The effects of urban expansion on spatial and socioeconomic patterns of the peri-urban areas: a case study of Isfahan city, Iran

By

Nasim Heidarinejad

A doctorate dissertation submitted to the Faculty of Spatial Planning at TU Dortmund University in partial fulfillment of the requirements for the degree of Doctor of Engineering

Examination Board:
Chairperson: Univ.-Prof. Dr.-Ing. Stefan Siedentop
First supervisor and reviewer: Univ.-Prof. Dr.-Ing. Dietwald Gruehn
Second supervisor and reviewer: Univ.-Prof. Dr. habil. Nguyen Xuan Thinh

Dortmund, December 2017

Declaration of authorship

I confirm that this thesis presented for the degree of Doctor of Engineering has

i) been composed entirely by myself,

ii) been solely the result of my own work,

iii) not been submitted for any other degree or professional qualification.

Nasim Heidarinejad

Dortmund, December 2017

Acknowledgments

This is a great opportunity to express my sincere gratitude to all those people who have supported me and had their contributions in making this thesis possible. First and foremost, I must thank the Almighty God for blessing, protecting and guiding me throughout this period.

It gives me great pleasure in expressing my deepest gratitude, especially to my supervisor, Univ.-Prof. Dr.-Ing. Dietwald Gruehn, for his constant guidance, support, motivation and untiring help. I am very much obliged to him, for his insightful comments and constructive criticisms at different stages. I could never complete the dissertation without his valuable advice and assistance in my research at various stages.

I am extremely grateful to my supervisor, Univ.-Prof. Dr. Habil. Nguyen Xuan Thinh, for his patient and meticulous guidance and suggestions during the completion of this dissertation. His comprehensive knowledge of remote sensing and urban modeling has been very helpful for me.

The next thank goes to the German Academic Exchange Service (Deutscher Akademischer Austauschdienst [DAAD]) that covered all expenses required to study in Germany.

It is my pleasure to acknowledge all colleagues and fellow students at the faculty of spatial planning for sharing knowledge and experience. Last but not the least I would like to extend my heartfelt respect and deep appreciation to my husband, my parents, and my sister for their love and great support throughout the whole process.

Thank you all

Nasim Heidarinejad

Dortmund, December 2017

Abstract

Although urban areas cover a very small fraction of the world's land surface, rapid urban expansion has significantly changed the landscape and formed immense environmental and social impacts. These effects are principally important in rapidly changing areas such as urban settlements in developing countries.

Over the last decades, several studies have focused on the field of urban expansion. However, the implications of this rapid urban expansion have not been sufficiently analyzed. They presented some major challenges. Although most developed countries have comprehensive land cover information, the relative lack of geospatial data sets is a serious and real problem in the developing countries. Moreover, the analysis of urban expansion suffers from a general lack of knowledge and understanding of physical and socioeconomic factors. With this in mind, the main objective of the dissertation is to develop an effective methodology for identifying and addressing significant spatial and socioeconomic patterns to support effective management and program planning towards a sustainable urban development. Isfahan city in Iran is introduced as the case study.

In order to achieve this aim, it is necessary to quantify the spatial and temporal dynamics of urban expansion which often requires spatial analysis. A combination of remotely sensed (RS) data and geographic information systems (GIS) technologies could provide an eminently suitable means of assessing urban planning.

Methodologically, the study proposed adopting a research paradigm that integrates spectral indexes (i.e., modified normalized difference water index (MNDWI), soil adjusted vegetation index (SAVI), and urban index (UI)) and the classification approach. This method was proposed to reduce seven bands of an original Landsat image into three thematic-oriented bands. The next step was to analyze the growth of the expansion ratio in Isfahan between 1990 and 2010. Two main indexes were applied to quantify the urban expansion, including urban expansion differentiation index (UEDI) and urban expansion intensity index (UEII). Furthermore, a set of spatial metrics was developed to quantify the urban spatial patterns. The study also developed a core set of quantitative variables to characterize socioeconomic form. Three quantitative variables were developed to measure three dimensions of socioeconomic patterns: the intensity of physical activity, the degree that activities are evenly distributed, and the extent that high-density sub-areas are clustered.

The results indicate that Isfahan city was characterized by significant rapid urban expansion, particularly over the first decade. The analysis of spatial patterns demonstrates that the city experienced phenomenal aggregated pattern in the central zones, leapfrogging pattern in the peripheral areas, as well as nodal and linear pattern in the middle regions of Isfahan city over the period considered. Through the adoption of socioeconomic measures, it is confirmed that local sprawl (discontinuity and strip development) was the dominant socioeconomic patterns of Isfahan city over 20 years. In other words, a sprawling pattern (job-based and population-based) was assured by the low value of the density and Moran coefficient, as well as the high score of Gini coefficient.

Geographically weighted regression (GWR) was suggested to explore the effects of urban expansion on the spatial patterns. The results generated from GWR indicate that patterns of urban expansion were affected by the intensification of the urban expansion in Isfahan city. In contrast, urban expansion had a significant positive relationship with the aggregation pattern in the central zones of the city. Moreover, to investigate the effects of urban expansion on the socioeconomic patterns, the Pearson correlation was applied. The results show that the expansion of the urban areas in Isfahan led to the decrease in density of population an employment, the increase of concentration in some districts, and the decrease of clustering. Overall, two obtained outcomes show that the city experienced a sprawling pattern over 20 years.

Making our cities more pleasant to live in is one of the main strategies being implemented as part of the national environment policy, which prioritizes maintaining a balance between urban expansion and protection of the environment and natural sites. In the case of Isfahan city, If the current expansion continues in the future, the new urban areas could develop in the fringe and rural areas and, therefore, the conflict between rapid urban expansion and limited land resource becomes more apparent.

Table of contents

Chapter IV

Chapter V

Chapter VI

Chapter VII

List of figures

List of tables

List of abbreviation

AIC	Akaike Information Criteria
AUER	Average Annual Urban Expansion Rate
BCI	Biophysical Composition Index
BRBA	Band Ratio for Built-up Area
BI	Bare soil index
CBD	Central Business District
CI	Contagion Index
CV	Cross-validation score
ENN_MN	Mean Euclidean Nearest Neighbor
EVI	Enhanced Vegetation Index
FRAC_MN	Fractal Index Distribution
GARI	Green Atmospherically Resistant Vegetation Index
GIS	Geographic Information system
GWR	Geographically Weighted Regression
GYRATE_MN	Radius of Gyration Distribution
IBI	Index-based Built-up Index
IJI	Interspersion and Juxtaposition Index
LPI	Largest Patch Index
NDISI	Normalized Difference Impervious Surface Index
LULC	Land use and Land change
NDBaI	Normalized Difference Bareness Index
MNDWI	Modified Normalized Difference Water Index
NDBI	Normalized Difference Built-up Index
NDVI	Normalized Difference Vegetation Index
NDWI	Normalized Difference Water Index
AREA_MN	Patch Area Distribution
PCI	Patch Cohesion Index
PI	Proximity Index

SAVI	Soil-Adjusted Vegetation Index
SHAPE_MN	Shape Index Distribution
TM	Landsat Thematic Mapper
UEII	Urban Expansion Intensity Index
UEDI	Urban Expansion Differentiation Index
UI	Urban Index

Chapter I

1. Introduction

There is relatively little awareness of immense environmental and social impacts of rapid urban expansion, which provided the motivation for this research. This chapter gives a brief overview of the importance of using modified methods to better understand the urban expansion process. Subsequently, the structure and general content of the research is described.

1.1. Background

Urbanization is a worldwide phenomenon that has increased significantly in the last century (Aguilera et al., 2011). In human civilization, the year of 2010 was the first time that the urban population had reached 3.5 billion people or crossed the 50 % mark and continued to grow, especially in developing countries, including in Africa and Asia (Nong et al., 2014). It is projected that the proportion of the urban population will reach 69.6 % by 2050 (Zhang, 2012).

Continued rapid urbanization is expected to add enormous pressure on rural and natural environments. Rural-to-urban migration flows have largely contributed to an extended urban expansion. One of the main effects of such a situation is therefore the powerful pressure exerted on the environment. The effects of urban expansion have been studied more in the last few decades due to the increased environmental awareness. Since the Stockholm Conference in 1972 (UN Stockholm Conference on the human environment), researchers have paid much more attention to the issues of urban changes, since the world's urban areas play a significant role in determining whether sustainable development is achievable (Mobaraki et al., 2012).

The review of the existing literature reveals that the urban expansion can be broadly categorized into two processes of internal and external expansion (Wilson et al., 2003). Every one of these processes may create different and distinct spatial forms (Mobaraki et al., 2012). External or peri-expansion is characterized by unconsolidated lateral physical expansion and sprawl (Doan and Oduro, 2012), while internal growth emerges in the form of compact city growth (Rahnama, 2006). Peri-expansion has affected natural and human systems at different geographic scales (Brockheroff, 2000; UNPD, 2000). This phenomenon significantly influences the functioning of local and global ecosystems and the services. As a contemporary form of urbanization, the peri-expansion, has been driven to a great extent by the need to accommodate rapidly growing population and to meet the attendant space demands of various socio-economic activities often at the expense of greenfield land (Appiah et al., 2014). This has exacerbated the effects of urban expansion and has resulted in the appearance of new patterns of urban expansion. This type of urban expansion has caused fragmentation, dispersion, and occupation of rural landscape (EEA, 2006). It is precisely for this reason that focusing on improving the sustainability is so critical to help cities to achieve a more sustainable urban system. Moving from sprawling form to a compact form has been proposed as one suggestion to reach sustainable development (Mobaraki et al., 2012).

The vast majority of urban expansion is currently hitting the developing countries more quickly than in developed countries (Li, 2012). In the last decades, Iran has been experiencing a phenomenal urban transformation (Mobaraki et al., 2012). The review of the existing literature reveals that structural features have led to the increasing growth of cities and urbanization (in number, population, and physical form) and the related problems after the Islamic revolution in 1979, for instance, housing, water supply, traffic jams, social welfare, security, health, etc. The war with Iraq accelerated these circumstances. In fact, the threat of an outside attack resulted in large movements of population. The massive population movements resulted in a remarkable urban transformation, especially in large cities. These cases have been experiencing a phenomenal urban expansion and tend to grow perhaps at a greater pace (Zanganeh Shahraki, 2007). According to estimates of the United Nations Population (2015), Iran's urban population is expected to double in roughly 50 years (from 2000 to 2050). Almost all of the Iran's total population growth in this period will be in urban areas and within a region that has already been urbanized significantly. Therefore, Iran has much more pressure in achieving sustainable development.

At this stage, Iran's spending priority should be geared to gaining a better understanding of the spatiotemporal urban expansion dynamics (Acheampong et al., 2016). In order to obtain a better understanding of urban expansion, urban-related issues have attracted increasing attention in recent years, ranging from spatial and temporal land cover patterns to urban growth scenarios by using remote sensing (RS), geographic information systems (GIS) and modeling (Zhang et al., 2009).

In contrast to the experience of developed countries, the shortage of database continues to limit urban studies in developing countries such as Iran. Moreover, the complexity of the urban systems should be taken into account as an obstacle in evaluating the expansion of city (Barredo et al., 2004). Therefore, urban analysis suffers from a lack of knowledge and understanding of the effects of urban expansion. Considering these limitations, it is also becoming inevitable then to develop an effective method in order to understand the urban expansion process.

1.2. Structure of the dissertation

This study is divided into seven chapters. After an introductory part in the first chapter, a theoretical background for this research is introduced in chapter 2. It provides a conceptual framework that emphasizes the importance of addressing land cover change, urban expansion, and spatial patterns. Moreover, it constitutes the basis for analyzing urban expansion. The third chapter of the dissertation is dedicated to state the problems regarding the urban expansion and to present the research objectives and questions of the study.

Chapter four presents an overall framework for the overall methods, techniques, and approaches to achieve the research objectives. It consists of five parts. In the first phase, a combination of maximum likelihood classifier and spectral index values (MNDWI, SAVI, and UI) are proposed to classify multi-temporal Landsat images. Consequently, the spatial extent and rate of urban expansion are analyzed and quantified. The extracted built-up area is then used as an input in FRAGSTATS 4.2 (McGarigal et al., 2012) to further describe and quantify the changing patterns and processes of the urban landscape. In addition, population and employment data are applied to analyze socioeconomic pattern. The last part outlines GWR to explore the spatiotemporal relationships between spatial patterns and urban growth.

The fifth chapter is concerned with the description of Isfahan city in Iran. Furthermore, a spatial database, including remote sensing data, spatial, and demographic variables is described. Chapter 6 presents and discusses the results generated by the methods in chapter 4. Finally, the last chapter deals with the answers to the research questions. Furthermore, based on the study findings, the development recommendations are also presented.

Chapter II

2. Theoretical background

The main emphasis of this session is placed on analyzing the effects of urban expansion. Therefore, Chapter 2 provides a brief theoretical outline of the subject. To have a comprehensive understanding of urban expansion key concepts and ideas related to the concept of urban expansion are explained. After that, related methods of analysis are introduced and compared to give the general impression of the advantages and disadvantages of these methods.

2.1. Conceptual basis

2.1.1. Urbanization, urban growth, and urban expansion

The review of the existing literature reveals that some main urban processes are sometimes used synonymously by the common people, although they are different. Therefore, defining the main urban processes is an important task before analyzing urban expansion.

The term "urbanization" refers specifically to an increase in the proportion of a country or region's population residing in urban settlements (Bloch et al., 2015). Positive rate of urbanization results when the urban population grows at a faster rate than the total population (UNICEF, 2012). The term "urban growth" refers to the absolute increase in the number of people who live in towns and cities. The pace of the growth of urban population depends on the natural increase of the urban population and the population gained by urban areas through both net rural-urban migration and the reclassification of rural settlements into cities and towns (UNICEF, 2012). These two terms are often confused in both academic and policy circles, but it is important to recognize the difference between them.

The term "urban expansion" indicates the spatial or physical enlargement of built-up areas. Bourne (1996) defined urban land expansion as one of the main indicators to measure the intensity of urbanization. He claimed that urban land expansion is the most easily identifiable characteristic of the process in the spatial dimension. Ewing (1994) defined that as the process of land conversion from non-built-up land use categories into built-up developed land over time. It is possible for a city to experience urban growth without expansion if this growth is absorbed within existing settlement boundaries. Conversely, expansion can occur without growth where new developments are created to facilitate lower population densities for an existing community (Bloch et al., 2015).

2.1.2. Urban spatial patterns and sustainability

Sustainable development refers to “development that meets the needs of the present without compromising the ability of the future generations to meet their own needs” (World Commission on Environment and Development, 1987). Due to the problems concerning peri-expansion the current urban growth is a great challenge for sustainable development (Mobaraki et al., 2012). The UN’s Agenda 21 and Habitat Agenda both suggested that the core objectives of urban sustainability should include: “a compact urban form, the preservation of open space and sensitive ecosystems, reduced automobile use, reduced waste, and pollution, the creation of livable and community-oriented human environments; decent, affordable, and appropriately located housing, improved social equity and opportunities for the least advantaged, and the development of a restorative local economy”.

The relationship between spatial patterns and sustainability is one of the main environmental concerns in current researches. Jenks et al., (1996) argued that there is a significant relationship between urban form and sustainable development, although it is not simple and straightforward.

As already stated, urban expansion can be broadly categorized into two types: internal and external expansion (Wilson et al., 2003), each of them may create a different spatial pattern (Mobaraki et al., 2012). External expansion is characterized by sprawl (Doan and Oduro, 2012), however, internal growth emerges in the form of compact city growth (Rahnama, 2006).

2.1.2.1. Sprawl pattern

There is growing global awareness and concern about sprawling pattern (Dieleman and Wegner, 2004). Urban sprawl is regarded as one of the main challenges of sustainable development and spatial planning. The term "urban sprawl" was introduced by Earle Draper, who was among the first city planners in the United States (Nechyba and Walsh, 2004). He defined this pattern as an unattractive and uneconomic form of city expansion. Since then, planners have been using the term to describe the undesired urban growth (Ghani et al., 2014). There is one basic difference between the causes of urban sprawl in a developed or developing country. Sprawl in developed countries is usually a matter of preference, however, in developing countries, this concept is fueled more by necessity (Pourahmad et al., 2007).

There are many attributes that can be associated with the term urban sprawl, although, there remains debate in the urban literature with regard to the development of an exact definition of the term. According to Gillham (2002), there are four key characteristics of sprawl. These characteristics are: leapfrogging or scattered development, commercial strip development, low density, and large expanses of single-use development.

Leapfrogging and scattered pattern goes beyond the urban fringe to create built-up communities that are isolated from developed center and have undeveloped infrastructure. In many ways, these can be seen as the most extreme examples of urban sprawl, with a highly inefficient use of land, and a greater need to build highways and other infrastructure. Leapfrogging development can be distinguished from satellite towns, a similar type of development beyond the urban fringe, by the former's much lower density (Heimlich and Anderson, 2001).

Commercial development, another aspect of urban sprawl, is characterized by huge arterial roads lined with shopping centers, gas stations, fast food restaurants, office complexes, parking lots, and many large signs (Irwin and Bockstael, 2007).

The third characteristics of urban sprawl is its low density. Density is a numerical measure of the concentration of individuals or physical structures within a given geographical unit. It is an objective and quantitative spatial indicator. Density is normally measured in terms of population density, or dwelling units per area (McConnell et al., 2006).

The final aspect of urban sprawl, the proliferation of single-use development and an almost exclusive reliance on automobiles for transportation, is just as important as density in the identification of urban sprawl, especially the negative environmental, economic and social effects. It has roots as a positive response to the problems of industrialized cities and is often created very deliberately through zoning legislation (Gillham, 2002).

The negative impacts of urban expansion on ecological cycles at all levels have been widely studied. Therefore, the particular issue in developing a sustainable city is to search for the most suitable urban forms that can help to sustain development. In urban development studies, a new word has emerged ‘compact city’ to attain the goal of sustainability.

2.1.2.2. Compact pattern

The term of " compaction" can be traced back to the Brundtland Commission report and the UNCED Agenda 21 proposals, published in the late eighties and the early nineties (Burgess, 2000). This concept designed to achieve the sustainable development within the urban environment and to compensate the key negative social, economic, and environmental impacts of urban sprawl. Currently, many researchers believe that through intensification of development within the city, many negative costs of urban sprawl have the potential to be overcome (Farris, 2001). Compact city policies have often been designed to reduce the use of private cars and to minimize the loss of open countryside (McConnell and Wiley, 2010). However, proponents of the concept claim more than just environmental benefits can be gained from a compact pattern; more compact cities are argued to be more socially sustainable because local facilities and services can be maintained, due to high population density, and therefore accessibility to goods and services is more equitably distributed (Williams et al., 2006). The high-density urban living is a prerequisite for vitality, vibrancy, cultural activities and social interaction. The rejuvenation of local economies, particularly in downtown areas neglected by urban decentralization and sprawl, can potentially also be achieved through intensification (Wiley, 2009).

One initial point to consider is the compactness of cities. Burton (2000) identified three processes to measure urban compactness: firstly, identification and definition of various aspects of urban compactness, secondly, developing indicators for measuring each of these aspects, and thirdly, calculating and reviewing the measure of indicators for a range of towns and cities. Generally, three aspects of the compact city (sustainable form) are identified: i) a high-density city, ii) a mixed-use city, and iii) an intensified city. The first two aspects are related to the form of the compact city, while the third focuses on the process of making the city more compact. Therefore, there is general agreement that the compact city model is based on an increase in density from current levels (McConnell and Wiley, 2010). Lock (1995) claimed that there is no technical or professional agreement reached on how best to measure density and that few planners are comfortable in distinguishing between net and gross residential density or overall town density. This disagreement makes it difficult to draw the components of urban intensification and to identify what types of intensification should be encouraged.

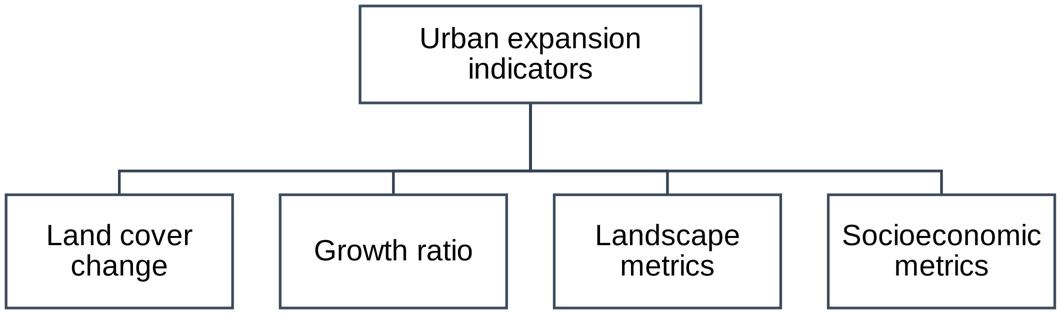
2.2. Analyzing of patterns of urban expansion

The early and later studies differ widely in methodology and assessment tools used. Early studies suggested indicators of urban expansion which were routinely based on population information, used either alone as population density per county, census block, etc. (Lopez and Hynes, 2003) or in conjunction with land cover information, such as the ratio of population to urban area or the amount of developed land per person (Hasse and Lathrop, 2003). While these studies are certainly useful for understanding the process of urban expansion, the primary shortcoming is that all rely on demographic data rather than explicit land use information. Li (2012) grouped the indicators of urban expansion into three main categories: (i) urban pattern, such as mixed-use, accessibility, and so on, (ii) growth ratio, such as growth rate of built-up area, etc., (iii) indicators of density, such as housing density, employment density and so on. Fina and Siedentop (2008) classified the indicators of the urban expansion into three classes: (i) density dimension, (ii) change of land use pattern, (iii) change of land use composition. Several indicators proposed by Western scholars, especially indicators of urban form, can be used as references.

This study aims to identify different indicators to investigate different impacts caused by the urban pattern. Therefore, the indicators of the urban expansion are grouped into four main dimensions (see Figure 2-1), (i) landscape metrics, such as degree of dispersion, degree of compactness and so on, (ii) growth ratio, such as growth rate of built-up area, etc., (iii) land cover changes, such as rate of farmland conversion, transformation of land cover from non-built-up to built-up area, (iv) socioeconomic metrics, such as population density, employment density and so on.

Figure 2-1.

Indicators of urban expansion.



2.2.1. Land cover change

To study the land cover, researchers need a tool to serve as an abstract representation of the situation in the field using well-defined diagnostic criteria (Foody, 2002). Classification describes the systematic framework with the names of the classes and the criteria used to distinguish them and the relation between classes. The rationale underlying the land cover classification using digital remote sensing data is that pixels within the same land cover class tend to group together or cluster in multispectral feature space and those groups of pixels from different cover classes tend to be separate from one another in multispectral feature space (Lu and Weng, 2007). Generally, the image classification procedures may be carried out as follows:

1) Design image classification scheme: they are usually information classes such as urban, agriculture, forest areas, etc.
2) Conduct field surveys and collect ground information and other ancillary data of the study area.
3) Preprocessing of the image, including radiometric, atmospheric, geometric and topographic corrections, image enhancement, and initial image clustering,
4) Select representative areas of the image and analyze the initial clustering results or generate training signatures.
5) Image classification algorithms running.
6) Post-processing: complete geometric correction and filtering and classification decorating (Lu and Weng, 2007).
7) Accuracy assessment: compare classification results with field studies.

There are four data collection tools available for gathering primary data, i) space remote sensing imagery, ii) aerial photographs, iii) sample surveys (area frame surveys), and iv) administrative data. Remote sensing is the science (and to some extent art) of acquiring information about the earth's surface without being in contact with it. This is done by sensing and recording reflected or emitted energy and processing, analyzing, and applying that information (Dadrasa et al., 2015). Aerial photographs are black and white, or color pictures of the earth's surface taken by a film camera on board an airplane, helicopter or balloon. An area frame survey is an alternative approach to acquiring land cover data or information about the agricultural sector. In contrast to remote sensing-based surveys, where the entire area is mapped, area frame sampling is based on the selection and observation of representative area samples. The purpose of sampling is to enable a valid generalization to be made without studying the whole area under investigation. Additionally, the administrative data deal with the functional dimension and describe the use of areas by the socioeconomic purpose. This information can be compiled by conducting surveys or censuses, and/or by using already compiled information from administrative and statistical registers, especially in built-up areas (settlements). The use of administrative data sources for statistical purposes is much depending on the original purpose of the registers. In land-use studies, the introduction of GIS-tools and geo-referenced information from registers has opened up for new and important data sources for land use statistics. Register information based on activity data and technical information about buildings and ground properties can be used alone or combined with observations from satellite images to form a good total data source to derive land use statistics.

Depending on the interaction between the analyst and the computer during classification, there are two types of classification: supervised and unsupervised. In the case of supervised classification, the analyst identifies in the imagery homogeneous representative samples of the different surface cover types (information classes) of interest (Lu and Weng, 2007). These samples are referred to as the training areas. The selection of appropriate training areas is based on the analyst's familiarity with the geographical area and the knowledge of the actual surface cover types present in the image. Thus, the analyst is supervising the categorization of a set of specific classes (Liu et al., 2009).

The Maximum Likelihood Classifier (MLC) is the most common parametric classifier which assumes normal or near normal spectral distribution for each feature of interest. This classifier is based on the probability that a pixel belongs to a particular class and takes the variability of classes into account by using the covariance matrix (Jensen, 2005).

Unsupervised classification is where the outcomes (groupings of pixels with common characteristics) are based on the software analysis of an image without the user providing sample classes. The computer uses techniques to determine which pixels are related and groups them into classes. The user can specify which algorithm the software will use and the desired number of output classes, but otherwise does not aid in the classification process. However, the user must have knowledge of the area being classified when the groupings of pixels with common characteristics produced by the computer must be related to actual features on the ground.

Although traditional classification method has been used successfully in mapping a range of land covers at a variety of spatial and temporal scales, there are some challenges in obtaining accurate land cover information in urban areas (Townshend, 1992). Consequently, misclassification problems are often found in the land cover maps generated from traditional methods. A key concern is that the derived land cover maps are often judged to be of insufficient quality for operational applications (Foody, 2002).

Over the past few decades, several scholars used spectral indexes, which have been proposed and used to identify a specific land cover when multiple materials are mixed in one pixel. Generally, they are grouped into three main categories: i) spectral vegetation indexes, ii) spectral urban indexes, and iii) spectral water indexes (Table 2-1).

Table 2-1.

List of common spectral indexes.

Type	Main Indexes and references
Spectral Vegetation Index	Normalized Difference Vegetation Index (NDVI) (Rouse et al., 1974); Enhanced Vegetation Index (EVI) (Huete et al., 1997); Simple Ratio (SR) (Jordan, 1969); Green Atmospherically Resistant Vegetation Index (GARI) (Gitelson et al., 1996); Wide-Dynamic Range Vegetation Index (WDRV) (Gitelson, 2004).
Spectral Urban Index	Normalized Difference Built-Up Index (NDBI) (Zha et al., 2003); Index-based Built-Up Index (IBI) (Xu, 2008); Urban Index (UI) (Bouhennache et al., 2015); Normalized Difference Bareness Index (NDBaI) (Zhao et al., 2005), Bare soil index (BI) (Rikimaru, 1997).
Spectral Water Index	Normalized Difference Water Index (NDWI) (Gao, 1995); Modified Normalized Difference Water Index (MNDWI) (Xu,2007); Water Band Index (WBI) (Peñuelas et al., 2011);

Zha et al., (2003) proposed a technique of combining the NDBI and the NDVI with a specific process to extract the built-up areas with an accuracy of 92.6%. Zha et al., (2010) proposed a new method based on Normalized Difference Built-up Index (NDBI) to automate the process of mapping built-up areas in the city of Nanjing, eastern China. The results at an accuracy of 92.6% indicated that compared with the maximum likelihood classification method, the proposed NDBI could serve as a worthwhile alternative for quickly and objectively mapping built-up areas. Xu (2007) used three indices, Normalized Difference Built-up Index (NDBI), Modified Normalized Difference Water Index (MNDWI), and Soil-Adjusted Vegetation Index (SAVI). Using this method, the seven bands of Landsat image were reduced to three thematic-oriented bands derived from above indices. The three new bands were then combined to compose a new image. This considerably reduced data correlation and redundancy between original multispectral bands. Hu (2007) proposed an Index-based Built-up Index (IBI). The three thematic indices used in constructing the IBI were the Soil-adjusted Vegetation Index (SAVI), the Modified Normalized Difference Water Index (MNDWI) and the Normalized Difference Built-up Index (NDBI). Respectively, these represented the three major urban components of vegetation, water, and built-up land.

The new index has been verified using the Landsat ETM+ image of Fuzhou city in southeastern China. The result showed that IBI could significantly enhance the land cover extraction, while effectively suppressing background noise. Deng and Wu (2012) proposed a biophysical composition index (BCI) for the derivation of urban biophysical compositions. Further, this research explored the applicability of BCI in various remotely sensed images at different spatial resolutions. Results indicated that BCI has a closer relationship with impervious surface abundance than those of Normalized Difference Vegetation Index (NDVI), Normalized Difference Built-up Index (NDBI) and Normalized Difference Impervious Surface Index (NDISI), with correlation coefficients of approximately 0.8 at various resolutions. Bouhennache et al., (2015) proposed a method, including three derived indexes SAVI the Soil Adjusted Vegetation Index, UI the Urban Index, and EBBI the Enhanced Built up and Bareness Index, which were stacked to form a new image. Subsequently, four urban, vegetation, water and soil land cover categories were extracted with their accuracy assessment. Bouzkri et al., (2015) proposed a new spectral index to detect land cover from medium spatial resolution satellite imagery data. The newly developed spectral was derived from band ratios and was compared with four previously used spectral indices, the Band Ratio for Built-up Area (BRBA), the Normalized Built-up Area Index (NBAI), the New Built-up Index (NBI), and the Normalized Built-up Index (NDBI). Indexes were used to extract the built-up area of Djelfa city, South Algiers.

Change detection is defined as the process of determining differences in the state of an object or phenomenon by observing it at different times (Im et al., 2007). The general goal of the change detection in remote sensing includes identifying the geographical location, recognizing and quantifying the type of changes, and finally assessing the accuracy results (Im and Jensen, 2005). Change information may be obtained either in the form of simple binary change (i.e. change vs. no change as in the case of image differencing, image rationing, etc.) or detailed from-to change as in the case of using post-classification comparison (Im et al., 2007). There are two groups of change detection techniques based on the unit of image analysis, first, the traditional/classical pixel-based methods, in which an image pixel is the fundamental unit of analysis, second, the object-based method, in which image objects are first created and then subjected to further analysis (Naveena and Wiselin, 2015). In the pixel-based change detection techniques, the spectral characteristics of an image pixel are exploited to detect and measure changes without taking into considering the spatial context. On the other hand, object-based change detection is performed by separately segmenting objects defined by a threshold from multi-temporal images and analyzing the changes based on the spectral information like averaged band values of the object or by extracting various features (i.e., geometry and image-texture) from the original objects (Naveena and Wiselin, 2015). A list of these techniques is summarized in Table 2-2.

Table 2-2.

Different methods of the change detection techniques.

		Description	Authors
pixel-based	Image Differencing	Subtracting the DN (digital number) value of one date for a given band from the DN value of the same pixel for the same band of another date.	Lu et al., (2004); Gao (2009)
	Image Rationing	Th ratio between two co-registered images.	Tiede et al., (2014)
	Image Regression	The subject image is assumed to be a linear function of the reference image and is adjusted to match the radiometric conditions of the reference image.	Schimek (2000)
	Vegetation Index Differencing	After computing, the vegetation index for two date's standard pixel-based approaches is applied to determine the change.	
	Change Vector Analysis	The pixel values are the vectors of spectral values and change vector can be computed by subtracting vectors for all pixels at different dates.	Chen et al., (2012)
	Principal Component Analysis	This method reduces data redundancy by transforming multivariate data to a new set of components with the assumption that areas of change are not highly correlated	Lillesand et al., (2008); Jolliffe (2002)
	Kauth-Thomas Transformation (KT)/Tasseled Cap Transformation	It involves fixed linear transformation of a multi-date and multiband dataset. Change is measured based on the brightness, greenness and wetness values.	Lu et al., (2004)
	Post-classification	each image is rectified and classified separately and then compared to generate a change matrix which is used to measure the changes.	Alphan et al., (2009); Tiede et al., (2014)

	Composite or Direct Multi-date Classification	Performing single analysis of a combined dataset of the two dates where initially multi-temporal and rectified images are stacked.	Sakti and Tsuyuki (2015)
	Machine Learning	The algorithm learns from training data and finds threshold values from the spectral features automatically for classifying change from no-change.	Bovolo et al., (2008); Larose, (2005)
	Texture analysis based	The image is divided into smaller windows instead of per-pixel comparison then the texture is computed, and the comparison is performed at window level.	Caridade et al., (2008)
	Multi-temporal Spectral Mixture Analysis	The multispectral image pixels are assumed to be defined in terms of sub-pixel proportions of pure spectral components that are related to surface constituents in a scene.	Okin (2001); Lu (2004); Somers and Asner (2013); Sakti and Tsuyuki (2015)
	Fuzzy Change Detection	The class with the highest probability is taken to be the actual class and change is measured by applying post-classification comparison.	Fisher et al., (2006); Ghosh et al., (2011); Durieux et al., (2008)
Object-based	Image-object Change Detection	The connectivity analysis is used to extract the objects from the master image and each of these objects was searched for a corresponding object in the second image.	Lefebvre et al., (2008); Hay et al., (2005)
	Class-object Change Detection	the extracted object is assigned to a specific class and changes are detected by comparing the independently classified objects from multi-temporal images.	Bergsjö, (2014); Im and Jensen (2005)
	Multitemporal-object Change Detection	In this approach, temporally sequential images are combined and segmented to produce spatially corresponding change objects.	Conchedda et al., (2008); Xiong et al., (2012)

Tauhidur Rahman (2016) examined the land cover changes in Saudi Arabia's eastern coastal city of Al-Khobar between 1990 and 2013. Specifically, he used classification method to classify Landsat data collected from 1990, 2001, and 2013 and then detected changes in the land cover within the study area. With overall classification accuracy, greater than 85%, the results indicated that urban built-up areas increased by 117% between 1990 and 2001 and 43.51% from 2001 to 2013. Silambarasan et al., (2014) analyzed major changes in land cover during the 2003-2013 period to understand urban sprawl patterns in and around Udupi town using satellite images and change detection methods. The study indicated that there was a significant increase in settlements and built-up land during the study period. The settlement and built-up land increased from 16.7 km^2 to 41.9 km^2 indicated an increment of 150% compared to 2003. Barren/wasteland showed a decrease due to conversion to settlement and built-up area. Wang et al., (2012) detected the urban expansion in the Greater Toronto Area (GTA) in a period of 29 years lasting from 1985 to 2013 using the optical remote sensing data. A time-series study was carried out and the change of the urban area and the non-urban area was analyzed bi-temporally and multi-temporally by using the post-classification comparison method. Landsat images used to examine the land use and land cover changes of GTA in a long time. The extent and spatial patterns of urban expansion were both analyzed quantitatively in the study. Subramani et al., (2014) took Panamarathupatti lake Salem city as the case to study the urban expansion and land cover change that took place in a span of 36 years from 1973 to 2009. The remote sensing methodology was adopted to study the geographical land use changes occurred during the study period. Change detection analysis showed that built-up area increased by 372.28%, agricultural area decreased by 65.16% and barren area reduced by 60.98%. Rizk Hegazy and Rashed Kaloop (2015) attempted to assess land cover change detection by using GIS in Mansoura and Talkha from 1985 to 2010. Change detection analysis showed that built-up area has been increased from 28 to 255 km^2 by more than 30% and agricultural land reduced by 33%. Afify (2011) assessed the nature and extent of land cover changes in New Burg El-Arab city through the period from 1990 to 2000 using Remotely Sensed Landsat Multispectral Images. Four change detection techniques namely: i) post-classification, ii) image differencing, iii) image rationing, and iv) principal component analysis were applied. The results indicated that the post-classification change detection technique provided the highest accuracy while the principal component analysis technique gave the least accuracy.

In Iran, Ahmadi and Nusrat (2010) analyzed the land use changes in the region near Neka River based on Landsat data from 1977 to 2001. Supervised/unsupervised classification approach, coupled with RS and GIS analyses, was employed to generate the change over land use/cover maps. To analyze landscape fragmentation, the land-use change was calculated using normalized difference vegetation index (NDVI). Based on the results of the analysis, the range of NDVI has changed from the reflection of 0.95 to 0.28 in 1977 to the reflection of 0.64 to 0.18 in 2001, which indicates that an increase in bare lands led to a decrease in forest lands. Matinfar (2010) examined Khoramabad, a city in Lorestan province of Iran, as the case study via three techniques of remote sensing: NDVI comparison, Principal Component Analysis, and the Post Classification. To carry out these three techniques, TM and ETM+ data obtained from Landsat Satellite within the years 1991 to 2002 was used to monitor environmental changes, especially the physical development of the area and its devastating effects on the green space. The result presented here indicates that the farming land area decreased between 1991 and 2002 by 14% from 4975 to 3672 ha. Also, the urban and non-arable land area increased from 5376 to 6678 ha. Kelarestaghi et al., (2010) detected the land use changes between 1967 to 2002 using satellite images, aerial photos, and digital topographic maps. Different suitable spectral transformations such as rationing, PCA, Tasseled Cap transformation and data fusion were performed on the images. The change detection analysis showed that the forest area decreased between 1967 and 2002 by 2.99% from 7322.22 to 6947.23 ha. Also, the area with irrigated land farms have been increased to 202.01 ha (1.61%) and the dry land farming area decreased to 9.2%.

2.2.2. Landscape pattern

As stated earlier, remote sensing capabilities greatly improve the ability to provide detailed information about the type, amount, and location of the land use conversion. Although, it lacks the ability to describe the underlying urban growth process that is responsible for the changing patterns of the landscape (Herold et al., 2005). The pattern of landscape is a highly integrative response to a variety of factors and processes in different sectors: natural site conditions, cultivation traditions preferring regional techniques, social development, as well as economic forces and even religious rules are working intertwined in a complex system in the past and the present (Bartel, 2000).

Landscape ecology emphasizes the interaction between spatial pattern and ecological process, therefore the methods by which spatial patterns can be described and quantified are necessary. There are three main situations where knowledge of the pattern is important for researchers. First, landscapes vary through time, and researchers may be interested in knowing whether the pattern is different at time t + 1 than it was at time t. Furthermore, they may want to know specifically how landscape pattern has changed. Second, they may wish to compare two or more different landscapes or places within a given landscape and determine how different or similar they are. Third, when considering options for land management or development, the researchers may need to evaluate quantitatively the different landscape patterns that result from the alternatives (Dunn et al.,1991).

Many analyses of landscape pattern have been conducted on land use/land cover data that have been digitized and stored within the GIS dataset. As summarized by Dunn et al. (1991), there are three main types of data to study the landscape pattern: i) aerial photography, ii) digital remote sensing, iii) published data, and censuses. In addition to these three sources, the field mapped data may be used for landscapes of smaller extent in which the investigator might map the spatial patterns of landscape elements of interest in a relatively small area.

2.2.2.1. Spatial metrics

Spatial or landscape metrics can be defined as quantitative indices to describe structures and patterns of a landscape. Generally, landscape pattern metrics fall into two general categories: those that quantify the composition of the map without reference to spatial attributes, and those that quantify the spatial configuration of the map, requiring spatial information for their calculation. Composition refers to features associated with the variety and abundance of patch types within the landscape. As composition requires integration over all patch types, composition metrics are only applicable at the landscape level. Configuration, on the other hand, refers to the spatial character and arrangement, position, or orientation of patches within the class or landscape (Table 2-3). Some aspects of configuration, such as patch isolation or patch contagion, are measures of the placement of patch types relative to other patches, other patch types, or other features of interest. Other aspects of configuration, such as shape and core area, are measures of the spatial character of the patches. Several metrics can be applied either in terms of individual patches or in terms of whole class or landscape, depending on the study emphasis sought. Software packages are widely used (e.g., FRAGSTATS, see McGarigal et al., 2002), and many metrics have also been integrated into existing geographic information system (GIS) software (e.g., Patch Analyst in ArcView; and module Pattern in IDRISI).

