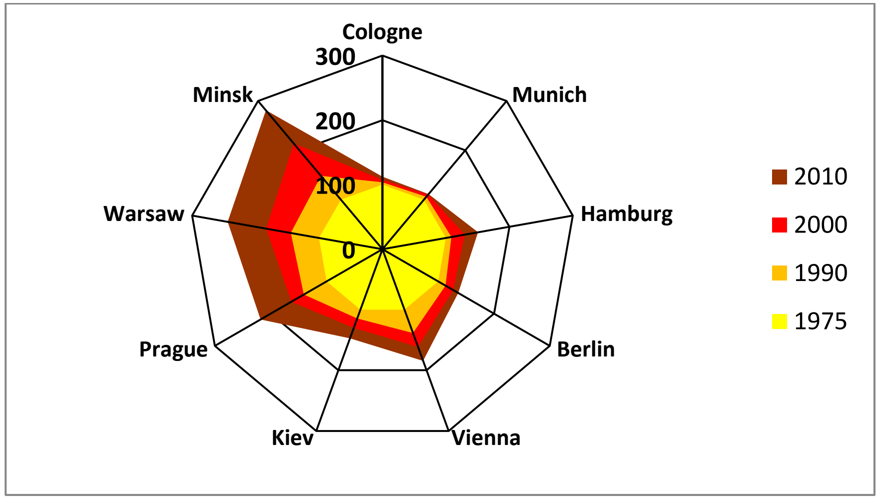


Fig. 4-16 Growth (in percent) of built-up area relative to its size in 1975, (core city)

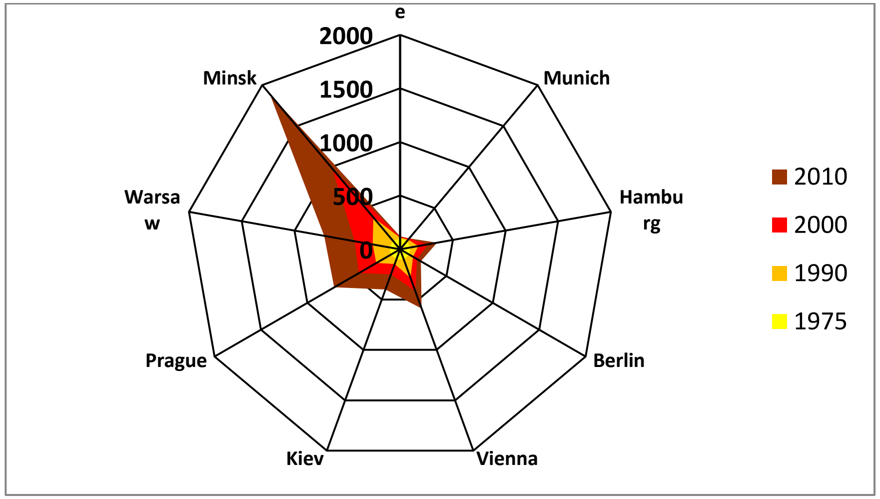


Fig. 4-15 Growth (in percent) of built-up area relative to its size in 1975, (periphery)

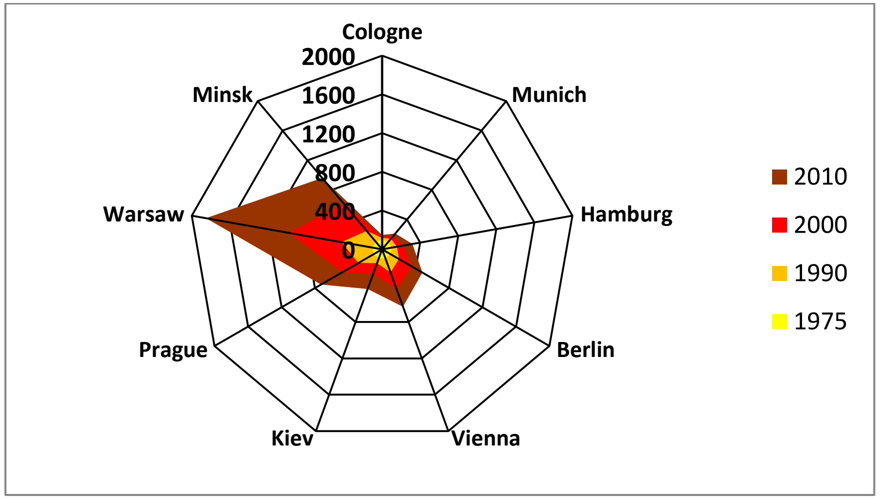


Fig. 4-17 Growth (in percent) of built-up area relative to its size in 1975, (hinterland)

4.2.2 Analysis of Landscape Metrics based on various spatial levels

To analyze spatial pattern of selected cities landscape metrics have been applied on four out of five previously used levels, namely: core area, periphery, hinterland and entire extent. Its spatial dimensions as well as the extraction procedure were described in detail in chapter 3.2.3.

4.2.2.1 Built-Up area/Class area (CA)

The analysis of built-up areas on all four levels (core area, periphery, hinterland, entire extent) reveals immense growth rates in Eastern European cities. Prague, Warsaw, Minsk are cities with higher rate of increase. Figure (4-14 to 4-21) prove this growth dynamics. However, the fastest growing city among Western data-sets is Hamburg with 62% spatial growth of urbanized area comparing to its size occupied in 1975. Interesting is fact that the built-up area of Eastern European cities in 1975 (except Kiev) is constantly smaller comparing to Western cities.

4.2.2.2 Mean Patch Size (MPS/AREA_MN)

Generally we see clearly bigger mean patch size values of urbanized patches for the case of West European cities when compared to Eastern ones. Western cities occupy much bigger areas with respect to patch sizes especially comparing cities on entire extent level and core city level. It signifies that they are more compact. Greater dynamics in 2000 and 2010 time step can be noticed in west European cities. This trend is illustrated in figure (4-22 to 4-25).

4.2.3.3 Mean Patch Size Coefficient of Variation (MPSCV/AREA_CV)

The best relation of mean patch size coefficient of variation is visible on core city level, where in Western cities variability of the mean patch size decreases compared to East European cities, because number of patches is decreasing (especially at core city level) and their area is enlarged. On contrary in Eastern Europe the variability of mean patch sizes rises because of the appearance of numerous patches occupying small areas. In this example decreasing values of mean patch size coefficient of variation signify growing dispersion among urbanized patches.

4.2.3.4 Number of Patches (NP)

Entire extent

In the representative cities of west European cities (Cologne, Munich, Hamburg, Berlin) the number of patches has been decreasing constantly since the 1990s. Before 1990 constant growth in number of patches can be noticed. Ongoing decrease in number of patches can be associated with re-densification processes going on since that time-step. Vienna shows this development since the year 2000. On contrary, the number of patches grows massively until 2000 in Kiev and Prague, whereas Warsaw and Minsk indicate constant growth throughout the years. Prague and Warsaw stay as the patchiest cities, which hint at a very dispersed spatial pattern. All relations are to be found on figure (4.30-4.33).

Core area

In the core area spatial level constant decrease of number of patches can be observed for Western European cities such as: Cologne, Munich, Vienna. It means that urbanized patches have been constantly disappearing or they have been merged with other ones. Therefore cities on this spatial level are dense in number of patches and in time. In the East European cities main trend shows decrease number of patches since 2000 (Kiev, Prague) or from 1990 (Warsaw), where concerning Minsk, number of patches stays constant.

Periphery

Number of patches on periphery level displays similar relation as in entire extent level. Western European cities have been decreasing in number of patches constantly, whereas their Eastern European counterparts have been growing in number of patches until 2000 year. City of Kiev and Prague have started to decrease in number of patches since 2000 year. Very dispersed pattern of patches on this level is kept in both cities, namely Warsaw and Prague.

Hinterland

The hinterland spatial level reveals decreasing number of patches since 1990 in cities like: Cologne, Munich, Hamburg. The same trend, however since 2000 have started in Berlin. Nevertheless Vienna shows constant growth in number of patches. On contrary Eastern European cities such as: Kiev, Prague shows decreasing number of patches since 2000 year, where the remaining Eastern cities increase in number of patches.

4.2.3.5 Patch density (PD)

All spatial levels show similar relations with respect to the patch density. In Western European cities the patch density decreases either constantly over time or from 1990s on. Constant decrease in values of patch density index occurred in Munich and Cologne. Cities such as: Hamburg and Vienna reveal decreasing values since 1990s. Eastern agglomerations behave in the opposite manner – here patch density constantly increases over time, or as for example of Kiev and Prague grow till year 2000 and then decreases. Growing patch density can be associated with ongoing development of built-up areas, as number of patches is increasing too. However the patch density can support statement, that re-densification process started earlier in the West (1990) than East Europe (2000).

4.2.3.6 Largest Patch Index (LPI)

The calculated values of the *Largest Patch Index* are constantly growing for the cases of East European cities on the spatial levels of the entire extent of analysis and the core city level. Big increase of LPI values has started since the year 2000 which indicates enlargement of cities. Moreover Warsaw and Minsk point out new urban units emerging within its periphery area. However, Cologne, Berlin and Hamburg show comparatively high LPI values on the peripheral spatial level too. It means highly compacted urban pattern. On the other hand the city of Cologne represents the biggest urbanized unit within its hinterland area. The reason for that is neighboring with cities such as Bonn and Leverkusen.

4.2.3.7 Largest Patch Index $(1\text{-}5)_{land}$

The index represents the LPI derived for the biggest 5 patches related to the area of the entire extent. Generally for Western European cities it is typical that the only significant patch is the biggest one. Concerning Eastern European cities the conclusion is that the second biggest patch is relevant too, which means new urban units rising in core city neighborhood. Comparing cites among each other conclusion is that Kiev, Warsaw and Minsk reveal big differences in size of the biggest patch between 2000 and 2010 year. In addition the modified Largest Patch Index depict Cologne and its neighboring area consisting of three relatively big urban patches (Fig. 4-42).

4.2.3.7 Largest Patch Index $(1\text{-}5)_{urb}$

Eastern European cities reflect significance in size of the second patches. In comparison to Western cities such dependency cannot be observed (fig. 4-51 to 4-59). We see clear dominance of the first patch concerning size in Western European cities. Consequently, cities like Warsaw, Prague and Kiev show a decrease in size of the biggest patch until 2000 year.

Since that year, the only significant patch regarding to its size in mentioned above cities is the biggest one. Minsk and Warsaw represent units with the highest growth rate for the largest 5 patches. The largest patch of their Western counterparts decreases slowly and constantly over time. Here, taking the example of Cologne, the city is characterized by highly developed periphery (neighboring cities such as Bonn and Leverkusen dominate the spatial pattern) as well as the hinterland area (fig 4-21, 4-41).

4.2.3.8 Euclidian Nearest Distance Mean (ENN_MN)

With respect to the *Euclidian Nearest Distance Mean* constantly growing values of mean distances among patches in Western European cities can be observed. The reason for that behavior can be explained as absorption of small patches signifying small villages by another, bigger units growing in close neighbor. Distances between patches decrease in peripheries and hinterland level of Prague, Warsaw and Minsk, so that densification processes can be calculated.

4.2.3.9 Euclidian Nearest Distance Coefficient of Variation (ENN_CV)

In the majority of cases a decreasing variability in values of *Euclidian Nearest Distance Coefficient of Variation* from 2010 towards 1975 for the representatives of Western European cities cannot be detected. It is related to the decreasing number of patches as well as to re-densification processes taking place in Western European cities. Regarding Eastern Europe dependencies are exactly the opposite – the number of urbanized patches is constantly growing, so that variability rises over time. In other words pattern of Eastern European cities is more dispersed than their Western counterparts.

4.2.3.10 Shannon's Entropy

As described in chapter 3.2.4.9 Shannon's Entropy index measures the degree of spatial concentration or dispersion of a geographical variable *x (e.g. built-up area)* among *n* zones and signifies whether land development is dispersed or rather compact.

Results obtained by calculation of Shannon's entropy index are presented as maps containing all four time steps with the particular mean value calculated by a fixed moving window and assigned to aggregated 1km x 1km raster cells. The spatial level of this analysis equals the entire AOI. Here highest values were marked as colors approaching red, where low values are represented by colors closer to green. All values have been assigned to classes with equal width of interval (0.06). Interval was computed as subtraction of maximum and minimum value that occurred in the entire data set. Consequently received digit was divided to 6 as we would like to have such a number of classes. Division to 6 classes shows in the best way occurring magnitude and direction of urban sprawl in case of cities under consideration.

Results signify that core city centers are getting more and more compact over time, whereas dispersion of built up areas is notified in the periphery and the hinterland level (see appendix D). Quantitative measures confirm visual interpretation and depict the biggest dynamics in the Shannon's entropy values occurring in two, periphery and hinterland levels (see fig. 4.68 – 4.70).

To represent visually in more appropriate manner magnitude and direction of sprawl, two approaches have been chosen. At first we implemented adding operation of all aggregated Shannon's Entropy raster maps (1km x 1km) accordingly to each city AOI (Appendix E). Every map has been classified according to the rule given above. The only exception is that the length of interval has been changed (0.02) and greater number of classes was introduced - 7. Using this classification approach we did not lose information and we convey information in straight forward way.

The selected approach shows all cities are increasing in their level of spatial compactness throughout the years on core city level. However, in the case of Prague, Warsaw and Minsk decreasing values have been observed since the year 2000. That confirms again ongoing re-densification processes, although with 10 years delay compared to Western Europe. On the other hand high values means land fragmentation and occur particularly on the spatial levels of periphery and hinterland. Analyzing the periphery level we see that land fragmentation has stopped in Western cities earlier (1990/2000 year) where in East European cities fragmentation of built-up area is sustained in time.

Second approach aiming to depict magnitude and direction of urban sprawl was applied as simple subtraction of raster files according to following formula (raster $_{t+1}$ – raster $_{t}$), (see appendix F). Here the map legend depicts four different classes, namely:

- pixels in light green – signify that there is no change in Shannon's entropy values between two neighboring time steps. Range of values greater/equal -0.001 and smaller/equal 0.001
- pixels in blue – depict values smaller than -0.001 and denote increasing land compactness over time
- pixels in red – imply values bigger than 0.001 and mean land fragmentation
- pixels in white – cover the places in the AOI without data, as no urbanized area has been classified there

The analysis is done for all cities expect Munich and Cologne. It has to be underlined that entire urban footprint for following cities consist of two classifications that have been done by various persons (approximately 70% have already existed before, where 30% had to be done in scope of this master dissertation). During mosaicking of both urban footprints relevant differences in their accuracy (level of details) have been noticed, therefore we decided to normalize them. Unfortunately that operation has huge influence to subtraction method, applied here. Maps can be browsed in appendix F.

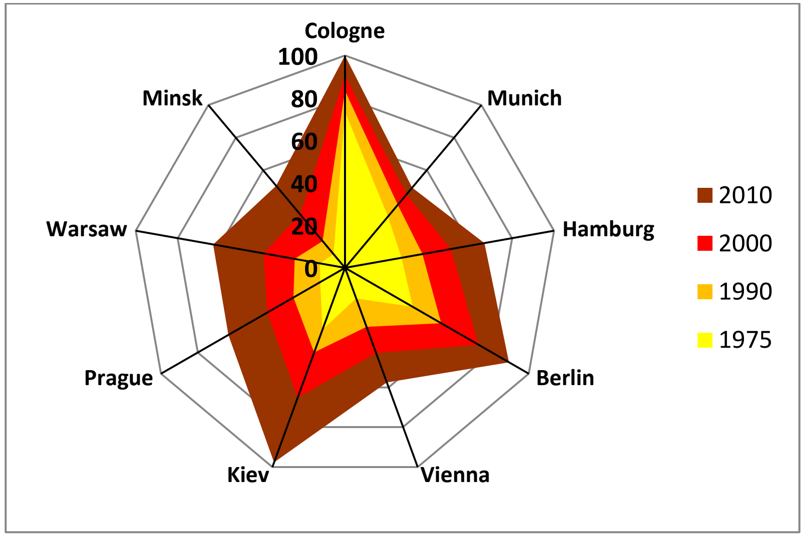


Fig. 4-18 Built-up area (entire extent)

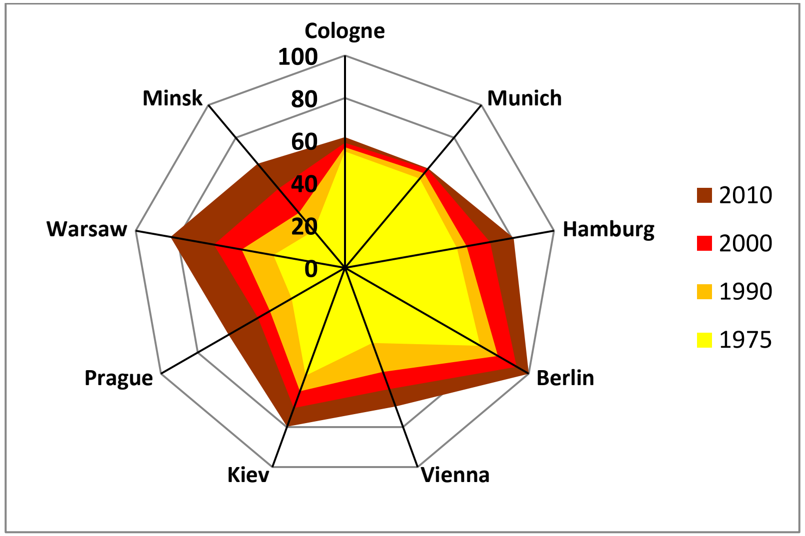


Fig. 4-20 Built-up area (core area)

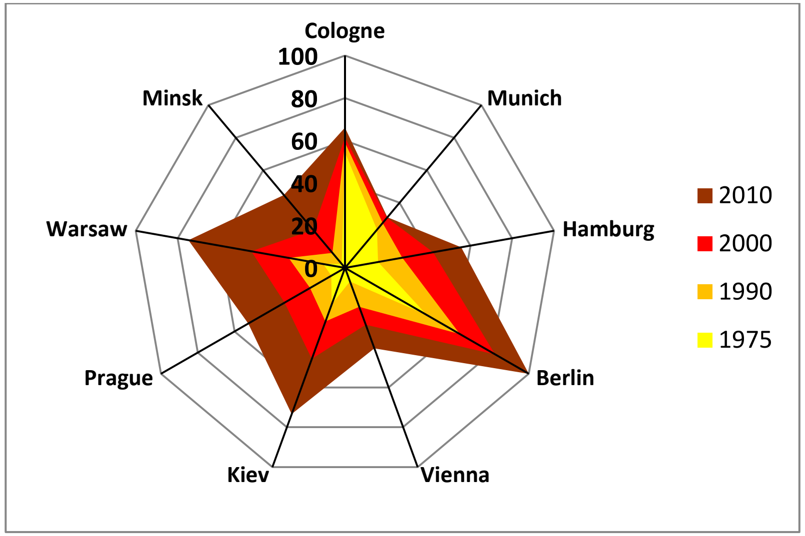


Fig. 4-19 Built-up area (periphery)

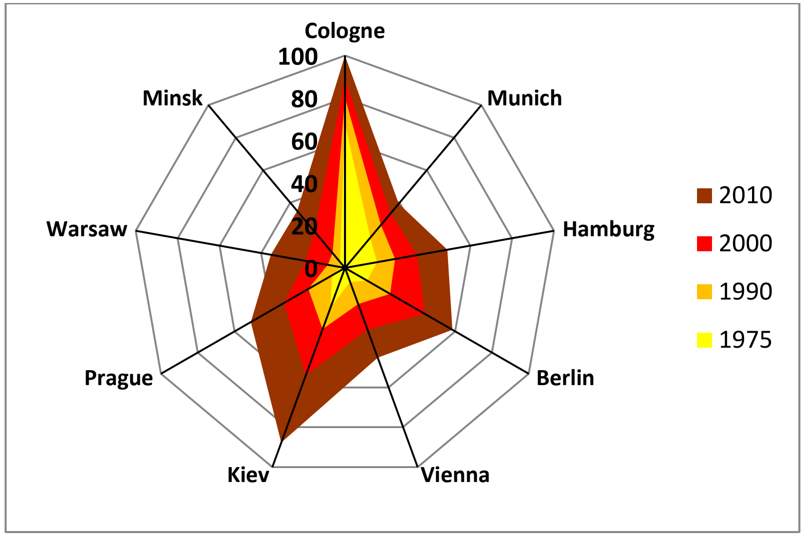


Fig. 4-21 Built-up area (hinterland)

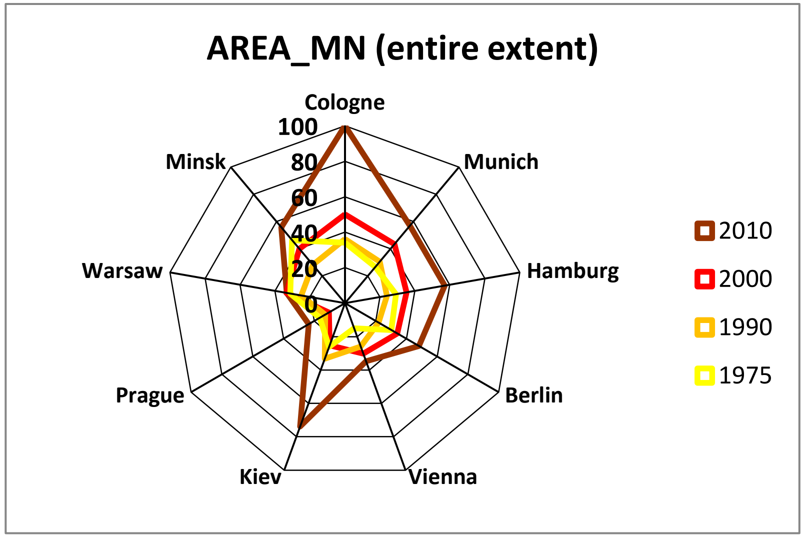


Fig. 4-22 Mean Patch Size (entire extent)

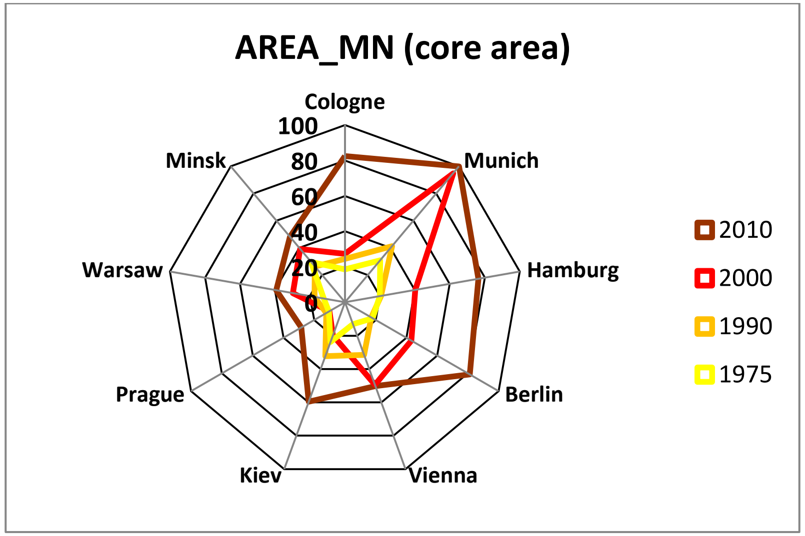


Fig. 4-24 Mean Patch Size (core area)

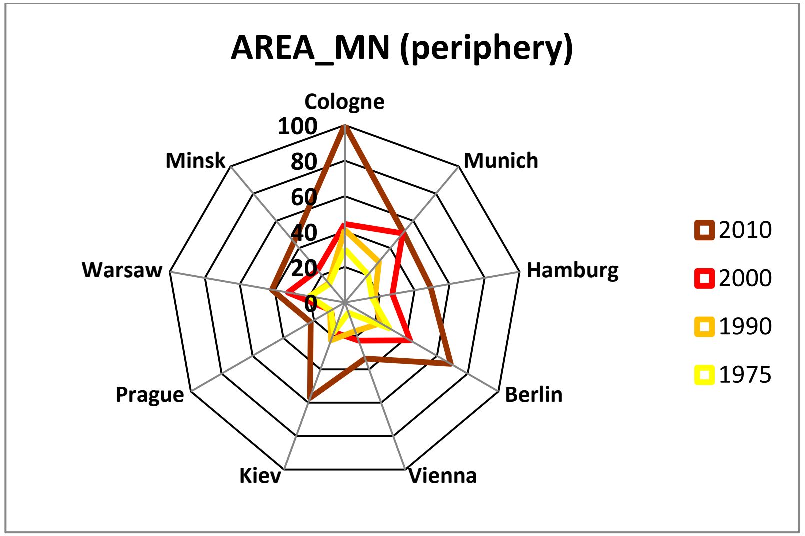


Fig. 4-23 Mean Patch Size (periphery)

