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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

Det är allmänt känt att de nuvarande befolkningsprognoserna och trenderna förutspår en kontinuerlig ökning av världens befolkning de kommande årtiondena. Detta leder till ökade krav på naturresurser och livsutrymme. En global följd av detta är att många stadsområden växer kraftigt och nya bosättningar samt tätorter bildas. De efterföljande långsiktiga konsekvenserna för miljön och för oss människor är dock mindre uppenbara. Data och metoder för att observera och kvantifiera förändringar som är resultatet av urban tillväxt behövs för att ta itu med de utmaningar som nuvarande och framtida urbaniseringstrender medför. Detta arbete är inriktat på inrättandet av analytiska ramverk för att upptäckta urbana tillväxtmönster baserat på rymdburen fjärranalysdata i flera skalor, spatiala och temporala upplösningar, samt på utvärderingen av miljökonsekvenserna genom väletablerade koncept såsom landskapsmetrik och ekosystemtjänster, deras vidareutveckling och kombination. Urbaniseringen varierar globalt och visar stora geografiska och tidsmässiga skillnader. Den nya och ofta ostrukturerade tillväxten i stadsområden är numera tydligast i Afrika och Asien. Framförallt Kina har haft en snabb urbanisering sedan 1970-talet. Behovet av nya bostäder, kommersiella och industriella områden leder till nya stadsregioner som utmanar hållbar utveckling, bevaring och skapandet av en hög levnadsstandard samt bevarandet av ekologiska funktioner. I artikel I utvärderades urbaniseringsmönstret över två decennier, 1990-2010 i de tre tätbefolkade områden, Jing-Jin-Ji, Yangtze River Delta och Pearl River Delta, som representerar de viktigaste kinesiska storstadsregioner gällande ekonomisk aktivitet. För att analysera urbana tillväxtmönster på storstadsnivå analyserades Stockholm och Shanghai. De representerar två väldigt olika stadsmiljöer och deras stadsnära områden utvärderas inom samma tidsram som den regionala analysen med hjälp av Landsat data. Tanken att integrera rumsliga attribut i ekosystemtjänstutvärderingar försummas ofta i litteraturen och undersöktes genom att göra en systematisk kombination av ekosystemtjänster och landskapsmetrik samt med hjälp Sentinel-2A multispektral data och historiska satellitbilder utvärdera spatio-temporala förändringsmönster i Peking mellan 2005 och 2015. För att undersöka urbana tillväxtmönster på en mer detaljerad nivå undersöktes förändringar i marktäcket inklusive urbana grön- och blå infrastruktur i Shanghais stadskärna genom analys av högupplösta IKONOS och GeoEye-1 bilder mellan åren 2000 och 2009. De metoder som kombinerades och utvecklas i undersökningarna bygger på i

huvudsakligen fritt tillgängliga fjärranalysdata vilket underlättar användning och vidareutveckling av nya metoder.

Huvudsakliga stegen som genomfördes innan klassificeringen bestod av co-registreringar och mosaicking. I den regionala studien användes Tasseled Cap transformeringar för att öka möjligheten att skilja klasserna åt följt av en pixelbaserad Random Forest klassificering. I studien som jämförde Stockholm och Shanghai användes GLCM faktorer följt av en pixelbaserad SVM klassificering för att bedöma markanvändningen. Marktäckesförändringar bestämdes genom en förändringsanalys baserad på klassifikationerna. I artikel III och IV användes objektbaserad dataklassificering med SVM efter bildsegmentering i KTH-SEG. Efter kontroll av tillförlitligheten och finjustering av klasserna användes urbaniseringsindex, ekosystemtjänster och landskapsmetrik för att mäta och karakterisera den urbana tillväxten och de efterföljande konsekvenserna för miljön och den urbana populationen.

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 miljökonsekvenser 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 fokusering 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 byggprojekt, t.ex. i samband med de olympiska spelen i Peking 2008 och inför världsutställningen i Shanghai 2010. Dessa trender upphäver inte de negativa urbaniseringseffekterna utan de antyder ett paradigmskifte i stadsplanering och design mot mer trygga och hållbara boendemiljöer.

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 näringstillförsel, 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 tillväxtens konsekvenser.

Nyckelord: Fjärranalys, Urbanisering, Markanvändning/Marktäcke, Miljöpåverkan, Landskapsmetrik, Ekosystemtjänster

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Jan Haas
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List of Acronyms

CNY	- Chinese Yuan Renminbi
CONTAG	- Contagion
CWED	- Contrast-Weighted Edge Density
ES	- Ecosystem Services
GLCM	- Grey Level Co-occurrence Matrix
GLS	- Global Land Survey
HDB	- High Density Built-Up
LDB	- Low Density Built-Up
LM	- Landscape Metrics
LPI	- Largest Patch Index
LSI	- Landscape Shape Index
LULC	- Land Use Land Cover
NP	- Number of Patches
OA	- Overall Accuracy
OBIA	- Object-Based Image Analysis
PA	- Producer's Accuracy
PLAND	- Percentage of Landscape
PD	- Patch Density
RBF	- Radial Basis Function
RF	- Random Forest
SAR	- Synthetic Aperture Radar
SVM	- Support Vector Machine
SWIR	- Short Wave InfraRed
TC	- Tasseled Cap
TEEB	- The Economics of Ecosystems and Biodiversity
UGI	- Urban Green Index
UGS	- Urban Green Spaces
UA	- User's Accuracy
UI	- Urban Land Index
UX	- Urban Expansion Index

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 benefiters (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.

I. Haas, J. and Ban, Y., 2014. Urban growth and environmental impacts in Jing-Jin-Ji, the Yangtze River Delta and the Pearl River Delta. *International Journal of Applied Earth Observation and Geoinformation* 30:42-55.

II. Haas, J., Furberg, D. and Ban, Y., 2014. Satellite monitoring of urbanization and environmental impacts — A comparison of Stockholm and Shanghai. *International Journal of Applied Earth Observation and Geoinformation* 38:138-149.

III. Haas, J. and Ban, Y., 2016. Mapping and Monitoring Urban Ecosystem Services Using High-Resolution Satellite Data *(submitted to IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing).*

IV. Haas, J. and Ban, Y., 2016. Spatio-temporal urban ecosystem service analysis with Sentinel-2A MSI data (*submitted to Remote Sensing of Environment).*

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

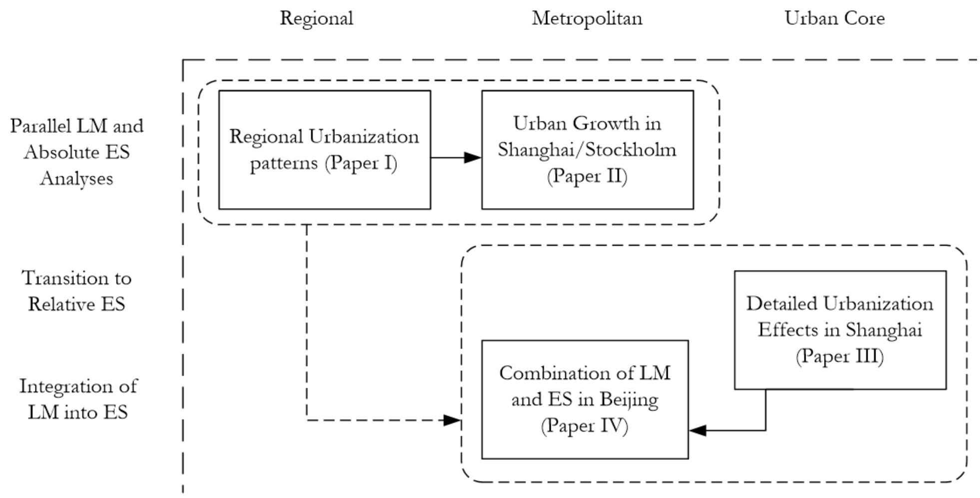


Figure 1 Contextual relation of the papers.

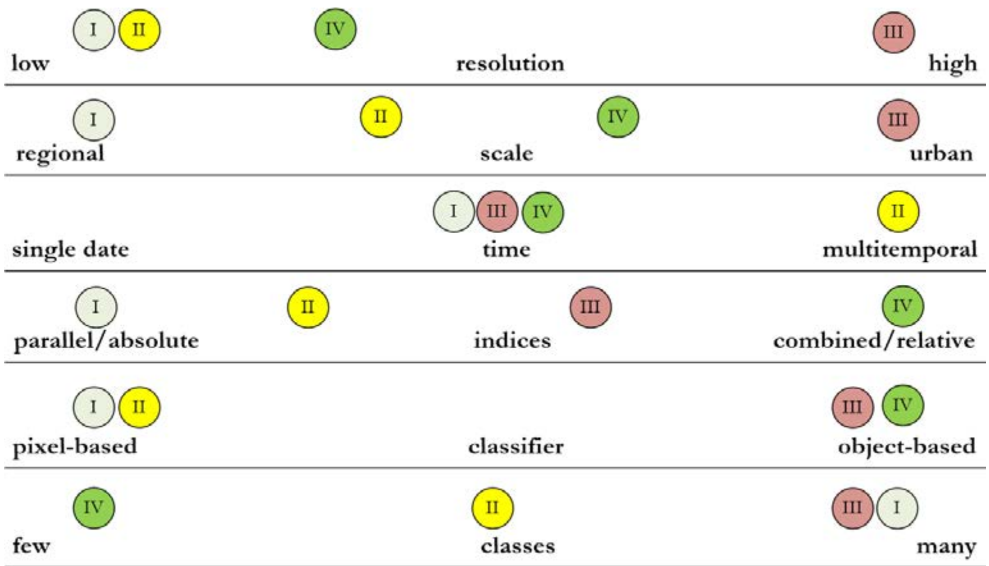


Figure 2 Categorization of the papers' analytical parameters.

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 2nd 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 WoldView-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 as 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 Sentinal-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 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, supressed 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 benefiters 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 Ayanu 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 (Mörtberg 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 (Bezák and Lyytimäki, 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 Martín-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 Šímová 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 patters 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 spatio-temporal 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 km^2. The Yangtze River Delta is located at the Chinese East coast bordering the East Chinese Sea covering about 118,000 km^2. 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 km^2 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 km^2. 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 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.

P#	*Mission*	*Bands used (res.)*	*Scenes*	*Date*	*Study Area*
I	Landsat 5 TM GLS	R/NIR/SWIR (30)	38	1987-1990	Jing-Jin-Ji, Pearl and Yangtze River Delta

I	HJ-1A/B CCD	R/NIR/SWIR (30)	12	2009-2011	Jing-Jin-Ji, Pearl and Yangtze River Delta
II	Landsat 5/7 TM/ETM+	R/NIR/SWIR (30)	12	1989-2010	Shanghai and Stockholm
III	GeoEye-1	RGB/NIR (1.84m, pan-sharpened 0.46m)	2	2009-10-04	Shanghai
III	IKONOS	RGB/NIR (3.2m, pan-sharpened 0.82m)	2	2000-07-22	Shanghai
IV	Landsat 5 TM	R/NIR/SWIR (30)	1	2005-07-09	Beijing
IV	Sentinel-2A	RGB/NIR (10m) R/NIR/SWIR (20m)	1	2015-09-13	Beijing

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.

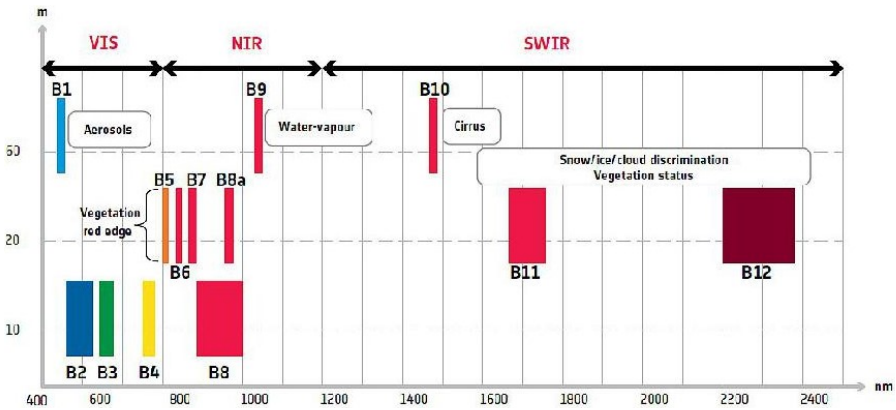


Figure 3 Sentinel-2 MSI spatial resolutions and wavelengths (Source: eoPortal Directory, ESA).

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.

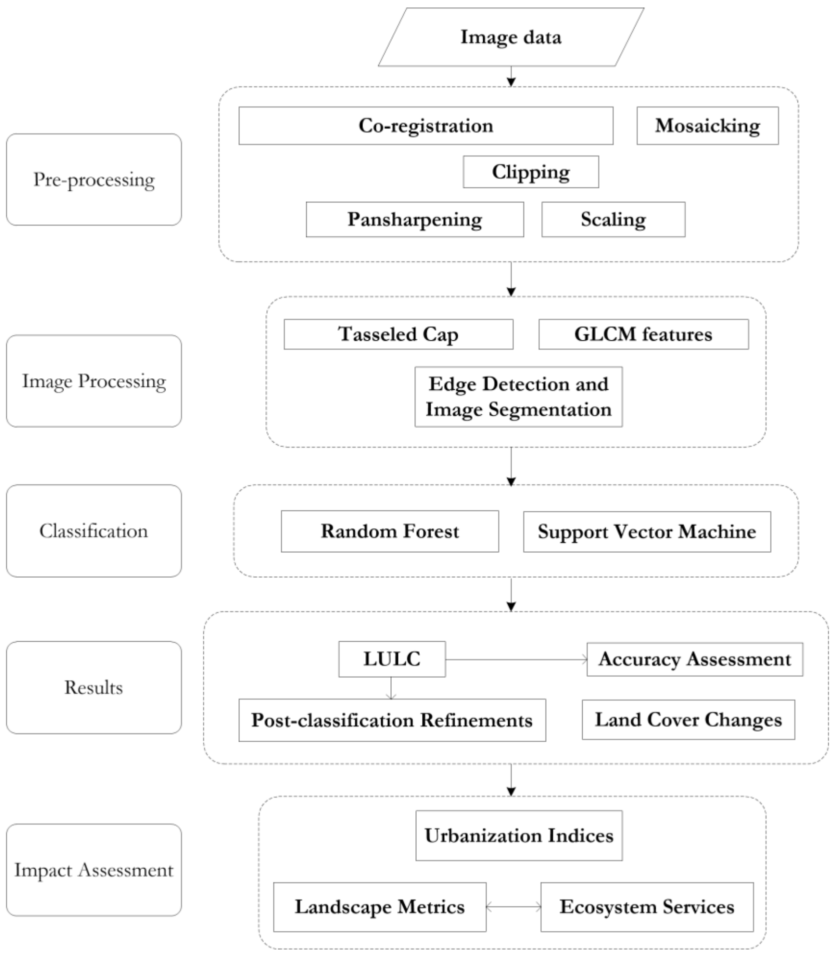


Figure 4 Methodology flowchart.

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 2 Image segmentation parameters.

P#	*Canny threshold*	*segment grow*	*segment merge*	*min/max segment size*
III	0.02-0.04	0.5/0.5	0.5/0.5	8/500
IV	Landsat: 0.07-0.14 Sentinel-2A: 0.05-0.1	0.5/0.5	0.5/0.5	2/500

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:

$$K(x_i, x_j) = \exp(-\gamma \, ||x_i - x_j||^2), \gamma > 0 \qquad (4.1)$$

where γ = 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 3 SVM classification characteristics.

P#	*Approach*	*Input Features*	*Initial Classes*	*Aggregated Classes*
II	pixel-based	Landsat: R, NIR, SWIR, GLCM	27	7/8
III	object-based	IKONOS, GeoEye-1 RGB/NIR (mean/std. dev.)	11	8
IV	object-based	Landsat: R, NIR, SWIR S2: VIS, VNIR and SWIR	13	6

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:

$$UI=\frac{UL}{TL}\times 100\% \tag{4.2}$$

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:

$$UX_r = \frac{UL_{t2}\text{-}UL_{t1}}{UL_{t1}} \times 100\% \qquad (4.3)$$

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:

$$UGI = \frac{UGS_{t2} - UGS_{t1}}{(HDB_{t2} + LDB_{t2}) - (HDB_{t1} + LDB_{t1})} \times 100\% \qquad (4.4)$$

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.

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

4.5 Ecosystem Services

ES were calculated and valuated 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:

$$\mathrm{E} = \sum_{\mathrm{k}}(\mathrm{A_k} \times \mathrm{V_k}) \qquad (4.5)$$

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.

P#	*Study*	*Res.*	*Classifier*	*Overall accuracy*	*Kappa*	*Classes*
I	Jing-Jin-Ji 1990	30	RF (pixel-based)	88.06	0.86	8
I	Jing-Jin-Ji 2010	30	RF (pixel-based)	87.94	0.87	8
I	Pearl River Delta 1990	30	RF (pixel-based)	85.22	0.83	8
I	Pearl River Delta 2010	30	RF (pixel-based)	87.63	0.86	8
I	Yangtze River Delta 1990	30	RF (pixel-based)	82.57	0.80	7
I	Yangtze River Delta 2010	30	RF (pixel-based)	86.13	0.84	7
II	Shanghai 1989	30	SMV (pixel-based)	88.08	0.86	7
II	Shanghai 2000	30	SMV (pixel-based)	87.82	0.86	7
II	Shanghai 2009	30	SMV (pixel-based)	89.36	0.88	7
II	Stockholm 1989	30	SMV (pixel-based)	90.01	0.88	6
II	Stockholm 2000	30	SMV (pixel-based)	88.98	0.87	6
II	Stockholm 2010	30	SMV (pixel-based)	88.22	0.86	6
III	Shanghai 2000	<1	SVM (object-based)	85.04	0.82	8
III	Shanghai 2009	<1	SVM (object-based)	84.29	0.84	8

IV	Beijing 2005	30	SVM (object-based)	84.76	0.82	6
IV	Beijing 2015	20	SVM (object-based)	90.23	0.89	6

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.

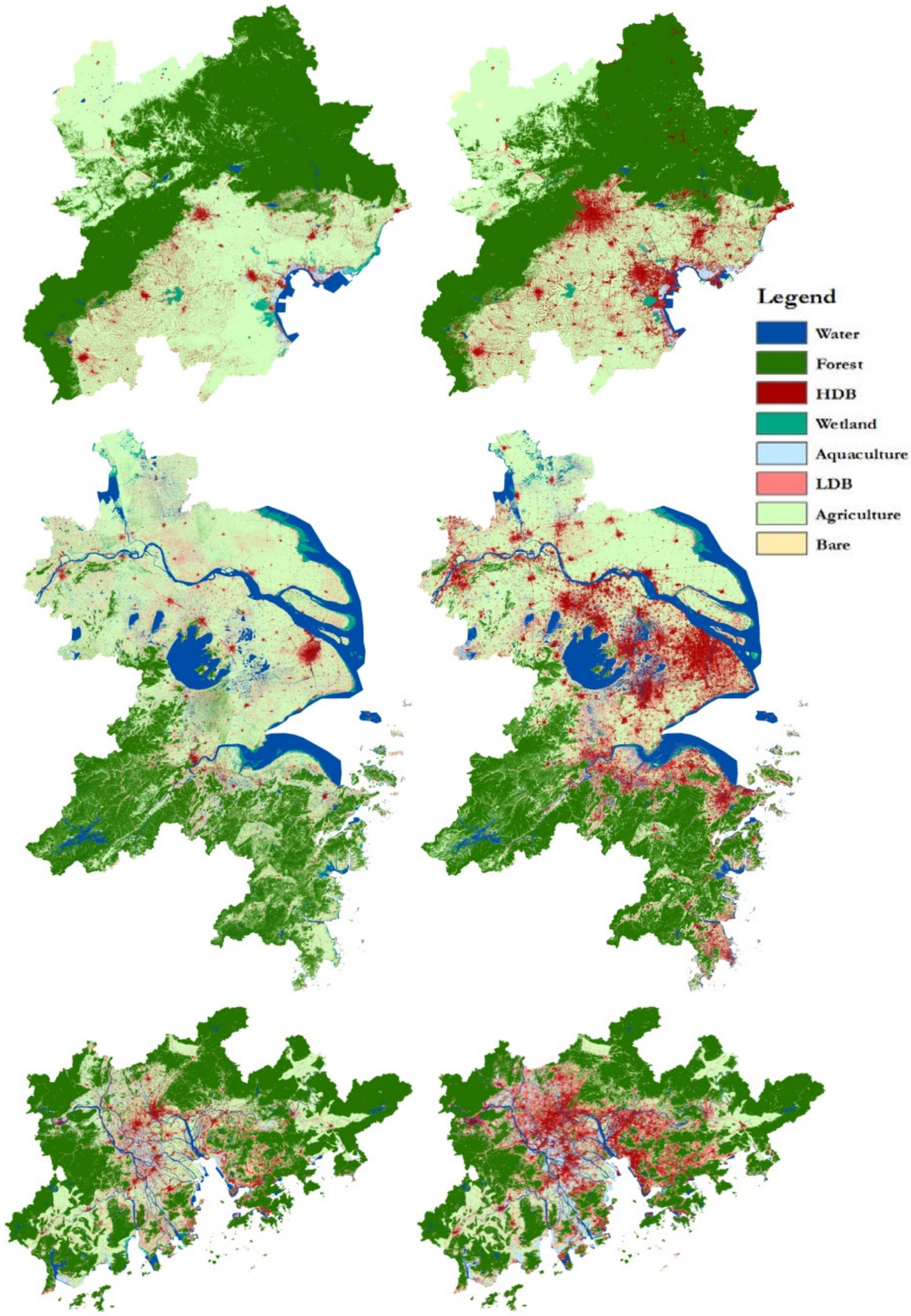


Figure 5 Classification results from 1990 (left column) and 2010 (right column). Jing-Jin-Ji is shown in the upper row, Yangtze River Delta in the central row and the Pearl River Delta in the lower one (Paper I).

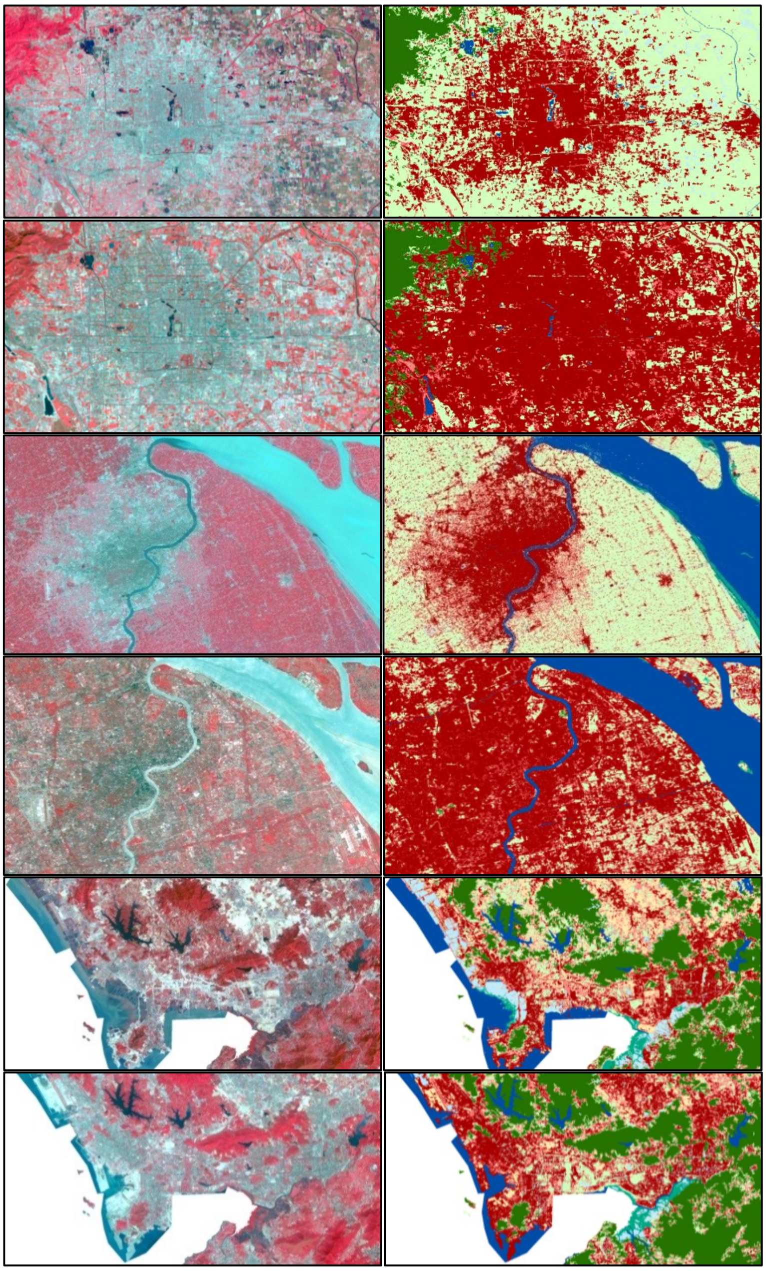


Figure 6 Detailed excerpts and their respective areas in FCC images in the left. The six rows show the following areas in descending order: Beijing 1990, Beijing 2010, Shanghai 1990, Shanghai 2010, Shenzhen 1990 and Shenzhen 2010 (Paper I).

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 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%.

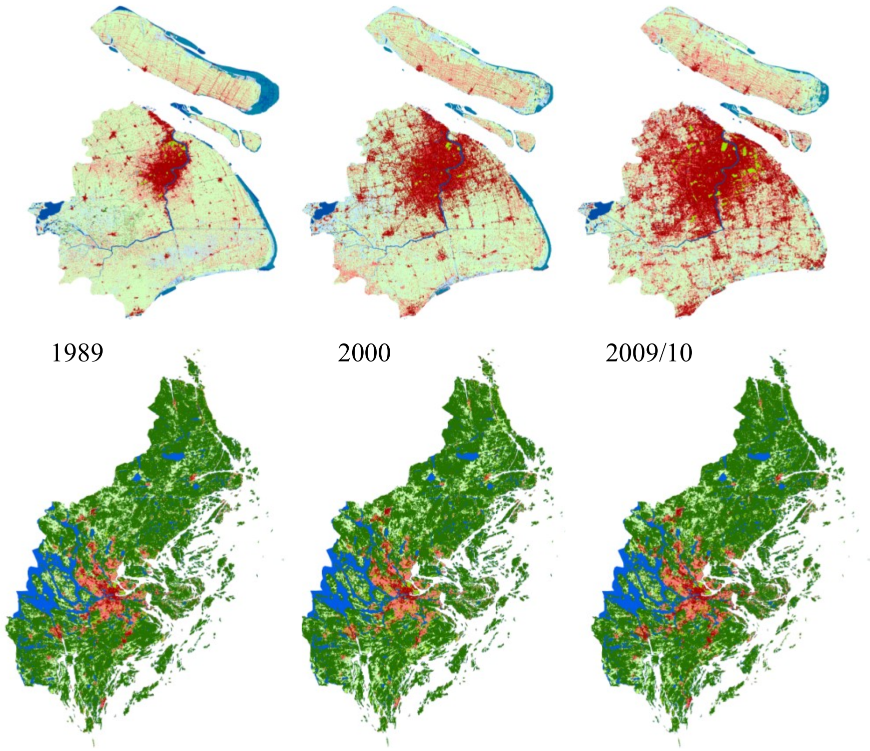


Figure 7 Classification result (Shanghai in the upper and Stockholm in the lower row and 1990, 2000 and 2010 classifications from left to right (Paper II).

From the results, two very different urbanization patters 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.

