Remote Sensing of Urbanization and Environmental Impacts

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Abstract

It is a well-known fact that current population forecasts and trends predict a continuous increase in world population in the upcoming decades. This leads to increased demands for natural resources and living space. As a consequence, urban areas have been growing considerably and new settlements and urban agglomerations keep emerging on a global scale. Data and methods to observe and quantify the changes of and induced through urban growth are thus needed to address the challenges of present and future urbanization trends. This thesis research focuses on the establishment of analytical frameworks for the detection of urban growth patterns based on spaceborne remote sensing data at multiple scales, spatial and temporal resolutions and on the evaluation of environmental impacts through the well-established concepts of landscape metrics and ecosystem services, their extension and combination. Urbanization does not progress uniformly but shows large spatial and temporal disparities. The unprecedented and often unstructured growth of urban areas is nowadays most apparent in Africa and Asia. China in particular has undergone rapid urbanization already since the late 1970s. The need for new residential, commercial and industrial areas leads to new urban regions challenging sustainable development and the maintenance and creation of a high living standard as well as the preservation of ecological functionality. In Paper I, spatio-temporal urbanization patterns at a regional scale were evaluated over two decades using Landsat and HJ-1 data from 1990 to 2010 in the three densely populated regions in China, Jing-Jin-Ji, the Yangtze River Delta and the Pearl River Delta that represent the most important Chinese urban agglomerations. Investigating urban growth patterns on metropolitan scales, the two diverse cities of Stockholm and Shanghai and their urban hinterlands were evaluated within the same time frame as the regional analysis using Landsat images. The idea of integrating influential spatial measures into ecosystem service studies is far too often neglected in published research and was therefore investigated. Through a systematic combination of the ecosystem services and landscape metrics concepts spatio-temporal change patterns in Beijing from 2005 to 2015 were evaluated through Sentinel-2A multispectral data and historical satellite images. Investigating urban growth patterns at an even more detailed level, changes in urban land cover and green and blue spaces were investigated with high-resolution IKONOS and GeoEye-1 data in Shanghai’s urban core between 2000 and 2009. The methods that were combined and developed mainly rely on freely accessible remotely
sensed data facilitating unrestrained use and continuous development in the field.

Major initial methodological steps involved image co-registration and mosaicking. In the regional study, Tasseled Cap transformations were applied to increase class separabilities prior to pixel-based Random Forest classifications. In the comparative study between Stockholm and Shanghai, a pixel-based SVM classifier was used on multispectral data and GLCM features for land cover classification. LULC changes were then determined using post-classification change detection. Object-based image classification using SVM was performed after image segmentation in KTH-SEG in Papers III and IV. After accuracy assessment and post-classification refinements, urbanization indices, ecosystem services and landscape metrics were used to quantify and characterize urban growth and ensuing consequences for the natural environment and on the urban population.

The results show that an increase in urban areas to varying degrees could be observed in all studies. China’s three most important urban agglomerations, Jing-Jin-Ji, the Pearl River Delta and the Yangtze River Delta including the megacities of Beijing and Shanghai showed the most prominent urbanization trends. Stockholm’s urban extent increased relatively little over the past 25 years with minor negative impacts for the natural environment. On a regional and metropolitan scale, urban expansion progresses predominately at the expense of agricultural areas and to a lesser extent also forests and wetlands where present, the latter implying more severe consequences due to the manifold ecological functions wetlands and forests possess. Focussing less on the expansion of built-up and impervious areas as such, but investigating the patterns of urbanization at higher detail and closer towards city cores, trends that counteract the negative effects of urban expansion can be detected. Both in Shanghai and Beijing, redesign of older, low-rise building blocks into urban green spaces in form of parks can be detected alongside large construction projects such as the 2008 Olympic Games in Beijing or the 2010 World Exhibition in Shanghai that replaced ecologically speaking less favourable urban features with modern complexes interspersed with green infrastructure. These trends do not cancel out the negative effects of urban growth in general but suggest a paradigm shift in urban planning and design in favour of more pleasant and sustainable living conditions. The classification outcome over Beijing from the latest study suggests an increase in high and low density built-up space of 21% over the past
decade. Ecosystem service bundles accounting for spatial characteristics of service providing areas show major losses for food supply, noise reduction, runoff mitigation, waste treatment and global climate regulation services through landscape structural changes in terms of decreases in service area, edge contamination and fragmentation.

Methodological frameworks to characterize urbanization trends at different scales based on remotely sensed spaceborne data were developed and the establishment of a closer link between the fields of urban ecology and remote sensing were attempted. Medium-resolution data at metropolitan and regional scales is considered sufficient to quantify and evaluate urbanization patterns. For detailed urban analyses high-resolution (<5m) data are recommended to capture as much variation in urban green and blue spaces as possible. The well-known concepts of landscape metrics and ecosystem services have additionally been combined to create a more differentiated and synoptic impression of urban growth effects.

**Keywords:** Remote Sensing, Urbanization, Land Use/Land Cover (LULC), Environmental Impact, Landscape Metrics, Ecosystem Services
Sammanfattning


En ökning av stadsområden i varierande grad kunde observeras i alla studier. Kinas tre viktigaste urbana storstadsregioner, Jing-Jin-Ji, Pearl River Delta och Yangtze River Delta, inklusive megastäderna Peking och Shanghai hade markant störst urbaniseringstrend. Stockholms stadsområde ökade relativt lite under de senaste 25 åren med betydligt mindre negativa konsekvenser för den naturliga miljön än i Shanghai. På regional- och storstadsnivå fortskrider urbanisering huvudsakligen på bekostnad av jordbruksområden och i mindre utsträckning även skogar och våtmarker. En minskning av de sista medför allvarligare miljökonssekvenser på grund av de många ekologiska funktioner som finns i våtmarker och skogar. Med mindre fokus på utbredning av bebyggda och belagda ytor och istället fokusera på att analysera centralt belägna urbaniseringsmönster med hög detaljrikedom, kan trender som motverkar negativa urbaniseringsaspekter upptäckas. Både i Shanghai och Peking kan en omstrukturering av äldre, låg och tät bebyggelse till urbana grönområden i form av parker och golfbanor upptäckas. Dessutom ersattes ekologiskt mindre gynnsamma stadsdelar som industriområden med nya byggnader och grönstruktur genom stora byggeprojekt, t.ex. i samband med de olympiska spelen i Peking 2008 och inför världsställningen i Shanghai 2010. Dessa trender upphäver inte de negativa urbaniseringsaspekterna utan de antyder ett paradigmskifte i stadsplanering och design mot mer trygga och hållbara boendemiljöer.

huvudsakligen fritt tillgängliga fjärranalysdata vilket underlättar användning och vidareutveckling av nya metoder.
Den sista studiens klassificeringsresultat från Beijing tyder på en 21% ökning av tät- och glesbebyggda områden under det sista årtiondet. Ekosystemtjänster med hänsyn taget till spatiala serviceegenskaper visar att förändringarna har gett en betydande minskning i tillgång till näringsstillsförsel, ljuddämpning, översvämningsskydd, avfallshantering och global klimatreglering. Detta beror på strukturella förändringar i landskapet med minskning av grön och blå områden, påverkan i gränszonerna och fragmentering av landskapet.

Ett metodiskt ramverk för att karakterisera urbaniseringstrender baserat på rymdburen fjärranalysdata i flera skalor togs fram och samtidig skapades ett starkare band mellan de två områdena ekologisk urbanisering och fjärranalys. Data med upplösningar mellan 20-30m anses tillräckligt för att kunna kvantifiera och utvärdera urbaniseringstrender. För detaljerade urbaniseringsanalyser rekommenderas högupplöst data (<5m) för att fånga så stor variation i urbana grön och blå områden som möjligt. De välkända koncepten landskapsmetrik och ekosystemtjänster har även kombinerats för att tillsammans skapa en mer differentierad och tydlig bild av den urbana tillväxterns konsekvenser.

**Nyckelord:** Fjärranalys, Urbanisering, Markanvändning/Marktäcke, Miljöpåverkan, Landskapsmetrik, Ekosystemtjänster
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# Table of Contents

Abstract ........................................................................................................ iii

Sammanfattning ............................................................................................ vi

Acknowledgements ....................................................................................... ix

1 Introduction ............................................................................................... 15
   1.1 Rationale .......................................................................................... 15
   1.2 Research Objectives ........................................................................ 19
   1.3 Thesis Organisation .......................................................................... 20
   1.4 Statement of Contribution ............................................................... 21

2 Background ............................................................................................... 23
   2.1 Remote Sensing of the Urban Environment ...................................... 23
       2.1.1 Urban Observation Sensors ......................................................... 23
       2.1.2 Urban Extent Extraction ............................................................... 24
       2.1.3 Urban Land Cover Mapping ......................................................... 25
       2.1.4 Remote Sensing of Urban Climate ............................................... 29
       2.1.5 Remote Sensing of Urban Environment and Ecosystem Services .... 30
   2.2 Indicators of Environmental Impact .................................................. 34
       2.2.1 Ecosystem Services .................................................................. 35
       2.2.2 Landscape Metrics .................................................................... 38
       2.2.3 Urbanization Indices .................................................................. 41

3 Study Areas and Data Description ............................................................ 42
   3.1 Study Areas ...................................................................................... 42
       3.1.1 Jing-Jin-Ji, the Yangtze River Delta and the Pearl River Delta ........ 42
       3.1.2 Shanghai ................................................................................... 43
       3.1.3 Stockholm .................................................................................. 43
       3.1.4 Beijing ....................................................................................... 44
   3.2 Remote Sensing Data ........................................................................ 44
   3.3 Ancillary Data .................................................................................... 46

4 Methodology ............................................................................................. 47
   4.1 Image Processing .............................................................................. 48
       4.1.1 Image Pre-processing ................................................................. 48
List of Figures

Figure 1 Contextual relation of the papers. .................................................................21
Figure 2 Categorization of the papers’ analytical parameters. .................................21
Figure 3 Sentinel-2 MSI spatial resolutions and wavelengths (Source: eoPortal Directory, ESA). .......................................................... 46
Figure 4 Methodology flowchart. .............................................................................47
Figure 5 Classification results from 1990 (left column) and 2010 (right column). Jing-Jin-Ji is shown in the upper row, Yangtze River Delta in the central row and the Pearl River Delta in the lower one (Paper I). .......................................................... 61
Figure 6 Detailed excerpts and their respective areas in FCC images in the left. The six rows show the following areas in descending order: Beijing 1990, Beijing 2010, Shanghai 1990, Shanghai 2010, Shenzhen 1990 and Shenzhen 2010 (Paper I) .................. 62
Figure 7 Classification result (Shanghai in the upper and Stockholm in the lower row and 1990, 2000 and 2010 classifications from left to right (Paper II) ......................................................... 64
Figure 8 Classification result (IKONOS 2000 classification left and GeoEye-1 2009 classification right (Paper III). ............................................................. 66
Figure 9 Detailed classification excerpt (GeoEye-1 2009 FCC image and classification in the upper row, IKONOS 2000 FCC and classification in the lower one, Paper III). ................................................................. 68
Figure 10 Classification result for Beijing in 2005 (left) and for 2015 (right) (Paper IV). 69
Figure 11 Land cover changes in Jing-Jin-Ji, Yangtze River Delta and Pearl River Delta 1990-2010 (Paper I) ................................................................. 73
Figure 12 Changes in PLAND in Shanghai and Stockholm 1989-2000-2010 (Paper II). ................................................................. 74
Figure 13 Changes in PLAND in Beijing between 2005 and 2015 (Paper IV) .......... 76
Figure 14 Landscape characteristics in Beijing 2005 and 2015 (Paper IV) ............. 77
Figure 15 LULC change in central Shanghai (Paper III) ........................................ 82
Figure 16 Ecosystem supply and demand budgets in the Shanghai core (Paper III) ...... 83
Figure 17 Ecosystem service bundle changes and share of spatial influence (Paper IV) ...... 86
List of Tables

Table 1 Overview of multispectral data that was used in the studies including mission, product and instrument, spatial resolution, bands, number of images used, acquisition period and coverage. .................................................................44
Table 2 Image segmentation parameters. .................................................................51
Table 3 SVM classification characteristics. .................................................................54
Table 4 LM and their application throughout the studies ........................................57
Table 5 Summary of overall classification accuracies, Kappa coefficients, amount of classes, classifier and spatial resolutions distributed among Paper I to IV. .........................59
Table 6 Comparison of UI, UX, UGI in Paper I and II. ..............................................70
Table 7 Detailed changes in biomes and ES value quantification over Jing-Jin-Ji, Yangtze River Delta and Pearl River Delta between 1990 and 2010 (Paper I). ......................79
Table 8 Ecosystem Service values in USD in Shanghai from 1989-2010 (Paper II). ......81
Table 9 Ecosystem Service value changes in USD in Stockholm from 1989 to 2010 (Paper II). ........................................................................................................................................81
Table 10 Ecosystem balances and land use/land cover changes in % in Shanghai (Paper III). ...................................................................................................................................82
Table 11 Ecosystem service bundle changes in percent in Beijing from 2005 to 2015 (Paper IV). ...................................................................................................................................85
<table>
<thead>
<tr>
<th>Acronym</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>CNY</td>
<td>Chinese Yuan Renminbi</td>
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<td>CONTAG</td>
<td>Contagion</td>
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<tr>
<td>CWED</td>
<td>Contrast-Weighted Edge Density</td>
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<td>ES</td>
<td>Ecosystem Services</td>
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<td>GLCM</td>
<td>Grey Level Co-occurrence Matrix</td>
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<td>GLS</td>
<td>Global Land Survey</td>
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<td>HDB</td>
<td>High Density Built-Up</td>
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<td>LDB</td>
<td>Low Density Built-Up</td>
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<td>Landscape Metrics</td>
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<td>Largest Patch Index</td>
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<td>Landscape Shape Index</td>
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<td>LULC</td>
<td>Land Use Land Cover</td>
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<td>NP</td>
<td>Number of Patches</td>
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<td>Overall Accuracy</td>
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<td>Object-Based Image Analysis</td>
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<td>Producer’s Accuracy</td>
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<td>Percentage of Landscape</td>
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<td>Patch Density</td>
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<td>Synthetic Aperture Radar</td>
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<td>Support Vector Machine</td>
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<td>SWIR</td>
<td>Short Wave InfraRed</td>
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<td>TC</td>
<td>Tasseled Cap</td>
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<td>TEEB</td>
<td>The Economics of Ecosystems and Biodiversity</td>
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<td>Urban Green Index</td>
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<tr>
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<td>Urban Green Spaces</td>
</tr>
<tr>
<td>UA</td>
<td>User’s Accuracy</td>
</tr>
<tr>
<td>UI</td>
<td>Urban Land Index</td>
</tr>
<tr>
<td>UX</td>
<td>Urban Expansion Index</td>
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</tbody>
</table>
1 Introduction

1.1 Rationale

It is well-known that urban areas have been expanding over the past decades and latest world population trends suggest a further increase of human beings. According to the latest World Population Prospects report by the United Nations (2015), the world population reached 7.3 billion as of mid-2015 implying that the world population has increased by approximately one billion people during the past twelve years. About 4.4 billion people currently live in Asia and 1.38 billion in China alone being the world’s largest country in terms of absolute population. Throughout the past 35 years, China has experienced an unrivalled growth in population and urban areas. The advent of rapid urbanization can be regarded as a consequence of economic and political reforms in China during the late 1970s. Lin (2002) identifies the three most important factors that made accelerated growth and finally rapid urbanization possible as: de-collectivization, agricultural reconstruction and rural industrialization. Rapid urbanization in China is characterized not only by a socio-economic transition from villages towards urban villages and urban communities (Liu et al., 2010b) but also by de-agriculturalization and industrialization processes, thus affecting four aspects of urbanization connotation: population, economy, society and land (Chen et al., 2010).

Energy consumption, a measure of a more and more urban society has constantly risen since the first stages of Chinese urbanization in 1978 and most prominently in the beginning of the current century. Nowadays, urbanization is still proceeding and the annual energy consumption is rising every year. World population is constantly increasing and it is projected that an increase by more than one billion people within the next 15 years can be expected, reaching 8.5 billion in 2030, 9.7 billion in 2050 and 11.2 billion by 2100. Out of these, the larger part will become city dwellers as opposed to living in rural areas. According to the latest World Urbanization Prospects (United Nations, 2014), 54% of the 2014 world population lived in cities and it is projected that by 2050, the percentage will have increased to 66% with Africa and Asia urbanizing faster than other regions. By then, continuous population growth and urbanization are projected to have added 2.5 billion people to the world’s urban population with nearly 90% of the increase concentrated in Asia and Africa. China, India and Nigeria are expected to account for 37% of the projected growth of the world’s urban population up to 2050.
The detrimental effects that urbanization can have upon the natural living environment (humans included) are manifold (Schneider et al., 2012). Widely known consequences of urban growth include increased temperatures in urban areas, flood risks and landslides, air, sound and light pollution, increased energy consumptions and waste generation leading to increased dependencies of humans on ecosystems and biodiversity as was emphasized by Guo et al. (2010). The importance of urban green infrastructure in maintaining ecosystem services (ES) not only in fast growing regions in Asia or Africa, but also under current European land use change trends was stressed by Maes et al. (2015). Here it is stated that as further urban and industrial expansion can be expected, ES are anticipated to decrease across Europe between 10 and 15% by 2050 relative to a 2010 baseline. In order to measure the magnitude of urbanization phenomena and their impacts, accurate, consistent and timely data at global, regional and local scales are necessary. Remote sensing technology provides us continuously with a plethora of different data sets that can be utilized to assess current and future urbanization patterns and to measure ensuing effects on the environment that can contribute to a more sustainable development, e.g. by setting policy priorities to promote inclusive and equitable urban and rural development (United Nations, 2014).

Remote sensing technology has already shown its suitability to map and monitor complex urban land cover patterns for various applications in different environments (e.g. Weng and Quattrochi, 2006; Gamba and Aldrighi, 2012; Ban et al., 2014; Ban et al., 2015). Spaceborne remote sensing data can contribute considerably in deriving urban land use and land cover information, especially when no other data is available or where in-situ data collection is problematic and resource-intensive, e.g. in areas that are difficult to access or subject to unregulated urban growth. Numerous studies have investigated high (Gamba et al., 2011; Myint et al., 2011; Qian et al., 2015a, Niu et al., 2015) to medium (e.g. Furberg and Ban, 2012; Wang et al., 2012b; Furberg and Ban, 2013; Chen et al., 2015) and coarse resolution (e.g. Schneider et al., 2003; Giri et al., 2005) earth observation data for urban land cover mapping and urban growth monitoring with medium to coarse resolution earth observation data and over the past years. Initiatives that focus on detection of urban areas at global scales with medium- to coarse-resolution data have emerged (e.g. Schneider et al., 2009; Esch et al., 2013; Pesaresi et al., 2013) benefitting amongst others from methodological and computational progress. Methods to assess land use and land cover change, its spatio-temporal
patterns and environmental impacts is becoming more important as urban areas continue to grow at local, global and local scales.

An overview of the role remote sensing can play for global monitoring and assessment of urban areas is presented in Weng et al. (2014a). Major areas of current research to address the impacts of human settlements are their extraction from space, mapping of urban extent and urban land cover and associated changes at both regional and global scales, risk analysis in urban areas in terms of health and hazards, e.g. flooding or landslides, mapping and monitoring of urban biophysical parameters and the further development of analytical methods integrating new earth observation data and latest advances in remote sensing imaging science. In a recent review, Wentz et al. (2014) discuss trends and knowledge gaps in urban remote sensing. The need to understand local environmental impacts of urbanization, global environmental change as a result of urbanization and the impacts of urban living on human well-being are emphasized and urban remote sensing science is believed to play a foundational role in global environmental change observation. Continuous data delivery and method development can contribute to capture multi-dimensional aspects of urbanization. It is emphasized that the different scales at which urbanization is investigated require different spatial, temporal and spectral resolutions.