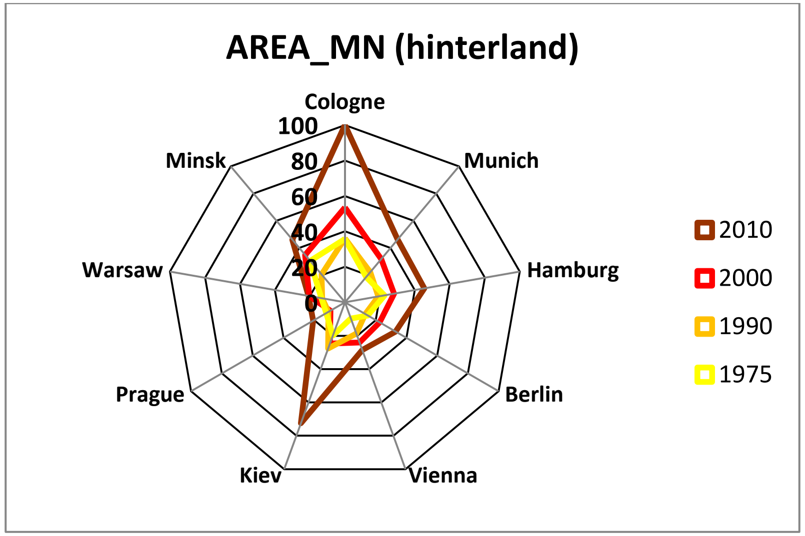


Fig. 4-25 Mean Patch Size (hinterland)

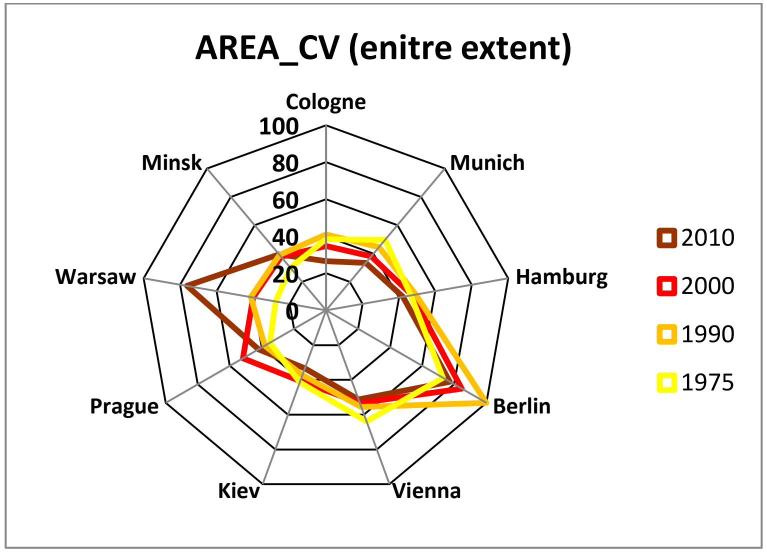


Fig. 4-26 Mean Patch Size Coefficient of Variation (entire extent)

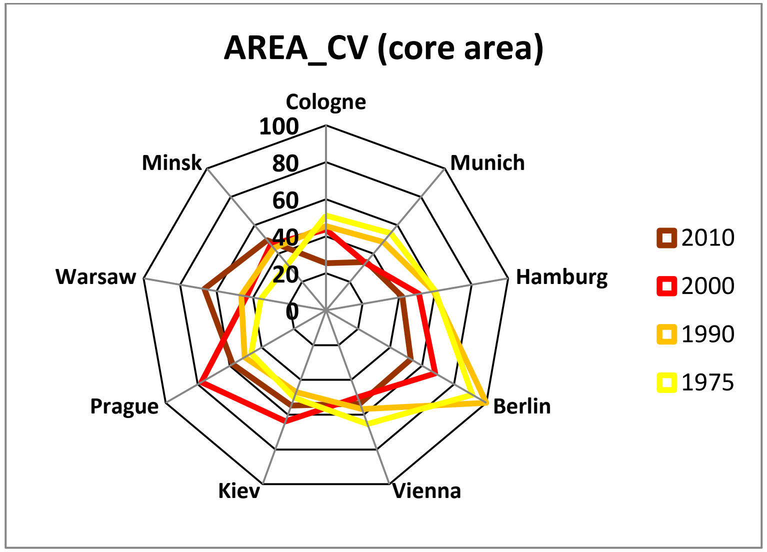


Fig. 4-28 Mean Patch Size Coefficient of Variation (core area)

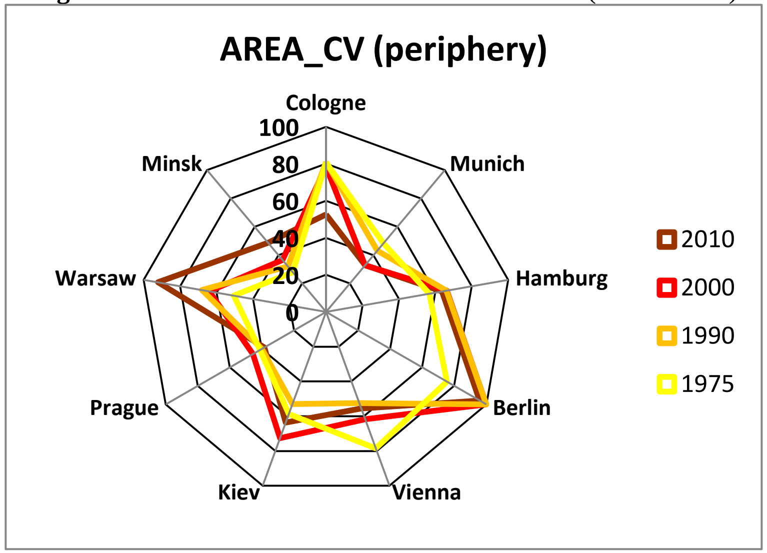


Fig. 4-27 Mean Patch Size Coefficient of Variation (periphery)

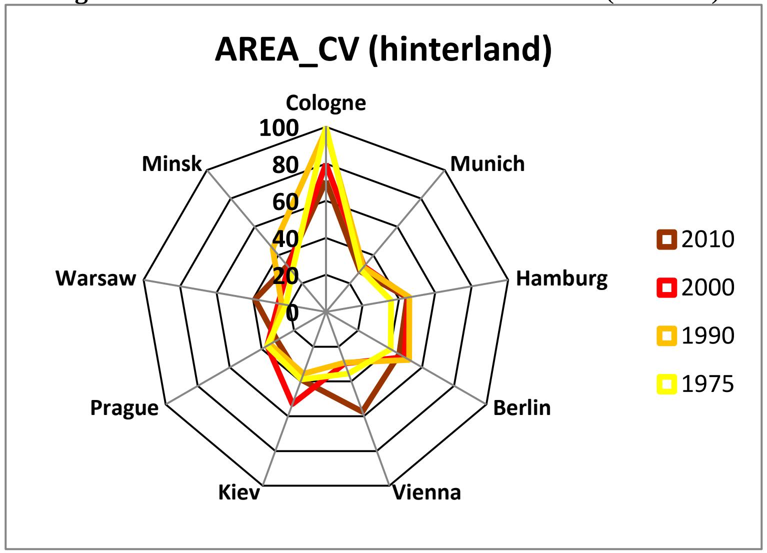


Fig. 4-29 Mean Patch Size Coefficient of Variation (hinterland)

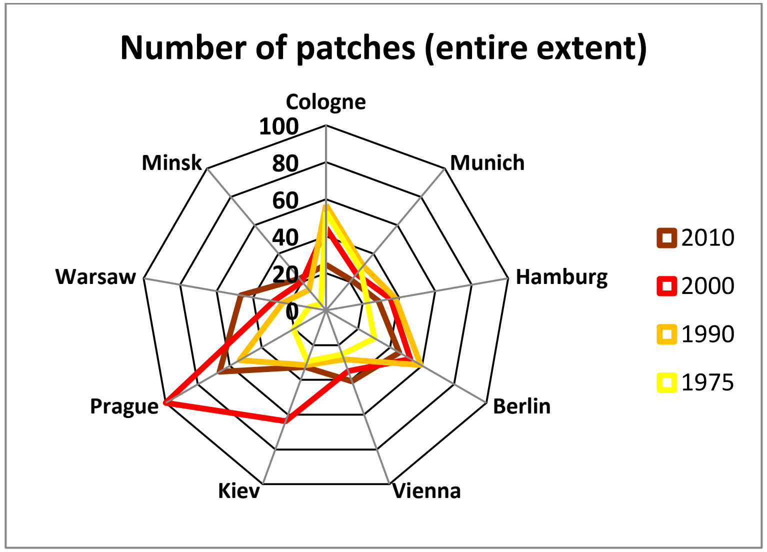


Fig. 4-30 Number of Patches (entire extent)

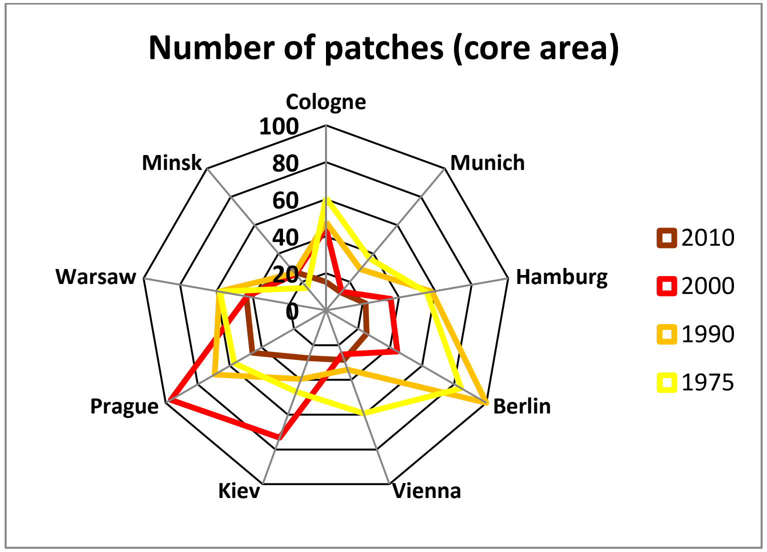


Fig. 4-32 Number of Patches (core area)

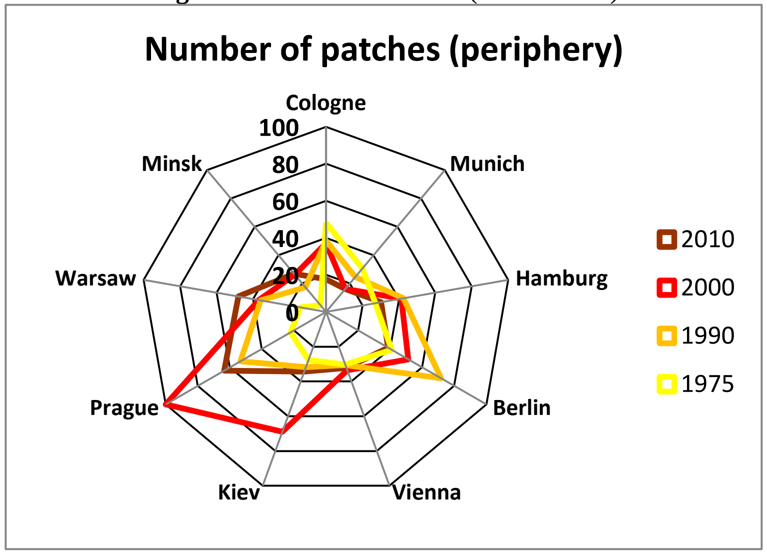


Fig. 4-31 Number of Patches (periphery)

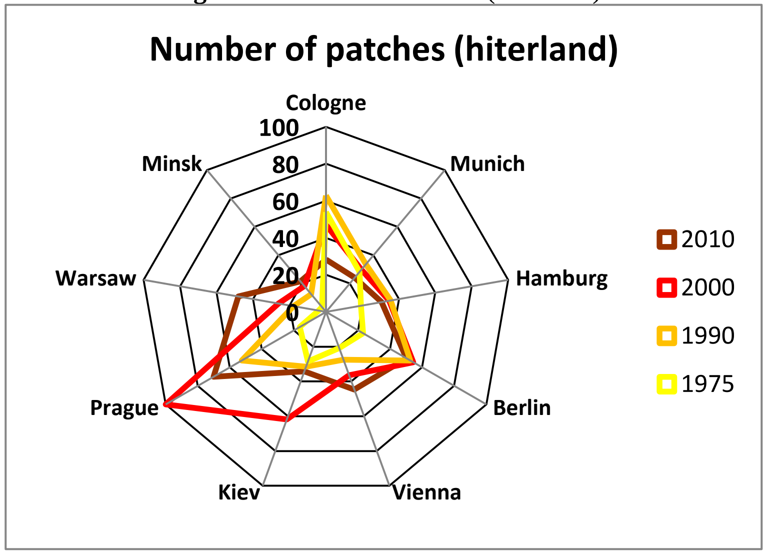


Fig. 4-33 Number of Patches (hinterland)

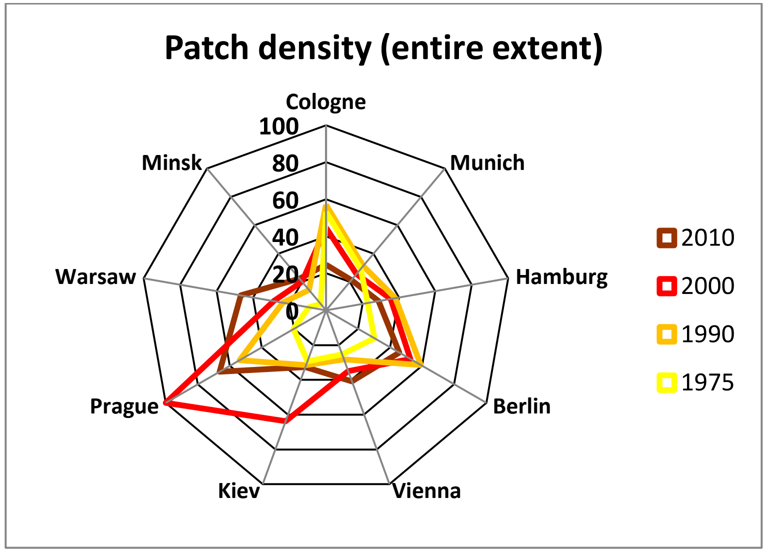


Fig. 4-34 Patch density (entire extent)

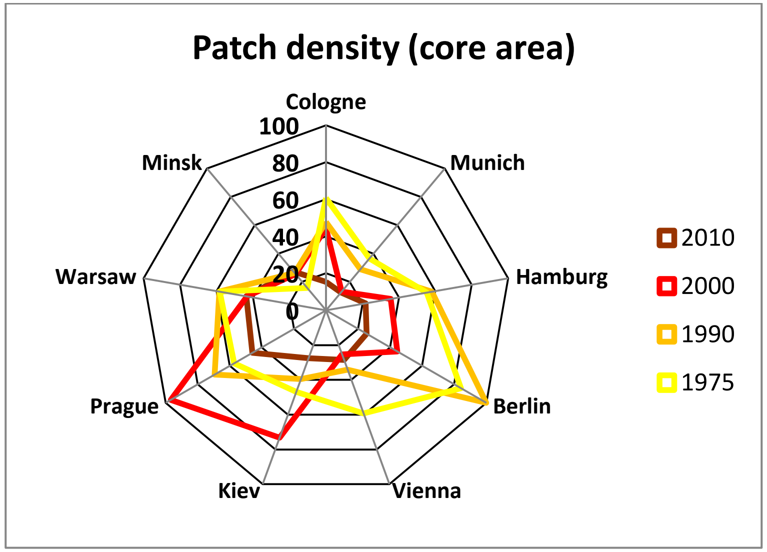


Fig. 4-36 Patch Density (core area)

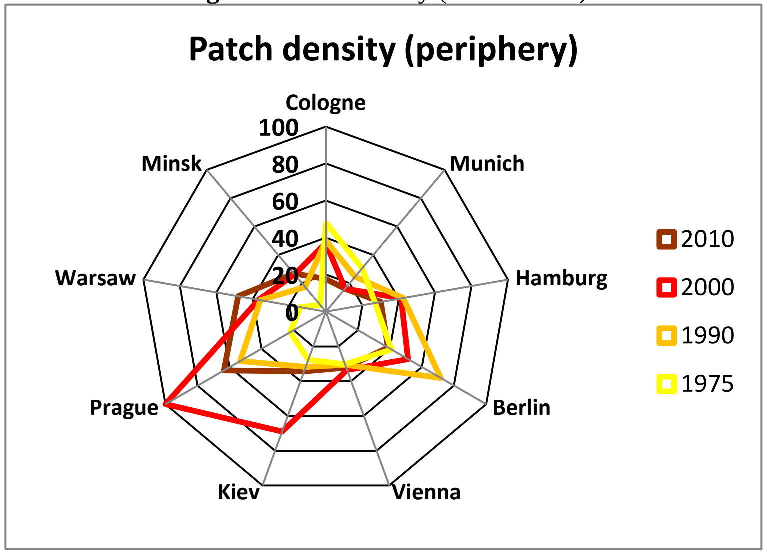


Fig. 4-35 Patch Density (periphery)

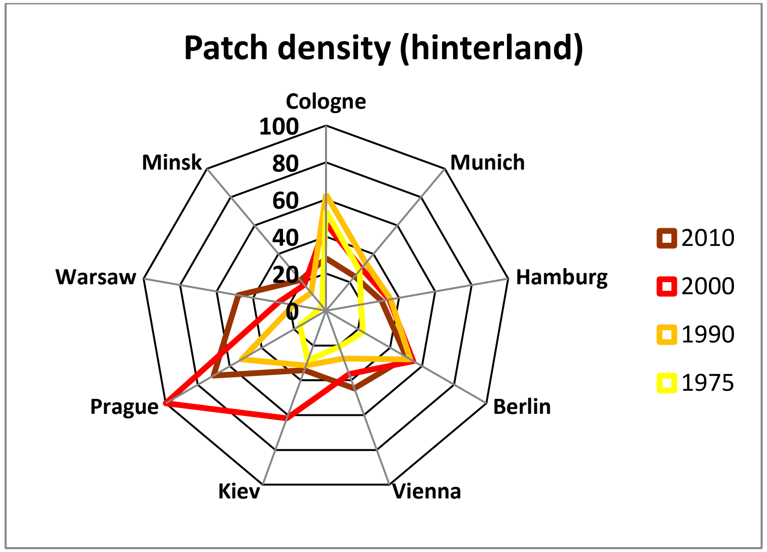


Fig. 4-37 Patch Density (hinterland)

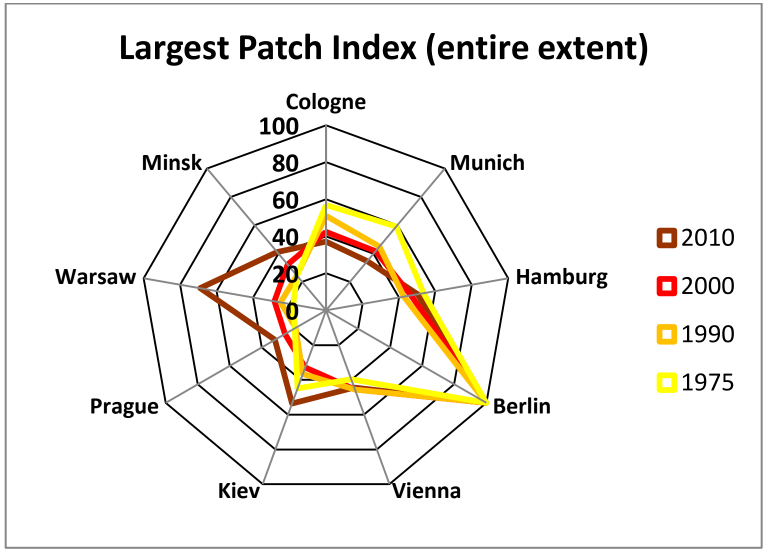


Fig. 4-38 Largest Patch Index (entire extent)

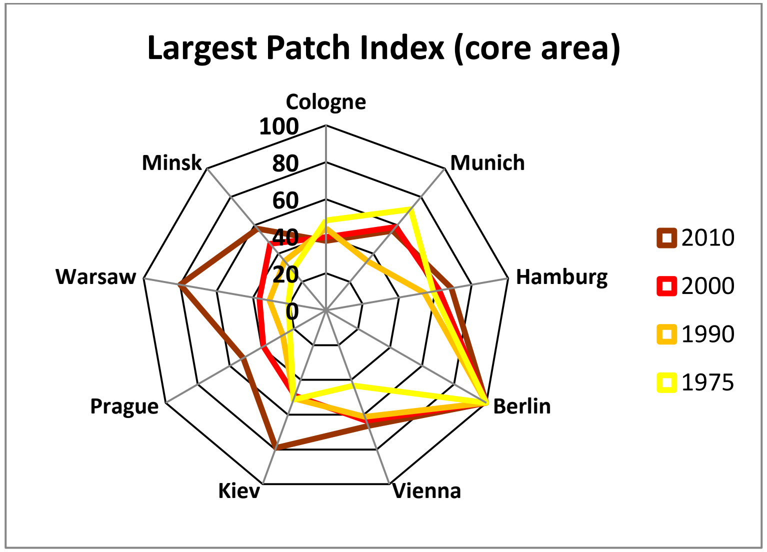


Fig. 4-40 Largest Patch Index (core area)

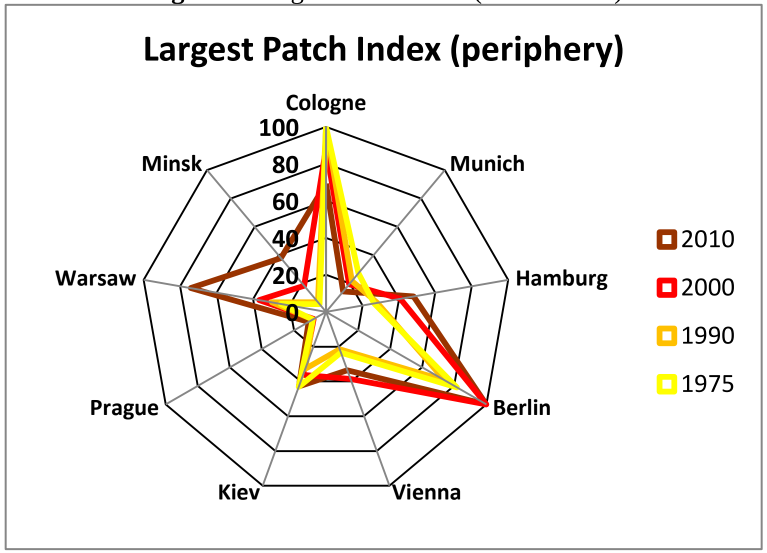


Fig. 4-39 Largest Patch Index (periphery)

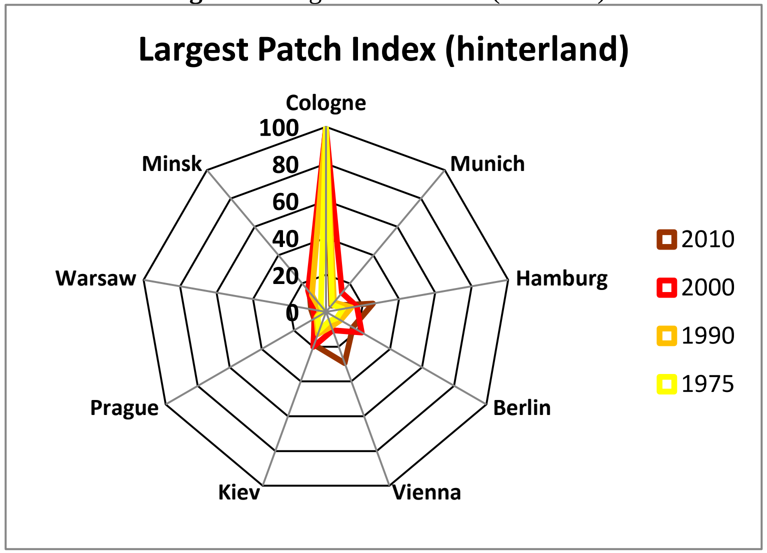


Fig. 4-41 Largest Patch Index (hinterland)