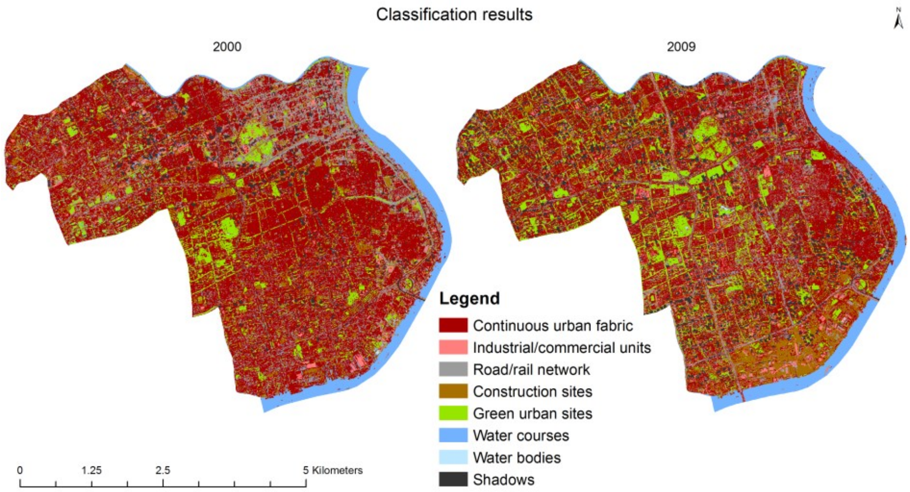


Figure 8 Classification result (IKONOS 2000 classification left and GeoEye-1 2009 classification right (Paper III).

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

Park, South of Yan'an Elevated Road) 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.

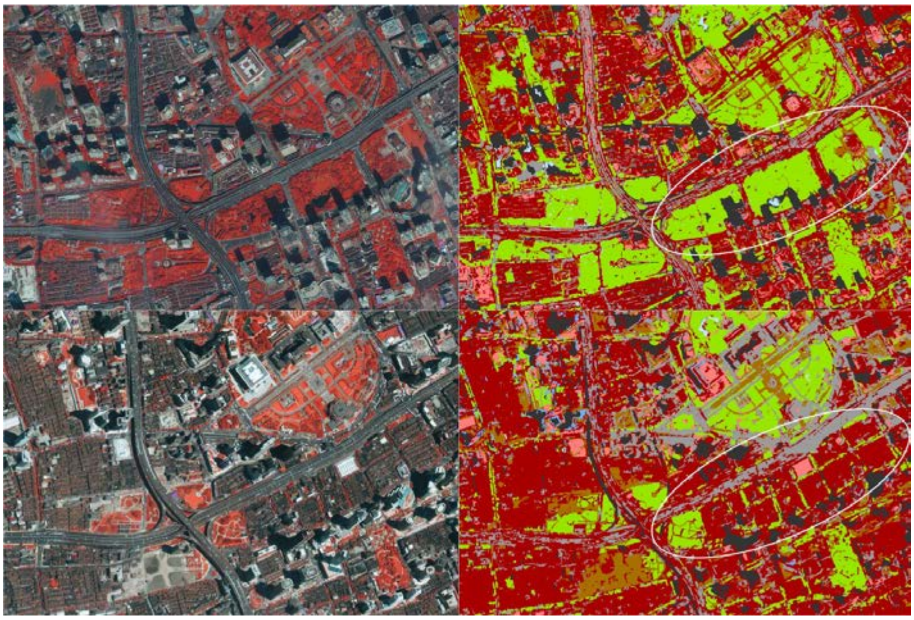


Figure 9 Detailed classification excerpt (GeoEye-1 2009 FCC image and classification in the upper row, IKONOS 2000 FCC and classification in the lower one, Paper III).

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.

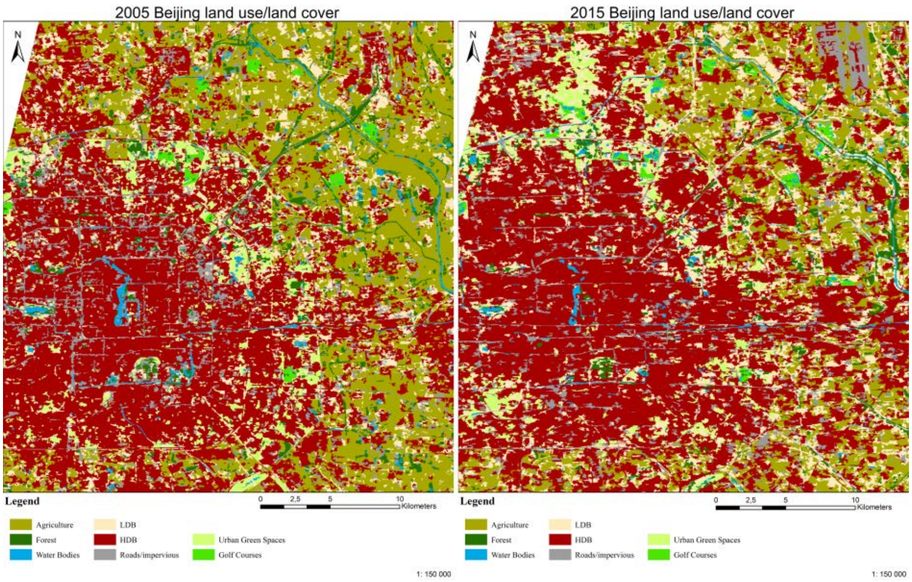


Figure 10 Classification result for Beijing in 2005 (left) and for 2015 (right) (Paper IV).

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.

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.

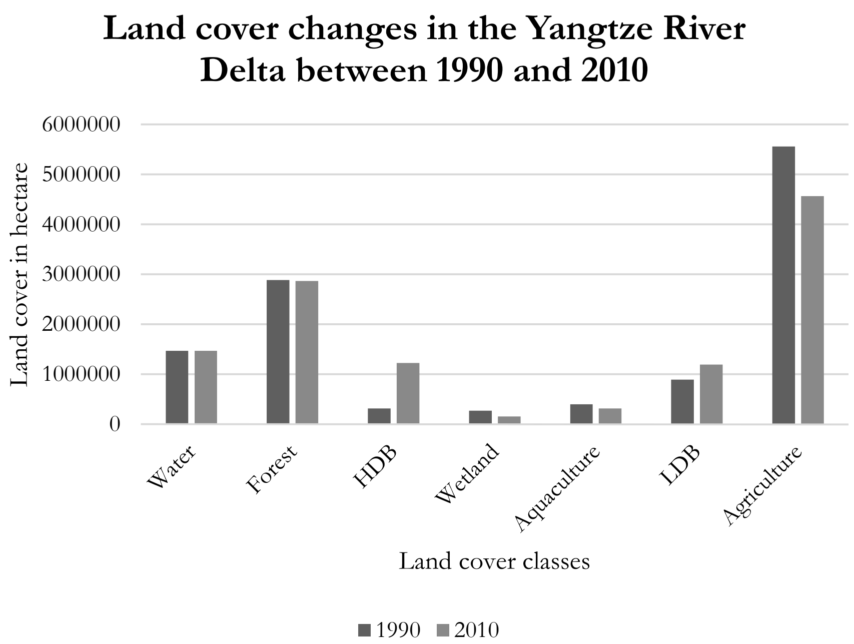
Data set	*UI*	*UX*			*UGI*
Jing-Jin-Ji 1990	4.69	140.66			
Jing-Jin-Ji 2010	11.67				
Pearl River Delta 1990	11.80	77.70			
Pearl River Delta 2010	20.98				
Yangtze River Delta 1990	10.26	100.07			
Yangtze River Delta 2010	20.53				
		UX89-00	*UX00-10*	*UX90-10*	
Shanghai89	20.99	44.73	54.76	123.98	0.039
Shanghai00	30.48				
Shanghai10	47.01				
Stockholm89	11.45	7.04	4.92	12.30	0.299
Stockholm00	12.26				
Stockholm10	12.86				

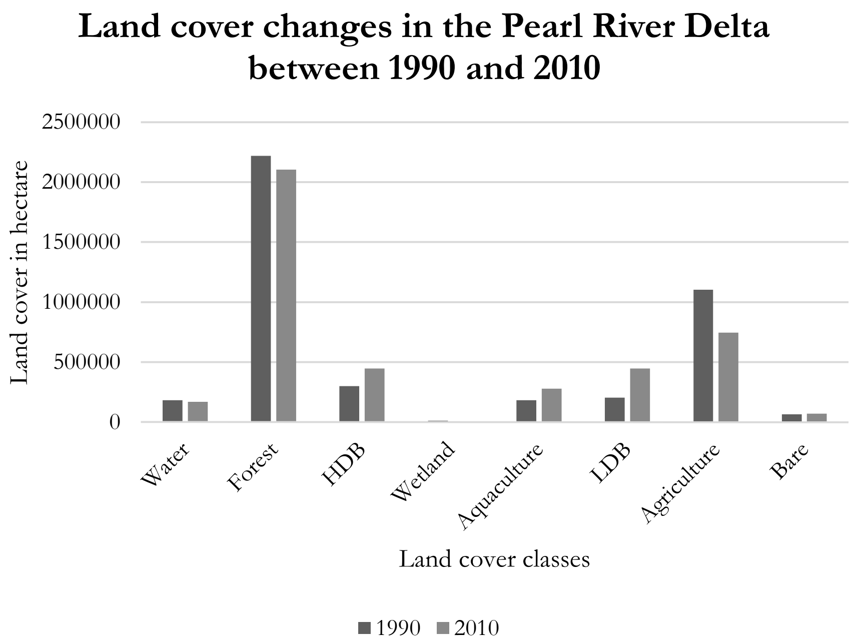
In Paper I, urban land increased in all study areas. Jing-Jin-Ji and Yangtze River Delta experienced the largest absolute increase in built-up areas with about 12,000 km^2 in the Yangtze River Delta and in Jing-Jin-Ji, whereas the Pearl River Delta grew only about 4,000 km^2. This can be explained by 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
6000000
5000000
4000000
3000000
2000000
1000000
0
Land cover in hectare
Water
Forest
HDB
Wetland
Aquaculture
LDB
Agriculture
Land cover classes
1990
2010


Land cover changes in the Pearl River Delta between 1990 and 2010
2500000
2000000
1500000
1000000
500000
0
Land cover in hectare
Water
Forest
HDB
Wetland
Aquaculture
LDB
Agriculture
Bare
Land cover classes
1990
2010

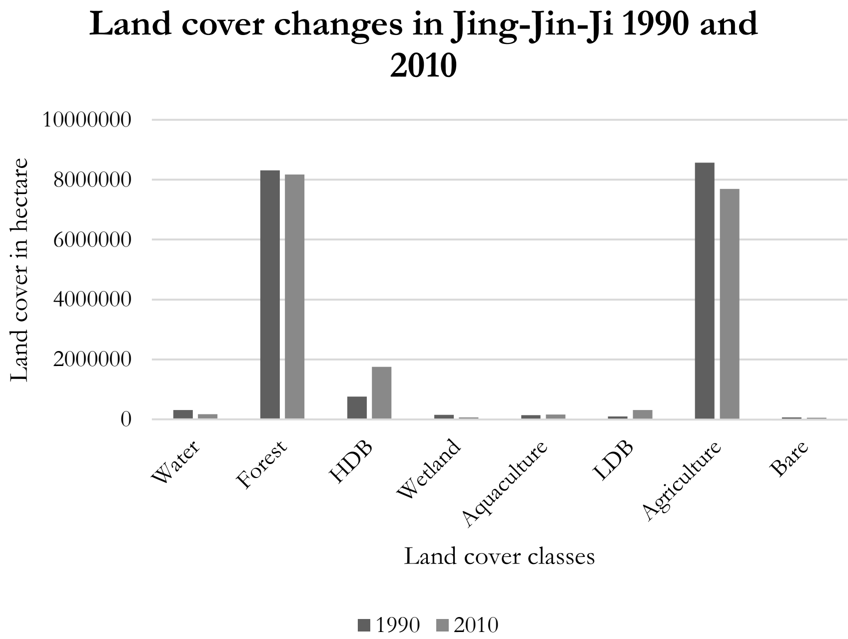
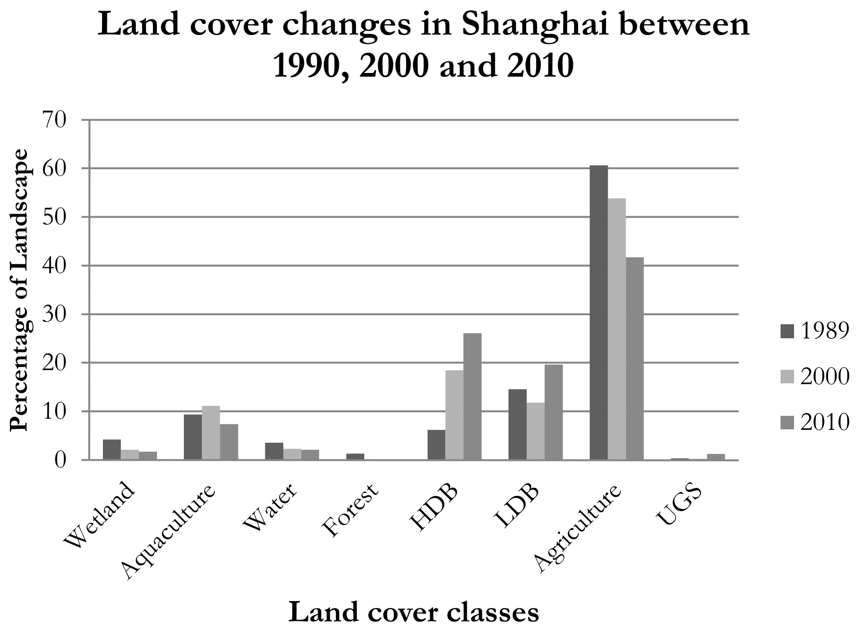


Figure 11 Land cover changes in Jing-Jin-Ji, Yangtze River Delta and Pearl River Delta 1990-2010 (Paper I).

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.



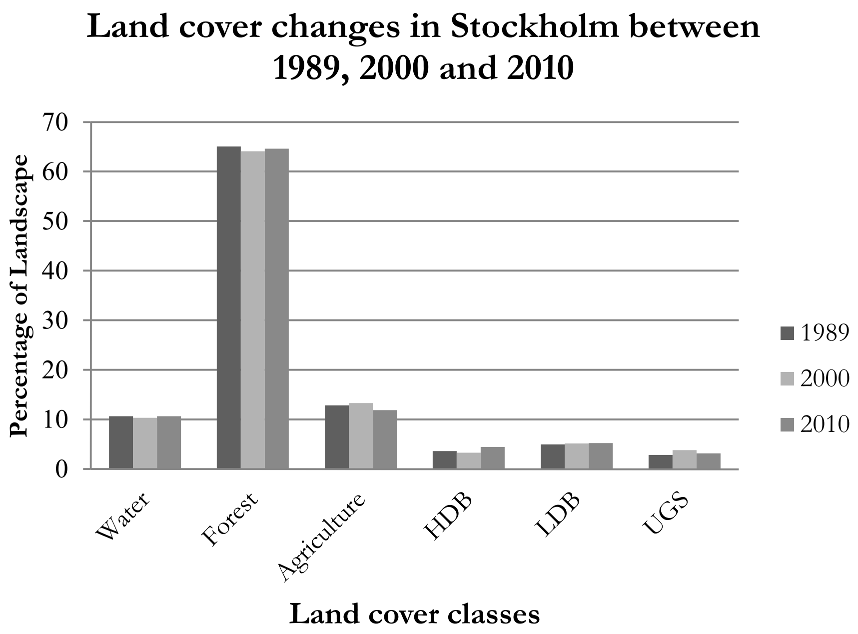


Figure 12 Changes in PLAND in Shanghai and Stockholm 1989-2000-2010 (Paper II).

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%.

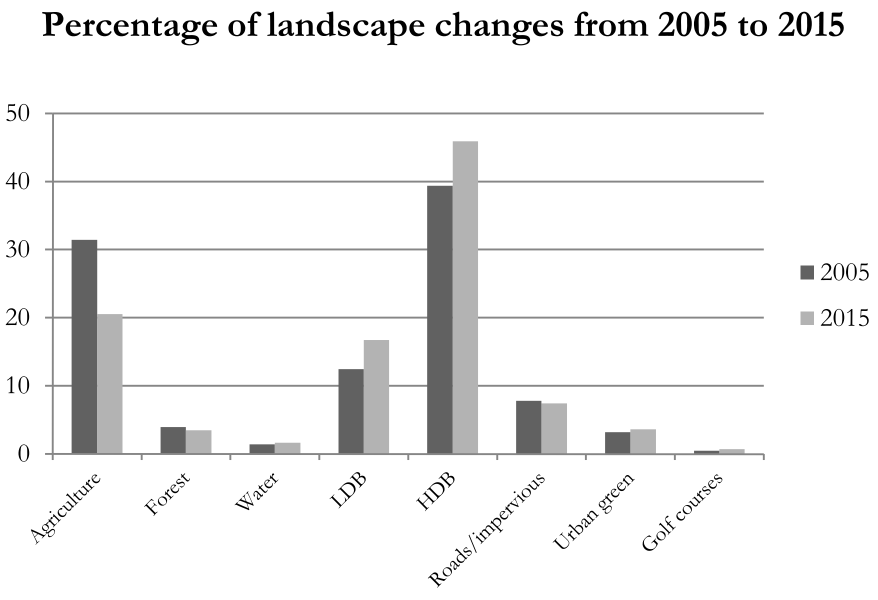


Figure 13 Changes in PLAND in Beijing between 2005 and 2015 (Paper IV).

The spider diagram in Figure 14 visualizes land pattern changes quantified through LM.

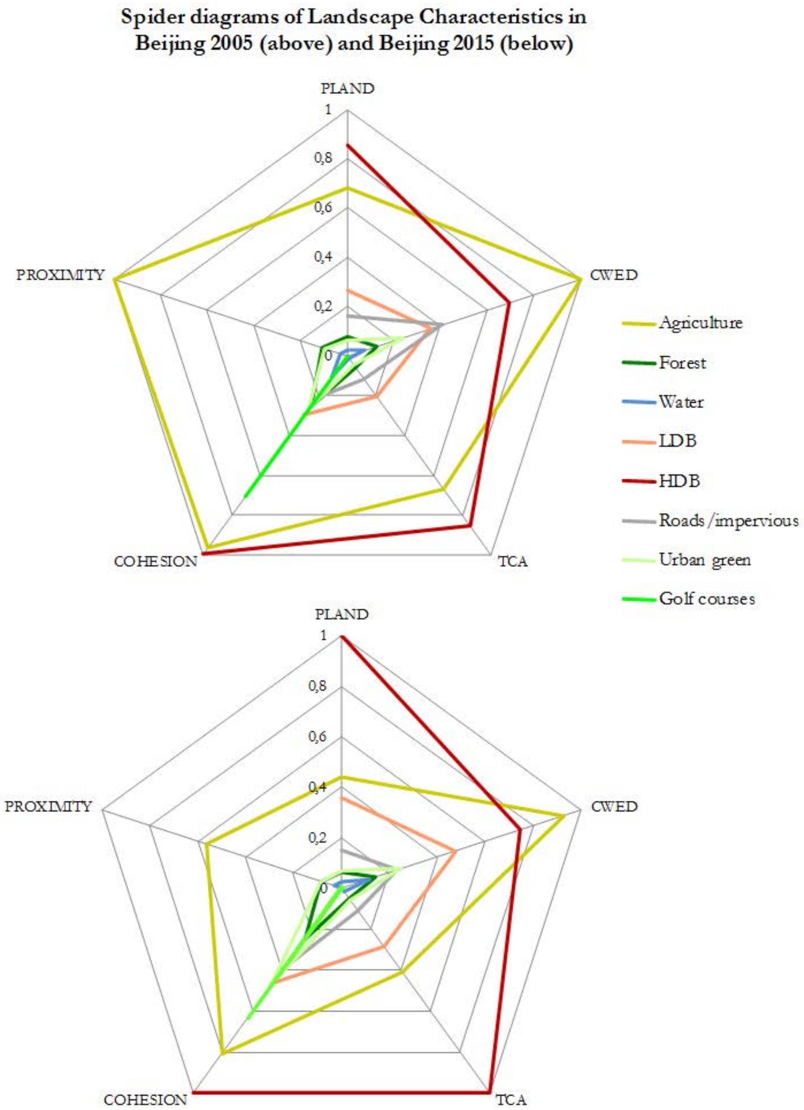


Figure 14 Landscape characteristics in Beijing 2005 and 2015 (Paper IV).

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).

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

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).

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

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

Biome	*1990*	*2000*	*2010*	*Total abs. Loss*	*Percentage 89-10*
Lakes/Rivers	645.82	627.47	645.66	0.16	<-1%
Forest	450.77	444.19	447.72	3.05	<-1%
Cropland	8.46	8.76	7.83	0.63	<-1%
UGS	65.78	87.78	73.29	-7.51	+11%

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).

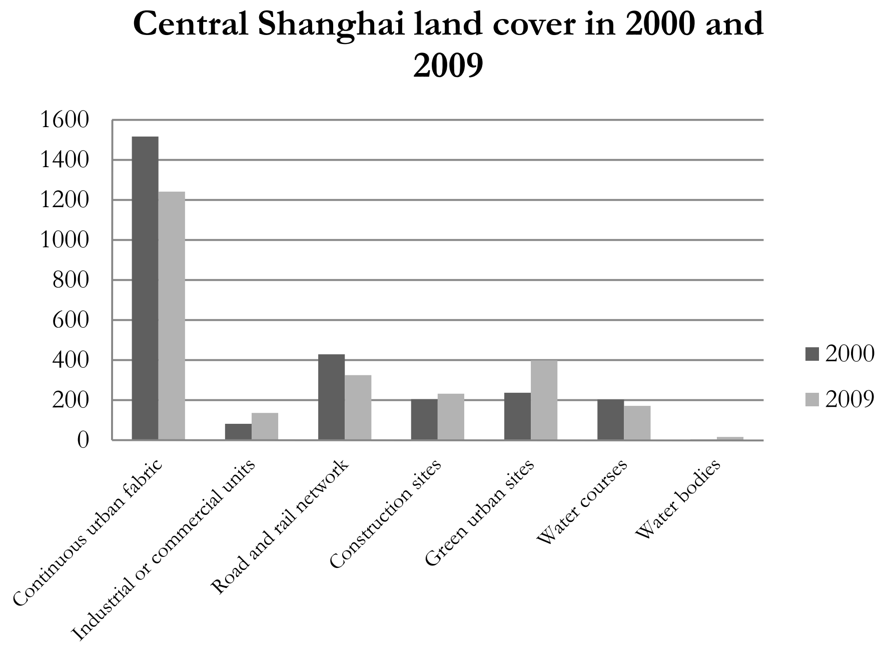


Figure 15 LULC change in central Shanghai (Paper III).

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).

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

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.

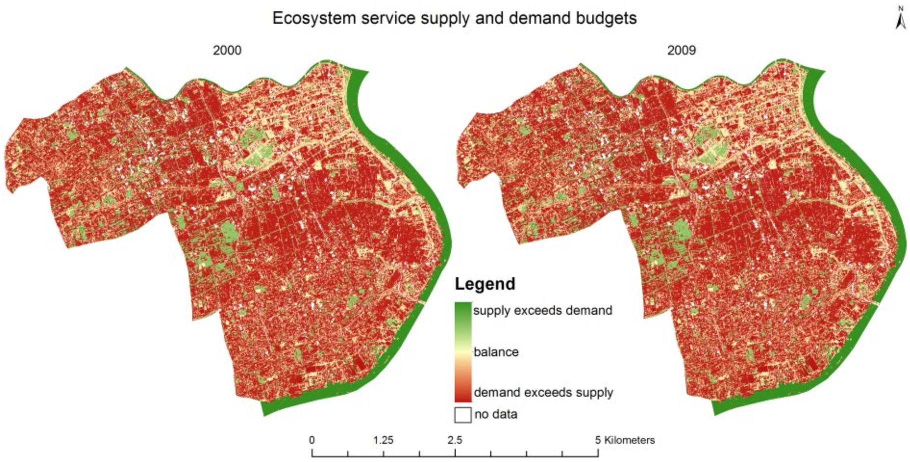


Figure 16 Ecosystem supply and demand budgets in the Shanghai core (Paper III).

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).*

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

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 focusses 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.

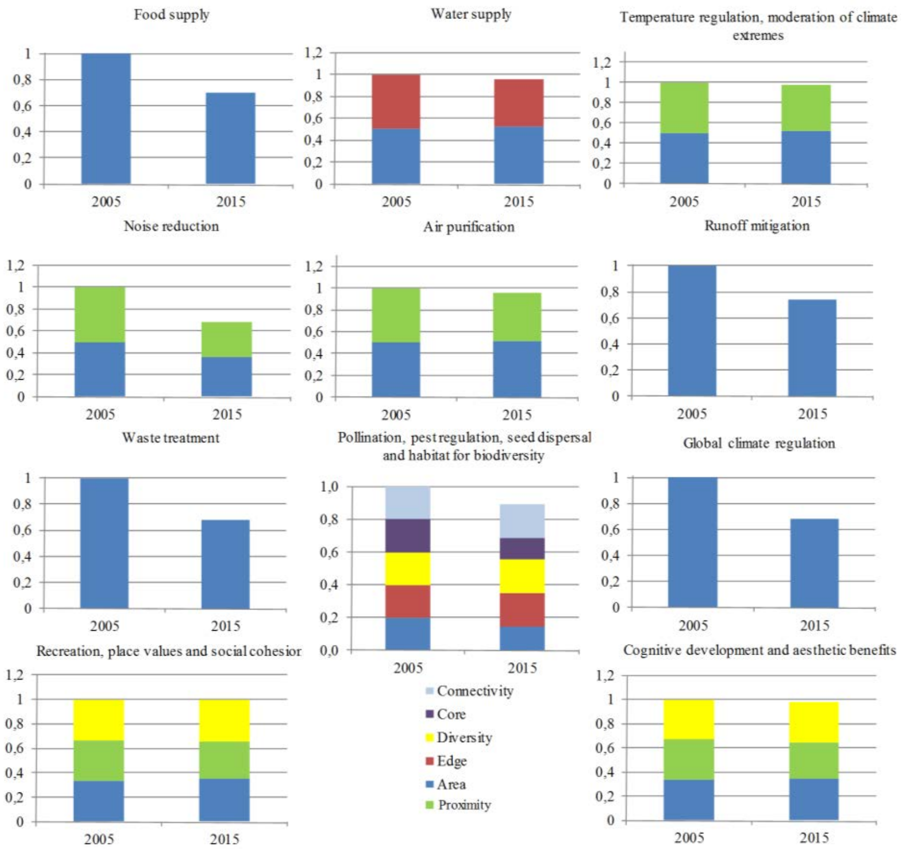


Figure 17 Ecosystem service bundle changes and share of spatial influence (Paper IV).

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 straight forward 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-facetted 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 (Syrbe 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 if 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 km^2 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 successions 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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Urban growth and environmental impacts in Jing-Jin-Ji, the Yangtze, River Delta and the Pearl River Delta

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ABSTRACT

This study investigates land cover changes, magnitude and speed of urbanization and evaluates possible impacts on the environment by the concepts of landscape metrics and ecosystem services in China's three largest and most important urban agglomerations: Jing-Jin-Ji, the Yangtze River Delta and the Pearl River Delta. Based on the classifications of six Landsat TM and HJ-1A/B remotely sensed space-borne optical satellite image mosaics with a superior random forest decision tree ensemble classifier, a total increase in urban land of about 28,000 km^2 could be detected alongside a simultaneous decrease in natural land cover classes and cropland. Two urbanization indices describing both speed and magnitude of urbanization were derived and ecosystem services were calculated with a valuation scheme adapted to the Chinese market based on the classification results from 1990 and 2010 for the predominant land cover classes affected by urbanization: forest, cropland, wetlands, water and aquaculture. The speed and relative urban growth in Jing-Jin-Ji was highest, followed by the Yangtze River Delta and Pearl River Delta, resulting in a continuously fragmented landscape and substantial decreases in ecosystem service values of approximately 18.5 billion CNY with coastal wetlands and agriculture being the largest contributors. The results indicate both similarities and differences in urban–regional development trends implicating adverse effects on the natural and rural landscape, not only in the rural–urban fringe, but also in the cities' important hinterlands as a result of rapid urbanization in China.