Despite the large variety of ways earth observation data can contribute to aspects of urban areas, only a small body of literature is concerned with making use of remotely sensed data for detailed urban ecological studies. The potential of remote sensing in general has proven useful for a wide range of ecological applications (e.g. Pettorelli et al., 2014; Yang et al., 2014, Rose et al., 2015, Turner et al., 2015) and the number of studies that make use earth observation data for ecosystem service analyses is steadily increasing. Landscape Metrics (LM) have been used before to characterize the spatial character of urbanization patterns (Seto and Fragkias, 2005) Urban ecosystem services are however rarely investigated and the majority of research conducted in the field is in form of case studies that adapt non-localized benefit-transfer valuation approaches (e.g. Pan et al., 2005). These do not account for spatio-temporal characteristics of service provision or demand. Only few recent studies systematically investigate more relative valuation approaches accounting for spatial distributions of service providers and benefiters (e.g. Syrbe and Walz, 2012).
Increasing spatial resolutions and improved data accessibility, e.g. through the recently launched ESA Sentinel-1/2 constellations are believed to further facilitate the use of remotely sensed data. Remote sensing studies for detailed urban ecological applications and of urban ecosystems and their services are however just emerging and the full potential remote sensing yields for the provision of information on state and pressure of biodiversity that is fundamental for many ecosystem services, is yet to be unlocked (Pettorelli et al., 2014) and satellite remote sensing data are currently considered underused within biodiversity research (Turner et al., 2015). Furthermore, there is currently a lack of standardized evaluation methods of urbanization effects upon the environment that enable cross-scale comparisons. One widespread evaluation method in form of an indicator to express ecological functionality and its implications for humans are ES. From the current state of urban ecosystem service retrieval from space, it becomes apparent that new accurate, reliable and time-efficient comprehensive methods are needed to accurately estimate and constantly monitor ES. The key benefits of earth observation data for LM and ES analyses lie in the ability to provide land use/land cover (LULC) data that might not always be present for a particular point in time. Being able to use the same underlying data for both LM and ES analysis is advantageous as opposed to having to collect data from different dates, thus introducing degrees of uncertainty through inconsistent data.

The concept of ecosystem functions and services (Daily, 1997; Millennium Ecosystem Assessment, 2005) and their valuation (Costanza et al., 1997; de Groot et al., 2002; de Groot et al., 2012) have been widely used and continuously extended and developed over the past decades. The often practiced method of attributing a monetary value in form of benefit transfers to the presence of ecosystems is however considered problematic for several reasons (Davidson, 2013) and new relative approaches keep emerging (Burkhard et al., 2012; Chan et al., 2012). With particular respect to urban areas, ES have just in recent years begun to grow in importance (Gómez-Baggethun et al., 2013; Gómez-Baggethun and Barton, 2013; Morel et al., 2014). The Economics of Ecosystems and Biodiversity (TEEB) published a manual on how to treat ES in urban management just less than five years ago (TEEB, 2011). There it is stated that there is no applicable general solution to how to evaluate urban ES and that it is critical to develop local approaches that are unique to each particular situation. No well-established and widely-used global scheme that comprises and values all urban ES exists yet according to the authors’
knowledge. As a result, a transition from monetary to relative valuation approaches that are linked to the function ecosystems fulfil is pursued in this work. Urban ecosystems and the functions they provide are evaluated based on their spatial attributes that are hypothesized to either increase or degrade the potential of an ecosystem to provide services. The approach is intentionally independent on the type of potential human benefiter and thus attempts to be easier applicable to diverse environments. One way to quantify the spatial influence on ecosystem service provision and to evaluate topological relations between services and benefitters (Syrbe and Walz, 2012) is to integrate the concept of LM in a cross-methodological approach. LM are a well-established concept originating from the field of landscape ecology and can be described as a range of variables to express landscape composition and configuration and to quantify their changes over time.

This thesis investigates the impacts of urbanization on the natural and managed green and blue environment through analysis of multitemporal satellite remote sensing data at different scales, from sub-meter data analyses within the urban boundary with high-resolution data to regional analysis considering the effects of urban growth on the urban hinterland with medium-resolution data. Different sensors and resolutions are needed for this purpose. Inner-urban analyses require high-resolution data to capture environmental details. Medium-resolution data on the other hand is more suited for metropolitan to regional analyses to describe urban growth patterns in a broader sense. As indication of environmental effects of urbanization, the concepts of ES, LM and urbanization indices were applied and combined as means of quantifying urban growth and its implications for the population and natural environment.

1.2 Research Objectives

The overall objective of this research is to investigate and compare urbanization trends, the resulting effects on the natural environment and ensuing implications for urban residents through multitemporal and multi-sensor satellite remote sensing analyses at various scales and resolutions. The second major objective is to develop analytical frameworks relying exclusively on remotely sensed data that can aid in more effective evaluations of environmental consequences of urbanization through the combination of urbanization indices and ecological concepts such as LM and ES. Secondary and particular objectives of this study are:
to evaluate the potential of remote sensing data for urban ecosystem studies and to establish a closer link between the disciplines

- to improve and extend the ecosystem service concept through integration of spatio-temporal characteristics based on landscape composition and configuration

1.3 Thesis Organisation

The thesis is organized into six chapters and is aggregated based on the findings in the four papers listed below. Chapter one presents the rationale and introduces the research topic. The objectives of this research are defined and an overview of how the thesis is organised is given alongside the statement of contribution. Chapter two introduces the state of the art of relevant research fields and discusses achievements, latest trends and challenges. Chapter three presents the study areas and summarizes the data that were used. Chapter four describes the methods and techniques that were applied and developed. Chapter five presents numerical and visual results followed by their interpretation and discussion. Chapter six summarizes and concludes the findings in the thesis and gives an outlook on future research in the field.


The following two figures display the contextual relations between the four Papers and their categorization in terms of data used, scale and analytical parameters.
1.4 Statement of Contribution

**Paper I**

All analyses and methodologies of paper I were developed and performed by the main author under the supervision of Professor Ban, the 2\textsuperscript{nd} author. Professor Ban initiated the ideas for this paper and has been involved in the development of the paper.
Paper II
Professor Ban, the 3rd author proposed the topic for this paper. Methodology development was performed by the first author together with the second author under the supervision of professor Ban. Study area description, image processing, classifications, post-processing, accuracy assessment, landscape metric analysis and the discussion part for Shanghai were performed by the first author and for Stockholm by the 2nd author, with the exception of the SVM classification which was performed by a departmental colleague, Martin Sjöström. Urbanization indices and ES were calculated by the first author. The abstract, introduction and data description parts were mainly written by the first author with editorial input from the second author. The selection and interpretation of LM are mainly based on the knowledge and previous research experience of the 2nd author.

Paper III
All analyses and methodologies of paper I were developed and performed by the main author under the supervision of Professor Ban, the 2nd author. Professor Ban initiated the ideas for this paper and has been involved in the development of the paper. Regarding image segmentation and classification in KTH-SEG, Alexander Jacob who is mainly responsible for the creation and implementation of the program assisted me with recommendations regarding parameter settings and with practical help.

Paper IV
All analyses and methodologies of paper I were developed and performed by the main author under the supervision of Professor Ban, the 2nd author. Professor Ban initiated the ideas for this paper and has been involved in the development of the paper.
2 Background

2.1 Remote Sensing of the Urban Environment

2.1.1 Urban Observation Sensors

There are two main sensor types that are usually used for urban mapping at high, medium or coarse spatial resolutions, i.e. optical and Synthetic Aperture Radar (SAR) sensors. Optical sensors capture the spectral response of the earth’s surface in the visible, near and shortwave infrared and thermal infrared part of the spectrum. Active SAR systems rely on the backscattering of radar signals based on the geometric features and surface characteristics of the ground features. SAR sensors have the advantages that they are independent of solar illumination and only little affected by atmospheric attenuations. Advantages of optical sensors can be seen in their ability to record reflectance in the infrared spectrum that is often used to detect and classify vegetation types and the additional recording capability to capture differences in thermal emissions of ground features. RGB image composites of the visible and infrared spectrum simplify image interpretation. Furthermore, large quantities of historical data exist, e.g. in the Landsat archives, that enable change analyses over longer periods of time.

As Weng et al. (2014b) state in a review of urban observing sensors, coarse optical sensors such as MODIS or NOAA-AVHRR feature resolutions higher than 100m and are predominately used for regional, continental or global mapping approaches. The advantages of coarse-resolution data lie in high temporal resolutions. Medium-resolution sensors such as TM/ETM+ aboard the Landsat satellites have been used extensively over the years to map and monitor urban areas due to the large body of historical global data that is available and that is still being generated today and as a result of free data access. Through the sensors’ capabilities to record information in the visible, infrared and thermal spectrum, medium-resolution optical sensors can capture a variety of very different features that are present in urban areas. Apart from Landsat, the SPOT satellite series has also provided long-term data at slightly higher spatial resolutions. Other optical satellite sensors are the ASTER system, the CCD Camera and IRS sensors aboard the HJ-1A/B satellites that present an equivalent to the Landsat satellite but with a higher swath width. Sentintel-2A/B satellites will provide global coverage at 10m to 60m spatial resolutions. High-resolution optical sensors with spatial resolutions...
better than 5m are often commercial but can provide valuable data sources when detailed urban analyses are performed. Examples of high-resolution and very-high-resolution platforms are the WorldView-satellite series, GeoEye, IKONOS and Quickbird. The main drawbacks of optical sensor systems are the dependency on solar illumination, that the recorded data can be affected by atmospheric effects, clouds and haze over urban areas and, especially in high-resolution data sets, also shadows. Coarse- and medium-resolution thermal infrared sensors can be used the derive land surface temperature that can help in distinguishing urban from rural areas. Man-made artificial features emit more thermal energy than the natural surroundings. In addition, coarse-resolution night time sensors such as the DSMP-OLS, as widely recognized global satellite data product or SNPP VIIRS can record the artificially emitted light generated in populated places. An extensive review of the mentioned sensors and application examples can be found in Weng et al. (2014b).

The spatial resolution of thermal images is generally lower than many optical and SAR systems and their advantage lies in higher temporal resolutions. Coarse-resolution SAR data are considered as important source for global mapping applications through their wide geographical coverage (Weng et al., 2014b). Medium-resolution SAR data is provided in resolutions from 10m to 30m enabling more detailed mapping of different urban features, especially useful here is SAR polarimetry (Niu and Ban, 2013). RADARSAT-1, ENVISAT ASAR or Sentinel-1 IW SAR are some examples of medium-resolution SAR sensors that can be used for urban land cover mapping. The combined use of SAR and optical data is a promising field that can result in better discrimination of urban features (Ban and Jacob, 2013) through the complimentary information the different sensor types can record. Fine-resolution SAR systems at spatial resolutions around 1m such as TerraSAR-X or COSMO/Skymed are also being used for urban land cover mapping (Gamba et al., 2011).

2.1.2 Urban Extent Extraction

Accurate information on the extent of urban areas and their changes target a variety of applications, e. g. urban growth monitoring, natural resources management, transportation development and environmental impact analyses (Weng et al. 2014a). Remote sensing has been used for a long time for urban extent mapping in terms of the detection of man-made features and sealed surfaces (Ridd, 1995). Optical (Schneider et al. 2009; Pesaresi et al., 2013), SAR (Gamba et al., 2011; Esch et al., 2013; Ban et al., 2015) and thermal infrared sensors (Matson et al., 1978) have been
used to in observing changes in extent of urban areas. A global map of urban extents has recently been produced recently by Zhou et al. (2015) based on DMSP/OLS nightlights data. Advances in global urban land cover mapping approaches are demonstrated in the study of Ban et al. (2015) who developed a method to efficiently extract urban areas from SAR data at 30m spatial resolutions based on spatial indices and Co-occurrence Matrix (GLCM) texture features at the example of 10 cities with very promising results. This important contribution suggests the further use of SAR data for global mapping applications. Another approach of mapping urban areas at a global scale is the study of Pesaresi et al. (2013) that present a framework for processing high- and very-high-resolution earth observation data for mapping of a global human settlement layer. Esch et al. (2013) proposed a fully automated processing chain that generates urban masks from very-high-resolution SAR data for the delineation of urban settlements. Urban extent mapping at global scales classifies the underlying land cover in either urban or non-urban or percentage of urban land cover at medium to coarse resolutions. This can be considered suitable if monitoring of urban extent changes is aspired. In order to evaluate urban growth patterns in a more qualitative way, the derivation of more detailed urban classes is suggested, i.e. the separation into different built-up categories at higher spatial resolutions.

2.1.3 Urban Land Cover Mapping

One application domain of remote sensing is urban land cover mapping as discussed in Ban et al., (2014), Gamba et al. (2014) or Gamba and Herold (2009). For a comprehensive overview of basic concepts, methodologies and case studies of remote sensing in urban environments, see Weng and Quattrochi (2006). Land cover mapping in complex urban environments is a challenge for several reasons as identified by Ban et al. (2010); Niu and Ban (2010) and Griffiths et al., 2010. The mixture of natural and man-made objects and their functionalities are not easy to separate. Especially in complex urban environments, the distinction between different built-up area classes, e.g. high density built-up areas (HDB), low density built-up areas (LDB), industrial, commercial or high-rise at small scale is a challenge. Another critical issue in urban areas concerns the spatial resolution.

Urban land cover mapping with medium-resolution spaceborne remote sensing data has been performed numerous times throughout the past years predominately at local and metropolitan scales. Many studies are based on Landsat data (e.g. Yang et al., 2003; Lo and Choi, 2004; Lee and
Lathrop, 2006; Furberg and Ban, 2012; Chen et al., 2015; Poursanidis et al., 2015; Zhang et al., 2015) that is very well suited for detecting changes over time due to the large image archive. SPOT data has as another medium-resolution image source with 20m resolutions also been often used in this context (Quarmby and Cushnie, 1989, Zhang and Foody, 1998; Furberg and Ban, 2013; Jebur et al., 2014, Tehrany et al., 2014). High-resolution optical data is an excellent data source for detailed urban land cover mapping as the studies of Myint et al. (2011), Mathieu et al. (2007a and 2007b) and Qian et al. (2015a and 2015b) have demonstrated. Such datasets are however not extensively used, most likely because of their commercial nature. Data in higher spatial resolutions are however considered advantageous for the discrimination of urban feature, e.g. for the detection of impervious surfaces, that are otherwise aggregated in mixed pixels (Hu and Weng, 2013). One data source that is underrepresented for urban land cover mapping is hyperspectral data that could prove valuable for the discrimination of different urban features and vegetation types (Herold et al. 2003a; Gamba et al. 2006).

Remote sensing based urban land cover mapping over the study area of Stockholm has been performed, by e.g. Kolehmainen and Ban (2008) who investigated three change detection methods to identify newly built-up urban areas from 1986 to 2004 based on SPOT image analyses. Furberg and Ban (2009) also analysed urban growth in the Stockholm municipality with 4 SPOT images dating from 1986 to 2008 and found an increasingly fragmented landscape. Analyses of further regional development trends in Stockholm were proposed in the study. Substantial urbanization in Stockholm from 1986 to 2006 and the impact of urban growth on the environment by indicators derived from remotely sensed and environmental data has recently been investigated by Furberg and Ban (2013).

Despite the challenges of SAR image interpretation in urban areas, speckle in SAR data and layover effects in urban areas, SAR data has been proven successful in several studies, e.g. Niu and Ban (2013 and 2015), Gamba et al. (2011) or Hu and Ban (2012). Through the combined use of optical and SAR data, increased classification accuracies can be achieved through the complimentary information each sensor provides. SAR/optical data fusion approaches were investigated by Ban et al. (2010) where the fusion of Quickbird multispectral and RADARSAT SAR data was performed for urban land cover mapping in the rural–urban fringe of the Greater Toronto Area. The presented object-based and knowledge-based
A classification approach was found effective in extracting urban land-cover classes. Another study by Ban et al. (2014) present a comprehensive review on the fusion of SAR and optical data for urban land cover mapping and change detection where state-of-the-art fusion and change detection methods are presented. Griffiths et al. (2010) integrate SAR data into multitemporal Landsat series to map urban growth in the Dhaka megacity region in Bangladesh followed by post-classification change detection. Another study that demonstrates the combined use of optical and SAR data is the work of Zhu et al. (2012) where PALSAR data was combined with Landsat ETM+ data for the classification of 17 urban and peri-urban land cover classes in the Greater Boston Area. The results demonstrate the value of combining multitemporal Landsat imagery with PALSAR data, and texture variables.

The following overview presents the most important recent works in urbanization in China and the effects on different aspects of the environment, predominately performed on multispectral data. Studies that consider China at the country level are named first before reference is given to region-specific and local studies. Early efforts of monitoring urbanization in China by remote sensing were made by Ji et al. (2001) where the speed of urban expansion in 100 municipalities was investigated. Ban et al. (2012) summarize satellite monitoring of urbanization in China for sustainable development. Wang et al. (2012b) investigated urban expansion for the whole of China for 1990, 2000 and 2010 where it could be found that urban areas increased exponentially more than twice. Similar to the findings in this thesis, urban expansion is found occurring mainly at the expense of cropland. Urban expansion proceeded faster in the second decade. Liu et al. (2012) analysed regional differences of urban expansion in China from the late 1980s to 2008 at a 1 km resolution at provincial, regional and natural scales and found steadily increasing urban areas. Largest increases could be observed from 2000 to 2008. The changes in surface cover greenness in China were analysed by Liu and Gong (2012) from 2000 to 2010. In addition to urbanization monitoring using multispectral data, SAR data have also been evaluated and used for urban land cover mapping and change detection in China (Ban and Yousif, 2012; Gamba and Aldrighi, 2012; Ban and Jacob, 2013; Yousif and Ban, 2013).

In a huge effort, Wang et al. (2012b) mapped all urban built-up areas in China with Landsat TM/ETM+ data for 1990, 2000 and 2010 and found that urban areas have increased exponentially more than twice over the
past 20 years. The increase from 2000 to 2010 was double as high as from 1990 to 2010. A summary of optical remote sensing capabilities and efforts in monitoring China’s environmental changes not exclusively limited to the effects of urbanization but generally was performed by Gong et al. (2012). Driving forces, environmental change, materials transport and transformation, concentration and abundance change, exposure and infection change of human and ecosystems and the resulting impacts were categorized. Furthermore, the potential of remotely monitoring these changes was assessed and studies on environmental change efforts over China with remote sensing reviewed. The question of food security and soil protection due to rapid urbanization was discussed by Chen (2007). A comprehensive evaluation of China’s urbanization and effects on both resources and the environment was performed by Chen et al. (2010). Profound urbanization effects on resources, energy and an increased pressure on the environment could be reported. The impact of urbanization on regional climate in Jing-Jin-Ji, the Pearl River Delta and Yangtze River Delta was analysed by Wang et al. (2012a). Spatial and temporal changes on surface air temperature, heat stress index, surface energy budget and precipitation due to urbanization could be confirmed. Chen et al. (2013) investigated the development of urbanization and economic growth in China from 1960 to 2010. Their main findings were that China’s urbanization process has progressed faster than the economic growth since 2004. Chan and Shimou (1999) assess two issues having affected Chinese urbanization since the late 1970s. Firstly, the relationship between economic development and the protection of arable land is investigated and secondly, the quest for coordinated development in both rural and urban areas is discussed. Deng et al. (2008) investigate the driving forces and extent of urban expansion in China from the late 1980s to 2000 by analysis of remote sensing and socioeconomic data. The negative effects on health as a result of the transition from a rural to an urban society are summarized in Gong et al. (2012). The impact of urbanization in terms of changes in ES was investigated in e.g. Zhao et al. (2004), Wang et al. (2006), Hu et al. (2008), Li et al. (2010 and 2011) and Liu et al. (2011).