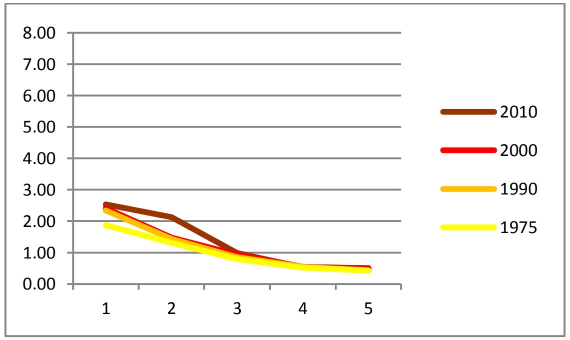


Fig. 4-42 Largest Patch Index $_{(1\text{-}5\ \text{land})}$ Cologne

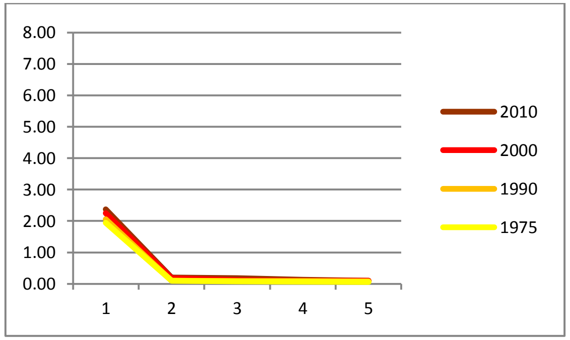


Fig. 4-43 Largest Patch Index $_{(1\text{-}5\ \text{land})}$ Munich

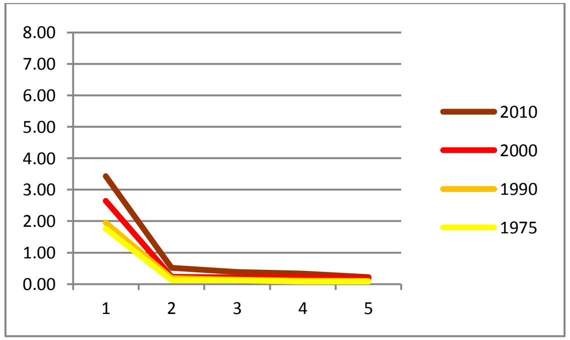


Fig. 4-44 Largest Patch Index $_{(1\text{-}5\ \text{land})}$ Hamburg

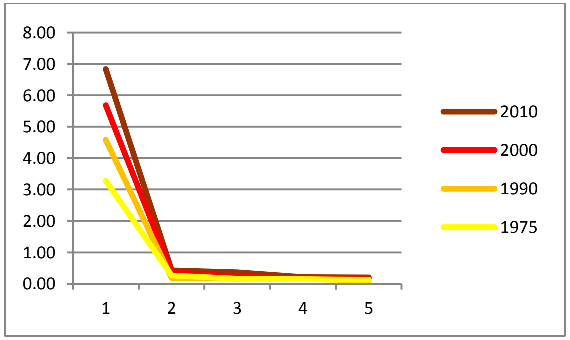


Fig. 4-45 Largest Patch Index $_{(1\text{-}5\ \text{land})}$ Berlin

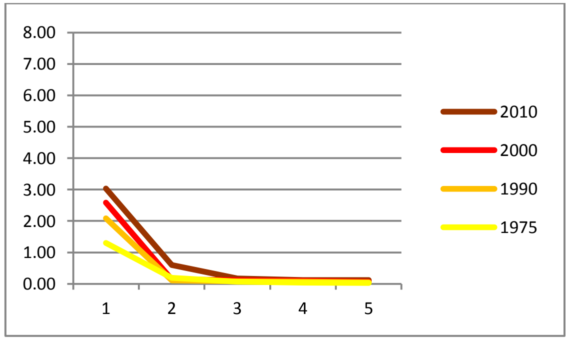


Fig. 4-46 Largest Patch Index $_{(1\text{-}5\ \text{land})}$ Vienna

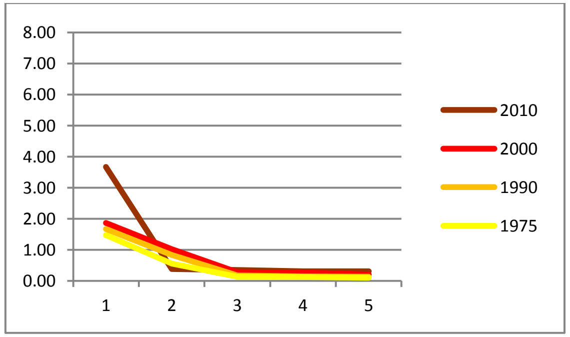


Fig. 4-47 Largest Patch Index $_{(1\text{-}5\ \text{land})}$ Kiev

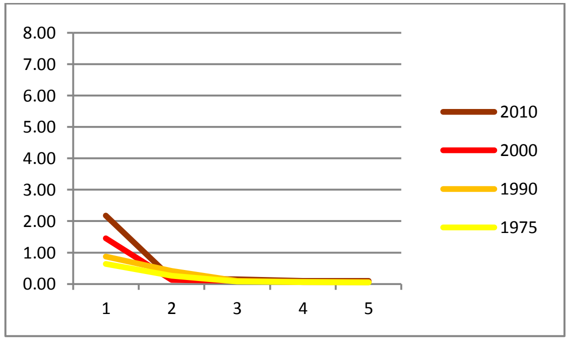


Fig. 4-48 Largest Patch Index $_{(1\text{-}5\ \text{land})}$ Prague

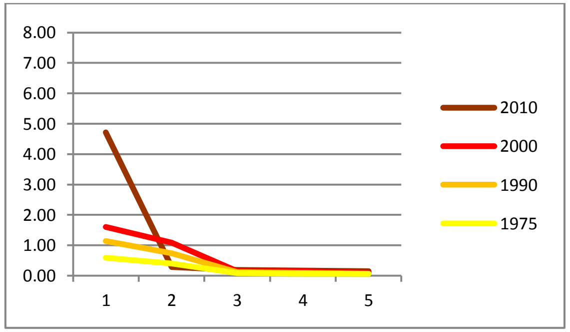


Fig. 4-49 Largest Patch Index $_{(1\text{-}5\ \text{land})}$ Warsaw

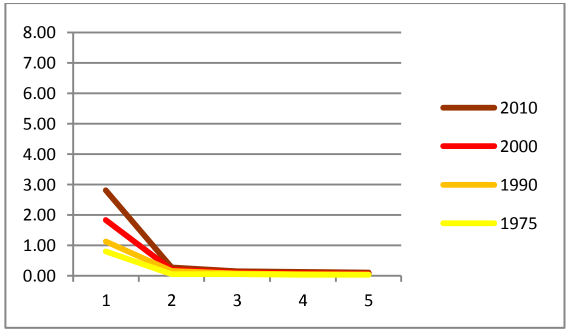


Fig. 4-50 Largest Patch Index $_{(1\text{-}5\ \text{land})}$ Minsk

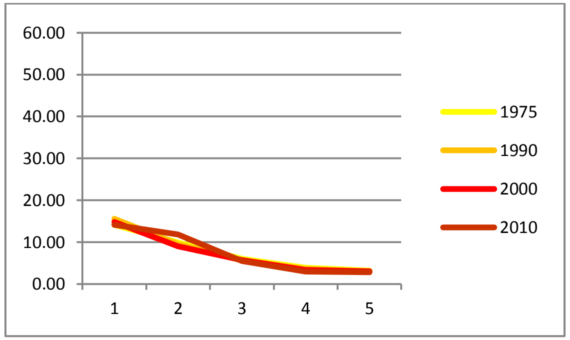


Fig. 4-51 Largest Patch Index $_{(1\text{-}5\ urb)}$ Cologne

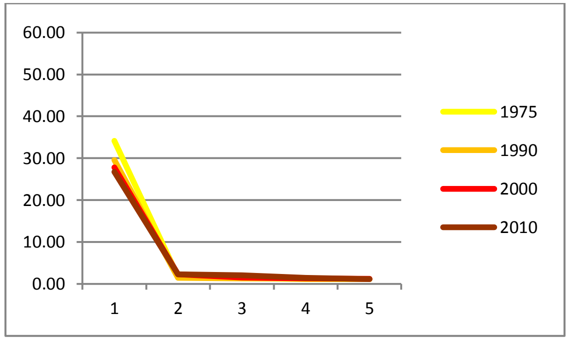


Fig. 4-52 Largest Patch Index $_{(1\text{-}5\ urb)}$ Munich

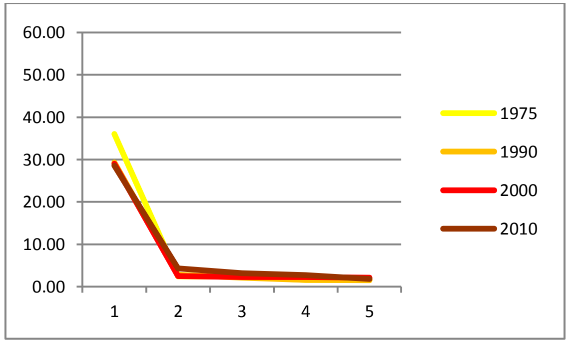


Fig. 4-53 Largest Patch Index $_{(1\text{-}5\ urb)}$ Hamburg

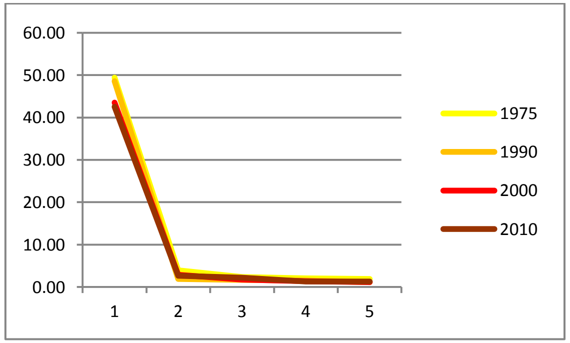


Fig. 4-54 Largest Patch Index $_{(1\text{-}5\ urb)}$ Berlin

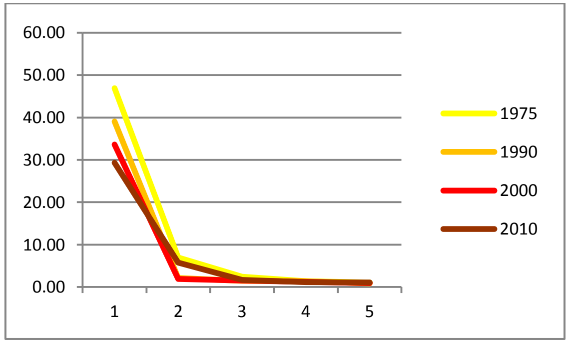


Fig. 4-55 Largest Patch Index $_{(1\text{-}5\ urb)}$ Vienna

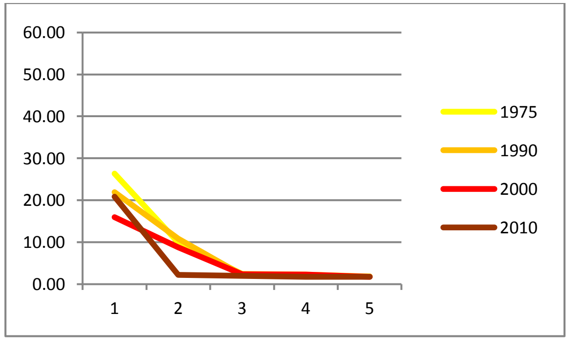


Fig. 4-56 Largest Patch Index $_{(1\text{-}5\ urb)}$ Kiev

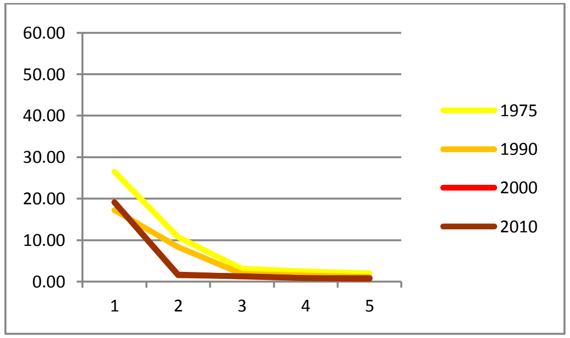


Fig. 4-57 Largest Patch Index $_{(1\text{-}5\ urb)}$ Prague

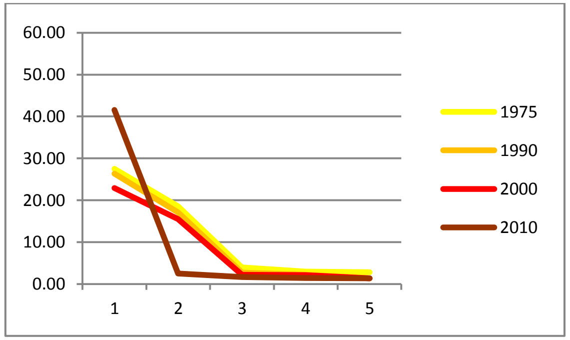


Fig. 4-58 Largest Patch Index $_{(1\text{-}5\ urb)}$ Warsaw

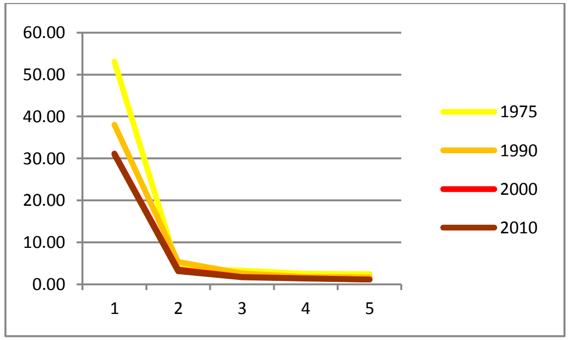


Fig. 4-59 Largest Patch Index $_{(1\text{-}5\ urb)}$ Minsk

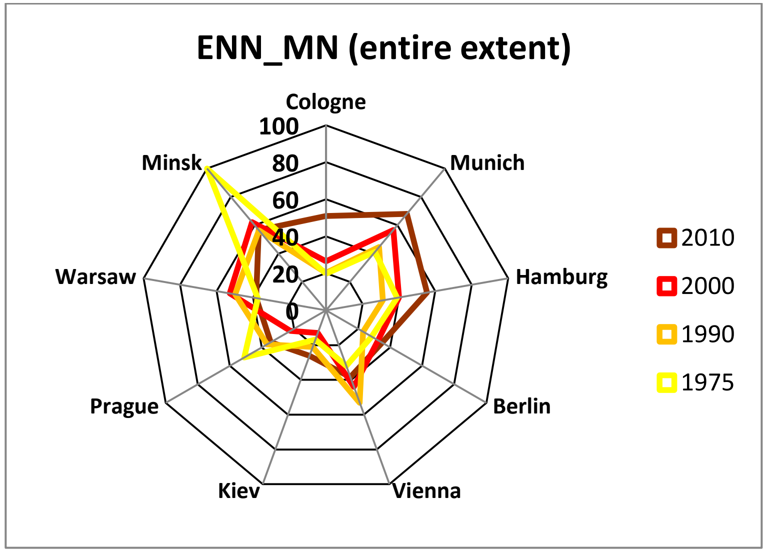


Fig. 4-60 Euclidian Nearest Distance Mean (entire extent)

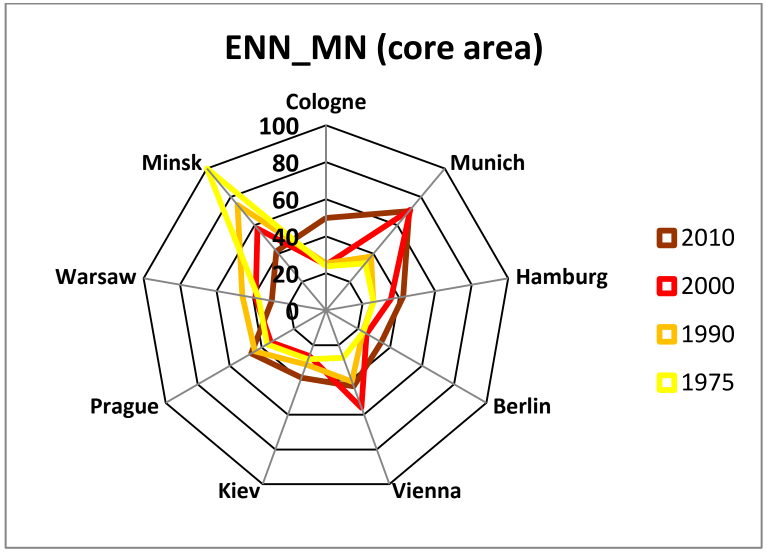


Fig. 4-62 Euclidian Nearest Distance Mean (core area)

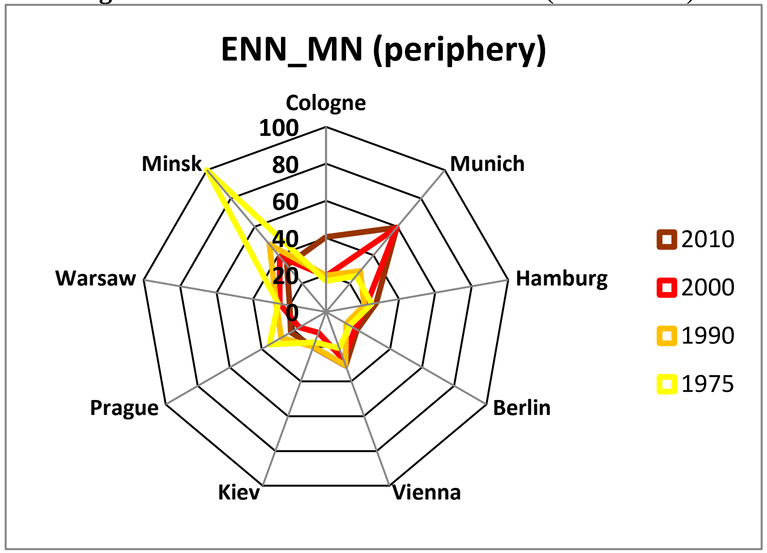


Fig. 4-61 Euclidian Nearest Distance Mean (periphery)

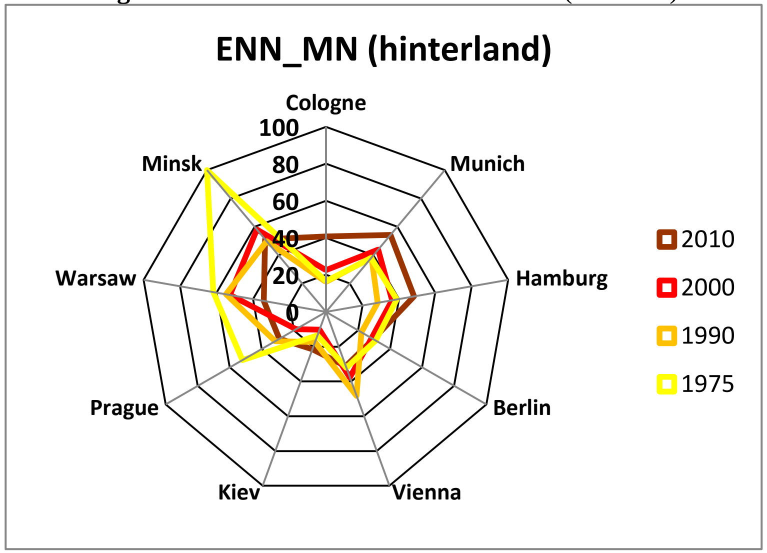


Fig. 4-63 Euclidian Nearest Distance Mean (hinterland)

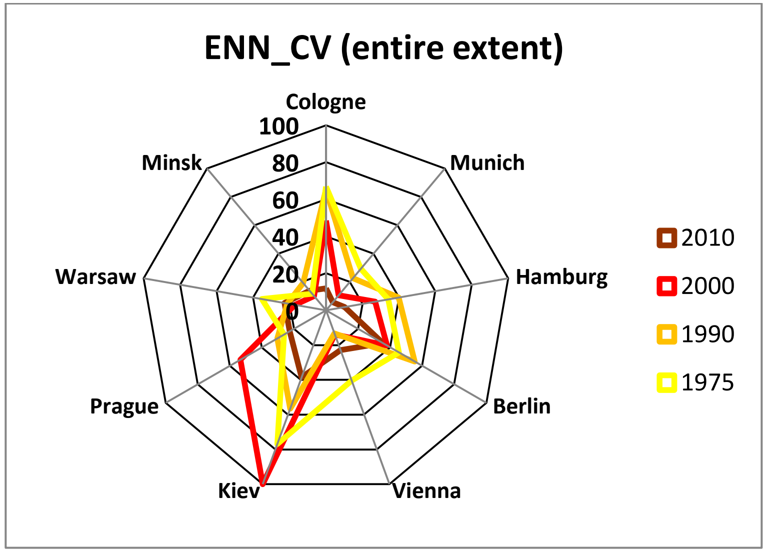


Fig. 4-64 Euclidian Nearest Distance Coefficient of Variation (entire extent)

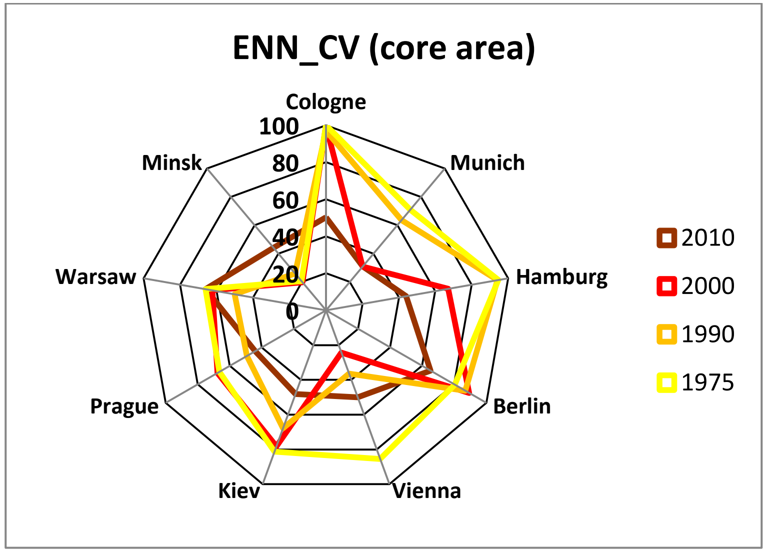


Fig. 4-66 Euclidian Nearest Distance Coefficient of Variation (core area)

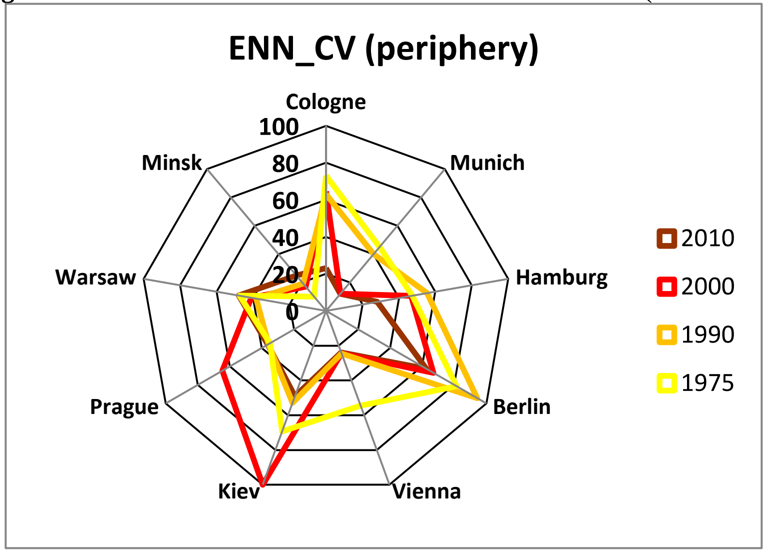


Fig. 4-65 Euclidian Nearest Distance Coefficient of Variation (periphery)

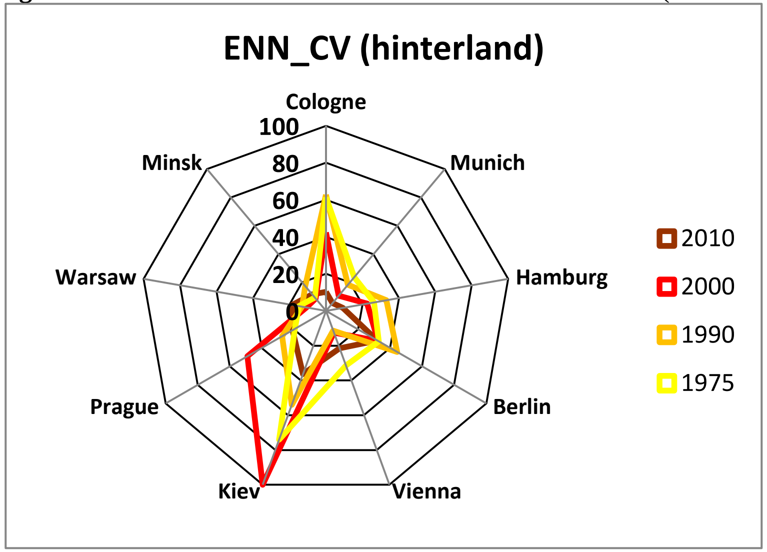


Fig. 4-67 Euclidian Nearest Distance Coefficient of Variation (hinterland)

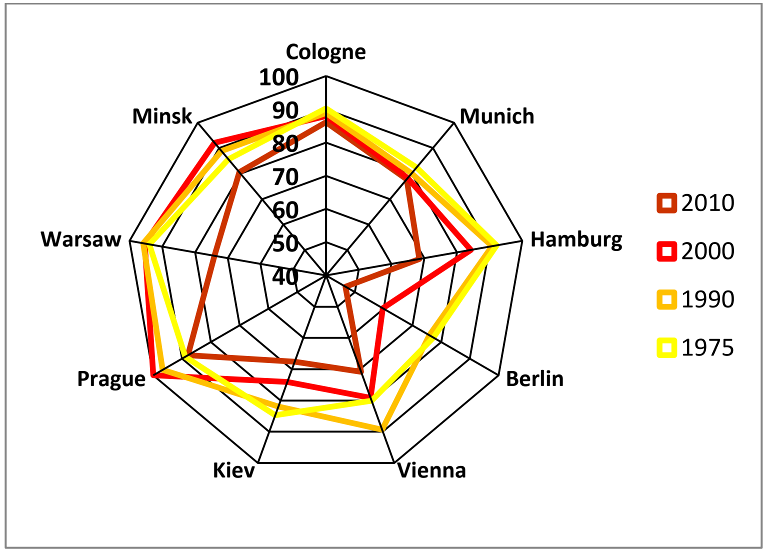


Fig. 4-68 Relative Shannon's entropy values (core area)

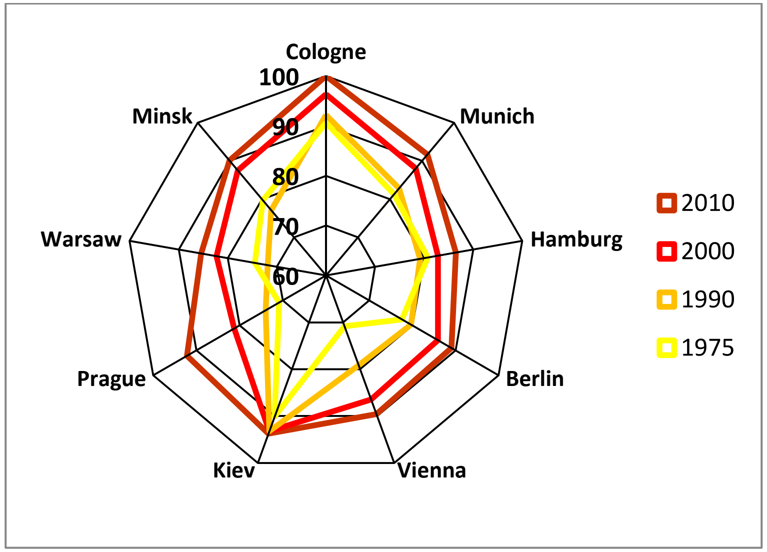


Fig. 4-70 Relative Shannon's entropy values (hinterland)

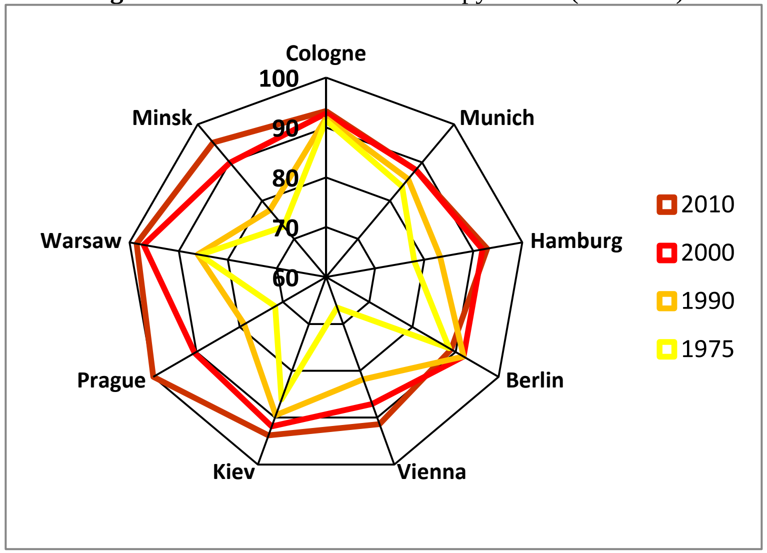


Fig. 4-69 Relative Shannon's entropy values (periphery)

5. MAIN FINDINGS

In this chapter the higher-ranking goal is to support the hypothesis given in the abstract of the succeeding master thesis: Is there any significant difference in spatial and pattern development of east and west European cities?