Table 2-3.

Metrics for quantifying landscape pattern.

	Aspects	Description	Common metrics
Composition type	Proportional Abundance of each Class	The proportion of each class relative to the entire map.	-
	Richness	The number of different patch types.	Patch richness density (PRD); Relative patch richness (RPR)
	Evenness	The relative abundance of different patch types, typically emphasizing either relative dominance or its complement, equitability.	Simpson's evenness index (SIEI); modified Simpson's evenness index (MSIEI)
	Diversity	A composite measure of richness and evenness and can be computed in a variety of forms.	Shannon’s Diversity Index (SHDI), Simpson’s Diversity Index (SIDI), Shannon’s Evenness Index (SHEI)
Configuration Type	Patch size distribution and density	Patch size distribution can be summarized at the class and landscape levels in a variety of ways (e.g., mean, median, max, variance, etc.), or, alternatively, represented as patch density, which is simply the number of patches per unit area.	Largest Patch Index (LPI), Patch Area Distribution (AREA_MN), Radius of Gyration Distribution (GYRATE_MN)
	Patch shape complexity	Shape complexity relates to the geometry of patches, whether they tend to be simple and compact, or irregular and convoluted. Its measures are based on the relative amount of perimeter per unit area, and often standardized to a simple Euclidean shape (e.g., circle or square).	Perimeter-Area Fractal Dimension (PAFRAC), Perimeter-Area Ratio Distribution (PARA_MN), Shape Index Distribution (SHAPE_MN), Fractal Index Distribution (FRAC_MN)

	Core Area	Core area integrates patch size, shape, and edge effect distance into a single measure and represents the interior area of patches after a user-specified edge buffer is eliminated.	Total Core Area (TCA), Number of Disjunct Core Areas (NDCA), Disjunct Core Area Density (DCAD)
	Isolation/Proximity	The tendency for patches to be relatively isolated in space (i.e., distant) from other patches of the same or similar (ecologically friendly) class.	Proximity Index Distribution (PROX_MN), Similarity Index Distribution (SIMI_MN), Euclidean Nearest Neighbor Distance Distribution (ENN_MN), Functional Nearest Neighbor Distance Distribution (FNN_MN)
	Dispersion	The tendency for patches to be regularly or contagiously distributed (i.e., clumped) with respect to each other.	Percent like adjacencies (PLADJ), clumpiness index (CLUMPY), patch cohesion index (COHESION)
	Contagion and Interspersion	The tendency of patch types to be spatially aggregated; that is, to occur in large, aggregated or “contagious” distributions	Contagion (CONTAG), Aggregation Index (AI), Interspersion & Juxtaposition Index (IJI), Landscape Division Index (DIVISION)
	Subdivision	The degree to which a patch type is broken up (i.e., subdivided) into separate patches (i.e., fragments), not the size (per se), shape, relative location, or spatial arrangement of those patches	Number of patches (NP), patch density (PD), Landscape division index (DIVISION), Effective mesh size (MESH)
	Connectivity	The functional connections among patches. Connections might be based on strict adjacency (touching), some threshold distance, some decreasing function of the distance that reflects the probability of connection at a given distance, or a resistance-weighted distance function.	Patch Cohesion Index (COHESION), Connectance Index (CONNECT), Traversability Index (TRAVERSE)

Source: McGarigal and Marks (1995).

In numerous studies, landscape metrics have been used to describe changes in a landscape through the urban expansion process. Just a few are discussed here to provide examples of the insights that have been produced by the application of landscape metrics. Other examples of the use of landscape metrics in empirical studies and spatial models will be found in the subsequent chapters.

Aguilera-Benavente et al., (2014) analyzed the urban growth patterns using spatial metrics in Algarve (southern Portugal). The results showed differences in urban land use patterns and associated processes at each scale, with stable land use patterns predominating at the 1: 100,000 scale, whereas the 1: 25,000 scale showed a move towards more dispersed pattern. These results have enabled an assessment of the principal differences in urban growth patterns observed at both scales, and the implications for planning. Salvati (2014) studied changes (1949-2008) in the structure of a Mediterranean urban area (Rome, Italy). Using a quantitative approach based on land-use indicators and landscape metrics, distribution and fragmentation of built-up areas were analyzed from high-resolution and diachronic digital maps covering the investigated area (1,500 km^2). The analysis of the changing urban structure during the study period allowed for an indirect evaluation of planning impact on Rome's expansion. City's morphology changed rapidly due to urbanization. While in the first examined phase (1949-1974) metrics indicated compactness and densification trends, the fractal dimension of urban settlements increased in the subsequent period. The study identified the indicators better characterizing Rome's expansion as a contribution to the understanding of long-term urban dynamics in the Mediterranean region. Dasgupta et al., (2009) analyzed temporal remote sensing data of diverse spatial and spectral resolutions for Greater Bangalore. The city was divided into eight zones, to analyze the landscape metrics using classified data from 1973 to 2010. The study revealed that the city was more compact in 1973 and began to disperse in all directions with a decrease in the ratio of open space and increase in the number of urban patches as well as urban density. Ji et al., (2006) explored the spatial analytical methods to identify both general trends and more subtle patterns of urban land changes. Both the remotely sensed data and landscape metrics were used to characterize long-term trends and patterns of urban sprawl. The landscape metrics were analyzed across jurisdictional levels to understand the effects of the built-up expansion on the forestland and non-forest vegetation cover. The results of the analysis suggest that at the metropolitan level both areas of non-forest vegetation and the forestland became more fragmented due to development while large forest patches were less affected. Herold et al., (2002) developed a methodology using information on image spatial form to describe urban land-use structures and land-cover changes. The analysis was based on spatial analysis of land-cover structures mapped from digitally classified aerial photographs of the urban region Santa Barbara, CA. Landscape metrics were calculated for segmented areas of homogeneous urban land use to allow a further characterization of the land use of these areas. Several important structural land-cover features were identified for this study. For two test areas in the Santa Barbara region, changes (urban growth) in the urban spatial land-use structure described and quantified with landscape metrics. The analysis showed the importance of the spatial measurements as second-order image information that can contribute to the most detailed mapping of urban areas and towards a more accurate characterization of spatial urban growth pattern.

In Iran, Jaafari et al., (2016) developed an integrated application of satellite imagery interpretation and landscape ecology approach to quantify and analyze the landscape dynamics of Jajroud reservation area, Iran. The digital images collected by satellite at 1986, 2000, and 2010 were classified following an ensemble classification method. Landscape metrics-based analysis of temporal patterns of LULCs indicated that Jajroud reservation area has been undergoing rapid and drastic changes over the past 25 years. Based on the class area metrics at the landscape level, the changes were mostly due to the conversion of degraded rangeland and orchard to the urban category. The impervious area expanded approximately five-fold from 1986 to 2010. Based on Largest Patch Index, the dominant land-cover class across the study time frame was degraded rangeland that decreased from 1986 to 2010. The study demonstrated that integrated application of satellite imagery and landscape metrics can be a useful and easy-to-implement tool for environmental impact assessment of an ongoing urbanization process. Assar Khaniki (2015) studied the process of landscape changes based on physical and quantitative evaluation using landscape metrics and perceptual and quantitative evaluation in Ray city, Iran. The results have cleared an image of the structural changes and the great change of people's perception during the time. Based on the results, Ray's landscape was under the process of fragmentation over the last five decades. Seifolddini and Mansourian (2014) determined the spatial-temporal pattern of urban growth in Tehran metropolitan area. They used historical maps and satellite images to determine the urban growth patterns for Tehran for the period 1921–2011. Spatial metrics were used to analyze the spatial-temporal pattern of urban growth at two levels: Tehran's metropolitan area as a whole and within the concentric zones in this area. Results indicated that urban growth rate in Tehran metropolitan area should be divided into three major periods: (i) rapid growth rate (1921–1976), (ii) very rapid growth rate (1976–1986), (iii) slow and consistent growth rate (1986–2011). The results also cleared that urban growth in Tehran city followed tidal waves pattern and consequent phases of growth.

2.2.2.2. Urban-rural gradient model

From an ecological point of view, an urban-rural gradient model represents the structural and functional differences of transitional patches which can capture the spatiotemporal complexity of urban dynamics (Nong et al., 2014). This paradigm has proved to be a useful tool for studying the ecological patterns of urban growth. The use of the gradient approach has improved our understanding of how organisms respond to the continuous process of urbanization with humans as an integral part of ecosystems (McDonnell and Pickett, 1990). The studies of urban-rural gradients have predominantly been quantified using concentric zones from the urban core outwards using GIS methods.

Kroll et al., (2012) presented a method to quantify and map the supply and demand of three essential provisioning services – energy, food, and water – along with the rural-urban gradient of the eastern German region Leipzig–Halle. This urban region has experienced significant socioeconomic dynamics and land use changes since the German reunification in 1990. Park (2015) compared the connectivity values along the different urban gradient in the Phoenix metropolitan area. A GIS-based landscape connectivity model was developed and applied to this region. A GIS-based concentric buffering technique was employed to delineate conceptual boundaries for urban, suburban, and rural zones. Singh Boori et al., (2015) explored a multi-buffer ring method to investigate the spatial and temporal dynamics of urban growth in the Kuala Lumpur the metropolitan area by using geographical information systems (GIS) and remote sensing images from 1989 to 2014. The multi-buffer rings were created for every 1 km distance from 1 to 50 km from the city center to the outside. Then, the intersection with classified maps for all three dates was performed. Aguilera-Benavente et al., (2014) proposed the methodology consisted of selected buffer zones to identify urban sectors. In their research, a series of the buffer zone were applied around the coastline. Li and Thinh (2013) compared the land-cover change patterns in the developing and the developed countries. In their study, Xuzhou city and Dortmund city region were selected as study areas. Urban growth patterns and processes of the two study areas were investigated and compared through land-cover change detection, GIS-based buffer analysis, and jaggedness degree. Suja et al., (2013) employed GIS-based buffer gradient model to evaluate the spatiotemporal characteristics of urbanization in Thiruvananthapuram district. Satellite images were used for different time stages. The results of the analysis display the interactions in regional urbanization. Tian et al., (2011) conducted the landscape metrics analysis across concentric buffer zones to elucidate some landscape pattern characteristics for five urban areas in the Yangtze region of China. Xiaowen et al., (2010) employed a combination of remotely sensed data, urbanization metrics, and GIS-based buffer gradient analysis to analyze the overall spatiotemporal characteristics of urban expansion in the Shanghai region, China and to explore the urbanization of its major satellite cities and their interactions. The results indicated that the overall spatiotemporal changes in the urbanization gradient were largely influenced by the distance from the urban center of the case study. Taubenböck et al., (2009) detected temporal and spatial urban sprawl, re-densification and urban development in the tremendously growing 12 largest Indian urban agglomerations. The study applied the combination of landscape metrics and zonal based gradient analysis to characterize the spatial pattern of the cities. The results painted a characteristic picture of the spatial pattern, gradients, and landscape metrics, and, thus illustrated the spatial growth and future modeling of urban development in India. Schneider and Woodcock (2008) examined the similarities and differences in urban form and growth that have occurred across 25 mid-sized cities. They buffered each city's center in an increasing step-wise manner, calculating the percentage of the total urbanized area within the circular area at each interval. Seto and Fragkias (2005) quantified the annual rate of urban land-use change for four cities in southern China. The classified images were used to generate annual maps of urban extent and landscape metrics were calculated and analyzed spatiotemporally across three buffer zones for each city for each year. The study presented that for a comprehensive understanding of the shapes and trajectories of urban expansion, a spatiotemporal landscape metrics analysis across buffer zones is an improvement over using only urban growth rates. Thinh (2003) divided the city into several circular zones with the common center in the city center to record spatial distances in the Dresden region. Using GIS-produced models, the author computed some metrics to measure the degree of urban sprawl. The result indicated that urban growth and its characters are not the same, for the city. Xiang (1996) conducted a GIS-based buffer analysis on the North Carolina watershed in support of landscape planners' planning activities. The study accomplished a series of tasks that would have been extremely difficult if done in conventional ways. One of them was calculating and mapping variable riparian buffer zones. Nong et al., (2014) studied the distance effects on urban growth pattern from the center and fringe of urban patches using buffering analysis. Their objective was to quantify the speed, growth modes, and resultant changes in landscape pattern of urbanization and to examine the diffusion-coalescence and the landscape structural homogenization processes in Hanoi capital cities.

2.2.3. Socioeconomic pattern

Economists and other social scientists have tried to study urban patterns rigorously over the last century. The earliest commonly cited works were carried out by German scholars such as von Thünen (1826) and somewhat later by Lösch (1944). The economy of location has been a fertile academic field for some forty years and is enjoying resurgence due partly to the high profile of recent work on the economics of location by generalist economists such as Krugman (1991). However, this academic resurgence is nothing compared to the eruption of interest in urban form by a wider range of political and social commenters. However, the real explosion of interest in urban socioeconomic form has been due to the growing concern and exploding reference to urban sprawl. Urban socioeconomic pattern refers to the spatial pattern of human activities at the certain time. In a general sense, the socioeconomic patterns can be analyzed in various geographical scales (metropolitan area, city, and neighborhood). Tsai (2005) argued that this classification is for two reasons. First, some socioeconomic variables operate only at certain levels, such as the jobs-housing balance variable. Second, some socioeconomic dimensions (such as density) may carry different meanings at different levels and may differently affect human activities, such as travel behavior. Reviewing the literature reveals that urban researchers have developed several dimensions of socioeconomic patterns. Generally, they were grouped into three categories: spatial distribution, density, and spatial autocorrelation.

2.2.3.1. Spatial distribution

The distribution of socio-economic features defines the needs for transportation and services in urban space (Tuia, 2007). The Urban transition, began in the 1950, induced an important change in the conception and planning of cities. Urban areas were growing fast and mobility was increasing exponentially following the metropolization processes. Some phenomena like peri-urbanization or sub-urbanization changed the urban landscape and modified the socioeconomic distribution of features between the city and its countryside. Polycentric structures and functional could not be analyzed with classical urban theories and urban dynamics became more and more complex (Batty, 2005). Planning in this period was principally caused by hierarchical development.

Cities also organized themselves in regional systems with specialized poles and growing suburbs. The complex dynamic of the intra-and inter-urban structure increased the need for mobility and the impact on the environment and society in these regions (Batty, 2005). The key dimension to analyze the socioeconomic pattern is the distribution assessment. This dimension probes the degree to which activities are equally or unequally distributed within a study area (Tuia, 2007).

One of the major uses of population census is the insight it provides into the patterns of population settlement. Data on population distribution among the administrative areas are important because they are useful in connection with social, economic, and administrative planning and provide basic data for making population projections. The spatial distribution of population denotes the spatial pattern due to the dispersal of population, formation of agglomeration, linear spread, etc. In other words, this dimension refers to the degree to which development is concentrated in a few parts of a city. The main factors in determining the population distribution are: climate, topography, soil and mineral resources, accessibility like distance from water resources and natural harbors, cultural factors, political boundaries, government policies, types of economic activities, technology, including type of transportation facilities, social organization and finally, demographic factors like changes in natural increase and migration.

Reviewing the literature reveals that there are many measurements to study the distribution (or inequality), among which the Gini coefficient, Shannon’s entropy, and the coefficient of variation are perhaps the most well-known. The coefficient of variation (CV), the ratio of the standard deviation of the mean, was first introduced by Karl Pearson in 1896 and was applied later by several researchers (Banik et al., 2012; Curto, and Pinto, 2009; Nairy and Rao, 2003; Kelley, 2007). In several studies, Shannon's entropy was applied to analyze the population distribution. It quantifies the unevenness in the distribution of population. A statistical concept of entropy was introduced by Shannon in the theory of communication and transmission of information (Shannon, 1948). This indicator has been applied in several studies to measure the patterns of the population either dispersed or concentrated over time (Singh and Leonardsson, 2014; Sudhira et al., 2004; Weng, 2001; Yeh and Li, 2001). The Gini coefficient is a measure of inequality of a distribution developed by the Italian statistician Corrado Gini and published in 1921. It has been usually used to measure income inequality but can be used to measure any form of uneven distribution (for example population distribution). Several scholars applied this index to analyze the social and economic pattern of the city using the population and employment variables (Tsai, 2005; Craig and Ng, 2001; Glaeser et al., 2008; Malpezzi and Guo, 2001).

2.2.3.2. Density

Density, as a distinct dimension of the urban pattern**,** can characterize density-based sprawling patterns (Galster et al., 2001; Malpezzi and Guo, 2001). The concepts of population distribution and density are closely related to each other. However, these two concepts are different, as distribution is based on location, while density is a ratio. Population density is the ratio of people to physical space. It shows the relationship between population and the size of the area in which it lives. The density of population is usually computed by measuring land consumption per capita. Several scholars have devised many types of density measurements for utilization in different situations with the aim of arriving at a better indicator of the socioeconomic pattern. Average density, maximum track density, population density gradients and percentile-based density have been more applied in the literature. Surely, the simplest measurement and one used by urban economists and others is the average density of the urban area. Far too many papers to cite focus on the negative exponential density gradient and its many derivatives and extensions. The negative exponential function was used for the first time by the German scholar Bleicher (1892). In many respects, the function was popularized by the work of Clark (1951) in geography. Several papers have examined differences among functions theoretically and using simulation methods.

One approach to measuring density which can effectively analyze the urban sprawl and detect change over time is density gradient (Alberti et al., 2001). The density gradient is defined as the rate at which density falls (according to distance) from the location of the reference. Thus, a positive density gradient denotes a decline in density away from the reference location (Ng, 2010). Colin Clarke (1951) introduced the concept of population density gradient in the 1950s. He argued that the density of population declines exponentially with distance from the central business district. This relationship is normally portrayed in a graph in which X-axis represents the distance from CBD, while Y-axis represents the population density. The central business district (CBD) is critical to population density modeling.

2.2.3.3. Spatial autocorrelation

This dimension is a measure of spatial dependency that quantifies the degree of spatial clustering or dispersion in the values of a variable measured across a set of locations. The degree of clustering refers to the degree to which high-density sub-areas are clustered or randomly distributed (Tsai, 2005). Theoretically, this dimension characterizes spatial-structure-based sprawl and compactness. The measurements of spatial autocorrelation could estimate the level of clustering. The spatial autocorrelation theory has been a key element of geographical analysis for more than twenty years. Several measurements of spatial correlation were proposed so that we can investigate the spatial process of geographical evolution from different points of view. Although there are various correlation measurements, two commonly used models are the Moran's index and the Geary's coefficient. The former is a generalization of Pearson's correlation coefficient and the latter is analogous to the Durbin-Watson statistic of regression analysis. In theory, the Moran's index is somewhat equivalent to the Geary's coefficient and they can be substituted for one another. However, in practice, the Moran's index cannot be replaced by the Geary's coefficient and vice versa due to a subtle difference of statistical treatment. Compared with the Geary's coefficient, the Moran's index is more significant to spatial analysis. Chen et al., (2012) applied the Moran's index to identify the degree of clustering in 29 Chinese cities in 2000. His work was a methodological study which simplified the process of autocorrelation analysis. Limin and Yaolin (2012) focused on the spatial autocorrelation and the spatial distribution of urban land prices Taking Hubei province, China, as a case study area. Spatially autocorrelation degree, spatial autocorrelation pattern and the mechanism of its formation were discussed. The study employed the Moran's index to analyze spatial autocorrelation degree and its change along with continuity order. They also adopted spatial clustering based on a kind of composite distance to probe into the clustering characteristic of the land prices.

Chapter III

3. Research design

This chapter directs the researcher in planning and implementing the study in a way that is most likely to achieve the intended goals. It is a blueprint for conducting the study. This part of the dissertation is to briefly state the problems related to the urban expansion and to outline the research objectives and questions of the study.

3.1. Statement of problem

During the late 1980s and early 1990s, the concept of sustainability became increasingly widely accepted (WCED, 1987). The concept of sustainable development refers to the development that meets the needs of the present without compromising the ability of future generations to meet their own needs. However, there are major potential problems for those attempting to implement sustainability throughout the world's cities, as the concept appears to conflict with urbanism at a fundamental level. Iran experienced many of the problems related to urban sprawl development over the past fifty years. Experiences of rapid urban population growth in Iran after 1940s affected landscape that today is characterized by chronic traffic congestion, poor air quality, natural habitat loss, and spiraling infrastructure costs (Taherkhani et al., 2007). Generally, there are three main concerns related to urban sprawl in Iran: (i) the informal settlements, (ii) the rate of land consumption, and (iii) the air pollution that the urban pattern is causing (Bahrami et al., 2010).

3.1.1. Informal settlements

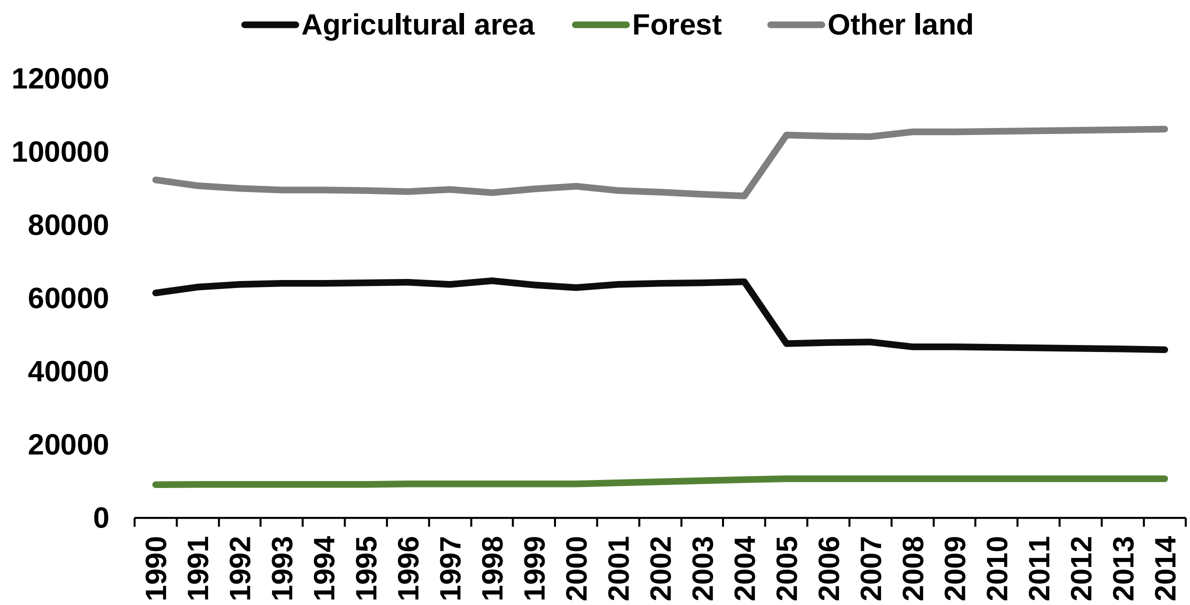
Unsustainable growth difficulties are projected to grow in Iran in the future, with a projected urban population of 91.5 % by the year 2050 (United Nations, 2015). This population growth will mean a substantial rise in the number of dwellings required. According to the Ministry of Housing and Urban Development of Iran, 34 percent of informal settlements dwellers were residing around the metropolitan cities (of more than one million populations), 44 percent was staying around the larger cities (of 250,000 to one million populations), while another 22 percent was concentrated around the medium cities (of 250, 000 populations and below). The purpose of the strategic urban development planning in Iran is to set a strategy of providing the country with the required number of dwellings to house its growing population but to accommodate them in a way that did not further degrade the natural environment, economic viability, and social equity. In other words, the aim of the strategy is to ensure growth in a way that meets the best interests of the inhabitants.

The most important objective of execution of urban development plans in Iran is pushing formation and expansion of cities towards planned program (Khalaj and Lashkari, 2010). In other words, using urban development plan as a medium to regulate physical environment is an undeniable necessity, while accommodating over 84 million people in the urban areas over the next 40 years (United Nations, 2015). To achieve these goals, future growth in Iranian major cities will need to occur in a very different way to how it has happened in the past (Ebrahimi-Masoumi, 2012; Kalantari Khalilabad and Hatami Nejad, 2006; Hosseini et al., 2010; Shahraki et al., 2011).

3.1.2. Land consumption

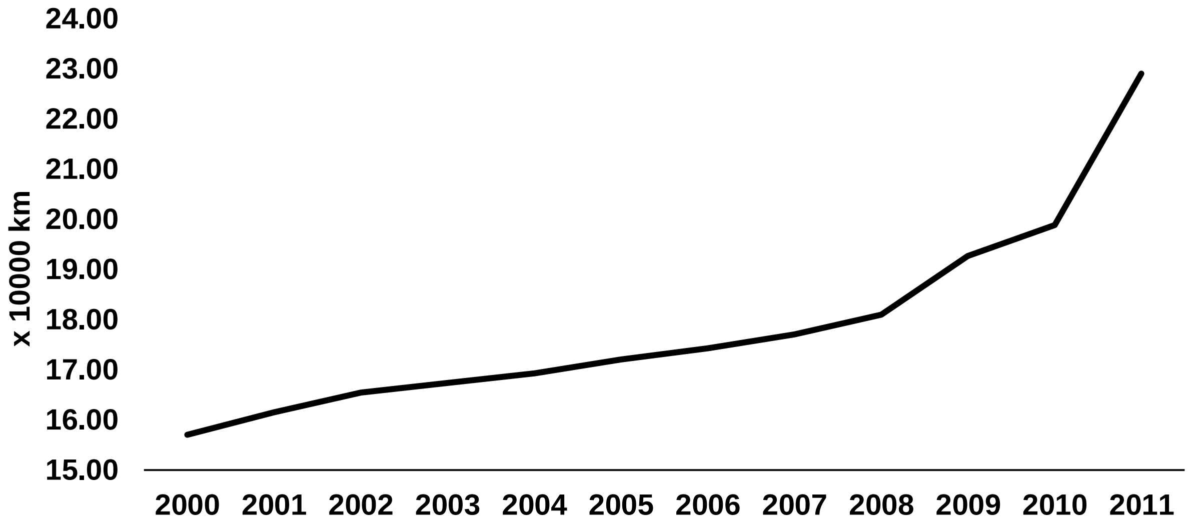
In Iran, agricultural lands have more rapidly changed over the past 50 years than any time before and are expected to accelerate in the future. According to the FAO Statistical Yearbook (FAO, 2014), during 1990-2014 the agricultural land of Iran has decreased from 61500 to 45953.2 ha. In other words, over about 25 years, more than 15500 ha. of agricultural lands have changed to non-agriculture (Figure 3-1).

Figure 3-1.
Changes in the agricultural area in Iran, 1990-2014.



Sprawl consumes land with ferocity, due to its highly inefficient form. This generally includes a surprisingly high percentage of land in sprawled urban areas being devoted to the needs of the automobile. According to the Knomea (2011), the total road network change in Iran was 15.18 % from 2000 to 2011. This report shows that over 11 years the total road network increased from 157 km to 229 km (Figure 3-2).

Figure 3-2.
Total road networks, Iran, 2000-2011.



3.1.3. Air pollution

Air pollution in all major cities of Iran has reached a dangerous and alarming level. There are many international and domestic reports on the subject of air pollution in Iranian cities. These various reports have all expressed real concerns and even detailed the causes of such calamity. The issue has become so pressing that the Iranian clerical regime’s environmental protection agencies and authorities also expressed concerns.

In Iran, the link between sprawl and air pollution is becoming increasingly significant. In Tehran, the capital city of Iran, the air quality index hovered around 159, which is three times more than the world health organization’s advised maximum (between 0 and 50) during the last quarter of 2015. Regulation has markedly improved air emissions from industrial areas in the past thirty years, leaving the greatest percentage of emissions these days coming from automobiles. According to the UNEP report (2015), almost 75% of Tehran’s air pollution comes from vehicles.

Southworth (2001) also identified three main factors which led to rapid increase in travel in major cities over the last decades, firstly, social and demographic growth and change within the population which has led to increases in disposable incomes, the number of households and vehicle ownership levels (for example in Tehran 60% of people use their personal cars), secondly, the use of more efficiently fueled vehicles and faster travel times, and thirdly, changes in the built environment.

The third factor is a specific reference to urban sprawl which has radically changed the types, mix, density and spatial arrangements of land. Generally, the issues related to peri-urban development in Iranian cities are summarized as follows:

1) A significant share of the peri-urban expansion can be explained by illegal settlements growing in the urban fringes of Iranian cities (IDEM, 2012),
2) The persistent horizontal growth of Iranian cities requires a continuous extension of the network of public services to peri-urban areas, even when the infrastructure in central areas is not used to its full potential,
3) This urban sprawl also has significant consequences in terms of transportation. The peri-urban housing means longer journeys, increased demand for transportation investments, increased urban congestion and intense air pollution (Duany et al., 2002),
4) It is quite clear that the concentration of social, environmental, and legal problems in peri-urban areas make them ill-suited for population growth where it nevertheless tends to occur at an accelerated pace (IDEM, 2012).

As outlined above, the negative environmental, economic, and social effects of urban sprawl are widespread, diverse, and clearly at odds with the concept of sustainability. The UN's Agenda 21 and Habitat Agenda (2015) both suggested that the objectives of urban sustainability should include: 'a compact urban form; the preservation of open space and sensitive ecosystems; reduced automobile use; reduced waste and pollution; the creation of livable and community-oriented human environments; decent, affordable, and appropriately located housing; improved social equity and opportunities for the least advantaged; and the development of a restorative local economy.'

3.2. Research objectives

With this in mind, the main objective of this research is to develop a suitable methodology for analyzing the urban expansion from four different aspects (growth ratio, land cover change, spatial patterns, and socioeconomic forms) to identify the peri-urban areas in Isfahan city to facilitate the effective urban planning towards sustainable development. To achieve this broad objective, the task is split into several sub-tasks, namely:

1) To identify and quantify the pace, amount, differentiation, and intensity of urban expansion (as the first indicator) in the case study using growth ratio analysis and GIS analytical techniques;
2) To provide and compare the land cover information (as the second indicator) for the investigation of city area using Remote Sensing images and the application of quantitative measures;
3) To explore the spatial processes and patterns of urban expansion (as the third indicator) using the spatial metrics and GIS analytical techniques;
4) To characterize socioeconomic form of the case study quantitatively (as the fourth indicator) using the spatial and socioeconomic data,
5) To examine the relationships between the above-mentioned indicators to determine the effects of urban expansion;

To sum up, this research aims to characterize quantitatively city pattern across the spatial units within the selected time span in general and also to distinguish compactness from sprawl in urban and peri-urban areas in particular.

3.3. Taxonomy of research questions

The current project has been set out to answer main questions. Based on the above research objectives, the following research questions are also posed to assist in the analysis:

The primary research questions are searching the existence of peri-urban expansion in the case study. Qualitative methods are more appropriate to answer the questions since they help to build a context for more knowledge on urban expansion and its patterns. In other words, answers give a clearer understanding of concepts and evidence that we can measure them. The secondary type of questions, Base-rate Questions (BRQs) help to describe how and when the urban expansion commonly appears. Finding Answers to this type of questions describes the process of occurrence of the urban expansion in the case study. Relationship Questions (RQs) focus on how the urban expansion relates to other concepts. Through answering these questions, the effects of the urban expansion on socioeconomic factors are examined (Table 3-1).

Table 3-1.

Research questions and objectives.

Research Sub Questions			Research Objectives
Knowledge-focused Research Questions (RQ)	Exploratory (Existence)	Which metrics should be applied to quantify amount, differentiation, and intensity of urban expansion?	To identify and quantify the pace, amount, differentiation, and intensity of urban expansion (as the first indicator) in Isfahan city using growth ratio analysis and GIS analytical techniques;
	Base-rate (Process)	How to develop a new technique to extract urban built-up land features from Landsat Thematic Mapper (TM)?	To provide and compare the land cover information (as the second indicator) for the investigation of city area using remote sensing images and the application of quantitative measures;
		Which spatial metrics should be adapted to analyze the process and pattern of urban expansion?	To explore the spatial processes and patterns of urban expansion (as the third indicator) using the spatial metrics and GIS analytical techniques;
		Which quantitative variables can be adapted to quantify the urban socioeconomic patterns?	To characterize socioeconomic form of Isfahan city (as the fourth indicator) using the spatial and socioeconomic data,
	Relationship (Existence)	How to link the urban expansion with the spatial and socioeconomic patterns?	To examine the relationships between the above-mentioned indicators to determine the effects of urban expansion;

Chapter IV

4. Research methodology

The following chapter presents, based on the concepts developed in the earlier chapters, an intended research process to achieve the research objectives. There are several types of methods, strategies, and techniques to process input data to generate the research output in an efficient way with desired quality. The availability of data, the desired inputs, the strength of logistic support, including the software employed, and researchers' experience are the main factors that affect the choice of an appropriate methodology.

The methodology involves remote sensing techniques (RS), spatiotemporal analysis of spatial metrics, and statistical models. Generally, the methodology presented in this chapter can be categorized into six parts. First of all, the selection of the study period and the identification of study zones are justified in Section 4.1. and Section 4.2. The third part (Section 4.3.) presents a general land cover classification and change detection procedure which integrates RS and GIS. Consequently, the spatial extent and rate of the urban expansion are analyzed and quantified in Section 4.4. Then the built-up area that is extracted from the classified images is used as an input data in FRAGSTATS 4.2 (McGarigal et al., 2012) to further describe and quantify the changing patterns and processes of the urban landscape (Section 4.5). Regarding the spatiotemporal dynamics of spatial patterns, GWR is used to investigate the effects of urban expansion on urban growth patterns. Finally, the population and employment data are applied to analyze the socioeconomic pattern of the city (Section 4.6.). Furthermore, the regression model is used to investigate the effects of urban expansion on socioeconomic patterns.

4.1. Selection of the study period

Reviewing the literature reveals that the urbanization of Iran has experienced transformation over the last six decades through various events on a national and international scale. Several studies have already examined the driving forces of urban expansion in the major cities of Iran. There is a rich body of literature on the causes of urbanization and urban growth in Iranian cities which claimed that rural to urban migration is a major reason for rapid urbanization in Iran. Iranian scholars argued that employment opportunities and declining living conditions have forced the rural population to migrate to urban areas. Results of previous studies provide the effective framework for this research to review the policies and events that have affected the urban expansion to select the best study period. From 1980 to 1988, the major cities in Iran experienced continuous attacks from Iraqi missiles. The movement of people from the western parts to the eastern and central cities of Iran was one of the consequences of Iran-Iraq war. However, by the time this war ended in 1988, several cities of Iran had been destroyed and unplanned urban growth had been experienced in the urbanization process due to the mass migration of people from war-affected areas to other settlements. Because of population movements, the spatial and socioeconomic transformations have occurred over recent decades in Iranian cities. Thus, this research aims to study the urban expansion in the time after the Iran-Iraq war to examine the transformations of cities in this period.

The year 1990 was chosen because it coincides roughly with the end of Iran-Iraq war (1988) and the fourth Iranian census (1986). Moreover, the availability of the Landsat images was another reason to choose the period. According to Jensen (2007), the time interval between two images for the investigation of land use/cover changes (Anderson et al., 1976) should be between 5 and 10 years. The year 2000, was selected as the second study year, based on a 10-years interval between the selected time points. As stated earlier, several previous researches pointed out the key role of urban population in the growth of Iranian major cities. Therefore, the changes of urban population growth played an important role in the selection of the third study year.

According to the World Bank, (2015) report, the annual rate of urban population was 3.54 % in 1990, which decreased to 2.77 % in 2000. In the next 10 years, it fell down and reached the absolute minimum (2.0 %) in 2010 and remained fairly constant by 2015. Considering the change of annual urban population rate shows that over the first (uncontrolled transformations) and second decade (controlled expansion), the urban population increased at the rate of 0.7 %. In other words, the equal time intervals with an equal annual rate of the urban population provide the best opportunity to study the effects of urban expansion.

4.2. Identification of study zones using gradient model

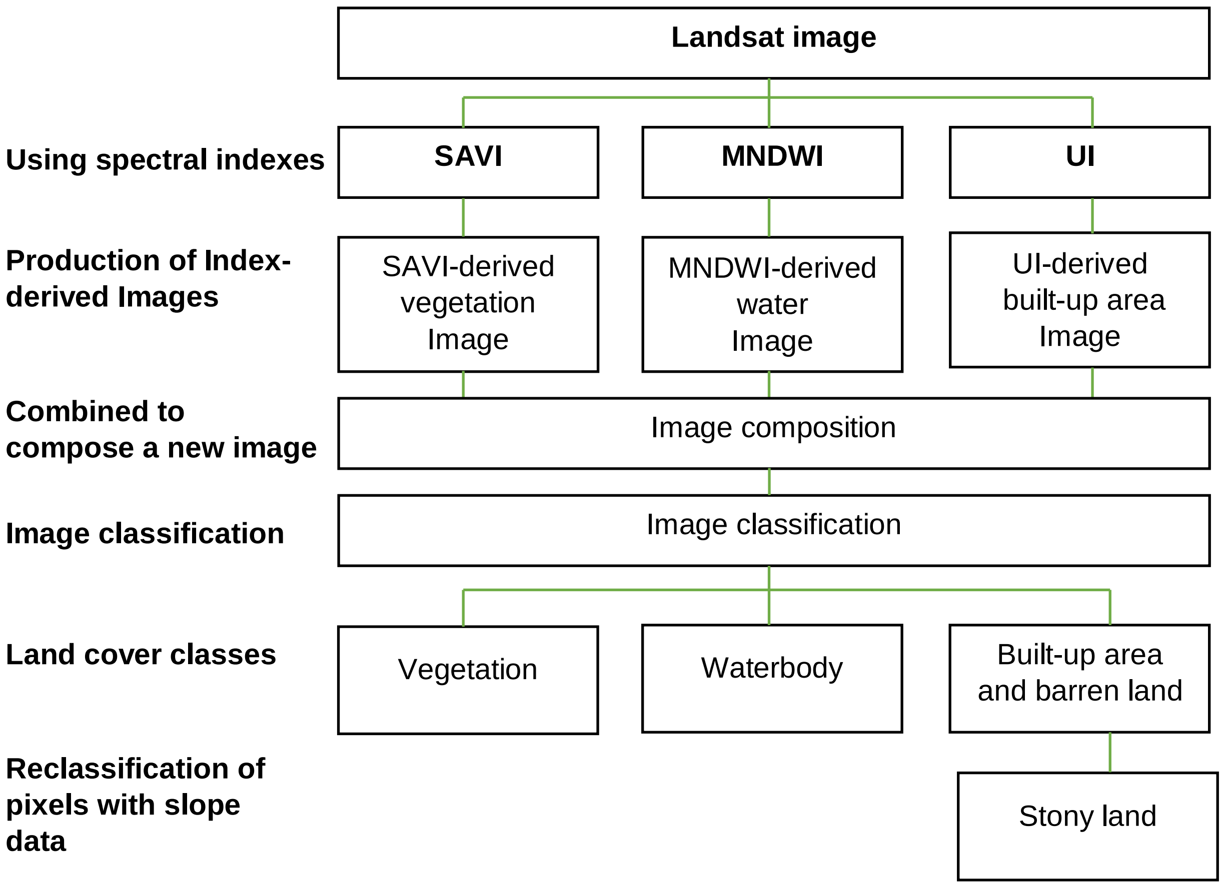
In general, the gradient model has been a useful technique to present the spatial and temporal changes of pattern between urban and rural areas. The current study addressed the urban expansion of the case study in both spatial and temporal contexts. To serve this purpose, buffer gradient analysis was employed by integrating the prospects of remote sensing and GIS. GIS-based buffer analysis was adopted in the research, which involved circular buffer zones surrounding the city center. At first, the center point of the city (referred as city-center) was considered at the central location of the central business district. A buffer zone system (21 concentric zones) was established with a width of 1 km covering the entire region designed to explore the overall expansion process over the area of Isfahan (comprising the Isfahan urban area and suburbs). The latest circular area was then divided into eight equal pie sections in eight directions (North N, Northeast NE, East E, Southeast SE, South S, Southwest SW, West W and Northwest NW). These multiple zones applied to extract the built-up area in different directions so that they can statistically be compared.