Studies of urban expansion and changing landscape patterns in the Pearl River Delta were performed by e.g. Li and Yeh (1998 and 2004), Lin (2001), Sui and Zeng (2001), Seto et al. (2002), Seto and Fragkias (2005), Yu and Ng (2007) or Güneralp and Seto (2008). Further urbanization studies in Beijing and in the Jing-Jin-Ji region were carried out by e.g. Deng and Huang (2004), Tan et al. (2005) or Guo et al. (2009). A recent study by Qian et al. (2015b) investigated the dynamics of greenspace
development in Beijing with high-resolution SPOT and ALOS data and found increases in a dynamically developing urban green structure from 2005 to 2009. High-resolution data was able to capture the dynamics of green space variations. Ban and Yousif (2012) and Yousif and Ban (2013) investigated effective urban change detection methods in rapidly growing urban environments such as Beijing and Shanghai. The Yangtze River Delta was analysed in terms of landscape and urban pattern changes, urban growth and its effects upon the environment by e.g. Xie et al. (2006), Deng et al. (2009), Hu et al. (2009a) or Kim and Rowe (2012). There are many LULC mapping studies based on remote sensing data for related to urban land cover change and ecological applications in Shanghai, most of all at the metropolitan and regional scale. Some studies analyse effects of local climate changes and urban heat island phenomena (Jin et al., 2011; Zhang and Ban, 2011), urban land expansion and their implications (Zhang et al., 2009; Zhang and Ban, 2010; Yue et al., 2014), urban and landscape pattern analyses (Han et al., 2009; Dai et al., 2010) or ecosystem service assessments (Zhao et al., 2004 and 2005; Haas et al., 2014; Haas and Ban, 2013).

2.1.4 Remote Sensing of Urban Climate

Urban areas influence the local microclimate in several ways, e.g. by air pollution, through particulate matter, altered wind speeds and directions, heat stress, suppressed or truncated succession of urban vegetation or changes in surface ozone concentrations. These negative effects have been identified as most striking in megacities (Baldasano et al. 2003) where it is pointed out that comprehensive solutions to tackle the problem are needed. Well-established and reliable practices in determining surface temperatures exist, i.e. through thermal remote sensing. The thermal sensor aboard satellites is able to capture the heat that is emitted from different surface features. Higher temperatures are recorded over sealed and built-up surfaces than in green and blue areas. Many studies estimate land surface temperature from medium-resolution Landsat data since the spatial resolution of Landsat’s thermal sensor is higher than e.g. from MODIS or NOAA-AVHRR and because the Landsat archive provides an excellent data source for long-term temperature observations since the early 1980s. Data from MODIS and NOAA-AVHRR are however valuable due to their high temporal resolution of up to twice a day. They have been successfully used in land surface temperature retrieval, e.g. NOAA-AVHRR (Klok et al., 2012) and TERRA-MODIS (Keramitsoglou et al., 2011; Hung et al., 2006). The latter study investigates the urban heat island effect in 18 megacities in Asia, including Beijing. The well-known
urban heat island effect describes the fact that temperature in urban areas are often higher than surface temperatures in surrounding suburban and rural areas that can lead to serious impacts on the economic and social system of cities (Akbari et al., 2016). One study that assesses the impact of urban expansion on the thermal environment of peri-urban areas using Landsat data was performed by Polydoros and Cartalis (2015). Using earth observation data for the measurement of temperatures over urban areas is advantageous in addition to ground-station based measurements since a continuous surface coverage is achieved at high temporal resolutions (Stathopoulou and Cartalis, 2007). An overview of satellite-derived products for the characterization of the urban thermal environment is given in Keramitsoglou et al. (2012). Apart from temperature measurements, satellite remote sensing can also give indications about particulate matter and air quality over cities (Gupta et al., 2006).

2.1.5 Remote Sensing of Urban Environment and Ecosystem Services

Direct remote sensing of ES is challenging as they are often intangible and are rather defined through ecosystem functions and processes that involve a temporal component, human beneficiaries and that they can only partly be attributed to land use and land cover. Especially biodiversity and habitat functions are difficult to sense remotely since they are very much dependent on species composition that is predominately determined through in-situ inventories and ground data collection (Gillespie et al., 2008) but even a considerable contribution of remote sensing to habitat mapping and their observation over time is postulated by Corbane et al. (2015). Feng et al. (2010) found that remote sensing data can also be used in three different ways for ecosystem service assessments (direct monitoring, indirect monitoring and in combination with ecosystem models) but it is also mentioned, that remote sensing data alone is not sufficient for an accurate assessment of ES, but that good in-situ measurements are additionally needed. The ways in which remote sensing data can contribute to ecosystem service studies are highlighted and summarized in the works of Ayano et al. (2012), Andrew et al. (2014) and de Araujo Barbosa et al. (2015) indicating a huge potential and growing interest in integrating remotely sensed data into ecosystem service studies and assessments. All these reviews fall however short of urban ES as a new application domain. Most ecosystem service studies that rely on remotely sensed data are performed at the landscape level, either determining actual values for a particular region, or investigating land use/land cover and the thus inherent ecosystem service value changes over time (Haas and Ban, 2013). Studies that derive detailed ecosystem
service relevant information with remote sensing in and for urban areas are scarce (Mathieu et al., 2007a, 2007b; Lakes and Kim, 2012; Haas et al., 2014) and generally lack the integration of spatio-temporal components or only target particular services or functions.

The general need for, usefulness and application of spaceborne remote sensing for numerous ecological applications and the observation of habitat loss or climate change is described in Kerr and Ostrovsky (2003). Three main areas of remote sensing in ecology are summarized by Aplin (2005). Firstly, simple land cover classification is useful for straightforward identification of vegetation types and derivation of habitats (Thomas et al., 2003). Secondly it is stated that integrated ecosystem measurements are invaluable in providing estimates of ecosystem function over large areas and that the integration of biophysical parameters such as leaf area index, net primary productivity or normalized difference vegetation indices derived by remote sensing is a valuable asset. For this and many more ecological applications, both active and passive spaceborne data has proven satisfactory (Lefsky et al., 2002). Many studies that make use of remote sensing data for ecological and ecosystem analyses mostly rely on land use/land cover classifications that serve as proxies for whole entities of ecosystems (Cohen and Goward, 2004; Zhao et al., 2004; Wang et al., 2006). Newton et al. (2009) comprehensively reviewed the use of remote sensing in the application domain of landscape ecology. It could be found that most of the studies integrate Landsat data and aerial photographs, demonstrating both the importance of multispectral data but also the need for high-resolution data that can contribute to biodiversity studies in particular. The direct measurement of biodiversity in terms of detection and discrimination of species assemblages, individual organisms or ecological communities can be achieved with sufficiently spatially and spectrally resolved data. Hedblom and Mörtberg (2011) provide an extensive review of remote sensing approaches to map and monitor biodiversity. Another result from the study of Newton (2009) was that surprisingly few studies employed very high-resolution digital image data from spaceborne platforms, such as Quickbird and IKONOS. These are however believed to be of particular value (Groom et al., 2006). Not only high-resolution data has been emphasized but also the potential of satellite remote sensing to aid in assessing spatio-temporal changes in the distribution of abiotic conditions (e.g. temperature, rainfall) and in the distribution, structure, composition and functioning of ecosystems Pettorelli et al. (2014). A recent review by Rose et al. (2015) summarizes the capabilities remote sensing has in addressing ten questions regarding
conservation biology, amongst others targeting species distributions and abundance, ecosystem resilience and response, ecosystem services or climate change monitoring. From the idea of regarding urban systems as ecological entities, Ridd (1995) tried to develop a standard for parameterizing the biophysical composition of urban environments. The approach of adapting a V-I-S (vegetation-impervious surface-soil) model within urban areas can be considered to be one of the first comprehensive attempts to systematically integrate remotely sensed data into urban ecological investigations. Regarding impervious surfaces as threats to ES such as water retention, flood risk increase, the impediment of biochemical soil-atmosphere exchange or as a non-point source pollution as a threat to water quality in urban areas, Weng (2012) provides a comprehensive review on direct and indirect remote sensing techniques for determination of impervious surfaces.

The importance of sustainable and ecological development in China and the implications for policies for ES are discussed in Liu et al. (2008) and the particular potential of high-resolution remote sensing data (i.e. Quickbird and IKONOS) is emphasized. Already Wulder et al. (2004) both emphasize the desire for ecosystem structure, diversity and function at finer spatial and temporal scales in general and argue that remote sensing offers advantageous data collection possibilities for ecological studies. Studies investigating the potential of high-resolution images for detection of urban ecosystems, their functions and services are rare and just emerging. The “Biotope Area Ratio” for assessment and management of urban ES is determined by classification of high-resolution multispectral data (IKONOS and Quickbird) by Lakes and Kim (2012). Mathieu et al. (2007b) use very high-resolution satellite imagery to map domestic gardens by applying image segmentation and an object-based classification strategy to IKONOS data. A similar strategy has also been successfully applied for mapping large-scale vegetation communities in urban areas (Mathieu et al., 2007a). Qian et al. (2015b) used high-resolution data to quantify the spatiotemporal urban green spaces (UGS) pattern in central Beijing and found it effective and important to aid capturing small scale changes in green structures not being captured by medium-resolution images. Li et al. (2015) compared the economic benefits of UGS estimated with NDVI at high-resolution data (0.6m) advantageous. Another study that investigated the use of high-resolution data (GeoEye-1) for mapping of ecosystem service supply and demands was recently performed with reliable results by Haas et al. (2014). Current bottlenecks in using high-resolution image analysis are their commercial
acquisition and the computational requirements to quickly and efficiently process large areas. However, with the simultaneous development of more reliable and faster analytical tools and freely accessible remotely sensed data at higher resolutions, remote sensing technology can make a great contribution in addressing the challenges of future urbanization growth through multiscale analyses of urban change patterns.

Several of the abovementioned studies have demonstrated the usefulness and potential of earth observation data in deriving various biophysical and environmentally related parameters. Most of the studies rely on medium-resolution multispectral data and only recent studies make use of high-resolution data for urban green and blue space classifications. There is however a consensus that such data is valuable for detailed urban mapping and analysis of urban ecosystems and their services. There are many studies that are devoted to mapping particular aspects of the urban environment but no overarching recommendations on the type of data and required sensor specifications that are best suited for mapping of urban ecological space.

The developments of urban remote sensing in the last years include e.g. the mapping of urban areas at global levels at medium to high-resolutions, a transition from pixel- to object-based image analyses and automatic extraction and mapping of urban extents and footprints. These trends have only partly influenced the field of monitoring and mapping remote sensing of the urban eco-space. ES, resilience and sustainability have become hot topics in the last years, yet there are only few studies that benefit from the abovementioned trends. In-situ data still plays an important role in collection of environmental data. As the abovementioned studies suggest, high-resolution spaceborne data has just recently become an interesting data source for ecosystem relevant analysis. Studies in the field of remote sensing for environmental applications, e.g. ecosystem services in and over urban areas, SAR and multispectral data fusion or hyperspectral remote sensing are scarce and their exploration could lead to more reliable and efficient information retrieval. The integration of high-resolution data and object-based classification approaches have thus been pursued in this thesis since they are believed to, in combination with spatial metrics, contribute to the further development of urban ecological concepts such as ES.
2.2 Indicators of Environmental Impact

Alongside three urbanization indices presented at the end of this section, two well-known indicators to quantify landscape changes as a result of urban growth were chosen in this study as ES and LM.

The ecology of cities can be described as both interdisciplinary and multiscale, incorporating both human and ecological relations of urban ecosystems (Pickett et al., 2008). There is currently a lack of standardized and comparable evaluation methods to effectively and efficiently analyse and monitor ecological functions and conditions in urban environments despite the popularity of integrating ecological concepts into current and future urban and community planning projects. Especially in densely populated, fast growing cities and regions, ecosystem conservation issues become crucial and remote sensing is believed to have the potential to greatly contribute to urban ecological studies where fieldwork is time consuming, resource intensive and where there is currently a lack of well-established standardized methods to evaluate the quantity and quality of urban eco-space (Feng et al., 2010). Cities are through their metabolism in form of flows and storage of energy and materials highly dependent on functioning ecosystems and ES of urban and peri-urban landscapes and surrounding regions (Mörberg et al., 2012) and there is a growing concern about the consequences of biodiversity loss for ecosystem functioning, for the provision of ES and for human well-being (Balvanera et al., 2006). Urban expansion and global land cover change patterns are known to pose a threat to biodiversity and thus ES (Grimm et al., 2008; McKinney, 2008; Seto et al., 2012; Güneralp and Seto, 2013) and the consequences of current and future urbanization effects for biodiversity conservation remain poorly understood (McDonald et al., 2008). Biodiversity is a key component in urban ecology and measuring it from space is challenging. Species richness is considered the most common indicator of biodiversity in urban ecosystems (McKinney, 2002) and is often measured through environmental variables or indices (Turner et al., 2003) and expressed through the occurrence and diversity of avifauna (Marzluff, 2005; Colding and Folke, 2009; Aronson et al., 2014). McKinney (2008) provides an extensive review of studies on the effects of urbanization on species richness by different taxonomic groups. Luck (2007) examined the relationship between human population density and biodiversity. The most convincing indication of the negative impact of increasing human population densities was a significant negative population correlation between density and the size of protected areas. Werner (2011) discusses
the difficulty of generally relating ecology and biological diversity of urban areas that differ fundamentally in aspects such as population density, built-up area shape, pattern and structure, hydrological and climatological differences, varying input of nutrient sources, pollutants, species composition etc. and that multiscale and multivariate analysis are needed.

In the light of past and present urbanization trends, timely and accurate information on the state, accessibility, distribution and supply of UGS plays an increasingly important role for sustainable urban development, conservation of ecosystem functionality and human well-being (Mörtberg et al., 2012). Urban vegetation is essential for urban ecosystems and for ES and can be determined by well-established methods in remote sensing. Indices can be used to quantify and describe biophysical properties of vegetation, e.g. leaf area index (Chen and Cihlar, 1996), net primary productivity (Field et al., 1995), or photosynthetically active radiation (Chen, 1996). The techniques and methods to derive these indices are well known and established and rely predominately on remote sensing of multispectral data. Urban green and blue structures in urban areas differ fundamentally from those in natural environments since they are influenced by anthropogenic factors such as population density, built-up area shape, pattern and structure, hydrological and climatological differences, varying input of nutrient sources, pollutants or species composition.

2.2.1 Ecosystem Services

The original concept of ES originated in the late 1970s (Westman, 1977) where the importance of nature conservation and accounting for the benefits of nature’s services was illustrated. In one of the first well-known definitions by Daily (1997), ES are defined as “the conditions and processes through which natural ecosystems, and the species that make them up, sustain and fulfill human life”. From this initial definition, the concept was further defined and developed to quantify ES for practical applications (Costanza et al., 1997; de Groot et al., 2002; Boyd and Banzhaf, 2007; de Groot et al., 2012; Costanza et al., 2014), LULC modeling (Nelson et al., 2009), urban planning (Gómez-Baggethun and Barton, 2013), regional planning (Frank et al., 2012) and to serve as tools in decision making (Daily et al., 2009; Fisher et al., 2009; TEEB, 2011). Recent international efforts of finding common ground for definition of ecosystems and their services are found in the Millennium Ecosystem Assessment (2005), TEEB (2010) or Haines-Young and Potschin (2012). Ecosystem functions and services described and defined in these efforts
are however not directly applicable to urban areas and a comprehensive scheme is needed. ES are traditionally split into four service categories – provisioning services that describe the material or energy outputs from ecosystems including food, water and other resources, regulating services that control the quality of air and soil or by providing flood and disease control, habitat or supporting services that ensure the maintenance of genetic diversity through habitat provision and cultural services that comprise recreational functions, tourism, aesthetic appreciation and inspiration for culture, art and design, spiritual experiences and a sense of place.

There are numerous approaches to the topic of how to valuate and monetize ES and the issue has been under discussion for a long time (Costanza et al., 1989). There are fundamental differences in how the absence or presence of ES, functions or goods should be monetized with respect to political prerequisites, cultural preferences or what kind of marketing principle a certain society or country follows. The well-known biome concept of Costanza et al. (1997) was developed for a global perspective in US dollars (USD) as monetary unit, primarily with the valuation concept of individuals’ ‘willingness-to-pay’. Several adaptations have been made throughout different studies, for instance through the development of a scheme adapted to the Chinese market (Xie et al., 2008). How to adequately valuate ecosystems is an issue that has not been completely resolved yet. There are well-established methods used in practice but they originate from a particular perspective at a particular scale at a particular point in time. The traditional way of value determination by attributing a fixed sum to each particular ecosystem (e.g. Costanza et al., 1997; de Groot et al., 2002, Xie et al., 2008; de Groot et al., 2012) is problematic for several reasons (Davidson, 2013). As a result of the problems with traditionally used benefit-transfer valuation approaches of ES, relative approaches keep emerging, e.g. through the analysis of supply and demands (Burkhard et al., 2012; Andersson et al., 2015; Baró et al., 2015) and further development of the ecosystem service concept is mirrored in studies that evaluate ecosystem synergies, trade-offs and bundles (Turner et al., 2014; Yang et al., 2015). For more detailed information on the economic development of ES, Gómez-Baggethun et al. (2010) present an extensive historical overview of the development of ES in economic theory and practice.

Initial pioneer work with ES in urban areas was done by Bolund and Hunhammar (1999) who identified six local and direct ES for Stockholm
that contribute to public health and increase the quality of life of urban citizens. Since then, several studies can be found that are devoted to analyses of singular or multiple ES with respect to one or many land use and land cover classes as summarized by Gómez-Baggethun et al. (2013). ES in general differ from more complex urban ES in several ways (Bezáň and Lyttimäki, 2011). A characteristic of urban ecosystems that is often neglected when assessing the quality of urban ecosystems is the fact that they are highly patchy, that the spatial patch distribution is characterized by a high degree of isolation and that edges are often shared with man-made artificial LULC features that may affect patch quality. A shortcoming of most ES approaches in general is the disregard of spatial patch characteristics and their influence on ecosystem service values although many studies emphasize the importance of spatial attributes at patch and landscape level for ecological functions that constitute the basis of ES (Syrbe and Walz, 2012). As Alberti (2005) emphasizes, not only patch interconnectivity but also patch structure in form of size, shape and edge are important for species survival and habitat patches toward the city centre are usually more isolated and managed (McKinney, 2008). Provisional services such as food or timber become less important within the urban boundary, because these services are generated elsewhere. Regulating services and cultural services play a superordinate role. Urban parks e.g. play a key role for the well-being of the urban population through both ecological and social functions that they provide (Chiesura, 2004). The particular importance of urban allotment gardens for socio-ecological ES was emphasized by Barthel et al. (2010). In addition to ecosystem functions present in rural areas, urban ecosystems also provide social functions through shared green spaces for urban dwellers and have a beneficent impact on human health (Tzoulas et al., 2007; Shanahan et al., 2015). Furberg and Ban (2013) stated that green patches have undisputedly a positive effect on city ecosystems (e.g. air quality, cooling effects, habitats and percolation). Apart from urban vegetation classes in form of forests, lawns and parks, some less obvious urban features, e.g. spontaneous roadside vegetation are also able to provide ES. Oberndorfer et al. (2007) e.g. summarize the ecological structures, functions and services of green roofs in urban areas. Even soils of urban, industrial, traffic, mining and military areas are believed to yield ES (Morel et al., 2014). However, the simple quantification and distribution of vegetation throughout a city might not enough to accurately determine urban ES. The distribution, composition, size, shape and relation of UGS towards each other is of importance, e.g. when assessing the dispersal capacity of species or when assessing the closeness of residential areas to green spaces.
that account for a healthier living environment. UGS research is still in its infancy and requires more interdisciplinary research between natural and social sciences as Niemelä (2014) points out. A recent quantitative review of urban ecosystem service assessments in terms of concepts, models and implementations was published by Haase et al. (2014). Here the growing popularity of the concept is monitored and issues, questions and trends of urban ES are discussed. It could be shown that studies dealing with spatio-temporal characteristics of urban ES are still rare but that they are needed.