1. Introduction

Alongside the continuous rise in global population, a simultaneous growth of urban areas is omnipresent. The increase in world population and the need for living space and search for employment results in migration from rural areas to cities and since 2008, more than half of the world's population resides in urban areas (United Nations, 2008). Over the past 30 years, China has experienced rapid urbanization and an immense growth in population as a consequence of economic and political reforms in 1978. Nowadays, urbanization is still proceeding at staggering speed. According to the National Bureau of Statistics of China, the total population in China has risen from 987 million at the end of 1980 to 1.341 billion in 2010. In order to adequately address the challenges for urban planning and a sustainable future development resulting from such a drastic increase in population, effective analytical methods to monitor the unprecedented growth of Chinese cities and techniques to evaluate the effect of urbanization upon the natural environment are crucial. The overall objective of this research is to investigate urban land cover changes and the resulting effects of urban growth on the environment by quantification of ecosystem services solely by remotely sensed data in form of multitemporal optical Landsat TM and HJ1-A/B image analysis. There are numerous studies on satellite monitoring of urbanization and different aspects of the impacts of urban growth at different scales over China. The following overview presents the most important and recent works on urbanization in China both at national and regional level.

2. Remote sensing efforts and urbanization in china

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. A comprehensive evaluation of China's urbanization and effects on both resources and the environment was performed

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by Chen et al. (2010). Profound urbanization effects on resources, energy and an increased pressure on the environment could be reported. The extent of urban expansion for the whole of China for 1990, 2000 and 2010 was recently determined by Wang et al. (2012b). Optical Landsat TM/ETM+ data were used to delineate built-up from natural land cover classes. It was found that urban areas increased exponentially more than twice. Similar to the findings in this study, urban expansion is found occurring mainly at the expense of cropland. Urban expansion proceeded faster in the second decade. The changes in surface cover greenness in China were analyzed by Liu and Gong (2012) from 2000 to 2010. Interestingly enough and contradictory to the expectation of a decrease in vegetation cover for reasons of urbanization and desertification, Normalized Difference Vegetation Index (NDVI) values were found increasing over the whole of China. In some areas though, i.e. Jiangsu and Shanghai, a decrease in greenness could be observed as a resulting effect of urbanization. In addition to urbanization monitoring using optical data, Synthetic Aperture Radar (SAR) data have also been evaluated for urban land cover mapping and change detection in China with promising results (Ban and Yousif, 2012; Gamba and Aldrighi, 2012; Ban and Jacob, 2013; Yousif and Ban, 2013).

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. Furthermore, a sustainable metropolitan development strategy is proposed. Lin (2002) gives a comprehensive overview of the growth and structural change of Chinese cities throughout different stages of urbanization, dating back to 1949. Another review that summarizes the achievements but also deficiencies of urban transformation in China from 1949 to 2000 was published by Ma (2002). 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. Recently, 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. It is advised that China should rethink under-urbanization and it is countermeasures in its development strategy. Continuous urbanization should focus on a qualitative rather than a quantitative development. 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) and resulting impacts of urbanization in terms of changes in ecosystem service values was investigated in e.g. Zhao et al. (2004), Wang et al. (2006), Hu et al. (2008) or Liu et al. (2011).

Liu et al. (2012) analyzed 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. Regarding previous work over the three regions analyzed in this research, studies of urban expansion and changing landscape patterns in the PRD were performed by e.g. Li and Yeh (1998, 2004), Lin (2001), Seto et al. (2002), Seto and Fragkias (2005), Yu and Ng (2007) or Güneralp and Seto (2008). Urbanization studies in Beijing and in the JJJ region were carried out by e.g. Deng and Huang (2004), Tan et al. (2005), Xie et al. (2007) or Guo et al. (2009). Ban and Yousif (2012) investigated effective urban change detection methods in rapidly growing urban environments such as Beijing and Shanghai. The YRD and Shanghai as its biggest metropolitan area were analyzed in terms of landscape and urban pattern changes, urban growth and its effects upon the environment by, e.g. Ren et al. (2003), Zhang et al. (2004, 2009, 2011), Xie et al. (2006), Zhao et al. (2006), Deng et al. (2009), Hu et al. (2009), Zhang and Ban (2010), Tian et al. (2011), and Kim and Rowe (2012). The impact of urbanization on regional climate in Jing-Jin-Ji (JJJ), the Pearl River Delta (PRD) and the Yangtze River Delta (YRD) was analyzed by Wang et al. (2012a). Spatial and temporal changes of surface air temperature, heat stress index, surface energy budget and precipitation due to urbanization could be confirmed.

All studies mentioned above all pursue a particular objective and are most often either targeting the entirety of China or investigate only one of the regions under consideration. Even if the analyses concern urbanization and its effects in particular, variations in data, temporal and spatial resolutions, time frame analyzed and methodologies exist, rendering comparative studies difficult. Amongst all the above mentioned studies, no comprehensive analysis of the three largest agglomerations (JJJ, YRD and PRD) with the same methodology, same data and the same comparable environmental impacts could be found that may enable regional comparisons and could eventually contribute to a more sustainable development, giving impetus to this study. The main contributions of this research are the presentation of an analytical framework to investigate urbanization processes and potential environmental impacts on a large scale, the combined use of landscape metrics and ecosystem services as environmental impact indicators and a comparison of the divergences, similarities and character of urban and landscape development of China's three most important regions.

3. Study area and data description

The study areas of Jing-Jin-Ji (JJJ) with the Bohai Economic Rim, the Yangtze River Delta (YRD) and the Pearl River Delta (PRD) are the largest areas of urban agglomeration and can be regarded as the most important centres of Chinese trade, commerce, manufacture and industry. The location of the study areas is presented in Fig. 1. In 2010, the study areas' combined population accounted for 27% of the total in China and the regions' gross domestic product (GDP) represented 43% of the national GDP. JJJ as China's northernmost metropolitan region with its major cities of Beijing and Tianjin is located in Hebei province and stretches from the municipalities of Beijing and Tianjin towards the Bohai Sea. 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 km^2.

The PRD is located in southern mainland China adjacent to the South China Sea and is considered one of the country's chief economic regions and manufacturing centres. The study area covers about 42,500 km^2 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.

The study area of the YRD covers an area of about 118,000 km^2 at the Chinese East coast bordering the East Chinese Sea. The region is characterized by a marine monsoon subtropical climate with cool dry winters and hot, humid summers. The YRD 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).

38 Landsat 5 GLS1990 and 12 HJ-1A/B scenes dating from 2010 were selected for monitoring bidecadal land cover change over the large study areas covering nearly 350,000 km^2 in total. The images lie predominately in the vegetation period. However, there are some variations in acquisition dates for both the Landsat images

Fig. 1. Study areas in China: JJJ (north), YRD (east) and PRD (south).

Source: Google Earth.

and the HJ-1A/B images. There is often only one suitable image close to 1990 available resulting in temporal deviations of up to three years from 1990. The HJ-1A/B images date from 2008 to 2011 and are selected based upon two criteria – closeness to the Landsat anniversary date and minimum cloud cover.

4. Methodology

The flowchart in Fig. 2 presents an overview of the complete methodology.

4.1. Satellite image pre-processing

As a first step, some HJ-1A/B images needed to be reprojected to match the coordinate system of the Landsat images that area as level 1G products already georeferenced and in most appropriate coordinate systems for the study area. Thereupon, each single HJ scene was co-registered to the best fitting Landsat scene with an average root-mean-square error of in horizontal and vertical directions of $X = 0.31$ and $Y = 0.27$ in total. The resulting images and the Landsat images were then aggregated into six mosaicked datasets over the regions as presented in Fig. 3.

4.2. Image mosaicking

Image mosaicking was performed manually in the PCI Geomatica® Ortho Engine with neighbourhood colour balancing. Colour balancing evens out the contrasts between images to reduce the visibility between the image seams and to produce a visually appealing mosaic. Different mosaicking methods with varying parameters were tested and neighbourhood colour balancing resulted in the most homogeneous mosaics. Neighbourhood colour balancing determines a set of coefficients that modify each image pixel based on the pixel values of the intersecting (neighbouring) pixels. 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. Visual inspections after each added scene ensured satisfactory mosaicking results.

4.3. Tasseled cap transformations

In order to increase the separabilities between land cover classes, tasselled cap transformations were processed on all mosaics resulting in distinctive brightness, greenness and wetness information. The transformation does not only reduce the data volume but also represents the initial Landsat data in a better interpretable fashion, thus aiding in delineating the land cover classes from each other. The tasselled cap concept was first developed by Kauth and Thomas (1976) and has since then been discussed and applied in numerous studies (Crist and Cicone, 1984; Crist, 1985; Crist and Kauth, 1986; Huang et al., 2002; Zhang and Ban, 2010). Recently, Chen et al. (2012) studied and evaluated tasselled cap transformation consistencies on HJ-1A/B CCD data. The derived tasselled cap transformation parameters are used in this study on the HJ-1A/B mosaics. The transformation parameters used on the Landsat TM and HJ1/B datasets are presented in Table 1.

4.4. Random forest classification

The mosaics were classified with a random forest classifier. Random forests are superior classifiers in comparison to other decision tree approaches. Considering classification accuracies, they can be compared to boosting omitting the drawbacks of boosting. Additionally, random forests are computationally speaking much lighter and faster than comparable methods (Breiman, 2001). Furthermore, they are nonparametric enabling a quick, non-erroneous implementation with comparable results. They also provide a way

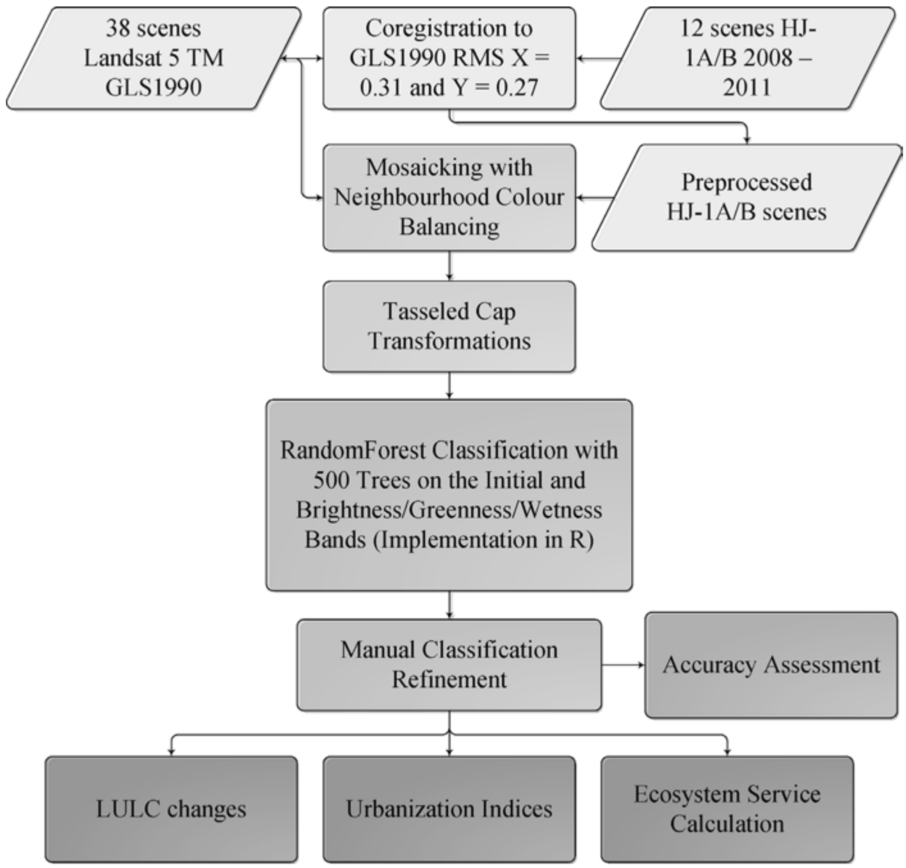

Fig. 2. Methodology flowchart.

of estimating the importance of individual variables in the classification scheme (Gislason et al., 2006). Random forests can handle both high dimensional data and use a large number of trees where the key issue is correlation reduction between the random classification variables. According to Breiman (2001), further advantages of random forests are that they are unexcelled in accuracy among current algorithms, the fact that they can be run efficiently on large databases, that they are robust to outliers and noise and finally that they can handle thousands of input variables without variable deletion.

However, only little focus has been set on the classification of remotely sensed data with random forests. Examples of studies investigating random forest classifications of remotely sensed data are found, e.g. in Gislason et al. (2006). Rodríguez-Galiano et al. (2011) investigated the classification of Landsat TM imagery by integration of uni- and multivariate textural measures in a random forest classifier. Both accuracies and kappa coefficients could be increased by addition of spatial variability. Recently, Rodríguez-Galiano et al. (2012) used random forests to classify land cover in the Mediterranean. Both multi-seasonal Landsat images and multi-seasonal texture was used in the classification process. Results indicate high classification accuracies and kappa coefficients.

The tasselled cap parameters and the initial bands were then used as classification input. 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 random forest classification (1 == desired class; 2 == any other class). 5000–15,000 training pixels were chosen in each classification step for class 1 and class 2, respectively. The training pixels were chosen distributed over the whole mosaic to include all different subcategories of a class (e.g. in terms of water bodies, training sites included rivers, lakes, sea, turbid, estuary, etc.). Several random forest classifications with continuously enhanced training areas were performed iteratively until a satisfactory result was achieved. In the classification, 500 labelled pixels for each of the 8 land-cover classes were chosen randomly and sequentially). In training, the random forest algorithm creates multiple trees with these random

Table 1
Summary of all tasselled cap transformation parameters.

	TM Band 1	TM Band 2	TM Band 3	TM Band 4	TM Band 5	TM Band 7
Brightness	0.3037	0.2793	0.4743	0.5585	0.5082	0.1863
Greenness	−0.2848	−0.2435	−0.5436	0.7243	0.0840	−0.1800
Wetness	0.1509	0.1973	0.3279	0.3406	−0.7112	−0.4572

	HJ Band 1	HJ Band 2	HJ Band 3	HJ Band 4
Brightness	0.3024	0.4010	0.5031	0.7033
Greenness	−0.1350	−0.3317	−0.6246	0.6940
Wetness	0.7562	0.3587	−0.5251	−0.1541
Fourth	0.5644	−0.7749	0.2847	−0.0044

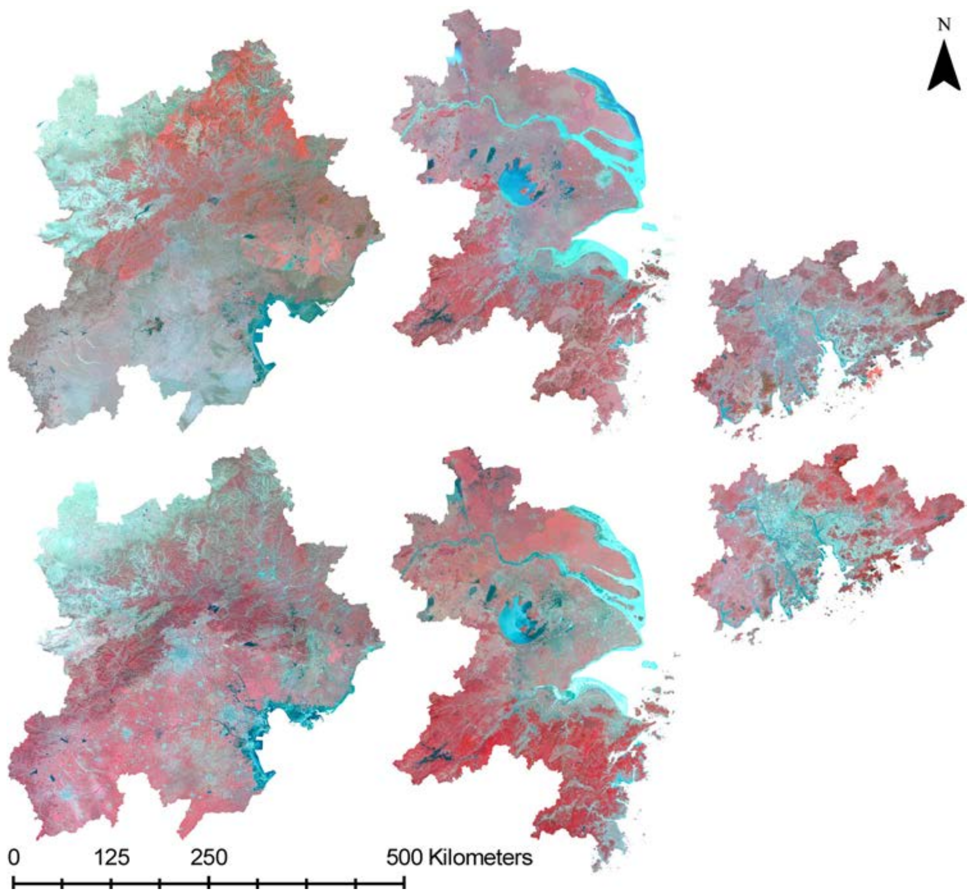

Fig. 3. False Colour Composites (FCC) of Jing-Jin-Ji, the Yangtze River Delta and the Pearl River Delta from left to right (LT5 GLS1990 mosaics in the upper row, HJ1-A/B mosaics in the lower one). Lively red colours denote vegetation and turquoise areas water bodies whereas bluish-pale regions indicate the absence of vegetation (urban, bare). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

samples by determining the split (for each node) on a subset of input variables (initial TM/ETM+ bands and HJ-1A/B bands, 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 random forest 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. 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, high density built-up, bare, wetlands and aquaculture. The remaining two classes, low density built-up and agriculture, were separated as a last step in a final random forest classification. Once all classes could be correctly extracted, they were mosaicked together. Some obvious misclassifications such as the occurrence of coastal wetlands in high density built-up areas and built-up areas in wetlands were manually reclassified where they could be detected.

The classification strategy chosen here can prove successful in similar future studies where images from the same season, preferably near the vegetation peak are used. The motivation for choosing this particular order was to minimize the confusion between classes by classifying and extracting the class with the highest separability from all other LULC classes first, in this case water bodies. By visually interpreting differences in-between bands and numerically comparing digital pixel numbers, the following classes with highest separabilities were determined. This approach is in principle feasible on any kind of remotely sensed data (not only on optical data sets from the vegetation season) and arbitrary amount of land cover classes, but an individual inspection of the imagery is required to determine the highest separabilities between the land cover classes that are to be delineated. However, it is advised to refrain from applying the scheme to very high-dimensional data with only small differences in digital brightness values and from classifications outside the field of remote sensing when a lot of classes need to be distinguished due to a low time-efficiency of the method. One advantage though is that the correctness of the classified LULC class can be immediately assured and that potential misclassifications can be addressed directly, thus reducing the likelihood of introducing further errors in the consecutive classifications.

4.5. Urbanization indices

In order to enable the comparison between the degrees of urbanization and the speed at which urban areas developed, two indices are used in this study. The Urban Land Index (UI) is the ratio between urban land and total land at a distinct point time. The Urban Expansion Index (UX) compares the amount of urban land of two time steps and is thus a relative measure of urbanization. UI is determined for each region for both 1990 and 2010 and UX once for each region as calculated by Hu et al. (2009) according to Eqs. (1) and (2).

$$UI = \frac{UL}{TL} \times 100\% \tag{1}$$

Table 2
Core set of landscape metrics used in the study.

Landscape composition metrics	Description
Mean Patch Area (AREA_MN)	Equals the sum, across all patches of the corresponding patch type, of the corresponding patch metric values, divided by the number of patches of the same type
Largest Patch Index (LPI)	Equals the percentage of the landscape comprised by the largest patch
Percentage of Landscape (PLAND)	The percentage of each class in the landscape.
Landscape configuration metrics	**Description**
Landscape Shape Index (LSI)	Measures the perimeter-to-area ratio for the landscape as a whole
Number of Patches (NP)	Equals the number of patches in the landscape

$$\mathrm{UX} = \frac{\mathrm{UL}_{2010} - \mathrm{UL}_{1990}}{\mathrm{UL}_{1990}} \times 100\% \tag{2}$$

where UL = amount of urban land and TL = amount of total land.

4.6. 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; Urban et al., 1987; Turner, 1989). Landscape Metrics 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. Land use changes at a regional scale/landscape level have proven valuable in numerous studies (O'Neill et al., 1999; Su et al., 2011; Furberg and Ban, 2012) and with special focus on urban regions (Herold et al., 2002; Luck and Wu, 2002; Seto and Fragkias, 2005; Aguilera et al., 2011). Evaluation of landscape fragmentation as a result of spatio-temporal land cover changes was performed using selected metrics generated with the Fragstats software (McGarigal and Marks, 1995) on the classified land cover maps. The core set of metrics used in the study is presented in Table 2. The choice of these particular metrics was motivated by a review of the most commonly used landscape metrics in urban and urbanization studies. The six metrics that were identified in Jain et al. (2011) that were chosen in this study are mean patch area, class area, largest patch index, landscape shape index, number of patches and percentage of landscape. Class area and percentage of landscape are considered redundant and thus class area is omitted. Out of a large portfolio of partly redundant landscape metrics, the metrics that were chosen in the study can be considered both complementary and diverse and the synergetic use and interpretation can lead to new insights in landscape pattern changes.

4.7. Ecosystem services

The concept of ecosystem services is applied to the regions as indicator of the effects of land cover changes in form of urbanization upon the natural environment. Many definitions and explanations of ecosystem services have been given over the years and one of the first and fundamental descriptions was issued by Daily (1997) that reads: 'Ecosystem services are the conditions and processes through which natural ecosystems and the species that make them up, sustain and fulfil human life.' A nowadays well-established valuation scheme for ecosystem services that attributes a monetary value to natural land cover classes as functioning ecosystem services was developed by Constanza et al. (1997). The definition of global ecosystem services and their respective values are defined for an American market primarily with the valuation concept of individuals' 'willingness-to-pay'. Further research was performed with different pricing approaches and different ecosystem services and biomes over the years, e.g. by De Groot et al. (2002). The scheme used in this research was especially developed by ecological experts for the Chinese market (Xie et al., 2008). The loss and gain of ecosystem functions and services is calculated for the land cover classes water, wetland, aquaculture, forest, bare/desert and cropland. The total biome area is first summed up and then multiplied by a monetary factor as presented in Eq. (3):

$$E = \sum_k (A_k \times V_k) \tag{3}$$

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.

The services that were defined in Xie et al. (2008) and that were drawn into consideration are food production (FP), raw materials (RM), gas regulation (GR), climate regulation (CR), water regulation (WR), waste treatment (WT), soil maintenance (ST), the maintenance of biological diversity (BD) and landscape aesthetics (LA). Not all of the land cover classes determined in the study yield a value according the abovementioned scheme. Values for aquaculture and urban environments have undefined ecosystem service values. Since the accurate determination of urban ecosystem services is not yet feasible on a global level and should rather be examined at a smaller scale, e.g. at the city level and because this study investigates urbanization at a regional scale, ecosystem services and their values for urban areas (e.g. urban green spaces, parks, golf courses, etc.) are disregarded. Aquaculture is neither a defined class in the scheme and is instead treated as water as closest related class. Table 3 depicts an excerpt of the ecosystem services and their market values in Chinese Yuan (CNY) as proposed by Xie et al. (2008).

5. Results

5.1. Classification results

The following figures show the classification results. Fig. 4 depicts the whole classified mosaics over JJJ, YRD and PRD whereas Fig. 5 gives a more detailed overview over three important megacities (Beijing, Shanghai and Shenzhen) where an increase in urban land cover is most prominent.

5.2. Classification accuracies

The classification accuracies and kappa coefficients of the classifications are summarized in Table 4. An average overall accuracy of 86% could be reached, with kappa coefficients of about 0.84. Table 5 presents the aggregated class accuracies for each classification.

As additional measures that describe quality and reliability of the classifications, allocation and quantity disagreement as suggested by Pontius and Millones (2011) were calculated and are presented in Table 6.

Table 3
Excerpt of ecosystem services and their market value in Chinese Yuan (CNY) as proposed by Xie et al. (2008).

Service		Forest	Agriculture	Wetland	Water/aquaculture	Bare
Provisioning	FP	148	449	161	238	9
	RM	1338	175	108	157	18
Regulating	GR	1940	323	1082	229	27
	CR	1828	436	6085	925	58
	WR	1837	346	6036	8430	31
	WT	772	624	6467	6669	117
Supporting	ST	1805	660	894	184	76
	BD	2025	458	1657	1540	180
Cultural	LA	934	76	2106	1994	108
Total		12,629	3548	24,597	20,367	624

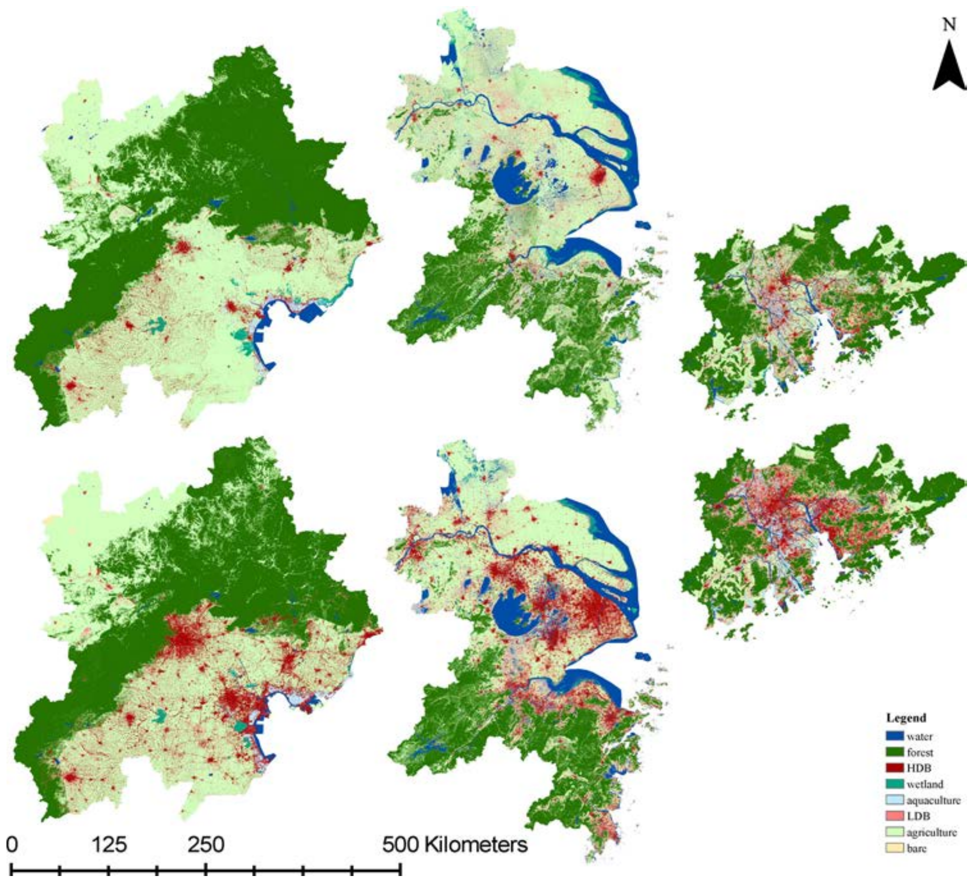

Fig. 4. Classification results from 1990 (left column) and 2010 (right column). JJJ is shown in the upper row, YRD in the central row and the PRD in the lower one.

Table 4
Comparison of overall classification accuracies and kappa coefficients for all classifications.

	JJJ 1990	JJJ 2010	PRD 1990	PRD 2010	YRD 1990	YRD 2010
Overall accuracy	88.06%	87.94%	85.22%	87.63%	82.57%	86.13%
Kappa coefficient	0.863	0.866	0.834	0.858	0.795	0.843

Table 5
Aggregated class accuracies for each classification.