Because of the complexity of the patterns, the landscape metrics and the multilevel analysis all findings are structured into three subgroups. In scope of the *first* one we would like to present conclusions related to the absolute spatial growth of the built-up area that have been based on the classified urban footprints and which are calculated for all spatially different levels. The *second* group deals with the presentation of general results according to the landscape metrics to provide insights on the spatial patterns of urbanization. At the very end in the *third* group the outcomes of Shannon's entropy are presented. The following outcomes give us new insight into understanding of urban class densification as well as compactness.

1) <u>Main similarities and differences in spatial development:</u>

Spatial growth of cities that has been calculated for all spatially different levels it is the most relevant indicator presenting significant differences in size, as well as speed of spatial development. Here change detection of urban footprints has been applied to assess undergone changes between time steps. In addition we correlate size of cities population against built-up area limited by administrative units. The conducted analysis provides that:

- Urbanized area in case of Eastern European cities in 1975 is much smaller comparing them to Western European cities.
- We perceive Eastern European cities are growing much faster than their Western counterparts. This phenomenon has been taking place approximately since 1990 and it is clearly visible at all levels of investigation. In addition two levels, namely periphery and hinterland, are described by the highest urban growth rates predominating significantly within the entire data set. However, the growth rate is higher in Eastern European cities.
- Concerning the size of population the biggest increases have been detected in East European cities between 1975 and 1990 and this is described as population boom. On contrary population of citizens in Cologne, Munich, Hamburg and Vienna is relatively stable over the period of analysis.

Consequently, to enhance understanding of differences in spatial growth and especially the patterns between Eastern and Western European cities succeeding landscape metrics (see chapter 3.2.4) have been implemented and computed. Based on them we can claim that:

- The class area analysis revealed higher rate increase in the area of East European cities. In addition, the trend of absolute built-up area growth is supported by:
    - Constantly growing number of patches over time, thus increasing patch density is measured.
    - Decreasing values of Euclidian nearest distance, which reveals densification processes.
    - Increasing values of mean patch size coefficient of variations mean higher dispersion among urbanized patches.
    - Increasing Largest Patch Index values since 2000 year signify more compactness form of cities patterns.
- As underlined previously, the size of Western European cities is larger equating to Eastern counterparts especially in 1975.
- Going further re-densification processes can be noticed in entire dataset for all cities of interest. Such processes deal with built-up area enlargement within already existing

city infrastructures, especially occurring in open space areas that somehow stayed untouched among block developments. In other words it can be explained either via vanishing completely small urbanized patches or impervious surface being absorbed by larger urban units. Mentioned processes have started earlier in Western Europe around 1990 and before (depending on the particular city) where only few city representatives of Eastern Europe show similar behavior with 10 years delay (Kiev, Prague). It has been affirmed among others by the decrease in number of patches since 2000 year as well as lower variability in distance (ENN_MN).

- Higher built-up area compactness on core city level in West European cities is confirmed by a constant decrease in number of patches and its low density inside core areas/within administrative units. The high mean patch size values keep this assumption too. In addition, the growing Euclidian Nearest Neighbor values between patches provide this hypothesis. Therefore variability in distance among patches distribution is decreasing over time.
  On contrary, the values of Mean Patch Size obtained for Eastern cities show the spatial dimension of patches much smaller over time due to their constantly growing number and density. For instance the number of patches in Warsaw and Minsk rises massively over time at majority of levels analysis. However, declining values at the core city level depend and vary from city to city. Such processes have started since 1990 in Warsaw or 2000 in case of Kiev and Prague, while Minsk stays at a constant level. It signifies that re-densification processes in half of East cities data set have been delayed in time approximately by 10 years.
- Generally patch density reveals higher values occurring in East European cities, however since the year 2000 values have been decreasing. In contrary, Western European cities reveal constantly decreasing number of patches in time. .
- The modified LPI related to urbanized area and computed for the largest five patches underline that a growing second urbanized patch is observed in Eastern European Cities, where in case of West cities we observe a large, dominating largest patch.

The magnitude and direction of urban sprawl have been assessed through Shannon’s entropy index. Here, three methods have been applied:

- In a first step aggregated 1 km x 1 km spatial resolution raster files, with assigned mean Shannon’s entropy value to each raster cell have been created. This solution provides insight to compactness or fragmentation of urban class. Aggregated 1 km x 1 km spatial resolution raster files with assigned mean values of Shannon’s entropy shows all cities increasing in level of compactness throughout the years especially on core city level (Fig. 4-68). However in Prague, Warsaw and Minsk decrease in values have started in 2000. That confirms again ongoing re-densification processes, although with 10 years delay in Eastern European cities. On the other hand, high calculated values mean land fragmentation and this occurs particularly on periphery and hinterland level (Fig. 4-69; 4-70). Analyzing the periphery level we see that land fragmentation has stopped in Western cities earlier (1990/2000 year), while in Eastern European cities fragmentation of built-up areas is sustained over time.
- Continuously addition maps have been created as a sum of aggregated 1 km x 1 km resolution maps for four time steps, as well as every city, with assigned mean value of Shannon’s entropy. The results provide visual interpretation of magnitude and direction of either urban class fragmentation or compactness. Overall fragmentation of urban pattern can be noticed on all spatial levels. Generally it varies and depends on cities spatial level.

- Subsequently subtraction maps have been done through raster subtraction (t+1 – t), where t+1 equals more recent time step. The following subtraction maps shows the biggest magnitude of neither urban patch compactness nor fragmentation between 1975 and 1990 on core area and periphery level in majority of cases. It confirms that growth of built up area have started since 1990. The cities of Prague and Kiev have been sprawling over time, while Minsk and Warsaw reveal that urban sprawl is slowing down since the year 2000.

Overall, we identify significant differences in spatial development among Eastern and Western European cities. However, the mentioned changes in urban patterns have started parallel with origins of two systems that have been influencing the sphere of politics and economy. Additionally we see changes in spatial pattern varying from city to city. However the most tremendous changes have started in 1990.

6. CONCLUSIONS

In this study, usefulness, potential as well as fusion of remote sensing and landscape metrics are underlined as efficient data and tools for gathering reliable datasets, monitoring spatial pattern and structure of enormously fast growing urban areas. With its vast swath and its various sensors (MSS, TM, ETM+) the Landsat mission make it possible to mapping cities since 1972 in an area wide manner, therefore development patterns as well as growth dynamics can be investigate closer and spatially more precise. It means that until today almost 41 years of urbanization can be monitored in a consistent way.

Definition of urban sprawl has not been clarified yet in literature (Ewing, 1994, 1997; Angel et al., 2007; Esch et al., 2012; Galster et al., 2001; Ji, 2008; Yeh and Li, 2001), therefore to enhance cognition of city patterns, the calculation of various spatial metrics has been performed on spatially different levels. The study shows that application of Shannon's entropy index strengthened understanding of magnitude as well as direction of changes in cities spatial structure.

The results presented in this master thesis show that despite of various geographic location and large areas of interest entire spatial data sets were derived in a consistent way. Combination of Geographic Information System and Remote Sensing enables to monitor urbanized areas more effectively, with less expenditure and worldwide. Increasing satellite data availability and its finer, spatial, temporal and spectral resolution allow mapping dynamics of urbanization processes with higher accuracy. As indicated in the introductory chapters Europe as well as the entire world is facing vast and immense urbanization processes. The magnitude of changes is rather expected to increase over time. Therefore the obtained results as well as applied methodology can be crucial while supporting urban planners, decision makers and its promising for future urban related studies.

The presented outcomes exemplify doubtlessly diverse patterns of spatial urban development in Eastern and Western parts of Europe. On the one hand we see compact and slowly growing Western European cities, tending to re-densification processes within their hinterland area. On the other hand, cities of Eastern Europe show immense and unlimited spatial growth. Although in some of them such as re-densification processes have already started too; however, with approximately 10 years delay. In this study we put attention only to 9 European cities. To achieve a total overview of urban sprawl processes as well as strengthening the understanding of similarities and differences in the development of spatial pattern entire data set should be extended by more cities that have been under influence of Socialism and Capitalism system.

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APPENDIX A – ORIGINAL DATA SETS

Sensor	**Hamburg**	**Path - Row**	**Vienna**	**Path - Row**	**Data source**
MSS	Oct 1972 Aug 1975	211/22 211/23	Nov 1972 Nov 1973 Nov 1973	204/27 204/26 205/26	USGS USGS USGS
TM	May 1989 Jun 1989 May 1989 Oct 2010 Jun 2010 Jun 2010	196/23 194/23 196/22 196/23 196/22 195/23	Jun 1991 Jun 1991 Jun 2010 Aug 2010	190/26 190/27 190/27 189/27	USGS USGS USGS USGS USGS USGS
ETM+	May 2000 May 2000	195/23 195/22	May 2000 Sep 2000 Sep 2000	189/27 190/26 190/27	USGS USGS USGS
Sensor	**Cologne**	**Path - Row**	**Munich**	**Path - Row**	**Data source**
MSS	Aug 1975 Aug 1975	212/24 212/25	May 1973 Aug 1972	208/26 208/27	USGS USGS
TM	Jul 1990 Jul 1991 Jul 1992 Apr 2011 Jun 2011 Aug 2011	197/25 196/25 197/24 196/25 197/24 197/25	Jun 1992 Aug 1991 Jul 2011 Sep 2011	193/26 193/27 193/27 193/26	USGS USGS USGS USGS USGS USGS
ETM+	Aug 2000 Aug 2003 Aug 2003	197/25 197/24 196/25	Jul 2003 Jul 2003	193/26 193/27	USGS USGS USGS

Tab. A-1 Overview of used Landsat data

Sensor	Berlin	Path - Row	Kiev	Path - Row	Data source
MSS	Aug 1972 Aug 1972	208/23 208/24	Jul 1976	195/25	USGS USGS
TM	Jun 1989 Jul 1989 Sep 1989 May 2011 Jun 2011	193/24 193/23 192/24 193/24 193/23	Jul 1989 Oct 2011	181/25 181/25	USGS USGS USGS USGS USGS
ETM+	Jun 1999 Sep 1999	193/23 193/24	Jun 2000	181/25	USGS USGS
Sensor	**Warsaw**	**Path - Row**	**Prague**	**Path - Row**	**Data source**
MSS	Jun 1978 cld Jun 1978	203/23 203/24	May 1974	206/25	USGS USGS
TM	Jun 1989 Jul 1992 Aug 2010 Aug 2010	188/023 188/024 188/23 188/24	Sep 1989 Aug 1991 Jun 2010 Jul 2010	192/25 191/25 191/25 192/25	USGS USGS USGS USGS
ETM+	May 2000 Oct 2000	188/24 187/24	May 2000 May 2000	191/25 192/25	USGS USGS
Sensor	**Minsk**	**Path - Row**			**Data source**
MSS	Sep 1973 Nov 1975	199/22 198/23			USGS USGS
TM	May 1988 Jul 1989 Jul 2010 Oct 2010	184/22 184/23 184/23 184/22			USGS USGS USGS USGS
ETM+	May 2000 Oct 2000	184/22 184/23			USGS USGS