Adequate ES valuation is challenging when urban ES are considered. Problematic here are amongst others the highly subjective valuation of social ES in ever more culturally diverse societies, competing beneficiary groups in limited urban space and the fact that the effects of anthropogenic activities upon underlying ecological functions are not yet fully understood. Hence, there is to date no well-established valuation scheme for urban ES. However, they are also believed to be influenced by spatio-temporal characteristics, as Martin-López et al. (2009) display. Projected continuous urbanization is believed to have a prominent impact on land use, ES and their beneficiaries which leads to major implications for conserving ES globally (Eigenbrod et al., 2011).

2.2.2 Landscape Metrics
The theoretical and conceptual basis for understanding landscape structure, function and change originated from the field of landscape ecology (Forman and Godron, 1986). Habitat fragmentation is a threat to species and in order to conserve and maintain these habitats, management of entire landscapes and not just of several components is needed. LM are a well-known concept that can be summarized as a range of variables that describe particular aspects of landscape patterns, interactions among patches within a landscape mosaic, and the change of patterns and interactions over time. One issue related to applying the concept of LM is the effect of changing landscape scale on the metrics. An attempt to investigate the relationships between pattern indices and changing landscape scale has been undertaken by Wu et al. (2002), where the responses of several commonly used LM to changing grain size, extent, and the direction of analysis was investigated. The metrics could be grouped into three different behavioural types. A review of scale effects on landscape indices behaviour was conducted by Šimová and Gdulová (2012).
A recent approach to globally describe land fragmentation in a standardized way was developed by Demetriou et al. (2013) that might prove valuable in future fragmentation studies of agricultural land in particular. Land use changes at a regional scale/landscape level are subject of numerous studies. Su et al. (2011) analysed the transformation of agricultural landscapes as a consequence of Chinese urbanization at the example of the Hang-Jia-Hu region with a set of five metrics as proposed by Leitão and Ahern (2002) that relate closely to sustainability. The six metrics that were considered important for a robust land use characterization are percentage of landscape (PLAND), patch density (PD), patch size standard deviation, edge density, area-weighted mean patch fractal dimension and contagion (CONTAG).

At the metropolitan level, Furberg and Ban (2013) used five LM (class area percentage, PD, area-weighted mean shape index, area-weighted mean perimeter to area ratio and connectance) to assess urban land cover changes and environmental impacts in Stockholm over a 20-year period. Furberg and Ban (2012) investigated urban sprawl and potential environmental impacts in the Greater Toronto Area between 1985 and 2005 by analyses of Landsat TM imagery and eight LM. Xie et al. (2006) integrated seven LM to perform an ecological analysis of newly emerging landscape patterns using the example of Suzhou, China. DiBari (2007) evaluated five landscape-level metrics for measuring the effect of urbanization on landscape structure. The findings indicate that all LM provided information about a specific aspect of landscape structure. Luck and Wu (2002) performed a gradient analysis coupled with LM to investigate urbanization in the Phoenix metropolitan region. Their findings showed that the spatial pattern of urbanization could be reliably quantified by the gradient-approach and six metrics (PD, patch richness, mean patch size, patch size coefficient of variation, landscape shape index (LSI) and area-weighted mean shape index). Herold et al. (2003b) used the combined application of remote sensing, seven LM (class area (CA), NP, edge density, largest patch index (LPI), Euclidian mean nearest neighbour distance, area-weighted mean patch fractal dimension and CONTAG) and spatial modelling to analyse urban growth in Santa Barbara, California.

Studies of integrated LM analyses with respect to urban environments are performed by e.g. Sun et al. (2012), where the spatiotemporal change in land use patterns in Lianyungang, China was investigated in a coupled human-environment system. Another recent study that used LM to describe difference in urban land cover development along a spatio-
temporal trajectory based on high-resolution satellite data was performed by Kane et al. (2014). Qi et al. (2014) analysed land use dynamics, land fragmentation, variation of ecosystem service value and underlying driving forces in the context of rapid urbanization in Taizhou city, China. Su et al. (2012) characterized landscape pattern and ES value changes as a result of urbanization in four eco-regions. Similar urbanization processes in terms of population growth, economic development and urban expansion and a loss of ES values could be observed. 10 metrics at the landscape and class level were considered. Seto and Fragkias (2005) investigated the spatiotemporal patterns of urban land use changes in four Chinese cities in the Pearl River Delta that underwent rapid urbanization. It could be found that a spatiotemporal LM analysis is an improvement over simply using only urban growth rates for comprehensive understanding of the shapes and trajectories of urban expansion. Six metrics were used in the study (CA, edge density, area-weighted mean patch fractal dimension, NP, mean patch size and patch size coefficient of variation). Herold et al. (2002) investigated the use of remote sensing and LM as second-order image information to describe structures and quantify changes in urban land uses. An interesting approach of using LM in hedonic price modelling of UGS amenity values at the example of Jinan City, China was developed by Kong et al. (2007). The LM deemed best to describe urban patterns were identified by Alberti (2005) as (PLAND, mean patch size (MPS), CONTAG, Shannon’s Diversity Index (SHDI), Aggregation Index (AI) and percent of like adjacencies (PLADJ). As mentioned in the section above, it is understood that the spatial composition and configuration of the landscape has an impact on functionality and quality of ecosystems that affects their respective services. Until now, very few studies have used LM to describe spatial influence on service provision and only subsets of services or one particular provisional class are considered (Sherrouse et al., 2011; Frank et al., 2012). In the latter interesting approach that attempts to relate LM to ES, Frank et al. (2012) try to enhance the assessment of ES with regard to landscape structural aspects. Although the study focuses on LULC modeling using cellular automata at the example of afforestation scenarios at the landscape level, a reference matrix was developed in order to link various LM to ecosystem functions based on findings in other studies. These functions however do not follow any convention or overarching concept, e.g. the definitions in the Millennium Ecosystem Assessment (2005) and apply to the specific case study which makes the continued use and adoption of the links in other studies difficult. However, the combined use of LM and ES is endorsed by the authors since it offers some advantages in terms of standardized
landscape assessments, fast interpretation of various land cover patterns, and the ability to easily compare scenarios. Furthermore, it is believed that conclusions can be supported on how to optimize regional patterns of land cover types to enhance the provision of ES. Syrbe and Walz (2012) point out another issue related with provision and benefit of ES at the landscape level. There is a clear difference between service providing areas and service benefiting areas that defines the value and potential use of ES. LM can be used to describe and assess the relationships between provisional, connecting and benefiting areas. It is argued however that not all services are suitable for analysis by LM (only the ones with a strong structural component) and that not all LM are of equal importance. For urban areas, e.g. the share of natural vs. artificial landscape elements seems to be among others a promising measure for this analysis. Despite these promising advances, a systematic overview of spatial influence on ecosystem function and service provision is still missing and in order to establish the links between ES and provisional patches, the type and magnitude of spatial influence must be understood. In general, a systematic and comprehensive combination of the landscape metric and ecosystem concept is still missing (Burkhard et al., 2010). Relating LM to ecological processes in general still needs to be investigated and is considered a major research topic in landscape ecology (Wu, 2013).

2.2.3 Urbanization Indices

As simple and straight-forward yet indicative measures of urban growth, urbanization indices have been developed. Liu et al. (2010a) for example created a landscape index that quantifies urban expansion using multi-temporal remotely sensed data. Three indices that can quantify the characteristics of urban land cover change patterns were used in this study. The first index UI is defined as the ratio between urban land and total land at a distinct point in time. The second index compares the amount of urban land of two time steps and is thus a relative measure of urbanization speed. Both indices are calculated as in Hu et al. (2009a) and Liu et al. (2012). The third index that was considered here is a measure that quantifies the development of UGS in comparison to simultaneous urban development to give a more relative indication of the character of urban development.
3 Study Areas and Data Description

3.1 Study Areas

Urbanization and its effects upon the environment were studied at three different spatial scales. A comparison of urban growth in Jing-Jin-Ji, the Yangtze River Delta and the Pearl River Delta was performed at a regional level whereas investigations of urban developments and ecological conditions in China and Europe were demonstrated at metropolitan levels in Stockholm, Shanghai and Beijing. A further study over Shanghai’s centrally located oldest city districts analysed detailed changes in urban patterns at high spatial resolution. The following sections briefly introduce the study areas.

3.1.1 Jing-Jin-Ji, the Yangtze River Delta and the Pearl River Delta

Jing-Jin-Ji, the Yangtze River Delta and the Pearl River Delta are China’s largest urban agglomerations and most important centres of Chinese trade, commerce, manufacture and industry. In 2010, the study areas’ combined population accounted for 27% of the total in China and the regions’ GDP represented 43% of the national GDP. Jing-Jin-Ji is the largest urbanized region in Northern China and includes municipalities of Beijing and Tianjin as well as Hebei Province. The region is rich in natural mineral resources, especially coal, iron and petroleum. The climate is humid continental and characterized by hot, humid summers and cold winters. The study area comprises roughly 185,000 km². The Yangtze River Delta is located at the Chinese East coast bordering the East Chinese Sea covering about 118,000 km². The region is characterized by a marine monsoon subtropical climate with cool dry winters and hot, humid summers and is part of the densely populated Jiangsu province in the north and Zhejiang province in the south with Shanghai municipality centrally located at the coast. The region’s biggest advantages lie in a well-established infrastructural network regarding both high-speed roads and harbour areas (Ma, 2008). The third study area in the regional analysis is the Pearl River Delta, located in southern mainland China adjacent to the South China Sea. It is considered to be one of the country’s chief economic regions and manufacturing centres, even though being considerably smaller than the other two regions. The study area covers about 42,500 km² in Guangdong province, one of the most densely
populated provinces with the largest absolute population in China. Major cities in the region are Guangzhou and Shenzhen and the special administrative region of Hong Kong. The climate is humid subtropical. According to Ma (2008), the region’s biggest advantage and threat at the same time is the extremely high degree of foreign investment.

3.1.2 Shanghai

Shanghai as China’s largest city and financial and economic centre is located in the Yangtze River Delta towards the East Chinese Sea at 31°12′0″ N and 121°30′0″ E, where the climate can be described as humid subtropical. Shanghai had a population of 23.9 million in 2013 and is expected to grow to 30.75 million by 2030 (United Nations, 2014). The urban centre is characterized by a blend of modern high-rise commercial and low-rise residential buildings interspersed with public plazas, religious and historical buildings, tourist attractions and urban green structures such as parks and tree-seamed alleys, complemented by construction sites and industrial and harbour areas. The metropolitan region surrounding the city centre comprises HDB, high-rise, commercial and industrial areas, urban parks, airports and ports and residential areas. The rural-urban fringe is characterized through cropland, villages and strips of rural residential areas and farms. Water occurs in the form of sea, lakes and rivers, aquacultures and both coastal and inland wetlands. Naturally grown forests are scarce and connected tree stands can mostly be found in the city centre in form of managed urban parks.

3.1.3 Stockholm

Stockholm, the capital of Sweden and the largest city in Scandinavia is located at 59°19′46″ N and 18°4′7″ E in the heart of Scandinavia, representing the cultural, economic and political centre of Sweden. The climate is characterized as humid continental. In 2010, the population of Stockholm’s metropolitan area reached 2.05 million inhabitants with the municipality being the largest contributor with around 850,000 people living centrally compared to 1.63 million in 1989. A constant increase in population is expected and by 2030 it is estimated that 2.5 million people will reside in Stockholm’s metropolitan area (Office of Regional Planning, 2010). The Stockholm County boundary limits the study area covering approximately 7,150 km². Major land cover classes in the area are low density and high density built-up areas including industrial and commercial areas, forest, agricultural and open land, UGS in form of parks and water. The region’s characteristic “green wedges” or large forested areas, which are situated relatively close to the city centre provide several of the
Stockholm region’s essential ES. Other important green areas in Stockholm are summarized by Ernstson et al. (2010) as allotment and domestic gardens, urban parks, cemeteries and protected areas, urban forests and golf courses. Closely related to this study, Andersson et al. (2007) focus on three types of Urban Green Spaces (UGS) in Stockholm: cemeteries, city parks and allotment gardens as well-defined green open spaces of comparable age and size but with different organizational structures. They are said to contribute mainly to pollination, seed dispersal and pest regulation services. Apart from these two studies, the concept of urban ES was introduced at the example of Stockholm for the very first time (Bolund and Hunhammar, 1999).

3.1.4 Beijing

Beijing, the capital of China is located at the northern edge of the North China plain and surrounded by Hebei Province at 39°55′ N and 116°23′ E. Beijing is currently China’s second largest and the world’s eighth largest city with a population of 19.5 million in 2014 and the city is expected to grow further up to 25.7 million citizens until 2030, making it the world’s fifth largest city (United Nations, 2014). Thus ES play an important role for many urban residents and visitors. The urban core is characterized through HDB areas in form of the traditional Hutong areas and modern, high-rise complexes with commercial and residential function. LDB areas exist as well in form of newly built aggregations of low-rise single-family homes interspersed with green spaces and in form of public spaces and parks with buildings, footpaths, lawns, trees and water bodies that represent the major ecosystem service provisioning classes in the urban core. There are agricultural areas to be found in the urban fringe that are however gradually replaced by artificial structures.

3.2 Remote Sensing Data

Optical data at various spatial resolutions were used throughout the studies. Tables 1 and 2 below summarize all datasets that were used in this thesis.

<table>
<thead>
<tr>
<th>P#</th>
<th>Mission</th>
<th>Bands used (res.)</th>
<th>Scenes</th>
<th>Date</th>
<th>Study Area</th>
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<td>38</td>
<td>1987-1990</td>
<td>Jing-Jin-Ji, Pearl and Yangtze River Delta</td>
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<tr>
<td>I</td>
<td>HJ-1A/B</td>
<td>CCD</td>
<td>12</td>
<td>2009-2011</td>
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<tr>
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<td></td>
<td>R/NIR/SWIR (30)</td>
<td></td>
<td>Jing-Jin-Ji, Pearl</td>
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<td></td>
<td>Delta</td>
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<tr>
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<td>TM/ETM+</td>
<td>12</td>
<td>1989-2010</td>
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<td></td>
<td></td>
<td>R/NIR/SWIR (30)</td>
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<td>Shanghai and</td>
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<td></td>
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<td>pan-sharpened 0.82m</td>
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<td>R/NIR/SWIR (20m)</td>
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<td>Beijing</td>
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**Landsat TM/ETM+**

Landsat satellites have delivered remotely sensed data since 1972 and a large repository of freely accessible data exists enabling multi-temporal and land cover change studies for various applications. Spatial resolutions have increased leading to new application domains. In this research, Landsat-5 TM and Landsat-7 ETM+ were used.

**HJ-1A/B**

HJ-1A/B can be considered the Chinese earth observation equivalent to the Landsat satellite family. The two CCD cameras record data in the spectral range of 430 to 900 nm at 30m spatial resolutions. Spatial and spectral resolutions are similar to those of Landsat which enables direct comparisons to Landsat-based studies. The scenes are however much larger in extent which supports more effective land cover mapping at regional scales.

**GeoEye-1/IKONOS**

Two scenes each from the GeoEye-1 and IKONOS sensors are the only high-resolution and commercial images that were used in the thesis. GeoEye-1 that was launched in 2008 provides 0.46m ground resolutions in the panchromatic band and 1.84m multispectral resolutions. The multispectral sensor operates at four bands between wavelengths of 450 nm (blue) to 920 nm (NIR) with a swath width of 15.2 km. IKONOS was launched as the first commercially available high-resolution satellite sensor in 1999. It has a multispectral sensor that operates in the visible and NIR and that capture data at 3.2m resolutions. The panchromatic band...
contains data in 0.82m resolution. Its application domain is seen amongst others in urban and rural mapping, mapping of natural resources and of natural disasters, agriculture and forestry.

**Sentinel-2A/B**

ESA’s new Sentinel-2 satellite constellation is designed as the continuation and expansion of the SPOT satellite series. Sentinel-2A was successfully launched on June 23rd, 2015 and the launch of Sentinel-2B is scheduled for the second half of 2016. Sentinel-2 carries a high-resolution multispectral imager (MSI) with 13 spectral bands at wavelengths from 443 nm to 2190 nm with a swath width of 290 km and spatial resolutions of 10m, 20m and 60m. The mission is foremost intended to provide information for agricultural and forestry practices, e.g. through effective yield prediction and applications related to Earth’s vegetation. Satellite images are expected to be used, amongst others to determine various plant indices such as leaf area chlorophyll and water content indexes (Drusch et al., 2012). Other application domains are considered to be land use and land cover change; monitoring coastal and inland waters; risk mapping and disaster mapping. The constellation will circle the globe on a polar, sun-synchronous orbit with a revisit time of 5 days at the equator (Drusch et al., 2012). Figure 3 depicts all 13 Sentinel-2 bands.

![Figure 3 Sentinel-2 MSI spatial resolutions and wavelengths](Source: eoPortal Directory, ESA)

### 3.3 Ancillary Data

One ambition of this thesis is to base the analysis on freely available data to promote further methodological development and foster application of the methods in future studies. Therefore, only freely available ancillary was utilized. Shapefiles were used to clip the images to study regions in terms
of administrative borders. These shapefiles and newly generated ones were further used for post-processing purposes in form of reclassifications under masks. High-resolution Google Earth images were used as basis for the selection of training and validation data in addition to fieldwork.

4 Methodology

Some of the methods that were used in multiple times throughout the papers are only described once. Parameter adaptions and modifications used in the methods are added to the respective method. The flowchart in Figure 4 gives a simplified overview of all major analytical steps. Detailed flowcharts are presented in each paper, respectively.

![Methodology flowchart](image-url)
4.1 Image Processing

4.1.1 Image Pre-processing

Co-registration
Image co-registration was performed in Paper I to co-register the HJ-1A/B scenes to the Landsat scenes using a polynomial approach. Each HJ-1A/B image was co-registered to the Landsat images that are as level 1G products already georeferenced in UTM with an average root-mean-square error of all co-registrations in horizontal and vertical directions of $X = 0.31$ and $Y = 0.27$ pixels, respectively. The data used in Paper II originates from the same Landsat source (GLS) already issued in UTM and does not need to be co-registered. Since accurate geopositioning information is given for the Quickbird and IKONOS scenes they did not need to be co-registered. The same holds true for the Landsat TM and Sentinel-2 data in Paper IV.

Mosaicking
Image mosaicking was performed when the study area exceeded the spatial extent of the acquired scenes, which was the case in Paper I, II and III. Mosaicking was done based on neighbourhood colour balancing that evens out the contrasts between images to reduce the visible differences between the image seams and to produce a visually appealing mosaic. Neighbourhood colour balancing determines a set of coefficients that modify each image pixel based on the pixel values of the intersecting pixels. In Paper I, the mosaicking was done by selecting one central scene for each mosaic that contained as many land cover features as possible and that yielded the best atmospheric conditions (minimum haze and cloud cover). Consecutively, images were added one by one, each being matched to the growing mosaic. Mosaicking of the data sets used in Paper III was performed with the same technique but was less time-consuming since only two images per decade needed to be mosaicked. No adjustments were needed for the mosaics in Paper III, since the scenes originated from the same sensor on the same date with the same atmospheric conditions.