	JJJ 1990	JJJ 2010	PRD 1990	PRD 2010	YRD 1990	YRD 2010
Water	82.9	98.3	99.9	99.9	99.5	88.3
Forest	94.9	82.1	98.1	76.7	94.9	89.4
HDB	92.6	80.5	95.2	90.0	91.4	92.3
Wetland	99.9	98.0	79.3	98.3	76.8	64.1
Aquaculture	79.9	92.0	71.6	87.7	63.4	90.8
LDB	55.6	48.2	66.2	78.5	70.4	84.7
Agriculture	99.7	93.9	88.5	81.0	78.7	94.4
Bare	96.9	99.4	82.0	96.4	–	–

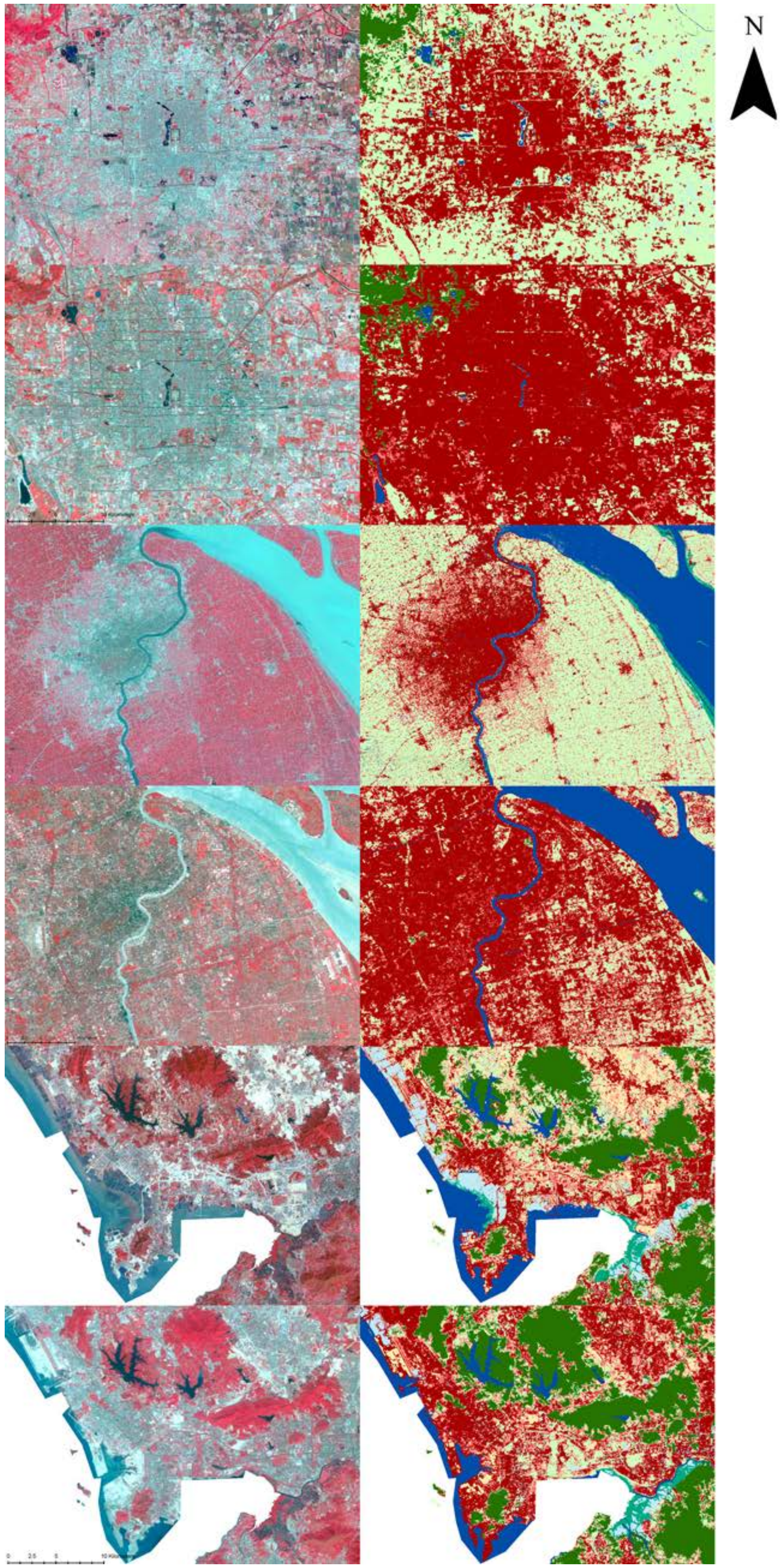

Fig. 5. Detailed excerpts from the classifications (right column) and their respective areas in FCC images in the left. The six rows show the following areas in descending order: Beijing 1990, Beijing 2010, Shanghai 1990, Shanghai 2010, Shenzhen 1990 and Shenzhen 2010.

Table 6
Allocation and quantity disagreement in percent according to Pontius and Millones (2011).

	Allocation disagreement	Quantity disagreement
JJJ 1990	5.13	7.93
JJJ 2010	0.52	2.92
YRD 1990	7.34	8.26
YRD 2010	5.90	3.39
PRD 1990	4.40	2.87
PRD 2010	6.90	12.08

5.3. Urbanization indices and land cover changes

Table 7 presents both urbanization indices UI and UX as well as the total amount of urban land as the sum of high density built-up and low density built-up areas in hectares.

The increase in urban areas occurred predominately at the expenses of cropland in all regions. A decrease in wetlands and natural coastal areas could be observed as well whereas bare areas and woodlands did not seem to change significantly. The main causes for the reduction and partly complete disappearance of coastal wetlands and shallow coastal water areas is the creation of aquacultures and land-reclamation.

5.4. Landscape metrics

5.4.1. Percentage of landscape (PLAND)

The changes in percentage of landscape are shown in Fig. 6. A decrease in agricultural land of ca. 5.5% alongside a simultaneous increase in high density built-up areas of about 6.4% can be observed as major changes in relative landscape composition. The second largest change is an increase in low density built-up areas of about 1%. Changes in water, forest, wetland, aquaculture and bare areas account for less than 1% of change, respectively. In the YRD, largest increases are observed for high density built-up (8.8%) and low density built-up areas (3.2%). Decreases in percentages of agricultural land (11.7%) and wetland of about 1% could be found. Changes that account for less than 1% for each land cover class could be observed in water, forest and aquaculture. Regarding the percentage of landscape in the PRD, largest changes can be observed in low density built-up (7.9% increase), high density built-up (4.3% increase), aquaculture (2.1% increase), agriculture (10.9% decrease) and forest areas (2.8% decrease). The percentage of landscape of water and bare areas decreased less than 1%, respectively.

5.4.2. Number of patches (NP)

Fig. 7 gives an overview over the number of patches in the landscape. The number of patches is a simple measure of subdivision and fragmentation of different patch types. In JJJ, agricultural patches increase while the total agricultural area decreases indicating a more fragmented rural landscape. Increased amounts of patches are also observed for the built-up classes high density built-up and low density built-up.

Table 7
Comparison of UI, UX and total hectares of urban land.

	UI	Hectares urban land	UX
JJJ1990	4.69	863,320	140.66
JJJ2010	11.67	2,077,658	
PRD1990	11.80	503,167	77.70
PRD2010	20.98	894,129	
YRD1990	10.26	1,209,850	100.07
YRD2010	20.53	2,420,570	

Table 8
Comparison of LSI and NP for JJJ/YRD/PRD.

	LSI 1990	LSI 2010	NP 1990	NP 2010
JJJ	154.02	180.46	89,117	130,540
YRD	232.21	240.74	161,359	194,959
PRD	247.56	281.56	49,306	65,945

5.4.3. Largest patch index (LPI)

The largest patch index at the class level quantifies the percentage of total landscape area comprised by the largest patch and is thus a measure of dominating land cover type. Largest patch indices for high density built-up areas increased in all regions, indicating the agglomeration of built-up areas into larger, more densely built-up patches. The largest patch indices for JJJ, YRD and PRD are shown in Fig. 8.

5.4.4. Mean patch area (AREA_MN)

The mean patch area metric for JJJ, the YRD and PRD is displayed in Fig. 9. Mean patch area equals the area sum of all patches of a specific land cover class divided by the total number of patches of the same class. In JJJ, a rise in high density built-up mean patch size can be observed. Both the number of patches and the total urban area are increasing for high density built-up areas.

Table 8 summarizes the landscape shape index values and the number of patches. The landscape shape index increases all over the study areas indicating a continuous landscape irregularity and complexity. The PRD shows the highest degree of landscape shape complexity both in 1990 and 2010. As the landscape shape index describes the perimeter-to-area ratio of the complete landscape, higher values indicate more edge between different patches and more dispersed patch types. That can be attributed to a more complex patch shape and/or an increasing number of patches (as found in the analysis). The relative change in landscape complexity and increase in number of patches is highest in JJJ, followed by the PRD and YRD. JJJ is still least complex due to the large coherent patches of forested mountainous areas and agricultural areas towards Inner Mongolia.

5.5. Ecosystem services

Ecosystem service values were calculated according to Eq. (3) based on the scheme of Xie et al. (2008). In total, a decrease in ecosystem service values from approximately 148.2 to 139.2 million CNY in JJJ, from 100.8 to 92.5 in the YRD and from 39.6 to 38.4 in the PRD could be observed. Substantial losses can be observed in JJJ and the YRD whereas the PRD only shows slight ecosystem service 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 ecosystem service values. Secondly, an increase in aquaculture can be detected that contributes to ecosystem services and thirdly, urbanization comes predominately at the cost of cropland that yields low ecosystem service values. Table 9 summarizes the losses in ecosystem services for each biome.

6. Discussion

An increase in built-up areas, especially high density built-up can be seen in all classifications. In JJJ, 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 northern 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

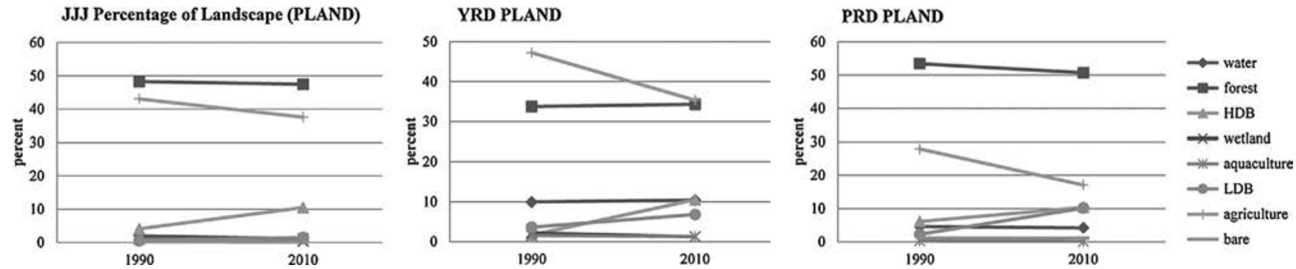

Fig. 6. Percentage of Landscape (PLAND) for JJJ, YRD and PRD from 1990 to 2010.

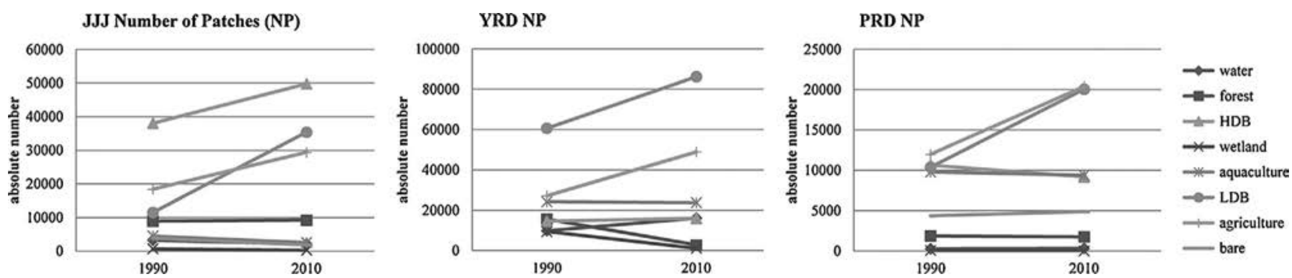

Fig. 7. Number of Patches (NP) for JJJ, YRD and PRD from 1990 to 2010.

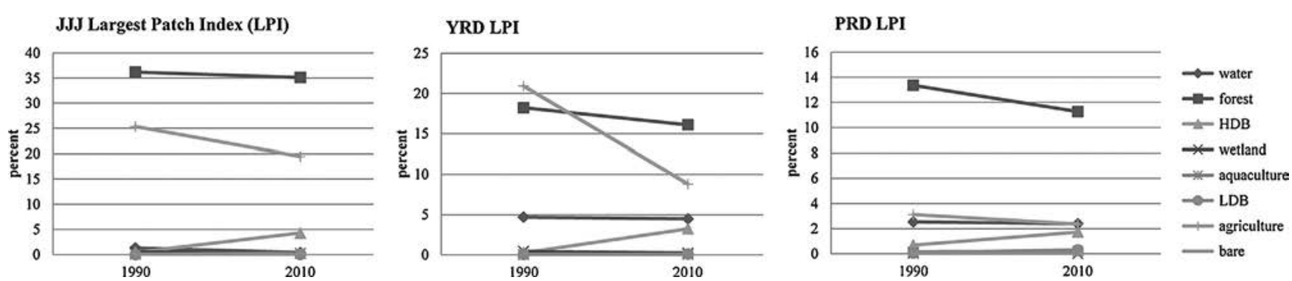

Fig. 8. Largest Patch Index (LPI) for JJJ, YRD and PRD from 1990 to 2010.

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. Regarding the YRD, 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 JJJ, no significant changes in inland water areas can be observed. Forested areas seem to have remained unchanged as well. The increase in high density built-up and low density built-up areas comes at the cost of cropland and a distinct loss of coastal wetlands and coastal waters as a result of land-reclamation in south-east Shanghai. The degradation of natural coastal wetlands took primarily place at the south-eastern shore of Pudong where wetlands have been transformed into high density built-up 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 be observed in the detailed overview of Shanghai in Fig. 5. Land-reclamation for agricultural use, new aquacultures and high density built-up areas at the expense of wetlands and water also occurs in the PRD, especially along the coast between Shenzhen and Shajingzhen as can be seen in Fig. 5 or in the example of Hong Kong International Airport. The increases in high density built-up and low density built-up areas alongside a decrease in agricultural land and to a certain extent forest in the coastal hinterlands are the most prominent changes in the PRD. 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 and have nearly completely vanished. Bare areas in the form of pits, quarries and aquacultures seem to remain unchanged.

Generally it can be observed that the delineation of low density built-up areas from high density built-up areas is most problematic with accuracies as low as 48% in one specific case. The reason for

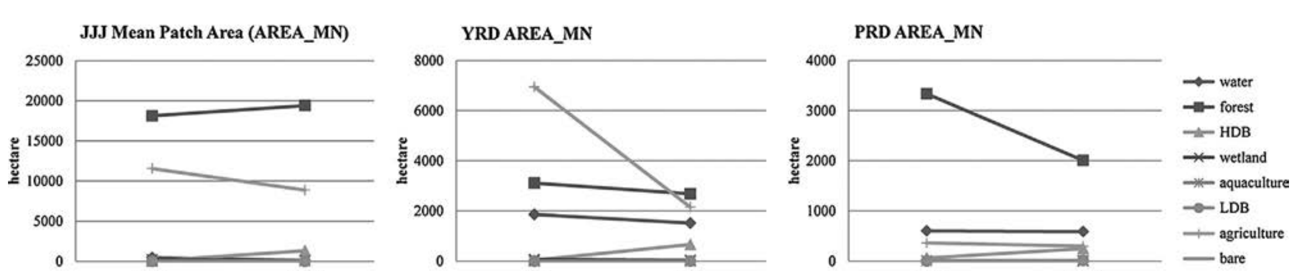

Fig. 9. Mean Patch Area (AREA_MN) for JJJ, PRD and YRD from 1990 to 2010.

Table 9
Detailed changes in biomes and ecosystem service value quantification in billion CNY over JJJ, YRD and PRD between 1990 and 2010.

		Hectare	Billion CNY
JJJ	Water	−134,121	−2.732
	Forest	−138,259	−1.746
	Wetland	−78,501	−1.931
	Aquaculture	+22,390	+456
	Agriculture	−868,838	−3.083
	Bare	−16,855	−11
		$\sum$	−9.045
YRD	Water	−2823	−57
	Forest	−14,378	−182
	Wetland	−113,231	−2.785
	Aquaculture	−88,740	−1.807
	Agriculture	−991,544	−3.518
		$\sum$	−8.350
PRD	Water	−12,189	−248
	Forest	−114,918	−1.451
	Wetland	−9065	−223
	Aquaculture	+95,328	+1.942
	Agriculture	−356,195	−1.263
	Bare	+6076	+4
		$\sum$	−1.241

this is the fact that low density built-up 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 in themselves are often treated as separate building blocks and are classified as high density built-up. Roads that are often narrower than the spatial resolution of 30 m are also treated as low density built-up areas since both the actual paved road and the surrounding land cover determine the spectral reflectance of the pixels in question. All in all, when looking at ecosystem services at such a large scale as the study areas and especially with respect to the valuation scheme that is applied in this research, these confusions do not play a major role since anyhow no ecosystem service value is attributed to urban land cover. 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. Overall accuracies between 83% and 88% suggest that the majority of land use and land cover classes could be correctly classified but the interpretation of the results should nevertheless be cautiously performed. An error margin of about 15% should be kept in mind when drawing conclusions about the loss of ecosystem service values and land cover changes. However, the classes that make up the largest share of land cover (forest, agricultural, water and high density built-up areas) were classified with higher average accuracies than the land cover classes that only constitute a small share of the total land use (low density built-up areas and wetlands).

As can be seen from Table 9, urban land increased in all study areas. JJJ and YRD experienced the largest absolute increase in built-up areas with about 12,000 km^2 respectively whereas the PRD grew only about 4000 km^2. 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 JJJ according to the UX, where urban areas increased by about 148%, followed by the YRD where urban areas roughly doubled. The smallest relative increase with approximately 78% growth in urban areas can be observed in the PRD. Land cover transitions to both high density built-up and low density built-up areas are apparent in all regions and come at the expense of predominately cropland in all study areas. At the same time, other natural land cover classes are decreasing at a smaller but noticeable extent. Aquacultures increase in the PRD alongside a decrease in natural wetlands which nearly disappeared completely. Bare areas do not change significantly over time, neither in JJJ nor in the PRD.

The changes in percentage of landscape are based on classification accuracies and it should be noted that the percentages here can deviate with about 15%. As both the number of patches and amount of high density built-up and low density built-up land increase, the development of new urban patches is suggested rather than a continuously fragmented urban landscape. Comparable to JJJ, low density built-up and high density built-up patches increase alongside an increase in total land cover in the YRD, indicating the evolvement of newly built-up patches. Also similar to JJJ, agricultural areas in the YRD and PRD show increased amounts of patches alongside a decrease in areas which indicates fragmentation. The decrease in wetlands both in number of patches and areas does not suggest fragmentation but simply the disappearance of complete patches. Forested areas do not significantly change in terms of area but show a reduced amount of patches. One explanation for this could be small patches south of Taihu Lake that were classified as forest in the 1990 classification. Investigation of these patches by visual exploration of high resolution images suggests misclassifications and confusion with vegetated fields. Regarding the changes in numbers of patches in the PRD, more low density built-up and agricultural patches can be found as major change. Interpretation of changes in patch numbers and amount of land cover suggests a similar development as in JJJ and the YRD – fragmentation of agricultural areas and development of new low density built-up patches. Interestingly, high density built-up areas show a slight decrease in amount of patches at a simultaneous growth of high density built-up areas. This suggests a development of high density built-up areas adjacent to each other, in connection with already existing patches and/or an enlargement of already existing high density built-up areas. Regarding the largest patch indices, it can be said that large coherent forested and agricultural areas characterize the study areas, both in 1990 and 2010. Although the maximum patch size is decreasing, both forest and rural areas still account for over 50% of the landscape. The largest patch indices for high density built-up patches are found increasing indicating the growth of a large urban agglomeration (best observed in Beijing, Tianjin and Tangshan). Similar to JJJ, large connected mountainous forests and agricultural land dominate the landscape at both time steps in the YRD. The largest high density built-up patch area is found increasing. This could indicate the growth of a single high density built-up urban area (e.g. Shanghai) and/or the coalescence of existing cities to urban agglomerations (e.g. the axis Changzhou–Wuxi–Suzhou). Largest patch index values for the PRD indicate that the by far largest patch is forest similar to the other study areas. The largest agricultural patch is found decreasing, but not as drastically as in the other regions. The reason for this could be a more heterogeneous landscape composition already in the 1990s by the relatively speaking high amount of aquacultures and natural river courses that fragment the landscape already at that time. This heterogeneous landscape could also be the reason for relatively low largest patch index values in general in the PRD. The only noteworthy largest patch index rise could be found for high density built-up areas suggesting further cohesive development of urban areas or the agglomeration into larger urban clusters. The relative growth in area is higher than the growth in amount of patches, indicating that the enlargement and growth of already existing urban areas occurs more often than the evolution of additional smaller high density built-up patches. The mean patch areas for forest tend to increase as well. This is a result of small variations in total forested area and the number of forest patches. Bearing confusion between forest and vegetated fields in mind, the interpretations that could be made are highly speculative and no definite response of forested areas to the growth of urban areas should be reported. Visual inspections however show a slight increase of urban areas in mountain forest valleys, but this is not believed to affect the mean patch area significantly. The decrease in agricultural mean patch area can both be attributed to the decrease in the percentage of landscape and to an increase in patches indicating a more fragmented landscape. The largest change in mean patch area in the YRD can be observed in agricultural areas. This can both be explained by the reduced amount of agricultural areas and by increase in patches as a result of a continuously fragmented landscape. Mean patch sizes of high density built-up areas increase as a result of a large increase in total high density built-up area. Through a simultaneous slight increase in number of patches, high density built-up urban development can be characterized as enlargement of existing urban patches and the aggregation of patches rather than the development of dispersed new patches. Forest and water mean patch sizes decrease as well. As their respective total areas do not change significantly, the mean patch area reduction can be attributed to an increased amount of patches. An increase in forest patches is however unrealistic and is most likely due to misclassifications as explained above. An increased patchiness of water seems to be unrealistic as well since inland water bodies (lakes and rivers) are found not to have changed significantly. A reduction in coastal wetlands and water areas as a result of land reclamation and the confusion with wetlands could be reasons for the decreases in mean patch area. Two major change observations can be made in the PRD. First of all, the mean patch area of forests decreases significantly. Investigating the number of patches and the percentage of landscape, the ratio can be explained by the total decrease of forested areas since the number of patches remained stable. This suggests a decrease in patch sizes rather than a fragmentation of existing forest patches. Misclassifications and confusion with agriculture could be an explanation. Furthermore, a rise in mean patch size of high density built-up areas could be detected. This is a result of decreasing numbers of patches combined with an increase in high density built-up areas. Visual explorations of the classified mosaics confirm the development and agglomeration of larger urban areas instead of small disaggregated high density built-up patches. Changes in landscape complexity are believed to be a result of the increase of urban patches, especially in high density built-up areas in all regions.

The largest loss of ecosystem service values of about 9.05 billion CNY was detected in JJJ, 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. Ecosystem service losses in the YRD are nearly as high as in JJJ and sum up to about 8.35 billion CNY. The main reason for this loss is the reduction of arable land in favour of high density built-up and low density built-up land and the loss of coastal wetlands south-east of Shanghai where Hangzhou Bay meets the East China Sea due to land- reclamation. The ecosystem service value gains and losses in the PRD are rather balanced in comparison to the YRD and JJJ but still sum up to ca. 1.24 billion CNY. The substantial but relatively smaller loss in the PRD can be explained by an increase in aquacultures in the area alongside a smaller growth in urban areas. The largest contributors to the loss are the decreases 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.

Regarding the land cover changes calculated by the percentage of landscape metric, the numbers might seem quite low and the significance of the changes that in turn influence ecosystem service values can be questioned. However, it needs to be pointed out that the huge study areas include large proportions of the landscape where no or very little change occurs, e.g. large forested mountainous areas, plains, lakes or sea. Excluding these land cover classes from the total area would result in higher percentages of land cover changes. The question of how reliable the results are can only be partly answered by the accuracy assessment. Since traditional accuracy assessment by omission and commission errors and overall accuracies do not sufficiently consider errors in location and quantity of the classified pixels, additional measures of accuracy as suggested by Pontius and Millones (2011) have been introduced. Quantity disagreements lie in the range from 3 to 12% and allocation disagreements from 0.5 to 7%. The average quantity disagreement is around 6%. This means a 6% deviation of the estimated increases in built-up areas and ecosystem service losses should be recognized when drawing conclusions from the study.

A limitation to the approach pursued here of estimating possible environmental impacts lies in the usefulness of ecosystem services as ecological and economic indicator according to 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.

One interesting study that attempts to establish closer links between ecosystem services, their functions and landscape structure aspects was conducted by Frank et al. (2012). In their approach, three ecosystem services (ecological functioning, aesthetic value and economic wealth) of a landscape are considered. As pointed out by the authors, there are only few interdisciplinary studies that target the combined use of the concepts of ecosystem services and landscape metrics, e.g. Sherrouse et al. (2011) or Yapp et al. (2010). Burkhard et al. (2010) state that a combination of the two concepts is missing for practical applications in landscape planning. Despite all the lack of clarity between the concepts, some relations can be assumed when regarding ecosystem services devoid of a monetary assessment. Although the concepts of landscape metrics and ecosystem services are based on different approaches they can both express implications of landscape change on ecological functioning. As ecosystem services are derived from the amount of land cover, landscape metrics consider the shape or ecologically important land cover classes, their spatial distribution and interactions with each other. The ecosystem services that are believed to be least influenced by the changes in landscape pattern but instead by the mere changes in hectares are assumed as gas and climate regulations, nutrient cycling, waste treatment, food production and raw materials. On the contrary, ecosystem services that are provided by and require the presence of animals, e.g. pollination, biological control, habitat/refugia and genetic resources are not only negatively affected by the reduction in size but are believed to also suffer from a continuous fragmentation and disconnection of the landscape through new anthropogenic areas. Fragmentation and an increased landscape complexity and thus more edge that is shared between different land cover classes is also considered to negatively affect regulatory services such as disturbance regulation and water regulation, water supply, erosion control and soil formation processes. The construction of new residential areas can be sometimes regarded positive in terms of recreational and cultural values through an increase in accessibility for a larger share of the population.

Apart from a disputable valuation scheme (varying valuation approaches and values), urban areas yield, according to the well-known valuation schemes presently used, no ecological values. Urban green spaces and low density built-up areas are though considered ecologically important and should therefore play a role in urban and regional studies. An ecosystem service valuation scheme that comprehensively defines urban ecosystem services and attributes a value to them is still missing. This would be a valuable asset for further urbanization studies and could provide further insights in nature and quality of urban developments. Relating landscape metrics to ecological processes still needs to be investigated and is considered a major research topic in landscape ecology (Wu, 2013). The landscape pattern is believed to significantly influence ecological processes and thus ecosystem functioning in the landscape. Landscape fragmentation is considered profoundly altering ecological and socioeconomic processes. The spatial optimization of landscape pattern for environmental purposes presents interesting research opportunities and requires further interdisciplinary approaches. One future aspect of combined ecosystem and landscape pattern analysis can be the identification of optimal landscape patterns (Wu, 2013).

7. Conclusion

This study can be regarded as one of the first approaches to analyze the speed and magnitude of urbanization, possible environmental implications by the concept of ecosystem services and the composition and configuration of the landscape characterized by landscape metrics were investigated in a comparative study at a regional scale over two decades from 1990 to 2010 in JJJ, the YRD and the PRD. Similar urbanization trends in terms of land use and land cover changes could be observed between JJJ, the YRD and the PRD but differences in impacts on ecosystem services, and speed and magnitude of urban expansion could be found. A substantial reduction in ecosystem service functions and values could be observed in all study areas as a result of rapid urbanization in China. 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 could be identified and quantified. Urban areas in the study areas grew with about 28,000 km^2. Urban growth in JJJ and the YRD were with approximately 12,000 km^2 about three times higher than in the PRD (ca. 4000 km^2). Over a 20 year time frame, urban areas grew to about 140% of their initial extent in JJJ, thus having expanded most of all regions. Urban areas doubled in the YRD and grew about 80% in the PRD. In terms of relative distribution of land cover classes in the form of landscape percentage, an increase of high density built-up and low density built-up areas could be observed in all areas alongside a decrease in wetlands and increasingly fragmented agricultural areas. An increase in landscape complexity can be found in all three regions. The most heterogeneous landscape pattern could be found in the PRD, not only as a result of urban development but also partly attributed to a natural predisposition of the landscape prior to urbanization. The negative effects of urbanization upon natural land as a qualitative measure were determined by the concept of ecosystem services. Losses in ecosystem services values could be estimated with 9.05 billion CNY in JJJ, 8.35 billion CNY in the YRD and 1.24 billion CNY in the PRD, respectively. The loss of both large areas of arable land and of ecologically important wetlands together accounts for about 68% of the total loss of ecosystem services in the regions. A total growth of about 28,000 km^2 of urban areas could be observed in the study areas resulting in a total loss of roughly 18.5 billion CNY. This distribution of losses coincides with the increase in built-up areas that are higher in JJJ and the YRD than in the PRD. This study demonstrates the need for a more sustainable future urban development in these regions if the negative effects for the natural environment and eventually the urban population are to be ameliorated. The combined use of landscape metrics, urbanization indices and ecosystem services is found to enable quick relative comparisons between different regions or for the analysis of a particular urban area but the evaluation of explicit implications of urbanization for intricate ecological processes requires a deeper understanding of the linkages between ecosystem functions and landscape changes which could be a valuable contribution of future research.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.jag.2013.12.012. These data are .kml-files of the study areas to be viewed e.g. in Google Earth.