4.3. Mapping and monitoring of land cover change

The land cover change information can be achieved from the RS data by applying a range of approaches such as visual interpretation, land cover classification, and change detection. In the subsequent sections, first, the improved RS image classification method is proposed based on the literature review in chapter 2.2.1. Then, the land cover change detection is conducted. Generally, the applied methodology is illustrated in Figure 4-1.

Figure 4-1.

Classification scheme for land cover mapping.



4.3.1. Image classification

Before developing the land cover classification, the Anderson classification system level I (Anderson et al., 1976) with four land cover classes (urban or built-up land, vegetation, barren land, and water body) was adopted in this study. Urban or built-up land category is characterized by intensive land use where the landscape has been altered by human activities. Additionally, vegetation refers to all lands used primarily for the production of food and some of the structures associated with this production. In addition to the agricultural land, vegetation contains also forestland. Barren lands are also characterized by thin soil and the lack of vegetative cover in a non-urban setting. All areas periodically water covered are included in the category of the water body. All water bodies should be delineated as they exist at the time of data acquisition. Though the system was originally developed for the USA, it is the most commonly used land cover system across the world (Yuan et al., 2005).

In the Anderson classification system level I, areas lacking vegetation and composed of rock or rock faces are included in the barren land category. The present study categorized this class in a new class including rock faces, rock slides and cliffs (stony land). These exposed types have a large vertical component.

Table 4-1.

Land cover classification system.

Land cover categories	Sub-categories
Urban or built-up land	Residential, Commercial and services, Industrial, Transportation, communications and utilities, Industrial and commercial complexes, Mixed urban or built-up land, other urban or built-up land
Vegetation	Cropland and pasture, Orchards, groves, vineyards, nurseries and ornamental horticultural areas, Confined feeding operations, Other agricultural lands Deciduous forest land, Evergreen forest land, Mixed forest land
Waterbody	Streams and canals, Lakes, Reservoirs, Bays, and estuaries
Barren land	Dry Salt Flats, Beaches, Sandy Areas other than Beaches
Stony land	Rock faces on mountains, Rock Slides, Cliffs

Source: author`s illustration based on Anderson et al., 1976.

Although conventional classification design has been applied strongly in mapping a range of land covers at a range of spatial and temporal scales, there are some challenges in obtaining proper land cover information in urban areas (Townshend, 1992). Some different land cover classes may be enclosed in one pixel of satellite image because of the medium spatial resolution of Landsat image. It can cause the difficulty for separating one specific land cover class from other classes using spectral characteristics (Ji and Jensen, 1999).

Consequently, misclassification problems are often found in the land cover maps generated from traditional methods. A key concern is that the land cover maps derived from satellite images are often judged to be of insufficient quality for operational applications (Foody, 2002). This study used spectral indexes to identify a specific land cover when multiple materials are mixed in one pixel.

Ridd (1995) divided the urban ecosystem into three components, i.e., impervious surface material, green vegetation, and exposed soil and ignored water surfaces. However, the water body is an important component of the urban surface and has to be taken into consideration in this study. Accordingly, the urban cover is grouped into four generalized categories, i.e., built-up land, barren land, vegetation, and open water. Based on these four core elements, three indices, UI, SAVI, and MNDWI, are selected to represent the major land cover classes.

In areas where vegetation land is low, and the soil surface is exposed, the reflectance of light in the red and near-infrared spectral can influence vegetation index values (Huete, 1988). SAVI takes advantage of the high vegetation reflectance in NIR spectral range such as TM band 4 and high pigment absorption of red light, such as TM band 3 (Jensen, 2005). Although nearly everyone working with the remote sensing of vegetation knows the Normalized Difference Index (NDVI), this study employed SAVI to highlight vegetation features due to its advantage over NDVI when applied in an area with low plant cover such as the urban areas. SAVI can work in the area with plant cover as low as 15 percent, while NDVI can only work effectively in the area with plant cover above 30 percent (Ray, 1994). The Soil-Adjusted Vegetation Index (SAVI) is expressed as follows:

$$\mathrm{SAVI} = \frac{(\mathrm{TM}_4 - \mathrm{TM}_3) \times 1 + \mathrm{I}}{\mathrm{TM}_4 + \mathrm{TM}_3 + \mathrm{I}} \quad (1$$

where TM4: Reflectance value of band 4 (near infrared) of TM sensor; TM3: Reflectance value of band 3 (red) of TM sensor. I is a correction factor ranging from 0 for very high densities to 1 for very low densities. A value of 0.5 was used in this study to produce enhanced vegetation image as the study region has an intermediate vegetation density. An increase in the range of SAVI can present the discrimination of vegetation from built-up land or barren land.

After producing the vegetation image using SAVI, the built-up land image was produced using the Urban Index (UI) with the following equation:

$$\mathrm{UI} = \frac{\mathrm{TM}_7 - \mathrm{TM}_4}{\mathrm{TM}_7 + \mathrm{TM}_4} \quad (2$$

where TM4: Reflectance value of band 4 (near infrared) of TM sensor; TM7: Reflectance value of band 7 of TM sensor.

UI values derived from multi-temporal images were applied to aid in separation of build-up land areas from barren land. This was used instead of the Normalized Difference Built-up Index (NDBI) because the urban features are more distinguishable in UI rather than NDBI and the best results are obtained when band 7 is used instead of band 5 (Bouhennache et al., 2015; Pratibha et al., 2014). Generally, the increase in the range of SAVI can present the discrimination of vegetation from built-up land or barren land.

Modified Normalized Difference Water Index (MNDWI), derived from multi-temporal images, were used to aid in separation of water from a background that is dominated by build-up land areas. Xu (2005) reported that MNDWI produced better results than the Normalized Difference Water Index. The modified NDWI (MNDWI) is expressed as follows (McFeeters,1996):

$$\mathrm{MNDWI} = \frac{\mathrm{Green} - \mathrm{MIR}}{\mathrm{Green} + \mathrm{MIR}} \quad (3$$

where MIR is a middle infrared band such as TM band 5. Compared with the NDWI, the contrast between water and the built-up land of the MNDWI will be considerably enlarged owing to increasing values of water feature and decreasing values of built-up land from positive down to negative (Hu, 2007).

After producing SAVI, MNDWI, and UI images, a new image dataset was created, which used these three new images as three bands. The change from an original seven-multispectral-band image into the three-thematic-band image largely reduces correlation among bands. The three new bands were then combined to compose a new image. The supervised classification method was used to extract land cover features from the new images composed of the three thematic-oriented bands. The supervised classification was performed using a maximum likelihood algorithm based on the signatures of training regions. Consequently, four major urban land cover classes, vegetation (high values of SAVI), water (high values of MNDWI), built-up area (high value of UI), and barren land (low value of UI) are well separated.

As stated earlier, the present study separates the stony land (including rock faces on mountains, rock slides), which have a large vertical, from the barren land. In the post classification refinement, the slop data was used to identify the stony land. In this study, the stony land was expected to be found in the areas with slope higher than

15 degrees. Therefore, the barren land pixels with slope higher than 15 degrees should be reclassified as stony land.

To control the results, quantitative accuracy assessment was performed. The error matrix is the most widely used technique to check the accuracy of land cover maps derived from remote sensing images (Foody, 2002). The error matrix compares the classified image with a reference image on the class by class basis. Consequently, a total of 352 random points was generated. Finally, the classified data reference data were compared and statistically represented in the form of error matrix.

4.3.2. Land cover change detection

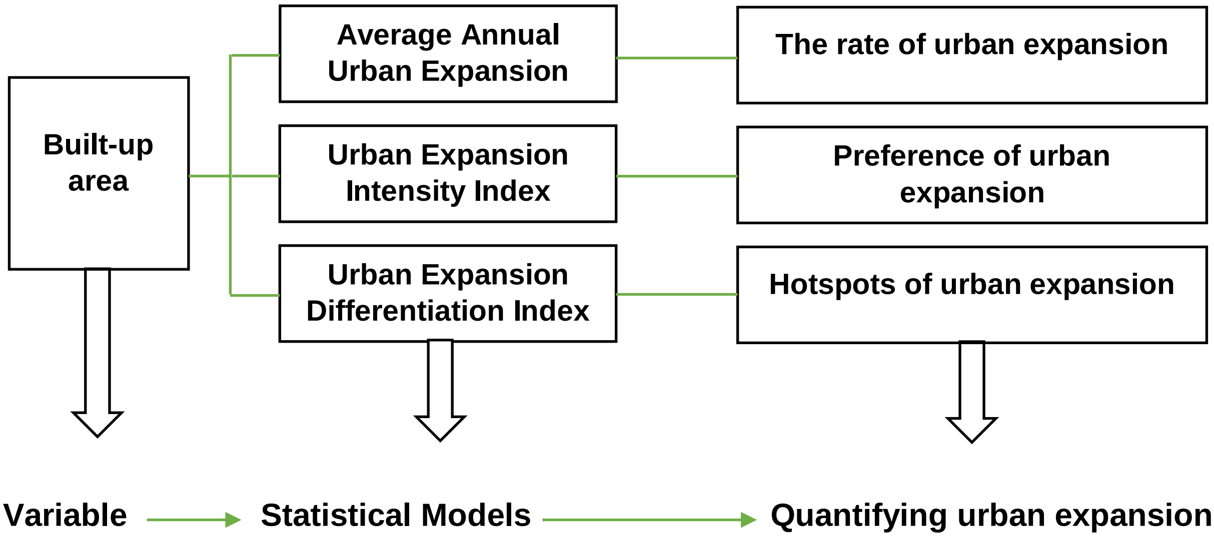
The main goal of change detection in remote sensing includes identifying the geographical location, recognizing and quantifying the type of changes and finally assessing the accuracy results (Im and Jensen, 2005). In this study, post classification was selected as a change detection method to identify the changes in land covers in different intervals. The post-classification method generated a two-way cross matrix, providing “from-to” land cover conversion information. A new thematic map containing the different combination of “from-to” change information was also produced for each period.

4.4. Growth ratio analysis

Several studies have attempted to identify and quantify the pace, amount, and intensity of urban expansion using growth ratio indexes and GIS analytical techniques. Among the commonly used metrics are Landscape Expansion Index (LEI) (Liu, et al., 2009), Urban Expansion Intensity Index (UEII) (Hu et al., 2007) and Urban Expansion Differentiation Index (UEDI). A combined approach was adopted in this study to quantify urban expansion. The general methodology of this part is illustrated in Figure 4-2.

Figure 4-2.

Used methodology of growth ratio analysis.



Average Annual Urban Expansion Rate (AUER) is the first statistical index to calculate the average annual urban expansion rate. This index computes the mean annual rate of expansion of built-up land in the case study over the study period (Acheampong et al., 2016).

$$\mathrm{AUER_i} = \left[\left(\frac{\mathrm{ULA_{it2}}}{\mathrm{ULA_{it1}}}\right)^{\frac{1}{\Delta t}} - 1\right] \times 100 \qquad (4$$

Where $\mathrm{AUER_i}$ is Annual Urban Expansion Rate; $\mathrm{ULA_{it2}}$ and $\mathrm{ULA_{it1}}$ is the area in i unit at times $\mathrm{t_2}$ and $\mathrm{t_1}$, respectively. The AUER is not affected by the size of the spatial unit. Δt is the time span of the study.

In addition, Urban Expansion Intensity Index (UEII) was applied in the current study. UEII, as shown in Eq. 5, computes the average annual proportion of newly increased built-up land of a spatial unit, standardized by the total area of that spatial unit (Hu et al., 2007). The formula is (Li et al., 2015):

$$\mathrm{UEII_i} = \frac{|\mathrm{ULA_{it_2}} - \mathrm{ULA_{it_1}}|}{\mathrm{TLA_i} \times \Delta t} \times 100 \qquad (5$$

$\mathrm{UEII_i}$ is the urban expansion intensity index in i unit, $\mathrm{ULA_{it2}}$ and $\mathrm{ULA_{it1}}$ are the areas in i unit at times $\mathrm{t_2}$ and $\mathrm{t_1}$, respectively. $\mathrm{TLA_i}$ is the total area in i unit, Δt is the time span of the study. Urban expansion intensity can be used to evaluate changes in the quantity of urban area per unit time, so it is a key index for evaluating spatial changes of urban expansion. In the expansion process, due to the rule of urban driving factors and their spatial impacts, the urban expansions will be different in each zone. This phenomenon named preference of urban growth (Alsharif and Pradhan, 2013). In this research, UEII was employed to assess and analyze the urban spatial expansion quantitatively. Moreover, UEII was used to recognize the preference of urban growth in a certain period. The UEII reflects the potentials of urban expansions and it compares the intensity of urban cover changes in different time periods. In order to reveal the spatial evolution pattern of urban land expansion, the urban expansion intensity index (UEII) scores of the 21 concentric zones that make up the region are grouped into five UEII zones; 0 to 0.28 is slow development; 0.28 to 0.59 is low-speed development; 0.59-1.05 is medium-speed development; 1.05-1.92 is high-speed development; and >1.92 is very high-speed development (Alsharif et al., 2015).

Table 4-2.

Range of Urban Expansion Intensity Index.

Range	Potentials of urban expansions
0 > UEII > 0.28	lower development
0.28 > UEII > 0.59	low-speed development
0.59 > UEII > 1.05	medium-speed development
1.05 > UEII > 1.92	high-speed development
UEII >1.92	very high-speed development

Source: Acheampong et al., (2016).

Additionally, the Urban Expansion Differentiation Index (UEDI) calculates the proportion of the increased urban area in a unit (in proportion) to the total changed area. Unlike the UEII, UEDI quantifies the urban land expansion disparity between different spatial units, thereby making those units comparable (Acheampong et al., 2016). This metric is useful in evaluating urban land expansion differentiation and identifying urban expansion hotspots. The formula is (Li et al., 2015):

$$\mathrm{UEDI_i} = \frac{|\mathrm{ULA_{it_2}} - \mathrm{ULA_{it_1}}| \times \mathrm{ULA_{t_1}}}{|\mathrm{ULA_{t_2}} - \mathrm{ULA_{t_1}}| \times \mathrm{ULA_{it_1}}} \times 100 \qquad (6$$

$\mathrm{UEDI_i}$ is the urban expansion differentiation index in i unit, $\mathrm{ULA_{it_1}}$ and $\mathrm{ULA_{it_2}}$ are the total areas in i unit at times $\mathrm{t_2}$ and $\mathrm{t_1}$, respectively. Generally, there could be three possible categories of UEDI: (i) when the constituent spatial unit (i.e. zone) has a differentiation index >1 in which case, the district is categorized as fast growing area in relation to the whole study area; (ii) where the differentiation index of the district is

<1 in which case the district is categorized as slow growing area in relation to the case study, and (iii) when the differentiating index of the district is equal to 1 in which case the district is categorized as moderate growing area in relation to the study area (Acheampong et al., 2016).

Table 4-3.

Range of Urban Expansion Differentiation Index.

Range	Urban expansion differentiation
UEDI >1	Fast growing area
UEDI = 1	Moderate growing area
UEDI <1	Slow growing area

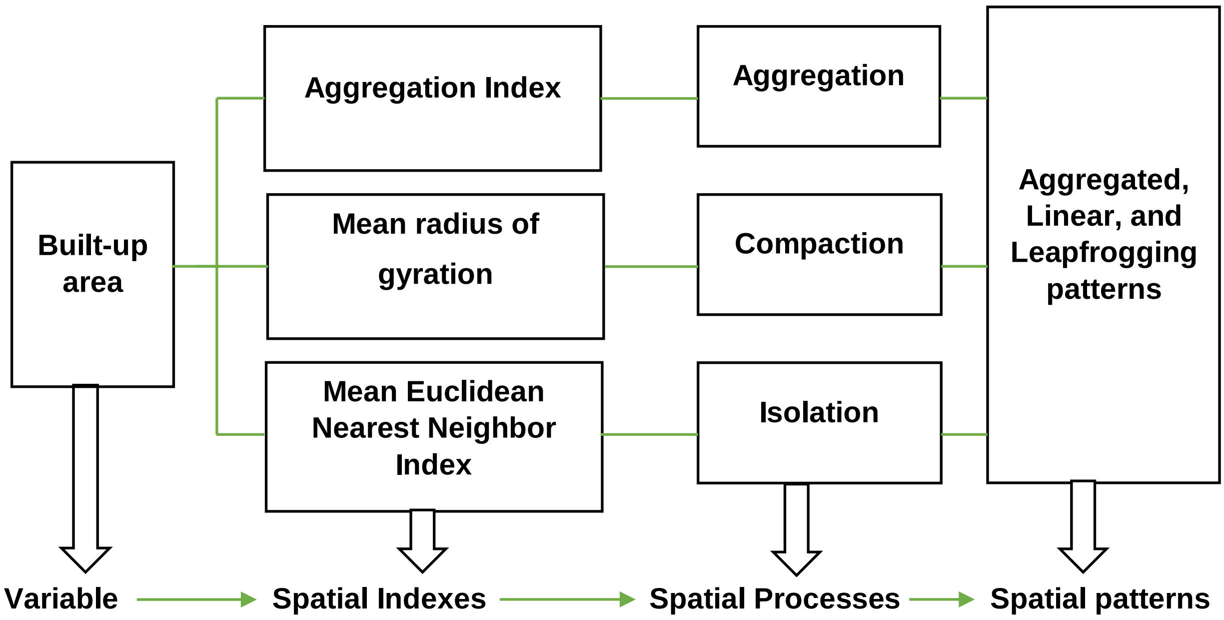
Source: Acheampong et al., (2016).

4.5. Analysis of the urban spatial pattern

In this study, the analysis of land cover change and growth rate study provides helpful information for understanding the various processes in the study area. Accordingly, for the purposes of understanding the main patterns of urban expansion, which resulted in the spatial patterns in the city, three dimensions were identified. These dimensions should cover the patterns of expansion. The general methodology of this analysis is illustrated in Figure 4-3. Moreover, the underlying cause-effect relationships in urban growth process need to be explored and analyzed.

Figure 4-3.

The used methodology of spatial pattern analyses.



4.5.1. Spatial metrics for quantifying urban spatial pattern

For the purposes of understanding the main patterns of urban expansion, which resulted in the spatial patterns in the city, three dimensions are identified. The general methodology of this analysis is illustrated in Figure 4-3.

To outline the urban spatial pattern, various landscape metrics were calculated using Fragstats 4 (McGarigal et al., 2012). Nonetheless, it is difficult to find a connection between metric values and pattern. Indeed, most of the metrics are correlated among themselves (McGarigal et al., 2012). Furthermore, it seems impossible that a single metric can fully describe a spatial pattern. So, the choice of metrics absolutely depends on the purpose of the study. Based on the objective, to quantify the spatial characteristics of the urban land, the landscape heterogeneity is represented in two classes: urban and non-urban. Built-up was defined as urban land, while, other classes reclassified into the non-urban land. According to the objectives of this study, three class-level metrics were selected which are sensitive to the changes in composition, as well as spatial configuration. Table 4-4 provides description of the spatial metrics used in the study.

One of the most important steps in analyzing the urban pattern is quantifying the aggregation level of spatial patterns (Hong et al., 2000). The Aggregation index refers to the number of the adjacencies of a specified land cover class divided by the maximum possible number of like adjacencies involving that class may be more effective, since it allows focusing on one class at the time (Alberti, 2008). Since it is class specific, it is more precise than other indexes which measures overall landscape aggregation. Thus, AI provides a quantitative basis to correlate the spatial pattern of a class with a specific process. Since AI is a ratio variable, map units do not affect the calculation. It can be compared with the classes from the same or different landscapes, or even the same classes from the same landscape under different resolutions (Hong et al., 2000).

Compactness Indexes are calculated to determine to what extent the urban footprint approximates a circle. This study applied the Mean Radius of Gyration as a suitable tool to measure patch extent and connectivity that retains actual measurements units (meters). Mean radius of gyration index equals the mean distance (m) between each cell in the patch and the patch centroid (Botequilha et al., 2006).

Mean Euclidean Nearest Neighbor (ENN_MN) measures the distance to the nearest neighboring patch of the same type based on shortest straight-line distance computed from cell centers (McGarigal and Marks, 1995). The values for ENN are always larger than zero, without limit. ENN approaches zero as the distance to the nearest neighbor decreases. The minimum ENN is constrained by the cell size and is equal to twice the cell size when the neighbor patch rule is used. The upper limit is constrained by the extent of the landscape, which in this research is the size of the block. ENN is undefined if the patch has no neighbors (i.e., no other patches of the same class) (McGarigal, 2012).

Table 4-4.

The characteristics of applied spatial Indexes.

$AI = \left[\frac{g_{ii}}{max - g_{ii}}\right](100)$ (7) Units: Percent	g_{ii}= the number of like adjacencies (joins) between pixels of patch type (class) i, based on the single-count method, $max - g_{ii}$= the maximum number of like adjacencies (joins) between pixels of patch type (class) i, based on the single-count method.
Range	$0 \leq AI \leq 100$, Given any P_i, AI equals 0 when the focal patch type is maximally disaggregated; AI increases as the focal patch type is increasingly aggregated and equals 100 when the patch type is maximally aggregated into a single, compact patch.
$MGYRATE = \sum_{r=1}^{z} \frac{h_{ijr}}{z}$ (8) Units: Meters	hijr =distance (m) between cell ijr [located within patch ij] and the centroid of patch ij (the average location), based on cell center-to-cell center distance; $z =$ number of cells in patch ij
Range	GYRATE ≥ 0, without limit, GYRATE = 0 when the patch consists of a single cell and increases without limit as the patch increases in extent. GYRATE achieves its maximum value when the patch comprises the entire landscape.
$ENNMN = \frac{\sum_{j=1}^{n} h_{ij}}{n_i}$ (9) Units: Meters	hij =distance (m) from patch ij to the nearest neighboring patch of the same type (class), based on patch edge-to-edge distance, computed from cell center to cell center
Range	ENN > 0, without limit. ENN approaches 0 as the distance to the nearest neighbor decreases. The minimum ENN is constrained by the cell size and is equal to twice the cell size when the 8-neighbor patch rule is used or the distance between diagonal neighbors when the 4-neighbor rule is used. The upper limit is constrained by the extent of the landscape. ENN is undefined and reported as "N/A" in the "basename ". patch file if the patch has no neighbors (i.e., no other patches of the same class).

Since our objective is to estimate the spatial characteristics of the urban land, the metrics are computed at the class level. In setting the spatial metrics the following factors are considered:

Aggregation index:

1) It allows focusing on one class at the time (the built-up area in this research),
2) It provides a quantitative basis to correlate the spatial pattern of a class with a specific process (one of the research objectives),
3) It can be compared to classes from the same or different landscapes, or even the same classes from the same landscape under different resolutions.

Mean Euclidean Nearest Neighbor:

1) It can be applied at the class level,
2) Independent of the patch size,
3) It does not need to establish a neighborhood radius.

Mean radius of gyration:

1) It can be applied at the class level,
2) It provides good differentiation at lower values,
3) It weights each patch by its area.

4.5.2. Exploring the effects of urban expansion on spatial patterns

In order to understand the effects of urban growth on the spatiotemporal patterns, changes in spatial metrics values were used as dependent variables. The results of urban expansion quantification using the growth ratio indexes (UEII and UEDI) were used as independent variables to understand the effects of urban expansion on the spatial patterns. Moreover, the changes in spatial metrics values (AI, GYRATE_MN, and ENN_MN) were used as dependent variables.

Geographically Weighted Regression (GWR) is one of the several spatial regression techniques increasingly used in geography and other disciplines. GWR provides a local model of the variable by fitting a regression equation to every feature in the data set (Fotheringham et al., 2002). Unlike conventional regression, which produces a single regression equation to summarize global relationships among the explanatory and dependent variables, GWR generates spatial data that express the spatial variation in the relationships among variables. The maps generated from these data play a key role in exploring and interpreting spatial relationships. GWR equation may be expressed as (Fotheringham et al., 2002):

$$\hat{y_i} = \beta_0(u_i v_i) + \sum_k \beta_k(u_i v_i) x_{ik} + \varepsilon_i \qquad (10)$$

where $\hat{y_i}$ is the estimated value of the dependent variable for observation i, β_0 is the intercept, β_k is the parameter estimate for variable k, x_{ik} is the value of the kth variable for i, ε_i is the error term, and $(u_i v_i)$ captures the coordinate location of i.

The assumption is that observations nearby one another have a greater influence on one another's parameter estimates than observations further apart. The weight assigned to each observation is based on a distance decay function centered on observation i. In the case of areal data, the distance between observations is calculated as the distance between polygon centroids. The distance decay function, which may take a variety of forms, is modified by a bandwidth setting at which distance the weight rapidly approaches zero. The bandwidth may be manually chosen by the analyst or optimized using an algorithm that seeks to minimize a cross-validation score (CV). Alternatively, the bandwidth may be chosen by minimizing the Akaike Information Criteria (AIC) score (Nakaya et al., 2005).

$$\mathrm{AIC_t} = 2n \log_e(\hat{\sigma}) + n \log_e(2\pi) + n\left\{\frac{n + \mathrm{tr}(S)}{n - 2 - \mathrm{tr}(S)}\right\} \qquad (11)$$

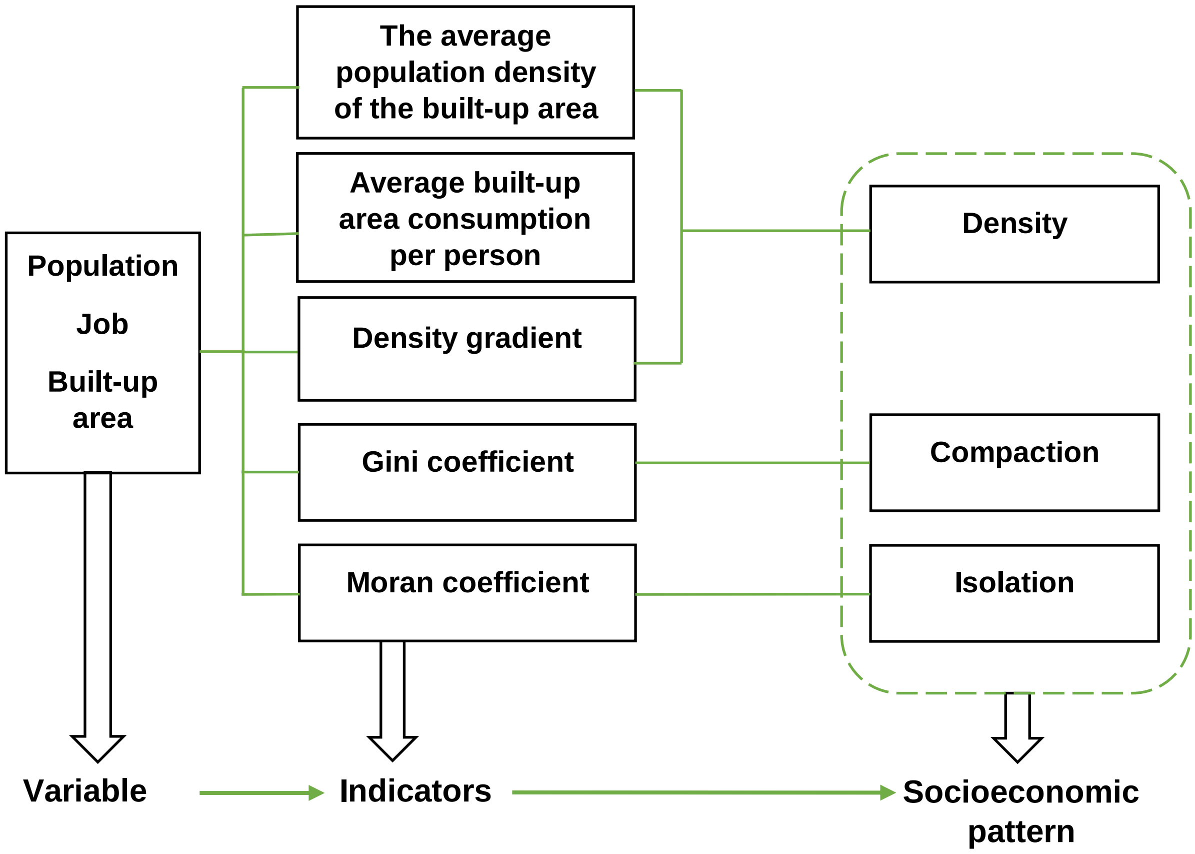
The AIC method has the advantage of taking into account the fact that the degrees of freedom may vary among models centered on different observations. Moreover, the user may choose a fixed bandwidth that is used for every observation or a variable bandwidth that expands in areas of sparse observations and shrinks in areas of dense observations. Thus, in this study $\mathrm{AIC_t}$ method was used for GWR model. The model with lower $\mathrm{AIC_t}$ value suggests the stronger ability of regression model in reflecting reality (Griffith, 2008).

4.6. Socioeconomic pattern

This part aims to characterize the socioeconomic form of the city and to distinguish compactness from sprawl. It defines the different dimensions of city form, accompanied with appropriate quantitative indexes. The general methodology of this analysis is illustrated in Figure 4-4:

Figure 4-4.

The used methodology of socioeconomic analyses.



4.6.1. Urban density functions

In this study, the Euclidean distance Algorithm was applied to quantify the distance to other areas, and four regression models: linear, exponential, power and logarithmic regressions were constructed. The following equations were used to derive an urban density gradient for the 3 considered years:

$$\rho(r) = a + br \quad (12$$

Linear regression: where r = distance from the center of the urban area (km), b = slope, and a= intercept (Alberti, 2008).

$$\rho(r) = ae^{-rb} \quad (13$$

Exponential regression: where $a =$ maximum population density, $r =$ distance from center of urban area, and $b =$ exponential decay coefficient or density gradient (km^{-1}).

$$\rho(r) = ar^b \qquad (14$$

Power regression: where r =distance from center of urban area, $\rho(r) =$ population density at distance r from CBD (km^{-2}), $a =$ intercept (population density (km^{-2}) at distance zero from CBD and b =growth/decay rate.

$$\rho\,(r) = a + b\ln(r) \qquad (15$$

Logarithmic regression: where $r =$ distance from the center of urban area (km), a is the intercept and $b\ (ln)$ =slope.

In general, the density function analysis used two variables: Euclidean distance r from the city center and corresponding population density $\rho(r)$. Having two variables in GIS, the data set was exported for regression analysis. Such density approach adds important elements to test hypotheses about the relationships between the urban and ecological functions along with an urban-to-rural gradient (Alberti, 2008). Through comparing the changing pattern of density gradients over time, the process of spatial evolution can be assessed (Ng, 2010).

4.6.2. Degree of distribution

In the dissertation, the Gini coefficient was applied to measure inequality of population or employment distribution by spatial units in an urban area. Higher Gini coefficients (i.e. close to 1) mean that population or employment density is extremely high in fewer sub-areas. A Gini coefficient close to zero means that population or employment is evenly distributed in an area. The Gini coefficient can be calculated as Tsai (2005):

$$\mathrm{Gini} = 0.5\sum_{i=1}^{N}|X_i - Y_i| \qquad (14)$$

where N is the number of sub-areas; X_i is the proportion of land area in sub-area i; and Y_i is the proportion of population or employment in sub-area i (Penfold, 2001).

4.6.3. Degree of clustering

Among all indexes used by researchers to analyze the clustering pattern, the global Moran is the well-known measurement to analyze the spatial autocorrelation and estimation of clustering level (Tsai, 2005). The Moran coefficient is defined as:

$$\mathrm{Moran} = \frac{N \sum_{i=1}^{N} \sum_{j=1}^{N} W_{ij} (X_i - X)(X_j - X)}{\left(\sum_{i=1}^{N} \sum_{j=1}^{N} W_{ij}\right)(X_i - X)^2} \tag{11}$$

where N is the number of sub-areas; X_i is population or employment in sub-area i; X_j is population or employment in sub-area j; X is the mean of population or employment; and W_{ij} denotes the weighting between subareas i and j (Paradis, 2016). Another index, the Geary coefficient is similar to the Moran coefficient, but instead of focusing on deviations from the mean, it examines deviations of each observation area relative to another. The earlier studies provided little knowledge on the local sprawling patterns (Sokal and Oden, 1978; Cliff and Ord, 1981).

Chapter V

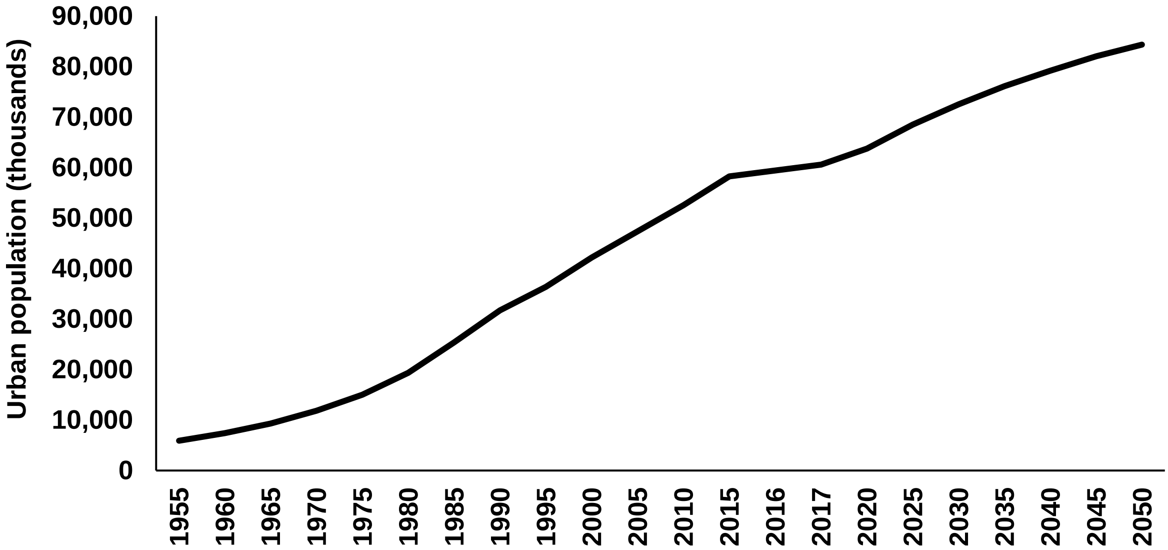
5. Introduction to the study area

This chapter firstly describes the urban changes in Iran. Then, the study area of Isfahan city in Iran is introduced. Consequently, based on the objective of the study, a spatial database is further described, which includes the RS images and other spatial variables.

5.1. Urban growth and urbanization in Iran

The population in Iran has expanded over the past 50 years and will continue to grow in the coming decades, although how fast is a matter of some dispute (United Nations, 2015). Figure 5-1 summarizes urban population trends and projections in Iran from 1955 to 2050.

Figure 5-1.
Urban growth in Iran, 1955 – 2050.



Source: Author’s calculations using United Nations report, 2015.

Figure 5-1 shows a 10-fold increase in the size of Iran’s urban population between 1955 and 2017 (from around 6 million to roughly 60 million). According to the United Nations report (2015), the urban population in Iran would be expected to double in roughly 50 years (from 2000 to 2050).

Additionally, it worth mentioning that the number of urban settlements in Iran with municipal governments grew from 272 in 1966 to 1139 in 2011 and is expected to reach 1800 by 2050. In other words, urban growth in Iran is not simply a matter of population growth in existing settlements. It also involves the emergence of new areas with urban population densities (see Table 5-1).

Table 5-1.

The number of urban settlements, Iran, 1966-2050.

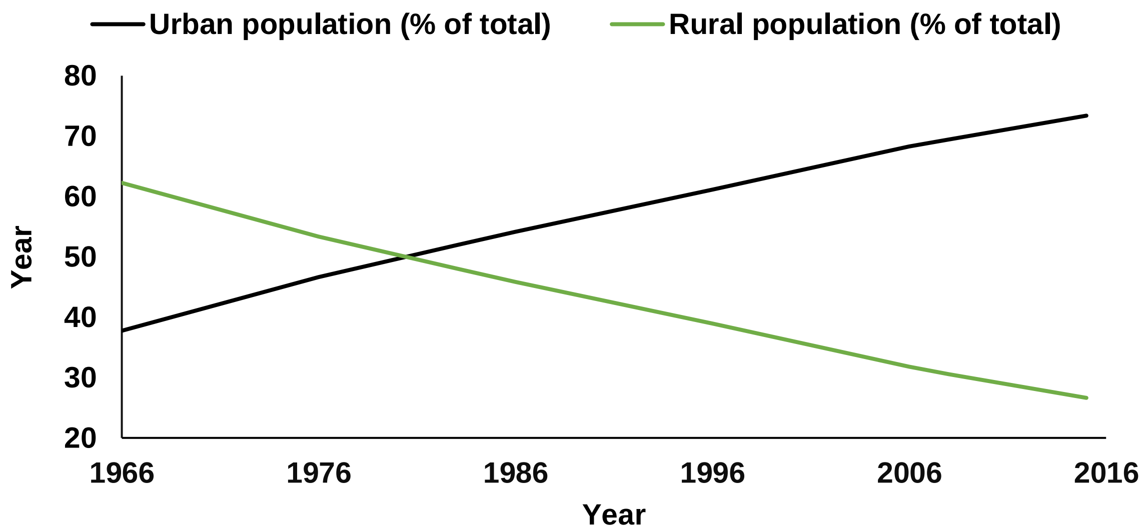
Year	1966	1976	1986	1996	2006	2011	2050
Number of urban settlements	272	373	496	612	1012	1139	1800

Source: SCI, 2006.

According to the United Nations report (2015), Iran has experienced rapid urbanization processes over the past five decades. In 1981, for the first time in Iran, the urban population exceeded the rural population, and Iran's population has remained predominantly urban thereafter (Figure 5-2). In 1966, more than 60 percent of people in Iran lived in rural settlements and less than 40 percent in urban settlements. In 2015, 73 percent of Iran's population was urban. The urban population is expected to continue to grow so that by 2050, Iran's urban population will be 91.5 % urban and 8.5 % rural (United Nations, 2015).

Figure 5-2.

Urban and rural population (% of total), Iran, 1966-2015.



5.2. Projection of urban expansion in Iran

The growth of Iran's urban population in both absolute and relative terms has naturally been accompanied by the expansion of existing built-up areas and as noted above, the emergence of new identifiable urban settlements. Overall, the physical expansion of built-up areas is expected to continue in the coming decades, although there is considerable uncertainty about how much expansion will take place. The key variables are population growth and, critically, population density.

Table 5-2.

Population density, cities with more than 500.000 population, 2010.

Major cities	Population	Urban Area (sq.km2)	Density (P/sq.km2)
Tehran	8846782	730	12118.87945
Mashhad	2749374	298	9226.087248
Isfahan	1791069	350	5117.350000
Karaj	1614626	858	1881.848485
Tabriz	1484988	168	8839.214286
Shiraz	1460665	245	5961.897959
Ahvaz	1460665	233	6268.948498
Qom	1074036	117	9179.794872
Kermanshah	851405	104	8186.586538
Urumiah	667499	88	7585.215909
Rasht	639951	62	10321.79032
Zahedan	560725	91	6161.813187
Kerman	534441	117	4567.871795
Arak	526182	60	8769.7
Hamadan	525794	57	9224.45614

According to Demographia World Urban Areas (2016) and the author's calculations, Iranian cities with populations in excess of 500.000 contained 25 million people, and their total built-up area at average densities of some 7,000 persons per square kilometer was of the order of 360 square kilometers in 2011. If average densities continue to decline at the annual rate of 1.7 % – as they have during the past decade (Angel et al., 2005) – the built-up area of cities in Iran will rise to more than 11,000 square kilometers by 2050. It means, by 2050 its urban land area can be expected to triple. The 1.6 times increase in urban population, compared to 3 times increase in urban area, showed that the rate of urban expansion will exceed the rate of urban population growth in Iran, resulting in the greater physical expansion. This conclusion confirmed the results of research, carried out by Angel et al., (2005) in the case of cities in the developing countries.