Tab. A-1 Overview of used Landsat data

APPENDIX B – CLASSIFICATION RESULTS

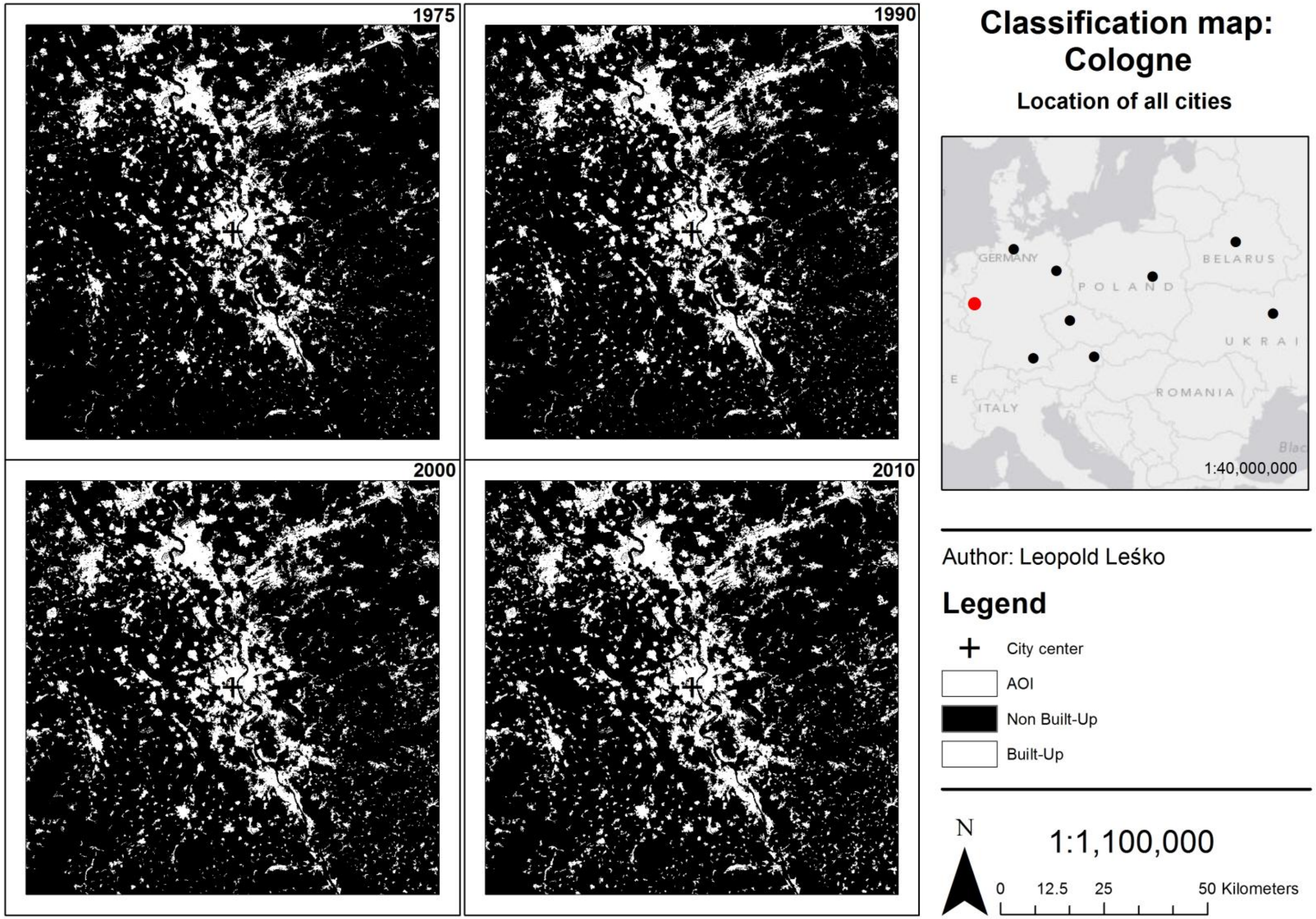

Fig. B-1 Land cover classification, Cologne 1975-2010

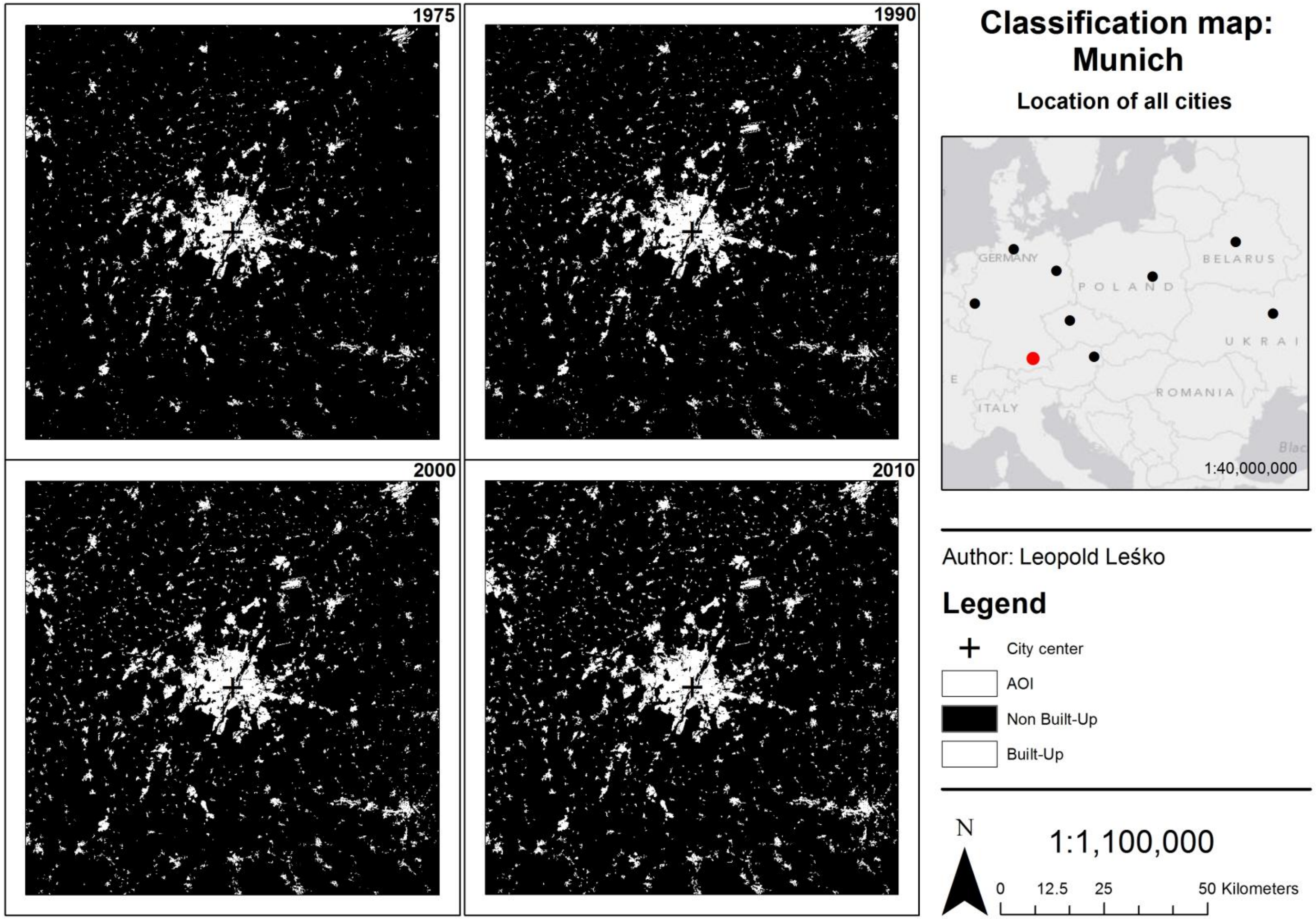

Fig. B-2 Land cover classification, Munich 1975-2010

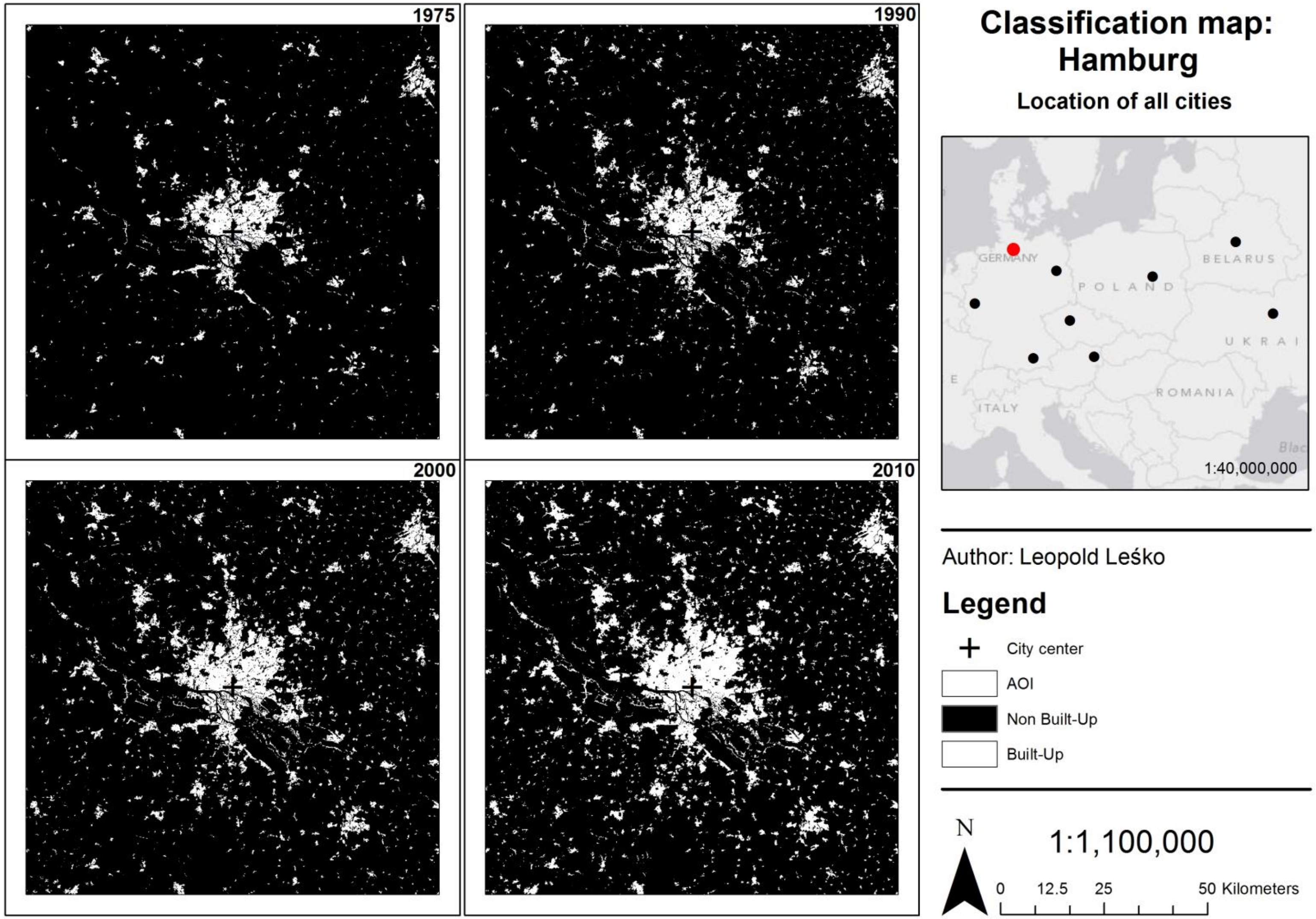

Fig. B-3 Land cover classification, Hamburg 1975-2010

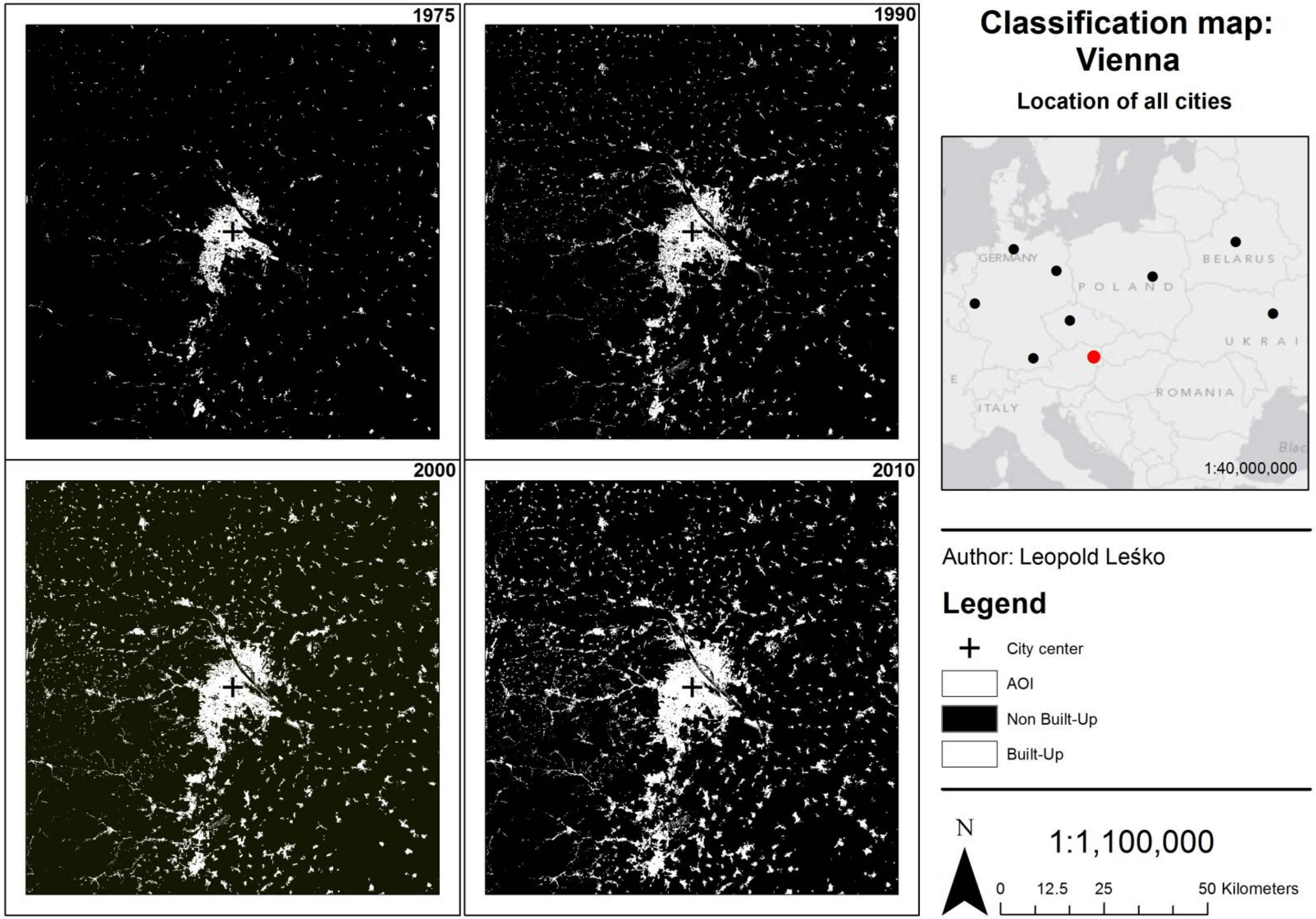

Fig. B-4 Land cover classification, Vienna 1975-2010

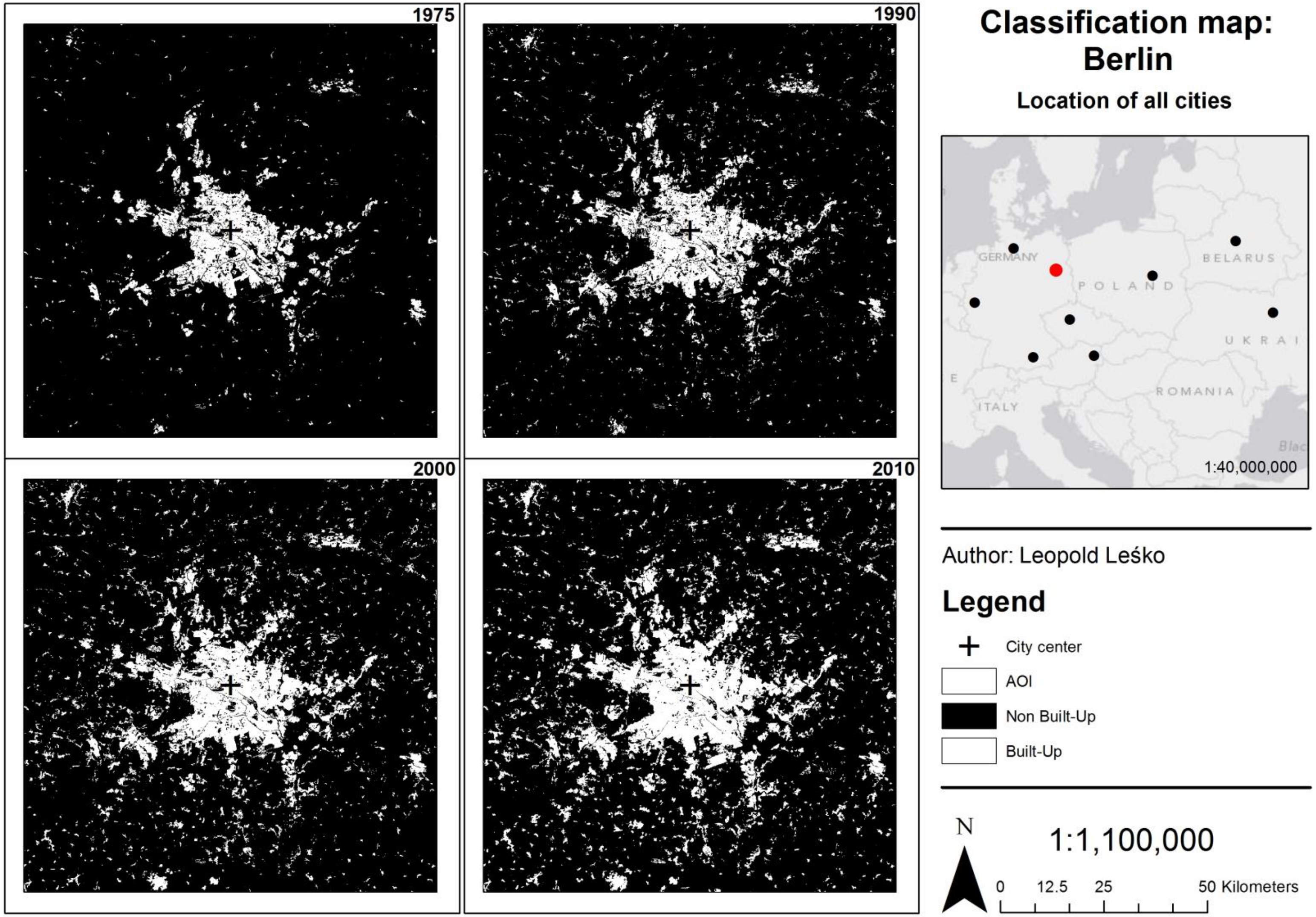

Fig. B-5 Land cover classification, Berlin (1975-2010)

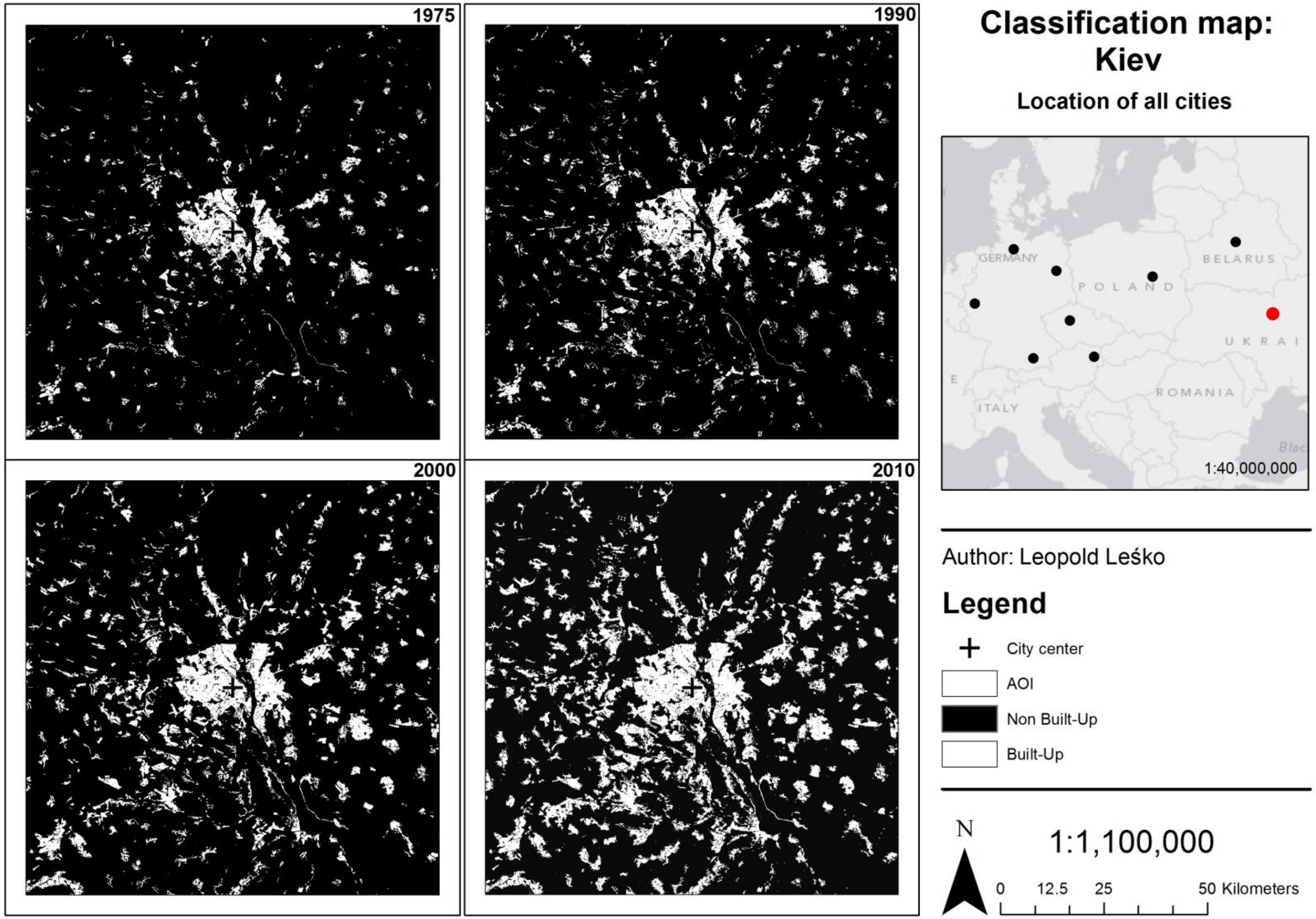

Fig. B-6 Land cover classification, Kiev 1975-2010

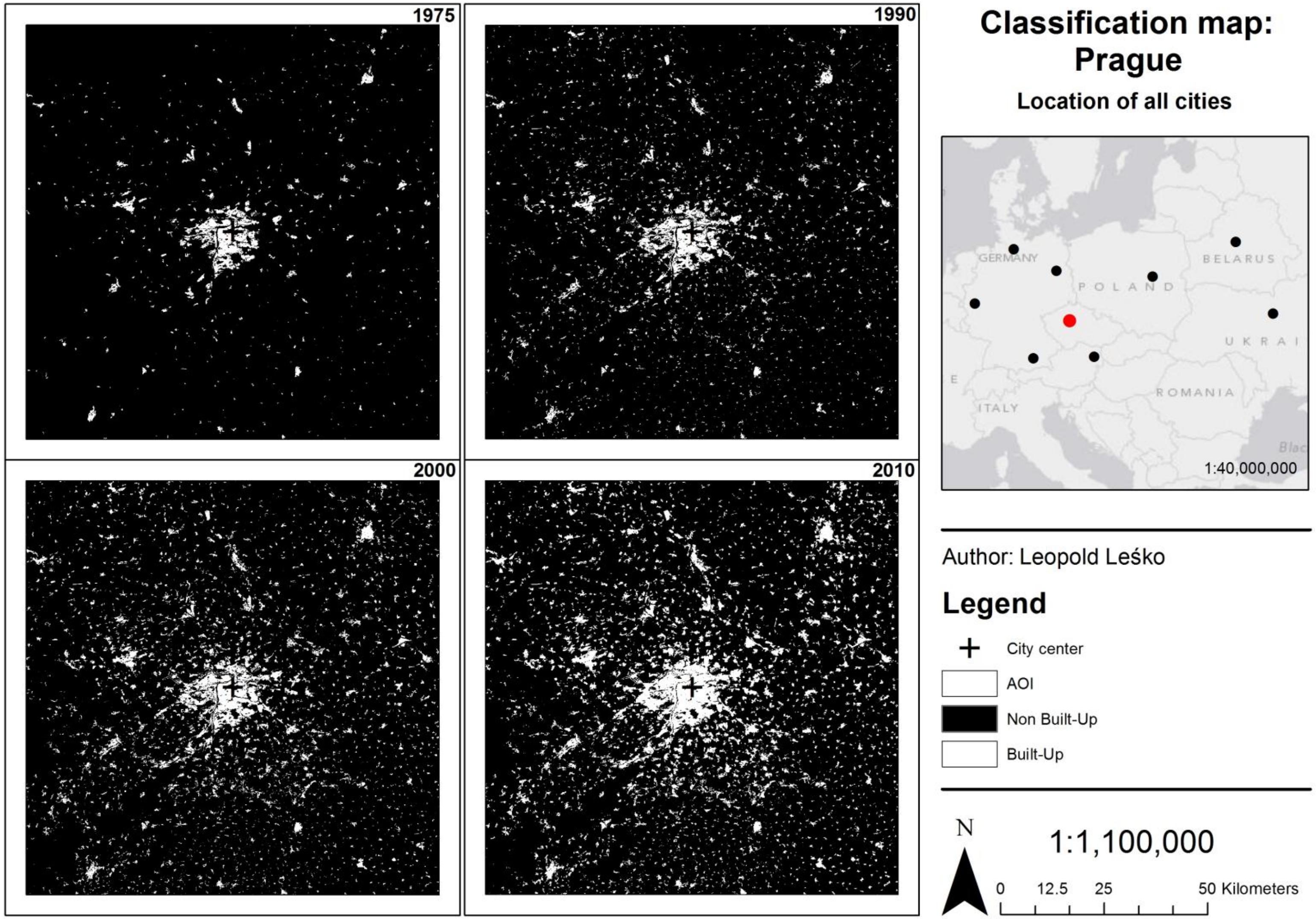

Fig. B-7 Land cover classification, Prague 1975-2010

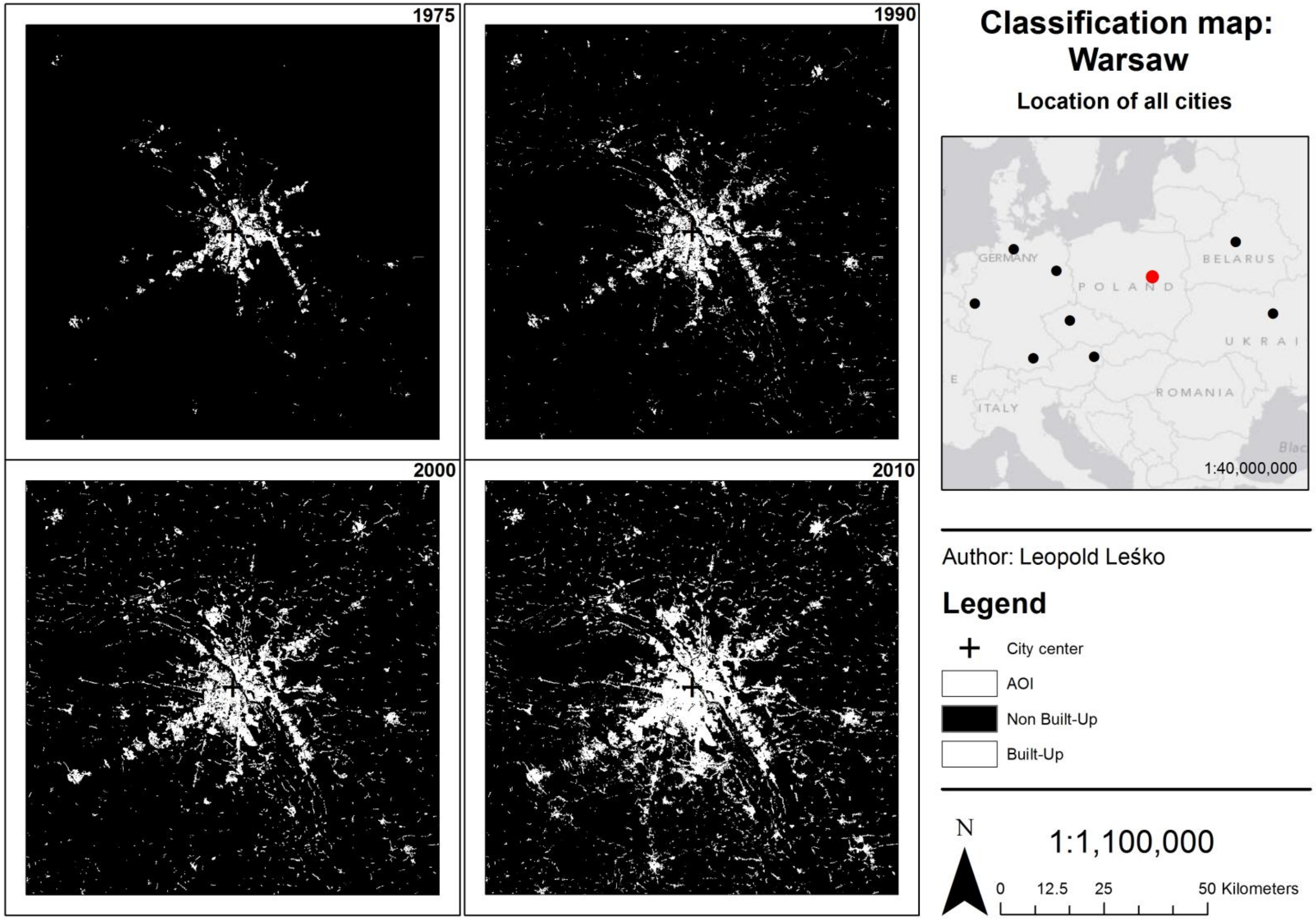

Fig. B-8 Land cover classification, Warsaw 1975-2010

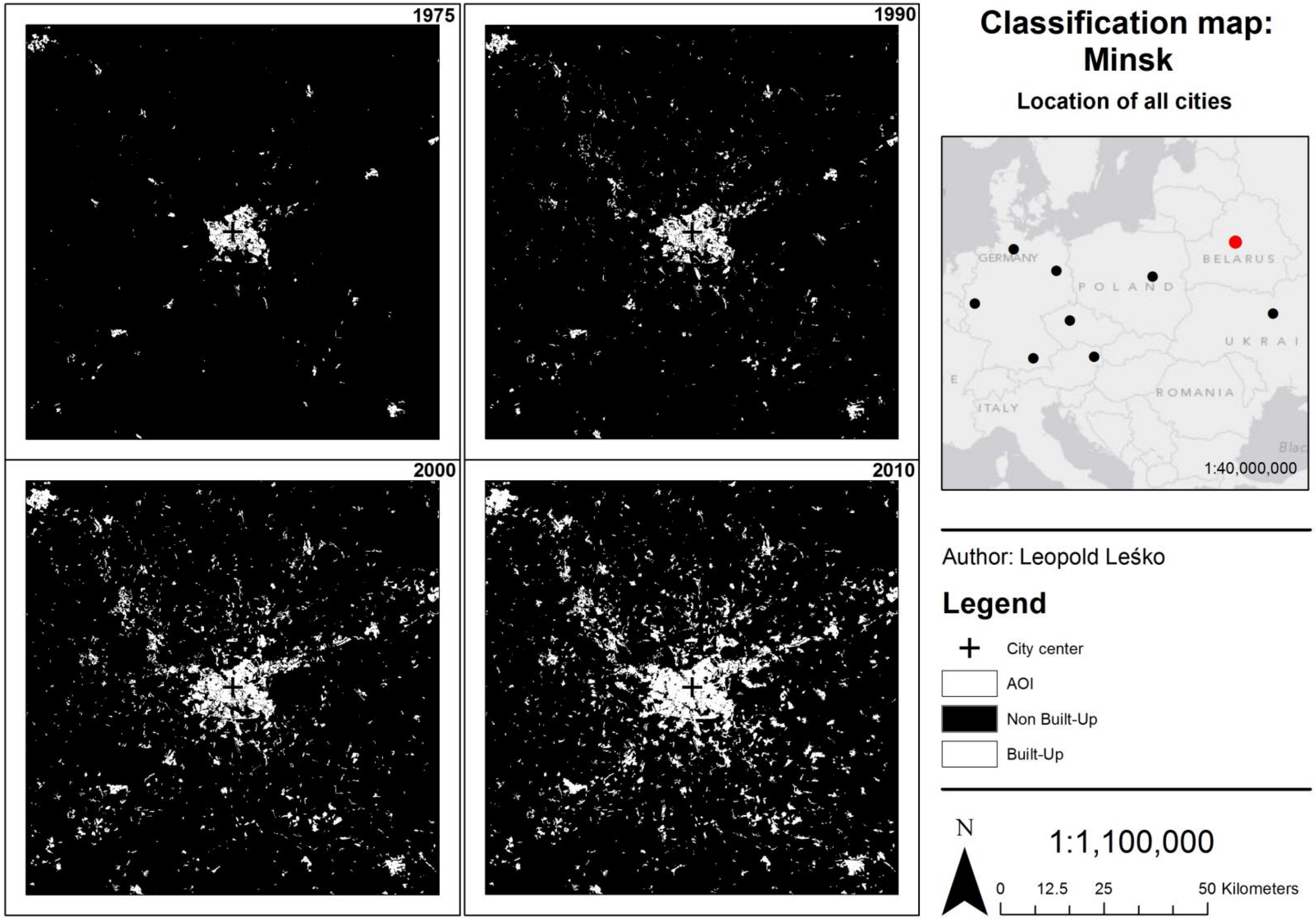

Fig. B-9 Land cover classification, Minsk 1975-2010

APPENDIX C – ACCURACY ASSESEMENT TABLES

Cologne 2010	Built-Up	Non Built-Up	
Built-Up	79	21	100
Non Built-Up	7	93	100
	86	114	200
Overall Accuracy	86.00%		
User's Accuracy			**Commision**
Non Built-Up	93.00%		7.00%
Built-Up	79.00%		21.00%
Producer's Accuracy			**Ommision**
Non Built-Up	81.58%		18.42%
Built-Up	91.86%		8.14%
Kappa	72.00%		

Tab. C-1 Accuracy assessment, Cologne 2010

Munich 2010	Built-Up	Non Built-Up	
Built-Up	84	16	100
Non Built-Up	4	96	100
	88	112	200
Overall Accuracy	90.00%		
User's Accuracy			**Commision**
Non Built-Up	96.00%		4.00%
Built-Up	84.00%		16.00%
Producer's Accuracy			**Ommision**
Non Built-Up	85.71%		20.00%
Built-Up	95.45%		4.55%
Kappa	80.00%		

Tab. C-2 Accuracy assessment, Munich 2010

Hamburg 2010	Built-Up	Non Built-Up	
Built-Up	76	24	100
Non Built-Up	4	96	100
	80	120	200
Overall Accuracy	86.00%		
User's Accuracy			**Commision**
Non Built-Up	96.00%		4.00%
Built-Up	76.00%		24.00%
Producer's Accuracy			**Ommision**
Non Built-Up	80.00%		20.00%
Built-Up	95.00%		5.00%
Kappa	72.00%		

Tab. C-3 Accuracy assessment, Hamburg, 2010

Berlin 2010	Built-Up	Non Built-Up	
Built-Up	74	26	100
Non Built-Up	7	93	100
	81	119	200
Overall Accuracy	83.50%		
User's Accuracy			**Commision**
Non Built-Up	93.00%		7.00%
Built-Up	74.00%		26.00%
Producer's Accuracy			**Ommision**
Non Built-Up	78.15%		21.85%
Built-Up	91.36%		8.64%
Kappa	67.00%		