Clipping
All data was then clipped to the respective study areas through ancillary vector data. Clipping extents were either defined by the spatial extent of the scenes or by administrative boundaries.
Pan-sharpening

In Paper III, the high-resolution data was pan-sharpened to 0.5m resolution (GeoEye-1) and 0.8m resolution (IKONOS) with the least squares statistical based automatic fusion approach developed by Zhang (2002) that maximises detail increase while minimizing colour distortion.

Scaling

The images that were used in the object-oriented classification approach with KTH-SEG were linearly scaled to 8-bit radiometric resolution, since previous research showed that 8-bit data produced better segmentation results (Ban and Jacob, 2013). This also decreased the computational effort and makes the approach more time-efficient.

4.1.2 Texture Analysis with Grey-Level-Co-occurrence-Matrix

Haralick et al. (1973) proposed 14 GLCM measures as second-order statistical texture features that can be used as a measure of the relationships of digital brightness values between neighbouring pixels in an image. The advantageous use of GLCM features integration in LULC classifications has been shown in general (Li et al., 2013) and in urban environments in particular (Herold et al. 2003c; Furberg and Ban, 2012; Gamba and Aldrighi, 2012). The integration of GLCM can increase classification accuracies as has been proven useful in several studies, e.g. in the Random Forest (RF) approach by Rodríguez-Galiano et al. (2012), in a Support Vector Machine (SVM) classification (Hu and Ban, 2008) or in a classification by artificial neural networks (Ban and Wu, 2005) and is therefore suggested in the study. Research over the years has however shown that not all features are equally important and that they are partly redundant. Referring to the studies of Baraldi and Parmiggiani (1995), Clausi (2002) and Huang et al. (2009), the following six measures and/or a combination of them was identified as meaningful: contrast, correlation, entropy, homogeneity, mean and variance. Three further parameters (window filter size, grey level quantization and angular specifications) are important for GLCM calculation and their settings described are in the methodology section.

GLCM texture features were integrated in the SVM classification in Paper II. From the originally 14 GLCM features proposed by Haralick et al. (1973), variance (VAR) was calculated on Landsat bands 4 and 5 in this research. Too large window sizes however tend to smoothen out smaller, often linear features that should be kept in the classification (i.e. roads).
The optimum window filter size varies from study to study and from underlying spatial resolutions. Best results for land cover classifications could be achieved with window sizes from 5x5, e.g. Hu et al. (2009b) up to 13x13 (Treitz et al., 1996). Highest classification accuracies could be achieved for urban features with a window size of 11x11 by Wu et al. (2004) that was chosen in the study. Since no angular specifications (in what direction the GLCM features are to be calculated) are considered relevant as in most other studies (Du et al. 2009), no discrete cardinal orientation is required.

4.1.3 Tasseled Cap Transformations
The Tasseled Cap (TC) concept was first developed by Kauth and Thomas (1976) and has since then been discussed and applied in numerous studies (Crist and Kauth, 1986; Huang et al., 2002; Zhang and Ban, 2010). The transformation does not only reduce the data volume but also represents the initial Landsat data in a better interpretable fashion by creating three distinct bands that express greenness, brightness and wetness of the scene. TC transformations were considered in the classification because they are found to improve the delineation of wetlands in the regional study which is otherwise difficult (Baker et al., 2007). The spectral response in multispectral data of wetlands is very different according to the wetland type. Wetlands can therefore be easily confused with water, aquaculture or agriculture. The TC concept has also been proven valuable in land cover mapping (Wu, 2004), detection of impervious surfaces (Yuan et al., 2008), urban environments (Deng and Wu, 2012) and change detection applications (Ridd and Liu, 1998). For instance, Seto et al. (2002) successfully compared change vectors of TC brightness, greenness and wetness of Landsat TM data from 1988 and 1996 to monitor land use change in the PRD. Chen et al. (2012) studied and evaluated TC transformation consistencies on HJ-1A/B data. In order to increase the separabilities between land cover classes (mostly wetlands), TC transformations were performed in Paper I resulting in distinctive brightness, greenness and wetness bands. The TC transformation parameters used to transform the HJ-1A/B mosaics originate from Chen et al. (2012).

4.1.4 Image Segmentation
In recent years and with increasing spatial resolutions, object-based image analysis (OBIA) methods have enjoyed increased popularity since they are considered advantageous over traditional pixel-based approaches. Blaschke (2010) provides a comprehensive literature review and summary
of studies that use object-based image analysis methods. Segmentation and classification usually results in superior classification accuracies compared to pixel-based approaches. Especially in terms of urban feature discrimination, object-based approaches have shown superior classification capabilities. Shackelford and Davis (2003) present an object-based approach for urban land cover classification from IKONOS images with a fuzzy pixel/object approach over dense urban areas resulting in high classification accuracies. Especially the distinction between buildings and other impervious surfaces could be improved considerably by object-based image segmentation. Another example of successful application of image segmentation is the works of Mathieu et al. (2007a, 2007b). Other examples where object-based classification approaches were successfully implemented for urban land cover mapping are the studies of Ban et al. (2010), Myint et al. (2011) and Niu and Ban (2013) but their suitability for classification of ecologically relevant space could also be shown, e.g. through habitat (Corbane et al., 2015) or biotope mapping applications (Tiede et al., 2010).

In this research, image segmentation was performed in Papers III and IV using the KTH-SEG algorithm (Ban and Jacob, 2013). KTH-SEG is an edge-aware region growing and merging algorithm. By creating an edge-no-edge decision layer using an enhanced Canny edge detector, segment growing is divided off-edges and along edges. The homogeneity criteria for both growing and merging are defined by a weighted sum of change in mean and change in standard deviation. Merging is performed using a mutual best neighbour approach, followed by threshold merging. Growing is limited to the minimum segment size and merging to the maximum segment size. The parameters for the segmentations were empirically determined, and are presented in Table 2 below:

<table>
<thead>
<tr>
<th>P#</th>
<th>Canny threshold</th>
<th>segment grow</th>
<th>segment merge</th>
<th>min/max segment size</th>
</tr>
</thead>
<tbody>
<tr>
<td>III</td>
<td>0.02-0.04</td>
<td>0.5/0.5</td>
<td>0.5/0.5</td>
<td>8/500</td>
</tr>
<tr>
<td>IV</td>
<td>Landsat: 0.07-0.14</td>
<td>0.5/0.5</td>
<td>0.5/0.5</td>
<td>2/500</td>
</tr>
<tr>
<td></td>
<td>Sentinel-2A: 0.05-0.1</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

4.2 Classification

Based on literature, trends in classification approaches of remote sensing data, RF and SVM were found to be effective and have hence been used throughout the studies that compose this thesis.
4.2.1 Random Forest Classification

RFs are considered superior classifiers amongst other decision tree approaches. They were developed to improve classification performance and to overcome limitations of existing decision tree classifiers in terms of sensitivity to noise, computational load and the need for parametric statistical modeling of each data source (Benediktsson et al., 2007). Considering classification accuracies, they can be compared to boosting while being computationally less demanding. Additionally, RFs are computationally ‘much lighter and faster than comparable methods’ (Breiman, 2001). Furthermore, RFs are nonparametric, enabling a quick implementation with comparable results. They can handle both high dimensional data and build a large number of trees where the key issue is correlation reduction between the random classification variables leading to low error rates comparable to the Adaboost classifier (Freund and Schapire, 1996). According to Breiman (2001), further advantages of RFs are that they are unexcelled in accuracy among current algorithms which can be run efficiently on large databases. They are robust to outliers and noise and, finally, they can handle thousands of input variables without variable deletion. Benediktsson et al. (2007) present an overview over multiple classifier systems for remote sensing applications and compared their performance. RF were found to perform equally well regarding classification accuracies as bagging or boosting but they were considerably faster. One more advantage of the RF classifier is that it can handle categorical data, unbalanced data as well as data with missing values, which is still not possible with SVMs (Pal, 2005).

The RF classifier was used in Paper I. The implementation was done in the open source Statistical Data Analysis package R 2.15.0 with the CRAN RandomForest Package (Liaw and Wiener, 2002). Apart from the widely known well performances of RF, the classifier was chosen over an SVM approach because of data handling. An SVM classification for the regional comparison was performed but cancelled and discarded due to extremely long classification processing times. The RF classifier grows multiple classification trees. Each tree is grown using a training subset of predictor samples that are chosen at random (in the classification, 500 labelled pixels for each of the 8 land cover classes are chosen sequentially). In training, the RF algorithm creates multiple trees with these random samples by determining the split (for each node) on a subset of input variables (initial TM/ETM+ and HJ-1A/B RGB and NIR bands plus brightness, greenness and wetness). Each tree is grown to the largest possible extent without pruning. 500 trees in total are generated that way. Regarding the
classification of a pixel, each tree in the RF casts a unit vote for the most popular class for each input variable. The final class of the pixel is then determined by majority voting, that means that the pixels are classified by taking the most popular voted class from all the tree predictors in the forest. The law of large numbers ensures convergence. The key to accuracy in the RF classifier is low correlation and bias. Because each tree is only using a portion of the input variables in a RF, the algorithm is considerably lighter than conventional bagging with a comparable tree-type classifier (Benediktsson et al., 2007). In order to avoid misclassifications, sequential one-vs.-all classifications were performed where one class is distinguished from all other classes once at a time. Each land cover type was classified separately in a binary RF classification. Once the delineation of a particular class was satisfactory the classified layer was filtered to remove unwanted singular pixels or small aggregations of misclassified pixels. Based on the filtered layer, a mask was created by removing the correctly classified pixels. The area mask was then used to extract the remaining pixels from the mosaics. The classification order that proved most successful is water, forest, HDB, bare, wetlands and aquaculture. The remaining two classes, LDB and agriculture were separated as a last step in a final RF classification. Once all classes could be correctly extracted, they were mosaicked together. Some obvious misclassifications such as the occurrence of coastal wetlands in HDB areas and built-up areas in wetlands were manually reclassified where they could be detected.

4.2.2 Support Vector Machine Classification

SVM is an effective classifier that originated from the field of machine learning. The classifier is able to distinguish between multi-modal classes within high-dimensional feature spaces (van der Linden et al., 2007). Furthermore, SVM demonstrate the potential of multi-source classifications. Mountrakis et al. (2011) summarized remote sensing applications of SVMs. Their largest advantage over other classifiers in the field of remote sensing lies in their ability to generalize well even with limited training samples. Another advantage is that no prior information on the underlying data distribution is needed and only few training data are required, rendering SVM suitable for different datasets with a low computational cost. The review is concluded by highlighting the advantages and superiority of SVM over other classifying algorithms like self-adaptability, quick learning pace and limited requirements on training sample size. Recently, Qian et al. (2014) compared the performance of different machine learning classifiers on very high-resolution data for
object-based land cover classifications and found SVM and normal Bayes superior over classification and regression tree (CART) and K nearest neighbour classifiers.

SVM classification approaches were chosen in Papers II-IV. SVM classifications in Paper II were performed in ENVI 5.0 and in KTH-SEG in Paper III and IV through an implementation of the java libSVM library (Chang and Lin, 2011). SVM input vectors are non-linearly mapped to a high-dimension feature space where a decision surface (hyperplane) is constructed to distinguish between arbitrary data distributions (Cortes and Vapnik, 1995). A radial basis function (RBF) kernel was used. The data points that lie closest to the hyperplane are called support vectors and are crucial elements of the training set. The kernel function is a function that gives the weights of nearby data points in estimating target classes. The RBF is mathematically defined as shown in Equation 4.1:

\[ K(x_i, x_j) = \exp(-\gamma ||x_i - x_j||^2), \gamma > 0 \]  

(4.1)

where \( \gamma = \) the gamma term in the kernel function for all kernel types except linear

The required parameters were automatically determined through a grid-search approach in KTH-SEG and empirically chosen as \( \gamma = 0.2 \) as the inverse of the number of bands in the input image with a penalty parameter of 100 (default). In every classification, sub-classes were distinguished first before aggregation into final LULC. Table 3 summarizes original and aggregated classes.

<table>
<thead>
<tr>
<th>P#</th>
<th>Approach</th>
<th>Input Features</th>
<th>Initial Classes</th>
<th>Aggregated Classes</th>
</tr>
</thead>
<tbody>
<tr>
<td>II</td>
<td>pixel-based</td>
<td>Landsat: R, NIR, SWIR, GLCM</td>
<td>27</td>
<td>7/8</td>
</tr>
<tr>
<td>III</td>
<td>object-based</td>
<td>IKONOS, GeoEye-1 RGB/NIR (mean/ std. dev.)</td>
<td>11</td>
<td>8</td>
</tr>
<tr>
<td>IV</td>
<td>object-based</td>
<td>Landsat: R, NIR, SWIR S2: VIS, VNIR and SWIR</td>
<td>13</td>
<td>6</td>
</tr>
</tbody>
</table>
4.2.3 Accuracy Assessment

Accuracy assessment was performed in the studies to evaluate the classification result and to identify the type and amount of confusion between classes. Approximately 1,000 and 10,000 pixels were randomly selected and homogeneously distributed across images. Kappa coefficient, overall accuracy (OA), user’s accuracy (UA), producer’s accuracy (PA) and confusion matrices were selected as accuracy measures. Validation sample selection was performed under the premises that all instances of a class were covered in an appropriate amount and that the areas were equally split over the entire study area. The assessments were performed on the final classification after aggregation of subclasses but before post-classification refinements. In paper I, an additional alternative accuracy assessment approach was chosen that describes quality and reliability of the classifications, i.e. allocation and quantity disagreement as suggested by Pontius and Millones (2011).

4.2.4 Post-classification Refinements

Post-classification refinements were undertaken for several reasons, the first one being to correct some obvious misclassifications identified through PA and UA and visual inspection of the classification outcomes under respective masks. Reclassification under urban masks was also performed to establish a differentiation between agricultural land use and urban vegetation classes found in parks and golf courses motivated through further LM and ES analyses. Furthermore, small unwanted aggregations of pixels or single pixels belonging to erroneous land cover classes were filtered out from the classification. This is an important step prior to LM analysis since smallest patches or even single pixels are treated as patches in the calculation of metrics. In order to establish a meaningful relation between patches and their distribution, only real meaningful landscape patches should be considered in the analysis.

4.3 Urban Indices

The first two indices, Urban Land Index (UI) and Urban Expansion Index (UX) as briefly outlined in the methodology section were calculated in Paper I and II. The first index UI is defined as the ratio between urban land and total land at a distinct point in time expressed in percent as follows:

\[ UI = \frac{UL}{TL} \times 100\% \] (4.2)
The UX compares the amount of urban land of two time steps as relative measure of urbanization speed. Is calculated according to Equation 4.3:

\[
UX_t = \frac{UL_{t2} - UL_{t1}}{UL_{t1}} \times 100\% 
\]

where
- \(UL\) = amount of urban land
- \(TL\) = amount of total land

The Urban Green Index (UGI) is calculated additionally in Paper II as the ratio of UGS increase divided by the sum of increases in HDB and LDB areas as shown in Equation 4.4:

\[
UGI = \frac{UGS_{t2} - UGS_{t1}}{(HDB_{t2} + LDB_{t2}) - (HDB_{t1} + LDB_{t1})} \times 100\% 
\]

where
- \(UGS\) = amount of urban green spaces
- \(HDB\) = amount of high density built-up land
- \(LDB\) = amount of low density built-up land

4.4 Landscape Metrics

The evaluation of landscape patterns through LM were performed in Paper I, II and IV. The metrics were calculated with the Fragstats software (4.1/4.2) (McGarigal et al., 2012) and were chosen based on the objective of the papers. The choice of the metrics used in Paper I were motivated by a review of the most commonly used LM in urban and urbanization studies. In Paper II, where the focus is set on investigating metropolitan instead of regional urbanization patterns, a deviating set of metrics was used. Here, the area-weighted mean metrics are used rather than their simple mean equivalents since they provide a landscape-centric perspective of landscape structure. This landscape-centric perspective is best suited to this research since two different landscapes are being studied and compared. The contrast-weighted edge density index (CWED) is used for similar reasons (as opposed to using the total edge contrast index): the CWED standardizes edge to a per unit area basis that facilitates comparison between landscapes of different size. Edge is quantified from the perspective of its functional significance and thus landscapes with the same CWED would be presumed to have the same total magnitude of edge effects. The metrics in Paper IV were chosen based on their capabilities of describing spatial characteristics of ES providing LULC. More detailed information on the metrics used in the studies can be found
in McGarigal and Marks (1995) and McGarigal et al. (2012). The following Table lists all metrics used in the research:

**Table 4.** LM and their application throughout the studies.

<table>
<thead>
<tr>
<th>Paper #</th>
<th>Landscape metric</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>Area-weighted Mean Patch Size (AMPS)</td>
</tr>
<tr>
<td>1</td>
<td>Mean Patch Area (AREA_MN)</td>
</tr>
<tr>
<td>3</td>
<td>Class Area (CA)</td>
</tr>
<tr>
<td>2,3</td>
<td>COHESION</td>
</tr>
<tr>
<td>2</td>
<td>Contagion (CONTAG)</td>
</tr>
<tr>
<td>2,3</td>
<td>Contrast-Weighted Edge Density (CWED)</td>
</tr>
<tr>
<td>1,2</td>
<td>Largest Patch Index (LPI)</td>
</tr>
<tr>
<td>1</td>
<td>Landscape Shape Index (LSI)</td>
</tr>
<tr>
<td>1</td>
<td>Number of Patches (NP)</td>
</tr>
<tr>
<td>2</td>
<td>Patch density (PD)</td>
</tr>
<tr>
<td>1,2,3</td>
<td>Percentage of Landscape (PLAND)</td>
</tr>
<tr>
<td>2</td>
<td>Area-weighted Mean Patch Shape Index (PSI_AM)</td>
</tr>
<tr>
<td>3</td>
<td>Shannon’s Diversity Index (SHDI)</td>
</tr>
<tr>
<td>3</td>
<td>Total Core Area (TCA)</td>
</tr>
</tbody>
</table>

4.5 Ecosystem Services

ES were calculated and evaluated in four different ways. In the comparative study between Stockholm and Shanghai (Paper II) the valuation scheme after Costanza et al. (1997) was used since it is well-established enables global comparisons. For the regional study the valuation scheme particularly designed for a China market after Xie et al. (2008) used. Both approaches multiply the amount of service providing class with a respective fixed value according to the following Equation:

\[ E = \sum_k (A_k \times V_k) \]  \hspace{1cm} (4.5)

where  
- \( E \) = estimated ecosystem service value  
- \( A_k \) = area in hectare of land use category k  
- \( V_k \) = value coefficient for land use category k

ES were determined through expressing their supply and demands in Paper III, partly to avoid the problems inherent in pecuniary schemes and since there is still a lack of a well-established absolute scheme in urban areas. ES supply and demand and the resulting balances were calculated according to the valuation matrices presented in Burkhard et al. (2012). The supply values attributed to each class are defined as the sum of all
ecological integrity, regulating, provisioning and cultural services and mirror the capacities of ecosystems and their functions to supply services. The idea behind quantifying demand values is that human-dominated land cover types usually provide less ES than pristine natural areas. However, in these areas where a large share of the population spends much time (e.g. continuous dense urban fabric and industrial, infrastructural and commercial areas), there is an increased need for the population to benefit from ES. The demand is thus defined with regard to the amount of people that spend time in such areas and the ecosystem functions the land use/land cover classes provide and lack. Both the supply and demand values were first summed up independently before the demand was subtracted from the supply. The resulting budgets were then scaled from 0 to 1 where 0 indicates a high demand of ES and 1 the highest potential of land use/land cover to provide ES. The supply values attributed to each class are defined as the sum of all ecological integrity, regulating, provisioning and cultural services and mirror the capacities of ecosystems and their functions to supply services. Areas that lack the provision of these services are considered neutral or being in service demand based on human interaction, LULC and their anticipated structural design, use and functioning. In order to enable inter-urban comparisons, supply and demand budgets were related to the LULC in the study area by multiplying the area with the attributed budget values per class. An initial integration of the LM concept through area, connectivity, core, diversity, edge and proximity measures in Paper IV. Instead of evaluating LULC classes directly in terms of their spatial attributes, ES bundles were generated according to their underlying LULC’s similar service provision capacities and LM that are used to evaluate spatial influence on service provision. LM were generated for the landscape as a whole and for each land cover class individually. The resulting values were normalized and aggregated for each ecosystem service bundle in 2005 and 2015. The 2015 bundle values were compared to the ones from 2005 as baseline and the changes in percent of service provision were observed. As mentioned earlier and due to difficulties in ecosystem service valuation, only the spatial effects on service provision capacities and their relative changes over time devoid of pecuniary couplings were quantified here.
5 Results and Discussion

The results and discussion section is divided in two major parts. In the first section, the most important results from each study are briefly summarized and discussed. The second part consists of more general discussions. These are less related to the specific outcomes of the studies but rather attempt to discuss the approaches and methods that were applied, developed and combined in this research in an overarching manner, and how the presented works fits into the literature and its contribution to the research topic.