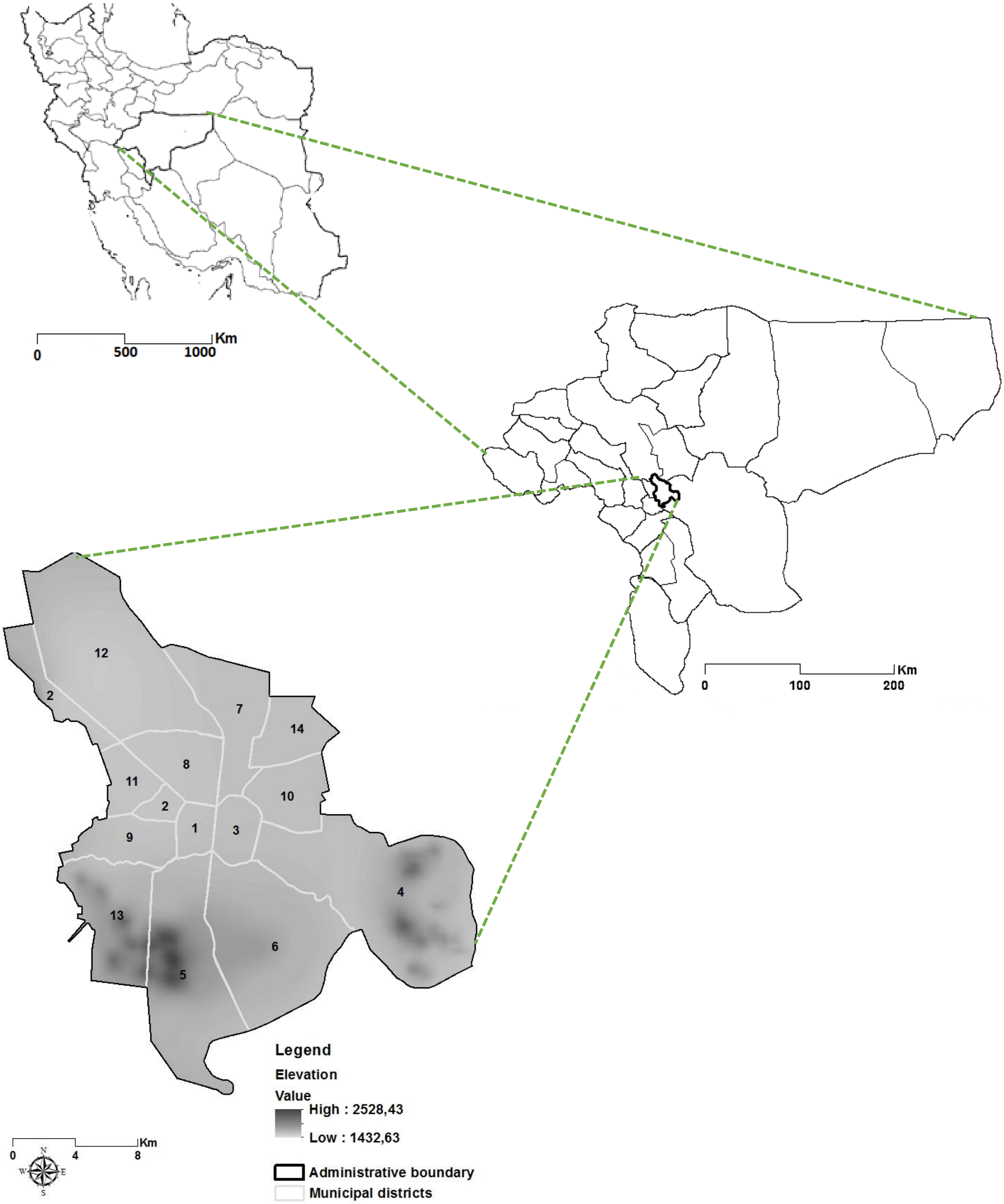
5.3. Study area

Isfahan city (32°39′35″N, 51°40′17″E) is located in the lush plain of the Zayanderud river, at the foothills of Mount Zagros. This city has a semi-arid climate, with an average annual temperature of 16.2 ℃ and annual precipitation 121 mm. The nearest mountain is Mount Soffeh which is situated just south of Isfahan. No geological obstacles exist within 90 kilometers north of Isfahan, allowing cool northern winds to blow from this direction. In total, the minimum height of the city is 1.550 m around Zayanderud and the maximum is 2.232 m in Soffeh (Figure 5-3).

Isfahan is suited on the main north-south, and east-west routes crossing Iran. With a total administrative area of approximately 493.8 km² and a population of 1791069 (2010), it is regarded as the third largest city in Iran, after Tehran and Mashhad. In 2000, the number of municipal districts in Isfahan increased from 11 to 14. These fourteen municipal districts are naturally divided by the Zayanderud river into southern and northern districts. The southern districts naturally delimited by the Zayanderud river on the north and Soffeh on the southwest. In total, districts 1 and 3 are considered as the central urban districts, while the majority of districts are composed of urban and rural areas. Isfahan was flourished during the 16th century under the Safavid dynasty (1502 – 1736) when it became the capital city of Iran for the second time in the history. Even today, the city of Isfahan retains much of its past glory. It is famous for its Islamic architecture, with many beautiful boulevards, covered bridges, palaces, mosques, and minarets. Today, relying on the great capabilities of its people and its abundant God-gifted natural resources as well as its human resources, Isfahan is regarded as one of the major centers contributing to the macro economy of the country, since it accounts for 7.1 percent of Iran's GDP. The share of Isfahan in the country's industry stands at 4.6 percent and it has achieved the top-ranking status as far as employment is concerned in the country. Industrial machinery, auto spare parts, electricity, and electronics, IT and ICT, pharmaceuticals, petrochemical, cement, tiles, and ceramics, are the major industries in Isfahan city.

Figure 5-3.

Location of study area (Isfahan) and its topography.



Isfahan was flourished during the 16th century under the Safavid dynasty (1502 – 1736) when it became the capital city of Iran for the second time in the history. Even today, the city of Isfahan retains much of its past glory. It is famous for its Islamic architecture, with many beautiful boulevards, covered bridges, palaces, mosques, and minarets. Today, relying on the great capabilities of its people and its abundant God-gifted natural resources as well as its human resources, Isfahan is regarded as one of the major centers contributing to the macro economy of the country, since it accounts for 7.1 percent of Iran's GDP. The share of Isfahan in the country's industry stands at 4.6 percent and it has achieved the top-ranking status as far as employment is concerned in the country. Industrial machinery, auto spare parts, electricity, and electronics, IT and ICT, pharmaceuticals, petrochemical, cement, tiles, and ceramics, are the major industries in Isfahan city.

Generally, the main reasons why Isfahan was chosen as the case study are summarized as follows:

1) Social reason: it is regarded as the third largest city in Iran, after Tehran and Mashhad.
2) Economic reason: the share of Isfahan in the country's industry stands at 4.6 percent and it has achieved the top-ranking status as far as employment is concerned in the country.
3) Suitable case to study the spatial patterns: In Isfahan, the majority of municipal districts are composed of urban and rural areas.
4) Proper sample to study the compact and scattered development: In the sixteenth century, Isfahan became the capital of an Islamic State and flourished as a commercial center. Today the old city still retains much of its character.

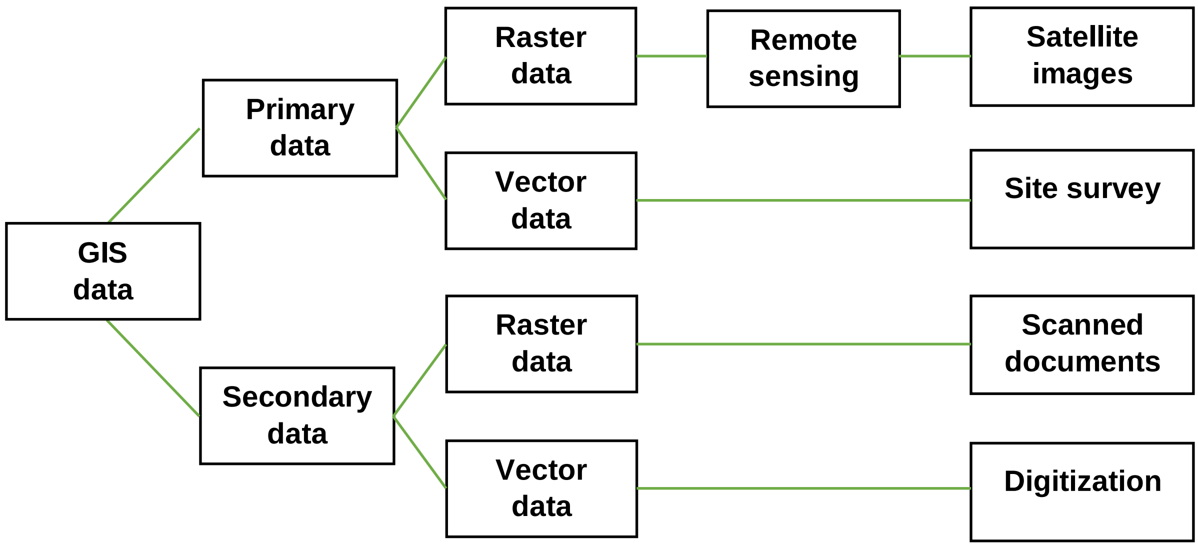
5.4. Research data

In order to attain the research objectives, it is important to have timely information about urban expansion according to the same definition of urban boundaries, the same criteria, and data sources. To be able to monitor cities, data set should become available. However, data scarcity remains a problem today. Although most developed countries have comprehensive land cover information, the relative lack of geospatial data is a serious situation in the developing countries, particularly in Iran.

Generally, in the current study, the data collection was done from both primary and secondary data sources. The primary data collected were the multispectral satellite images. The secondary data collected included the demographic details from the primary census abstracts in the study area for 1986, 1996, and 2006, from the Directorate of Census Operations of Iran. As the current study is a GIS project, the first issue or decision that is how to incorporate data into the system. This is the process called "data capture". In this project, two main types of data capture were used: primary data and secondary data (Figure 5-4). Secondary sources were digital and analog data sets that were originally captured for another purpose and converted into a suitable digital format for use in a GIS project.

Figure 5-4.

The framework of the GIS data collection.



5.4.1. Primary data

In the current study, the primary GIS data capture techniques used the remote sensing and surveying technologies to capture the data using either raster data capture or vector data. Besides the typical advantages of remote sensing images, Landsat images with medium spatial resolution and multiple spectral present a convenient data source for land cover study because they are free of charge and maximize the possible temporal monitoring period. Table 5-3 lists the acquisition dates and sensors for the selected satellite images. The Landsat Thematic Mapper (TM) data was adopted as the basis for image analysis and land cover classification from 1990 to 2010. The scenes were cloud-free and were acquired on a date within three years of the respective country's population census. Satellite images were classified into different categories depending on their resolution. A spatial resolution lower than 4 meters is classified as a high-resolution satellite, a spatial resolution between 4 – 30 meters is classified as a medium resolution satellite and a resolution greater than 30 meters is classified as a low-resolution satellite. The images had a resolution of 30 meters and were therefore classified as medium resolution. Each scene was georeferenced to the Universal Transverse Mercator (UTM) projection and the WGS-84 datum.

To assess the accuracy of the classification, it is necessary to have ground truth data. In the current study, the ground truth data was derived from interpreting high-resolution images, existing classified imagery, and GIS data layers such as topographic maps. A set of random points across the entire input dataset (123 samples) were created in Arc GIS and the attribute table of the sample points were updated with the visual interpretation of high-resolution images of Google Earth Pro for the last images of 2010 and 2000, whereas visual interpretation of the topographic map of 1991 was used for the first image of 1990 (Figure 5-5).

5.4.2. Secondary data

According to the data availability, the possible raster, vector and demographic datasets were selected in this study, which are listed in Table 5-3. All data set used in this study were geometrically referenced to the WGS 1984, UTM zone 39 N projection system.

Slope layer was extracted from 30 m DEM which was obtained from the Bureau of Urban Planning of Isfahan. This layer was changed to percent slope.

The socioeconomic patterns in the case study can be best analyzed by the access that a location has to socioeconomic center. A central business district (CBD) is the commercial and business center of a city. Geographically, it often coincides with the "city center" or "downtown". These centers can reflect the accessibility effect on land use development at different levels. This layer was digitized on the 2010 Landsat satellite image.

Transportation plays an important role in the urban growth because a good transportation system increases the accessibility of land and decreases the cost of construction. Diverse modes of transportation have different effects on the urban development. In this study, expressways (limited access roads), freeways (controlled access roads), and major roads (city arterial road) were considered. They were adopted from the Bureau of Urban Planning of Isfahan and digitized on the three Landsat images.

Administrative boundaries are legally documented and attributed jurisdictional boundaries. These boundaries define the rights, responsibilities, and interests of the land. The Bureau of Urban Planning has developed administrative limits for each year. The updated shapefiles of Isfahan city were adopted to derive administrative boundaries from 1990 to 2010.

Industrial zone refers to the part of a city with high industrial development. In Isfahan, several industrial zones had been developed by the government to allow for an optimal allocation of capital. The Isfahan Industries and Industrial Parks Organization provided the location of industrial zones in Isfahan city. The provided shapefile was adopted to derive the location of the industrial zone in the case study from 1990 to 2010.

The rural area or countryside is a geographic area that is located outside towns and cities. The Bureau of Urban Planning of Isfahan defines the word rural as “...all population, housing, and territory not included within an urban area. " and presents the status and changes of rural centers to urban areas. The shapefile was adopted to derive the information on the rural centers in the case study from 1990 to 2010.

Demographic data refer to the Decennial Census and other surveys of individuals and households administered by the Census Bureau. In this study, the demographic data was obtained from the Iranian statistical center, which is one of the Census Bureau's partnerships and publishes the demographic data every 10 years.

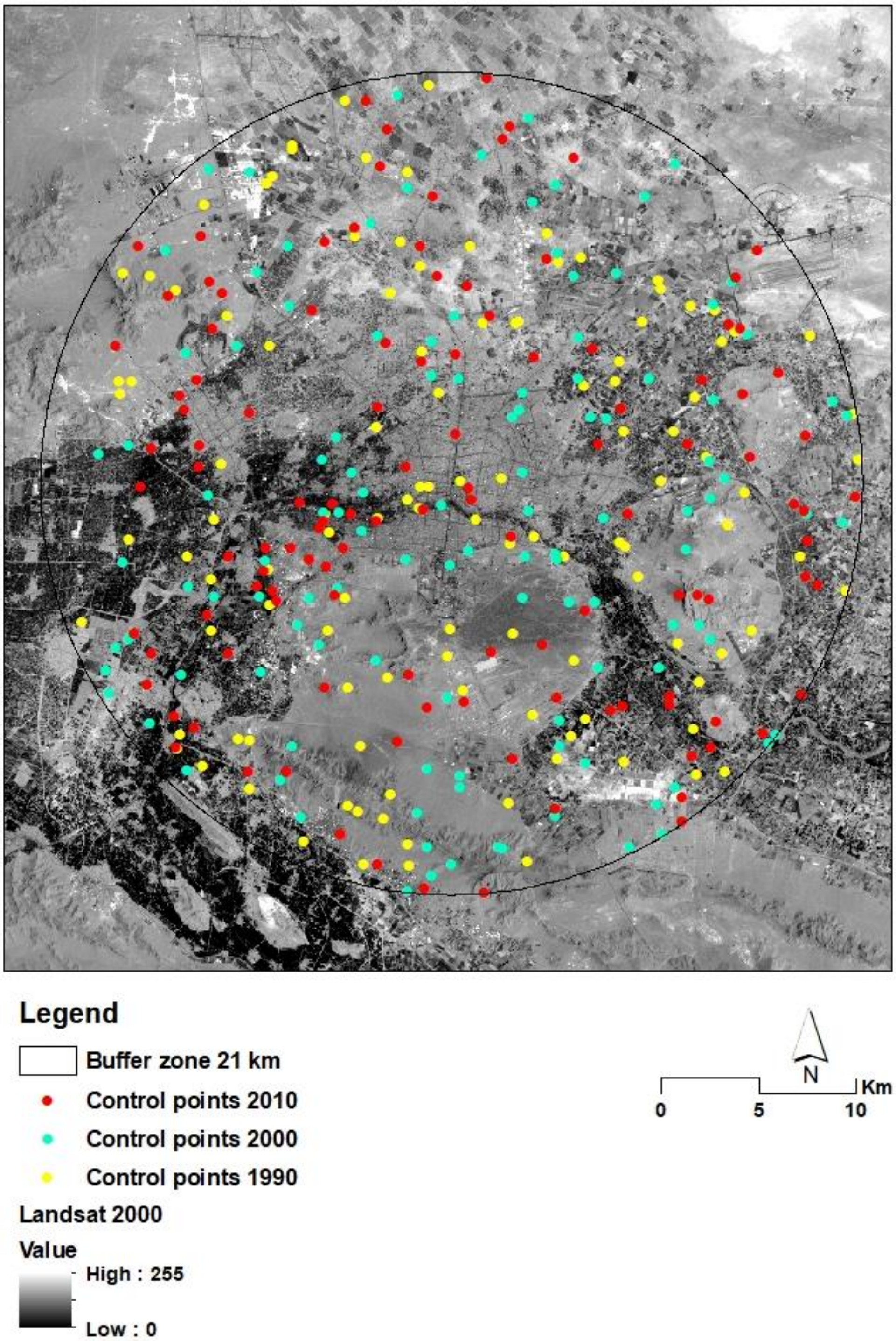
Table 5-3.

List of the dataset used in the study.

Variable	Year	Description and Sources	
Raster data			
Landsat TM	Sep. 17, 1990	30 m (path 164, row 37)	USGS
Landsat TM	Jul. 26, 2000	30 m (path 164, row 37)	
Landsat TM	Apr. 01, 2010	30 m (path 164, row 37)	
Topographic maps	1991, 2003	1:4000 The topographic maps were adopted from the Bureau of Urban Planning of Isfahan as the raster data as an image file format.	
Vector data			
CBD	2010	The central business district (CBD) was digitized on the 2010 Landsat satellite image.	
Road network	1992, 2001, 2013	The road network of Isfahan city was adopted from the Bureau of Urban Planning as the Zipped GIS shapefiles and divided into: major roads, express way and freeway.	
Administrative boundaries	1990-2000, 2000-2010	The administrative lines were adopted from the Bureau of Urban Planning of Isfahan as the Zipped GIS shapefiles before and after the change of municipal districts in 2000.	
Industrial Zones	1990-2010	In early 2010, Isfahan Industries and Industrial Parks Organization has developed the list of the established industrial zones as the GIS shapefiles over three decades (1990-2010).	
Rural centers	1990-2000, 2000-2010	The rural centers were adopted from the Bureau of Urban Planning of Isfahan (the rural centers of Isfahan province) as the Zipped GIS shapefiles and were modified using the administrative boundary layers of Isfahan city.	
Demographic data			
Population	1986, 1996, 2006	In this study, demographic data refer to the Decennial Census by the Census Bureau. The demographic data was adopted from the Statistical Research Data Center of Iran generally at the municipal district level.	
Employment	1986, 1996, 2006		

Figure 5-5.

The map of sampled points for the accuracy assessment.



Chapter VI

6. Research result and discussion

In the earlier chapters, it was tried to explain the importance of the urban expansion. To assess the performance of the recommended methods described in the previous chapter, as well as to provide a better understanding of the urban expansion in Isfahan city, the methods have been applied based on available data. This chapter presents findings of major methodologies undertaken in the research.

6.1. Land cover change

The land cover analysis can serve as a suitable tool to analyze ecosystem changes and their environmental implications at various temporal and spatial scales. As noted earlier, one of the central objectives of this study is to generate an empirical data set analysis of urban expansion in Isfahan city, and this part describes how the objective is to be accomplished. The first task of the research is to develop a detailed classification of land cover and extraction of developed or built-up land. Following status determination, digital change detection is adopted as the process of determining and/or describing changes in land-cover properties based on co-registered multi-temporal remote sensing data. The basic idea in using remote sensing data for change detection is that the process can identify the change between two or more dates that is uncharacteristic of normal variation. In the current study, post-classification comparisons of derived thematic maps attempt to quantify the different types of change.

6.1.1. Accuracy assessment

The efficiency of the proposed classification approach based on spectral indexes, MLC, and post-classification was assessd in this part of the study. A total of 123 samples were used for assessing the accuracy. The overall accuracy presents the percentage of pixels classified into the correct classes. Table 6-1 presents the accuracy assessment results and clearly, shows that the accuracy values of land cover classification based on the spectral-derived images are high.

Table 6-1.

Results of the accuracy assessment (%)

Land cover class	1990		2000		2010	
	Producer's	User's	Producer's	User's	Producer's	User's
Built-up area	81.48	91.66	90.69	92.85	91.30	91.30
Vegetation	91.66	89.79	84.21	91.42	91.176	91.17
Waterbody	100	90	100	90	100	90
Bare land	87.5	87.5	85	85	78.94	83.33
Stony land	100	90	90	90	80	80
Overall accuracy	90		89		90.6	

The classification results indicate that the proposed classification approach is useful in extracting land cover information from Landsat images especially in urban areas. The accuracies meet the minimum USGS total accuracy set out by Anderson et al. (1976), consequently, the classified results can be applied as a data source for further analysis.

6.1.2. Land cover classification

The land covers of Isfahan city were grouped into five generalized categories, i.e., built-up land, vegetation (non-forest and forest), water body, barren land, and stony land. Based on three main elements of land cover – urban land, vegetation, and open water- three indices UI, SAVI, and MNDWI, were selected to represent theses three major land-cover classes, respectively. This study employed SAVI to highlight vegetation features due to its advantage over NDVI when applied in an area with low plant cover such as the urban areas of Isfahan city.

The rationale for using SAVI is that in an area with low green cover, the reflectance of light in the red and near-infrared spectral can influence vegetation index values (Huete, 1988). SAVI was obtained using the reflectance value of band 4 (near infrared) and band 3 (red) of TM sensor. It ranged from more vegetated to less vegetated, which were presented with the white and black color, respectively. The application of land cover classification system (without transformation of the images) in the water bodies with the built-up land in the background like the cases of Isfahan city was a difficult task because the information extracted from the water bodies in this region is often mixed up together with the built-up land. The modified NDWI (MNDWI) was obtained using the middle infrared band (such as TM band 5) and the green band. MNDWI enhanced the contrast between the built-up land and the water bodies much more than classification directly. The built-up land images were produced using the UI index. The UI index was used instead of NDBI, as the urban features are more distinguishable in UI. This Index was obtained using the reflectance value of band 4 (near infrared) and that of band 7 of TM sensor.

The study combined UI with SAVI and MNDWI to highlight land cover features. This combination can improve the extraction accuracy. After producing SAVI, MNDWI, and UI derived images, a new image dataset was created, which used these three new images as three bands (Image enhancement). Further extraction of urban built-up land was carried out based on this new data set. The change from an original seven-multispectral-band image into the three-thematic-band image largely reduced correlation among three bands.

Supervised classification functions were applied to classify images using maximum likelihood decision rule. The five classes of land cover (built-up areas, water bodies, vegetation land, barren land, and stony land) were identified for the years 1990-2010. The proportion of different types of land cover in the study area (surrounded by a 21 km buffer zone) are summarized in Table 6-2.

Table 6-2.

Proportion of land cover classes in the study area (1990-2010).

Year	1990		2000		2010	
	km^2	%	km^2	%	km^2	%
Built-up	338.2857	24.2	584.8335	41.8	638.9217	45.7
Vegetation	689.2623	49.3	493.866	35.3	469.7982	33.6
Water bodies	2.5002	0.18	5.247	0.38	5.7024	0.41
Barren land	340.8957	24.4	285.5682	20.6	255.4614	18.3
Stony land	26.7336	1.92	28.1619	2.01	27.7929	1.99

In 1990, the majority of the land cover classes were categorized as vegetation land (49.3 %), whereas the built-up area class accounted for only 24.2 % of the total land area. In this year, barren land, stony land, and water sources covered 24.4 %, 1.92 %, and 0.18 %, respectively.

For the year 2000, the built-up area accounted for 41.8 % of the total study area, whereas 35.3 % of area was covered with vegetation as well as green areas. Obviously, by the end of 2000, the total urban land throughout the study area reached 584.83 km^2 (an increase of approximately 17.6 % compared to 1990). In contrast, the vegetated land decreased by 14% in the same period. Moreover, total water bodies increased by 5 % during the first analysis period, whereas the barren land decreased by 2.3 %.

In 2010, the areas covered by vegetation accounted for 33.6 % of the study area, however, the built-up areas accounted for 45.7 %. Over the second period, the built-up area continued to increase from 584.83 km^2 to 638.92 km^2 .

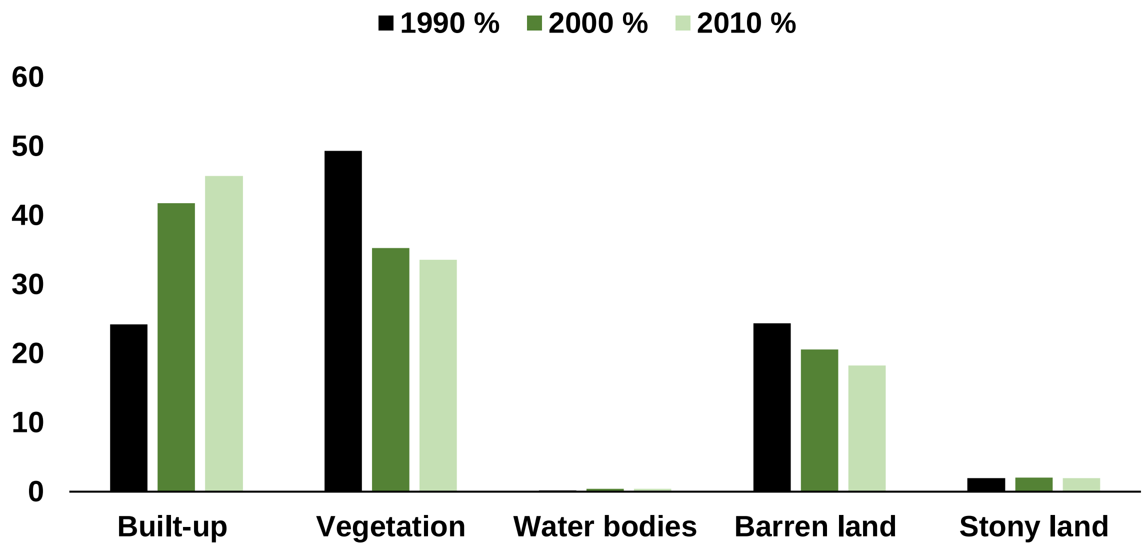
In general, an extreme land cover change occurred in the study area was mainly characterized by a significant increase in the built-up land and an intensive decrease in the vegetation area. The built-up area, as the main growth type, increased from 338.28 km^2 in 1990 to 638.92 km^2 in 2010. The apparent significance of the results is that the study zone experienced a rapid urban growth from 1990 to 2010.

As stated earlier, from 1980 to 1988, the major cities in Iran experienced continuous attacks from Iraqi missiles. The movement of people from the western parts to the eastern and central cities of the country was one of the consequences of Iran-Iraq war. This rapid movement required more built-up land than ever before, which also led to relatively high urbanization speed. The incredible pressure of rapid urbanization on non-urban land was reflected by the high loss of vegetation land. A large amount of non-urban land was converted into built-up land. Over two decades, the areas covered by the vegetation have decreased by 195.39 km^2 and 24.06 km^2, respectively.

The findings of this research in the case study (including Isfahan city and its suburbs) highlighted the fragility of environmental resources in the study area, due to urban encroachment and the absence of planning tools. In other words, the increased pressure placed on natural systems containing vegetation resources due to an ever-increasing demand for the built-up area.

Figure 6-1.

Proportion of land cover classes in the study area (1990-2010).



As stated earlier, Isfahan city located in the sub-range of Zagros. The nearest mountain is Mount Soffeh (Kuh-e Soffeh), which is situated just south of Isfahan (see chapter 5). The classification of satellite images revealed that approximately 2 % of the study area was covered with rock faces in the mountains, rock slides, and cliffs. Mount Soffeh located a few kilometers away from the city, but due to the fast and continued expansion of the city, it is now included in the administrative boundary of Isfahan.

According to Table 6-2, the number of waterbodies increased over 20 years from 1990 to 2010. It should be mentioned that in the late 2010s, after an upward trend in waterbody proportion in this period, Zayandeh Roud, the largest river on the central plateau of Iran, dried up. The river basin was made up by the eastern slopes of Mount Zagros.

6.1.3. Land cover change in Isfahan city from 1990 to 2010

To further assess the results of land cover conversions, the post classification comparison of change detection was carried out using Arc Map 10.6. The cross-tabulation method was used to determine quantities of conversions from a particular land cover to another land cover category later. The matrices of land cover changes during the study period show a summary of the major land cover conversions (Table 6-3).

The average overall amount of Isfahan land change between 1990 and 2010 was 43 percent, meaning that 609.79 km^2 of the 1397.6 km^2 changed one or more times.

The most important change was related to the vegetation. Between 1990 and 2000, about 80.9037 km^2 of total land were converted to vegetation cover, while 276.3 km^2 of vegetation area were converted to other land cover classes. Developed land, including the built-up surfaces are associated with urban and exurban growth. This category also includes transportation systems and many other dispersed built-up lands. The increase in developed land from 1990 to 2000 (327.34 km^2) was almost equal to the loss of vegetation area.

Generally, the obtained outcome for the case study indicated that a total of 368.42 km^2 of land was converted into built-up land accounting for about 68.11 % of the total land cover change area during 1990-2010. As indicated earlier, the vast majority of the built-up land came from the conversion of vegetation to urban uses. Specifically, 69.07 % of the increase in the built-up land were converted from vegetation area in the periods 1990-2000. It reflected the huge demand for built-up land and limited land resources over the first study period.

Although the results (Table 6-3) give the “from-to” information about the land cover, they do not answer the question of where land cover changes are occurring. Figure 6-2 shows the location of major land cover conversions for the case study for understanding the spatial pattern of change during the study period.

In the case study, the urban expansion was observed in different types. The main expansion of the built-up area took place along the periphery of existing built-up area. Moreover, infill growth located in central zones of Isfahan city.

Figure 6-2.

Classified land cover maps of Isfahan city 1990-2010.

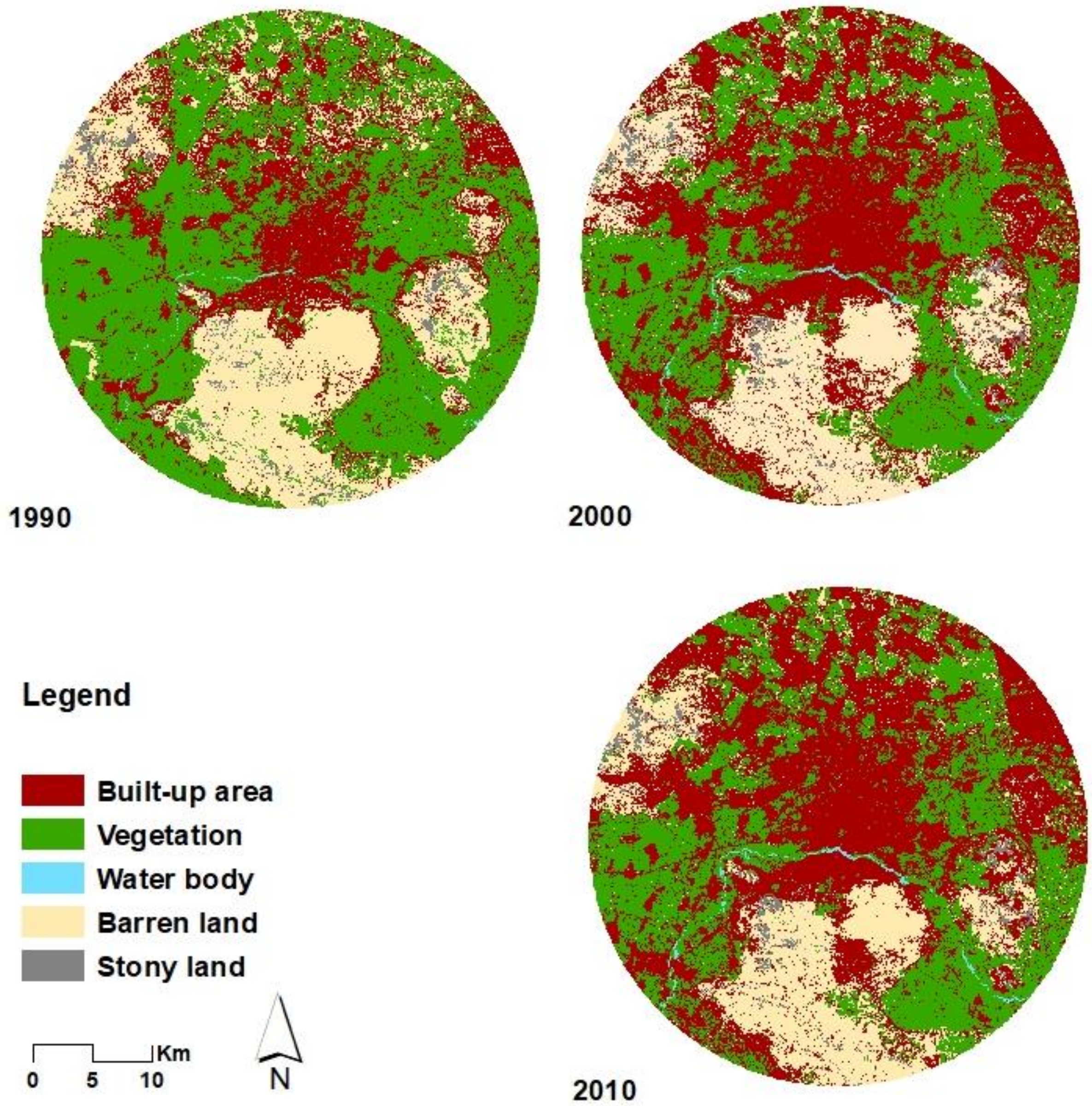


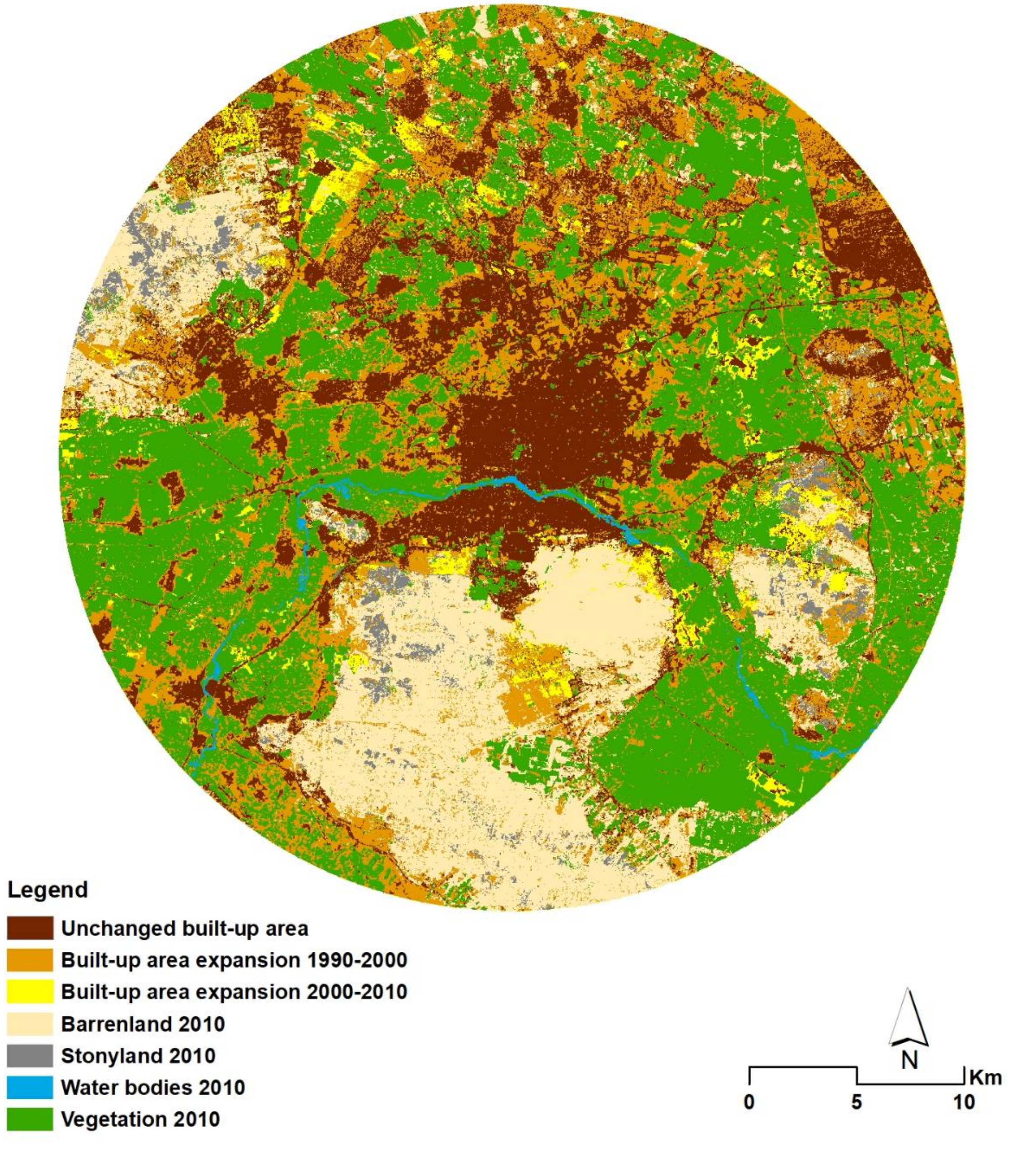
Table 6-3.

Post-classification matrix of study area (1990-2010) ($\mathbf{km^2}$).

		1990					
2000	LC	Built-up area	Vegetation	Water bodies	Barren land	Stony land	Total
	Built-up area	257.4909	226.1223	0.2169	97.5735	3.4299	584.8335
	Vegetation	47.8809	412.9623	0.6228	30.8349	1.5651	493.866
	Water bodies	0.8163	2.7657	1.6533	0.0117	0	5.247
	Barren land	30.3318	45.2628	0.0054	196.4331	13.5351	285.5682
	Stony land	1.7649	2.1492	0.0018	16.0425	8.2035	28.1619
	Total	338.2848	689.2623	2.5002	340.8957	26.7336	
		2000					
2010	LC	Built-up area	Vegetation	Water bodies	Barren land	Stony land	Total
	Built-up area	583.9335	24.8013	0	30.0141	0.1728	638.9217
	Vegetation	0.8451	468.3321	0.0045	0.4095	0.207	469.7982
	Water bodies	0.0549	0.405	5.2425	0	0	5.7024
	Barren land	0	0.3276	0	255.1338	0	255.4614
	Stony land	0	0	0	0.0108	27.7821	27.7929
	Total	584.8335	493.866	5.247	285.5682	28.1619	

Figure 6-3

Spatial distribution of built-up are in the case study (1990-2010).



6.2. Growth ratio of Isfahan city from 1990 to 2010

Previous part presented a general overview of the land cover and the changes that occurred in the study area. This section provides an insight into the urban growth ratio in Isfahan city during the study period.