Tab. C-4 Accuracy assessment, Berlin 2010

Vienna 2010	Built-Up	Non Built-Up	
Built-Up	86	14	100
Non Built-Up	3	97	100
	89	111	200
Overall Accuracy	91.50%		
User's Accuracy			**Commision**
Non Built-Up	97.00%		3.00%
Built-Up	86.00%		14.00%
Producer's Accuracy			**Ommision**
Non Built-Up	87.39%		12.61%
Built-Up	96.63%		3.37%
Kappa	83.00%		

Tab. C-5 Accuracy assessment, Vienna 2010

Kiev 2010	Built-Up	Non Built-Up	
Built-Up	59	41	100
Non Built-Up	1	99	100
	60	140	200
Overall Accuracy	79.00%		
User's Accuracy			**Commision**
Non Built-Up	99.00%		1.00%
Built-Up	59.00%		41.00%
Producer's Accuracy			**Ommision**
Non Built-Up	70.71%		29.69%
Built-Up	98.33%		1.67%
Kappa	58.00%		

Tab. C-6 Accuracy assessment, Kiev 2010

Prague 2010	Built-Up	Non Built-Up	
Built-Up	76	24	100
Non Built-Up	3	97	100
	79	121	200
Overall Accuracy	86.50%		
User's Accuracy			**Commision**
Non Built-Up	97.00%		3.00%
Built-Up	76.00%		24.00%
Producer's Accuracy			**Ommision**
Non Built-Up	80.17%		19.83%
Built-Up	96.20%		3.80%
Kappa	73.00%		

Tab. C-7 Accuracy assessment, Prague 2010

Warsaw 2010	Built-Up	Non Built-Up	
Built-Up	63	37	100
Non Built-Up	3	97	100
	66	134	200
Overall Accuracy	80.00%		
User's Accuracy			**Commision**
Non Built-Up	97.00%		3.00%
Built-Up	63.00%		37.00%
Producer's Accuracy			**Ommision**
Non Built-Up	72.39%		27.61%
Built-Up	95.45%		4.55%
Kappa	60.00%		

Tab. C-8 Accuracy assessment, Warsaw 2010

Minsk 2010	Built-Up	Non Built-Up	
Built-Up	66	34	100
Non Built-Up	3	97	100
	69	131	200
Overall Accuracy	81.50%		
User's Accuracy			**Commision**
Non Built-Up	97.00%		3.00%
Built-Up	66.00%		34.00%
Producer's Accuracy			**Ommision**
Non Built-Up	74.05%		25.95%
Built-Up	95.65%		4.35%
Kappa	63.00%		

Tab. C-9 Accuracy assessment, Minsk 2010

APPENDIX D – CHESSBOARD APPROACH MAPS (1 km x 1 km)

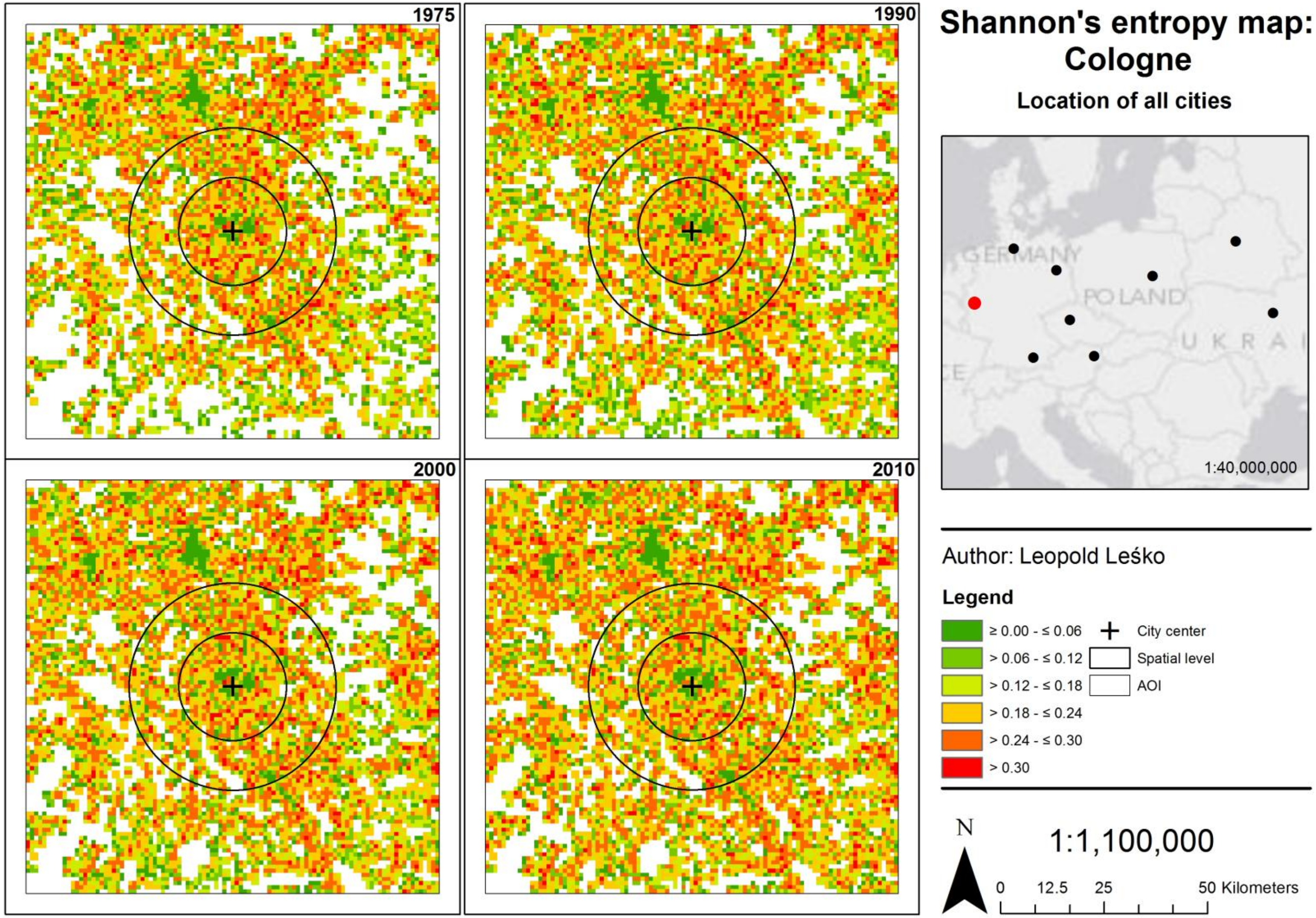

Fig. D-1 Shannon’s entropy map, Cologne 1975-2010

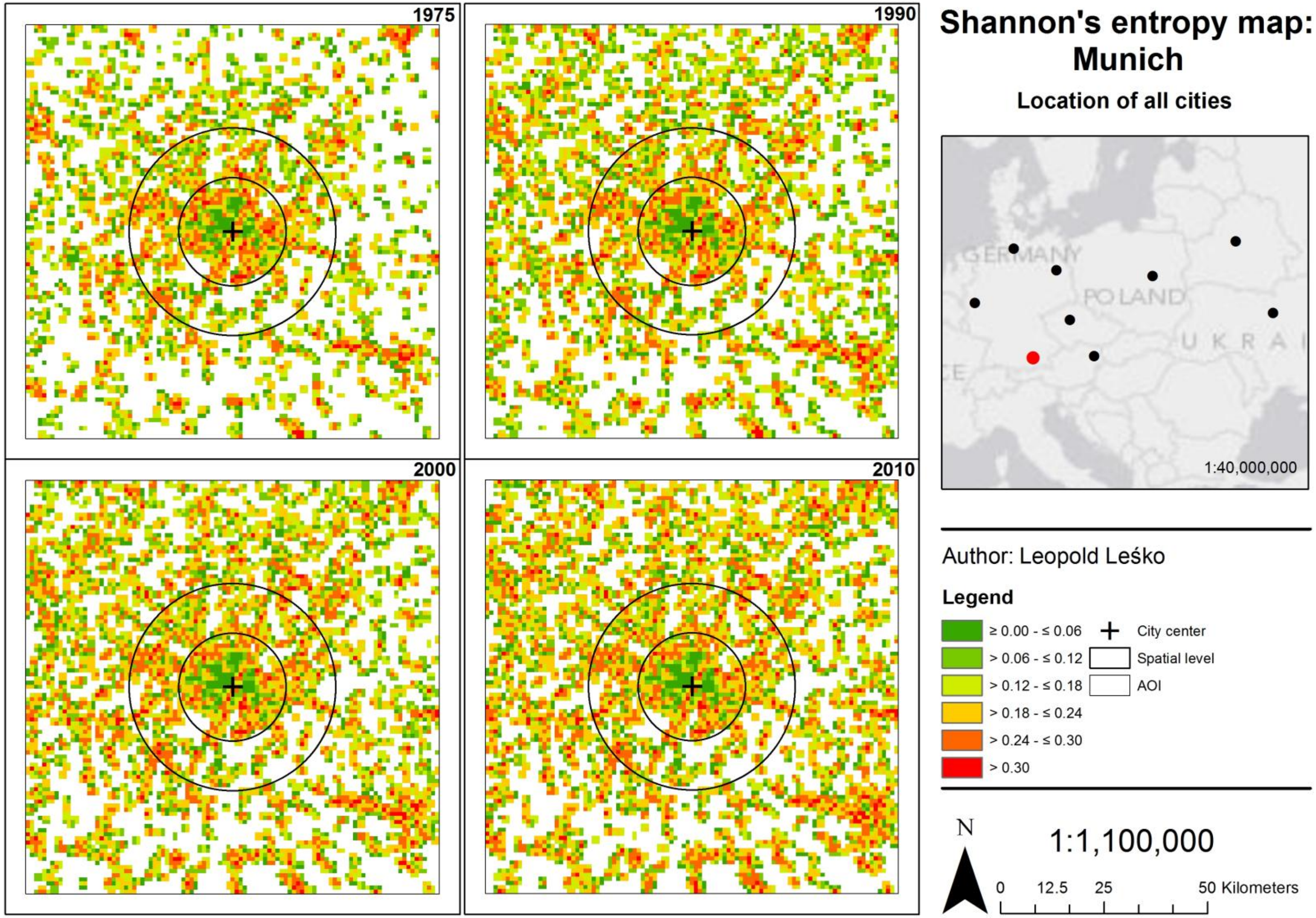

Fig. D-2 Shannon's entropy map, Munich 1975-2010

APPENDIX D – CHESSBOARD APPROACH MAPS (1 km x 1 km)

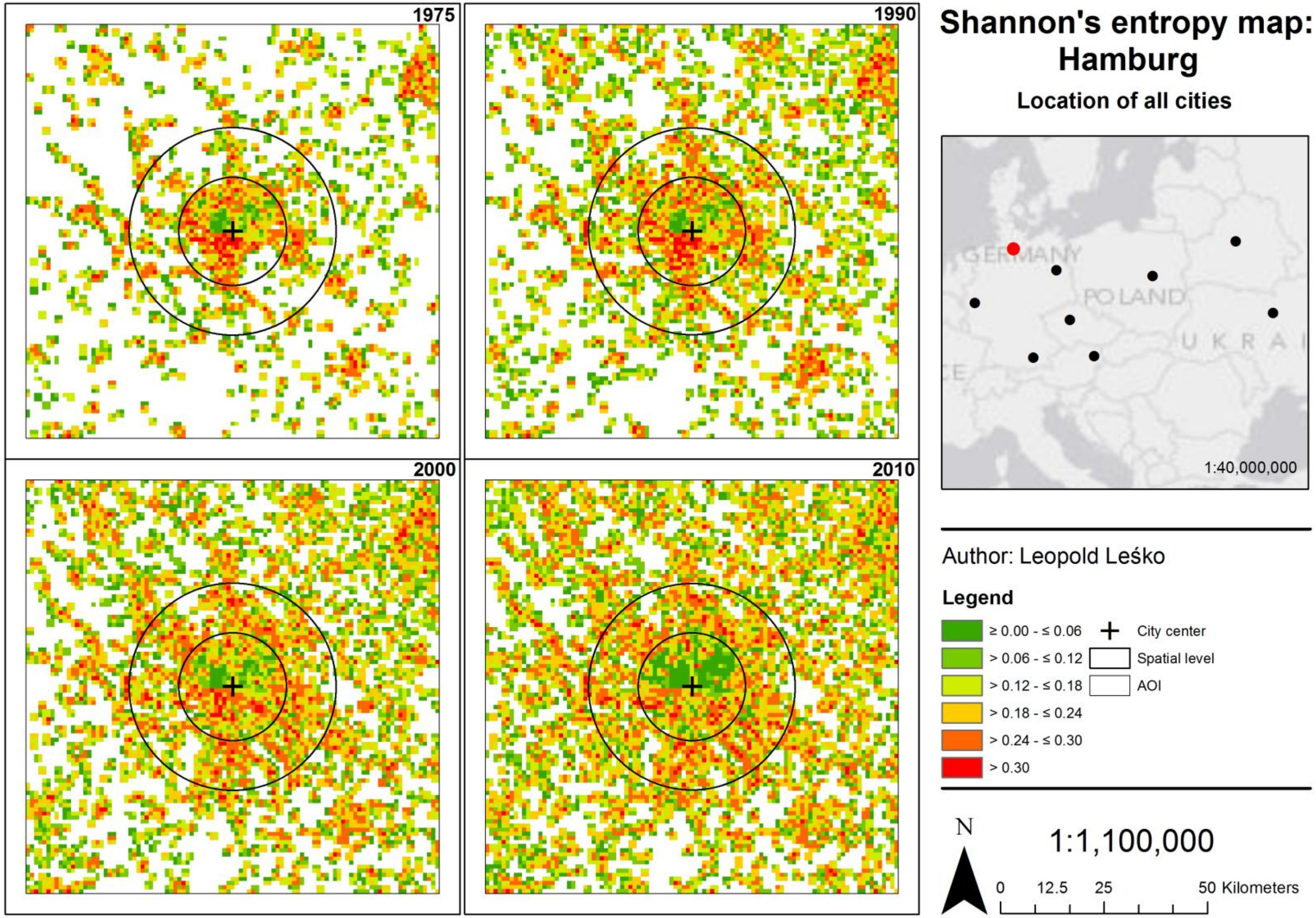

Fig. D-3 Shannon's entropy map, Hamburg 1975-2010

APPENDIX D – CHESSBOARD APPROACH MAPS (1 km x 1 km)