5.1 Results

5.1.1 Classification Results

The classification outcomes and some detailed classification excerpts after post-classification from each study are presented in Figures 5 to 10 alongside a brief discussion of the classification results. A summary of classification accuracies is presented in Table 5 below. For the detailed confusion matrices, reference is given in the respective papers:

Table 5 Summary of overall classification accuracies, Kappa coefficients, amount of classes, classifier and spatial resolutions distributed among Paper I to IV.

<table>
<thead>
<tr>
<th>P#</th>
<th>Study</th>
<th>Res.</th>
<th>Classifier</th>
<th>Overall accuracy</th>
<th>Kappa</th>
<th>Classes</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>Jing-Jin-Ji 1990</td>
<td>30</td>
<td>RF (pixel-based)</td>
<td>88.06</td>
<td>0.86</td>
<td>8</td>
</tr>
<tr>
<td>I</td>
<td>Jing-Jin-Ji 2010</td>
<td>30</td>
<td>RF (pixel-based)</td>
<td>87.94</td>
<td>0.87</td>
<td>8</td>
</tr>
<tr>
<td>I</td>
<td>Pearl River Delta 1990</td>
<td>30</td>
<td>RF (pixel-based)</td>
<td>85.22</td>
<td>0.83</td>
<td>8</td>
</tr>
<tr>
<td>I</td>
<td>Pearl River Delta 2010</td>
<td>30</td>
<td>RF (pixel-based)</td>
<td>87.63</td>
<td>0.86</td>
<td>8</td>
</tr>
<tr>
<td>I</td>
<td>Yangtze River Delta 1990</td>
<td>30</td>
<td>RF (pixel-based)</td>
<td>82.57</td>
<td>0.80</td>
<td>7</td>
</tr>
<tr>
<td>I</td>
<td>Yangtze River Delta 2010</td>
<td>30</td>
<td>RF (pixel-based)</td>
<td>86.13</td>
<td>0.84</td>
<td>7</td>
</tr>
<tr>
<td>II</td>
<td>Shanghai 1989</td>
<td>30</td>
<td>SMV (pixel-based)</td>
<td>88.08</td>
<td>0.86</td>
<td>7</td>
</tr>
<tr>
<td>II</td>
<td>Shanghai 2000</td>
<td>30</td>
<td>SMV (pixel-based)</td>
<td>87.82</td>
<td>0.86</td>
<td>7</td>
</tr>
<tr>
<td>II</td>
<td>Shanghai 2009</td>
<td>30</td>
<td>SMV (pixel-based)</td>
<td>89.36</td>
<td>0.88</td>
<td>7</td>
</tr>
<tr>
<td>II</td>
<td>Stockholm 1989</td>
<td>30</td>
<td>SMV (pixel-based)</td>
<td>90.04</td>
<td>0.88</td>
<td>6</td>
</tr>
<tr>
<td>II</td>
<td>Stockholm 2000</td>
<td>30</td>
<td>SMV (pixel-based)</td>
<td>88.98</td>
<td>0.87</td>
<td>6</td>
</tr>
<tr>
<td>II</td>
<td>Stockholm 2010</td>
<td>30</td>
<td>SMV (pixel-based)</td>
<td>88.22</td>
<td>0.86</td>
<td>6</td>
</tr>
<tr>
<td>III</td>
<td>Shanghai 2000</td>
<td>&lt;1</td>
<td>SVM (object-based)</td>
<td>85.04</td>
<td>0.82</td>
<td>8</td>
</tr>
<tr>
<td>III</td>
<td>Shanghai 2009</td>
<td>&lt;1</td>
<td>SVM (object-based)</td>
<td>84.29</td>
<td>0.84</td>
<td>8</td>
</tr>
</tbody>
</table>
The classification results of the regional analysis (Paper I) are presented in Figures 5 and 6 below. The overall accuracies for all classifications are higher than 80% (kappa > 0.80). The detailed accuracy assessments can be found in Paper I. Water bodies, forest, HDB and agricultural areas could be separated well. Wetlands and aquacultures proved difficult to distinguish in the Yangtze River Delta as their spectral responses are similar for shallow water. LDB areas are confused with HDB or agriculture throughout the study areas, due the fact that LDB areas both contain buildings and adjacent greenspaces.

From the results, an increase in built-up areas, especially HDB is apparent in all classifications. In Jing-Jin-Ji, the largest urban growth can be detected around Beijing, Tianjin and Tangshan predominately at a loss of agricultural areas. The large forested areas located in the north-western part of Hebei province did not change noticeably and bare areas in the north towards Inner Mongolia remained basically unchanged although some new or enlarged urban clusters can be spotted there. Some of the coastal wetlands south of Qinhuangdao disappeared completely and some wetlands east of Tianjin decreased in extent. Construction of new aquacultures in the Bohai Bay can be observed at the cost of coastal waters and wetlands. In the Yangtze River Delta, an increase in built-up areas is even more prominent, particularly in the northern part of Zhejiang and in the southern part of Jiangsu provinces along the axis Changzhou-Wuxi-Suzhou and Shanghai. Similar to Jing-Jin-Ji, no significant changes in inland water bodies and forests can be observed.

<table>
<thead>
<tr>
<th>Year</th>
<th>Area</th>
<th>Method</th>
<th>Overall Accuracy</th>
<th>Kappa</th>
<th>Categories</th>
</tr>
</thead>
<tbody>
<tr>
<td>Beijing</td>
<td>2005</td>
<td>SVM (object-based)</td>
<td>84.76</td>
<td>0.82</td>
<td>6</td>
</tr>
<tr>
<td>Beijing</td>
<td>2015</td>
<td>SVM (object-based)</td>
<td>90.23</td>
<td>0.89</td>
<td>6</td>
</tr>
</tbody>
</table>

60
Figure 5 Classification results from 1990 (left column) and 2010 (right column). Jing-Jin-Ji is shown in the upper row, Yangtze River Delta in the central row and the Pearl River Delta in the lower one (Paper I).
Figure 6 Detailed excerpts and their respective areas in FCC images in the left. The six rows show the following areas in descending order: Beijing 1990, Beijing 2010, Shanghai 1990, Shanghai 2010, Shenzhen 1990 and Shenzhen 2010 (Paper I).
Increases in HDB and LDB areas come also cost of cropland and a distinct loss of coastal wetlands and coastal waters as a result of land-reclamation can be observed in south-east Shanghai. The degradation of natural coastal wetlands took primarily place at the south-eastern shore of Pudong where wetlands were transformed into HDB areas. This effect of urbanization and the design of a completely new part of the city on the eastern side of Huangpu River (Pudong) can best be seen in the detailed overview of Shanghai in Figure 6. Land-reclamation for agricultural use, new aquacultures and HDB areas at the expense of wetlands and water also occurs in the Pearl River Delta, especially along the coast between Shenzhen and Shajingzhen as shown in Figure 6 above or at the example of Hong Kong International Airport. The increase in HDB and LDB areas alongside a decrease in agricultural land and to a certain extent forest in the coastal hinterlands are the most prominent changes in the Pearl River Delta. The largest increases in built-up land can be identified in Shenzhen and Guangzhou. The few coastal wetlands that were present in the 1990s gradually disappeared were nearly completely vanished in 2010. Aquaculture and bare areas in the form of pits, quarries remained unchanged. Generally, it can be observed that the delineation of LDB areas from HDB areas is most problematic with accuracies as low as 50%. The reason for this is the fact that LDB areas consist of multiple features, a combination of green spaces, farms or villas, rural strips of buildings with surrounding farmland or urban parks with historical buildings. The buildings themselves are often treated as separate building blocks and are classified as HDB. Roads that are often narrower than the spatial resolution of 30 meters are also treated as LDB areas since both the actual paved road and the surrounding land cover compose the pixel in consideration. From an ES analysis perspective at regional scale, the confusion between built-up areas is not relevant since no built-up space provides any ES. Further confusions between water, aquaculture and wetlands occur. These classes are difficult to separate due to the fact that all of them contain a major amount of water and apart from rivers, lakes and open water also vegetation. Wetlands are less confused with open water but on the contrary with vegetated fields due to the high proportion of inherent biomass. Crops that are inundated over larger periods of time, e.g. rice, might be treated as wetlands but since they are managed and yield less biodiversity and serve the purpose of food production, they should be denoted as agriculture.
The classified mosaics of the Stockholm/Shanghai metropolitan analyses are presented in Figure 7 below. The overall classification accuracies for all classifications are higher than 85% (kappa >0.85). The detailed accuracy assessments can be found in Paper II. Water, agriculture, UGS, HDB and aquaculture all exceed 90% in class average. The discrimination of wetlands was problematic as they are confused with water bodies and agriculture. There are only few tree-covered areas that were confused with agriculture. LDB areas were hardest to distinguish for the same reasons as mentioned above in Paper I, resulting in accuracies not exceeding 72%.

From the results, two very different urbanization patterns can be observed. The major difference is the increase in HDB and LDB areas in Shanghai while no major visual LULC changes can be discerned from the Stockholm classification. The expansion of HDB areas in Shanghai occurred in the urban-rural fringe where LDB seemed to have developed into HDB areas. This effect is more prominent in the first decade. At the same time, new HDB urban clusters emerged as decentralized
development in the rural hinterland. These new clusters are linked to the urban core through major traffic axes. Further urban development alongside these axes and additional urban cluster growth can be observed in the second decade. As LDB areas were evolving into HDB areas during the first decade, they did seem to grow in-between newly developed HDB areas in the second decade. From 1990 to 2000, a clear change on Chongming Island can be observed, where coastal wetlands transformed into agricultural land and aquacultures. Further land reclamation can be detected in the south-eastern part of Pudong, where coastal wetlands transformed into rural and built-up areas. This development is most prominent from 2000 to 2010. Some UGS present in 1990 were kept while others became fragmented or disappeared completely. On the other hand, a growth in UGS in the urban-rural fringe can be observed, most prominently in the second decade. The most problematic class distinction is the classification of LDB areas for similar reasons as in the regional study. LDB are composed of both buildings and surrounding green spaces and sometimes paved surfaces in addition. The problem is the distinction of both these features together as an entity instead of separating them into HDB (single pixels without vegetation) and agriculture or forest. Furthermore, there is more than one kind of LDB area in Shanghai. Outside the city boundaries, e.g. on Chongming Island, there are rural strips of settlements surrounded by gardens that seam agricultural land. Additionally, single farms with gardens and villages can be found. Within the city boundaries, LDB areas comprise mostly villa areas or lower storey houses surrounded by UGS. The latter type of built-up areas can easily be confused with urban parks that contain historical buildings or single large buildings that serve no residential function but rather express cultural and recreational values and should thus not be considered as LDB areas. There are relatively few forested areas in the study area (less than 1% of land cover) rendering the classification and distinction of these error-prone. Largest misclassifications are observed between forest and agriculture (vegetated fields). Urban forests are considered as UGS and manually reclassified. In the Stockholm classifications there was a slight over-detection of LDB and UGS in the 2000 classification as well as an under-detection of HDB areas. This was mainly attributable to noise in the 2000 image which decreased the spectral differences between these areas. Agricultural areas were slightly under-detected in 1989 and 2010 and forested areas slightly over-detected for these years due to a certain type of bright vegetation that was confused with forest. UGS was also consistently difficult to classify because of its spectral similarity to
agricultural and LDB areas. The use of rural and urban masks helped to improve the classification of UGS somewhat.

The classification result from Paper III is presented in Figure 8 below. The overall classification accuracies for the IKONOS 2000 classification are 84.29% with a kappa coefficient of 0.82 and 85.57% (kappa: 0.84) for the GeoEye 2009 classification, respectively. Only very little confusion between the natural classes green urban, water courses, water bodies and shadows exists. Largest confusions exist between road and railroad network, continuous urban and industrial/commercial classes in both classifications due to their similar spectral responses. Some distinctions can be made from roof spectral responses, but this only helps in anticipating the building type in some cases, e.g. residential or industrial. The confusion with roads and buildings is largest when flat grey roofs are present.

From the results, visual inspection of the classification outcome suggests changes in the urban LULC pattern, however not in terms of additional growth in built-up space as in the other studies since Shanghai’s central districts were already highly urbanized in 2000. Instead, a very different urban pattern change emerges. A prominent increase of green urban sites, both in the form of larger, newly created green patches (parks) and in the form of increased greening alongside roads at the expense of continuous urban fabric can be observed. Mostly, densely built-up low-rise continuous urban blocks with residential function are transformed into urban parks (exemplified and encircled in Figure 9 by the creation of Yanzhong Square.

Figure 8 Classification result (IKONOS 2000 classification left and GeoEye-1 2009 classification right (Paper III)).
but also into high-rise blocks with commercial and residential function interspersed with urban greenery. Industrial areas were mostly present in form of ports in the south of the study area on the north bank on Huangpu River. These areas were under heavy reconstruction in 2009 resulting in a huge construction site for the 2010 World Expo. The reason for the slight increase in industrial and commercial areas can thus be rather found in an increase in high-rise buildings with commercial function since industrial areas seemed to have decreased. With the increase of the commercial/industrial class, a simultaneous decrease in the road- and railroad network has been observed which is considered unrealistic and believed to be a result of confusion between these two and the continuous urban classes in both classifications. Overall, there are very few water bodies in the form managed ponds in urban parks in the study area. Alongside the creation of new parks and greenspaces, the amount of water bodies also slightly increases but still remains very low. On top of the small increase there might be a slight overrepresentation of water bodies in the 2009 image through confusion with shadows. Central Shanghai’s dynamic development is illustrated by the continuous presence of construction sites that shift in location but remain about the same in size and numbers. Construction sites that were present in 2000 predominately turned into parks, green spaces or high-rise residential and commercial complexes whereas construction sites found in the 2009 images nearly exclusively replace very densely built-up low-rise continuous urban areas.
Papers III marks the transition to a relative ES assessment. Hence, the CORINE classification scheme (Bossard et al., 2000) was used in here since it is the basis of the proposed scheme of Burkhard et al. (2012).

The classification results from Paper IV are shown in Figure 10 below. The overall classification accuracy is 84.76% for the 2005 result and 90.23% for the 2015 classification. The detailed classification accuracy assessments can be found in Paper IV.
Well distinguished classes are agriculture, forest and water in 2005 and HDB/LDB areas, agriculture, forest and water in 2015. Some confusion between high density built-up areas and exists however, that is most likely a result of misclassifications of construction sites, e.g. Beijing Capital Airport, that have both the spectral signatures of bare soil (and thus agriculture). Also, roads are confused with other built-up classes. This is partly due to spectral responses similar to those of other built up space and to the fact that narrow linear shape of road segments fall below the spatial resolution of the sensors. Many roads are narrower than the 30m spatial resolution of the 2005 dataset and are thus merged with adjacent land cover in form of mixed pixels that make their distinction difficult and error-prone. The higher spatial resolution in the 2015 image set was advantageous in the detection of roads whose confusions with HDB and LDB areas could be reduced. From the results, visual inspection of the classification outcomes suggest and increase in built-up high density and low density urban areas and urban green spaces at the expense of agricultural land. The expansion of Beijing Capital International Airport in the upper right corner of the study area can be quite clearly seen through the creation of new runways in the east. Newly built-up areas to both sides of the airport are also quite apparent. The development of new urban green spaces is most prominent in the north of the city centre in form of the Olympic Park.

Figure 10 Classification result for Beijing in 2005 (left) and for 2015 (right) (Paper IV).
5.1.2 Urbanization Indices

Table 6 presents the urbanization indices UI and UX and UGI for the regional analysis in Paper I and the comparison between Stockholm and Shanghai in Paper II.

Table 6 Comparison of UI, UX, UGI in Paper I and II.

<table>
<thead>
<tr>
<th>Data set</th>
<th>UI</th>
<th>UX</th>
<th>UGI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jing-Jin-Ji 1990</td>
<td>4.69</td>
<td>140.66</td>
<td></td>
</tr>
<tr>
<td>Jing-Jin-Ji 2010</td>
<td>11.67</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pearl River Delta 1990</td>
<td>11.80</td>
<td>77.70</td>
<td></td>
</tr>
<tr>
<td>Pearl River Delta 2010</td>
<td>20.98</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yangtze River Delta 1990</td>
<td>10.26</td>
<td>100.07</td>
<td></td>
</tr>
<tr>
<td>Yangtze River Delta 2010</td>
<td>20.53</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shanghai89</td>
<td>20.99</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shanghai00</td>
<td>30.48</td>
<td>44.73</td>
<td>54.76</td>
</tr>
<tr>
<td>Shanghai10</td>
<td>47.01</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Stockholm89</td>
<td>11.45</td>
<td>7.04</td>
<td>4.92</td>
</tr>
<tr>
<td>Stockholm00</td>
<td>12.26</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Stockholm10</td>
<td>12.86</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

In Paper I, urban land increased in all study areas. Jing-Jin-Ji and Yangtze River Delta experienced the largest absolute increase in built-up areas with about 12,000 km² in the Yangtze River Delta and in Jing-Jin-Ji, whereas the Pearl River Delta grew only about 4,000 km². This can be explained by the fact that not so much open arable and bare land is available for development due to the large areas of aquaculture (that also increased) and forested mountainous areas that remained unchanged. The relative increase in urban land is largest in Jing-Jin-Ji according to the UX, where urban areas increased by 148%, followed by the Yangtze River Delta where urban areas doubled. The smallest relative increase with approximately 78% growth in urban areas can be observed in the Pearl River Delta. In the metropolitan comparison in Paper II, a constant increase of urban land can be observed over each decade in Shanghai. Urban land increased by ca. 45% from 1990 to 2000 and another 55% from 2000 to 2010. The total increase in built-up areas is about 125% from 1990 to 2010. Urban expansion proceeded slightly faster in the second decade than in the first. Urban growth in Stockholm is as well apparent but at a much slower pace, especially from 2000 to 2010. Urban expansion both in terms of speed and spatial extent occurs predominately from 1989 to 2000. Stockholm’s urban areas expanded with circa 12% of their original extent. Both speed and magnitude of urbanization in Shanghai exceeds the one of Stockholm by a factor of ten, where areas more than...
doubled. Both Stockholm and Shanghai show a positive development regarding UGS although with large differences. In Shanghai, UGS roughly quadrupled over two decades. Simultaneously, urban areas grew about 25 times as much as UGS. In Stockholm, UGS grew about 11% and the absolute UGS development is about a third in comparison to the development of urban built-up space.