The rate of urban expansion reflects the construction and development of the city in terms of domain or space and is also the basic step for urban expansion analysis. Thus, water bodies, vegetation, and barren land were integrated into one class of ground objects. In other words, binary processing was adopted for classified images, then two classes of ground objects, i.e., land for construction and land not for construction, were derived. Moreover, the man-machine interactive method was adopted in combination with false-color remote sensing images for manual visual interpretation, then the interpreted images were digitized to delineate directly the boundaries for the built-up area, and to extract topic images with boundary outline for the built-up area of Isfahan in 1990, 2000, and 2010. Then, the central point of the city (referred to as city center) was considered at the central location of the central business district. Then based on this point, one large circle was drawn so that the circle covered the contiguous urban pixels (referred to as the urban extent) of the latest temporal instant and this circular area was then divided into eight equal pie sections in eight directions. It is worth mentioning that the radius of the circle should be large enough so that it includes the entire urban extent within it.

Reviewing the literature shows that the gradient model has also been a useful technique to present the spatial and temporal variations in the pattern between urban and rural areas. In the framework of the development of a GIS-based information system on spatial pattern analysis, the GIS-based buffer analysis was adopted in the research which involved circular buffer zones surrounding the city center. Each unit was employed as a basic spatial unit to characterize distance-dependent urban growth behavior with their values for a given period. The buffer zone system (21 concentric zones) was established with a width of 1 km covering the entire region (comprising the Isfahan urban area and suburbs).

With this in mind, the built-up lands were extracted as an expansion indicator to form a binary image with the built-up land class assigned a value of 1 and all non-built-up land classes to a value of 0. Finally, non-urban areas of the city were masked out using the vector polygon representing the last buffer zone (21st), and only built-up lands were left (Figure 6-4).

To calculate the built-up area for every sector, the urban grid for city needed to be clipped using the concentric and directional shapefiles. The total urban area for each zone was then calculated by multiplying the number of urban pixels by the area of each pixel.

Increasing annually at an average rate of 4.2 %, the total built-up land of the city increased from an estimated 164.39 km^2 in 1990 to 277.04 km^2 in 2010 (Figure 6-5). Breaking the analysis down into the first 10-year period (i.e., 1990-2000) and the last 10-year period (i.e., 2000–2010), it is found that the pace of urban expansion in the city occurred at a decreasing rate within the latter period. This is evidenced by the fact that the Annual Urban Expansion Rate (AUER) decreased from 4.2 % between 1990 and 2000 to 1.1 % between 2000 and 2010. Indeed, the extent of the urban expansion between the two time periods was confirmed by expanding the built-up area depicted in Figure 6-4.

In absolute terms, the total developed land area in the city increased by approximately 112.65 km^2 over the period 1990-2010. Moreover, approximately 74.5 % (83 km^2) occurred during the first period compared with 25.5 % (28.7 km^2) during the next 10 years. Thus, the quantum of urban expansion that occurred over the first period was about 2.9 times that of the second 10 years.

Figure 6-4.

Illustration of the built-up areas in Isfahan (1990-2010).

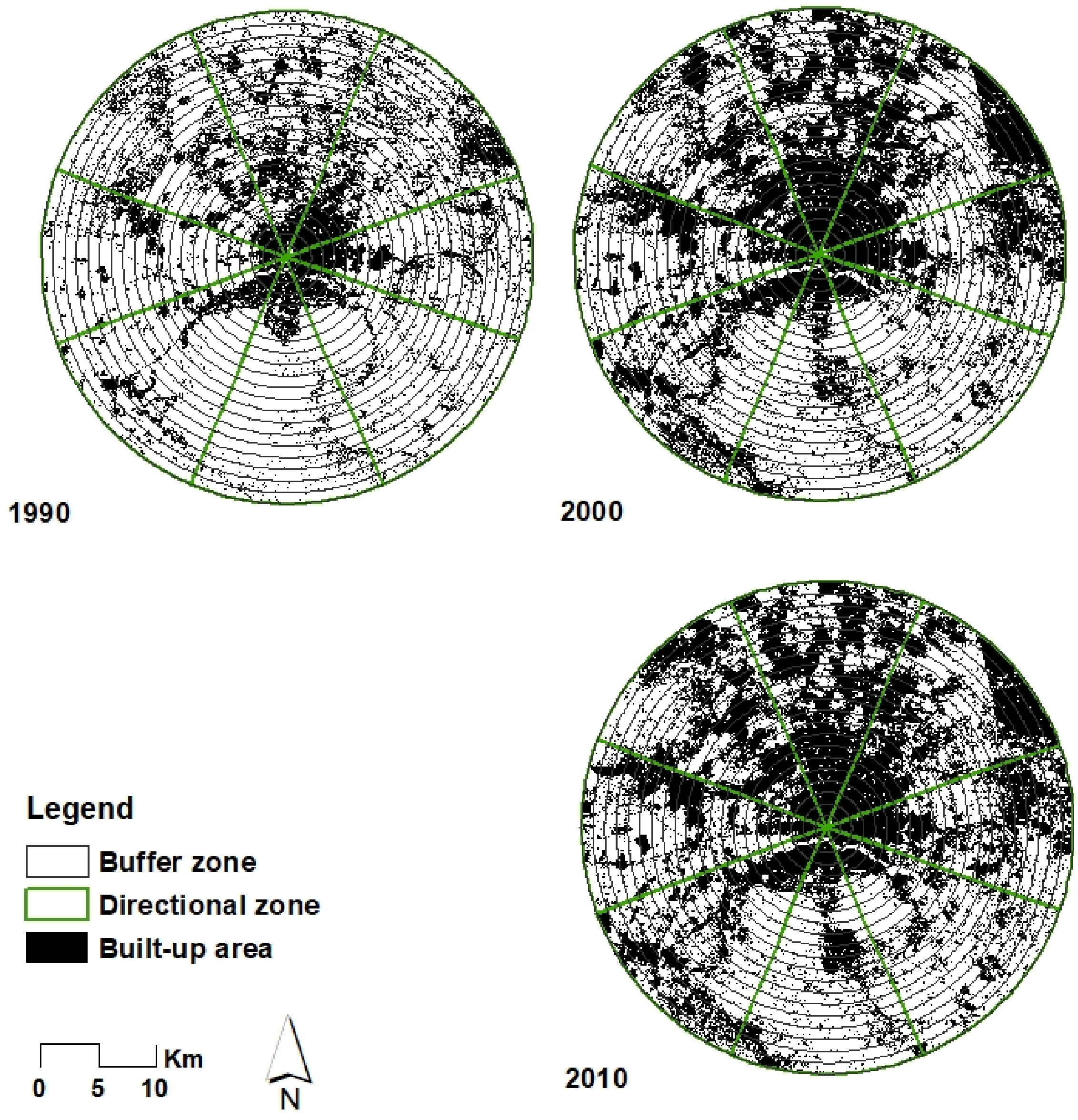
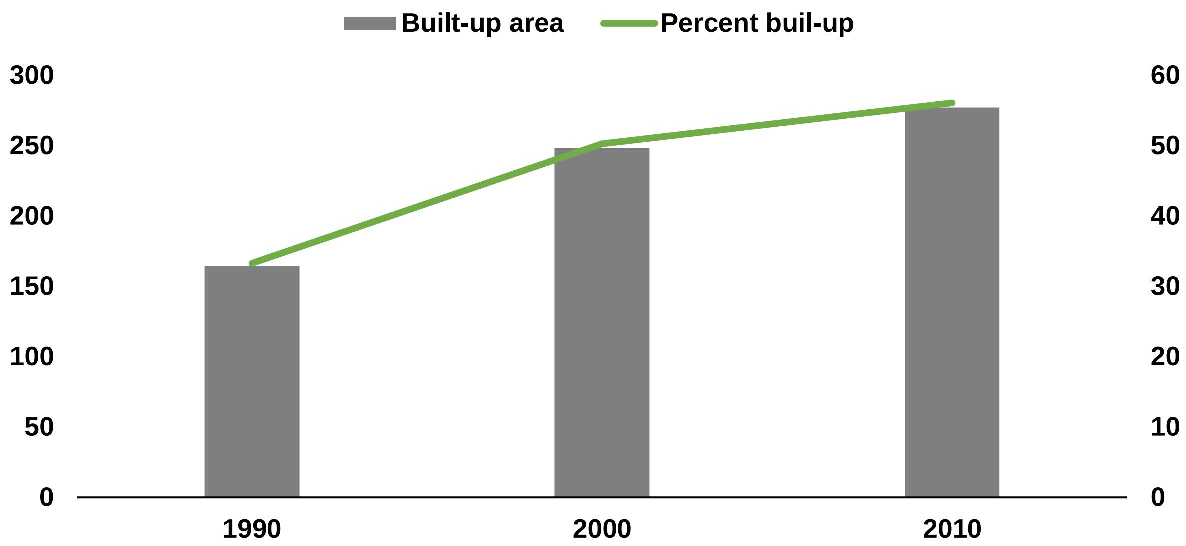


Figure 6-5.

Share of urban area in total land area, Isfahan city, 1990-2010.



6.2.1. Temporal evolution characteristics of urban land expansion

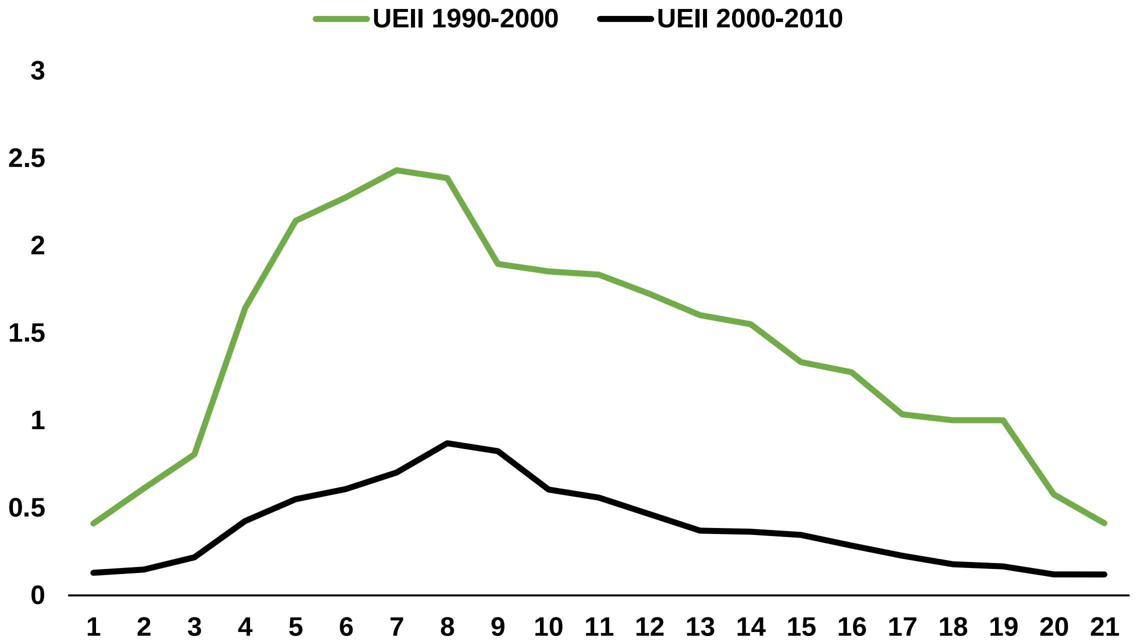
The process of urbanization will be different in each region and in each direction. This phenomenon expressed the preference for expanding urban area. The urban expansion intensity index (UEII) normalizes the annual urban expansion rate of each study unit by its land area.

In the current study, it was applied to recognize the preference of urban expansion in the case study over 20 years. Figure 6-6 (I) compares the intensity of built-up area across the city's different zones from 1990 to 2010.

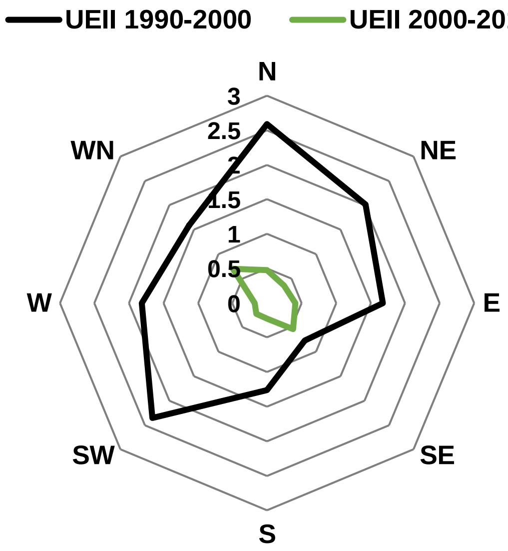
Figure 6-6 shows a rapid rise in urban intensity from the city core to 8 km with a peak value of 2.38, which suggests that this area experienced a high intensity of urban expansion. From 8 km away from CBD, the illustrated curve followed a gradual and smooth downtrend as the distance increased and the intensity of expansion decreased in the peripheral zones. The result implied that the active area of high intensity development located in the middle zones of Isfahan city. Compared with the first period, the intensity decreased significantly from 2000 to 2010.

Figure 6-6.

Changes of UEII across the city's concentric and directional zones.



(I)



(II)

Figure 6-6 (II) compares the expansion intensity Index in Isfahan across the city's directional zones over 20 years. It can be clearly seen that the N and NW directions experienced the highest values of the index throughout the study period. In other words, the expansion preferences located in these two directions over 20 years.

6.2.2. Spatial evolution characteristics of urban land expansion

Unlike UEII, UEDI identifies expansion hotspots by normalizing the rate of urban expansion of study zones by that of the whole city, thereby improving the comparability of the expansion among the spatial units (Acheampong et al., 2016).

Figure 6-7 (I) exhibits value changes in the UEDI index in a period of 20 years. According to the graph, the trend is totally unstable and has swung extremely. The statistics of UEDI showed the starting point of close to 0 (central zones) over the first period which increased during the following buffer zones. The analysis showed that in more recent years, the case study has been expanding outwardly from the initial core. Indeed, over the last 10 years, nearly all middle-located zones increased their UEDI score.

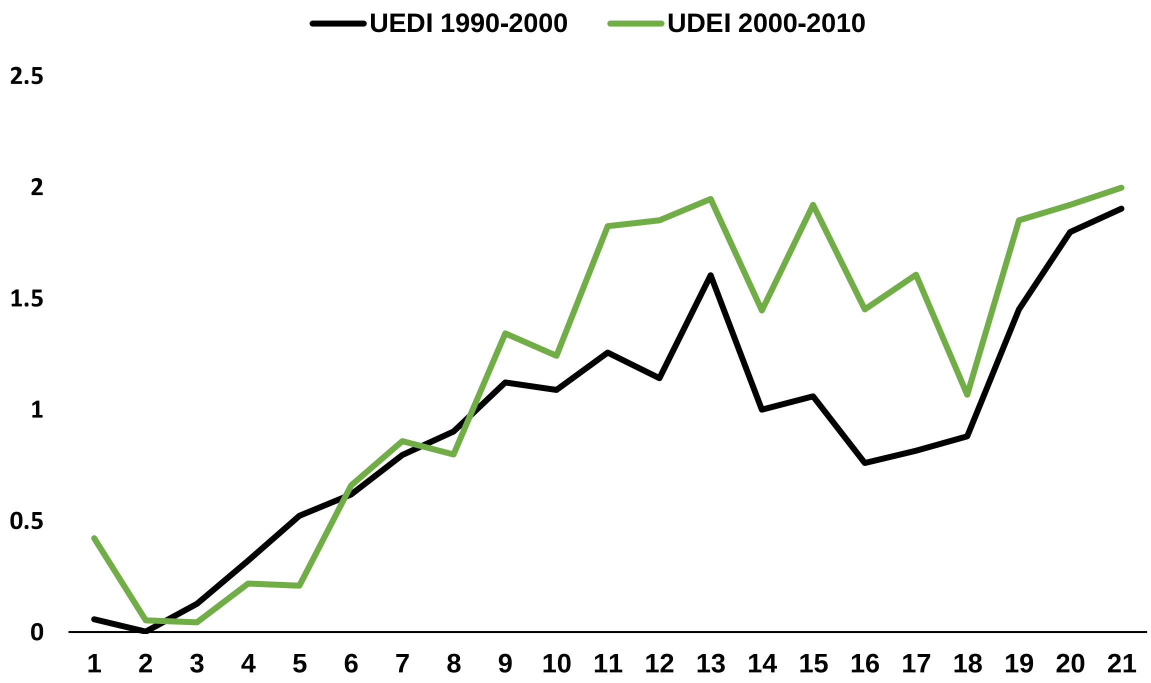
Over the first 10 years, zones W and SW with the very high UEDI scores expanded their built-up area higher than Isfahan city as a whole. Unlike the former period, WN and SE showed the highest expansion differentiation during the second interval.

With this in mind, the pattern of UEDI in Isfahan city (hotspot) was examined with regard to the three selected landscape patterns in Isfahan city. As explained earlier, there are three broad possible classes of differentiation index namely; high (i.e. UEDI>1), moderate (i.e. UEDI = 1) and low (i.e. UEDI<1). Based on the obtained values, the upper class of the UEDI was categorized further into 'very high' and 'high'; similarly, the lower class was classified further into ''low'' and ''very low''. Figure 6-8 shows five classes of UEDI scores in the city using the Jenks Natural Breaks method in ArcGIS.

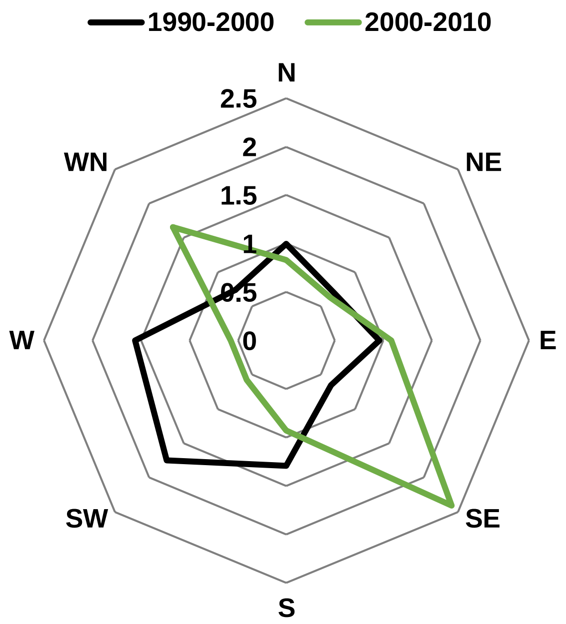
The results obtained indicated that over two decades, the hotspots of urban expansion located in the peripheral regions. The pace of expansion in the directions W and SW denoted very high speed, while NE and ES experienced the slowest pace of expansion. In the next 10 years (i.e. 2000 – 2010), however, expansion within Isfahan city was shifting away from western direction to the southeastern direction.

Figure 6-7.

Changes of UEDI across the city's concentric and directional zones.



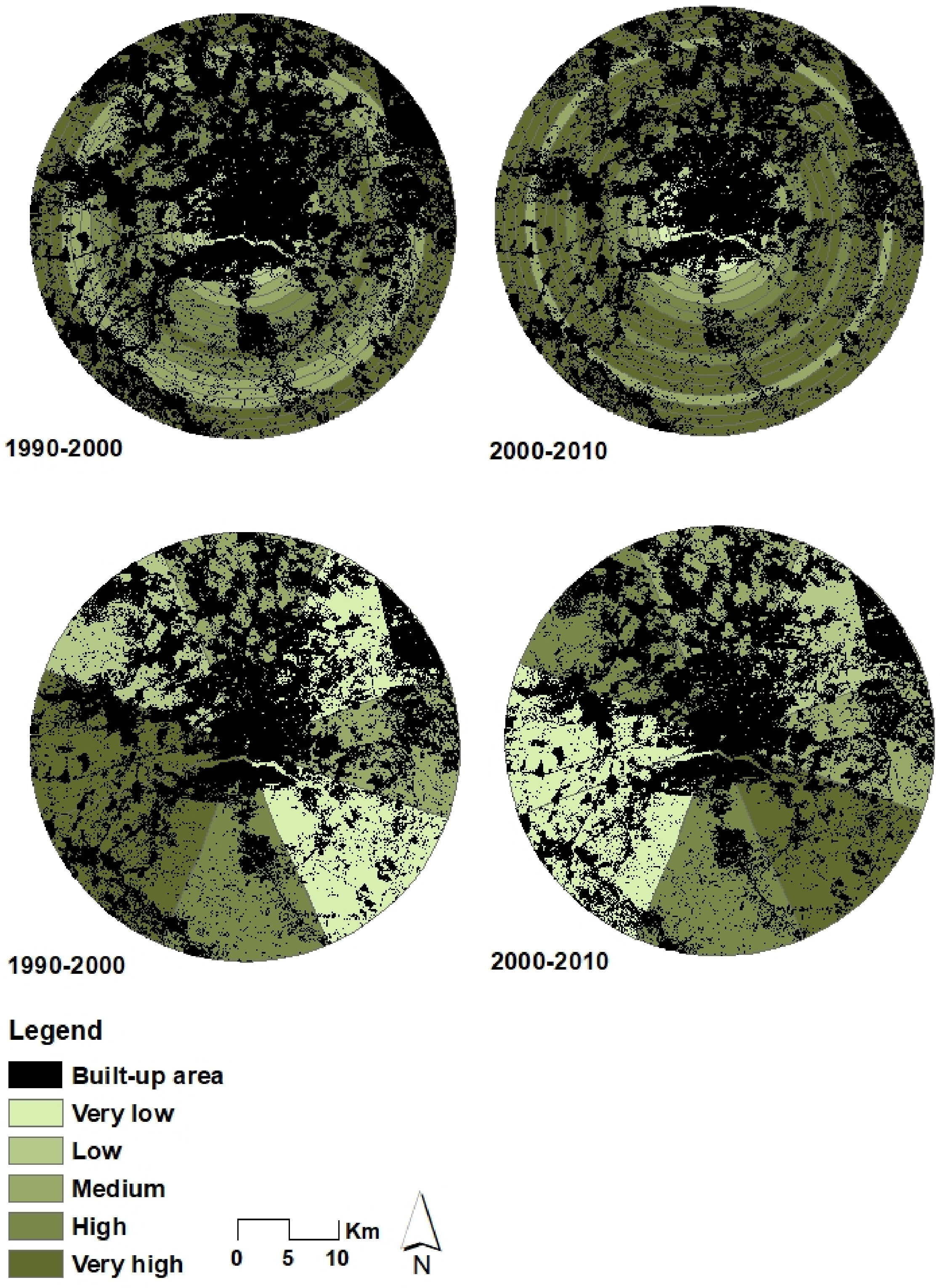
(I)



(II)

Figure 6-8.

Urban expansion hot spots in the case study (1990-2010).



In addition, by comparing the results of UEII and UEDI, it can be found that the development of new built-up areas is in inverse relation with the distance to the existing built-up area.

Furthermore, the significant differences in the share of new developed built-up land across buffer zones showed different urbanization processes in the spatial units.

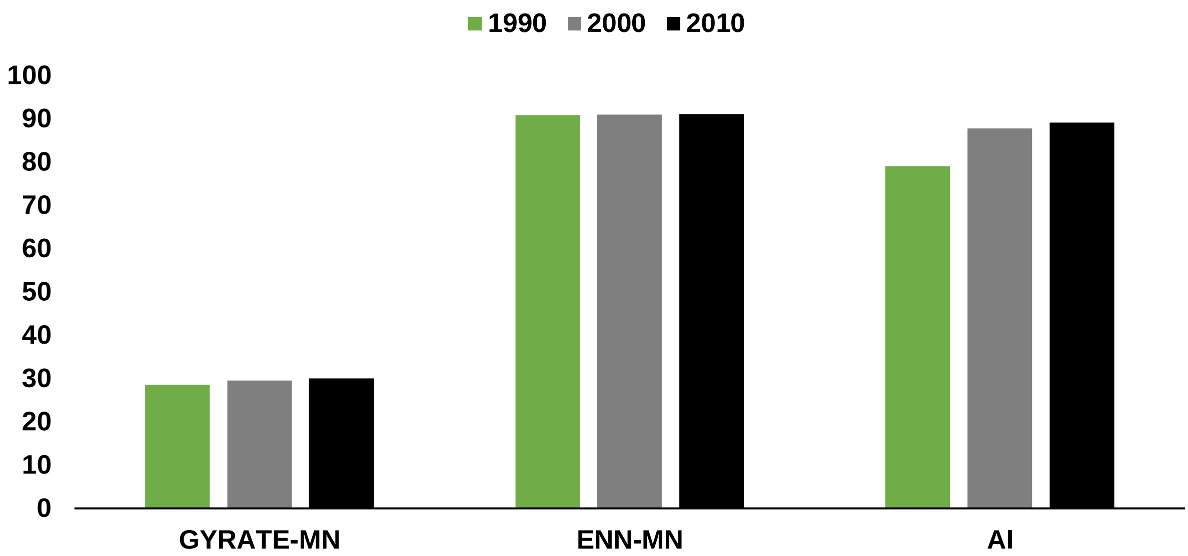
6.3. Urban expansion processes in Isfahan city, 1990-2010

In order to analyze and compare the process of urban expansion, three spatial metrics were used in the study time durations. The spatial metrics were applied to explain the main characteristics of the urban pattern (aggregation, compactness, and isolation) at the micro- and macro-scale. On a macro-scale level, the spatial metrics were interpreted for Isfahan city as a whole. This was followed by a micro-level analysis of spatial patterns across the concentric and directional zones.

Figure 6-9 provides information about the temporal variation in the values of spatial metrics in Isfahan city from 1990 to 2010. Generally, the allocation of urban area included the growth of new individual urban patches, which were illustrated by the increase in AI. The increasing aggregation indicated the tendency of the built-up patches towards the creation of the aggregated patches. Furthermore, the increasing trend of ENN_MN showed that the isolation process grew throughout the study period. Moreover, according to the GYRATE_MN, the city experienced a decreasing trend of compaction. In general, the sprawling development and fragmented growth of existing urban area in Isfahan are illustrated by the increases in GYRATION_MN and AI.

Figure 6-9.

Temporal change of spatial metrics in Isfahan city (1990-2010).

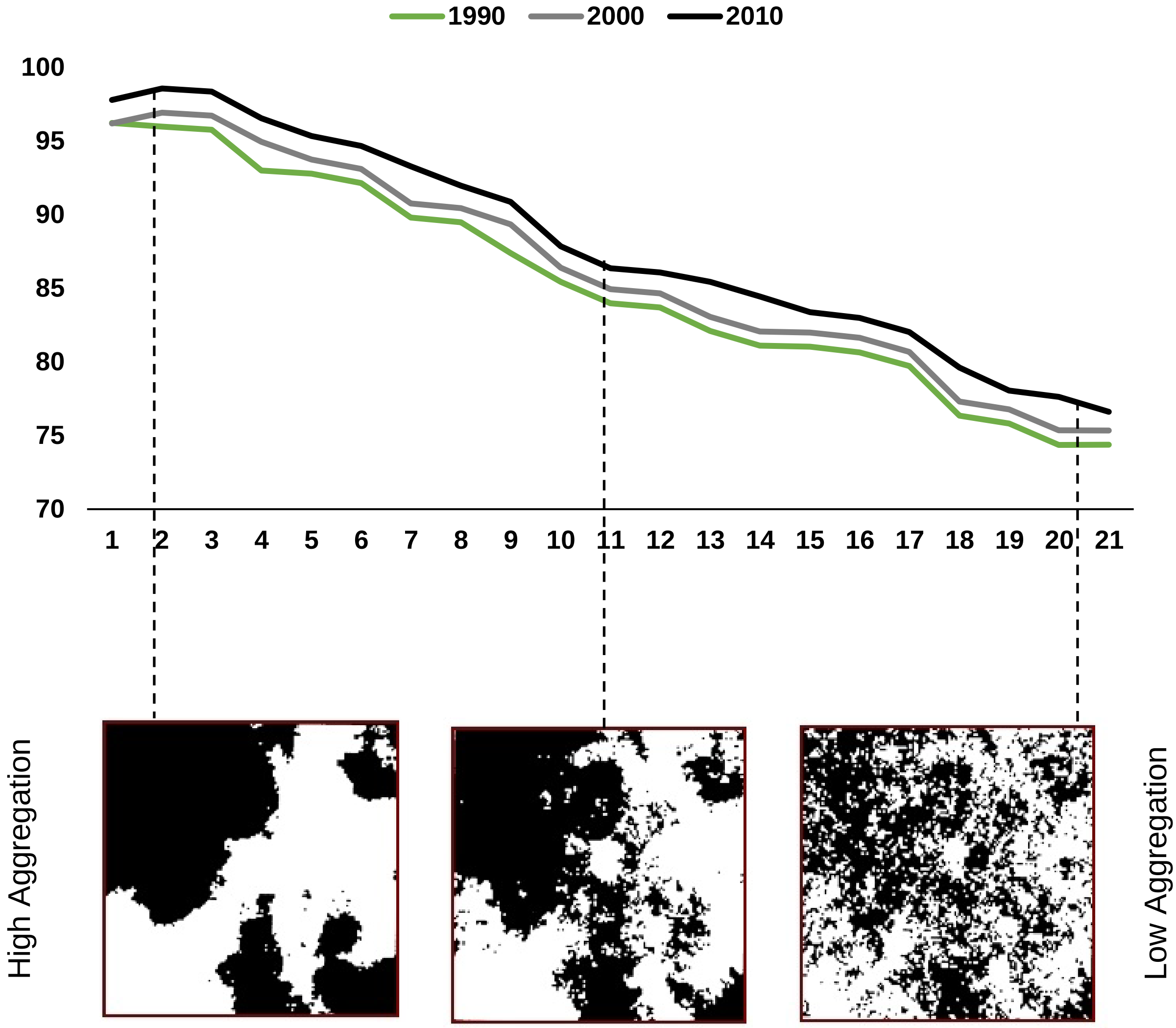


To further understand the urban expansion pattern in Isfahan city, the temporal changes in spatial metrics were interpreted across the spatial units. Figure 6-10 depicts the trend in the value of the aggregation index over 20 years commencing from 1990. The graph demonstrates a similar negative trend in the value of AI across 21 concentric zones over 20 years. The value of the aggregation index fell dramatically with the distance from the city core. Overall, the central zones of Isfahan had the stronger values of the aggregation index. The situation may be attributed to the appearance of small built-up patches around the periphery of the city and in the peri-urban regions. This could happen as the city extends outward in the form of scattered development.

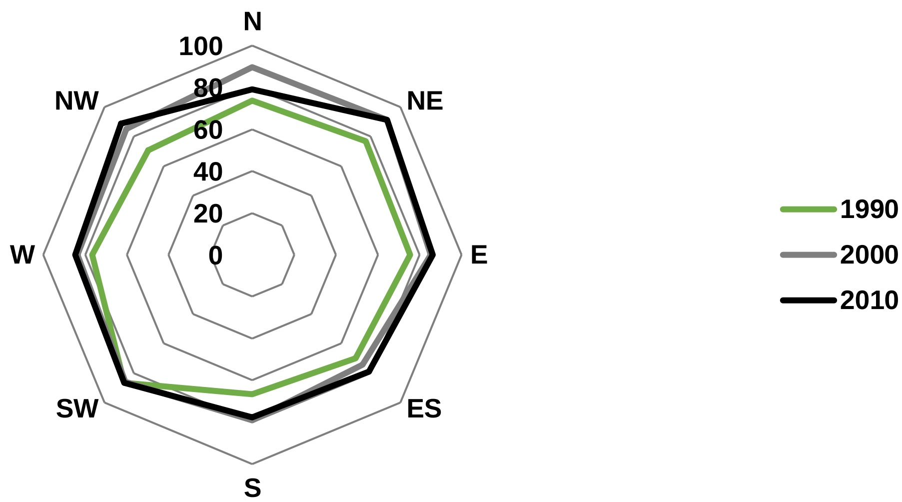
The next illustration (Figure 6-10 (II)) shows AI in the case study across the directional zones and indicates the share of each spatial unit from the aggregation process from 1990 to 2010. In 1990 the large value of AI, according to the chart, was recorded in SW, NE, and W. In 2000, the largest amount of AI came from NE and N. In the last year, NE, and NW experienced the clustering of patches to form patches of a larger size.

Figure 6-10.

Change of AI at the micro level



(I)



(II)

In order to explore the compaction process at the micro level, the Gyration Index was applied within the buffer and directional zones. Figure 6-11 shows the change in the value of the Gyration Index in Isfahan city between the years 1990 and 2010. As an overall trend, it is clear that the Gyration Index decreased fairly rapidly and reached at the lowest score at a distance of about 5 km from the city core, before climbing towards the peripheral zones. In conclusion, Figure 6-11 (I) shows that the elongation (not compaction) process was increasingly prevalent in the peripheral zones of Isfahan city. The radar graph (Figure 6-11 (II)) compares the Gyration Index across the directional units within a time span of 20 years. As it can be seen, in 1990 the SW, NE, and W sectors recorded the high values of the gyration index. It also presents a similar trend for the last year, but the high proportions of Gyration Index belonged to NE and NW. Overall, the Gyration index rose across the directional zone of Isfahan city from 1990 to 2010.

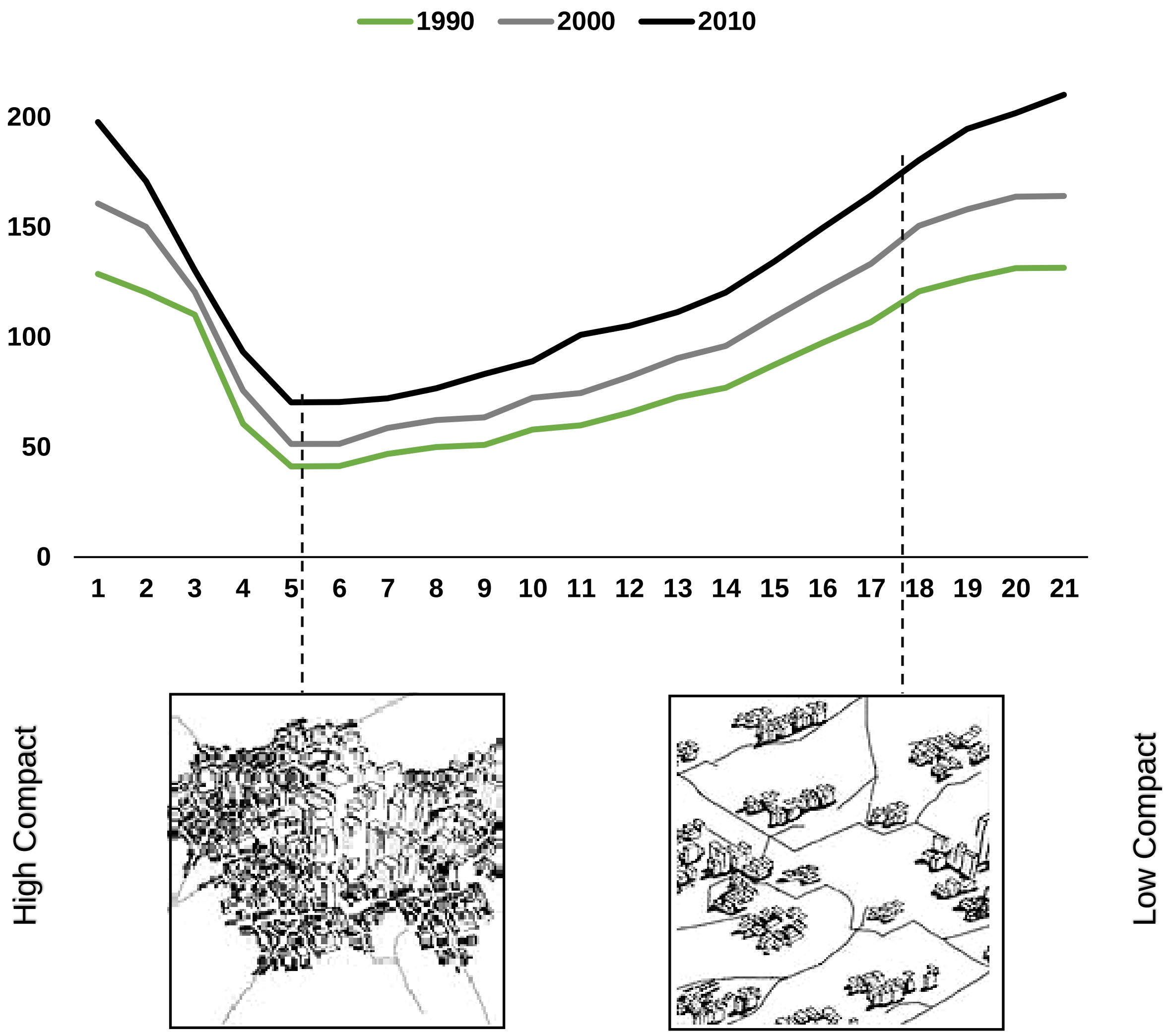
The next process (isolation) was examined using ENN_MN index, which refers to an increase in the distance that separates patches of the same category type. The line graph illustrates the change of ENN_MN across the concentric zones between 1990 and 2010, while the radar chart shows which directions had the highest Index values over the study period (see Figure 6-12). Overall, it can be seen that the value of ENN_MN increased in both directional and concentric zones. Furthermore, the value of the index in central zones was much lower than peripheral zones, and it followed the same pattern throughout the period. The graphs started at a rather similar amount, but they increased significantly around the peripheral areas. By far the highest proportion of isolation process belonged to N and NW.

Temporally, rapid expansion in Isfahan went through two periods. In the period of 1990-2000, the rapid development in the urban fringe led to the increase in the size of the main urban area, which is illustrated by an increase in AI. Furthermore, a dispersal of new development on isolated areas separated from other areas by vacant land can be observed on the urban-rural fringe area. It indicated that the city expanded through leapfrog expansion.

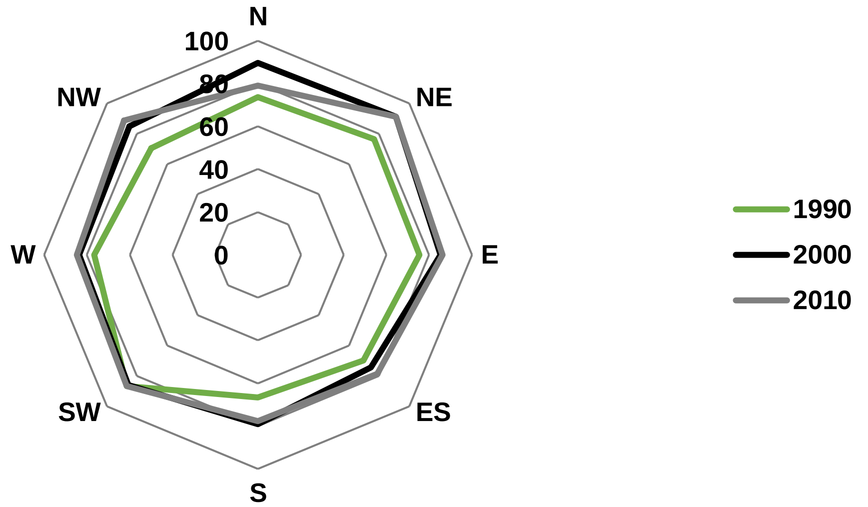
For the period of 2000-2010 the intensity of urban expansion slowed down. Over this period, the city experienced the slight increase in GYRATION_MN and the aggregation of patches significantly increased. It can be resulted that the continued growth in Isfahan focused on the extension of urban patches, which was indicated by the significant increase in AI, and the slight increase in Gyration.

Figure 6-11.