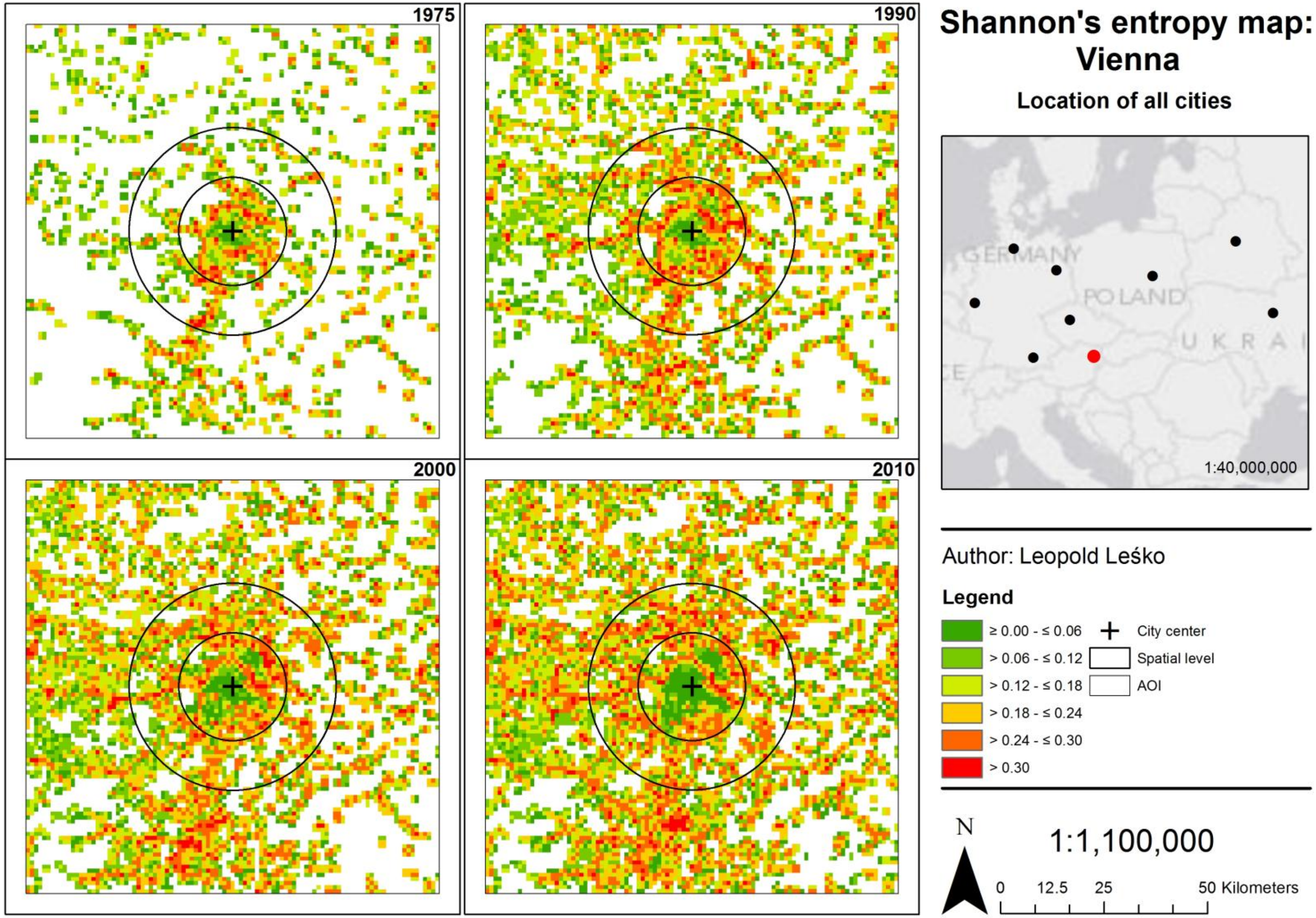

Fig. D-4 Shannon’s entropy map, Vienna 1975-2010

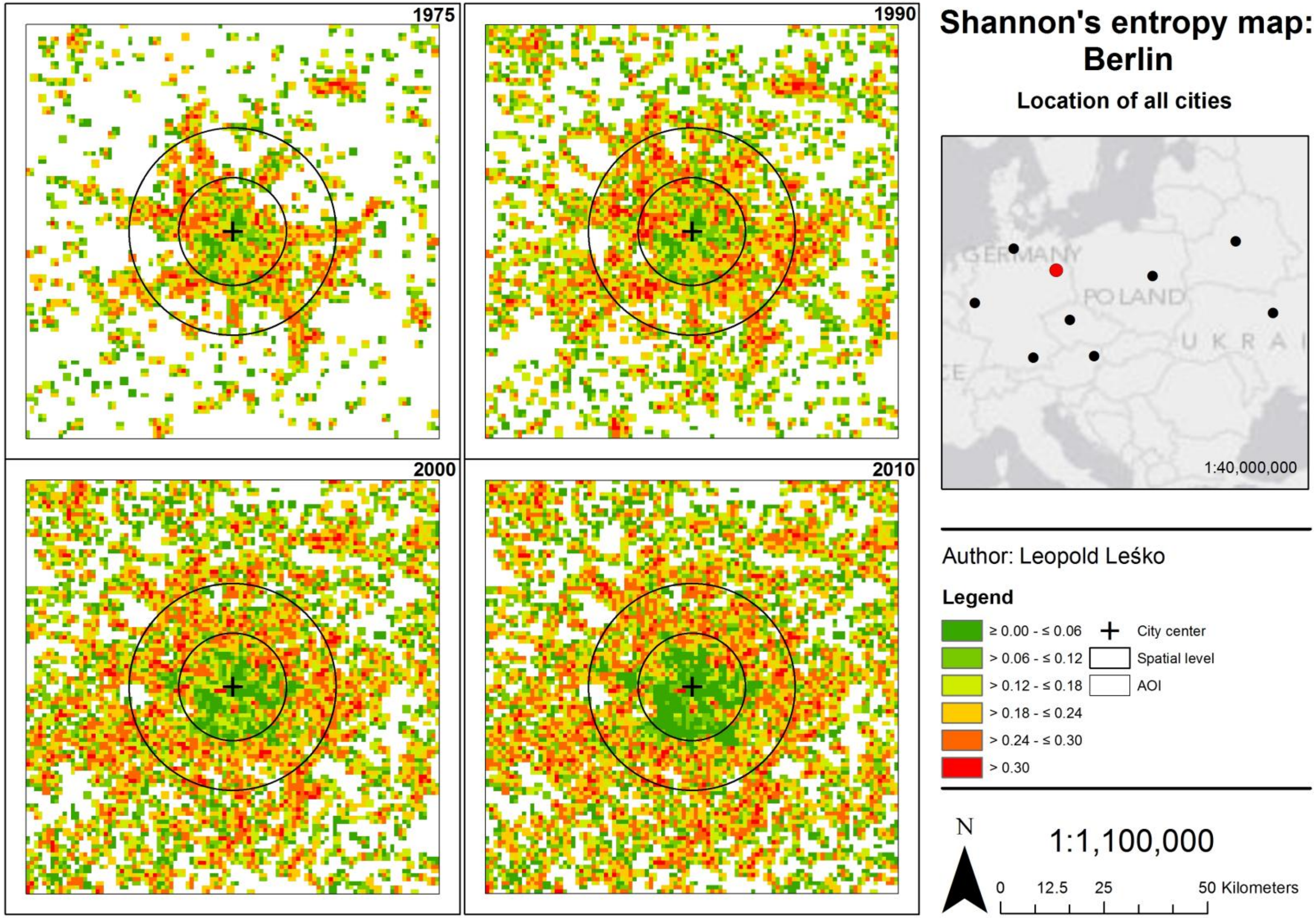

Fig. D-5 Shannon's entropy map, Berlin 1975-2010

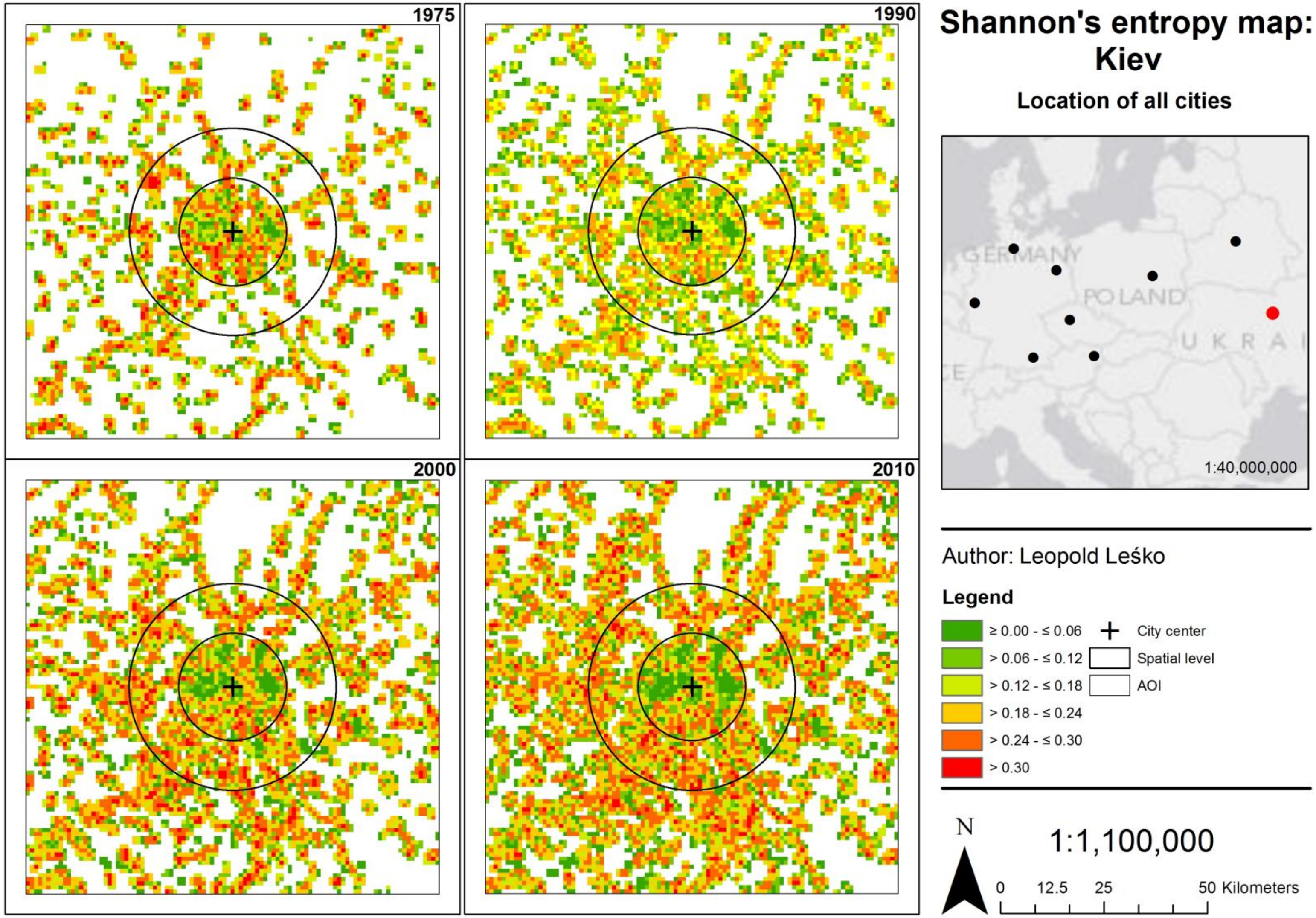

Fig. D-6 Shannon's entropy map, Kiev 1975-2010

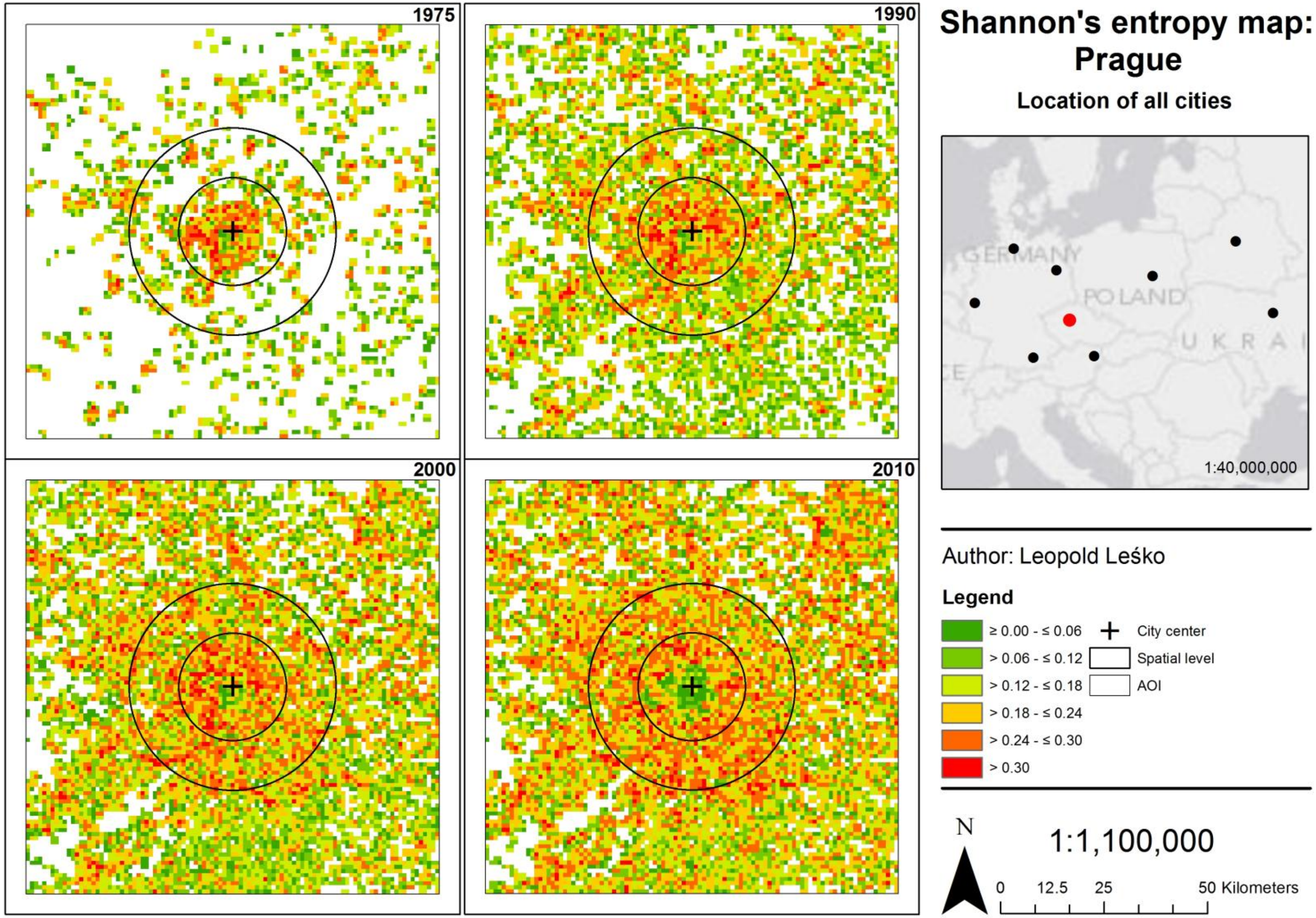

Fig. D-7 Shannon's entropy map, Prague 1975-2010

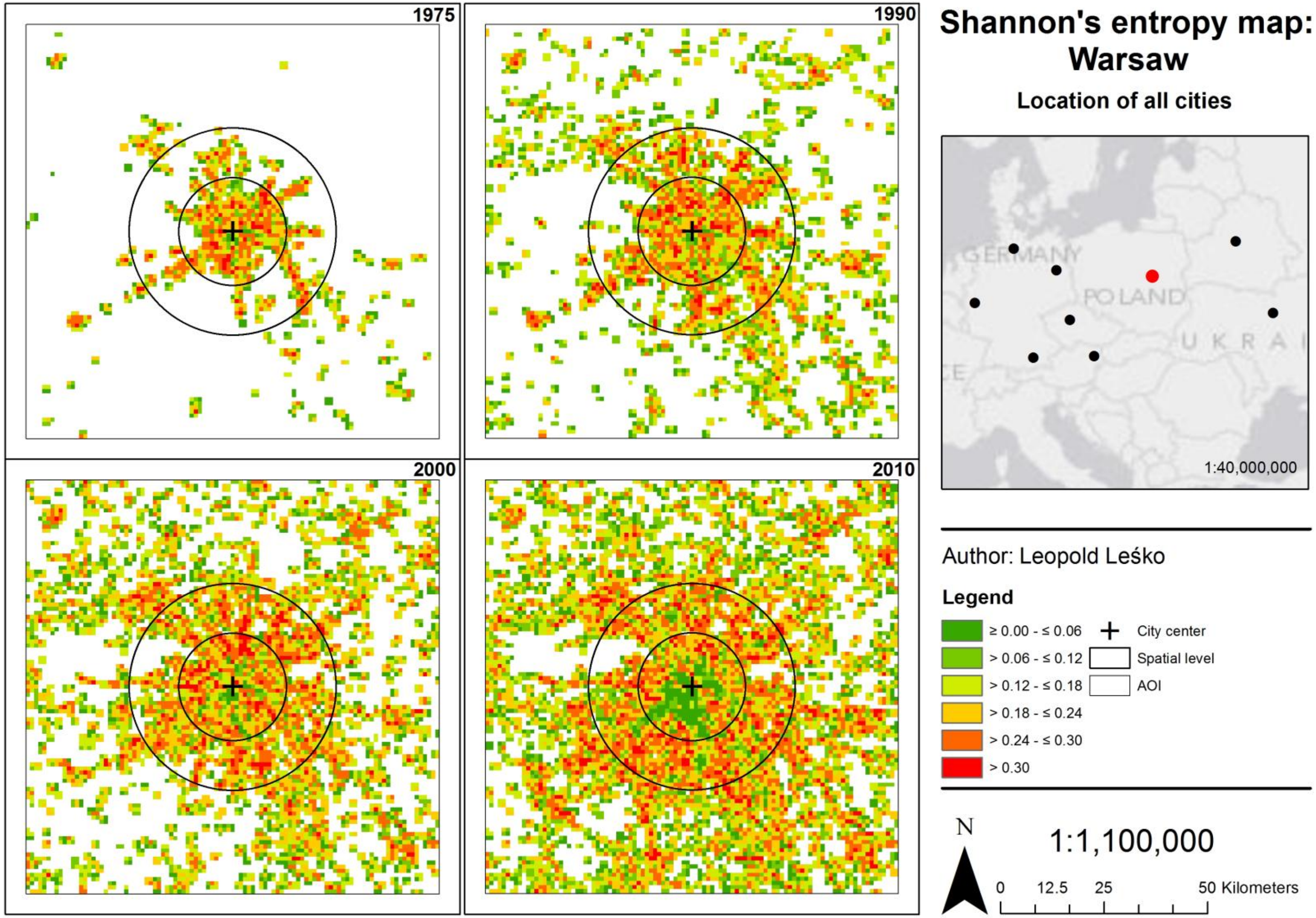

Fig. D-8 Shannon's entropy map, Warsaw 1975-2010

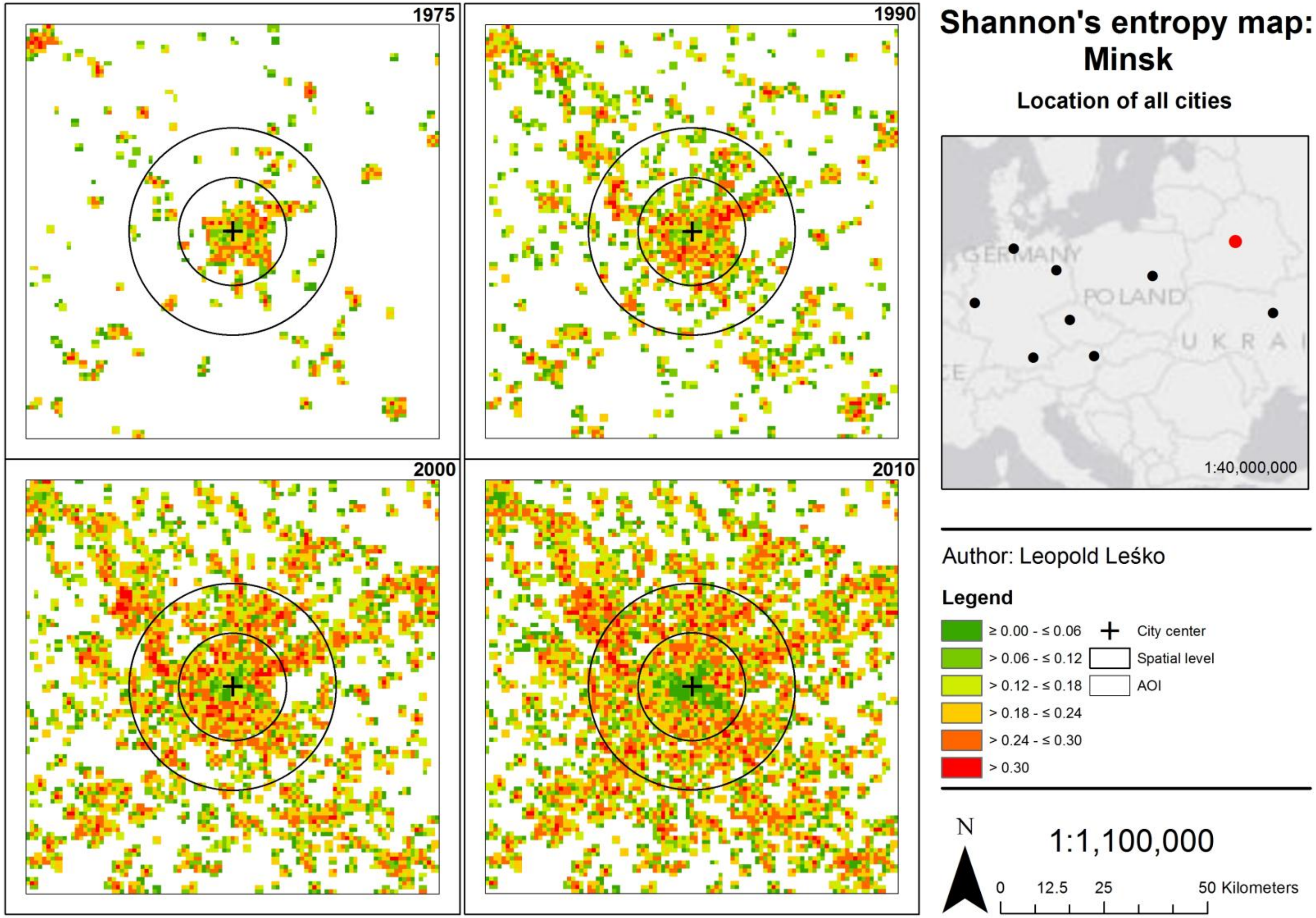

Fig. D-9 Shannon's entropy map, Minsk 1975-2010

APPENDIX E – CHEESBOARD APPROACH MAPS (1 km x 1 km, addtion maps)