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Satellite monitoring of urbanization and environmental impacts—A comparison of Stockholm and Shanghai

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ABSTRACT

This study investigates urbanization and its potential environmental consequences in Shanghai and Stockholm metropolitan areas over two decades. Changes in land use/land cover are estimated from support vector machine classifications of Landsat mosaics with grey-level co-occurrence matrix features. Landscape metrics are used to investigate changes in landscape composition and configuration and to draw preliminary conclusions about environmental impacts. Speed and magnitude of urbanization is calculated by urbanization indices and the resulting impacts on the environment are quantified by ecosystem services. Growth of urban areas and urban green spaces occurred at the expense of cropland in both regions. Alongside a decrease in natural land cover, urban areas increased by approximately 120% in Shanghai, nearly ten times as much as in Stockholm, where the most significant land cover change was a 12% urban expansion that mostly replaced agricultural areas. From the landscape metrics results, it appears that fragmentation in both study regions occurred mainly due to the growth of high density built-up areas in previously more natural/agricultural environments, while the expansion of low density built-up areas was for the most part in conjunction with pre-existing patches. Urban growth resulted in ecosystem service value losses of approximately 445 million US dollars in Shanghai, mostly due to the decrease in natural coastal wetlands while in Stockholm the value of ecosystem services changed very little. Total urban growth in Shanghai was 1768 km^2 and 100 km^2 in Stockholm. The developed methodology is considered a straight-forward low-cost globally applicable approach to quantitatively and qualitatively evaluate urban growth patterns that could help to address spatial, economic and ecological questions in urban and regional planning.

Introduction

Cities as functional centres of human agglomeration are, and have always been of tremendous importance. Due to a global increase in population and urbanization rates, accurate land use and land cover information is crucially important to support functional and sustainable development as well as the preservation of ecological and environmental conditions and processes in urban areas. Therefore, tools and methods are needed for the evaluation of urbanization and its environmental impacts. Remote sensing can provide timely and reliable information on urban land cover at local, regional and even global scales (Ban and Jacob, 2013; Niu and Ban, 2013; Ban et al., 2014a,b), urban change detection (Ridd and Liu, 1998; Ban and Yousif, 2012) or urbanization studies that target impact analyses of urban expansion on the natural environment (Zhang et al., 2011; Haas and Ban, 2014). More recently, the idea of remotely sensing ecosystem services (ES) or supporting information that helps in determining ecosystem functions has enjoyed increasing popularity (Lakes and Kim, 2012) although it must be said that the formation of well-established links between ES and remote sensing (Feng et al., 2010) and between ES and landscape metrics (LM) should be further explored (Syrbe and Walz, 2012).

LM derived from processed remote sensing data are well-established tools to measure land cover fragmentation which in turn may indicate environmental impacts on habitat and connectivity (Forman and Godron, 1986; Turner, 1990). LM have proved, in the field of landscape ecology, to be good predictors of an ecosystem's ability to support important ecosystem functions (Turner and Gardner, 1991). ES as indicators of functional ecosystems and ecological conditions have been used in practice since the beginning of the 1990s (De Groot, 1992; Costanza et al., 1997; Daily, 1997). Continuing research expanded the concept to urban areas (Bolund and Hunhammar, 1999), different valuation schemes (De Groot et al., 2002; Xie et al., 2008) and to remote sensing of ES (Feng et al.,

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2010). Efforts that integrate ES as possible indicators of environmental impacts resulting from urbanization are found in Li et al. (2010). To be able to compare the effects of urbanization on the environment at a common scale and to enable comparisons with other studies, the well-known valuation scheme of Costanza et al. (1997) is used. It should be however noted that ES values calculated here do not represent actual ES values for several reasons (qualitative differences between urban, rural and global importance of ecosystems functions and services; a lacking standardized urban valuation scheme; varying marketing and pricing principles and that they should rather be regarded relative to each other and to LULC changes).

For the planning goal of developing Stockholm into the most attractive metropolitan area in Europe (Office of Regional Planning, 2010), sustainable ecological development is crucial. Urbanization in the Stockholm region 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). In one of the first studies to highlight ES in an urban context, Bolund and Hunhammar (1999) identified the six ES that are regarded as most important for Stockholm as air filtering (gas regulation), micro-climate regulation, noise reduction (disturbance regulation), rainwater drainage (water regulation), sewage treatment (waste treatment), and recreational/cultural values. Some studies have focused on evaluating environmental impacts of urban growth in Stockholm city on the municipal level (Mörtberg et al., 2007; Andersson et al., 2009), but very little research is found at the county level. One such study was recently performed by Mörtberg et al. (2012) who model two scenarios of future development of Stockholm's metropolitan area and evaluate LULC changes and urban sprawl in terms of their impact on a prioritised ecological profile.

Numerous studies exist that investigate the effect of urbanization on the environment in Shanghai, e.g. in terms of changes in erosion and sedimentation and heavy metal concentrations in soils, ecological footprint analyses, effects on the eco-environment in terms of water resources, water quality (Ren et al., 2003), air pollution and increased urban heat island effects (Li et al., 2012), changes in plant diversities, changes in extent and pattern of urban areas (Zhang and Ban, 2008; Hu et al., 2009; Zhang et al., 2009; Li et al., 2010; Zhang and Ban, 2010; Ban and Yousif, 2012) or urban growth simulations (Zhang et al., 2011). Most of these studies only shed light on one particular aspect of urbanization or its effects. An exception is the study of Haas and Ban (2014) that use a similar approach as proposed here with the exception that regional instead of intra-urban development trends are observed.

As there is to date no comprehensive valuation scheme for ecologically important areas within urban areas, the value definition for urban green spaces (UGS) in addition to the scheme from Costanza et al. (1997) is a novel feature that in combination with the newly devised urban green index (UGI) might be an asset in further urbanization studies in respect to sustainability and ecological urban development. The combined approach of using LM and ES as tools for evaluating the effects of urbanization captures not only the spatial component of urban development in terms of landscape composition/configuration and possible impacts on the natural and rural environment, but also integrates an economic factor that extends the implications of LULC changes to a societal dimension. Ideally, the results from this study can provide insight into ways of how the two different regions are urbanizing and indicate which areas need management attention in order to promote more sustainable and environmentally friendly growth.

The study aims to assist in finding a standardized environmental impact evaluation and assessment approach that works in diverse environments and ideally could be applied to urban areas around the world. Well-established and reliable remote sensing techniques and environmental indicators are combined and their application tested to quantify and compare urban development and to draw preliminary conclusions about resulting environmental impacts through the use of LM and ES valuation in the two diversely growing metropolitan regions of Stockholm, Sweden and Shanghai, China between 1989 and 2010. The geographic setting, population, environmental conditions and rates of population growth and urban expansion differ sharply between the two locations and present a good case study setting for testing the methodology's applicability in different regions.

Study area and data

Study area

The study areas for the comparison are diverse, both in location, climate, population and development over the past decades. Stockholm is the largest city in Scandinavia and the cultural, economic and political centre of Sweden. 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. 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 7150 km^2. Major LULC classes in the area are low-density residential areas (LDB), high density built-up areas (HDB) including industrial/commercial areas, forest, agricultural/open land, parks/urban green areas and water. The region's characteristic "green wedges" or large forested areas are located relatively close to the city centre but extend further beyond, providing several of the region's essential ES.

Shanghai, located at the Chinese east coast, is currently the largest Chinese city with a total population of 23.03 million in 2010 and is both a major Chinese financial and economic centre. An increase in population up to 28.4 million is expected by 2025 (United Nations, 2012). The total area of Shanghai covers about 6340 km^2. The landscape is composed of high density built-up areas, high-rise, commercial and industrial areas, UGS, airports, ports and residential areas. Urban areas are surrounded by agriculture with villages and strips of rural residential areas and farms. Water bodies occur in the form lakes and rivers, aquaculture and wetlands (inland and coastal). Naturally grown forests are scarce and connected tree stands can mostly be found in the city centre in form of managed UGS. The LULC classes in the study are defined as HDB, LDB, UGS, agriculture, forest, water, wetlands and aquaculture.

Data

A set of Landsat TM images was chosen as data source for the study as Landsat provides global reliable coverage, enabling repeatable analyses and comparative studies. The dataset consists of twelve Landsat TM images from around 1989, 2000 and 2010. All images are part of the global land survey (GLS) series and were acquired through the USGS Earth Explorer. In some cases, the difference in image dates is not exactly 10 years but can deviate up to a year due to the fact that there simply are no images available at the same anniversary or that images that lie closer to the decennial anniversary suffer from high cloud cover or haze in the case of Shanghai. The images were however taken during the peak vegetation season (from May to September) and are considered the most suitable Landsat images for the purpose of the study. The six false colour composites (FCC) in Fig. 1 depict excerpts from the original Landsat mosaics and cover the central parts of the study areas prior to classification.

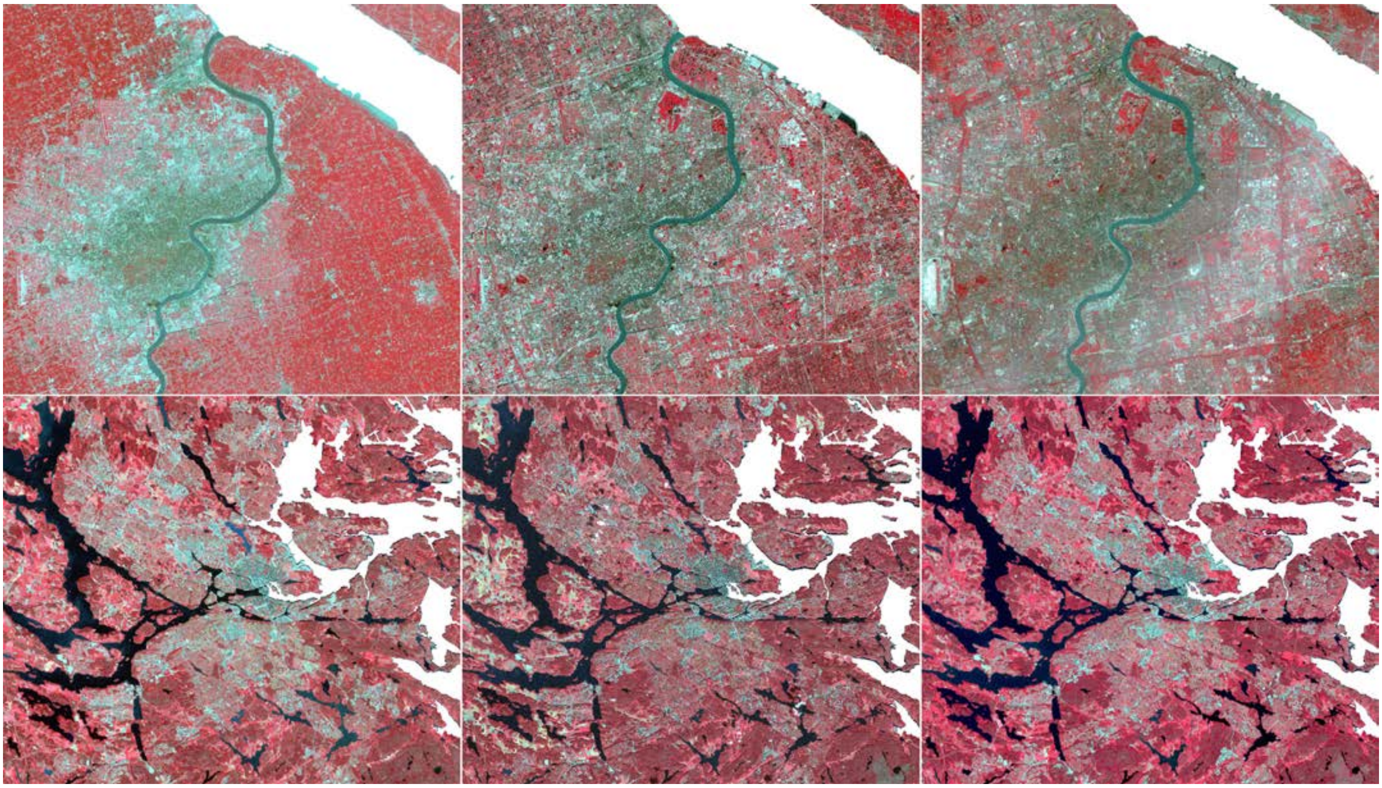

Fig. 1. Six FCC mosaic excerpts of the study areas of Shanghai (upper row) and Stockholm (lower row) from 1989 (far left), 2000 (central) and 2009/2010 (far right).

Methodology

Image pre-processing

The data used in the analysis originates from the same source (GLS) and is as a L1G/L1T product already issued in the most appropriate coordinate system for the study and does not need to be co-registered. Two images are needed to cover each study area. The mosaicking was performed with neighbourhood colour balancing.

GLCM features

The concept of grey level co-occurrence matrix (GLCM) texture features was first proposed by Haralick et al. (1973) and can be described 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 already been shown in particular over urban areas (Shaban and Dikshit, 2001; Herold et al., 2003). From the originally proposed 14 GLCM features, standard deviation (variance) was calculated with an 11×11 filter, 256 grey levels and directional invariance on Landsat bands 4 and 5. The feature and window size were chosen based on trials as well as the 11×11 filter's previous successful use in obtaining high-accuracy urban LULC classifications (Wu et al., 2004) and the significance and applicability of variance as revealed by previous studies (Furberg and Ban, 2012).

Pixel-based support vector machine (SVM) classification

Landsat bands 3–5 and the above mentioned GLCM features were used in the classification. A pixel-based SVM classifier separating classes by optimally defining the hyperplane between class boundaries was chosen to distinguish between agriculture, forest, HDB, LDB, UGS and water (wetlands and aquaculture only present in Shanghai). Several subclasses needed to be distinguished in an initial classification step in order to reduce confusion before aggregating them into the final LULC classes. UGS consist mostly of urban parks with open land, forest, water and golf courses and were reclassified from areas within the city boundary that were initially classified as forest and agriculture.

Manual classification refinements

Some obvious misclassifications in Shanghai were manually corrected by reclassification under masks. Confusion between HDB and wetlands was identified in coastal areas and central Shanghai. Aquaculture in urban areas was reclassified into water bodies (lakes and rivers). Some confusion between LDB areas and agriculture within the urban boundary could be removed as well as confusion between bare fields (agriculture), LDB and HDB outside the city. Finally, small unwanted aggregations of pixels or single pixels belonging to erroneous LULC classes were filtered out. This not only increases classification accuracies but is also a crucial step prior to landscape metrics 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 correctly identified landscape patches must be considered. The refinement process and filtering for the Stockholm classifications were similar to that of Shanghai, i.e. urban and rural masks were used to correct the more consistent misclassifications, most often caused by confusion between HDB and bare agricultural fields and between forest and LDB areas.

Urbanization indices

As comparison of speed and magnitude of urbanization, two indices were calculated for all three decades and both study areas. The urban land index (UI) as the ratio of urban land and total land and the urban expansion index (UX) as the difference in urban land

Table 1
Core set of landscape metrics used.

Landscape composition metrics	Description
Percentage of landscape (PLAND)	The percentage of each LULC class in the landscape.
Patch density (PD)	Number of patches per square kilometre.
Area-weighted mean patch size (AMPS)	Area-weighted average patch size of a class of patches.
Largest patch index (LPI)	A simple measure of dominance; quantifies at the class level the percent of landscape area comprised by the largest patch.
Landscape configuration metrics	**Description**
Area-weighted mean patch shape index (PSI_AM)	Area-weighted average of the ratio of perimeter to minimum possible perimeter given the number of cells in the patch; measure of shape complexity.
Contrast-weighted edge density (CWED)	Measured in meters per hectare: CWED = 0 when there is no class edge in the landscape. CWED increases as the amount of class edge in the landscape increases and/or as the contrast along the class edges increases.
Cohesion	Measures the physical connectedness of the corresponding patch type; cohesion increases as the class becomes more clumped or aggregated in its distribution.
Contagion (CONTAG)	Measures the relative aggregation of different patch types at the landscape level; contagion approaches 0 when the patch types are maximally disaggregated and interspersed. CONTAG = 100 when all patch types are maximally aggregated, i.e. when the landscape consists of a single patch.

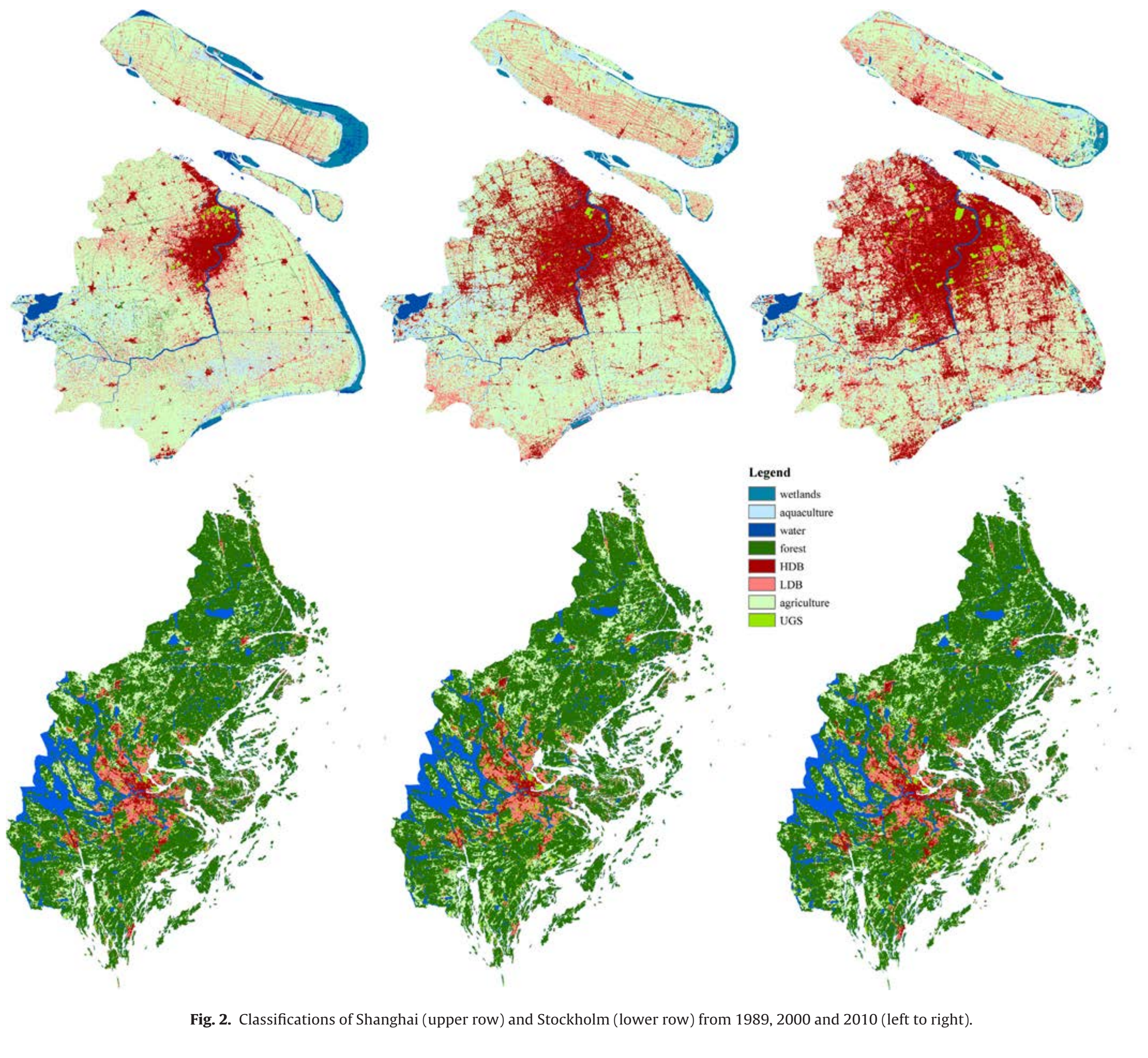

Fig. 2. Classifications of Shanghai (upper row) and Stockholm (lower row) from 1989, 2000 and 2010 (left to right).

Table 2
LULC classes and corresponding ecosystem service values in USD per hectare and year.

LULC class	Biome	Total value in USD per hectare and year
Wetland	Wetlands	14785
Aquaculture	Lakes/Rivers	8498
Water	Lakes/Rivers	8498
Forest	Forest	969
HDB	Urban	–
LDB	Urban	–
Agriculture	Cropland	92
UGS	(Forest + grasslands + water)/3	3233

over a period of time as calculated by Hu et al. (2009) are defined in Eqs. (1) and (2). An urban green index (UGI) was devised to quantify the development of UGS in comparison to simultaneous urban development. The index is calculated as the ratio of UGS increase divided by the sum of increases in HDB and LDB as defined in Eq. (3).

$$\mathrm{UI} = \frac{\mathrm{UL}}{\mathrm{TL}} \times 100\% \tag{1}$$

$$\mathrm{UX_r} = \frac{\mathrm{UL}_{t2} - \mathrm{UL}_{t1}}{\mathrm{UL}_{t1}} \times 100\% \tag{2}$$

$$\mathrm{UGI} = \frac{\mathrm{UGS}_{t2} - \mathrm{UGS}_{t1}}{(\mathrm{HDB}_{t2} + \mathrm{LDB}_{t2}) - (\mathrm{HDB}_{t1} + \mathrm{LDB}_{t1})} \tag{3}$$

where UL = amount urban land, TL = amount total land, UGS = amount urban green spaces, HDB = amount high density built-up, LDB = amount low density built-up.

Landscape metrics

Landscape metrics are a well-known concept and can be described as variables that describe particular aspects of landscape patterns. Landscape metrics are effective in analysing urban environments and have been applied in numerous studies, e.g. Herold et al. (2002) and Luck and Wu (2002). Evaluation of landscape fragmentation due to spatio-temporal changes was evaluated using selected landscape metrics (Table 1) proposed by McGarigal and Marks (1995), where full explanations of metrics calculations are given. The area-weighted mean metrics are used rather than their simple mean equivalents since they provide a landscape-centric perspective of landscape structure (they reflect the average conditions of a pixel chosen at random). This landscape-centric perspective is best suited here since two different landscapes are being studied and compared. The contrast-weighted edge density index or CWED is used for similar reasons (as opposed to using the total edge contrast index). 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.

Ecosystem services (ES)

The well-known scheme of Costanza et al. (1997) is applied to calculate ES values for each decade. Even though the actual, realistic ecosystem service values in Shanghai and Stockholm may not be obtained due to reasons stated above, a relative and thus indicatory observation of differences or similarities in urban developments can be made. Nevertheless, until there is a new comparable scheme fur urban ES and since one aim of this study is a comparison of possible environmental effects of urbanization in two different study areas, a common evaluation scheme that is based on the same principles is needed. The values generated in the study should not be taken literally but aim to mirror the different trends in urban developments. The scheme accounts for the following ES: gas regulation, climate regulation, disturbance regulation, water regulation, water supply, erosion control, soil formation, nutrient cycling, waste treatment, pollination, biological control, habitat/refugia, food production, raw materials, genetic resources and recreational and cultural services. Table 2 depicts the LULC classes identified in the study and the corresponding biomes and ES values per hectare and year from Costanza et al. (1997).

It should be noted that there is neither a value attributed to urban areas nor for UGS. Since UGS such as parks or golf courses are predominately composed of trees, water bodies and lawns, a value was defined by averaging the values of forest, grasslands and lakes/rivers. The valuation of golf courses and parks is disputable since the actual underlying ecosystem functions in urban areas are different from the ones in rural areas and integration of these two ecologically important classes in valuation schemes would be a valuable asset. Especially the ecological value of golf courses in terms of habitat provision and biodiversity has been stressed by Colding and Folke (2009). At the same time, UGS and golf courses lack some ecological functions and services present in rural green structure (e.g. food and raw material production).

Results and discussion

Classification results

The classified mosaics are displayed in Fig. 2 (Shanghai in the upper row, Stockholm in the lower row one). The 1989 images are found in the left column, 2000 in the centre one and 2009/2010 in the right one.

Classification and class accuracies for all mosaics are presented in Tables 3 and 4 below (SH = Shanghai and ST = Stockholm).

Water, agriculture, UGS, HDB and aquaculture all exceed 90% in class average. Wetlands seem somewhat problematic and forest and LDB areas were hardest to distinguish. Forest is mostly confused with vegetated fields in both areas. This confusion could be overcome by additional multitemporal data from another season in which the fields are bare or by integration of radar data whose backscatter signals are very different over forest and vegetated fields. The latter option could also improve the misclassifications of wetlands through soil moisture retrieval by means of dielectric

Table 3
Comparison of classification accuracies.

	SH1989	SH2000	SH2009	ST1989	ST2000	ST2010
Overall accuracy	88.08%	87.82%	89.36%	90.01%	88.98%	88.22%
Kappa coefficient	0.864	0.859	0.877	0.879	0.867	0.858

Table 4
Class accuracies and class average from all classifications.

	SH89	SH00	SH09	ST89	ST00	ST10	Class average
Water	95.6	95.4	99	98.2	99.4	99.4	97.8
Forest	76.5	70.4	87.2	81	78.3	76.6	78.3
HDB	94.6	95.8	84.8	91.9	92.2	89.3	91.4
LDB	67.8	65.4	71.9	88.7	84.7	87	77.6
Agriculture	93.7	94.9	89.3	95.8	94.5	94.2	93.7
UGS	99.5	99.5	95.9	86.3	89.1	87.8	93
Wetland	83.2	91.0	82.9	–	–	–	85.7
Aquaculture	97.4	78.3	96.6	–	–	–	90.8

surface properties and the distinction of LDB/HDB/agriculture through backscatter differences.

As can be seen from the confusion matrices of Shanghai, the most problematic class to distinguish is LDB with accuracies not exceeding 72%. This is due to the fact that there are two major components that make up LDB areas (buildings and surrounding green spaces and sometimes paved surfaces in addition). The problem is the distinction of both these features together as an entity and not 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 and seaming fields as well as single farms with gardens and roundish shaped villages. 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 also easily be confused with UGS that contain historical buildings or singular larger buildings that serve no residential function but rather express cultural and recreational values. There are relatively few forested areas in the study area (<1% of land cover) rendering the classification error-prone. Largest misclassifications occur between forest and agriculture (vegetated fields). Urban forests are considered as UGS and manually reclassified. It should be noted that HDB and LDB land cover classes are not restricted to urban areas, but can be found anywhere in the study areas. Urbanization is a process that is by no means restricted to existing urban boundaries but affects cities' hinterlands, peri-urban and rural areas likewise. Through the process of land transformation and evolution, urban areas and their boundaries are constantly redefined and therefore a deliberate definition of urban boundaries or the reference to older, already existing ones should not be the focus of the study since that would fail to grasp the developments in the urban fringe and beyond. It should however be mentioned that particular areas such as Chongming and its adjacent islands or areas around the study area boundary (i.e. in the south–west between Dianshan Lake and Jinshan are predominately rural areas dominated by agricultural production) and even though an increase of built-up areas can be observed, one should be cautious when discussing them in context of urbanization. From the Stockholm class accuracies, it can be seen that there was a slight over-detection of LDB and UGS in the 2000 alongside an under-detection of HDB areas. This was mainly attributable to noise in the 2000 image which dampened 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. The use of rural and urban masks helped to improve the classification of UGS somewhat.

Urbanization indices

As measure of speed and magnitude of urbanization and the degree of urban green space development, UI, UX and UGI for Shanghai and Stockholm were calculated, respectively (Table 5). Urban areas are composed of HDB, LDB and UGS.