Change of GYRATE_MN at the micro level



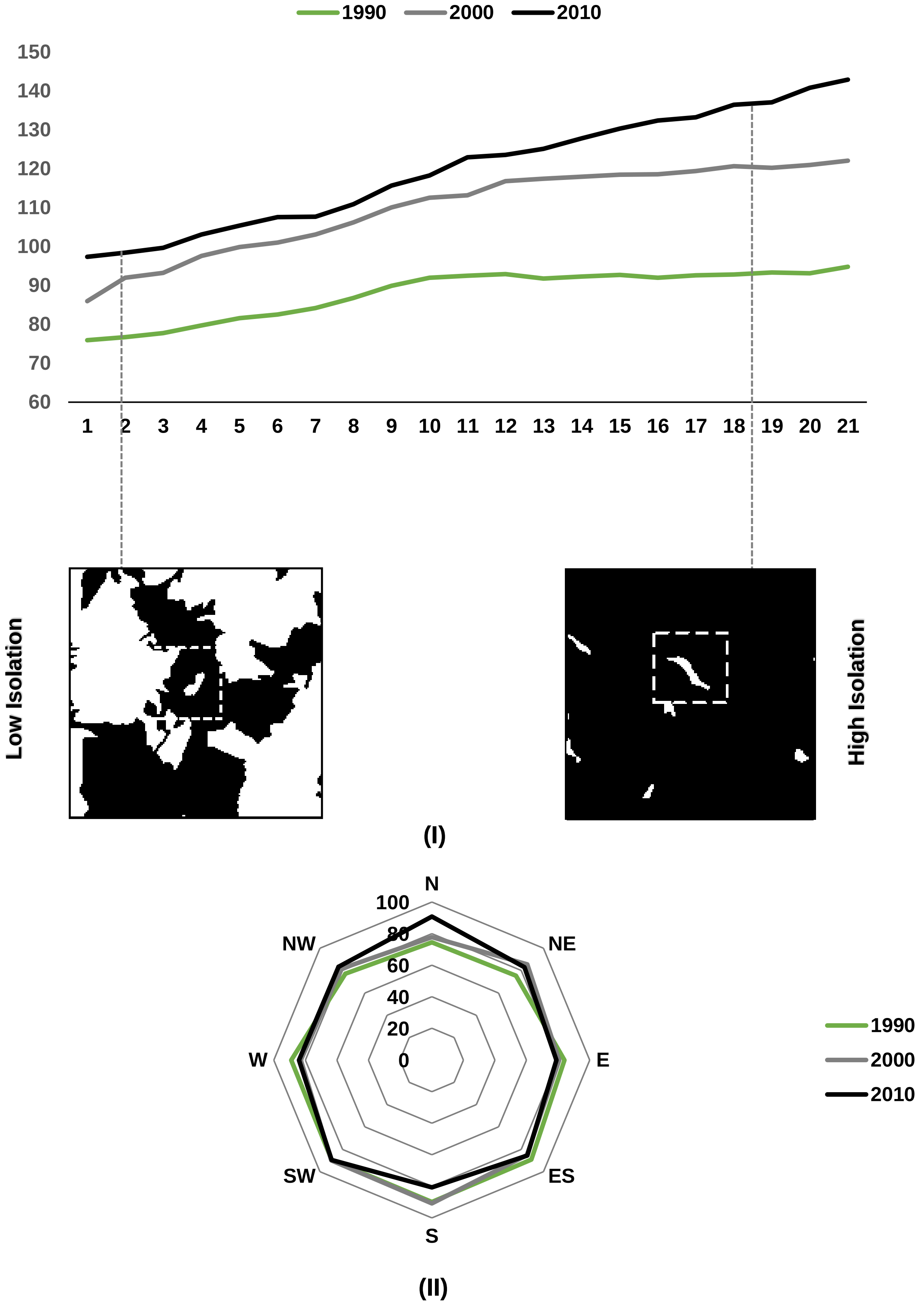
(I)



(II)

Figure 6-12.

Change of ENN_MN index at the micro level.



6.4. Urban expansion patterns in Isfahan city, 1990-2010

With this in mind, the relationships were established between the spatial processes described above and distinct urban expansion patterns. After calculating the values of spatial metrics for the study units, we were able to classify the metrics for each spatial unit into five classes (very high, high, medium, low, and very low). Tables 6-5 and 6-6 show the classification of metrics within the spatial units (directional and concentric zones) using the Jenks Natural Breaks method in ArcGIS (Figure 6-17).

The first type of urban spatial pattern, aggregated pattern, corresponds to the conventional type of urban growth in historical cities of Iran, new urban areas are added onto an already consolidated city. In the current research, this pattern was characterized by increased aggregation and generally by reduced dispersion. Table 6-6 shows the identified landscape patterns in Isfahan over 20 years. It can be clearly seen that the amount of AI was high considerably across the first eight rings. Moreover, among all 21 concentric zones, these eight units experienced the low values of isolation metrics.

In conclusion, the aggregated pattern (increased aggregation and generally by reduced dispersion) was the dominant landscape pattern at the distance of 8 km from CBD. This pattern of urban growth tends either to remain constant and unchanged or to decrease landscape fragmentation.

Moreover, the analysis of landscape pattern across the directional zones showed that the city experienced a strongly aggregated pattern in the N, NE, SW, and W sectors in 1990 (Table 6-5). Besides the mentioned zones, in 2000, the eastern direction also experienced the infilling growth and the intensification of the built-up areas. At the end of the study period, the western, southwestern, and eastern quarters continued to aggregate the built-up area patches.

The location of aggregated regions in Isfahan showed that the resulted patterns were strongly related to the geographic location of spatial units. For instance, the southwestern sector located between Zayanderud River on the north and Soffeh mountain on the south. In other words, these two natural elements were obstacles to expanding the built-up area.

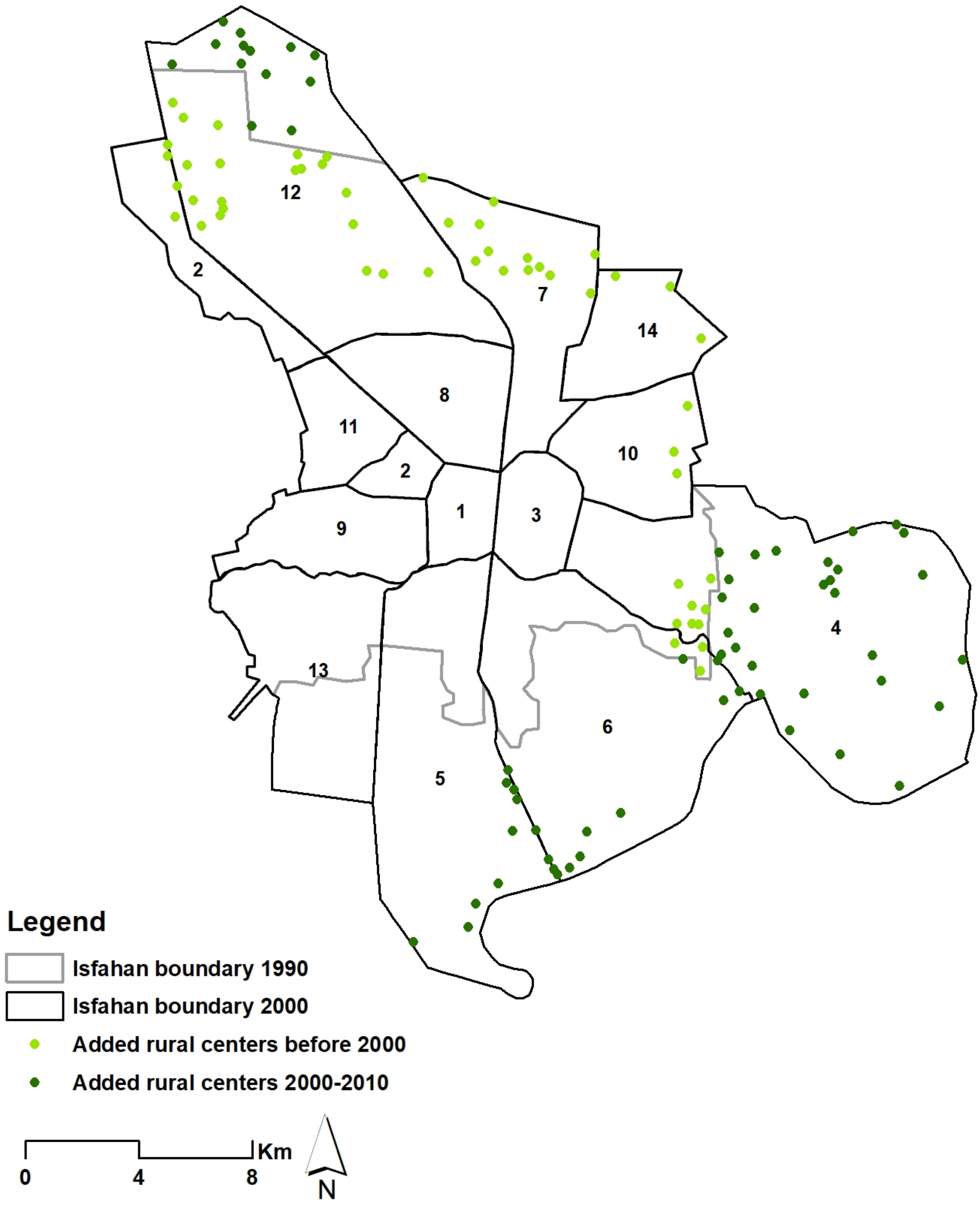
The second identified pattern (Leapfrogging pattern) occurs when developers build new residences some distance from an existing urban area, bypassing vacant parcels located closer to the city. In other words, developers choose to build on less expensive land farther away from an urban area rather than on more costly land closer to the city. In this type of urban pattern, the population began to distance itself from the city center. The leapfrogging pattern is dominated by decreased aggregation, increased compaction and increased dispersion.

Table 6-6 shows that the leapfrogging pattern occurred at the distance between 12 and 21 km from the city core with widely varying intensities. Exploring the direction of expansion showed that in 1990, the southeastern and northwestern sectors in the peripheral areas experienced the scattered pattern. By comparing the results of landscape pattern with the added rural centers to Isfahan city before 1990 it may be confirmed that the location of leapfrogging regions precisely corresponded to the swallowed rural centers within a time span of 20 years (Figure 6-13). In 2000, the zone located in the southeastern part of the city showed a scattered form of expansion with disjointed patches of built-up area. Moreover, such expansion caused the encroachment of the city into surrounding rural hinterland and agricultural areas in the south part of Isfahan. This situation provided an opportunity to expand the built-up area beyond the city limits and resulted in a leapfrogging pattern towards the south. In 2010, scattered and non-contiguous residential development was the dominant form in the southern and southeastern directions of Isfahan city.

In Isfahan, during the interval from 1990 to 2000, which corresponds to an urban development period after the Iran-Iraq war, too little has been done to accommodate heavy rural migration to urban centers. Illegal housing, which was originally the preferred housing method for the immigrants since 1980's, turned into a housing method. On the other hand, the urban sprawl become apparent on the valuable lands located at the peripherals.

Figure 6-13.

Illustration of added rural centers to Isfahan (1990-2010).



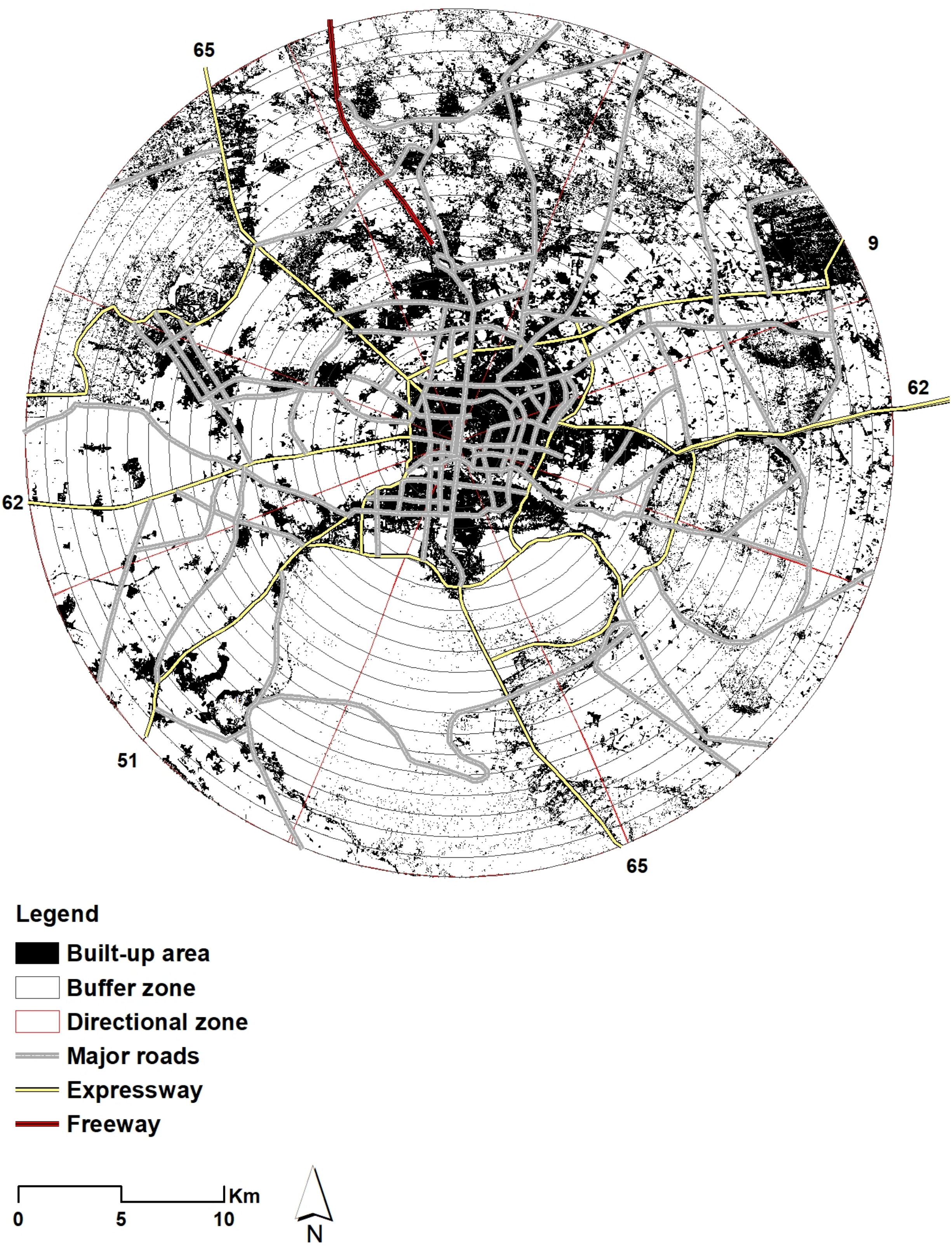
The next pattern refers to the urban growth around the road networks. In this type of pattern, two main processes are identified: increased or stable aggregation and decreased compaction.

Table 6-6 shows that the linear pattern was the major landscape pattern in a region between 9 and 11 km from the city center. Although this pattern occurred across the same buffer zones, it was identified in different directions over 20 years. From the information provided, it appeared that 2000 and 2010, the development of Highway 65 in the northwestern sector of Isfahan caused the ribbon sprawl characterized by the concentration of development along the transportation corridor outward from the urban core.

Along with the linear sprawl occurred on lands adjacent to the highway 65, the development and improvement of major roads in N and NE (62 and Isfahan N-freeway), resulted in the conversion of non-urban lands to built-up areas, so that in 2000, these two directions experienced a strong linear pattern along with their road networks (Figure 6-14).

Figure 6-14.

Location of main road networks in Isfahan city.



The last identified spatial pattern largely reflects existing industrial and commercial urban growth near the main transportation nodes. The Nodal pattern is dominated by decreased aggregation along with increased dispersion and compaction.

According to Tables 6-5, the nodal pattern occurred in the region between zone 12 and 14 km over 20 years. In 1990, there was an overlapping between the leapfrogging pattern and nodal pattern in the northwestern direction. As Figure 6-15 shows, Isfahan power plant, Isfahan oil refinery, as well as two main Industrial zones located in this direction. The establishment and development of these industrial nodes caused the growth of built-up area in this zone. In 2000, the southeastern sector had also a nodal pattern across the concentric zones from 12 to 14 km. This development was the result of an increase in urban surfaces around the industrial complexes in SE. In the last year of the study, the southeastern zone continued to decrease the aggregation and decrease both the compaction and isolation processes and was therefore characterized as the nodal pattern.

Table 6-4 shows the relationship between the four patterns identified (aggregated, linear, leapfrogging, and nodal) and the spatial processes (aggregation, compaction, and dispersion) determined by the metrics (Aggregation Index, Gyration Index, and isolation Index).

Table 6-4.

Relationship between the patterns and the spatial processes.

Spatial metrics	Four urban patterns and three spatial processes associated											
	Aggregated			Linear			Leapfrogging			Nodal		
	Agg. +	Com	Iso. -	Agg. +	Com -	Iso.	Agg. -	Com +	Iso. +	Agg. +	Com +	Iso. +
AI	+			+			-			+		
GYRATE					+			-			-	
ENN			-						+			+

Aggregation (Agg.), Compaction (Com.) and Isolation (Iso.): “+” Increase, “−” Decrease.

Figure 6-15.

Location of main industrial zones in Isfahan city.

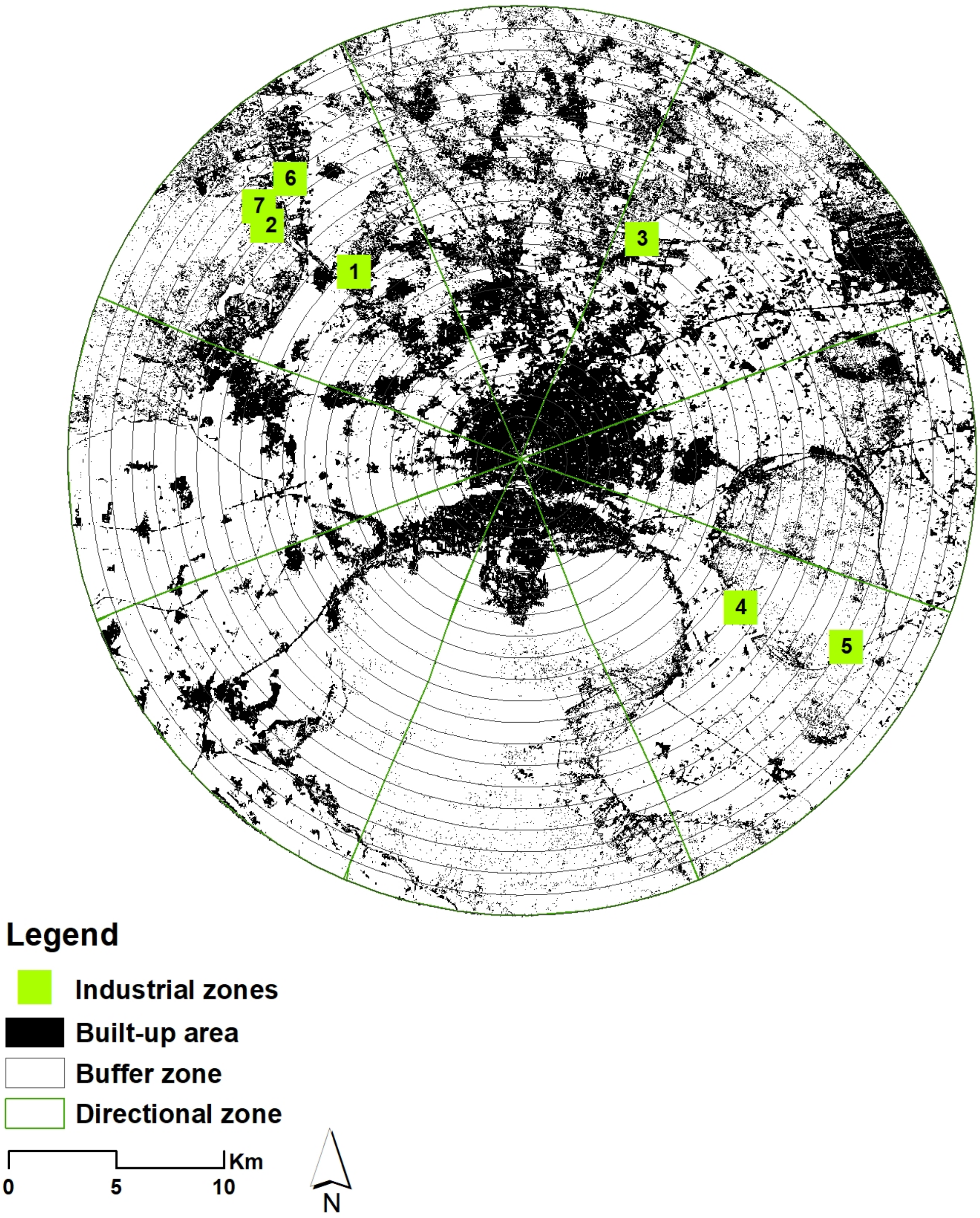


Figure 6-16.

Four identified patterns in Isfahan city, 1990 – 2010.

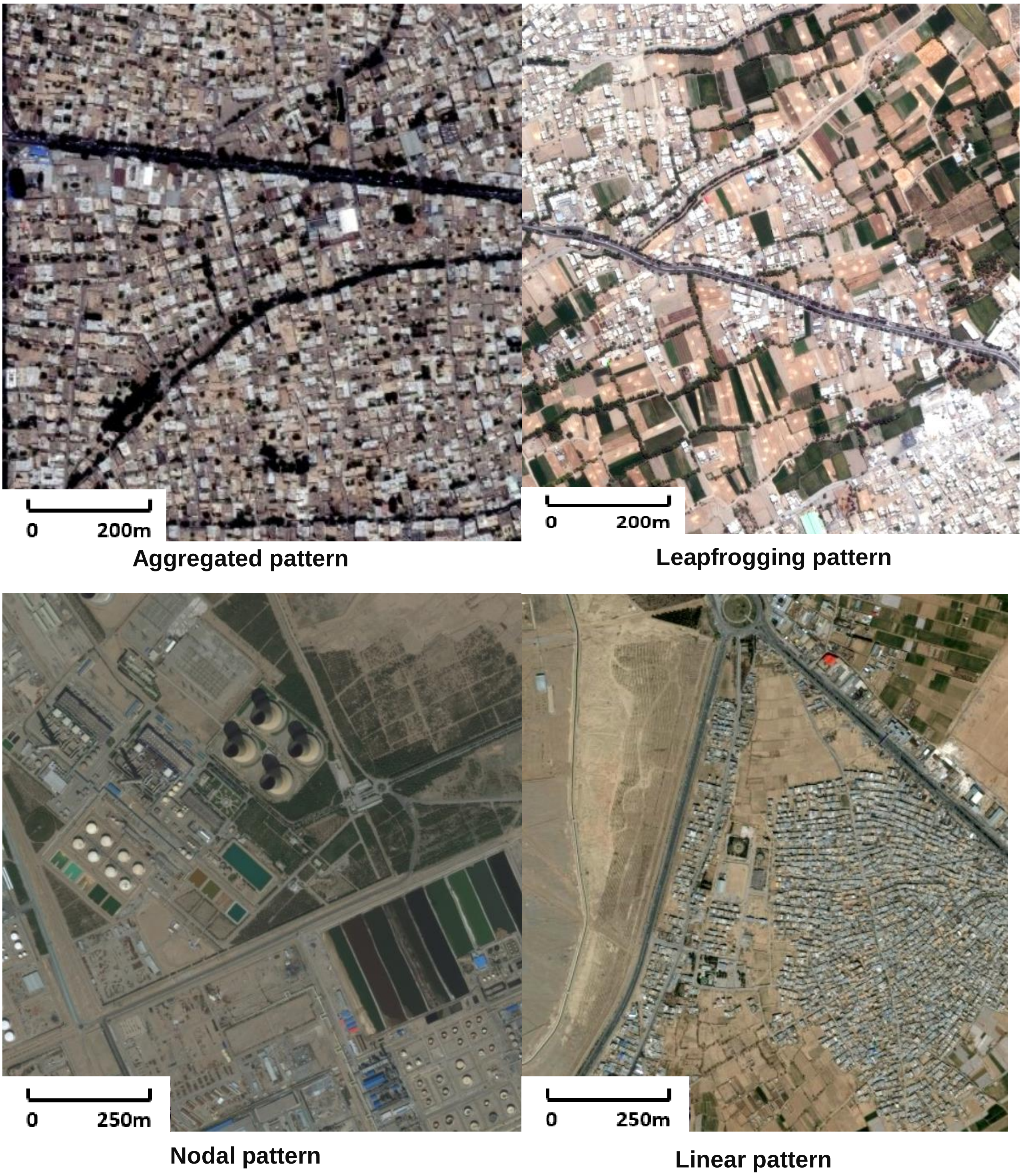


Table 6-5.

Identified patterns across the directional zones of Isfahan city.

	1990				2000				2010			
	AI	GYR.	ENN	Spatial patterns	AI	GYR.	ENN	Spatial patterns	AI	GYR.	ENN	Spatial patterns
N	+	+/-	--	Aggregated	++	++	+/-	Linear	+	++	+/-	Linear
NE	++	+/-	--	Aggregated	++	++	+/-	Linear	++	++	+/-	Linear
E	+/-	+/-	+/-	-	+	+/-	--	Aggregated	+	+/-	--	Aggregated
ES	--	--	+	Leapfrogging	+/-	-	+	Leapfrogging/Nodal	+/-	--	+	Leapfrogging/Nodal
S	--	--	++	Leapfrogging	--	+/-	++	Leapfrogging	--	--	+	Leapfrogging
SW	++	+/-	-	Aggregated	+	+/-	-	Aggregated	+	+/-	-	Aggregated
W	+	+/-	-	Aggregated	+	+/-	-	Aggregated	+	+/-	-	Aggregated
WN	-	-	+	Leapfrogging/ Nodal	+	+	+/-	Linear	++	+	+/-	Linear

"++" very high, "+", "+/-" medium, "-" low, "-" very low.

Table 6-6.

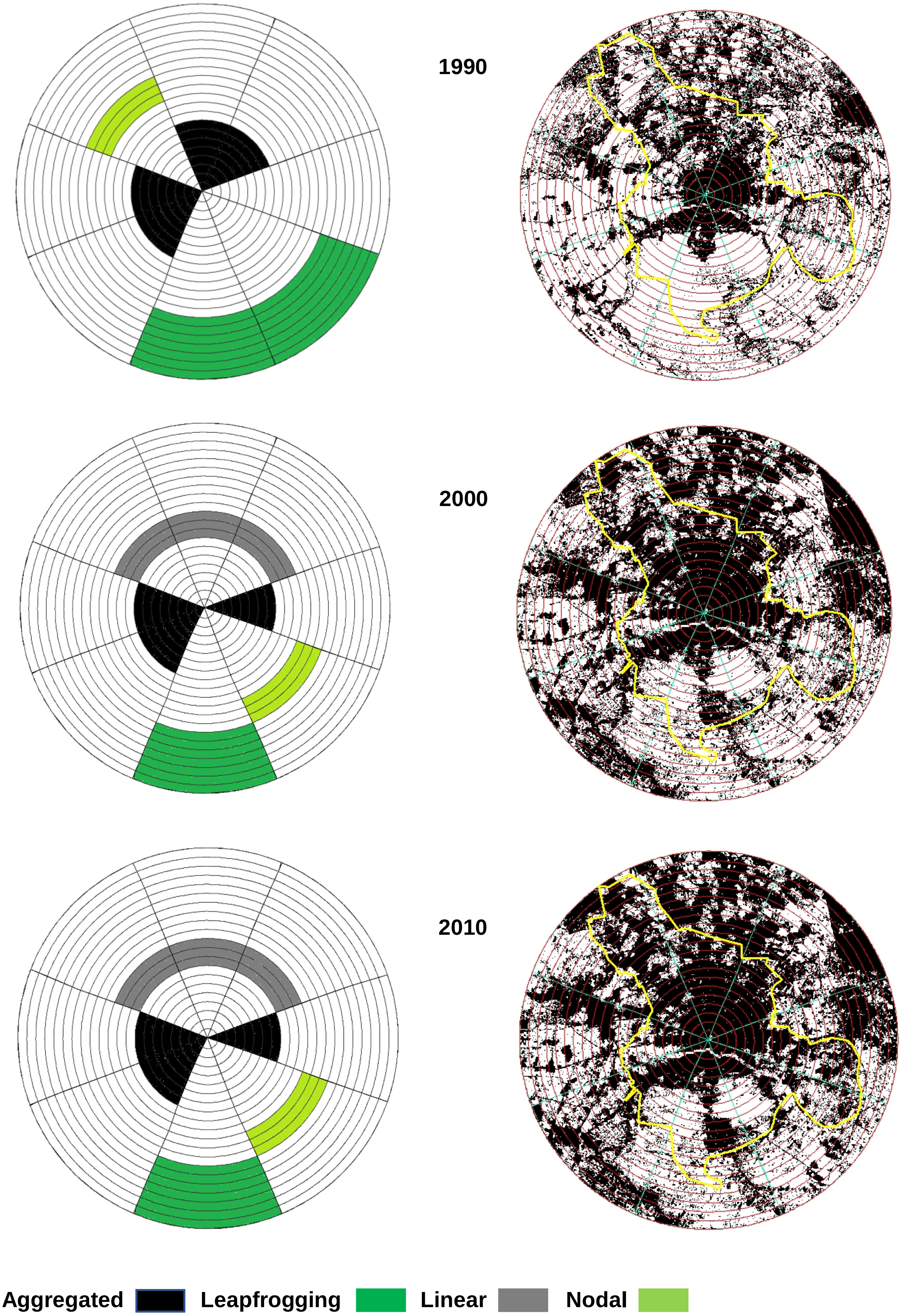
Identified patterns across the concentric zones of Isfahan city.

	1990				2000				2010			
	AI	GYR.	ENN	Spatial patterns	AI	GYR.	ENN	Spatial patterns	AI	GYR.	ENN	Spatial patterns
1	++	++	--	Aggregated	++	++	--	Aggregated	++	++	--	Aggregated
2	++	-	--	Aggregated	++	-	--	Aggregated	++	-	--	Aggregated
3	++	-	--	Aggregated	++	-	--	Aggregated	++	-	--	Aggregated
4	++	--	--	Aggregated	++	-	--	Aggregated	++	-	--	Aggregated
5	++	--	-	Aggregated	++	--	-	Aggregated	+	--	-	Aggregated
6	+	--	-	Aggregated	+	--	-	Aggregated	+	--	-	Aggregated
7	+	--	-	Aggregated	+	-	-	Aggregated	+	-	-	Aggregated
8	+	--	+/-	Aggregated	+	-	+/-	Aggregated	+/-	-	-	Aggregated
9	+/-	+/-	+/-	Linear	+/-	+/-	+/-	Linear	+/-	+/-	+/-	Linear
10	+/-	+/-	+/-	Linear	+/-	+/-	+/-	Linear	+/-	+/-	+/-	Linear
11	+/-	+/-	+/-	Linear	+/-	+/-	+/-	Linear	+	+/-	+/-	Linear
12	-	+/-	+	Leapfrogging/Nodal	-	+	+	Leapfrogging/Nodal	-	+/-	+/-	Leapfrogging/Nodal
13	-	+	+	Leapfrogging/Nodal	-	+	+	Leapfrogging/Nodal	-	+/-	+	Leapfrogging/Nodal
14	-	+	+	Leapfrogging/Nodal	-	+	+	Leapfrogging/Nodal	-	+	+	Leapfrogging/Nodal
15	-	+	+	Leapfrogging	-	+	+	Leapfrogging	--	+	+	Leapfrogging
16	-	++	++	Leapfrogging	-	++	++	Leapfrogging	--	++	++	Leapfrogging
17	--	++	++	Leapfrogging	--	++	++	Leapfrogging	--	++	++	Leapfrogging
18	--	++	++	Leapfrogging	--	++	++	Leapfrogging	--	++	++	Leapfrogging
19	--	++	++	Leapfrogging	--	++	++	Leapfrogging	--	++	++	Leapfrogging
20	--	++	++	Leapfrogging	--	++	++	Leapfrogging	--	++	++	Leapfrogging
21	--	++	++	Leapfrogging	--	++	++	Leapfrogging	--	++	++	Leapfrogging

“++” very high, “+”, “+/-” medium, “-” low, “-” very low.

Figure 6-17.

Identified patterns of urban expansion in Isfahan, 1990-2010.



6.5. Effects of urban expansion on urban spatial patterns

As stated earlier, UEII and UEDI are two spatial indexes to measure the urban expansion (growth ratio indexes). They are considered as independent variables to explore the relationship between urban expansion and spatial patterns. Moreover, the value of the spatial metrics is assumed as the dependent variables. GWR was adopted as an effective model to investigate the relationship between these two kinds of variables. The Adjusted R^2 and $\mathrm{AIC_t}$ values generated by GWR model for different periods are presented in Table 6-6.

Table 6-7.

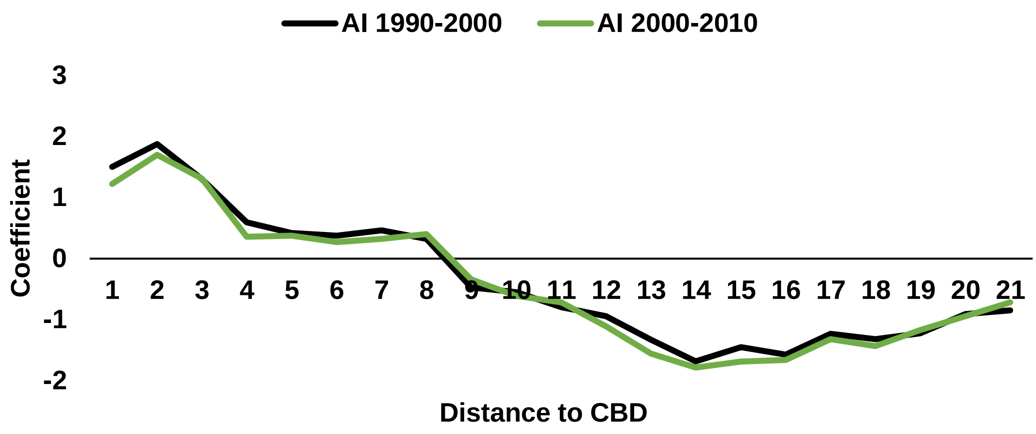
Results of GWR analysis, 1990-2010.

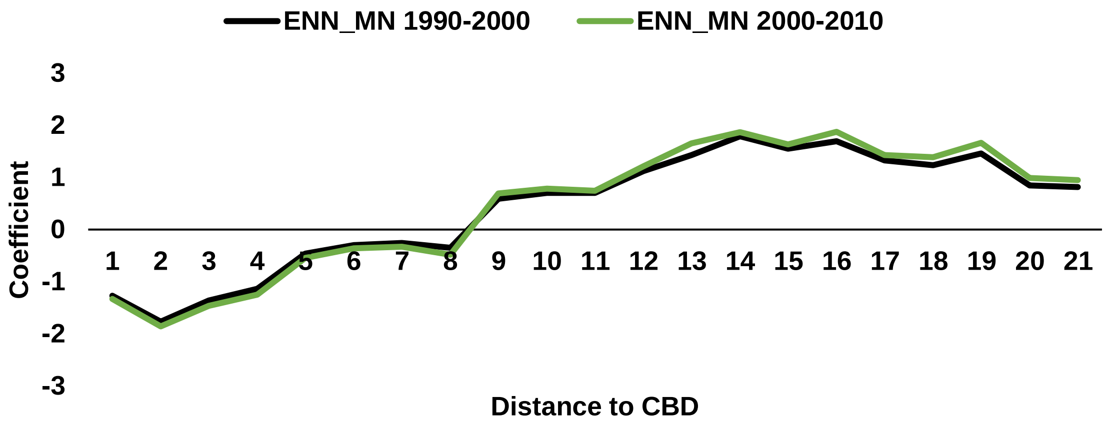
Period	Spatial metrics	Adjusted R^2		$\mathrm{AIC_t}$	
		UEII	UEDI	UEII	UEDI
1990-2000	AI	0.51	0.29	160.8	164.0
	GYRATE_MN	0.84	0.12	157.2	187.9
	ENN_MN	0.57	0.21	252.3	262.2
2000-2010	AI	0.54	0.27	147.3	152.3
	GYRATE_MN	0.72	0.14	168.8	187.2
	ENN_MN	0.60	0.17	249.4	256.8

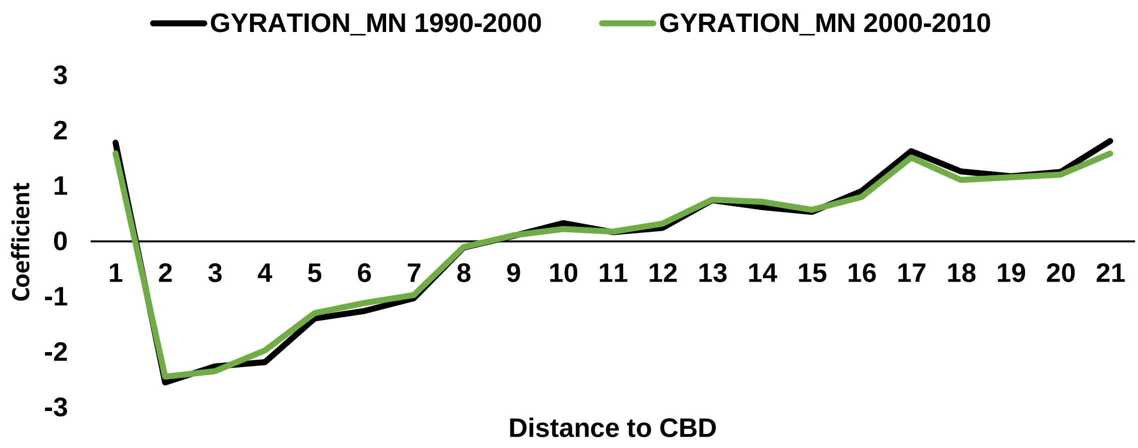
Overall, Table 6-7 shows higher R^2 and lower $\mathrm{AIC_t}$ values for UEII compared with UEDI. Comparison of the two independent variables indicates that the urban intensity index has a stronger correlation with the spatial patterns. In other words, the changes of spatial patterns are significantly associated with the intensity of urban expansion.

Figure 6-18.

Trend of the coefficients obtained from GWR model.







It can be clearly seen that the coefficient was varied noticeably across the buffer zones. The spatial change of coefficient expresses that the relationships between spatial metrics and the UEII values vary spatially across the concentric zones. As is observed in the following diagrams, the trend of coefficients for each spatial pattern had not considerable changes during two decades.

The first diagram shows the relationship between UEII and AI across the buffer zones over two decades. At the onset of trend, a significant positive correlation is identified at a distance of 8 km from CBD, indicating that the intensification of expansion could result in the increase in aggregation process. Temporally, the effects of urban expansion did not change considerably across the buffer zones. It confirmed the obtained results of the urban pattern. The resulted negative coefficients in the distance 8 km away from the city core implied that the higher value of UEII resulted in the decrease in the aggregation process. In other words, the rapid urban expansion caused a decrease in forming larger patch and increase in land fragmentation within the peripheral zones of Isfahan.

The second graph depicts the change of values in the relation between ENN_MN and UEII in concentric sectors. In general, the isolation index showed both the negative and positive values. From the city core up to zone 8 km a negative relationship was identified during the study period. It indicated that within a distance of 8 km from the city core the intensification of urban expansion resulted in the decrease in the isolation process. On the other hand, the urban expansion had a significant positive impact on the increase in ENN_MN, outwards the buffer zone 8. Comparing the trendline value of AI with that of ENN_MN indicated that they showed an opposite trend.

As shown in Figure 6-18, the effects of expansion on the variations of GYRATION_MN value fluctuated in different zones during the study period. The areas with more significant negative effects located at a distance of 6 km from the CBD. The positive relationship between the expansion intensity and the compaction index (Gyration index) showed the buffer zone 7 up to the peripheral zones the intensification of urban expansion resulted in the increase in Gyration index, therefore the compaction process propped within this region.