5.1.3 Landscape Metrics

Regional Study in Jing-Jin-Ji/Pearl River Delta and Yangtze River Delta (Paper I)

Land cover changes observed in the regional study (Paper I) are shown in Figure 11 below. In Jing-Jin-Ji, a decrease in agricultural land of ca. 5.5% alongside a simultaneous rise in HDB areas of about 6.4% can be observed as major changes in relative landscape composition. In the Yangtze River Delta, largest increases are observed for HDB (8.8%) and LDB areas (3.2%). Decreases in percentages of agricultural land (11.7%) and wetlands of about 1% could be found. Largest changes in the Pearl River Delta can be observed in LDB (7.9% rise), HDB (4.3% rise), aquaculture (2.1% rise), agriculture (10.9% decrease) and forest (2.8% decrease). All other changes account for less than 1%.
Land cover changes in the Yangtze River Delta between 1990 and 2010

Land cover changes in the Pearl River Delta between 1990 and 2010
Figure 11 Land cover changes in Jing-Jin-Ji, Yangtze River Delta and Pearl River Delta 1990-2010 (Paper I).

It can be summarized that although some differences between the regional developments could be identified, negative effects for the rural and natural ecologically important environment in terms of landscape fragmentation and degradation of farmland and important wetlands occurred in all study areas. In terms of the relative distribution of land cover classes in the form of landscape percentage, an increase of HDB and LDB areas could be observed in all study areas alongside a decrease in wetlands and increasingly fragmented agricultural areas. An increase in landscape complexity is also observed in all three regions. The most heterogeneous landscape pattern could be found in the Pearl River Delta, not only as a result of urban development but also partly attributed to a natural predisposition of the landscape prior to urbanization.

Metropolitan Study in Shanghai/Stockholm (Paper II)

Land cover changes and LM at the metropolitan level in the Stockholm/Shanghai study in Paper II and their interpretation is summarized in the following paragraphs. Figure 12 shows changes in PLAND in Stockholm and Shanghai.
Figure 12 Changes in PLAND in Shanghai and Stockholm 1989-2000-2010 (Paper II).
In Shanghai, a significant increase in the percentage of built-up areas and UGS can be observed alongside a decrease in natural land cover classes, most of all in agricultural land. The amount of forested areas decreased, but since there are hardly any forests in the study area apart from those included in UGS, the decrease is negligible. In the first decade from 1990 to 2000, urban areas grew by 45% or 638 km$^2$. Between 2000 and 2010, the amount of urban areas increased by another 55% or 1,130 km$^2$. Urban areas more than doubled and increased by 124% corresponding to 1,768 km$^2$ over the 20-year period. Urban areas in Stockholm County grew by about 7% or 57 km$^2$ between 1989 and 2000 and by about 5% or 43 km$^2$ between 2000 and 2010. The percentage of urban growth between 1989 and 2010 was over 12% corresponding to 100 km$^2$. With regard to landscape composition metrics, the most significant proportional changes are with regard to loss of agricultural/open land in favour of low-density and HDB areas. In light of the information contained in the confusion matrices, it is worth noting the slight over-detection of LDB and parks in the 2000 classification as well as an under-detection of HDB areas. Agricultural areas were slightly under-detected in 1989 and 2010 and forested areas slightly over-detected for these years. Taking this into account, parks also changed little, increasing slightly over the 20-year period.

Between 1989 and 2010, both HDB and LDB areas in Stockholm County grew mainly at the expense of agricultural areas. In general, there were more dramatic changes in urban LULC classes in the first decade and subtler ones in the second in terms of growth, changes in size, shape and connectedness. Given the increased edge contrast and taking into account the shrinkage and attrition of agricultural areas, it seems that HDB areas have appeared in more natural areas, while LDB has grown in direct connection with existing urban areas. HDB areas often have greater negative influences on surrounding natural areas since they are characterized by either industrial/commercial enterprises and/or a large population density with a small or no amount of green or blue space. LDB areas have slightly less impact due to the presence of some vegetation (which might act as a conduit or buffer) and less intense economic/social human activity. In short, the Stockholm landscape is becoming more fragmented and negative impacts on the regional ecosystem are increasing, albeit at a much slower rate than one might find in other major cities, as the results for Shanghai suggest. The metropolitan development in Shanghai is still characterized by the transition from a rural region into a highly urbanized one in the rural-urban fringe and the urban hinterland.
The development of HDB and LDB areas proceeded at the cost of natural land cover, predominately through the transformation of cropland into urban areas and infrastructure. Urban development from 1989 to 2000 occurred mostly in the rural–urban fringe with the development of HDB areas. The second decade of urban development was mainly characterized by a decentralized growth of both LDB and HDB areas. Simultaneously, a centralized development of UGS in form of green corridors along major roads, golf courses and UGS took place that did not happen during 1989 and 2000. The relative growth of urban areas exceeds the creation of UGS by a factor of 25 but the amount of green spaces has quadrupled at the same time between 2000 and 2009. Counteracting the negative effect of urbanization in both study areas is the fact that UGS are growing alongside urban areas. UGS have been kept as they were over the years with new UGS being developed at the same time.

Metropolitan Study in Beijing (Paper IV)

Landscape changes in Beijing from 2005 to 2015 are displayed in Figure 13 below. Most noticeable changes are a decrease of agricultural areas to 65% of their original extent in the rural-urban fringe and increases in golf courses (50%) and low built-up areas (HDB plus LDB) with 21%.

**Percentage of landscape changes from 2005 to 2015**

![Figure 13 Changes in PLAND in Beijing between 2005 and 2015 (Paper IV).](image-url)
The spider diagram in Figure 14 visualizes land pattern changes quantified through LM.

Agricultural areas have decreased in extent, but their shared edge with artificial detrimental classes has slightly decreased as the CWED metric shows, most likely through the constructions of low-density residential
areas and transformation of high-density older agglomerations into urban green spaces in the rural-urban fringe. The landscape has become slightly more complex, most likely through an increase in 2005 underrepresented classes, i.e. golf courses and urban green spaces. There are less agricultural areas and forest but more water, urban green spaces and golf courses found in the direct vicinity of built-up areas. At the same time, the proximity to these ecosystem service providing classes in relation to the increase of built-up space has decreased for agriculture and forests but increased for water and golf courses. The relative proximity to urban green spaces has slightly decreased. In terms of connectivity, agriculture, forest and water bodies have become more fragmented. A simultaneous increase in water bodies suggests that unconnected new lakes and ponds in parks and golf courses were created instead of extending a network of watersheds and channels as the visual interpretations of the classification results confirm.

5.1.4 Ecosystem Services

This section presents the results in terms of current state and changes in ES. The development of ES as indicator throughout the papers is illustrated by first presenting the results from Papers I and II where absolute valuations were performed towards relative concepts (Paper III) and the integration of spatial measures (Paper IV).

**Absolute Valuation Results**

ES in the regional study were calculated according to valuation scheme presented by Xie et al. (2008) according to Equation (4.5). Substantial losses can be observed in Jing-Jin-Ji and the Yangtze River Delta whereas the Pearl River Delta only shows slight ES value changes. When investigating the land cover changes, three reasons for this low decrease can be identified. Firstly, there are hardly any wetlands in the area that yield highest ES values. Secondly, an increase in aquaculture can be detected that contributes to ES and thirdly, urbanization comes predominately at the cost of cropland that yields low ES values. Table 7 below summarizes the losses in ES for each biome.
Table 7 Detailed changes in biomes and ES value quantification over Jing-Jin-Ji, Yangtze River Delta and Pearl River Delta between 1990 and 2010 (Paper I).

<table>
<thead>
<tr>
<th></th>
<th>Biome</th>
<th>Hectare</th>
<th>Value in million Chinese Yuan Renminbi (CNY)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jing-Jin-Ji</td>
<td>Water</td>
<td>-134,121</td>
<td>-2.732</td>
</tr>
<tr>
<td></td>
<td>Forest</td>
<td>-138,259</td>
<td>-1.746</td>
</tr>
<tr>
<td></td>
<td>Wetland</td>
<td>-78,501</td>
<td>-1.931</td>
</tr>
<tr>
<td></td>
<td>Aquaculture</td>
<td>+22,390</td>
<td>+456</td>
</tr>
<tr>
<td></td>
<td>Agriculture</td>
<td>-868,838</td>
<td>-3.083</td>
</tr>
<tr>
<td></td>
<td>Bare</td>
<td>-16,855</td>
<td>-11</td>
</tr>
<tr>
<td></td>
<td>Σ</td>
<td></td>
<td>-9.045</td>
</tr>
<tr>
<td>Yangtze River Delta</td>
<td>Water</td>
<td>-2,823</td>
<td>-57</td>
</tr>
<tr>
<td></td>
<td>Forest</td>
<td>-14,378</td>
<td>-182</td>
</tr>
<tr>
<td></td>
<td>Wetland</td>
<td>-113,231</td>
<td>-2.785</td>
</tr>
<tr>
<td></td>
<td>Aquaculture</td>
<td>-88,740</td>
<td>-1.807</td>
</tr>
<tr>
<td></td>
<td>Agriculture</td>
<td>-991,544</td>
<td>-3.518</td>
</tr>
<tr>
<td></td>
<td>Σ</td>
<td></td>
<td>-8.350</td>
</tr>
<tr>
<td>Pearl River Delta</td>
<td>Water</td>
<td>-12,189</td>
<td>-248</td>
</tr>
<tr>
<td></td>
<td>Forest</td>
<td>-114,918</td>
<td>-1.451</td>
</tr>
<tr>
<td></td>
<td>Wetland</td>
<td>-9,065</td>
<td>-223</td>
</tr>
<tr>
<td></td>
<td>Aquaculture</td>
<td>+95,328</td>
<td>+1.942</td>
</tr>
<tr>
<td></td>
<td>Agriculture</td>
<td>-356,195</td>
<td>-1.263</td>
</tr>
<tr>
<td></td>
<td>Bare</td>
<td>+6,076</td>
<td>+4</td>
</tr>
<tr>
<td></td>
<td>Σ</td>
<td></td>
<td>-1.241</td>
</tr>
</tbody>
</table>

The largest loss of ES values of about 9.05 billion CNY was detected in Jing-Jin-Ji, where urbanization affects large amounts of agriculture as the main contributor, followed by water that was transformed into built-up areas and aquaculture in the Bohai Bay. ES losses in the Yangtze River Delta are nearly as high as in Jing-Jin-Ji and sum up to 8.35 billion CNY. The main reason for this loss is the reduction of arable land in favour of HDB and LDB land and the loss of coastal wetlands south-east of Shanghai where Hangzhou Bay meets the East China Sea due to land-reclamation. The ES gains and losses in the Pearl River Delta are rather balanced in comparison to the Yangtze River Delta and Jing-Jin-Ji but till sum up to 1.24 billion CNY. Biggest contributor to the loss is the decrease in agricultural and forested areas. The increase in aquaculture dampens these losses somewhat but cannot account for the loss of natural land in favour of managed and built-up land. The loss of both large areas of arable land and of ecologically important wetlands together accounts for about
68% of the total loss of ES in the regions. The total growth of about 28,000 km\(^2\) of urban areas in the three regions resulted in a total loss of roughly 18.5 billion CNY.

ES were calculated according to the valuation scheme by Costanza et al. (1997) for the comparative study between Shanghai and Stockholm, also according to Equation 4.5. A total loss of around 450 million USD can be observed in Shanghai with the largest decrease from 2000 to 2010. From 1990 to 2000, an absolute loss of 192 million USD is calculated. From 2000 to 2010, a reduction of 253 million USD of ecosystem service values is noted. This correlates with the relatively speaking higher increase in urban land during the same period. On the whole, the value of ES services in Stockholm has not changed considerably. An increase of about four million USD over a period of two decades was observed. This is mainly due to the increase in UGS in Stockholm between 1989 and 2010. A detected decrease in water and thus a decrease in Ecosystem Service values in 2000 seem unrealistic since the amount of water in 2010 equals the amount in 1989. Other changes are insignificant (less than 1%) and are believed to result from misclassifications.

A total loss of ES can be observed over the two decades in Shanghai for all land cover classes except for UGS. LDB areas are believed to yield some yet undefined ES values. In that case, the total losses would be reduced bearing in mind that LDB areas developed predominately on agricultural land. Concerning the relative occurrence of UGS with the increase in urban land, it can be stated that whilst the total amount of urban land in Shanghai doubled, the occurrence of UGS quadrupled at the same time. The absolute increase in urban land however exceeds the creation and maintenance of UGS by far (25 times as much). The largest contributor to the loss in ecosystem service values in terms of area is agriculture. Due to the relatively speaking lower ecosystem service value of agriculture, the biggest contributors to the monetary loss are wetlands. Tables 8 and 9 below summarize the ES balances for Shanghai and Stockholm from 1989/90 to 2010 in terms of total value in each decade, total absolute loss and the percentage of change from the first to the last decade:
Table 8 Ecosystem Service values in USD in Shanghai from 1989-2010 (Paper II).

<table>
<thead>
<tr>
<th>Biome</th>
<th>1990</th>
<th>2000</th>
<th>2010</th>
<th>Total abs. Loss</th>
<th>Percentage 90-10</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wetlands</td>
<td>421.20</td>
<td>212.80</td>
<td>169.26</td>
<td>251.94</td>
<td>-60%</td>
</tr>
<tr>
<td>Lakes/Rivers</td>
<td>743.53</td>
<td>772.83</td>
<td>549.60</td>
<td>193.93</td>
<td>-26%</td>
</tr>
<tr>
<td>Forest</td>
<td>8.79</td>
<td>0.78</td>
<td>0.46</td>
<td>8.33</td>
<td>-95%</td>
</tr>
<tr>
<td>Cropland</td>
<td>37.87</td>
<td>33.53</td>
<td>26.07</td>
<td>11.80</td>
<td>-31%</td>
</tr>
<tr>
<td>UGS</td>
<td>6.60</td>
<td>6.32</td>
<td>28.10</td>
<td>21.50</td>
<td>+425%</td>
</tr>
</tbody>
</table>

Table 9 Ecosystem Service value changes in USD in Stockholm from 1989 to 2010 (Paper II).

<table>
<thead>
<tr>
<th>Biome</th>
<th>1990</th>
<th>2000</th>
<th>2010</th>
<th>Total abs. Loss</th>
<th>Percentage 89-10</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lakes/Rivers</td>
<td>645.82</td>
<td>627.47</td>
<td>645.66</td>
<td>0.16</td>
<td>&lt;-1%</td>
</tr>
<tr>
<td>Forest</td>
<td>450.77</td>
<td>444.19</td>
<td>447.72</td>
<td>3.05</td>
<td>&lt;-1%</td>
</tr>
<tr>
<td>Cropland</td>
<td>8.46</td>
<td>8.76</td>
<td>7.83</td>
<td>0.63</td>
<td>&lt;-1%</td>
</tr>
<tr>
<td>UGS</td>
<td>65.78</td>
<td>87.78</td>
<td>73.29</td>
<td>-7.51</td>
<td>+11%</td>
</tr>
</tbody>
</table>

Positive for Stockholm’s regional ecosystem is that forested areas have remained relatively unchanged and still dominate the landscape, ensuring support for local ES. However, the increase in edge contrast for forest and the greater edge interface with urban areas that this implies has a negative impact as these areas are exposed to more adverse effects from urbanization. These effects were however not quantified at the time and should have a negative influence on ES. The only positive effect on ES provision at metropolitan levels in Shanghai is achieved through the increases in UGS – however, seen in conjunction with service deteriorating growth of built-up space, they are counteracting negative effects of urban development only little.

Relative Valuation Results

Moving from metropolitan to detailed urban ES results, the relative evaluation approach in terms of ES supply and demands (Burkhard et al., 2012) was adopted in Paper III. Land cover changes in central Shanghai as displayed in Figure 15 below implicate first and foremost an increase in UGS and decreases in continuous urban fabric (HDB).
Figure 15 LULC change in central Shanghai (Paper III).

Table 10 summarizes the CORINE classes, their respective extent in hectares, the percentage of change from 2000 to 2009, the attributed budget value from Burkhard et al. (2012) and the quantitative changes in hectares related to the qualitative changes in budget values.

Table 10 Ecosystem balances and land use/land cover changes in % in Shanghai (Paper III).

<table>
<thead>
<tr>
<th>CORINE class</th>
<th>LULC2000 in ha (A)</th>
<th>LULC2009 in ha (B)</th>
<th>Percent change</th>
<th>Budget value (BV)</th>
<th>Changes in ha (B-A)*BV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Continuous urban fabric</td>
<td>1,516.3</td>
<td>1,240.6</td>
<td>-18</td>
<td>-79</td>
<td>21,783</td>
</tr>
<tr>
<td>Industrial/commercial</td>
<td>81.1</td>
<td>136.3</td>
<td>+68</td>
<td>-82</td>
<td>-4,525</td>
</tr>
<tr>
<td>Road and rail networks</td>
<td>428.7</td>
<td>324.9</td>
<td>-24</td>
<td>-23</td>
<td>2,387</td>
</tr>
<tr>
<td>Construction sites</td>
<td>205.6</td>
<td>232.3</td>
<td>+13</td>
<td>-18</td>
<td>-481</td>
</tr>
<tr>
<td>Green urban areas</td>
<td>237.6</td>
<td>397.8</td>
<td>+67</td>
<td>18</td>
<td>2,882</td>
</tr>
<tr>
<td>Water courses</td>
<td>203.6</td>
<td>171.6</td>
<td>-16</td>
<td>52</td>
<td>-1,664</td>
</tr>
<tr>
<td>Water bodies</td>
<td>3.7</td>
<td>16.7</td>
<td>+350</td>
<td>50</td>
<td>650</td>
</tr>
</tbody>
</table>

By translating the urban classes resulting from the classifications into ecosystem service budgets, two ecosystem service supply and demand maps were generated as shown in Fig. 16 below. Urban LULC classes were evaluated in terms of their capacity (supply) and demand for 22 regulating, provisioning and cultural ES. Green land use/land cover classes denote
areas where supply exceeds demand. Urban classes shown in red indicate that demand exceeds supply and classes that hold a relatively speaking neutral balance by providing some ecosystem functions but falling short of others are shown in yellow. Classified shadows are not attributed any budget, hence the “no data” descriptor.

Figure 16 Ecosystem supply and demand budgets in the Shanghai core (Paper III).