A constant increase in urban land can be observed over each decade in Shanghai. Urban land increased by ca. 45% from 1989 to 2000 and another 50% from 2000 to 2009. The total increase in built-up areas is about 120% from 1989 to 2009. Urban expansion proceeded slightly faster in the second decade than in the first one. Urban growth in Stockholm is also apparent but at a much slower pace, especially from 2000 to 2009. Urban expansion both in terms of speed and spatial extent occurs predominately from 1989 to 2000. A meek increase of urban areas can be observed over two decades in Stockholm which corresponds to an expansion of about 12% of their original extent. Both urbanization speed and magnitude in Shanghai exceed Stockholm's tenfold. Both metropolitans show a positive development regarding UGS development, however there are major differences. In Shanghai, urban green areas 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.

Landscape metrics

In Shanghai, a significant increase in the percentage of built-up areas and UGS and an increase in LDB can be observed alongside a decrease in natural LULC classes (Fig. 3), most of all in agricultural land. In the first decade from 1989 to 2000, urban areas grew 45% (638 km^2). Between 2000 and 2009, the amount of urban areas rose by another 55% (1130 km^2). Over a 20 year period, urban areas more than doubled and increased by 124% (1768 km^2). Based on the statistics from the land use classifications of the Stockholm region, urban areas grew by about 7% (57 km^2) between 1989 and 2000 and by about 5% (43 km^2) between 2000 and 2010 in Stockholm County. The percent of urban growth between 1989 and 2010 was over 12% (100 km^2). The most significant changes are the loss of agricultural/open land in favour of LDB and HDB. Forest remained relatively unchanged during the two decades. 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.

An increase in HDB, agriculture and wetland patches was detected in Shanghai. Aquaculture does not change significantly over time indicating no change in terms of fragmentation and a slight decrease in patch density of water bodies in terms of lakes, rivers and coastal areas can be observed. LDB patches decreased from 1989 to 2000 and increased from 2000 to 2010. PD for HDB shows an inverted trend, suggesting a tightly coupled development between the two built-up classes. PD for HDB areas and agriculture increased overall. Taken with the percentage changes, it seems that many new patches of HDB were being formed where previously none existed while agricultural areas were shrinking leaving new smaller and more numerous patches of agriculture behind.

In Stockholm, the agricultural AMPS and patch density decreased steadily. This trend combined with the PLAND

Table 5
Urban land index, urban expansion index and urban green index.

	UI 1989	UI 2000	UI 2009/10
Shanghai	20.99	30.48	47.01
Stockholm	11.45	12.26	12.86
	UX 1989–2000(annual average)	UX 2000–2009/10 (annual average)	UX 1989/2009–10 (annual average)
Shanghai	44.73 (4.07)	54.76 (5.48)	123.98 (5.90)
Stockholm	7.04 (0.64)	4.92 (0.49)	12.30 (0.59)
	UGI 1989–2009/10		
Shanghai	0.039		
Stockholm	0.299		

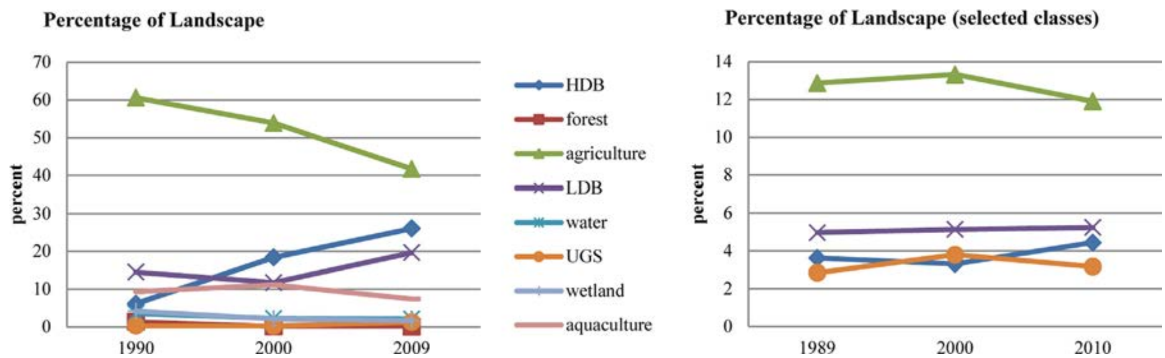

Fig. 3. Percentage of landscape in Shanghai (left) and Stockholm (right).

reduction indicates attrition within this class through the disappearance of patches as well as shrinkage. PD for LDB decreased while the AMPS increased overall between 1989 and 2010, indicating that neighbouring patches were combining to form larger (and fewer) patches as LDB areas increased. The trend for the growth of HDB areas was slightly different. PD for HDB increased over both decades and AMPS decreased, revealing that HDB areas were being added as new separate areas rather than as additions to existing patches. The relative decrease in HDB AMPS from 2000 to 2009 in Shanghai can be explained by the fact that the increase in HDB within the first decade occurred more centrally resulting in larger cohesive patches. At the same time, new and bigger patches were being added relatively close to existing HDB areas in the first decade, while mean patch sizes of agricultural areas decreased more quickly after 2000.

A clear trend away from agricultural land use towards HDB areas can be observed regarding the LPI, with the biggest change in the first decade in Shanghai. It is noteworthy that the increase in the percentage of LPI in HDB corresponds exactly to the decrease in LPI for agriculture for both decades. In Stockholm, LDB may occupy more area than HDB but tends to have more medium-sized patches whereas HDB is divided into one very large and many smaller patches. The non-linear trend for HDB and LDB is due to the previously mentioned HDB underestimation and LDB overestimation in the 2000 classification. Looking at the overall trends, it appears that LDB may soon overtake agriculture in terms of exerting more influence on the landscape through the presence of a greater largest patch.

In terms of shape complexity in Shanghai, man-made/managed objects with distinctive straight boundaries such as UGS and aquaculture naturally yield low values. Natural water bodies are slightly more complex since their edges follow local topography rather than human boundaries. LDB areas are comparable to water bodies in terms of shape complexity. Linear features such as rural strips and square shaped or roundish features such as villages are not particularly complex and did not change significantly over time. Agricultural patches however seemed to have decreased in shape complexity, probably because of the increased amount of edge that they share with less complex shaped LDB/HDB areas. In Stockholm, HDB and agricultural/bare land patches decreased in shape complexity for the same reason. LDB, on the other hand, increased in shape complexity, meaning a greater amount of edge interface with other (most likely) natural LULC types.

Differences in the progression of contrast-weighted edge density (CWED) for HDB, LDB and agriculture can be observed in Shanghai. HDB areas shared relatively few high contrast edges with other patch types in 1989 and this reflects their compact and centralised occurrence. After the first decade, urban sprawl can be observed in the urban–rural fringe where HDB areas developed next to LDB patches. At the same time, an increase in CWED for agriculture is present due to the development of HDB patches in Shanghai's rural areas. The second decade of urbanization is characterized by growth in LDB edge contrast and visual inspection of the classified images reveals a decentralized development of HDB and LDB areas in rural areas. For Stockholm, a greater amount of edge interface between forest and urban areas is observed. Contrast-weighted edge clearly increased for forest over both decades and increased overall for HDB areas, indicating that forest increasingly shared edges with urban areas (highest contrast to forest) while HDB increasingly shared edges with natural LULC types. This increased interface between natural LULC types and urban areas tends to have a negative impact on the flora and fauna found in the vicinity as it increases their vulnerability to adverse external effects.

No significant changes in cohesion as measure of the physical connectedness of corresponding patch types are noted. Contagion can be described as the tendency of patches to be spatially aggregated. The values in Shanghai continuously decreased from 57.27 to 52.79 – and more than two times faster in the second decade than in the first one, indicating a transition towards a more fragmented landscape with smaller and dispersed patches. From an ecological perspective, a higher degree of fragmentation, especially through built-up areas, and thus a lower degree of patch connectivity is considered a negative effect (the natural habitat areas for plants and animals are reduced and the ecological quality of habitat edges decreased through human-induced stress). Contagion values

Table 6
Ecosystem Service balances over two decades in Shanghai and Stockholm in million USD.

Biome	1989	2000	2010	Total absolute loss	Percentage 1989–2009/10
Shanghai Wetlands	421.20	212.80	169.26	251.94	−60%
Shanghai lakes/rivers	743.53	772.83	549.60	193.93	−26%
Shanghai forest	8.79	0.78	0.46	8.33	−95%
Shanghai cropland	37.87	33.53	26.07	11.80	−31%
Shanghai UGS	6.60	6.32	28.10	−21.50	+425%
Shanghai total value	1218	1026	773	445	−37%
Stockholm lakes/rivers	645.82	627.47	645.66	0.16	<−1%
Stockholm forest	450.77	444.19	447.72	3.05	<−1%
Stockholm cropland	8.46	8.76	7.83	0.63	<−1%
Stockholm UGS	65.78	87.78	73.29	−7.51	+11%
Stockholm total value	1171	1168	1175	−4	<1%

for Stockholm show a steady but less severe decrease from 58.96 to 58.00.

A compilation of spider diagrams (Fig. 4) displays the relationships and changes of six landscape metrics for Stockholm and Shanghai from 1989 to 2010. The three major axes each represent a different aspect of landscape pattern: PD and NP (number of patches) represent fragmentation, LPI and clumpy represent aggregation and CWED and LSI (landscape shape index) represent shape complexity. The metric forms in the spider diagrams for Stockholm do not change significantly over time due to the much slower rate of urban growth and less drastic land cover changes. Form differences between decades are clearer for Shanghai, especially for HDB. Yet what seems striking here is the apparent similarity of pattern between agriculture in Stockholm and LDB in Shanghai, and between forest in Stockholm and agriculture in Shanghai. Could it be that Stockholm, should it follow the rapid urbanization trend of Shanghai, would follow its diagram trend meaning that LDB would take on the pattern that agriculture had previously and agriculture would take on the previous pattern of forest while the metric values for forest would shrink drastically as it disappeared? This is an unlikely scenario since Stockholm's rate of urbanization is significantly slower than Shanghai's and given the very different

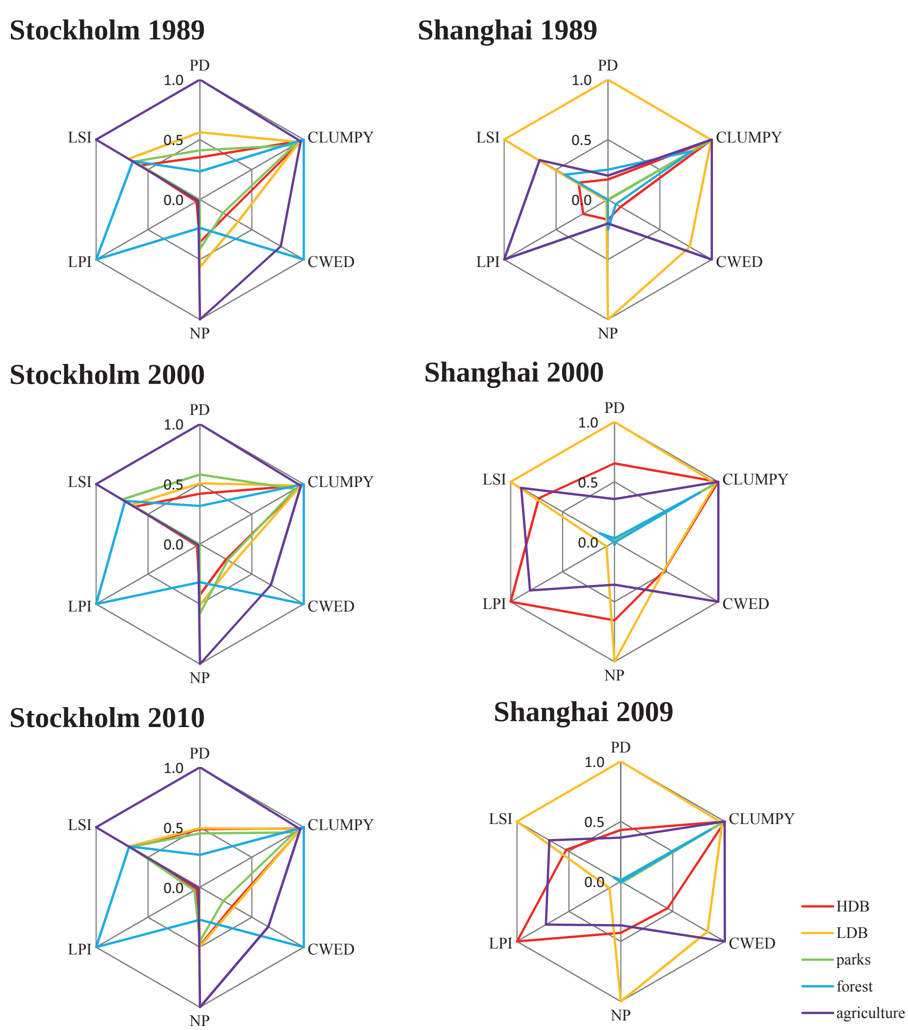

Fig. 4. Spider diagrams showing the compilation of six landscape metrics for Stockholm and Shanghai in 1989, 2000 and 2009/2010.

land management policies that are in place in each region. Studies of other more intermediately urbanizing cities with these same indicators would be needed in order to find out if indeed particular forms and sequences of LULC classes mark the progression towards a heavily urbanized and fragmented city region.

Ecosystem services analyses

The sums of all ES values for each decade and study area and for each contributing biome are summarized in Table 6. While ES values only increased slightly in Stockholm, LULC changes in Shanghai's metropolitan area result in large ES value losses.

A total loss in ecosystem service values can be observed over the two decades in Shanghai for all LULC classes except UGS. Relating the relative occurrence of UGS to 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, followed by water/lakes because they account for most ecosystem functions. A total loss of around 450 million USD can be observed in Shanghai with the largest decrease from 2000 to 2009. From 1989 to 2000, an absolute loss of 192 million USD is detected. From 2000 to 2009, a reduction of 253 million USD in ecosystem service values occurs. This correlates with the relatively speaking higher increase in urban land during the same period. On the whole, the values of ES in Stockholm have not changed considerably. The decrease in UGS in Stockholm from 2000 to 2010 and the drastic increase from 1989 to 2000 can be attributed to an over-detection of UGS in 2000. The decrease in water in 2000 is considered a misclassification. Other changes in terms of forest and agriculture are very small (less than 1%) and perhaps not significant but would still indicate a slight loss of ES.

Discussion

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 more subtle ones in the second in terms of growth, changes in size, shape and connectedness. It is 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. 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.

The development in Shanghai can be characterized by the transition from a rural region into a highly urbanized one. 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 urban green spaces 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 urban green spaces are growing alongside urban areas. UGS have been kept as they were over the years with new urban green spaces being developed at the same time.

Numerous studies have shown that larger habitat patches support bigger and more stable fauna populations (Evans et al., 2009; Magle et al., 2009) and demonstrated the importance of habitat connectivity in urban landscapes (Magle et al., 2009). How ecosystem function is generally affected by urban development patterns has been studied and demonstrated by Alberti (2005). Patch characteristics have here been measured using landscape metrics and the results reveal that natural LULC patches in the two landscapes are losing connectivity and in some cases are shrinking. Both these trends are believed to have a negative influence on the provision of ES and specifically on biodiversity as they interfere with species dispersal and persistence. In addition, an increase in impervious surfaces that accompanies urban expansion tends to stress the regional hydrology as run-off and concentrations of pollutants increase, not to mention the greater water extraction that comes with higher population density. Results also indicated increased interspersal of urban areas with more natural LULC types leading to pressure on flora and fauna in natural areas as they are increasingly exposed to adverse effects from proximity to urban areas, e.g. disturbances from predatory species, human traffic, invasives, chronic noise or light pollution.

It could be shown that LULC changes most prominently in Shanghai are characterized by increased fragmentation, more complex shapes and more edge that is shared between natural and man-made LULC patches. The hypothesized ecological consequences of these landscape changes are manifold and widely discussed (Dale et al., 2000; Debinski and Holt, 2000).

An increase in edge shared with other patch types (very prominent in Shanghai between agricultural land and HDB) can have adverse effects in terms of temperature increases, humidity decreases, higher wind velocities and the amount of light reaching canopy and ground. As a result, vegetation is altered consequently influencing succession and species communities. These edge effects are not only influencing the actual edges but can permeate the remnant vegetation patch for tens of meters (Chen et al., 1992). Regarding fragment size and area, it can be said that smaller fragments will contain a higher proportion of edge habitat than larger fragments (Forman and Godron, 1986). The effects of biodiversity loss can be mitigated to a certain degree if the fragments are still connected through green corridors that enable genetic interchange and increase dispersal capacities. Especially in urban environments, these movement corridors are however often disrupted by roads. Considering the growth in Shanghai from 1989 to 2000 (Fig. 2), newly built roads are prominent, especially in the northern and eastern parts of the city. This fragmentation results in increased patch isolation, decreased patch size and increased patch exposure to external disturbances leading to a decreased viability of ecosystems (the capability of an ecosystem to preserve its integrity and host its original biodiversity).

In Shanghai, the importance of wetlands as key ecosystems are discussed in Su and Zhang (2007) and their degradation and fragmentation should be avoided. Some of the largest environmental issues attributed to urbanization in Shanghai are identified as degradation and pollution of air and water resources (Zhao et al., 2006), but also local climates, soil pollution and biodiversity losses are considered problematic. Regarding ecosystem functionality, wetlands have the potential to ameliorate all of these negative effects and the importance for conservation of the wetlands in and around Shanghai is stressed.

The ecosystem service valuation results showed a large loss of ES clearly for Shanghai but less so for Stockholm. Urban ES analyses work relatively well for cities like Shanghai where urban growth and landscape changes are extreme, but it is less indicative when applied to regions where urbanization and landscape changes over decades are more subtle and where ecologically important urban features such as allotment gardens (Barthel et al., 2007) are present in reality but not accounted for in existing schemes. Current valuation approaches are not refined enough to capture the smaller yet important losses in terms of ecosystem service functions and their consequences for urban residents. What can however be deduced, are relative changes in the ecological patterns of landscapes that enable comparative studies between heterogeneous study areas regardless of their spatial or historical predispositions.

One particular problem associated with the approach of using ES as ecological indicators is the question of valuation, mentioned earlier and discussed i.e. for the Jiuduansha Wetland in Shanghai (Su and Zhang, 2007). There are numerous approaches to the issue of how to valuate ecosystem services that have been in discussion for a long time (De Groot et al., 2002). There are fundamental differences in how one should monetize the absence or presence of ecosystem services, functions or goods with respect to political prerequisites, cultural preferences and societal marketing principles. Assigning ecosystem service values to urban LULC classes is even more complex than determining service values to natural, rural LULC classes due to the limitation of space, the closer interaction with humans and the thus connected multiple land uses and additional functions not present in rural or natural environments. In that respect, ES cannot account for the actual value of ecological aspects within Stockholm or Shanghai but suffice as a relative comparative indicator.

Furthermore, it is important to determine not only the land cover classes but also the attributed land use. Different land cover classes can e.g. contribute to the same ecosystem service (e.g. both wind parks and hydropower stations contribute to energy provisioning services but the spatial distribution and characteristics are diverse). On the other hand, a land cover class that has the same spectral response in remotely sensed imagery might have a different kind of land use attached to it. Urban forests, for example might have in common that they account for a regulating service in terms of flood regulation or water and air purification, but one forest could be used as an urban park where old forest stands are part of a culturally important area thus satisfying the criteria of providing a socio-cultural service while another forest area is used for wood production thereby being mostly of provisional value. Thus, the question of what qualifies for an ecosystem and what services are to be attributed are also a question of definition. Another issue is the potential service benefiter/non-benefiter groups. The actual potential of providing an ES should be valued since it is unclear if anyone eventually benefits from the service, and if someone does, who it will be?

Conclusions

In this study, a combination of urbanization indices, LM and ES based on Landsat LULC classifications was used to quantify urbanization effects in terms of possible negative ecological consequences and to identify differences and changes in urban growth patterns of two diverse metropolitan areas. It was found that remote sensing at medium resolution is able to quickly provide a reliable overview of urbanization trends and patterns, while the synthetic interpretation of the abovementioned concepts of LM, ES and urbanization indices can lead to a deeper understanding of environmental impacts of urban growth.

Large regional differences but also similarities in landscape composition and configuration changes could be observed, which could be explained by differences in urban planning and political decisions as well as differences in initial urban structures. The used methods are well-established and can be quickly implemented to gain insights into urban growth at metropolitan and regional levels. While the LM analysis was successful in capturing pertinent information about changes and impacts for different LULC in both locations, the ES approach as applied here was successful for Shanghai but less so for Stockholm and further refinement of the ES evaluation approach for non-megacity regions should be undertaken.

The results from this study also show that the applied methodology can reveal valuable information about urban expansions and environmental impact in diverse metropolitan regions. Specifically, the speed and magnitude of urban growth in Shanghai exceeds the one of Stockholm by far. In total, urban areas in Shanghai increased by 120% (1768 km^2). In Stockholm, a 12% (100 km^2) increase in urban areas could be observed. This increase in both highly populated densely built-up areas and low-density residential areas and villages comes predominately at the expense of cropland loss in both study areas. From the LM, it can be deduced that the growth of HDB areas was mainly responsible for increased fragmentation in both of the city regions as new patches were added in previously more natural areas, while LDB areas tended to expand through consolidation with pre-existing patches.

Urban green spaces in Stockholm grew by about 11% and in Shanghai by 425% over two decades. Putting these numbers in perspective, an urban green index (UGI) as a ratio of UGS and HDB/LDB areas can be calculated that relates the increase in UGS to the parallel growth in urban areas. Even though Shanghai is one of the cities that grew quickest during Chinese rapid urbanization, the trend towards a better living quality and 'green thinking' could be interpreted by the increased design and maintenance of urban green spaces. The losses in terms of ecosystem service values have however increased even more after 2000. Relatively little urban development was detected over 20 years in Stockholm. The modest expansion of urban areas was accompanied by an increase in urban green spaces (mainly golf courses) that may increase the life quality for Stockholm's residents and the attractiveness for the region's visitors. This growth in UGS actually increased ES due to the higher ecosystem service values attributed to UGS than the ones for cropland that vanished. In 1989, ecosystem service values were equally high in both study areas. Whereas the value in Stockholm even slightly increased, a substantial loss in Shanghai was observed reducing the value of ES to 63% of their initial value.

It could be shown that the developed method can deliver reliable and indicative information of urbanization patterns at the landscape level in two diverse study areas. The comparative study demonstrates the method's potential to be applicable for urban expansion pattern analyses around the globe. The further analysis based on the classified images, combined landscape metrics, urbanization indices and ecosystem services to evaluate spatio-temporal developments and environmental and economic impacts of urbanization patterns. As discussed previously, it is well known that landscape changes that can be described with landscape metrics such fragmentation, loss of connectivity or edge contamination can affect ecosystem functionality. Currently, the concept of ecosystem services attributes values to ecological important space based on the ecosystems' areas. Spatial distribution and ecosystem shape are generally not accounted for when service values are determined and the exploration of the detailed effects of landscape shape and pattern on ecosystem values would be an interesting aspect of future research.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.jag.2014.12.008.

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III

Mapping and Monitoring Urban Ecosystem Services Using Multitemporal High-Resolution Satellite Data

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ABSTRACT

This study aims at providing a new method to efficiently analyse detailed urban ecological conditions at the example of Shanghai, one of the world's most densely populated megacities. The main objective is to develop a method to effectively analyse high-resolution optical satellite data for mapping of ecologically important urban space and to evaluate ecological changes through the emerging ecosystem service supply and demand budget concept. Two IKONOS and GeoEye-1 scenes were used to determine land use/land cover change in Shanghai's urban core from 2000 to 2009. After pre-processing, the images were segmented and classified into seven distinct urban land use/land cover classes through SVM. The classes were then transformed into ecosystem service supply and demand budgets based on ecosystem functions. Decreases of continuous urban fabric and industrial areas in the favour of urban green sites and high-rise areas with commercial/residential function could be observed resulting in an increase of at least 20% in service supply budgets. Main contributors to the change are mainly the decrease of continuous urban fabric and industrial areas. The overall results and outcome of the study strengthen the suggested application of the proposed method for urban ecosystem service budget mapping with hitherto for that purpose unutilized high-resolution data. The insights and results from this study might further contribute to sustainable urban planning, prove common grounds for inter-urban comparisons or aid in enhancing ecological intra-urban functionality by analysing the distribution of urban eco-space and lead to improved accessibility and proximity to ecosystem services in urban areas

Keywords: Ecosystem services, High-resolution satellite data, IKONOS, GeoEye, Urban land use/land cover, Segmentation, SVM

1. INTRODUCTION

In the light of past and present urbanization trends, timely and accurate information on the state, accessibility, distribution and supply of urban green spaces plays an increasingly important role for sustainable urban development, conservation of ecosystem functionality and human well-being. There is currently a lack of standardized and intercomparable evaluation methods to effectively and efficiently analyse and monitor important 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 and fast growing cities and regions, ecosystem conservation issues become crucial issues 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 [1].

One concept that has been dedicated increased attention throughout the past decades is the one of ecosystem services [2]. Until today, the idea has been further developed, modified, redefined, extended, popularized and used in many studies [3]–[5]. How to adequately (e)valuate urban 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 according to [3] and [5] is however problematic for several reasons [6]. In a recent article Sander and Zhao [7] discuss valuation discrepancies and difficulties of urban green and blue spaces and mention differences from global approaches and that ecosystem values are also dependent from neighbourhoods and user-groups with different socio-economic status. A novel relative approach of evaluating land use/land cover in terms of both the potential to provide and to support ecosystem services but also of the lack and demand for ecosystem services was proposed by Burkhard et al. [8] and adapted in this study. Not only the valuation but also the definition and importance of ecosystem services for urban areas in particular is still in its infancy since ecosystem services in urban areas differ from ecosystem services viewed from a landscape-centred perspective. Initial pioneer work with ecosystem services in urban areas was done by Bolund and Hunhammar [9] who identified six local and direct ecosystem services for Stockholm that contribute to public health and increase the quality of life of urban citizens as air filtering, micro-climate regulation, noise reduction, rainwater drainage, sewage treatment and recreational/cultural values. 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 [10]. 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 land use/land cover features that may affect patch quality. On the other hand, some advantages of urban ecosystems exist, e.g. that they are maintained or that natural disasters such as wildfires are reduced in urban areas whereas human-induced ecosystem management is more prevalent. The benefits of functioning ecosystems are manifold and described in detail in numerous studies [11]. A recent quantitative review of urban ecosystem service assessments in terms of concepts, models and implementations was published by Haase et al. [12]. Here the growing popularity of the concept is monitored and issues, questions and trends of urban ecosystem services are discussed. It could be shown that studies dealing with spatio-temporal characteristics of urban ecosystem services are still rare but that they are needed.

Feng et al. [1] found that remote sensing data can be used for ecosystem service assessments in three particular ways (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 ecosystem services, but that good in-situ measurements are additionally needed. The integration of remote sensing into ecosystem service concepts in general was recently reviewed in de Araujo Barbosa et al. [13], but the review falls unfortunately short of urban ecosystem services. Ayanu et al. [14] discuss the application of remote sensing in quantifying and mapping the supplies and demands of ecosystem services. The general usefulness and suitability of remotely sensed data for ecosystem services mapping and monitoring is emphasized and different possibilities to link remotely sensed data to ecosystem services are provided, e.g. through radiative transfer models, land use/land cover, through provision of input data for biophysical models and regression models. Similar to the study of [13], the services addressed in this review however are more importance in a landscape perspective and the section devoted to demand falls short of any methodological suggestions and does address urban areas or high-resolution images only marginally indicating the infancy of this 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 [15] or comparing different change patterns in diverse environments [16]. 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 ecosystem services. The observation of quantitative transitions from natural ecologically important land cover classes to urban ones might not suffice since not all man-made structures yield equal ecological values. When comparing e.g. paved roads with tree-seamed avenues or industrial areas with green rooftops in residential areas surrounded by small gardens, it is clear that a qualitative distinction needs to be made as well. The functions of urban green and blue spaces are manifold but threatened by urban expansion and urban sprawl that could lead to major environmental consequences, e.g. biodiversity losses, fragmentation and degradation of remaining natural areas, negative impacts on hydrology in terms of deterioration of surface water quality and increased storm water runoff, the loss of productive soils, increase of air pollution, extension of the urban heat island and an increased energy consumption.