Generally speaking, the GWR analysis indicated that the spatial pattern of Isfahan city could be identified considerably by the expansion intensification. Using the

GWR model one of the objectives of this study, exploring the effects of urban expansion on the spatiotemporal patterns, was achieved.

6.6. Socioeconomic patterns

In this section, a set of quantitative analyses was prformed to characterize the socioeconomic-based pattern of urban expansion at the municipal level. To deal with the socioeconomic patterns, three dimensions (the function of density, the degree of clustering, the degree of distribution) were addressed to calculate the related indexes of the urban form (i.e. the Gini and Moran coefficients). Unlike the first dimension (i.e. density), two others have barely been explored.

As stated earlier, the classification of Landsat images and the extraction of the built-up area resulted in the built-up area matrix. The built-up area was used with the socioeconomic factors (population and employment) as the input data to describe different patterns of the city and to understand how they change over time. The municipal districts provided the spatial framework for measuring the population of the districts in the case study. The procedures described in chapter 4 provided a suitable method to calculate the total built-up area within the districts. For each unit, the population, employment, and built-up area were calculated for all three years. Measuring these three parameters, three preliminary key dimensions of the socioeconomic patterns were obtained. Table 6-8 provides the preliminary estimates of the population, employment and built-up areas in 1990, 2000, and 2010, as well as their annual rate of change for each district.

6.6.1. Density functions

Density is a basic dimension of the city form which has been used widely for the form analysis. The density measures which have been used in the urban literature to characterize urban form, are population, housing, and employment (Alberti et al., 2008). The general definition of population density is simply (Population/land area). This definition can be used for land areas of any size, from individual lots and residential blocks to entire regions. The Iranian census data center provides the necessary population data every 10 years. As the population plays two main roles in an economic system, one as supply (labor) and one as demand (consumer), the first step in examining socioeconomic development forms is the analysis of the pattern of the population density.

Average population density of built-up area

Table 6-8 represents information on the built-up areas of the municipal districts and their changes over time. It shows that from 2000 to 2010, district 6, increased the built-up area by 3,02 %, whereas its population decreased by -2.06 %. In contrast, zone 12 experienced a dramatic increase in the annual rate of population change, whoever the increase in annual built-up area changes was at a medium rate (1,83 %).

Table 6-8.

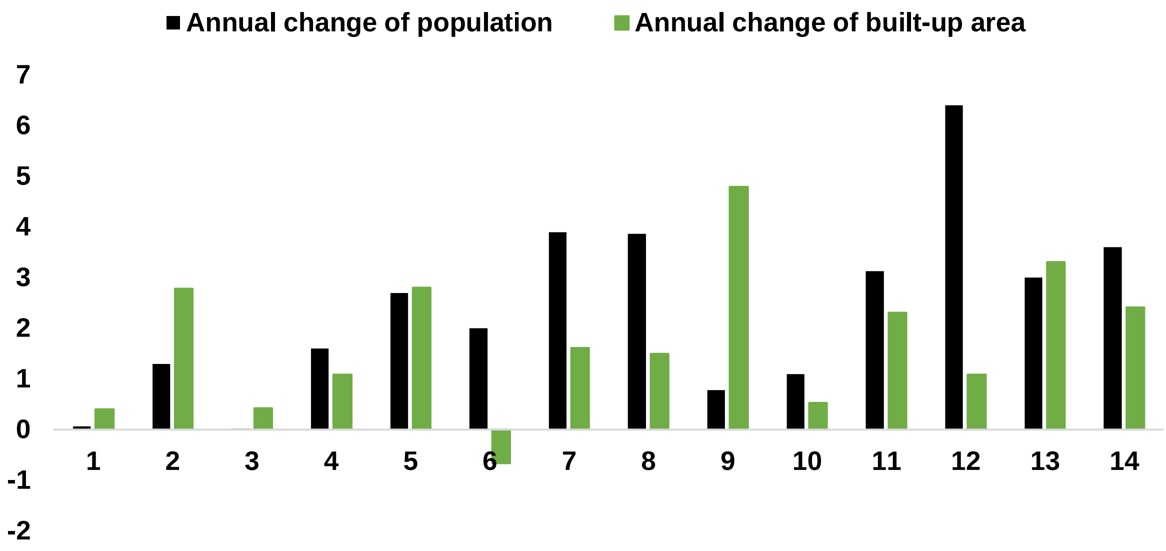
Annual changes of population and urban area in Isfahan.

	Population			Built-up area (km^2)		
	2000	2010	Annual change %	2000	2010	Annual change %
1	73655	74130	0,06	7.662109	7.718480	0.07
2	52036	59369	1,33	10.55718	11.14057	0.55
3	111655	111936	0,03	10.51617	10.61273	0.09
4	108859	128102	1,64	37.21566	45.66487	2.27
5	123691	163119	2,81	20.44603	23.12977	1.31
6	126514	102694	-2,06	19.94692	25.97211	3.02
7	106342	158600	4,08	22.63603	24.47759	0.81
8	162805	239834	3,95	18.30722	18.28793	-0.01
9	66293	71676	0,78	8.273085	8.313012	0.04
10	178638	198918	1,08	16.29575	16.74617	0.27
11	47001	64271	3,18	8.036012	8.044781	0.01
12	69123	131373	6,63	40.25035	47.64960	1.83
13	91900	123937	3,04	14.48281	15.25218	0.53
14	113565	163110	3,69	12.99384	13.44173	0.34
Total	1432077	1791069	2,26	247.6191	276.4515	0.07

Source: author's calculations.

Figure 6-19.

Annual change of population and built-up area across municipality districts.



To analyze the socioeconomic pattern of Isfahan city, in the next step, two important dimensions of density were calculated: the average population density of the built-up area and the average amount of built-up area taken up by each resident of the city (Table 6-9).

Table 6-9.

Average population density and average built-up area per person.

	Population			Built-up area			Av. Pop. density of built-up area			Average built-up area per person		
	1990	2000	2010	1990	2000	2010	1990	2000	2010	1990	2000	2010
1	81437	73655	74130	7.2527	7.6621	7.71848	11228	9612	9604	89.06	104.0	104.1
2	34502	52036	59369	6.3988	10.557	11.1406	5391	4928	5329	185.5	202.8	187.6
3	121164	111655	111936	10.392	10.516	10.6127	11658	10617	10547	85.7	94.2	94.8
4	77669	108859	128102	9.6498	37.215	45.6648	8048	2925	2805	124.2	341.9	356.5
5	133564	123691	163119	17.293	20.446	23.1297	7723	6049	7052	129.5	165.3	141.8
6	118945	126514	102694	11.011	19.946	25.9721	10802	6342	3954	92.6	157.7	252.9
7	121991	106342	158600	23.509	22.636	24.4776	5188	4697	6479	192.7	212.9	154.3
8	118174	162805	239834	33.606	18.307	18.2879	3516	8892	13114	284.3	112.4	76.2
9	61227	66293	71676	2.9421	8.2730	8.31301	20810	8013	8622	48.0	124.8	115.9
10	132575	178638	198918	12.526	16.295	16.7462	10583	10962	11878	94.5	91.2	84.18
11	34602	47001	64271	3.969	8.0360	8.04478	8718	5848	7989	114.7	170.9	125.1
12	-	69123	131373	-	40.250	47.6496	-	1717	2757	-	582.3	362.7
13	-	91900	123937	-	14.483	15.2521	-	6345	8125	-	157.6	123.1
14	-	113565	163110	-	12.993	13.4417	-	8739	12134	-	114.4	82.4

Figure 6-20.

Illustration of average population density of built-up area 1990-2010.

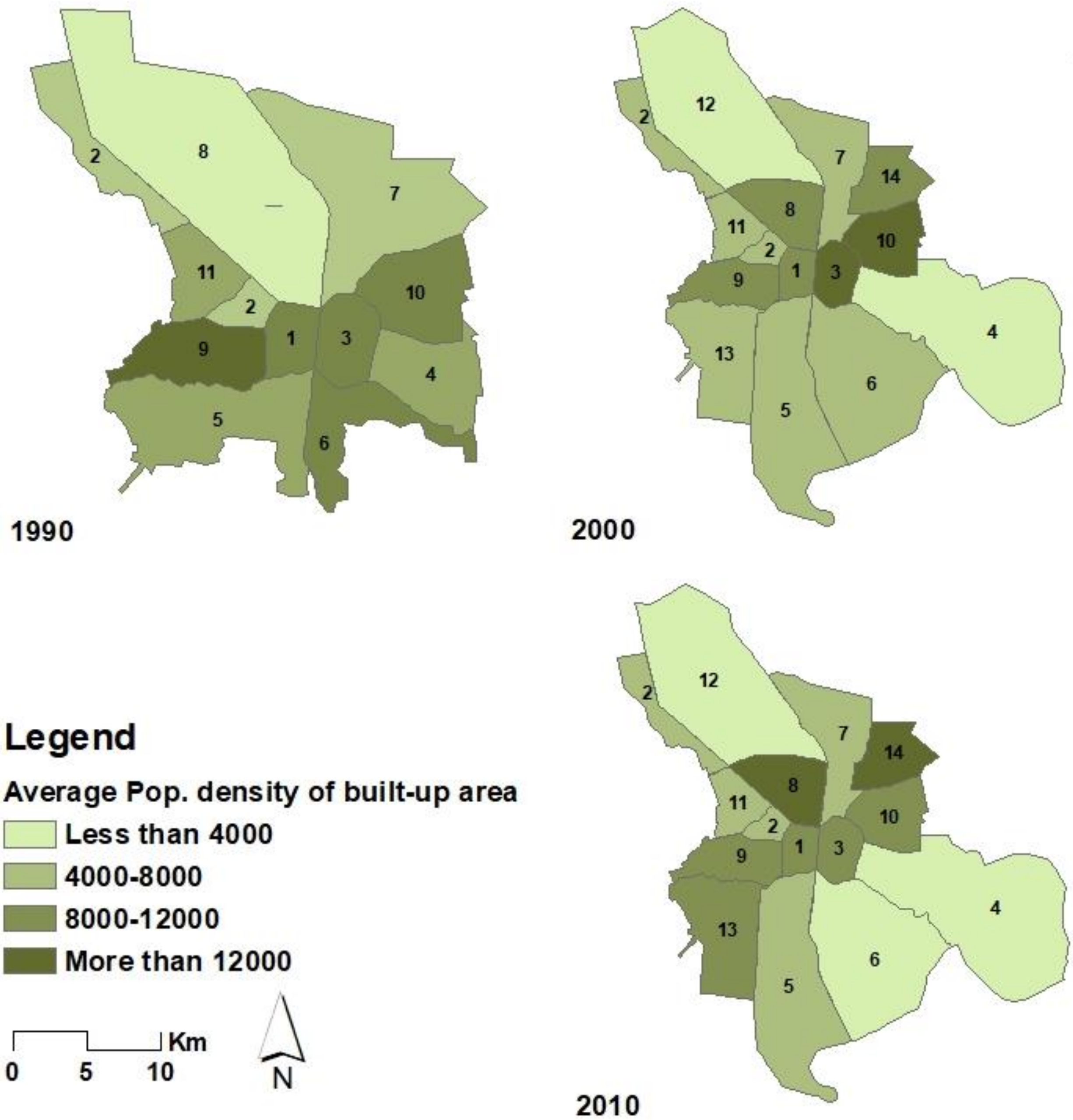
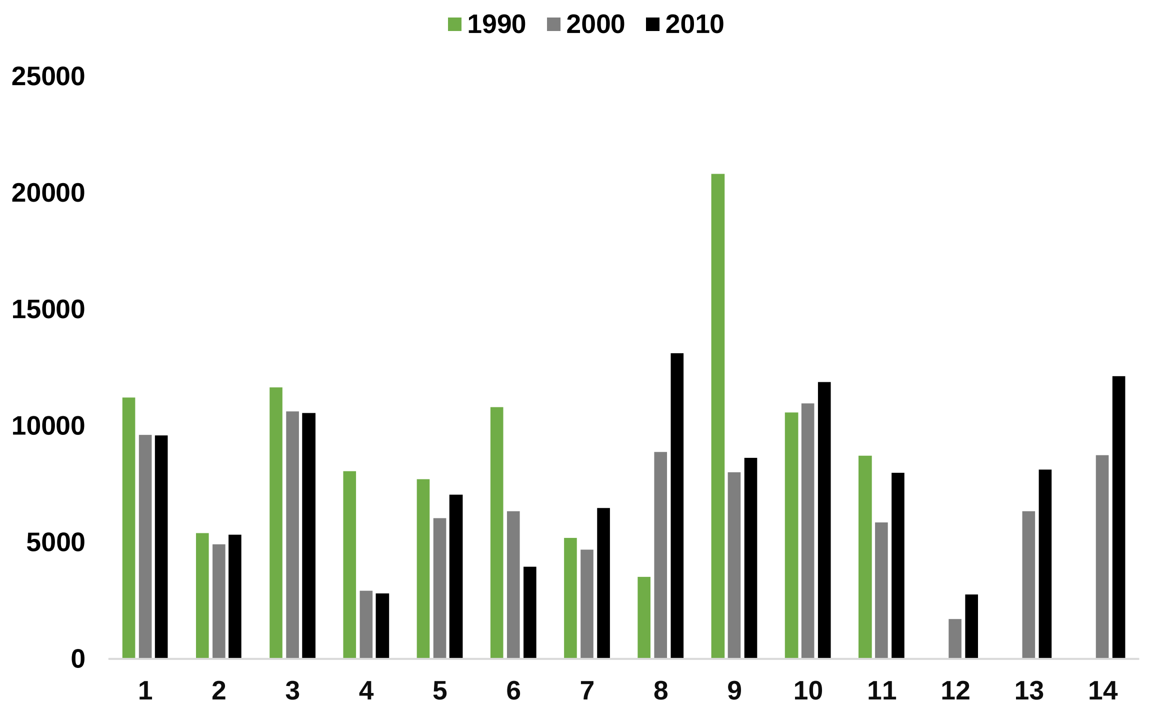


Figure 6-20 shows changes in the amount and class of the average population density of built-up area across the municipal districts in Isfahan city from 1990 to 2010. Overall, the average population density declined within peripheral zones over the time period, particularly across the southern and southeastern districts.

In 1990, the highest amount of the average population density belonged to district 9. This was far higher than district 8, which had an average population density less than 4000 persons per km^2. In 2000, after creating three new districts (12, 13, and 14), district 8, was characterized as a medium class and the northern district, district 12, showed the minimum value of the average population density. On average, over 10 years, the majority of districts reached the medium class of population density. Apart from the rise in districts 8 and 14 from 2000 to 2010, other districts experienced either the same or lower class of average population density. In sharp contrast to 2000, the peripheral districts had decrease in the average population density. The biggest rise was seen in district 8, as its category increased from very low to high throughout 20 years.

Figure 6-21.

Change of average density of the built-up area.



On average, the urban density decreased from 1990 to 2000 in the city, however, it experienced an uptrand in the next year, 2010. These results indicated that the expansion of the administrative boundary in 2000, resulted in a significant decrease of the overall density. However, during the next period, following the population growth in the city in a fixed administrative boundary, the density increased marginally.

Density gradient

The monocentric density function was fitted using both linear and non-linear least square models. The best model was chosen as one with the highest overall R^2 value. It can be seen (from the estimated models in Table 6-10) that the negative exponential model provided the best fit in all 3 years compared to others (Figure 6-22).

Table 6-10.

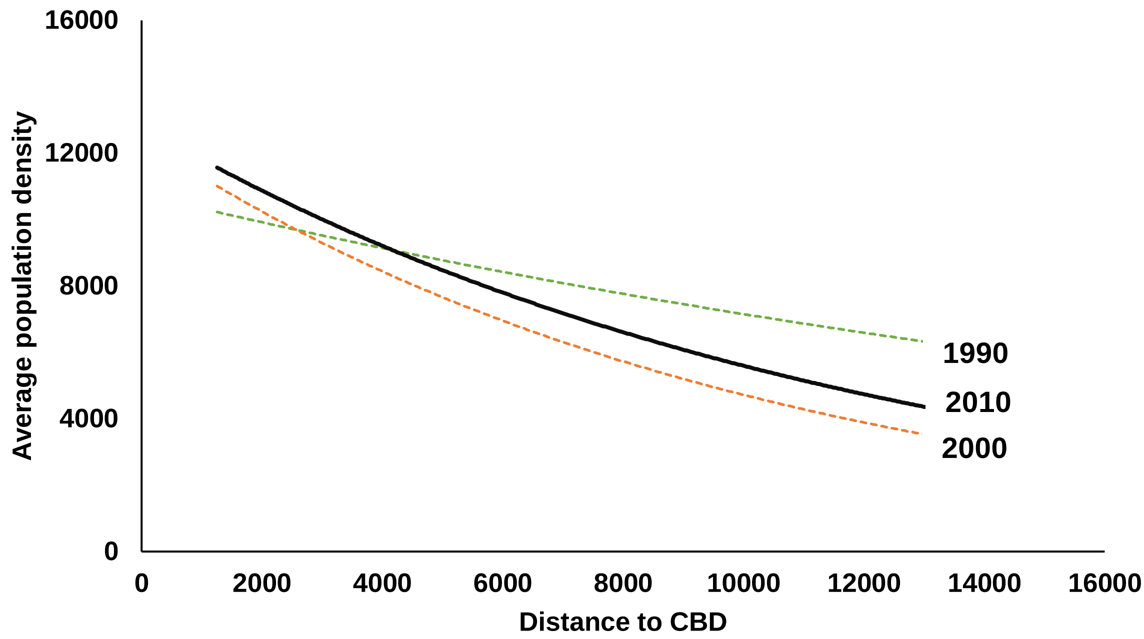
Results of regression models to test density gradient.

Model	Year	Equation	R^2
Linear	1990	$\mathrm{Y} = -0.5993\mathrm{x} + 12762$	0.2272
	2000	$\mathrm{Y} = -0.5267\mathrm{x} + 10601$	0.5479
	2010	$\mathrm{Y} = -0.513\mathrm{x} + 11506$	0.3472
Exponential	1990	$\mathrm{Y} = 13270\mathrm{e}^{-8\mathrm{E}-05\mathrm{x}}$	0.361
	2000	$\mathrm{Y} = 12432\mathrm{e}^{-\mathrm{E}-04\mathrm{x}}$	0.5453
	2010	$\mathrm{Y} = 12835\mathrm{e}^{-8\mathrm{E}-05\mathrm{x}}$	0.4009
Power	1990	$\mathrm{Y} = 183209\mathrm{x}^{-0.364}$	0,2804
	2000	$\mathrm{Y} = 332508\mathrm{x}^{-0,458}$	0.4024
	2010	$\mathrm{Y} = 182759\mathrm{x}^{-0.374}$	0.2687
Logarithmic	1990	$\mathrm{Y} = -2679\ln(\mathrm{x}) + 31948$	0.1656
	2000	$\mathrm{Y} = -2671\ln(\mathrm{x}) + 30034$	0.4644
	2010	$\mathrm{Y} = -2324\ln(\mathrm{x}) + 28008$	0.2348

The density gradient values presented a downtrend over 20 years (refers to Table 6-10). It is inferred that the city was exhibiting a tendency towards —spreading out or dispersion. However, in 2000, it had an increase and confirmed that in this period the city had the tendency toward compaction in some districts. The city center densities declined during the last few decades hinting that people were moving out from central areas to peripheral ones.

Figure 6-22.

Density gradient model in Isfahan city, 1990-2010.



6.6.2. Gini coefficient as a measure of distribution pattern

In this part of the study, the second and third dimensions of socioeconomic pattern are addressed.

The Gini coefficient was used as a measure of inequality of population distribution or inequality of employment distribution in Isfahan city. The population and employment data were obtained from Iranian Census Center (2006). Higher Gini coefficients (i.e. close to 1) refer to the fact that population or employment density is extremely high in fewer sub-areas. A Gini coefficient close to zero implies that population or employment is evenly distributed in an area (Table 6-11).

Table 6-11.

Gini index of population and job, Isfahan city (1990-2010).

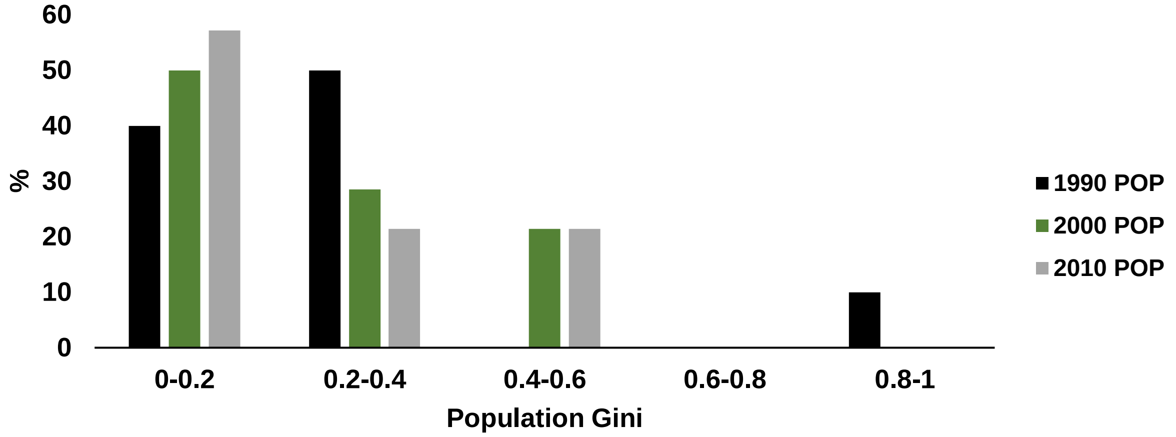
	1990		2000		2010	
	Pop.	Job	Pop.	Job	Pop.	Job
Gini coefficient	0.260	0.277	0.328	0.351	0.329	0.338

In 1990, the Gini index of the distribution of population in Isfahan was estimated at 0.26, showing a low degree of land concentration. The Gini coefficient of population reached the value of 0.328 in 2005 and 0.329 in 2010. In addition, the Gini coefficient of employment, which was 0.27 in 1990 in Isfahan, receded the values of 0.35 in 2000 and 0.338 in 2010. In general, over 20 years, population and activity inequality, as measured by the Gini coefficient, improved from 0.26 to 0.32 and 0.27 to 0.33, respectively.

Figure 6-23 reflects the value of Gini coefficient in Isfahan city. In 1990, 10% of the municipal districts in Isfahan experienced a high degree of the concentration of population and employment (0.8-1), while, in the following years, no district presented a perfect inequality.

Figure 6-23.

Gini index of job and population in Isfahan city 1990 – 2010.



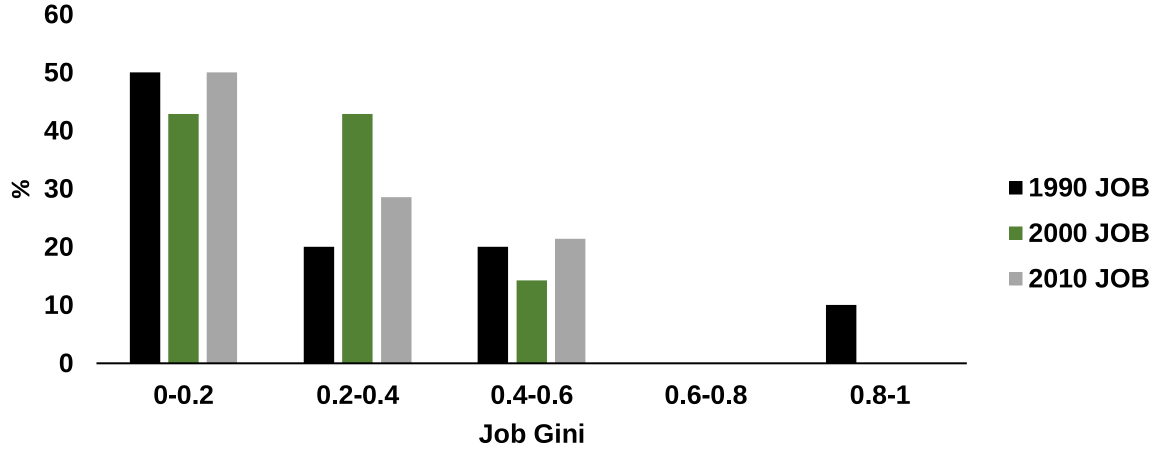


Figure 6-24 presents the value of Gini coefficient among the municipal districts of Isfahan from 1990 to 2010. The Gini index, which charts the distribution of population and job in District 8, was estimated at 0.89 and 0.8 in 1990, showing a high degree of land concentration. This district was the most concentrated region among other districts of Isfahan, from the socioeconomic point of view. Following the separation of district 12, the Gini coefficient of population decreased sharply by about 54%. Similarly, the value of the employment declined from 0.81% to 0.4% over 10 years.

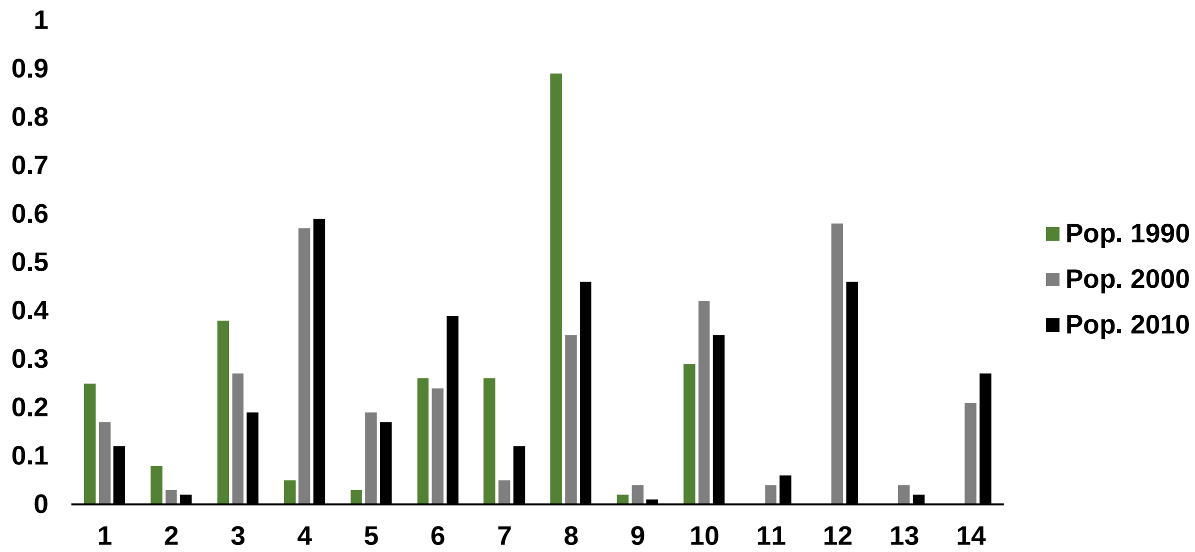
In Districts 4 and 12 (peripheral districts), the Gini index of job inequality stood at a high point of 0.6% and 0.54% in 2000. From 2000 to 2010, the inequality of employment, decreased by 0.1%. Although, the inequality of employment decreased in the above-mentioned districts, the activity distribution remained high.

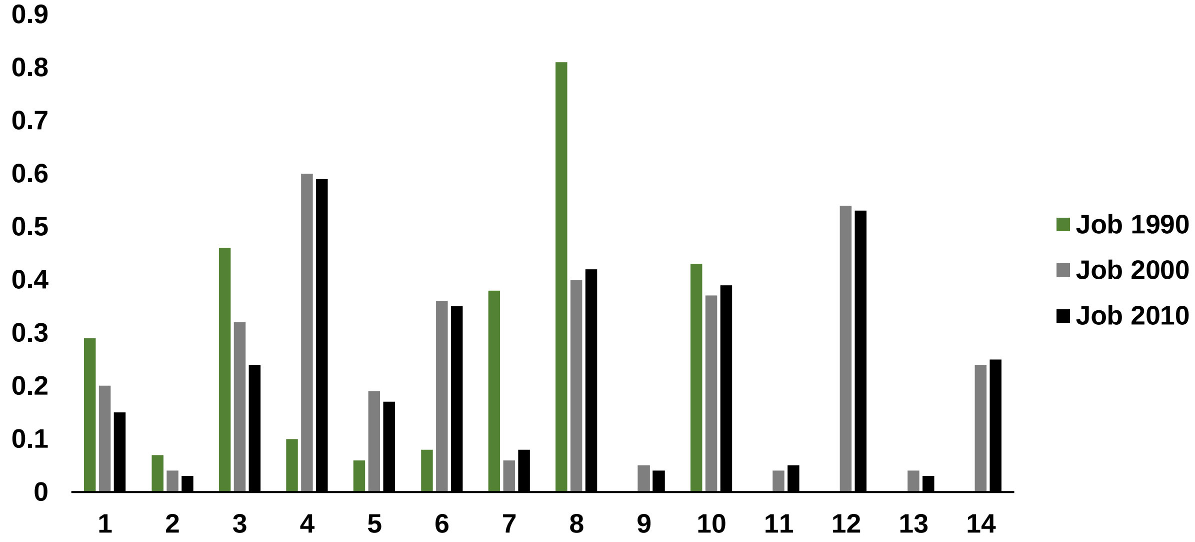
The Gini index presented a decreasing trend within two central districts (1 and 3) over 20 years. In District 1, the inequality of the population went from 0.25% to 0.15%. similarly, the Gini index dropped from 0.38% to 0.19% between 1990 and 2010.

In general, the peripheral districts had high coefficient values and the central districts showed the lower amount of index. Although, the Gini coefficient decreased in few districts, great inequality was identified, especially with respect to districts located in peripheral areas. The rise of the Gini index in peripheral districts indicated that not everybody had equal access to land.

Figure 6-24.

Gini index of job and population across the municipality districts of Isfahan.





6.6.3. Moran coefficient as the measure of clustering

In this part, the Moran coefficient investigated the degree of clustering in 14 municipal districts of Isfahan city. The Moran coefficient was calculated for both population and employment variables. To measure the Moran coefficient, an inverse distance-based weighting was applied. This method works based on the hypothesis that nearby neighboring features may have a larger influence on the computations for a target feature than features that are far away. To calculate the distances from each feature to neighboring features, distances were calculated by applying Euclidean distance method. This method is the straight-line distance between two points.

Over 20 years, the value of the Moran coefficient of the population changed from 0,23 in 1990 to 0,12 in 2010 (Table 6-12). In other words, the city had a highly compact pattern of the population variable in 1990, which varied to the compact pattern in 2000 and approached the sprawling form in 2010. In other words, during the study period, the population-based form of the city had the tendency towards the sprawl.

The average employment Moran coefficient was 0,2 in 1990. It decreased to 0,18 and 0,14 in 2000 and 2010, respectively. As a whole, for 20 years, the degree of clustering of employment changed from highly compact in 1990 to compact in 2000 and 2010.

Table 6-12.

Moran index of job and population in Isfahan city 1990-2010.

Years	1990		2000		2010	
Factor	Population	Job	Population	Job	Population	Job
Moran	0,232	0,200	0,193	0,188	0,119	0,142

6.6.4. Effects of urban expansion on socioeconomic patterns

The main objective of this part is to examine the effects of urban expansion on the socioeconomic patterns. To achieve the aim, the relationship between built-up area (as the main indicator of urban expansion) and three socioeconomic indicators were examined. According to Table 6-13, an increase in the urban area as a result of urban expansion, all else being equal, will cause a decrease in density. The decline in urban density may lead to the less dense transit-oriented development. Thus, low-density business sub-areas cannot cluster spatially to a certain degree due to agglomeration effects. The following addresses these relationships based on empirical correlation analysis.

First, correlation analysis shows that the more sprawled a city area is (the increase of urban area), the lower are the density and degree of clustering of high job density sub-areas. Table 6-13 shows that built-up area has a statistically negative relationship with density—the Pearson correlation coefficients of built-up area with population and employment density are -0.048 and -0.442, respectively, and the job-based Moran coefficient (the Pearson correlation coefficient is -0.827).

Table 6-13 also shows that sprawl is positively associated with the job-based Gini coefficient (the Pearson correlation coefficient is +0.915). The above findings together may explain why the urban areas tend to have relatively low concentration of employment in certain sub-areas; the Pearson correlation between population density and the employment-based Gini coefficient is -0.891.

Secondly, the higher density of urban areas is moderately associated with a higher degree of clustering of high-density sub-areas; the Pearson correlation coefficients of population and employment densities with the employment-based Moran coefficients are +0.520 and +0.392 respectively. Finally, the relationship between the concentration of population or employment in some sub-areas and the degree of clustering in high-density sub-areas is either moderately negative or statistically insignificant, as reflected by the correlation between the Gini and Moran coefficients.

Table 6-13.

Correlation between urban expansion and socioeconomic pattern.

		Built-up area	Density		Gini		Moran	
			Pop.	Job	Pop.	Job	Pop.	Job
Built-up area								
Density	Pop.	-0.048						
	Job	-0.442	+0.874					
Gini	Pop.	+0.972	-0.280	-0.220				
	Job	+0.915	-0.891	-0.044	+0.984			
Moran	Pop.	-0.899	+0.392	+0.789	-0.772	-0.648		
	Job	-0.827	+0.520	+0.869	-0.673	-0.532	+0.989	

Chapter VII

7. Research conclusion

The theoretical background provided an introductory framework of reference to the urban expansion and presented a brief overview of the main urban patterns related to urban development. Furthermore, the design and performance of the study was clearly described in chapter 3. In accordance with the research objectives, chapter 4 provided a methodological framework that integrates qualitative and quantitative methodologies. Moreover, the study area (Isfahan city) was introduced and the spatial data sets related to the urban expansion listed in chapter 5. Hence, the sixth section presented and analyzed the research results. Finally, the following chapter aims at providing answers to the research questions. In addition, the major findings are concluded and presented in this part. Moreover, based on the analysis of the results, recommendations for improvement are made.

7.1. Research questions

Which metrics should be applied to quantify amount, differentiation, and intensity of urban expansion?

To detect the acceleration of the expansion of Isfahan city, three spatial metrics were adopted. The first one, average annual urban expansion rate (AUER), quantified the mean annual rate of urban expansion in the period under review. The result estimated the rate at which the amount of built-up land of a spatial unit was differing. Furthermore, urban expansion intensity index (UEII) was computed to quantify the average annual proportion of newly increased built-up land of a spatial unit, standardized by the total area of that spatial unit. The intensity index was adopted to characterize the degree of discernment of urban expansion in different directions and indicate the growth of the built-up land of a spatial unit as a percentage of the total area of land during the study period. The third metric, urban expansion differentiation index (UEDI), was adopted to detect the ratio of the urban expansion rate of a spatial unit to the urban expansion rate of the study area. Unlike UEII, UEDI made it possible to quantify the urban land expansion inequality between different spatial units. With the aid of this metric, the spatial differentiation and the hotspots of urban expansion were identified.

How to develop a new technique to extract urban built-up land features from Landsat Thematic Mapper (TM)?

Several scholars applied the information obtained from remote sensing to identify built-up land from non-built-up area. Traditional multispectral classification has been the most favored method to identify the urban areas. However, this may not produce satisfactory results due to the heterogeneous nature of built-up land. Thus, many studies have not only used a single classification method to extract the built-up land, but also combined different methods to improve the extraction. In this research, a new technique was proposed as a tool to classify the land cover and extract information. The extraction was mainly based on a new image that was derived from three thematic indices, soil adjusted vegetation index (SAVI), urban index (UI), and modified normalized difference water index (MNDWI). Consequently, seven bands of the original Landsat images were reduced into three thematic-oriented bands which were derived from above indices. Accordingly, the three new bands were combined to compose a new image. This considerably reduced data correlation and redundancy between original multispectral bands, and thus significantly avoided the spectral confusion of the land cover classes. As a result, the obtained spectral signatures for the desired classes are more noticeable in the new composite image than in the original seven-band image, as the spectral clusters of the classes are well separated. Through a supervised classification on the new image, the urban built-up lands were finally extracted. Therefore, the technique is effective and reliable. Besides, the application of SAVI, MNDWI, and UI instead of NDVI, NDWI, and NDBI also contributed to the improvement, because these indices could significantly increase the spectral contrast between different land cover classes.

Which spatial metrics should be adopted to analyze the process and pattern of urban expansion?

The study of the expansion characteristics remains a major concern in many countries. Over the last 10 years, the landscape ecology has been increasingly used to study the spatial characteristics of urban processes, namely the spatial characteristics of urban patches (including their size, shape, and spatial distribution). Many spatial landscape properties can be easily quantified by using one set of metrics.

There is a large body of literature that highlights the importance of spatial metrics in the study of urban landscapes. Most of these studies have concentrated on the cities in the USA. Thus, there is clearly a need to explore the application of spatial metrics to cities in developing countries. This is particularly true for Iranian cities because of their unique morphological characteristics and because of the changes that they have experienced in the last years. For this purpose, this study studied three dimensions of spatial processes in Isfahan. Each dimension reflects the evolution of three selected spatial metrics. These metrics allowed us to determine the spatial characteristics of the urban expansion. It was rather difficult to select a reduced set of metrics since there was a broad range of metrics to choose from. In fact, the selection of metrics was done based on the research objectives. According to the research aims, the metrics were computed at the class level. This research applied three main spatial metrics (aggregation index, gyration index, euclidean index) to capture three growth processes (aggregation, compaction, and isolation), as well as four growth patterns (aggregated pattern, leapfrogging pattern, linear pattern, and nodal pattern).

The research results demonstrated the usefulness of the selected spatial metrics for the quantification and interpretation of the spatial characteristics and patterns in urban environments. Overall, three selected processes were quantified by spatial metrics, which allowed us to measure changes in the urban patterns. Moreover, this quantification provided us with a simple way of identifying the region with a greater urban dispersion or fragmentation in contrast to those with a greater compaction and stability in growth patterns. Furthermore, they can also be used to evaluate the spatial consequences of urban planning policies.

Which quantitative variables can be adopted to quantify the urban socioeconomic patterns?

Reviewing the literature reveals that the quantitative variables to distinguish between the socioeconomic forms and urban expansion, are still lacking. In order to characterize the socioeconomic form of Isfahan city and distinguish the compactness from sprawl pattern three dimensions were defined. In other words, the socioeconomic form was analyzed based on three clearly distinguishable elements: density, degree of equal distribution and degree of the clustering, represented by the population density, the Gini index, and the Moran coefficient, respectively. The Moran coefficient is capable of distinguishing compactness from sprawl. For overall socio-economic form, the more compact the urban area, the higher is the Moran coefficient. The local sprawl, comprising leapfrog and strip developments, will lower the value of the Moran coefficients. Based on the results of the study, the population and employment have been concentrated in some districts in the city (represented by the Gini coefficient).

How to link the urban expansion with the spatial and socioeconomic patterns?

To explore the relationships between urban expansion and spatial patterns, the GWR model was applied in this study. This model provides a local model of the variable or process by fitting a regression equation to every feature in the dataset. Therefore, it seems a suitable tool to provide detailed site information on the different roles of expansion in different parts of the study area, rather than generating an average coefficient for the entire area. To find out about the relationship between urban expansion and spatial patterns, two main growth ratio indexes (UEII and UEDI) were used. Overall, the results obtained showed a higher R^2 of UEII compared with UEDI. The comparison of these variables indicated that the urban intensity index had a stronger correlation with the spatial patterns. In other words, the changes of spatial patterns were significantly associated with the intensity of urban expansion. It could be concluded that the value of coefficient varied noticeably in different parts of the study area. In general, the central zones reflected the positive relation between UEII and AI, while UEII and ENN_MN showed the negative value of the index. In other words, in central zones, the higher intensity of expansion resulted in an increase in aggregation and led to a decrease in isolation process. It was also noted that in the peripheral zones, an increase in intensity caused an increase in isolation and a decrease in aggregation. The analysis of UEII and Gyration index also shows that the relation between these two variables is much stronger than two other metrics. In other words, the expansion intensity had affected spatial patterns in Isfahan city over 20 years, particularly the patterns of compaction.