Summing up the LULC changes quantified by budget values, an overall increase in ES budgets of 21,030 hectare-values or about 20% can be observed. Largest contributors to the budget changes was not the creation of more service supplies by increased green space but through the reduction of demand due to a decrease in continuous urban fabric and to a smaller extent a decrease in road and railway networks. The second most important factor determining the budget is an increasing demand for ES by increase in industrial and commercial units. The most important class actively contributing to service supply are urban green sites followed by water bodies. Despite the coinciding results from other studies, caution is advised when stating an increased ecosystem service supply of 20% for reasons of class confusion and due to the budgeting scheme that is not particularly designed for urban areas. Intra-urban demand and supply should be adjusted to just the needs of an urban as opposed to the needs of a rural population. Proximity to UGS and topological relationships among urban classes are also considered to be important factors in determining supply and demand budgets. Furthermore, there should be a further budget distinction between the urban green site class based on the land cover and also land use of the area under consideration, e.g. urban forests should ecologically speaking fulfil different ecosystem functions.
than grass surfaces or ornamental flower patches, that in the current scheme all are part of the urban green site class. Even through a 20% increase in supply values should be regarded with caution, higher service supply increases are realistic. Reasons for this are the following four assumptions: firstly, the transition from continuous urban fabric to UGS is the most common transition given all LULC changes. This transition takes place in areas surrounded by other low-rise densely built-up areas of continuous urban fabric with residential function. Thus, the proximity to urban green sites is increased for the surrounding remaining residential areas. At the same time, there is a reduction in population through the actual transition relaxing the demand on the newly created green spaces. Secondly, the increase of industrial and commercial areas weighs heavily in the budgeting process (second most important after the decrease in continuous urban fabric). It is however believed that the heavy demand of ecosystem supply is mostly attributed to the class because of the industrial subclass as potential areas of heavy pollution as stressor for ecosystems. Newly designed commercial areas however are considered having less negative effects through new technologies in building materials and design that decrease building energy consumption, do not contribute to pollution as industrial areas might and that even might provide some ecosystem supplies in the form of roof and façade greening or through cultural/recreational benefits urban dwellers can enjoy. Thus, the industrial/commercial class should not be given such a strong negative budget. Thirdly, the reduction of water courses has a heavy influence on budget values, being the most important supplier of ES per hectare. However, the observed reduction of water courses is due to misclassifications and should thus have not been included in the budget as negative factor. Lastly, construction sites that are in itself temporary and no final goal of urban planning are inherently attributed a negative supply value but in regard of the intended and anticipated land cover changes from continuous urban fabric and industrial areas towards green spaces and modern high-rise buildings with commercial/residential function, these areas should rather be regarded as potential future contributors to ecosystem supply values than representing a demand factor.

The last paper systematically extended ES with the LM concept and introduced not only spatial but also temporal measures in the analysis of LULC and ES changes in the megacity of Beijing at metropolitan scale and thus presents the most complete work in terms of combining different aspects of urban LULC change patterns. Urban growth in Beijing took form in increases of surface sealing, e.g. in the extension of Beijing Capital
International Airport and in newly LDB and areas in forms of residential zones. The increase in urban areas is partly counteracted by the simultaneous redesign of high-density low rise suburban agglomerations into managed UGS that can be visually confirmed by high-resolution imagery on several occasions in the urban fringe, coinciding with the findings of Qian et al. (2015a). Newly built-up urban space in the urban fringe is found to take the form of high-rise buildings, presumably with residential function to accommodate an increasing urban population. There are less agricultural areas and forest but more water, urban green spaces and golf courses found in the direct vicinity of built-up areas. At the same time, the proximity to these ecosystem service providing classes in relation to the increase of built-up space has decreased for agriculture and forests but increased for water and golf courses. In general, the only ‘natural’ classes that show improved ecological characteristics are urban green spaces and golf courses. Natural is put into quotation marks here since urban green spaces and golf courses are highly managed features that differ substantially from natural remnant vegetation when it comes to species richness, diversity and composition. Changes in spatial landscape characteristics influenced service provision bundles to change in their capacity to provide ES up to 24 percent. Table 11 summarizes the relative ES changes induced through urban growth in Beijing from 2005 to 2015.

Table 11 Ecosystem service bundle changes in percent in Beijing from 2005 to 2015 (Paper IV).

<table>
<thead>
<tr>
<th>Service bundles</th>
<th>% change</th>
</tr>
</thead>
<tbody>
<tr>
<td>Food supply</td>
<td>-30.19</td>
</tr>
<tr>
<td>Water supply</td>
<td>-4.27</td>
</tr>
<tr>
<td>Temperature regulation/Moderation of climate extremes</td>
<td>-1.87</td>
</tr>
<tr>
<td>Noise reduction</td>
<td>-32.12</td>
</tr>
<tr>
<td>Air purification</td>
<td>-4.28</td>
</tr>
<tr>
<td>Runoff mitigation</td>
<td>-25.81</td>
</tr>
<tr>
<td>Waste treatment</td>
<td>-32.43</td>
</tr>
<tr>
<td>Pollination, pest regulation and seed dispersal/Habitat for biodiversity</td>
<td>-11.51</td>
</tr>
<tr>
<td>Global climate regulation</td>
<td>-32.11</td>
</tr>
<tr>
<td>Recreation/Place values and social cohesion</td>
<td>-0.60</td>
</tr>
<tr>
<td>Aesthetic benefits/Cognitive development</td>
<td>-2.15</td>
</tr>
</tbody>
</table>

Most negatively affected by landscape structural changes through decreases in service area, edge contamination and fragmentation were noise reduction, waste treatment, global climate regulation, water/food supply and runoff mitigation services. Temperature regulation/moderation of climate extremes, recreation/place values and social cohesion, aesthetic benefits/cognitive development and least affected by the observed land cover changes. Especially the latter two
service bundles are positively influenced by the construction of urban green spaces and golf courses. The most influential LULC class changes are the increase in golf courses and the decrease in agricultural land, a trend that can be confirmed by Qian et al. (2015a), although the study focuses at a different, more detailed scale and uses a different classification scheme.

Figure 17 visualizes the changes in each service bundle alongside the contributions of each spatial attribute.

The changes in ecosystem service provisions as quantified in this study are purely related to an earlier point in time in the study area. How the presence or absence of ES is evaluated by the local population is not drawn into consideration here.
5.2 Discussion

5.2.1 Remote Sensing-Based Methodology Framework

Overall classification outcomes and accuracies suggest that the methodology and choice of RF and SVM classifiers were successful in the works presented above. Object-based classification approaches are recommended when satellite data are in high-resolution and when LM analyses are performed since spurious single pixels or small erroneous pixel aggregations can lead to incorrect metric results. Alternatively, these small pixel aggregations could alternatively be filtered out with the risk of removing correctly identified pixels. The classification approach and choice of classes to be mapped is motivated by two objectives that present a trade-off. At one hand, the distinction of as many relevant classes as possible is attempted to obtain the most detailed land cover change pattern with respect to ecologically relevant classes and different types of built-up features. On the other hand, more classes might lead to decreases in reliability of the results through misclassifications. The classes were thus chosen following the principle that the predominant natural land cover classes present in the study area are captured alongside at least two types of built-up space to obtain an as complete impression of urbanization patterns as possible. Classifications on high-resolution data have been experienced as time consuming, the bottleneck being the discovery of the right segmentation parameters at processing times of several hours and careful selection of training sites. The one-vs-all classification with RF was more straightforward but also required some post-classification refinements. Training site selection in the object-based SVM classifications was more time consuming when since the best homogenous image segments needed to be carefully chosen. One advantage of both-pixel- and object-based SVM was that the classifier only required few training samples. Once a basic training data set was established, the choice of training segments could be iteratively and quickly improved based on the classification output. High-resolution data was needed and found appropriate for the study in Paper III. Mosaicking of Landsat data in Paper I was time consuming and could be reduced by using more recent data recorded with larger swath widths, e.g. Sentinel-2A and HJ-1A/B.

5.2.2 Environmental Indicators

The methods and indicators that were used, combined and developed in this research attempted to evaluate and quantify the patterns of urban growth and the resulting implications for us and our natural environment.
It could be shown that scale considerations are a decisive factor for the suitability of the proposed methods. At regional levels, LM and absolute ES valuations might be sufficient to capture overall development trends. The advantage of using these two straight-forward approaches lies in the facts that the methods are well-established and uncomplicated to interpret thus highlighting their use in communicating conditions and changes to different actors, stakeholders or the public. Through this thesis has become apparent that the popularized ES concept is not free of issues that, if accurate and detailed ecological analyses are performed at metropolitan or urban scales, the concept as so often applied in its current form is not descriptive enough. The main issues being here highly and many-faceted subjective valuation approaches and the often neglected integration of spatial characteristics that both have been addressed, yet not solved in this thesis, although the integration of spatial measures in ES and the observation of relative changes in urban areas where up-to-date no well-established valuation scheme exists are considered important contributions that hopefully facilitate further research. Not only is the scale of the analysis decisive for the evaluation of ecological and sustainable development but also the mapping units and classes that are addressed. Not all urban built-up classes exert the same stress on and create the same demand for ES. Recognizing these differences and classifying urban constructs according to their ecosystem functionality should be pursued at high-resolutions. The data that was used throughout the thesis is considered appropriate for the respective analysis scales, especially in inner-urban areas, the use of high-resolution data is crucial. In direct connection to the integration of spatial measures stands the concept of LULC. It could be shown and was discussed that land use is fundamentally different from land cover and that this distinction should be drawn into consideration in assessing landscape pattern changes. In this respect, land use is rather associated with social and provisioning ecosystem functions and land cover with regulating and supporting functions. Furthermore, there is a lack of general agreement on the definition of some land cover classes and what functions they provide. Not all land use or land cover classes provide the same functions at the same scales and in the same areas. Maybe, remote sensing of ES should mainly be attempted through the derivation of biophysical parameters and not through land use and land cover to avoid this problem. This idea is partly addressed in regarding ES in the form of bundles that are based on similar functions. The classification approaches and choice of classes in this study are however considered suitable for further studies, especially the continuation of data fusion approaches that can lead to increased
classification accuracies. Accuracy assessment is out of conventionality most often performed through confusion matrices, kappa coefficients and the expression of misclassifications in omission and commission errors. Additional measures that account for quantity and allocation agreements and disagreements could aid in future studies to obtain a more complete impression of classification accuracy that could eventually lead to better classification outcomes. These are necessary for not only for reliable analytical results and correct conclusions, but in a wider sense to promote the further exploitation of the huge potential remote sensing yields for further studies.

The integration of spatial characteristics as proposed here is somewhat arbitrary and should be considered as an example of how such information can be integrated in valuation approaches. If a particular service, function, taxon or species is considered, adaptions to the type of special characteristics should be made, e.g. in the choice of the contrast table for the CWED metric, in the distance consideration of the TCA metric, or for the proximity measure for the urban population to ES.

The findings presented in this thesis regarding the increase in green spaces in Shanghai and Beijing correspond to the findings of Yang et al. (2014) where the trends of urban green coverage between 1990 and 2010 in 30 major Chinese cities was observed. Overall, the studied cities have become greener over the past two decades due to greening in old city districts and expanded built-up areas. In a regional context however, rapid urbanization is also found to have caused a dramatic turn-over in vegetation structures. The general usefulness of the ES concept as indicator can also be questioned as a result of their present stage of development and in the missing links between landscape pattern changes and the detailed implications for the functioning and condition of ecosystems. A conclusion that might be drawn from the application of ES in this research is that relative measures are more indicative of ecological changes than absolute measures as mirrored by the progress throughout this dissertation. I would like to point out that this does not necessarily mean that monetary approaches should generally be abandoned. They serve their purpose as demonstrative measure, for raising awareness, in large scale analyses at regional to nation-wide and continental scales to enable comparisons and induce a change in policies. However, one should not expect them to be an accurate indicator of ecosystem function quality, which is better defined through more refined analysis as the last paper indicates. This is especially true for urban ecosystems where the type of
services and proximity to those is play a major role and where service benefits are very subjectively evaluated. It could further be shown that absolute ES valuations as measure of environmental impact are very indicative for fast growing metropolitan regions. In Stockholm where only slight changes in ES could be detected and where there might be an ecologically speaking qualitative difference in built-up space than in Shanghai, straight-forward monetary evaluations based on LULC classifications might not suffice for accurate comparisons. Here, land use, ecological functionality and urban feature composition should be drawn into consideration to quantify changes. It is thus incumbent to the user to decide on the ES appraisal approach and the decision should be motivated by the objective and scalar considerations of the study. Through the quantification of service budgets inter-urban and inter-regional comparative studies can be performed and the largest service contributors or demanders can be easily identified. With that information, according planning measures can be taken, e.g. increases and preservation of largest contributors and redesign or reduction of demanders. One aspect that has not been addressed in this work but that is considered important for the practical integration of ES for planning purposes is the integration of policy and planning practices alongside stakeholder, actor, benefiter and other social construct involvements that eventually determine how ES are treated as e.g. discussed in Colding et al. (2006), Andersson et al. (2007) and Ernstson et al. (2008 and 2010).

5.2.3 The Contributions of the Thesis

The findings of the thesis do not only coincide with urban growth trends as found in other studies (e.g. Zhao et al. 2006; Yang et al., 2014; Qian et al., 2015a), but the methods follow the trend of investigating relative valuations of ES (Burkhard et al., 2012) integrating spatial characteristics in ES assessments (Sybe and Walz, 2012), evaluating ES bundles (Turner et al. 2014).

Through the work presented in this thesis, well-established methods in remote sensing and image processing were applied to investigate the quantitative and qualitative effects of urbanization. It could be found that different data resolutions and environmental impact indicators are needed based on the different objectives and scales of the studies. Based on the work, recommendations in terms of data requirements and ensuing environmental impact analyses are given.
Furthermore, the work done in the thesis can be seen as a contribution to the field of (urban) ecology and ecosystem science, where remote sensing is ascribed a great potential (Feng et al., 2010; de Araujo Barbosa et al., 2015; Rose et al. 2015). It was demonstrated how remotely sensed data can be used to evaluate the impacts of urban growth on the natural environment and on urban residents over large areas and at a higher level of detail in urban cores, thus hopefully contributing to more sustainable developments. This could be particularly important when there is no other data available, e.g. in fast growing regions with uncontrolled urban growth. The extension of the ecosystem service concept through integration of landscape metrics presents a new approach to obtain a more refined impression of urban growth effects.
6 Conclusions and Future Research

6.1 Conclusions

This research investigated urbanization trends and the resulting effects on the environment through multitemporal and multi-sensor satellite remote sensing analyses at various scales and the combination of urbanization indices and ecological concepts such as LM and ES.

Methodological frameworks to characterize urbanization trends at different scales based on remotely sensed satellite-borne data were developed and the establishment of a closer link between the fields of urban ecology and remote sensing were attempted. Medium-resolution satellite data (20-30m) at metropolitan and regional scales is considered sufficient to quantify and evaluate urbanization patterns. For detailed urban analyses however, high-resolution data at <5m are recommended to capture as much variation in urban green and blue spaces as possible.

Urban growth could be observed in all study areas, although in diverse forms, with varying impacts and at different speeds. Urbanization effects common to all study areas and across all scales are the decrease and fragmentation of cropland and degradation and disappearance of wetlands in favour of aquacultures and land-reclamation.

Urbanization at regional scales in the three important Chinese urban agglomerations Jing-Jin-Ji, the Pearl River Delta and Yangtze River Delta showed similar LULC change trends. Jing-Jin-Ji and the Pearl River Delta grew much faster and more extensively with more severe environmental consequences. In total, urban areas grew with approximately 28,000 km² between 1990 and 2010, corresponding to a loss in ES of 18.5 billion CNY. Urbanization effects at metropolitan levels in Shanghai and Beijing show similar trends that are quite different from Stockholm. Urban areas in Stockholm only increased with 12% implying less severe environmental consequences in terms of ES losses. Through investigation of the megacities of Beijing and Shanghai at higher spatial resolutions, more differentiated urbanization patterns can be observed. Not only a mere growth of built-up areas can be detected in the rural-urban fringes but also increases in managed UGS and redesign of existing built-up neighbourhoods can be found that exert a positive effect on some ES.
In the first two papers of this thesis, spatial distribution and morphological considerations of ES and relative valuation approaches were mentioned as interesting extensions to the existing concept. The ensuing papers gradually addressed these points, having led to the systematic integration of LM into the ES concept, through which a more accurate, relative, location-independent and thus more transferable method was proposed. Following the trend of evaluating ES on a more relative basis, the ES supply and demand concept was transferred from a landscape to an urban perspective and used to evaluate service provision changes in the inner city of Shanghai (Paper III). In Paper IV, urban growth patterns and their effect on ES provision were investigated in the Beijing metropolitan region. A systematic integration of LM to quantify spatial influences on ES providing patches was proposed here. Another new feature of the study is the split and categorization of green and blue LULC classes into ES bundles. These bundles represent one or two relevant urban ES that are equally composed through two to five land cover classes and that are considered to be equally affected by one to seven spatial characteristics. The approach developed in this study extended the ES concept to including the influence of spatio-temporal characteristics of ES provisional patches, thus resulting in a more realistic and comprehensive appraisal of ES than traditional monetary approaches.

Despite further development and adaptions of absolute ecosystem service valuations, the approach remains problematic. It could be shown that relative valuation methods accounting for spatial attributes can be used as measure to express changes in urban land cover and resulting implications in terms of ecosystem service provisions. The research has led from a parallel application of urbanization indices, well-established LM and ES to quantify changes in urban land cover patterns to a novel combined approach that is considered to give a more refined indication of changes in ecological conditions.

Limitations in the presented work are that so far only multispectral data has been used to characterize urban growth even though it is well-known that the integration of additional data can lead to better classification results. Fusion of multispectral data and SAR or the use of hyperspectral data has the potential to improve the land cover classifications. Another limitation can be seen in the fact that some steps require a high amount of manual processing, i.e. spatial analyses in the post-processing steps, that could be automatized in the future.
6.2 Recommendations and Future Research

With increasing spatial resolutions, computational capabilities and more open and free access to remotely sensed data, the further use of multispectral data in combination with spaceborne SAR and hyperspectral data for urban studies with ecological and environmental aspects will hopefully be fostered. Automated and optimized analytical methods are suggested for future development to further facilitate the effective use of high-resolution satellite data. Currently KTH-SEG features 8-bit data inputs for segmentation and classification, resulting in a more efficient processing with good outcomes. However, this may imply an information loss through downscaling from datasets in higher radiometric resolutions prior to segmentation and classification, which should be further investigated and evaluated. The KTH-SEG algorithm currently only uses mean and standard deviation of object brightness values as input features for the SVM classifier. Additional features such as morphology and topology of image objects could be used to decrease class confusions in the future. Large area OBIA approaches are currently time consuming and process parallelization or cloud computing approaches could facilitate enhanced operability and increased use of OBIA approaches.

Land use/land cover (LULC) is still often used as descriptor of land surfaces. It is recommended to abandon the acronym to enforce a clear split between land use and land cover which are essentially two different things. This has become very clear when investigating ES in urban areas, where land use is the decisive factor for both socio-cultural and provisional services and where land cover is more related to regulating, supporting and habitat services that are present even in the absence of humans. One option to at least partly overcome this problem could be the direct determination of ecosystem functions through the integration of biophysical parameters, directly linked to radar backscatter or spectral responses, thus avoiding a traditional classification into land cover types.

The establishment of a reference framework for the unanimous and complete definition of urban ES and their valuation would enable comparisons of a city’s or metropolitan region’s eco-conditions. The initial links that were established between ES and LM have demonstrated how spatial influence on service provision can be measured. Since many ecosystem functions are essentially species- and thus scale-dependent, additional metrics and/or parameter modifications might be considered when investigating particular services or a specific spatial influence. As
could be found through this research, urban growth does not only lead to a decrease in ES but causes a shift in service patterns. It is not surprising that provisional services attributed to cropland, i.e. food production change in favour of more recreational and social services that are considered more important in urban areas. This is the case for emerging and developed countries and knowledge-based economies where intensified food production takes place elsewhere and where the transport of goods into urban areas goes without saying. In other regions however, food production and water regulation services in the urban fringe might be crucial for survival. Monitoring these service trade-offs and linking these to different countries and economies might show interesting development trends.

The integration of additional satellite data from different sensors, e.g. SAR data or hyperspectral data would be an asset to the work presented in the thesis. This would most likely lead to increased classification accuracies and thus more reliable results. More detailed information on the character of the observed changes, e.g. in terms species assemblages and changes in vegetation structures and sucessions could thus also be obtained that could even give a more refined indication of ecosystem service changes, even at higher spatial resolutions for detailed urban analyses. Further development and improvements in terms of workflow enhancement would be the automatization of processes that require user interaction, i.e. training/validation sample selection or post-classification refinements.
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