Surprisingly few studies employed very high-resolution digital image data from space-borne platforms, such as Quickbird and IKONOS [17]. These are however believed to be of particular value [18]. The importance of sustainable and ecological development in China and the implications for policies for ecosystem services are discussed in Liu et al. [19] and the particular potential of high-resolution remote sensing data (i.e. Quickbird and IKONOS) is emphasized for their capabilities of efficiently and quickly detecting ecological effects across large areas. The advanced exploitation of high-resolution satellite imagery should be pursued and is very likely to give more insights into different aspects of urban land-cover and their developments at smaller scales that are needed for accurate ecological analyses. Previous studies investigating the potential of high-resolution images for studies of urban ecosystems and their respective functions, services and underlying land cover classes such as vegetation [20] are rare and just emerging. In the study of Lakes and Kim [21], the "Biotope Area Ratio" for assessment and management of urban ecosystem services is determined by classification of high-resolution multispectral data. Mathieu et al. [22] 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 [23]. Myint et al. [24] compared per-pixel vs. object-based classification of urban land cover extraction using high-resolution Quickbird imagery and found the object-based method superior in performance. Pu et al. [25] performed object-based urban detailed land cover classification with high spatial resolution IKONOS imagery and emphasized the advantageous use object-based over pixel-based approaches for urban classifications with such data. In Qian et al. [26] high-resolution (SPOT-5 and ALOS) data to quantify the spatiotemporal pattern of urban greenspace in central Beijing were used and the data was found effective and important to aid capturing small scale changes in green structures not being captured by medium resolution images. Parent et al. [27] combined high-resolution multispectral and LiDAR data for the classification of a forested urban landscape and managed to distinguish eight vegetated and non-vegetated land cover features with a rule-based object- and pixel-based classification approach. De Pinho et al. [28] used an integrated object based image analysis (OBIA) strategy that combines multi-resolution segmentation, data mining and hierarchical network techniques to address difficulties of intra-urban land cover mapping with IKONOS data. Li et al. [29] compared the economic benefits of urban green spaces estimated with NDVI and with high-resolution data (0.6m) and found the high-resolution data advantageous. Another study that investigated the use of high-resolution data (GeoEye-1) for mapping of ecosystem service supply and demands in was recently performed with reliable results by [30]. Ma et al. [31] tested the performance of the Chinese high-resolution ZY-1 02C satellite data for urban land cover mapping through an OBIA approach with integration of texture measures. Seven urban classes could be distinguished with a 92.63% classification accuracy. These and other studies suggest that the method and underlying data chosen in this study work well for urban classifications. Current bottlenecks in using high-resolution images more extensively is currently their acquisition (often commercial) and the computational requirements to quickly and efficiently process large areas, resulting in relatively speaking smaller study areas or long processing times. Both drawbacks are however believed to be resolved in the upcoming years with more high-resolution data readily available and further advances in computing capabilities, e.g. parallel processing or cloud computing.

Land use/land cover mapping based on remote sensing data for ecological applications related to urban land cover change over the study area Shanghai have been performed previously and studies that investigate the urban development in Shanghai in a regional context are manifold. Some studies analyse effects of local climate changes and UHI [32]–[35], urban land expansion and their implications [36]–[41], urban and landscape pattern analyses [16], [42], [43] or ecosystem service assessments [15], [30], [44]–[46]. In terms of classification approaches of remotely sensed images, Landsat data is the predominant data source and pixel-based maximum likelihood classifiers are mostly used although high-resolution data has also become a more popular source of information over the past years [35], [47]–[49]. Detailed urban classifications are, hence the abovementioned objectives of Shanghai-related studies, seldom found and the class definitions are rather motivated from a landscape that an urban perspective, i.e. there are often only 4 to 6 classes with only one or two urban built-up categories. In most of the studies, urban growth at various scales and different time frames and changes in land use/land cover can be found. However, a large share of the studies address Shanghai's expansion with respect to urban hinterlands and surrounding land cover and no study could be found that investigates ecosystem services at high spatial resolutions in the core urban area. Therefore, the objective of this study is to derive detailed urban land use and land cover information and to monitor changes in urban green structure in a densely populated urban core, solely based on high-resolution satellite data.

2. STUDY AREA AND DATA

Shanghai as China's largest city and financial and economic centre had a population of 23.9 million in 2013 and is expected to increase up to 30.75 million by 2030 [50]. The urban centre that is analysed in this study is characterized by a blend of modern high-rise commercial and low-rise residential buildings interspersed with public plazas, historical buildings and urban green structures such as parks and tree-seamed alleys, complemented by construction sites and industrial and harbour areas. The study area's location in Shanghai is displayed in Fig. 1 and covers approximately 3845 hectares. The pan-sharpened MS/NIR bands of two high-resolution GeoEye-1 scenes dating from 2009-10-04 and from two IKONOS scenes from 2000-07-22 were acquired to cover the study area. Shanghai's most central and oldest urban core areas, namely Huangpu District, Jing'an District and former Luwan

District (now merged with Huangpu District) were chosen as area of interest since significant land use/land cover changes occurred in the urban core due to the World Expo 2010. The major land use/land cover types in central Shanghai are high density low-rise residential areas, high-rise buildings with commercial and residential function, industrial complexes and harbour areas, the infrastructural road network, construction sites, the Huangpu River and urban green spaces and parks consisting of lawns and trees. The choice of classes was motivated by two factors: firstly and most importantly, the classes were chosen to match the ones that were used in the ecosystem service demand and supply modeling scheme from [8] that is in turn based on the CORINE classification scheme [51]. From the CORINE scheme, not all classes are relevant. Some classes only occur outside urban boundaries and some classes within urban areas are contextually different but spectrally speaking rather similar. The latter considerations make up the second factor for class choice, i.e. a subsection of the CORINE classes that are present in urban areas and that are expected to be classified without too much confusion.

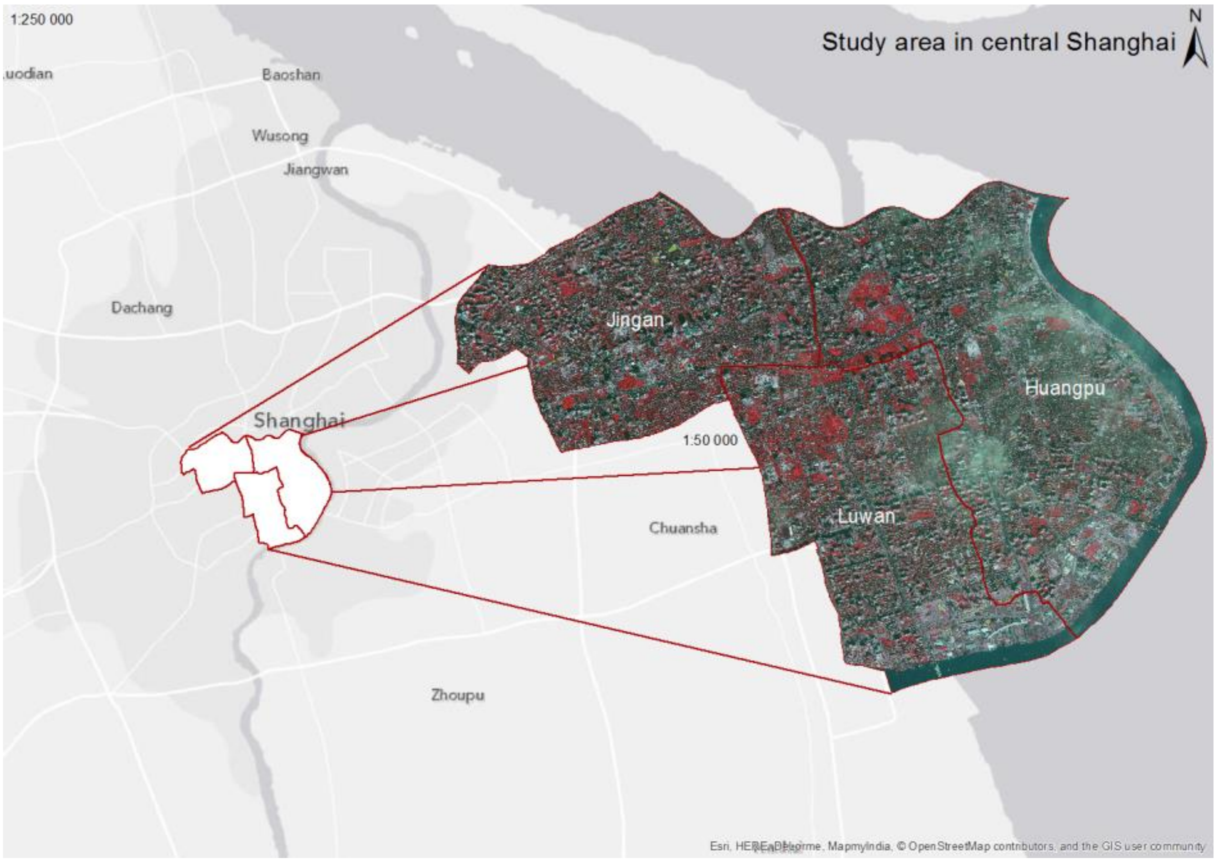

Figure 1. Study area covering Jing'an, Luwan and Huangpu districts in central Shanghai

3. METHODOLGY

The main methodological steps here involve image-mosaicking, pan-sharpening, radiometric resampling, clipping, segmentation and object-based Support Vector Machine (SVM) classification, followed by post-classification refinements and class aggregation, accuracy assessment and finally ecosystem balance modeling. The methodology is presented in Fig. 2. After image pan-sharpening, segmentation was performed on the pan-sharpened images using KTH-SEG, an edge-aware region growing and merging algorithm [52]. Then, post-segmentation classification was performed using an object-based SVM. Since no direct change detection was targeted, no geometric corrections, co-registration or image normalizations were performed. Based on the classification outcome, the method of calculating ecosystem service balances from land use/land cover as presented in [8] was used to evaluate the benefits urban Shanghai dwellers and visitors gain from the presence, or suffer from the absence of urban ecosystem services. A pilot study investigating the suitability of the methods was already performed on a Geo-Eye 1 image excerpt over Century Park in Pudong district, east of the current study area over central Shanghai, where the methods' applicability on high-resolution spaceborne satellite data could be confirmed [30].

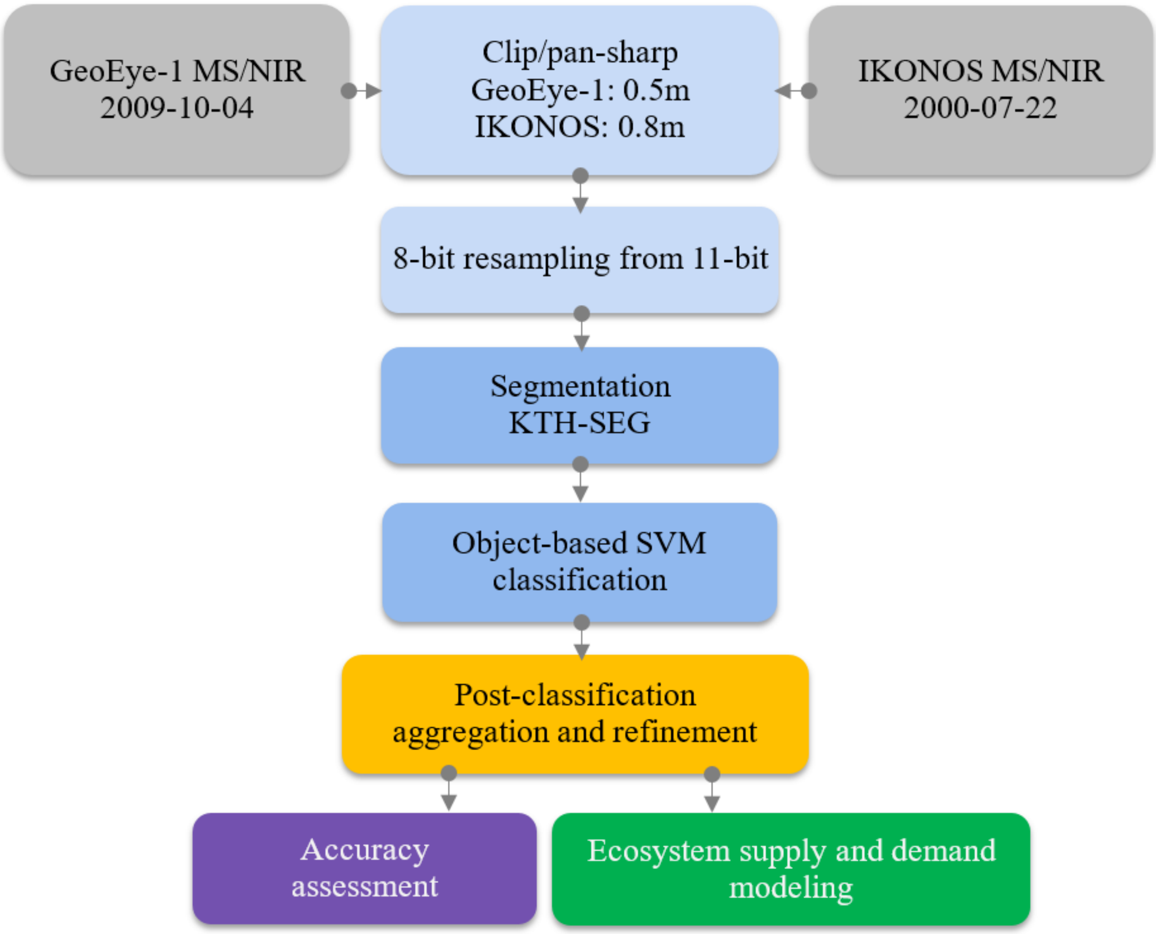

Figure 2. Methodology flowchart

3.1. Image pre-processing

Both the two adjacent IKONOS and GeoEye-1 scenes were first mosaicked together. No radiometric adjustment was needed since the scenes originated from the same sensor on the same date with the same atmospheric conditions. The two mosaics were then pan-sharpened with the least squares statistical based automatic fusion approach developed by Zhang [53] that maximises detail increase while minimizing colour distortion. The resulting pan-sharpened RGB and NIR bands of the GeoEye-

1 mosaic at 0.5m resolution and the same four bands of the IKONOS mosaic at 0.8m were then clipped to the study area extent and radiometrically resampled from 11 to 8 bits in order to reduce the processing times in the ensuing segmentation and classification steps.

3.2. Segmentation

In recent years and with increasing spatial resolutions, object-based image classification methods have enjoyed increased popularity since they are considered advantageous over traditional pixel-based approaches. Blaschke [54] provides a comprehensive literature review and summary of studies that use object-based image analysis methods. Segmentation and classification of high-resolution data results in superior classification accuracies compared to pixel-based approaches in most of the studies. Especially in terms of urban feature discrimination, object-based approaches have shown superior classification capabilities, even though OBIA analyses is considered complex and a challenge because of the large number of object attributes present in urban environments [28]. Shackelford and Davis [55] 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 relevant for this study is the work of Mathieu et al. [22] who map private gardens in urban areas using object-oriented techniques on very high-resolution IKONOS data. Even though high garden detection rates were recorded, the further contextual classification into different garden types based in green space composition was considered encouraging but in need of improvement. Other examples where object-based classification using high-resolution imagery proved superior to pixel-based approaches are the studies of [24] and [56]. These studies demonstrated that the object-based classifier performed significantly better than traditional per-pixel classifiers and the need for contextually treating urban features as objects rather than pixels is motivated. Image segmentation in this study was performed with the KTH-SEG algorithm that has been evaluated using ENVISAT ASAR and HJ-1 optical data for urban land cover classification and compared to the segmentation algorithm implemented in Trimble’s eCognition Developer 8 [52]. Haas et al. [30] have also shown KTH-SEG to be effective for high-resolution optical data. 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 into 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. For the segmentations in this study, the following parameters were empirically determined and found to generate the most suitable result: Canny threshold: 0.02-0.04; grow 0.5/0.5, merge 0.5/0.5, minimum and maximum segment sizes were chosen from 8 and 500 pixels. It should be noted that the

GeoEye-1 2009 mosaic and the IKONOS 2000 mosaic had to be split into 8 and 4 parts, respectively that were segmented and classified separately due to computational limitations.

3.3. Classification

The segments were classified with an implementation of the java libSVM library [57] in KTH-SEG. SVM is an effective classifier that originated from the field of machine learning. 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 [58]. A radial base function (RBF) kernel was used. The required parameters were automatically determined through a grid-search approach. Both mean and standard deviation of the digital numbers from the MS/NIR bands were chosen as features to classify the segments. During training site selection in the supervised classification process, several spectrally different sub-classes for were first distinguished before aggregation into CORINE classes as a following step (e.g. different roof classes needed to be separated based on colour prior to aggregation into contextual coherent classes). In total, training data for 11 subclasses was created independently on the generated segments. In the classifier training phase, the segments that had the largest overlap with the training polygons were selected as training segments for the classifier. The image segmentation and classification approaches presented here were selected based on their good performance in previous studies and their explicit recommendation for application in the domains of environmental monitoring and ecosystem-oriented natural resources management [54].

3.4. Post-classification processing

The classified sub-scenes were merged together and the 11 subclasses were aggregated into 1 shadow class and 7 distinct CORINE classes, i.e. continuous urban fabric, industrial/commercial units, road and railway networks, construction sites, green urban sites, water courses and water bodies. The study area also features some sports and leisure facilities but they were excluded as separate class since in the CORINE definition it explicitly states that these should not be surrounded by urban areas. Outdoor sports facilities are thus included in the urban green category. As can be seen from Fig. 1, some areas suffer from haze in the 2009 GeoEye-1 scene. These areas where the initial classification failed to correctly distinguish the desired classified, a separate classification with was performed and the erroneously classified areas replaced.

3.5. Accuracy assessment

Classification accuracy assessment was performed by selecting a minimum of 10,000 validation pixels homogeneously distributed across the images for each class in both classifications. Validation site selection was performed under two premises, i.e. 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 assessment was performed on the final classification after aggregation of subclasses and replacement of hazy areas. The validation sites did not coincide with the training sites and were chosen manually all over the scene. As measures of accuracy, kappa coefficient, overall, average, user's and producer's accuracies were chosen.

3.6. Ecosystem service supply and demand modeling

Ecosystem supply and demand and the resulting balances were calculated according to the valuation matrices presented in [8]. 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 ecosystem services 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 ecosystem services. 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 values ranging from -82 to +52 were then scaled from 0 to 1 where 0 indicates a high demand of ecosystem services and 1 the highest potential of land use/land cover to provide ecosystem services. Tab. 1 summarizes all classes that are considered for ecosystem service supply and demand modeling and their original and linearly scaled scores.

Table 1. Overview of CORINE land use and land cover classes and corresponding ecosystem service supply and demand balances

land use/land cover	*∑ capacities*	*∑ demand*	*balance (∑cap - ∑dem)*	*Scaled balance*
Continuous urban fabric	1	80	-79	0.022
Industrial or commercial units	3	85	-82	0
Road and rail networks	5	28	-23	0.440
Construction sites	3	21	-18	0.477
Green urban areas	34	16	18	0.746
Water courses	53	1	52	1
Water bodies	51	1	50	0.985

4. RESULTS

In total, 526,894 segments were generated by KTH-SEG for the IKONOS 2000 classification and 1,278,160 segments for the GeoEye-1 2009 classification. As the segmentation parameters remained the same for all segmentations, the numerical difference can be attributed to the different resolutions. The two classified mosaics are shown in Fig. 3.

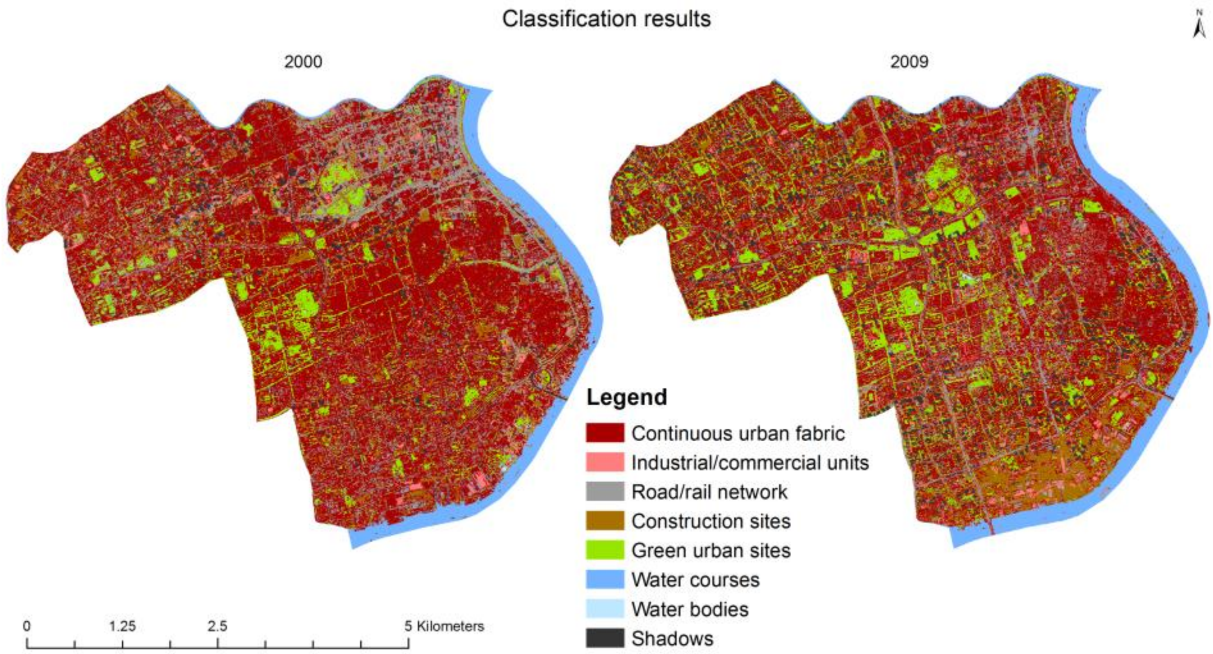

Figure 3. Classification results: IKONOS 2000 classification (left) and GeoEye-1 2009 classification (right)

Visual inspection of the classification outcome suggests changes in the urban land use/land cover pattern, the most prominent one being the 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. The detailed classification excerpts in Fig. 4 exemplify this trend by the creation of Yanzhong Square Park, South of Yan'an Elevated Road (encircled in Fig. 4).

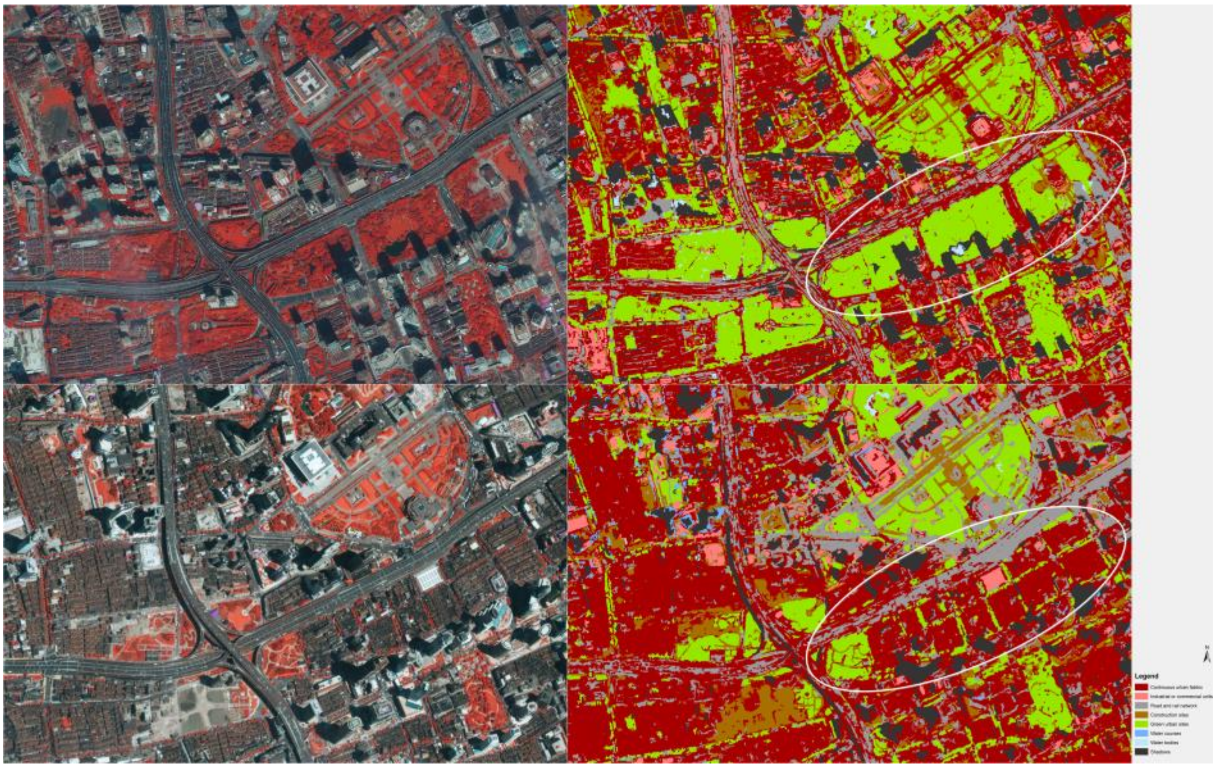

Figure 4. Detailed classification excerpt (GeoEye-1 2009 FCC image and classification in the upper row, IKONOS 2000 FCC and classification in the lower one).

Overall classification accuracies reached 84.29% for the IKONOS 2000 and 85.57% for the GeoEye-1 2009 classification and are presented with average accuracies and kappa coefficients in Tab. 2.

Table 2. Classification accuracies and kappa coefficients

	IKONOS 2000	GEOEYE-1 2009
Average accuracy	85.04%	85.51%
Overall accuracy	84.29%	85.57%
Kappa coefficient	0.82	0.84

Tab. 3 and 4 show the confusion matrices with User's Accuracies (UA) and Producer's Accuracies (PA) for both classifications. Largest confusions exist between road and railroad network, continuous urban and industrial/commercial classes in both classifications.

Table 3. IKONOS 2000 classification confusion matrix

	Continu. urban	Industrial/ commerc.	Road/rail network	Constr. sites	Green urban	Water courses	Water bodies	Shad.	**PA**
Cont. urban	**83.1**	1.1	10.2	4.8	0.6	0	0	0	**83.27**
Ind./comm.	19.7	**70.8**	0	8.1	0.2	0	1.1	0	**70.87**
Road/rail	26.3	0.6	**69.4**	3.6	0	0	0	0	**69.47**
Constr. sites	9.8	8.6	1	**80.6**	0	0	0	0	**80.60**

Green urban	2.9	2.2	2.2	0	**92.7**	0	0	0	**92.70**
Wat. courses	0.2	0	0.7	0	0	**99.1**	0	0	**99.10**
Wat. bodies	2.1	0.1	0.9	0	0.3	4.4	**92.1**	0	**92.18**
Shadows	4.1	0	0	0	0	0.8	0	**95.1**	**95.10**
PA	**56.95**	**85.77**	**83.32**	**81.97**	**99.02**	**98.22**	**94.58**	**100**	

Table 4. GeoEye-1 2009 classification confusion matrix

	Continu. urban	Industrial/ commerc.	Road/rail network	Constr. sites	Green urban	Water courses	Water bodies	Shad.	**PA**
Cont. urban	**84**	3	5.8	5.2	0.3	0.4	0	1.2	**84.08**
Ind./comm.	9.9	**69.5**	7.7	10.4	0	2.3	0	0.1	**69.57**
Road/rail	13.2	4.6	**81.3**	0.9	0	0	0	0	**81.30**
Constr. sites	17.1	1.8	1.2	**79.8**	0	0	0	0	**79.88**
Green urban	0.1	0.1	0	0	**99.6**	0	0	0.1	**99.71**
Wat. courses	0	0	0	0	0	**100**	0	0	**100**
Wat. bodies	0.2	0	4.3	0	0	0	**85**	10.4	**85.08**
Shadows	8.4	0	6.1	0	0.6	0	0.1	**84.7**	**84.79**
PA	**64.63**	**88.14**	**75.87**	**82.06**	**99.11**	**97.40**	**99.89**	**86.97**	

As mentioned above, the most prominent change is the creation of urban green sites in form of parks with trees, lawn and ponds and roadside greenery. In most of the cases, densely built-up low-rise continuous urban blocks with residential function are transformed, not only into urban green sites, 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 overall increase of 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. 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 shaded areas. Water courses on the other hand could be delineated with a high accuracy in the 2009 image. Water courses only occur in form of the Huangpu River delimiting the study area in the east and the Wusong River as the northern boundary of inner Shanghai. Visual interpretations of the classifications confirm that the 2009 classification is accurate and that the observed decrease of water courses is unrealistic. Reason for this is the confusion with shadows in the 2000 classification. The dynamic development of central Shanghai 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. Larger parts of the 2009 image were covered by shadows. One reason for this is certainly the fact that the solar illumination angle is much lower in the GeoEye-1 image resulting in high-rise buildings casting longer shadows (as seen in Fig. 4). Another contribution to the increased amount of shadows could be the increase in high-rise commercial or residential buildings replacing low-rise dense continuous urban fabric and industries.