The second analysis explored the effects of the urban expansion on the socioeconomic characteristics of Isfahan city using Pearson's correlation coefficient. The correlation analysis showed that the more scattered the city area, the lower the density and degree of clustering of high job or population density districts were. Hence, the dense built-up areas in Isfahan were moderately associated with a higher degree of clustering of high-density districts over the study period. Moreover, the relationship between the concentration of population or employment in some districts and the degree of clustering in high-density districts was either moderately negative or statistically insignificant, as reflected by the correlation between the Gini and Moran coefficients.

7.2. Research objectives

Sub-objective 1- To identify and quantify the pace, amount, differentiation, and intensity of urban expansion (as the first indicator) in Isfahan city using growth ratio analysis and GIS analytical techniques.

The multitemporal analysis of satellite images Landsat-TM between years 1990-2010 and the extraction of the built-up land resulted in a highly simplified and abstract representation of the study area. The analysis showed that an upward trend experienced between 1990 and 2010 continued during the analysis period. The city experienced an increase in the size of its built-up land from 164.39 km^2 in 1990 to 277.04 km^2 in 2010. It was found that a larger share (i.e. 83 %) of the additional built-up land accumulated over the 20-year period occurred in the first 10 years at an annual rate of 4.2 % between 1990 and 2000. In other words, the quantum of urban expansion that occurred over the first period was about 2.9 times that of the second 10 years. The expansion intensity index which was found to be relatively higher in the first 10 years decreased in the last 10 years.

The high value of AUER in 1990 coincided very well with the period of unprecedented urbanization in Iran after the Iraq-Iran war. When the war ended in 1988, several cities of Iran had been destroyed and unplanned urban growth had been experienced in the urbanization process due to the mass migration of people from the war-affected areas to other settlements. With rapid rise in the population came the increased demand for land for various activities and the concomitant expansion of existing built-up areas into greenfield areas. The war with Iraq reflected on the limitations of budget resources and destroyed the control of urban growth in Iran. Consequently, the number of cities and the rate of population growth increased considerably and subsequently the government applied reconstruction policies when the war ended in 1988.

The analysis was further broken down into specific directional and concentric zones. It was found that the pace and intensity of expansion were much more nuanced among spatial units located in buffer zones.

The central zones, comprising zones 1 and 3, had low intensity in the first study period. Indeed, the intensification of expansion decreased during the next period. This result agreed with the decreasing population trend in the central zones of the city from 1990 to 2000. The proportion of the population lived in two central districts of the city decreased from 12.1 to 7.8 over 10 years. This part of the city, which located partly in two central districts of Isfahan, had a population movement to the northern districts.

The highest value of UEII was recorded in the northern and northwestern directions over 20 years. Moreover, according to the census data of 1996, the population growth in the northern regions have been phenomenal from 1990 to 2010. However, the population growth rate had a decreasing trend over the last 10 years. The high intensification of the built-up area in the aforementioned directions could be explained by the fact that the lands located in the northern parts and also western parts of the city have undergone the most changes among other agricultural lands of Isfahan.

Indeed, the UEDI analysis revealed that over a period of 20 years, the hotspots of the expansion located in agricultural areas, often in peripheral regions. The UEDI analysis indicated that although the quantum of the built-up land change was significantly high in few zones, they were not necessarily the hotspots of urban expansion. Over 20 years, as the land price grew, the amount of vacant land within the city diminished. Therefore, the land in peri urban area became more attractive for spatial development. However, the core areas attracted the population through the redevelopment of existing land with higher densities with little lateral expansion. In general, the obtained results from these metrics reinforced our finding that Isfahan city has undergone peri-expansion from 1990 to 2010.

Sub-objective 2- To provide and compare the land cover information (as the second indicator) for the investigation of city area using remote sensing images and the application of quantitative measures.

Analyzing the urban expansion of the city and the resultant urban patterns always need accurate data on land cover change and the built-up area characteristics such as the size, shape, and spatial context. Thus, a technique is required to quickly reveal the data. This study proposed three spectral Indexes to transform images in extracting urban areas of Isfahan. The index-derived maps were further classified using the consistent method of classification. In other words, urban lands were mapped using a combination of the spectral and spatial information.

Based on the study of data obtained, Isfahan experienced a fast and unplanned development from 1990 to 2010. The area grew in a chaotic way and without proper infrastructure. The urban expansion was promoted without taking into consideration the uncontrolled conversion of land cover. The analysis of the land cover change indicated that the vegetation area was the less stable category over the study period.

In 1990, the majority of the land in Isfahan was devoted to vegetation (49.3 %), whereas the built-up areas accounted for 24.2 %. In 2010, the vegetation class covered 33.6 % of the study area, while the built-up areas accounted for 45.7 %. The change detection proved to be a useful tool to describe quantitatively land cover change patterns.

Sub-objective 3- To explore the spatial processes and patterns of urban expansion (as the third indicator) using the spatial metrics and GIS analytical techniques.

The analysis of the spatial extent and the rate of urban expansion and identification of the growth directions alone do not provide sufficient insight into the pattern of urban development. To bridge this gap, spatial metrics were used in this study. Three spatial metrics (aggregation index, mean euclidean nearest neighbor, and mean radius of gyration) were used to evaluate the urban expansion pattern and process at the class level. These metrics were selected based on the literature review to measure three main aspects of the landscape such as aggregation, compaction, and isolation.

The study of the urban pattern was conducted at two spatial scales (directional and concentric zones) from 1990 to 2010. The results revealed the processes and patterns of urban expansion over the entire study area. They indicated that the urban expansion substantially changed the urban landscape of the city with the significant land conversion and formation of new patches, as well as thereby increased fragmentation in the suburban areas. Based on the aggregation index, the process of forming the larger patches increased from 1990 to 2000. However, this result alone could not reveal the dominant pattern of the city. The increasing trend, as witnessed by gyration index from 1990 to 2010, showed the decrease in compaction process, particularly, in the vicinity of the urban fringe. In other words, the city experienced the process of elongation over 20 years. Moreover, the increasing trend was observed with respect to Euclidean nearest neighbor index throughout the study period. This upward trend revealed that the city experienced the isolation process. In general, the results at the macro level indicated that the city center and the central region have been relatively undergoing infill expansion. Nevertheless, to understand the spatial patterns of the city, the analysis at the city level was incomplete. In other words, the increasing trend observed by aggregation could not explain the leapfrogging pattern in suburban areas. Therefore, the analysis was narrowed down to 21 buffer zones to better localize changes in land occupation patterns. This method made it possible to discover and locate pattern changes in the vicinity of large highway networks or on the urban fringe. Such analyses would also permit more detailed analyses which could better identify small-scale dispersion processes, which were not detected by the adopted city level.

In the case of Isfahan, the increasing trend of AI and the decreasing trend of ENN_MN resulted in a combined residential pattern that aggregated the patches in the central zones. On the other side, the results obtained in the suburban areas showed decreasing aggregation, increasing compaction, as well as increasing isolation process in this period. These areas reflected the great degree of dispersion and leapfrogging pattern. This higher dispersion was interpreted regarding many environmental issues. For instance, the appearance of the new urban area within the rural landscape resulted in an increase in the interface between those land uses. Furthermore, two other dominant patterns were identified within the same distance from the city core: the linear pattern and the nodal pattern. The former pattern was identified along with highways, and the latter was seen around the main industrial zones in Isfahan. The results indicated that the location of the obtained patterns remained the same over 20 years, while the pattern changed in different directions.

Sub-objective 4- To characterize the quantitatively socioeconomic form of Isfahan city (as the fourth indicator) using the spatial and socioeconomic data.

The results presented that Isfahan had a high value of population-based Moran coefficient (0.23) in 1990. This high coefficient seems to be a reflection of its monocentric form with very high population density—greater than 12000 persons per square kilometer—in the core area. The job-based Moran coefficient (0.20) in 1990 also indicates that the city had a monocentric form with the high employment density. There were some districts with low-to-intermediate density (1000–2000 jobs per square kilometer) in places located discontinuously from the center; this form of development caused a decrease in the Moran coefficient in 2000. In 2000, the obtained lower employment-based Moran coefficient (0.188) showed that the city had a high-density center with the scattered development in peripheral districts. This socioeconomic form was less compact than that of 1990. The final year with a lower employment-based Moran coefficient equal to (0.14), indicated that the clustered districts may be relatively low compared with the previous years.

The quantitative socioeconomic variables capture many advantages of quantitative approaches, e.g. the ability to aggregate numerical information and providing a summary spatial description of urban areas without recourse to maps and the capability of capturing minor differences between urban forms.

Sub-objective 5- To examine the relationships between the above-mentioned indicators to determine the effects of urban expansion.

The application of GWR model to understand the relation between UEII and AI across the buffer zones showed that they had the significant positive correlation in central zones. It indicated that the intensification of expansion could result in the increase in aggregation process. The negative coefficients resulted in suburban areas implied that the higher value of UEII resulted in the decrease in the aggregation process. In other words, the urban expansion had different effects in different units. Moreover, the study of ENN_MN and UEII in concentric sectors showed a significant negative relationship between the urban intensity and isolation during the study period. It indicated that within the central zones, the intensification of urban expansion resulted in the decrease of isolation process. On the other hand, the urban expansion had a significant positive impact on the increase of ENN_MN in suburban areas. The obtained results of Gyration index reflected that in the peripheral zones, the intensification of urban expansion resulted in the increase of Gyration index, therefore the compaction process propped within this region.

Overall, the GWR analysis indicated that the spatial pattern of Isfahan city could be identified considerably by the expansion intensification. Using the GWR model, one of the objectives of this study, exploring the effects of urban expansion on the spatiotemporal patterns, was achieved.

The second analysis related to the exploration of effects of expansion on the socioeconomic patterns. To achieve the aim, the relationship between the built-up area (as the main indicator of urban expansion) and three socioeconomic indicators was examined. The results showed that the decline of urban density led to the less dense transit-oriented development. Thus, low-density business sub-areas could not cluster spatially to a certain degree due to agglomeration effects. In other words, the leapfrogging area located in the suburban regions of Isfahan, with the low density, had the low degree of clustering of high job density sub-areas. In contrast, sprawl was positively associated with the job-based Gini coefficient.

7.3. Recommendations

Analyzing the attributes of urban expansion in Isfahan provides a good example of the large sized Iranian cities. There is evidence from the study that as a result of urban expansion, urban fragmentation has increased in the suburban areas of Isfahan. This urban form may cause many ecological and environmental problems than a more compact pattern. Considering the severe loss of agricultural land due to the dispersed pattern in suburban areas, there is a pressing need for enhancing the effectiveness of urban land use planning and implementing land-use planning policies. Based on the major findings of this study, the following recommendations are given:

1- Compact city policies: This concept developed to implement sustainable development within the urban area and to overcome the negative social, economic and environmental effects of urban sprawl. Due to the intensification of the built-up area within the city, many difficulties related to urban sprawl may be overcome. Compact city policies have often been designed basically to diminish the use of private cars and to reduce the loss of open countryside. Although, more advantages can be obtained from intensifying urban areas. In other words, higher density results in maintaining the local facilities and services, and therefore accessibility to goods and services is more properly distributed. The rejuvenation of local economies, especially in downtown areas neglected by urban decentralization and sprawl, can possibly also be achieved through intensification. Therefore, at least theoretically, it appeared that a solution to the sustainable city problem had indeed been discovered in the planning of Iranian large cities.

2- Reducing of urban-rural inequalities: The reduction of urban-rural disparities remains the key strategy of controlling urban sprawl. Land use policies should be designed by taking into consideration of urban-rural inequalities. Urban-rural unity is an important pre-requisite for reducing of urban-rural inequalities, which may help improve regional development, achieve urban-rural equity and spatial and overcome the problem of urban sprawl. The establishment of a consolidated land administration is recommended to resolve the social conflicts. Moreover, to attain a compact pattern the ability of the government in the governance of urban fringe land use should be increased for efficient management of urban fringe land.

7.4. Prospects

The applied methodology in this study seems to be effective in analyzing urban expansion in Isfahan city and in providing a support for decision-making processes towards a sustainable development. However, results of this study are exclusive to the large Iranian cities. Further researches are required in different Iranian cities (medium size) to conclude on the efficiency and effectiveness of the tools. Moreover, owning to the spatial extent of the city, it is necessary to consider the driving forces of urban growth in different spatial units (directional and concentric zones). This could reveal detailed casual factors of urban expansion pattern at the local level. Furthermore, how to form an objective criterion which can be universally accepted to evaluate reasonability of spatial pattern of expansion is an important research project. At the end, how to control urban sprawl in urban fringe in Iran is a further research topic, especially how to make a good land use policy to restrain this phenomenon is also very important.

References

Acheampong R. A.; Agyemang, F., S., K.; Abdul-Fatawu, M. (2016). Quantifying the spatio-temporal patterns of settlement growth in a metropolitan region of Ghana. GeoJournal, pp. 1–18.

Afify, H. A. (2011). Evaluation of change detection techniques for monitoring land-cover changes: a case study in new Burg El-Arab area Alexandria Eng. J., 50: pp. 187–195 http://dx.doi.org/10.1016/j.aej.2011.06.00.

Aguilera, F.; Valenzuela, L. M.; Botequilha-Leitão, A. (2011). Landscape metrics in the analysis of urban land use patterns: A case study in a Spanish metropolitan area. Landscape and Urban Planning. 99, (3-4), 226 - 238.

Aguilera-Benavente, F.; Botequilha-Leitão, A.; Díaz-Varela, E. (2014). Detecting multi-scale urban growth patterns and processes in the Algarve region (Southern Portugal).

Ahmadi, H.; Nusrat, A. (2010). Vegetation Change Detection of Neka River in Iran by Using Remote-sensing and GIS. Journal of Geography and Geology Vol. 2(1): pp. 58-67.

Alberti, M., E. Botsford, and A. Cohen. (2001). Quantifying the urban gradient: Linking urban planning and ecology. In Avian ecology in an urbanizing world, ed. J. M. Marzluff, R. Bowman, R. McGowan, and R. Donnelly. New York: Kluwer.

Alberti, M. (2008). Advances in Urban Ecology: Integrating Humans and Ecological Processes in Urban Ecosystems. Springer Science+Business Media, Boston, MA. CrossRef.

Alsharif, A.A.; B. Pradhan (2013). Urban sprawl analysis of Tripoli Metropolitan city (Libya) using remote sensing data and multivariate logistic regression model. Journal of the Indian Society of Remote Sensing, pp. 1-15.

Anderson, J.R.; Hardy, E.E.; Roach, J.T.; Witmer, R.E. (1976), A land use and land cover classification for use with remote sensor data. U.S. Geological Survey Professional Paper 964. Washington, D.C.: U.S. Govt Printing Office.

Angel, S., S. C. Sheppard, et al., (2005). The Dynamics of Global Urban Expansion. Transport and Urban Development Department, The World Bank, p. 200.

Appiah, D. O.; Bugri, J. T.; Forkuor, E. K.; Boateng, P. K. (2014). Determinants of peri-urbanization and land use change patterns in peri-urban Ghana. Journal of Sustainable Development, 7(6), p. 95.

Assar Khaniki, Z.; Darabi, H.; dIrani-Behbahani, H. (2015). IntegratedAnalysis of Urban Landscape Fragmentation (Case Study: Historical-Religious City of Ray). Int. J. Environ. Res., 9(2): pp.511-522.

Bahrami, A.; Emadodin, I.; Ranjbar Atashi, M.; Rudolf Bork, H. (2010). Land-use change and soil degradation: A case study, North of Iran. Agriculture and Biology Journal of North America, 1(4): pp. 600-605.

Banik, Sh.; Golam Kibri, B. M.; Sharma, D. (2012). Testing the Population Coefficient of Variation. Journal of Modern Applied Statistical Methods. 1(11): pp.325-335.

Barredo, J. I.; Demicheli, L.; Lavalle, C.; Mccormick, N. (2004). Modelling future urban scenarios in developing countries: An application case study in Lagos, Nigeria. DOI: 10.1068/b29103.

Bartel, A. (2000). Analysis of landscape pattern: towards a top down indicator for evaluation of landuse. Ecological Modelling., 130: pp.87-94.

Batty, M. (2005). Cities and Complexity. Understanding Cities with Cellular Automata, Agent-Based Models, and Fractals. City and complexity.

Bleicher, H. (1892). Statistische Beschreibung der Stadt Franldurt am Main und ihrer Bevolkerung, Frankfurt am Main.

Bloch, R.; Fox, S.; Monroy, J.; Ojo, A. (2015). Urbanization and urban expansion in Nigeria. Research report. Urbanization research Nigeria.

Botequilha Leitão, A.; Miller, J.; Ahern, J.; McGarigal, K. (2006). Measuring landscapes: A planner's handbook (Washington: Island Press).

Bouhennache, R.; Bouden, T.; Taleb, A. A.; Chaddad, A. (2015). Extraction of urban land features from TM Landsat image using the land features index and Tasseled cap transformation. Recent Advances on Electro science and Computers.

Bourne, L. T. (1996). Dietary intake in an urban African population in South Africa, with special reference to the nutrition transition. South Africa, University of Cape town.

Bouzekri, S.; Aziz Lasbet, A.; Lachehab, A. (2015). A new spectral index for extraction of built-up area using Landsat 8 data. Journal Indian Remote Sensing.

Brockheroff, M. P. (2000). An urbanizing world. Population Bulletin, 55(3), pp: 3–44.

Burgess, R. (2000). A Global Perspective. The Compact City Debate in Compact Cities: Sustainable Urban Forms for Developing Countries; Burgess, R., Jenks, M., Eds.; Spon Press: London, UK; pp. 9–24.

Burton, E. (2000). The Compact City: Just or Just Compact? A Preliminary Analysis. School of Architecture, Oxford Brookes University, Gipsy Lane, Headington, Oxford OX3 OBP, UK.

Craig, S. G.; Ng, P. T. (2001). Using quantile smoothing splines to identify employment subcenters in a multicentric urban area. Journal of Urban Economics.1(49): pp.100-120.

Chen, X.; Chen, J.; Shi, Y.; Yamaguchi, Y. (2012). An automated approach for updating land cover maps based on integrated change detection and classification methods. ISPRS Journal of Photogrammetry and Remote Sensing. 71: pp. 86–95.

Clark, C. (1951). Urban Population Densities. Journal of the Royal Statistical Society, Series A. (General) 4: pp.490-496.

Cliff, A. D.; Ord, J. K. (1981). Spatial processes- models and applications. (London: Pion).

Curto, J. D.; Castro Pinto, J. (2009). The coefficient of variation asymptotic distribution in the case of non-iidrandom variables. Journal of Applied Statistics 36 (1): pp.21–32.

Dadrasa, M.; Shafria, H. Z.M.; Ahmada, N.; Pradhana, B.; Safarpourd, S. (2015). Spatio-temporal analysis of urban growth from remote sensing data in Bandar Abbas city, Iran. The Egyptian Journal of Remote Sensing and Space Science. 18 (1): pp.35–52.

Dasgupta, S.; Laplante, B. Murray, S.; Wheeler, D. (2009). Climate Change and the Future Impacts of Storm-Surge Disasters in Developing Countries. Working Paper 182.

Deng, C.; Wu, C. (2012). A biophysical composition index for remote sensing of urban environments. Remote Sens. Environ.127: pp. 247–259. http://www.sciencedirect.com/science/article/pii/S003442571200363X.

Dieleman, F.; Wegner, M. (2004). Compact city and urban sprawl. Built Environment 30(4), pp. 308-323.

Doan, P.; Oduro, C. Y. (2012). Patterns of population growth in peri-urban Accra, Ghana. International Journal of Urban and Regional Research, 36(6): pp. 1306–1325.

Duany, A. (2002). New urban post IV. Congress for the New Urbanism, p. 7.

Dunn, C, P.; Sharpe, D.M.; Guntenspergen, G.R.; Stearns, F.; Yang, Z. (1991). Methods for analyzing temporal changes in landscape pattern, in eds. Turner, M.G. and Gardner, R.H. Quantitative Methods in Lundscape Ecology: The Analysis and Interpretation of Lundscape Heterogeneity. Springer-Verlag: New York.

Ebrahimpour-Masoumi, H. (2012). A new approach to the Iranian urban planning, using neo-traditional development, PhD Dissertation, TU Dortmund, Dortmund.

EEA environmental statement (2006). Corporate document No 1/2006. http://www.eea.europa.eu/publications/report_2006_0707_150910.

Ewing, R. (1994). Causes, characteristics, and effects of sprawl: a literature review. Environmental and Urban Issues 21(2): pp. 1-15.

FAO (2014). The State of Food and Agriculture. food and agriculture organization of the united nations Rome, 2014.

Farris, J. T. (2001) The barriers to using urban infill development to achieve smart growth. Housing Policy Debate, 12: 1–30.

Fina, S.; Siedentopf, S. (2008). Urban sprawl in Europe – identifying the challenge. 978-39502139-5-9.

Foody, G. L. (2002). Status of land cover classification accuracy assessment. Remote Sensing of Environment 80: 185 – 201.

Ghani, N. L. A.; Abidin, S. Z. Z.; Khalid, N. E.A. (2014). Urban sprawl shape description. Malaysian Journal of Computing. 2 (1).

Gillham, O. (2002). The Limitless City: A Primer on the Urban Sprawl Debate. Washington, DC: Island Press.

Glaeser, E.L.; Kahn, M.; Rappaport, J. (2008). Why do the poor live in cities? The role of public transportation. Journal of Urban Economics 63 (1): pp. 1–24.

Hasse, J. E.; Lathrop, R. G. (2003). Land resource impact indicators of urban sprawl. Applied Geography 23, pp.159–175.

Heimlich, R. E.; Anderson, W. D. (2001). Development at the Urban Fringe and Beyond: Impacts on Agriculture and Rural Land. Agricultural Economic Report No. 803, Economic Research Service, Washington DC: U.S. Department of Agriculture.

Herold, M.; Scepan, J.; Clarke, K. C. (2002). The use of remote sensing and landscape metrics to describe structures and changes in urban land uses. Environment and Planning. 34, pp. 1443 – 1458.

Herold, M.; Couclelis, H.; Clarke, K.C. (2005). The role of spatial metrics in the analysis and modeling of urban land use change. Computers, Environment and Urban Systems, 29(4), 369-399.

Hong, Y. Y.; Morris, M.; Chiu, C. Y.; Benet-Martínez, V. (2000). Multicultural minds: A dynamic constructivist approach to culture and cognition. American Psychologist, 55: pp.709-720.

Hosseini, A.; Shabanifard M.; Rashidi M.; Saiydzade, M. R. (2010). Distribution and Determining of Urban Sprawl in Kerman with Emphasis on Kariz Water System, Physics International, 1(1), pp.9-15.

Huete AR (1988). A soil-adjusted vegetation index (SAVI), Remote Sensing Environ., 25(3): pp.295-309.

IDEM, (2012). National Report on Slum Conditions and Shelter Policy, Iran, Tehran.

Im, J.; Jensen, J.R. (2005). A change detection model based on neighborhood correlation image analysis and decision tree classification. Remote Sensing of Environment, 99(3): pp. 326-340.

Im, J.; Rhee, J.; Jensen, J.R.; Hodgson, M.E. (2007). An automated binary change detection model using a calibration approach. Remote Sensing of Environment 106, pp.89–105.

Irwin, E. G., Bockstael, N. E. (2007). The evolution of urban sprawl: evidence of spatial heterogeneity and increasing land fragmentation. Proceedings of National Academy of Sciences USA, 104: 20672–20677.

Jaafari, Sh.; Sakieh, Y.; Alizadeh Shabani, A.; Nazarisamani, A. (2016). Landscape change assessment of reservation areas using remote sensing and landscape metrics (case study: Jajroud reservation, Iran). Environment Development and Sustainability 17(5).

Jenks, M.; Burton, E. et al. (1996). The Compact City: A Sustainable Urban Form? E & FN Spon.

Jensen, J.R. (2005). Introductory Digital Image Processing: A Remote Sensing Perspective, Third ed. Prentice Hall, Upper Saddle River, New Jersey.

Ji, M.; Jensen, J.R. (1999). Effectiveness of subpixel analysis in detecting and quantifying urban imperviousness from Landsat Thematic Mapper imagery. Geocarto International, 14(4), 33-41.

Ji, W.; Ma, J.; Twibell, R. W. (2006). Underhill, K. Comput., Environ. and Urban Systems 30, pp.861–879.

Kalantari Khalilabad, H.; Hatami Nejad, H. (2006). Renovation Planning of Historical Area of Yazd, Fara Gostar Publications, Tehran.

Kelarestaghi, A.; Ahmadi, H.; Jafari, M. (2010). Land use changes detection and spatial distribution using digital and satellite data, case study: Farim drainage basin, Northern of Iran. BIABAN (Desert Journal).11(2): pp. 33-47.

Kelley, K. (2007). Sample size planning for the coefficient of variation from the accuracy in parameter estimation approach. Behavior Research Methods 39 (4): pp.755-766.

Khalaj, M.; Lashkari, E. (2010). Multipurpose Cadastre, Essential for Urban Development Plans in Iran. World Academy of Science, Engineering and Technology International Journal of Social, Behavioral, Educational, Economic, Business and Industrial Engineering.

Knomea (2011). World data atlas: Iran- total road network.

Kroll, F.; Müller, F.; Haase, D.; Fohrer, N. (2012). Rural–urban gradient analysis of ecosystem services supply and demand dynamics Land Use Policy 29: pp. 521–535.

Krugman, P. R. (1991). Geography and Trade. MIT Press.

Li, Q.; Fang, Ch.; Li, G.; Ren Zh. (2015). Quantitative Measurement of Urban Expansion and Its Driving Factors in Qingdao: An Empirical Analysis Based on County Unit Data. Journal of Resources and Ecology, 6 (3).

Li, Ch.; Thinh, N. X. (2013). Investigation and comparison of land-cover change patterns in Xuzhou city, China, and Dortmund city region, Germany, using multitemporal Landsat images. Journal of Applied Remote Sensing 073458-1 Vol. 7. file:///C:/Users/nheid/Downloads/Li_Thinh_Investigation.pdf.

Li, F. (2012). Investigation of urban sprawl on the basis of remote sensing data. A case study in Jiangning, Nanjing City, China.

Limin J.; Yaolin L. (2012). Analyzing the shape characteristics of land use classes in remote sensing imagery. ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume I-7.

Liu, M.; Hu, Y.; Chang, Y.; He, X.; Zhang, W. (2009). Land Use and Land Cover Change Analysis and Prediction in the Upper Reaches of the Minjiang River, China. Environmental Management 43: pp. 899-907.

Lock, D. (1995). Room for More Within City Limits?,Town and Country Planning, 64 (7): pp. 173–176.

Lopez, R.; Hynes, H. P. (2003). Sprawl in the 1990s mesurment, Distribution, and Trends. Urban Aff Rev Thousand Oaks Calif. Author manuscript; available in PMC 2006 Sep 20. http://www.ncbi.nlm.nih.gov/pmc/articles/PMC1570399/.

Lösch, A. (1944). The Economics of Location. New Haven: Yale University Press.

Lu, D.; Weng, Q. (2007). A survey of image classification methods and techniques for improving classification performance. International Journal of Remote Sensing, 28(5), 823-870. DOI: 10.1080/01431160600746456.

Malpezzi, S.; Guo, W.K. (2001). Measuring sprawl: alternative measures of urban form in U.S. metropolitan areas The Center for Urban Land Economics Research, University of Wisconsin, Madison, WI.

Matinfar, H. R. (2010). Change detection monitoring of Khoramabad Region(IRAN) via remote sensing. EGU General Assembly 2010, held 2-7 May, 2010 in Vienna, Austria, p.448

McConnell, V., Walls, M., Kopits, E. (2006). Zoning, TDRs and the density of development.Journal of Urban Economics, 59: 440–457.

McConnell, V. D.; Wiley, K. (2010). Infill development: perspectives and evidence from economics and planning. Resources for the Future. RFF Discussion Paper 10-13

McFeeters, S.K. (1996). The use of normalized difference water index (NDWI) in the delineation of open water features, International Journal of Remote Sensing, 17(7): pp.1425–1432.

McGarigal, K; Marks, B.J. (1995). FRAGSTATS: spatial pattern analysis program for quantifying landscape structure. General Technical Report PNW-GTR-351, USDA Forest Service, Pacific Northwest Research Station, Portland.

McGarigal, K.; Cushman, S.A.; Ene, E. (2012). FRAGSTATS v4: Spatial Pattern Analysis Program for Categorical and Continuous Maps. Computer software program produced by the authors at the University of Massachusetts, Amherst.

Mobaraki, O.; Mohammadi, J.; Zarrabi, A. (2012). Strategy for Sustainable Urban Development: A Case study of Urmia City, Iran. Greener Journal of Social Sciences, 2 (1), pp.41- 49.

Nairy, K. S; Rao, K. A. (2003). Tests of coefficient of variatin of normal population, Comm. Stat., Simulation and Computation, 32: pp. 641-661.

Nakaya, T.; Fotheringham, A. S.; Brunsdon, C.; Charlton, M. E. (2005). Geographically weighted Poisson regression for disease association mapping, Statistics in Medicine 24: 2695–2717.

Naveena, D. R.; Wiselin J. G. (2015). Change Detection Techniques - A Survey. DOI: 10.5121/ijcsa.2015.5205.

Nechyba, Th. J.; Walsh, R. P. (2004). Urban Sprawl. Journal of Economic Perspectives—Volume 18, Number 4, pp. 177–200.

Nong, D.; Lepczyk, Ch.; Miura, T.; Fox, J.; Spencer, J.; Chen, Q. (2014). Quantify spatiotemporal patterns of urban growth in Hanoi using time series spatial metrics and urbanization gradient approach. Environment, population, and health series.

Park, S. (2015). Environ Monit Assess.
http://www.ncbi.nlm.nih.gov/pubmed/26065890.

Pourahmad, A; Baghvand, A; Zangenehe Shahraki, S; Givehchi, S. (2007).The impact of urban sprawl up on air pollution. International Journal of Environmental Research 1(3): pp. 252–257

Pratibha, P. S.; Priya, M. H.; Duhita, S. D. (2014). Fusion Classification of Multispectral and Panchromatic Image using Improved Decision Tree Algorithm'', IEEExplore, 978-1-4799-3140-8/14/$31.00 ©2014 IEEE.

Rahnama, M. R.; Abbaszadeh, G. R. (2006). The comparative study of sprawl and compression in Sidney and Mashhad metropolitans. Geography and regional development magazine.

Ray, T.W. (1994). Vegetation in remote sensing FAQs, Applications, ER Mapper, Ltd., Perth, unpaginated CD-ROM.

Ridd, M.K. (1995). Exploring a V-I-S (Vegetation-Impervious Surface-Soil) model for urban ecosystem analysis through remote sensing: comparative anatomy for cities. International Journal of Remote Sensing, 16(2), 2165-2185.

Rizk Hegazy, I.; Rashed Kaloop, M. (2015). Monitoring urban growth and land use change detection with GIS and remote sensing techniques in Daqahlia governorate Egypt, Gulf Organisation for Research and Development
International Journal of Sustainable Built Environment.

Salvati, L. (2014). Changing Region: An Integrated Assessment. Journal of Urban and Regional Analysis 6(1): pp. 5-14.

Schneider, A.; Woodcock, C., E. (2008). Compact, Dispersed, Fragmented, Extensive? A Comparison of Urban Growth in Twenty-Five Global Cities using Remotely Sensed Data, Pattern Metrics and Census Information. Urban studies, 45(3): pp. 659–692.

Seifolddini, F.; Mansourian, H. (2014). Spatial–temporal pattern of urban growth in Tehran megapole, J. Geogr. Geol., 6: pp.70–80.

Seto, K. C.; Fragkias, M. (2005). Quantifying Spatiotemporal Patterns of Urban Land-use Change in Four Cities of China with Time Series Landscape Metrics. Landscape Ecology, 20 (7): pp 871-888. http://link.springer.com/article/10.1007/s10980-005-5238-8?no-access=true.

Shahraki, S. Z.; Sauri, D.; Serra, P.; Modugno, S.; Seifolddini, F.; Pourahmad, A. (2011). Urban Sprawl Pattern and Land-Use Change Detection in Yazd, Iran. Habitat International, 35(4), pp.521-528.

Shannon, C. E. (1948). A Mathematical Theory of Communication. Bell System Technical Journal.

Silambarasan, K.; Vinaya, M. S.; Babu, S. S. (2014). Urban Sprawl Mapping and Landuse Change Detection in and around Udupi Town: A Remote Sensing based Approach.

Singh, N.J.; Leonardsson, K. (2014). Partial migration and transient coexistence of migrants and residents in animal populations.

Singh Boori, M.; Netzband, M.; Choudhary, K.; Voženílek, V. (2015). Monitoring and modeling of urban sprawl through remote sensing and GIS in Kuala Lumpur, Malaysia. http://ecologicalprocesses.springeropen.com/articles/10.1186/s13717-015-0040-2.

Sokal, R.R.; Oden, N.L. (1978). Spatial autocorrelation in biology. 1. Methodology. Biological Journal of the Linnean Society, 10: pp. 199-228.

Southworth, F. (2001). On the potential impacts of land use change policies on automobile vehicle miles of travel. Energy Policy, 29: pp. 1271-1283.

Subramani.T; Sivakumar.C. T; Kathirvel.C.; Sekar.S. (2014). Identification of Ground Water Potential Zones in Tamil Nadu By Remote Sensing and GIS Technique. International Journal of Engineering Research and Applications, 4 (12): pp.127-138.

Sudhira, H.S.; Ramachandra, T.V.; Jagadish, K.S. (2004). Urban sprawl: metrics, dynamics and modelling using GIS. Int. J. Appl. Earth Observ. Geoinf. 5, 29–39.

Suja, R. Letha, J., Varghese, J., (2013). Evaluation of Urban growth and expansion using Remote sensing and GIS. International Journal of Engineering Research & Technology (IJERT). 2 (10).

Taherkhani, H.; Jadidian, K.; Fallah, M.; Vaziri, S. (2007). The Frequency of Intestinal Parasites in HIV Positive PatientsAdmitted To the Disease Consultation Center in Kermanshah Province. M Laboratory.

Taubenböck, H.; Wegmannb, M.; Roth, A.; Mehl, H.; Dech, S. (2009). Urbanisation in India – Spatiotemporal analysis using remote sensing data, Computers, Environment and Urban Systems, 33: pp. 1139-1156.

Tauhidur Rahman, M. (2016). Detection of Land Use/Land Cover Changes and Urban Sprawl in Al-Khobar, Saudi Arabia: An Analysis of Multi-Temporal Remote Sensing Data. International journal of Geo-Information.

Thinh, N. X. (2003). Contemporary spatial analysis and simulation of the settlement development of the Dresden city region. In A. Genauck and R. Heinrich (Eds.). the information society and enlargement of the European Union 17th international conference informatics for environmental protection, Cotbus, Part 1: concepts and methods, pp. 253- 261.

Tian, G.; Jiang, J.; Jang, Zh.; Zhang, Y. (2011). The urban growth, size distribution and spatio-temporal dynamic pattern of the Yangtze River Delta megalopolitan region, China. Ecological modelling (222): pp. 865-878.

Townshend, J. R. G. (1992). Land cover. International Journal of Remote Sensing, 13, 1319 – 1328

Tsai, Y. H. (2005). Quantifying Urban Form: Compactness versus 'Sprawl'. Urban Stud January. vol. 42 no. 1, 141-161.

Tuia, D.; Osse´ s de Eicker, M.; Zah, R.; Osses, M.; Zarate, E.; Clappier, A. (2007). Evaluation of a simplified top–down model for the spatial assessment of hot traffic emissions in mid-sized cities. Atmos. Environ. 41: pp.3658–3671.

von Thünen, J.H. (1826). Der Isolierte Staat in Beziehung auf Landwirtschaft and Nationalekonomie, pp. 11-12. Hamburg (1966 edition, Stuttgart: Gustav Fischer).

UNEP (2015). United Nations Environment Programme, ISBN: 978-92-807-3518-5.

UNICEF Annual Report (2012). World Population Prospects The 2012 Revision Volume II: Demographic Profiles, New York.

United Nations Population Division (UNPD) (2000). World urbanization prospects: The 1999 revision. New York, United Nations Population Division.

United Nations, World Population Prospects (2015). Key Findings and Advance Tables. Department of Economic and Social Affairs, Population Division.

Wang, L.; Li, C. C.; Ying, Q.; Cheng, X.; Wang, X. Y.; Li, X. Y.; Hu, L., Y.; Liang, L.; Yu, L.; Huang, H., B.; Gong, P., (2012). Monitoring China's Environmental Change with Remote Sensing. Chinese science bulletin. Vol.57 No.22: 2802-2812.

WCED, (1987). Our Common Future. World Commission on Environment and Development. Oxford University Press, Oxford.

Weng, Q. (2001). A remote sensing? GIS evaluation of urban expansion and its impact on surface temperature in the Zhujiang Delta, China. International Journal of Remote Sensing, 22(10): pp.1999-2014.

Wiley, K. (2009). An Exploration of the Impact of Infill on Neighborhood Property Values. Ph.D. Dissertation, The University of Maryland, Baltimore County (UMBC), Publication No. 10221

Wilson, E. H.; Hurd, J. D.; Civco, D. L.; Prisloe, S.; Arnold, C. (2003). Development of a geospatial model to quantify, describe and map urban growth. Remote Sensing of Environment, 86(3): pp. 275–285.

Williams, D.L.; Goward, S.; Arvidson, T. (2006). Landsat: Yesterday, today, and tomorrow. Photogrammetric Engineering and Remote Sensing, 72 (10): p. 1171.

Xiaowen, L.; Zhang, L.; Liang, Ch. (2010). A GIS-based buffer gradient analysis on spatiotemporal dynamics of urban expansion in Shanghai and its major satellite cities. International Society for Environmental Information Sciences 2010 Annual Conference (ISEIS). Procedia Environmental Sciences.

Xiang, W. N. (1996). GIS-based riparian buffer analysis: injecting geographic information into landscape planning. Landscape and Urban Planning. 34 (1): pp. 1-10. http://www.sciencedirect.com/science/article/pii/0169204695002065

Xu, H. (2005). A study on information extraction of water body with the Modified Normalized Difference Water Index (MNDWI), Journal of Remote Sensing, 9(5): pp.511–517.

Xu, H. (2007). Modification of normalized difference water index (NDWI) to enhance open water features in remotely sensed imagery. Int. J. Remote Sens. 27: pp. 3025–3033.

Yeh, A.G.O.; Li, X. (2001). Measurement and monitoring of urban sprawl in a rapidly growing region using entropy. Photogr. Eng. Remote Sens., 67(1): pp. 83-90.

Yuan, F.; Sawaya, K.E.; Loeffelholz, B.C.; Bauer, M.E. (2005). Land cover classification and change analysis of the Twin Cities (Minnesota) Metropolitan Area by multitemporal Landsat remote sensing. Remote Sensing of Environment, 98(2-3), 317-328.

Zanganeh Shahraki, S. (2007). The analysis of Tehran urban sprawl and its effect on agricultural lands, M.A. Thesis in Geography and Urban Planning, University of Tehran, (In Persian).

Zha, Y.; Gao, J.; Ni, S. (2003). Use of normalized difference built-up index in automatically mapping urban areas from TM imagery. Int. J. Remote Sens. 2003, 24, 583–594.

Zha, Y.; Gao, J.; Ni, S. (2010). Use of normalized difference built-up index in automatically mapping urban areas from TM imagery. International Journal of Remote Sensing. Volume 24, Issue 3, 2003. http://www.tandfonline.com/doi/abs/10.1080/01431160304987.

Zhang, X.; Arayici, Y. Wu, S.: Abbott, C.; Aouad, G. (2009). School of the Built Environment, University of Salford.

Zhang, H. (2012). Land use dynamics, urban expansion, and their effects on spatial patterns of wetland: the case of natural wetlands distribution area (NWDA) in Fuzhou city, southeastern China. Chinese geographical science. Vol. 22, No. 5, pp. 568-577.