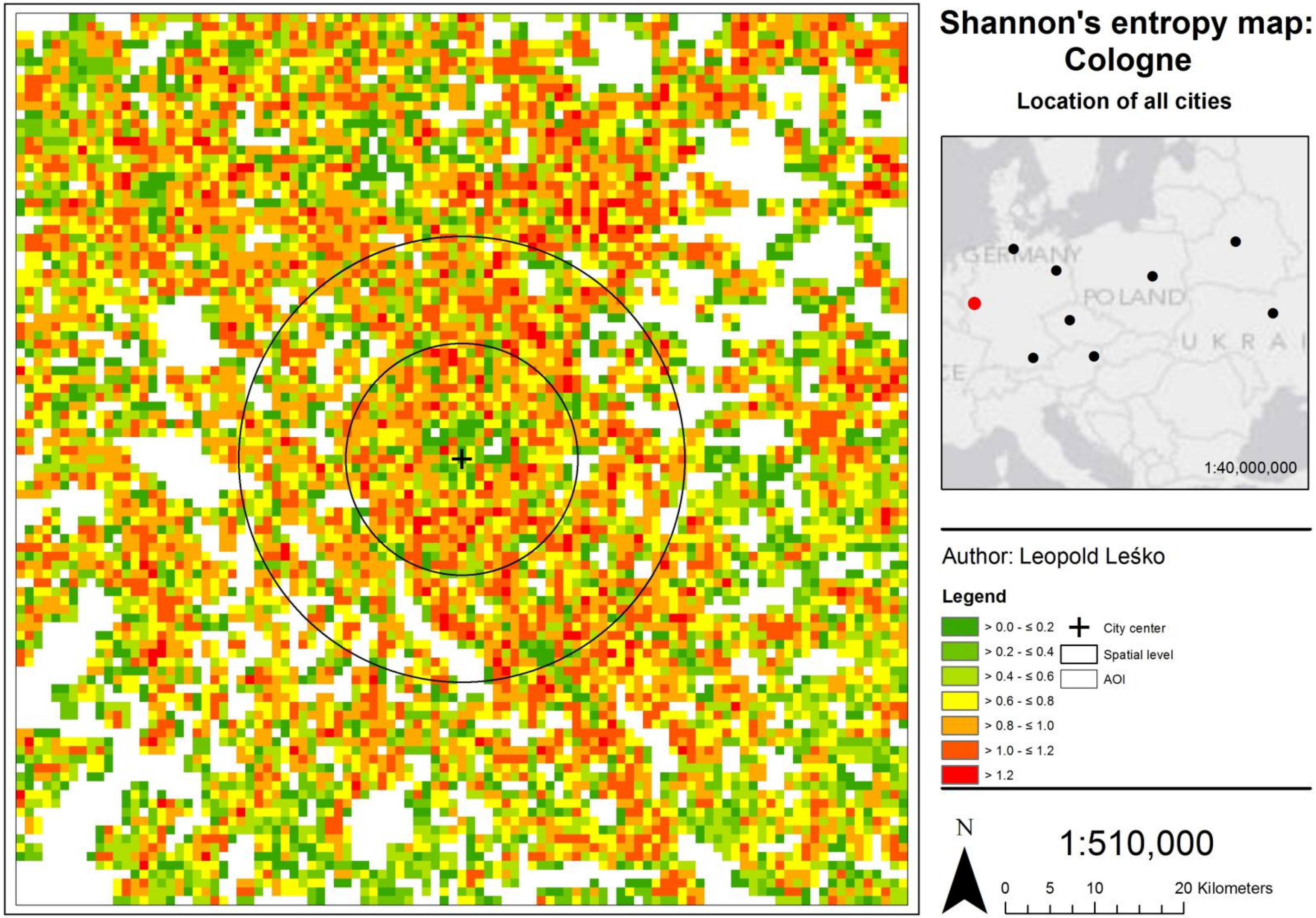

Fig. E-1 Sum of all Shannon's entropy maps, Cologne

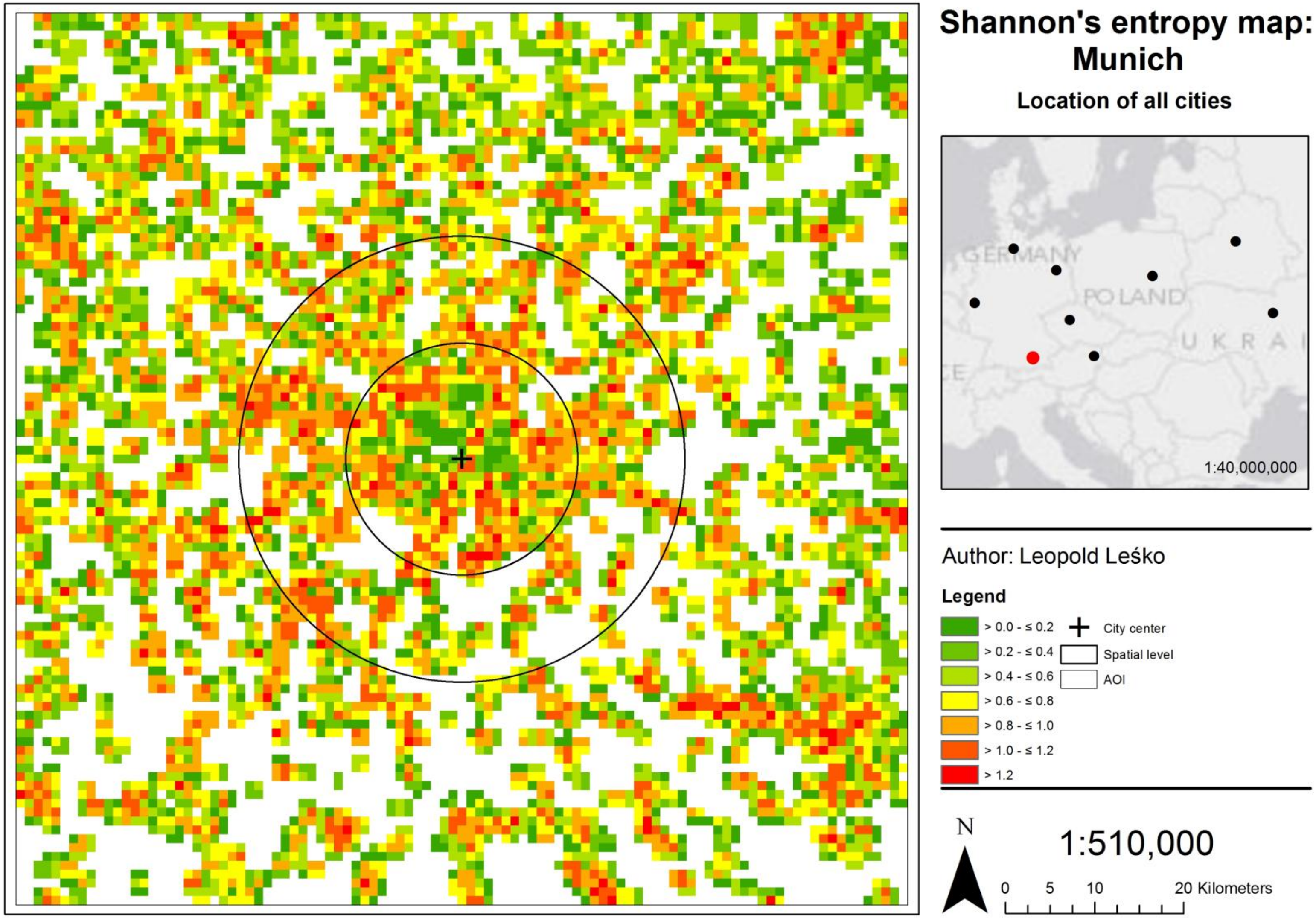

Fig. E-2 Sum of all Shannon's entropy maps, Munich

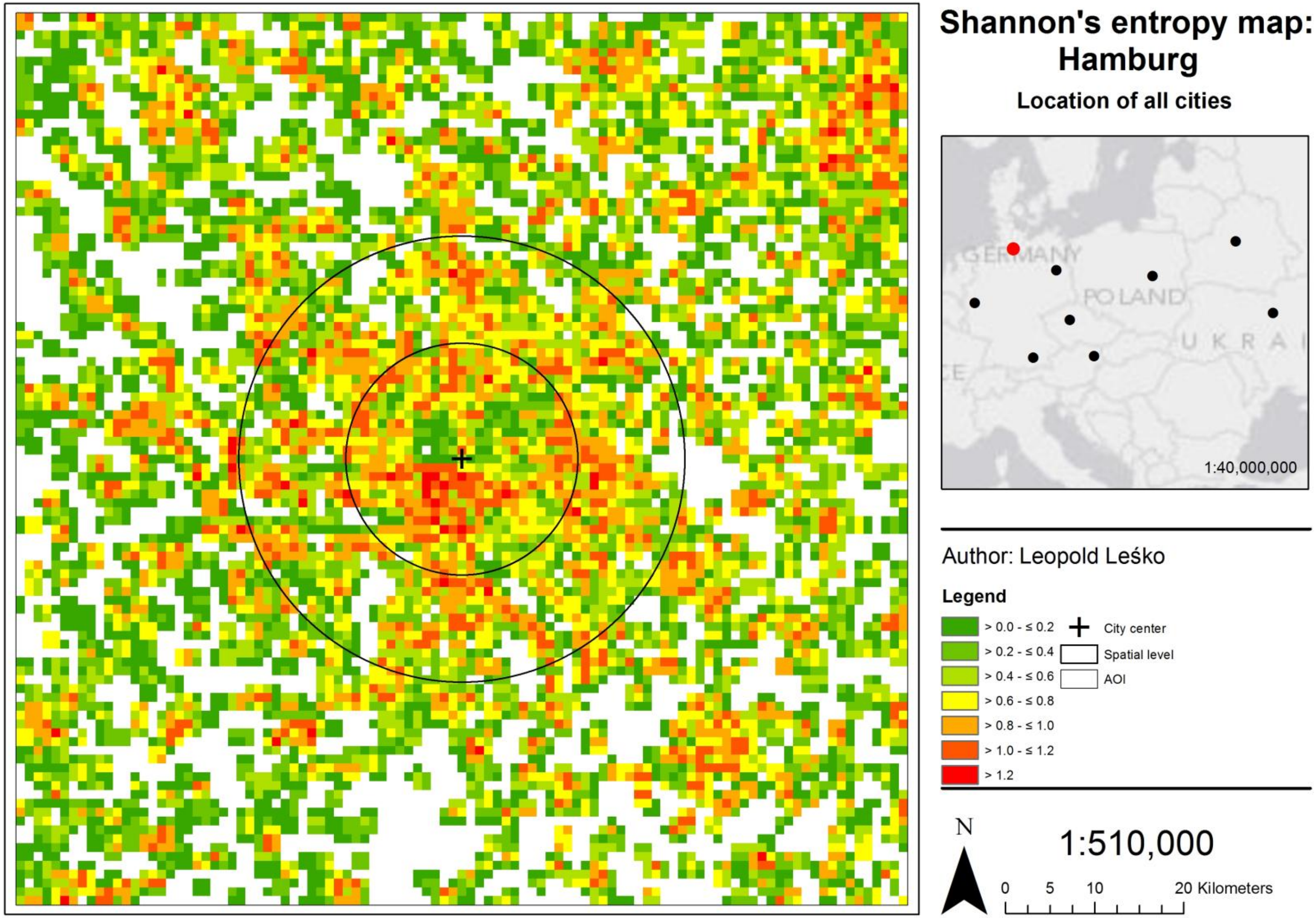

Fig. E-3 Sum of all Shannon's entropy maps, Hamburg

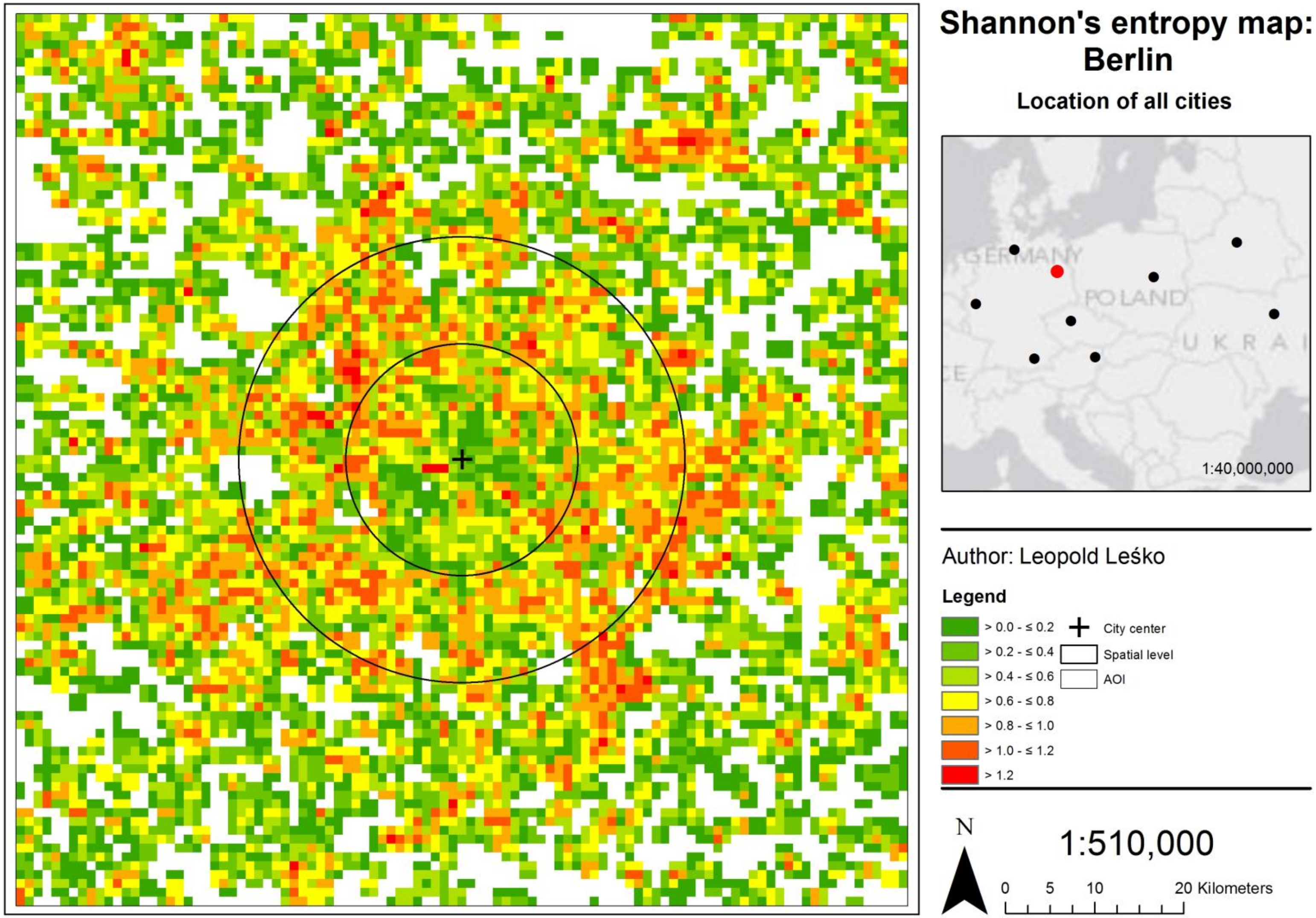

Fig. E-4 Sum of all Shannon's entropy maps, Berlin

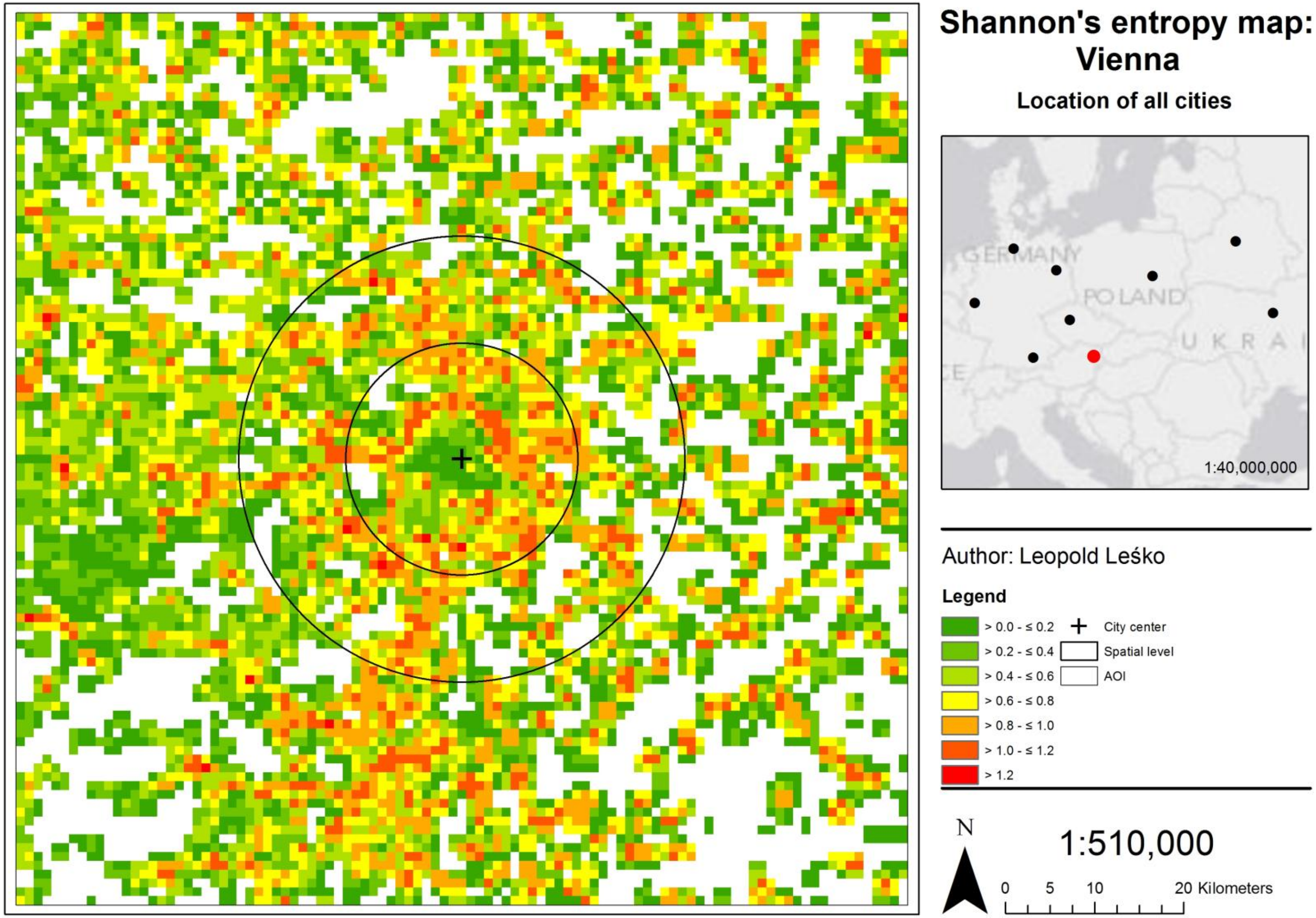

Fig. E-5 Sum of all Shannon's entropy maps, Vienna

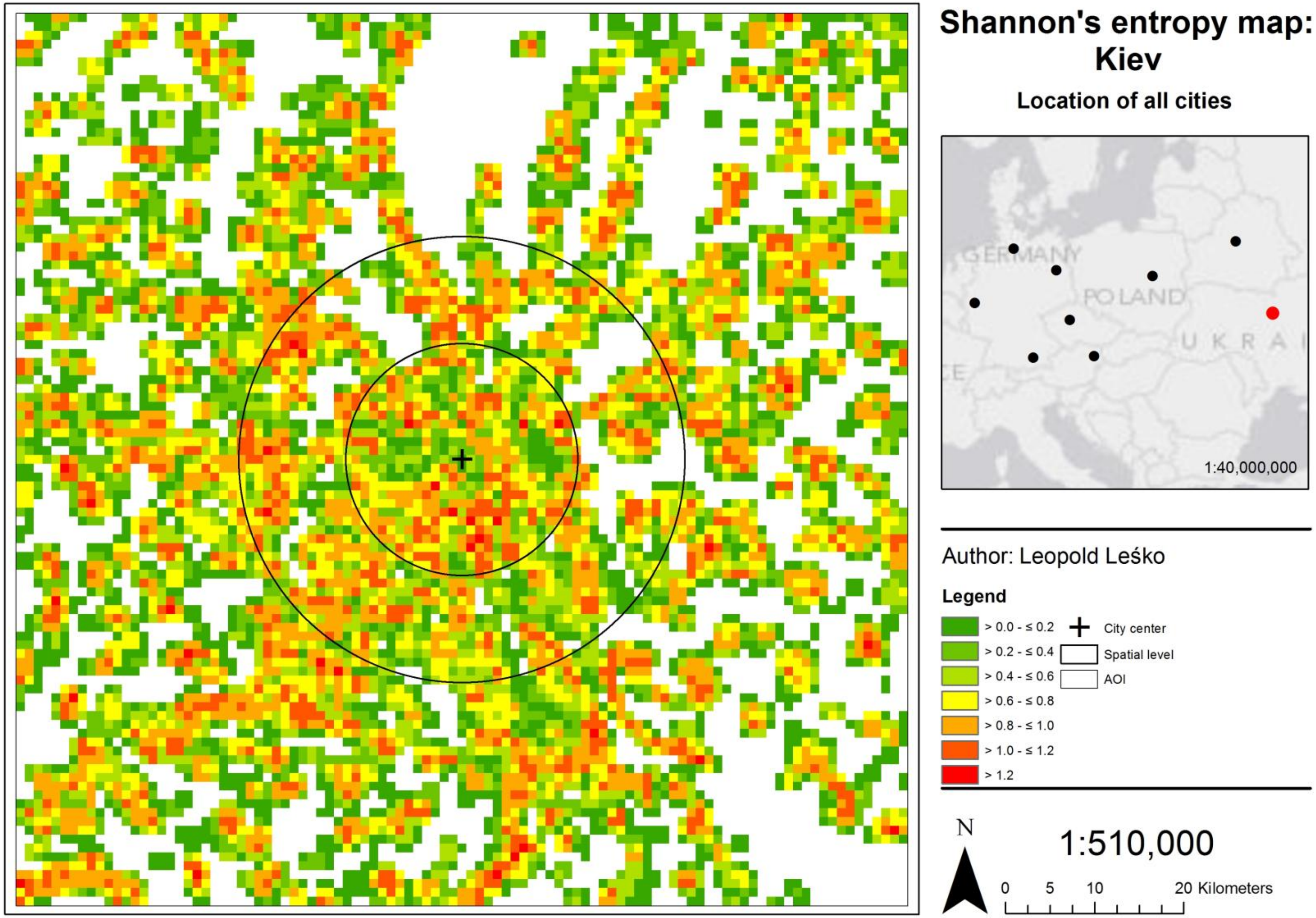

Fig. E-6 Sum of all Shannon's Entropy maps, Kiev

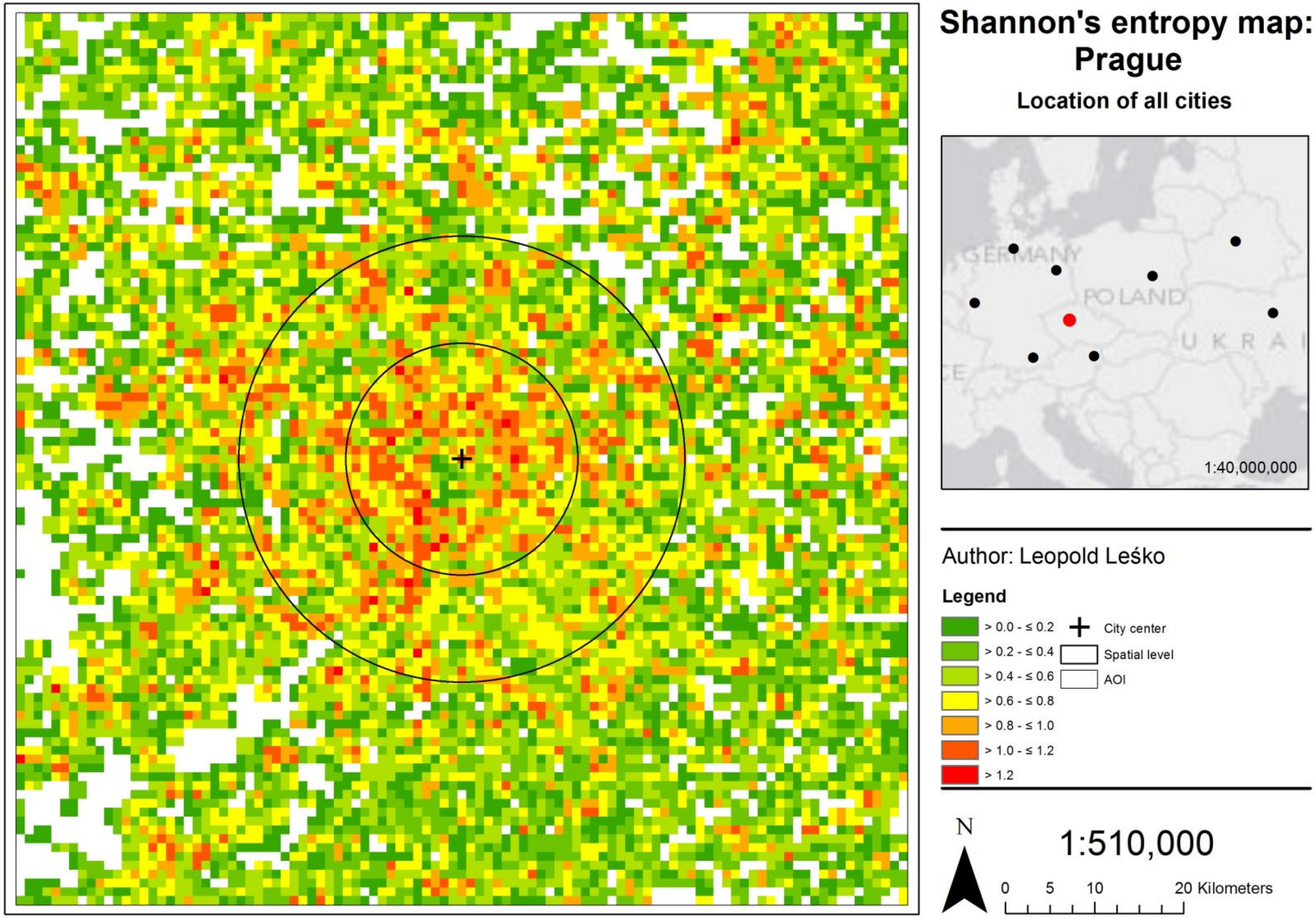

Fig. E-7 Sum of all Shannon's entropy maps, Prague

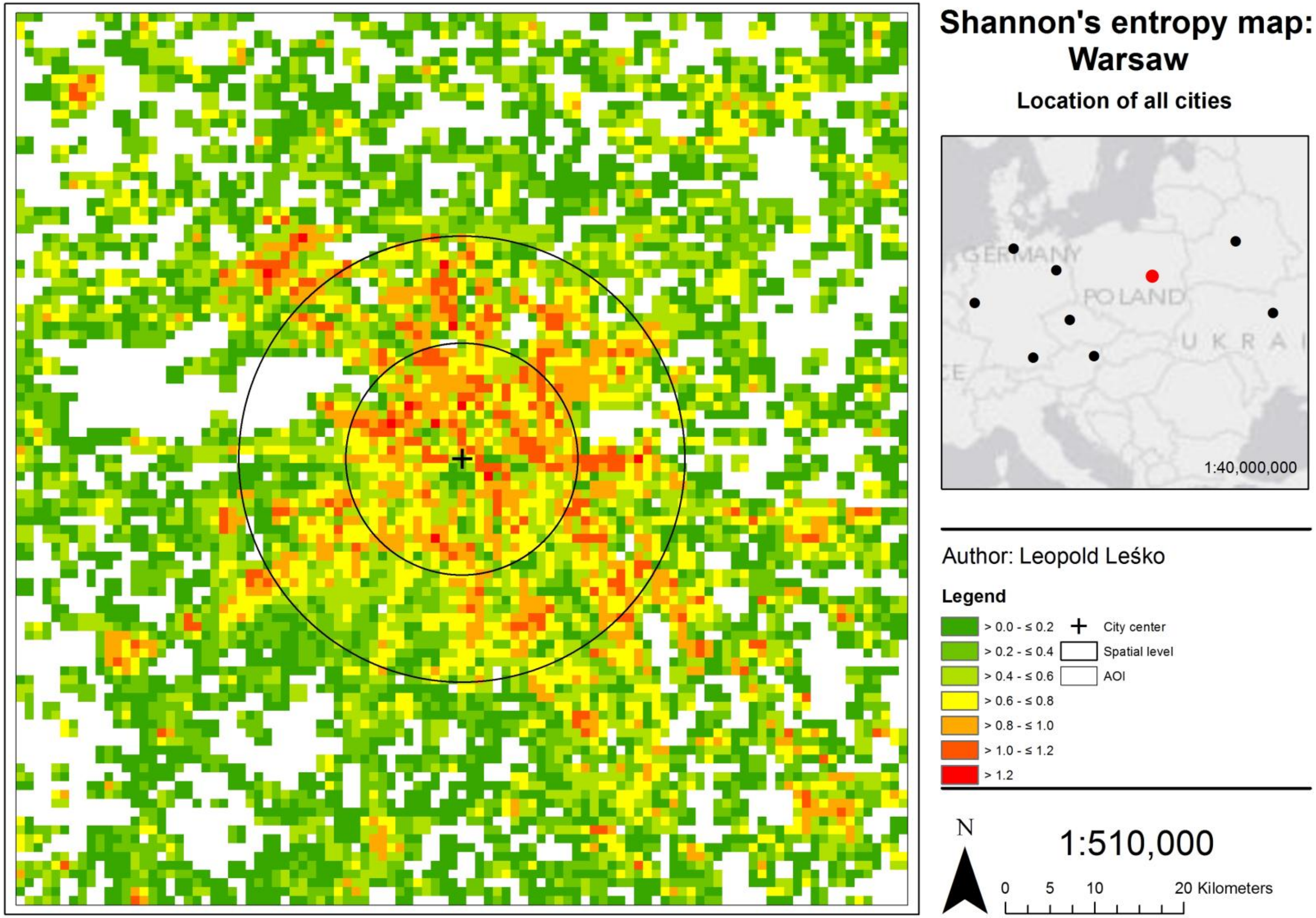

Fig. E-8 Sum of all Shannon's entropy maps, Warsaw

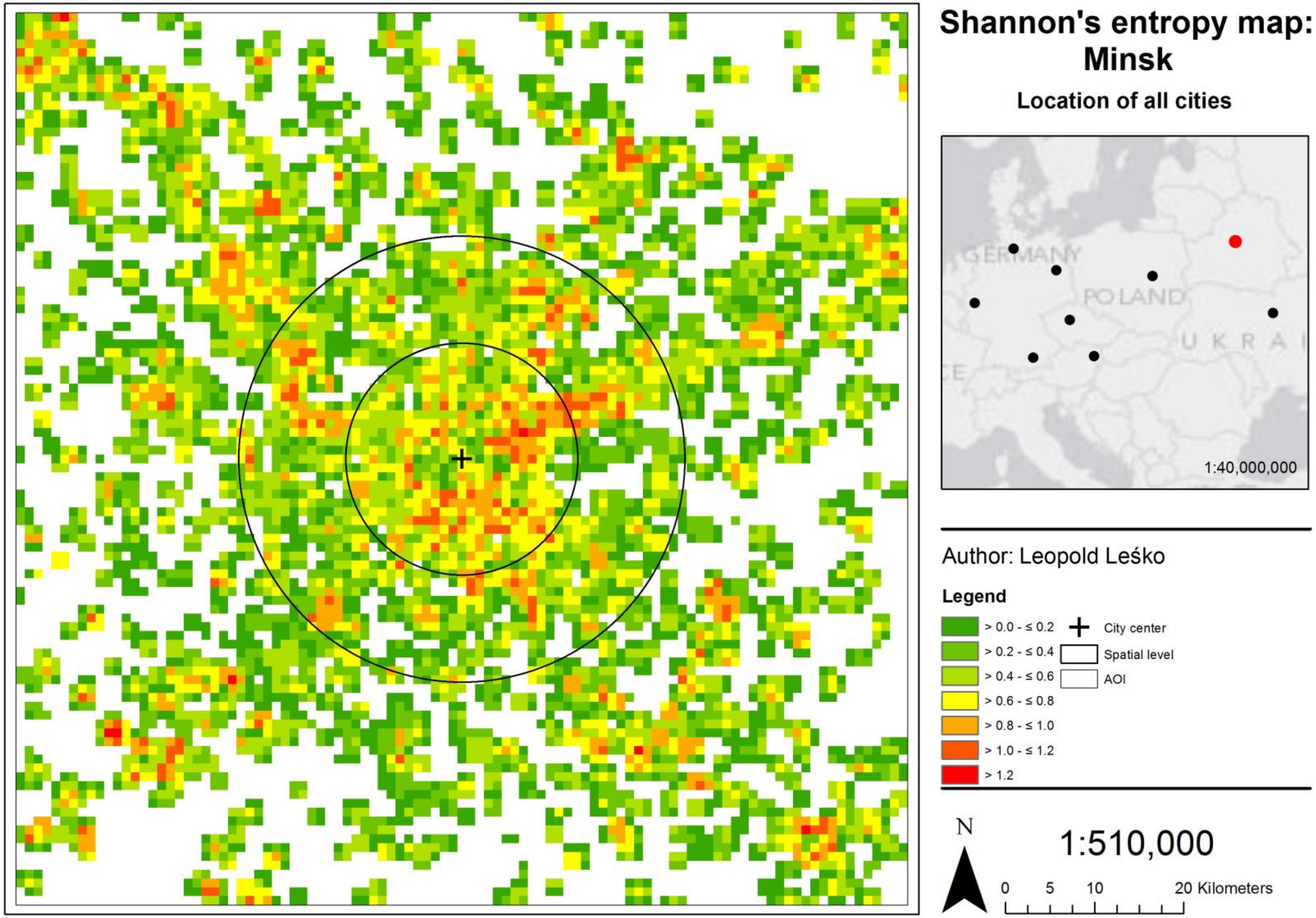

Fig. E-9 Sum of all Shannon's entropy maps, Minsk

APPENDIX F – CHESSBOARD APPROACH MAPS (1 km x 1 km, subtraction maps)

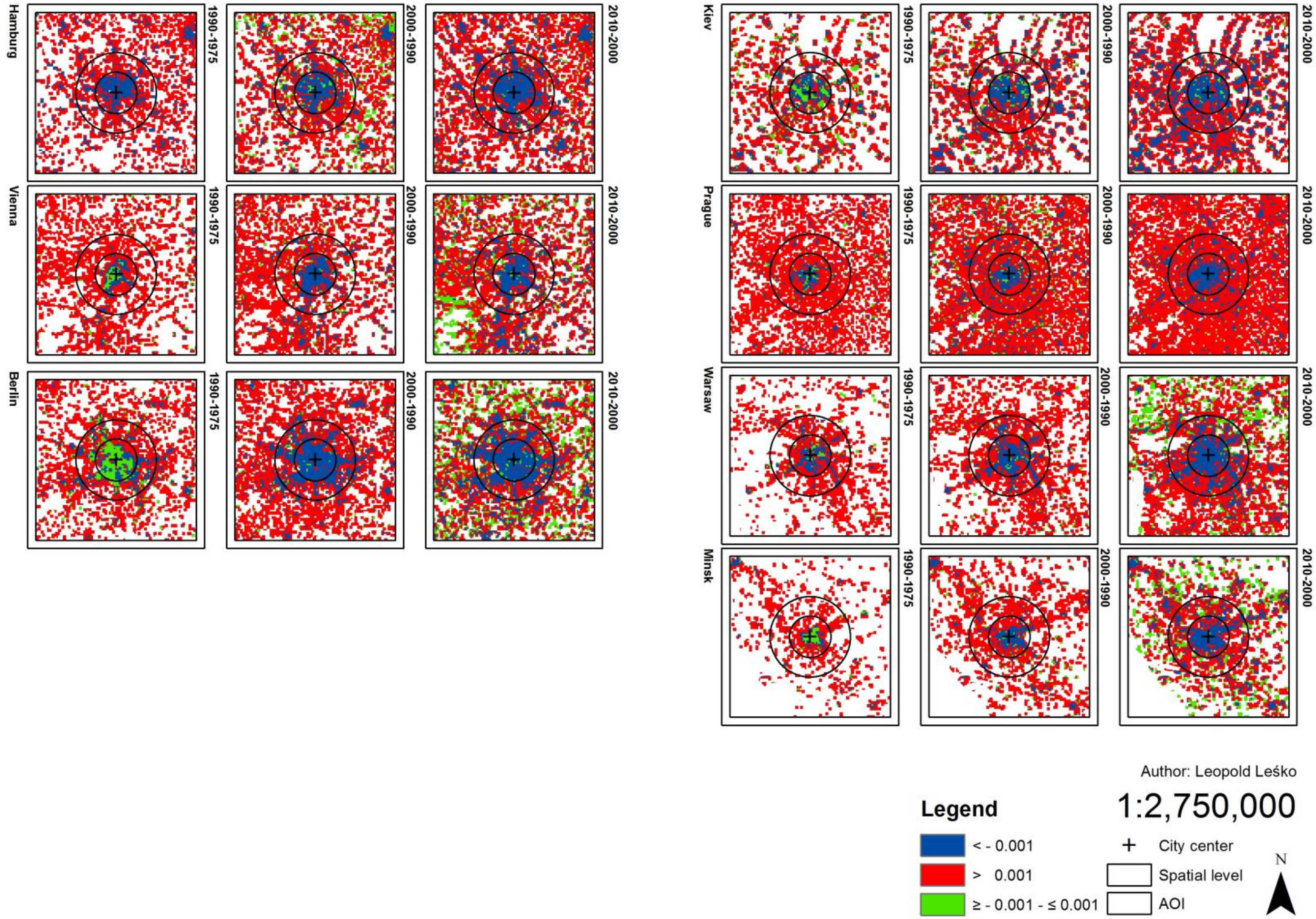

Fig. F-1 Shannon's entropy subtraction maps

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