Figure 5. Comparison between land use/land cover in central Shanghai in 2000 and 2009

Investigating the classification results in conjunction with the confusion matrices presented in Tab. 3 and 4 and the land use/land cover bar chart in Fig. 5, several other observations can be summarized. The reduction in continuous urban fabric in favour of urban green space is considered realistic. Visual explorations of the classification results confirm that the extent and amount of construction sites has remained stable. There are, also bearing the confusion matrices in mind, misclassifications between continuous urban fabric, industrial and commercial units and the road and rail network. A decrease in the extent of the infrastructural network could not be visually confirmed and the observed changes are ascribed to confusion with industrial/commercial and continuous urban fabric. Water courses and water bodies remained rather stable, as discussed above.

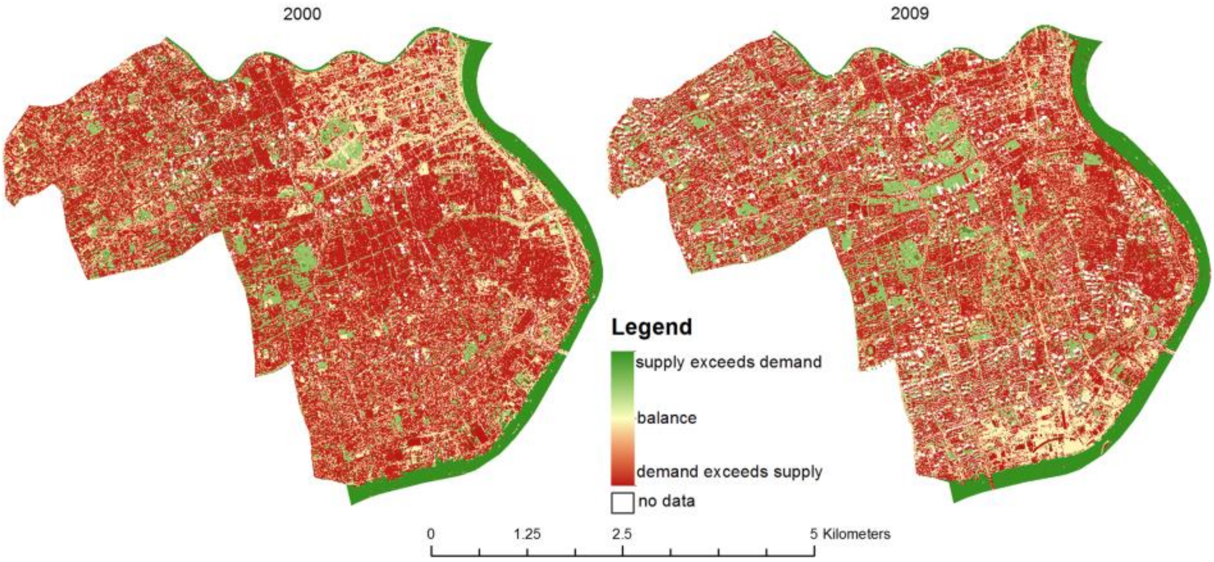

Figure 6. Ecosystem demand and supply budgets

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. 6. Urban land use/land cover classes were evaluated in terms of their capacity (supply) and demand for 22 regulating, provisioning and cultural ecosystem services according to [8]. 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. Tab. 5 summarizes the CORINE classes, their respective extent in hectares, the percentage of change from 2000 to 2009, the attributed budget value from [8] and the quantitative changes in hectares related to the qualitative changes in budget values. Based on the difficulty in putting price tags on ecosystem services, the fact that there is until today no homogeneous valuation scheme for ecosystem services in urban areas and following the trend of rather analysing ecosystem demands and services [8] and [59], no absolute monetary changes in ecosystem service are presented here. In order to obtain a better impression of the spatial distribution of ecosystem service changes, Fig. 7 below shows an overlay of the coregistered and to a 1 m resolution resampled scaled ecosystem service balances.

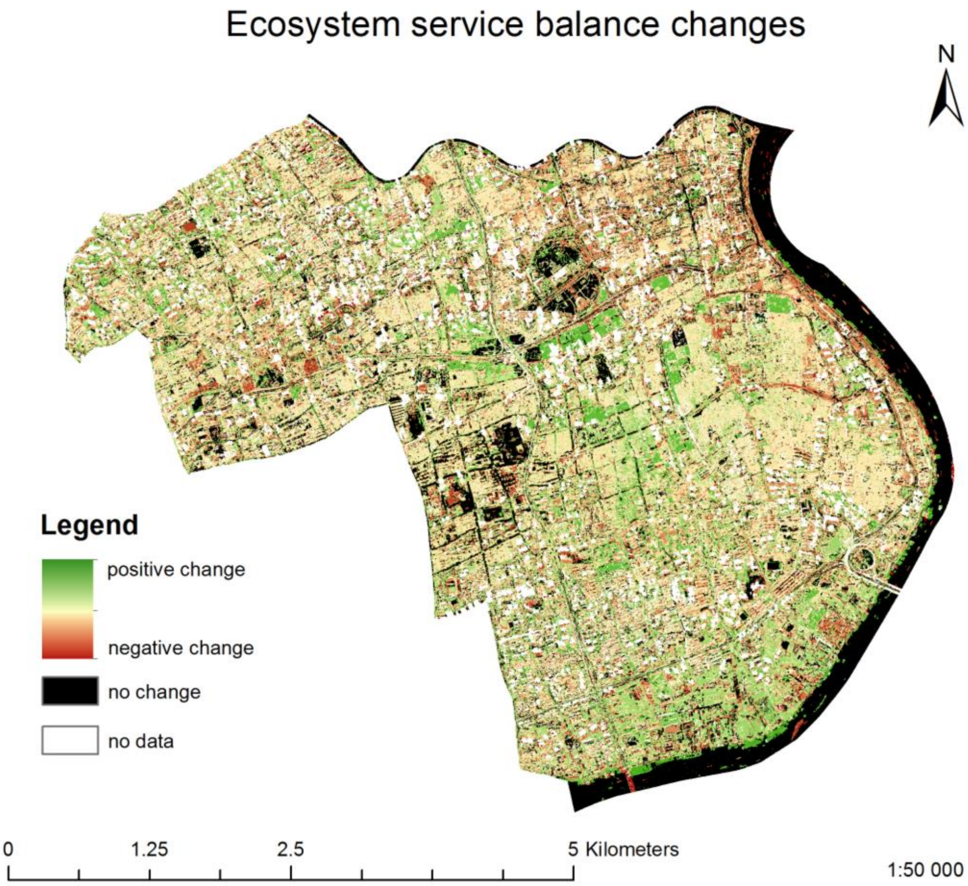

Figure 7. Ecosystem service balance changes from 2000 to 2009

Table 5. Ecosystem balances and land use/land cover changes in %

CORINE class	*LULC 2000 in ha (LO)*	*LULC 2009 in ha (L9)*	*Percent change*	*Budget value (BV)*	*Changes in ha* $(L9 - LO) * BV$
Continuous urban fabric	1,516.3	1,240.6	-18	-79	21,783
Industrial/commercial	81.1	136.3	+68	-82	-4,525
Road and rail networks	428.7	324.9	-24	-23	2,387
Construction sites	205.6	232.3	+13	-18	-481
Green urban areas	237.6	397.8	+67	18	2,882
Water courses	203.6	171.6	-16	52	-1664
Water bodies	3.7	16.7	+350	50	650

Summing up the land use/land cover 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 ecosystem services by increase in industrial and commercial units. The most important class actively contributing to service supply are urban green sites followed by water bodies.

5. DISCUSSION

The results show that the redesign from former industrial areas to become more environmentally friendly and increase of urban green spaces were consistent with the findings of Zhang et al. [60]. The same study also revealed an enhanced eco-efficiency of water and energy use as well as an improved overall environmental quality in Shanghai's central urban districts. The proposed straight-forward method of deriving urban land cover and linking it to ecological applications and evaluations based on high-resolution resolution data resulted in acceptable classification accuracies and provided interpretable results but could be improved for further studies. High-resolution data is regarded essential if urban areas devoid of their surroundings are analysed since detailed urban features such as alleys, lawns or single trees cannot be delineated with medium- to low-resolution data. This however results in one issue with the current approach related to data volume – high-resolution data is computationally speaking heavy and several sub-scenes needed to be classified separately in order to not to exceed the existing random access memory. This resulted in increasing the time needed for the classification and in slight differences in classification outcome of the sub-scenes due to unavoidable differences in choice of training data that needed to be chosen for each sub-scene. One drawback using high-resolution optical data are existing shadows and the decision to either mask them out or to replace them by ancillary data rests with the user and the scope of the study. Zhou et al. [61] present a comparative study of three methods for land cover classification of shaded areas from high-resolution imagery in urban environments. The method that performed best implied the replacement of shadows through multisource data fusion with images that were collected at different times of day. One other solution to overcome this problem that could be pursued in future studies is the integration of high-resolution radar data that is independent on solar illumination and much less affected by atmospheric attenuation, clouds or haze. Integration of radar data and integrating additional features, such as shape, perimeter or topological relationships of training sites in the SVM classification, which is now based only on brightness values and respective standard deviations for four bands, is believed to lead to improved classification accuracies. Despite the promising results of the presented methods by [61] ground-feature shadows in high-resolution satellite data remain a challenge for urban studies and further investigations are recommended [62]. Regarding the choice of classes, a further distinction into port areas and sports and leisure facilities could have been made but regarding the methodology this would have introduced additional steps, i.e. a rule-based classification including proximities and relative topological distributions of land use/land cover, and most likely resulted in further misclassifications, especially when considering the mixed land use of port, industrial and commercial areas. The CORINE definition of sports and leisure facilities is exclusively limited to places "not surrounded by urban areas" and has thus been disregarded here. Instead these areas were included in the urban green site category since conceptually speaking the largest benefits that urban dwellers would enjoy from both categories would be recreational and cultural services. These two ecosystem services also are quite similar regarding the balance scheme of [8] in terms of their supply and demand values.

An increase in ecosystem service supply seems realistic when visually investigating both the images and classifications and in terms of quantitatively comparing urban land use/land cover. This is consistent with the findings of Zhao et al. [36] that describe Shanghai's urbanization trend as characterized by a growth of green areas. Increases of green space in the inner part of the central urban area can be confirmed by Li et al. [33] and Cui and Shi[40]. Improved environmental conditions could be detected through a decreased urban UHI, especially in Luwan and Jing'an and through increased air quality in Huangpu and Jing'an [41]. Already between 1992 and 2000, more than 10 % of the area in the old downtown was converted to parks or green spaces, leading to a considerable increase of green space and the improvement of environmental quality in the urban core [32]. In the same study that analysed economic development, urban expansion and sustainable development in Shanghai, it is concluded that Jing'an and Luwan reached high levels of economic development and environmental quality serving as role models for districts in the old urban core. Both districts are said to have upgraded their industrial structure to producer oriented services. 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 urban green space 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 if a 20% increase in supply values should be regarded with caution, the authors believe that the actual service supply increase could even be higher. Reasons for this are the following four assumptions. Firstly, the transition from continuous urban fabric to urban green space is the most common transition given all land use/land cover 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. Even though no distinction between the two subclasses was made here since the original unmodified scheme from [8] was applied, the factual changes observed are reductions in industrial areas (i.e. the 2010 World Expo area) and increases in high-rise complexes with anticipated commercial and residential function. The general increase in building height can be confirmed by Shi et al. [63] where urban-three dimensional expansion in Shanghai is measured. The reduction of centrally located industrial areas and their relocation to suburban areas in order to improve urban air quality is also part of the environmental improvement program from the late 1990s [64] and a general trend away from primary and secondary towards tertiary industries can be noticed [38]. Especially in Huangpu, Luwan and Jing'an, the tertiary industry accounts for more than 90 % of the districts' GPDs [41]. Thus, the industrial/commercial class should not be given such a strong negative budget. For future research, either both classes should be treated separately, or a new more appropriate value should be assigned to the combined class. In this study however, where the budgeting scheme was firstly applied at an intra-urban scale with high-resolution data, the authors refrained from determining new values or classes in order to keep the existing scheme consistent in terms of relative class values. Thirdly, the reduction of water courses has a heavy influence on budget values, being the most important supplier of ecosystem services 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 approach of [8] is considered an excellent attempt to relatively evaluate ecosystem service budgets and services, the only drawback for urban applications is the choice of CORINE classes that are rather considered at a global than local level and an adaption of the scheme to urban areas would be an asset. One critical aspect of the ecosystem service and land use/land cover concepts in general is the attribution of values to classes. The first and foremost issue with attributing ecological functional value and thus ecosystem services is inherent in the definition of land use/land cover itself. Is the actual land use or the mere land cover considered? It is argued here that in order to determine accurate and reliable ecosystem service values, a distinction between land use and cover is essential. This inconsistency could be clarified if a clear distinction between the land cover and actual land use would be made in general or if ecosystem services would only be derived for land cover classes with value adaptions based on the known land use of the particular class. This however would involve a very thorough investigation of singular land cover patches and is not believed to be feasible by with remotely sensed data alone. In certain aspects, land use can obviously be remotely sensed, e.g. there is not much room for interpretation of land use for a football field, or at least one could state that the intended use is quite clear. In other less indicative land cover types, the usage might not be that obvious. Land ownership, benefiter groups and economic intention of the land cover patch under consideration can hardly be determined by space- or airborne sensors and the determination of land use relies on integration of ancillary data. Another far more complicated issue is related to who is actually benefitting from the services. There might be on particular peer group of humans that values old urban forest stands above all for the sheer visual beauty and the conception that the stand provides a habitat for a multitude of species, whereas another group mostly values the fresh air and recreational possibilities the forest provides, whereas another group would rather like the forest to be regarded as source for raw materials and food. This conflict of subjective appreciation complicates the objective valuation of ecosystem services and even more so if peer groups area considered that would not appreciate the forest stand at all but would the area rather have seen developed into an urban park with wide open lawns or maybe even into areas where economical bargains completely overwhelm ecological integrity. The thought of regarding land use/land cover in supply and demand terms is an enriching conceptual step away from absolute monetary valuation of services but cannot yet be a solution to the two abovementioned problems.

6. CONCLUSION

This study investigated the potential of high-resolution optical satellite data and the suitability of the proposed method for urban land use/land cover mapping with respect to ecologically relevant space in one of the most densely populated areas on our globe at the example of the three most central districts in Shanghai, namely Huangpu District, Jing'an District and former Luwan District (now merged with Huangpu District). Changes over a nine-year period were observed, quantified and qualitatively assessed by an adaption of the recently developed concept of ecosystem service supply and demand budget mapping conceptualized and designed by [8]. Classification was performed using an object-based SVM classifier on image segments generated with KTH-SEG, a recently developed segmentation algorithm. Overall classification accuracies of about 85% could be reached in both classifications distinguishing seven urban classes according to the CORINE classification scheme whose potential to provide beneficial regulating, provisioning and cultural ecosystem services and the need for these services was evaluated. In addition to the classes continuous urban fabric, industrial or commercial units, road and rail networks, construction sites, green urban sites, water courses and water bodies, one shadow class was determined that was excluded from the ensuing analyses. A decrease of continuous urban fabric and industrial areas in the favour of urban green sites and high-rise areas with commercial/residential function could be observed as most prominent development. Linking these changes to the potential supply and demand of ecosystem services, an increase of at least 20% in service supply budgets could be observed. Main contributors to that change are rather the decrease of continuous urban fabric and industrial areas than newly developed urban green sites since the relative demand values inherent in densely built-up and populated continuous urban and industrial areas is relatively speaking higher that the supplies provided by urban green sites. The overall results and outcome of the study strengthen the suggested application of the proposed method in combination with the underlying data for urban land cover mapping and ecological studies at high-spatial resolutions and endorse continued use of such data for urban mapping. One major contribution of this study is the establishment of a method that enables the qualitative assessment at a specific point in time or the analysis of changes in urban areas in terms of ecosystem services without any ancillary information and data. In addition, the new supply and demand concept was introduced in an urban as opposed to the regional context it initially was developed for and possible adaptions of the valuation scheme are discussed. In general, surprisingly very few studies exist that attempt to detect and classify ecological important space in urban areas with high-resolution data and to the authors' knowledge, this study is the first one to derive ecosystem service budgets with high-resolution data alone. The insights and promising results from this study will hopefully contribute to continued research in this direction in our unceasingly urbanized society. The application of the proposed methodology could aid in analysing the distribution of urban eco-space and lead to improved accessibility and closeness for urban dwellers to ecosystem services in urban areas with low or no ecosystem service supply, in integrating ecosystem services into sustainable future urban planning or in providing common grounds for inter-urban comparisons.

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IV

SPATIO-TEMPORAL URBAN ECOSYSTEM SERVICE ANALYSIS WITH SENTINEL-2A MSI DATA

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ABSTRACT

Continuous urbanization changes the surface of our globe raising questions of sustainability, ecological functionality and living quality in metropolitan regions. Remote sensing enables us to obtain timely and reliable information on the state of urban areas and their changing patterns. The objectives of this study are to evaluate the contribution of Sentinal-2A data for urban ecosystem service mapping and to evaluate spatio-temporal characteristics of ecosystem service provisional patches through landscape metrics as an extension of the ecosystem service concept. Changes in service patterns over a 10-year time frame are mapped in the megacity of Beijing, China using Landsat TM data from 2005 and Sentinel-2A data from 2015. Landscape metrics are generated based on the classification results to evaluate the changes of urban ecosystem service provision bundles. The images are segmented using KTH-SEG, an edge-aware region growing and merging algorithm. The segments are then classified using a SVM classifier according to a classification strategy that is designed to distinguish between four natural and managed urban classes based on underlying ecosystem function and three artificial urban structures, i.e. buildings and roads that negatively influence ecosystem service provision to varying degrees and in different ways. These negative impacts are quantified through seven spatial attributes of green and blue patches and their configuration, namely area (CA), connectivity (COHESION), core area (TCA), diversity (SHDI), edge effects (CWED), percentage of land cover (PLAND) and a proximity measure. The 2015 classification accuracy of 90.2% was higher than the 2005 classification accuracy with 84.7%. Beijing's urban development is characterized by a decrease in agricultural areas in the urban fringe in favour of new high and low density built-up areas, urban green space and golf courses. In total, high density and low-density urban areas have increased ca. 21%. Furthermore, the deconstruction of former high density low-rise suburban agglomerations into urban green space can be observed. The planar increase in urban areas is partly counteracted by the creation of managed urban green spaces. Ecosystem service bundles based on underlying land cover classes and similar spatial factors that influence service quality were derived for 2005 and 2015. Changes in landscape composition and configuration resulted in decreases of more than 30% in the bundles that represent food supply, noise reduction, waste treatment, global climate regulation. 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. The extension of the ecosystem service concept through spatio-temporal characteristics of ecosystem service provisional patches by landscape metrics is believed to give a more realistic appraisal of ecosystem services in urban areas.

Keywords: Ecosystem Services, KTH-SEG, Landscape Metrics, MSI, Sentinel-2, Urban land cover

INTRODUCTION

According to the latest findings of the world population prospects report (United Nations, 2015) there exist 7.3 billion human beings on our globe as of mid-2015. 19 percent (1.4 billion) of the global population lives in China alone, currently being the largest country in the world in measures of population. Out of these, 55.6 percent live in urban areas. 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). This raises subsequent questions of how anthropogenic influence might exert stress on urban ecosystems and how ecosystem quality can be maintained, not only in urban but also in rural areas, as the study from Maes et al. (2014) emphasizes. Remote sensing technology has already shown its potential to map and monitor complex urban land cover for various applications (Weng and Quattrochi, 2006).

There is a growing concern about ecosystem functioning, the provision of ecosystem services and human well-being through the loss of biodiversity (Balvanera et al., 2006). Cardinale et al. (2012) demonstrate how such a loss influences ecosystem functions and discuss the impacts this can have on ecosystem goods and services and according to the study of Newbold et al. (2015) it is very likely that human activities, especially the conversion and degradation of habitats, e.g. through urbanization processes will lead to global biodiversity declines. Urban expansion and global land cover change patterns are known to pose a threat to biodiversity and thus ecosystem services (Grimm et al., 2008; McDonald 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; McDonald and Marcotullio, 2011). Ecosystems in form of 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. Most studies on urban ecosystems focus on ecosystem function and/or biodiversity in fragments of indigenous landscape (Hester et al., 1999). This limitation excludes man-made and managed objects such as lawns, parks, golf-courses and alike, whose biodiversity function usually falls short of the one in naturally developed green spaces with remnant vegetation. It has to be noted though that urban green spaces can also harbour higher and stable biodiversity at smaller regional and local scales when compared to surrounding monocultures in rural areas that represent extremely simplified landscapes (Quigley, 2011). This can be confirmed by Alfsen et al. (2011) that report species richness in urban areas to be sometimes higher in urban green spaces and wetlands than in the surrounding countryside due to the introduction of non-native plants and animals.

One concept that can be used to express conditions and quality of our natural environment is ecosystem services. Ecosystem services have their origin in conservation biology (Ehrlich and Mooney, 1983) and have developed substantially over the past decades. In one of the first definitions by Daily (1997), ecosystem services 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 developed to quantify ecosystem services for practical applications (Costanza et al., 1997; de Groot et al., 2002; de Groot et al., 2012) to form comprehensive global schemes (MA, 2005; TEEB, 2010) and to serve as tools in decision making (Daily et al., 2009; Fisher et al., 2009). Ecosystem services 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 (TEEB, 2010). As a result of problems with commonly used benefit-transfer valuation approaches of ecosystem services (Davidson, 2013), relative approaches keep emerging, e.g. through the analysis of supply and demands (Burkhard et al., 2012; Baró et al., 2015) or ecosystem service trade-off and synergy analyses in form of ecosystem bundles (Turner et al., 2014; Yang et al., 2015). Because of their growing popularity, redefinitions and modifications of the concept, new unresolved issues keep emerging, several of them related to ecosystems, their functions and services in urban areas. Urban areas were initially excluded from the concept and disregarded in valuation approaches (Costanza et al., 1997) but it is understood that natural and some man-made urban features provide ecosystem services that are particularly important because of their direct impact on human health and security such as air purification, noise reduction, urban cooling and runoff mitigation (Gómez-Baggethun et al., 2013), competing benefiters in limited space and individual differences in service appreciation. In spite of that, there is no well-established definition and valuation scheme for ecosystem services in urban areas yet and the anthropogenic influence on urban ecosystem functions is hitherto not fully understood. Another drawback is that spatial attributes of ecosystem service providing patches are often not considered in ecosystem service studies despite it is argued that spatial characteristics of landscape patches influence ecosystem functions (Syrbe and Walz, 2012; Bagstad et al., 2013; Turner et al., 2013). 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; Faeth et al., 2011). A systematic overview of spatial influence on ecosystem function and service provision is still missing and in order to establish the links between ecosystem services and provisional patches, the type and magnitude of spatial influence must be understood. One concept that quantifies landscape composition and configuration is landscape metrics originating from the field of landscape ecology (Turner, 1989). Landscape metrics are a well-established 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. Until now, very few studies have used landscape metrics 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). The combined use of landscape metrics and ecosystem services is endorsed by Frank et al. (2012) since it offers advantages in terms of standardized landscape assessments, fast interpretation of various land cover patterns and the ability to easily compare scenarios. Up to date, a systematic and comprehensive combination of both concepts is still missing (Burkhard et al., 2010).

As one of the first studies regarding ecosystem services in an urban context, Bolund and Hunhammar (1999) identified the following services for Stockholm as most important: air filtering (gas regulation), micro-climate regulation, noise reduction (disturbance regulation), rainwater drainage (water regulation), sewage treatment (waste treatment) and recreational/cultural values. Since then, many studies can be found that are devoted to analyses of singular or multiple ecosystem services with respect to one or many land use and land cover classes as summarized by Gómez-Baggethun et al. (2013). Based on their findings, ecosystem services that are considered most important in an urban context were considered here. Direct remote sensing of ecosystem services is challenging as they are often intangible and are rather defined through ecosystem functions and processes that involve a temporal component, human benefiters and that can only partly 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 (Gould, 2000; Schmidtlein and Sassin, 2004; 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). The detection and discrimination of species assemblages, individual organisms or ecological communities can be achieved with sufficiently spatially and spectrally resolved data. The many direct and indirect ways in which remote sensing data can contribute to ecosystem service studies are highlighted and summarized in the works of Feng et al. (2010), Ayanu 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 ecosystem services as a new application domain. In general, remote sensing can contribute to ecosystem service studies by providing relevant spatial biotic and abiotic data such as soil moisture, temperature and elevation directly (Horning et al., 2010) either through the exploitation of the spectral and backscatter diversity of sensors and through the derivation of environmental surrogates such as productivity, topography, land cover, disturbance etc. (Andrew et al., 2014). Indirect couplings to ecosystem services can be made through land use and land cover classifications where the derived class stands representative for at least one ecosystem function or service. In urban areas, water bodies and planted city vegetation in forms of rivers and ponds, forest, street trees, lawns, gardens, parks, golf courses or other permeable surfaces play the most important role for the provision of services. Additional urban features such as façade and roof greening, spontaneous vegetation, unused land or derelict buildings also play a role although a less obvious one. Difficulties in determining these classes and underlying functions lie in their rather non-uniform multimodal composition, that they are defined through land use and not land cover, in their sparse occurrence, and in the fact that their presence and attributed ecological function can only be anticipated with higher degrees of uncertainty. Regarding biodiversity as fundamental concept of many ecosystem services, it is believed that the full potential remote sensing yields for the provision of information on state and pressure of biodiversity is yet to be unlocked (Pettorelli et al., 2014) and that satellite remote sensing data are currently underused within biodiversity research (Turner et al., 2015).

ESA's Sentinel-2A mission is considered to be highly relevant to environmental monitoring. The prime objectives of the mission are to provide systematic global acquisitions of high-resolution multispectral imagery with a high revisit frequency, to provide enhanced continuity of multispectral data provided by the SPOT (Satellite Pour l'Observation de la Terre) series of satellites and to provide observations for the next generation of operational products such as land cover maps, land change detection maps and geophysical variables (Drusch et al., 2012). Free data access, high temporal and spatial resolutions up to 10m are furthermore highlighted as some of the most important traits of the Sentinel family. This study investigates the potential of Sentinel-2A MSI data for urban land cover and ecosystem service mapping in particular. Ecosystem service bundles are derived in the Beijing metropolitan area in 2005 and 2015 and their spatio-temporal patterns are analysed through landscape metrics. The ecosystem service concept is systematically extended in this study to include spatio-topological characteristics and their influence on service providing areas. Changes over one decade are observed to give an indication of ecological and sustainable development in the light of urban growth.

STUDY AREA AND DATA

Beijing, the capital of China was chosen as study area. Beijing is located at the northern edge of the North China plain and surrounded by Hebei Province at 39°55′N and 116°23′E. As China's currently second largest city in terms of population after Shanghai, ecosystem services play an important role for many urban residents and visitors. The urban core is characterized through high density built-up areas in form of the traditional Hutong areas and modern, high-rise complexes with commercial and residential function. Low density built-up 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. Figure 1 below shows the 1,370 km^2 large study area.

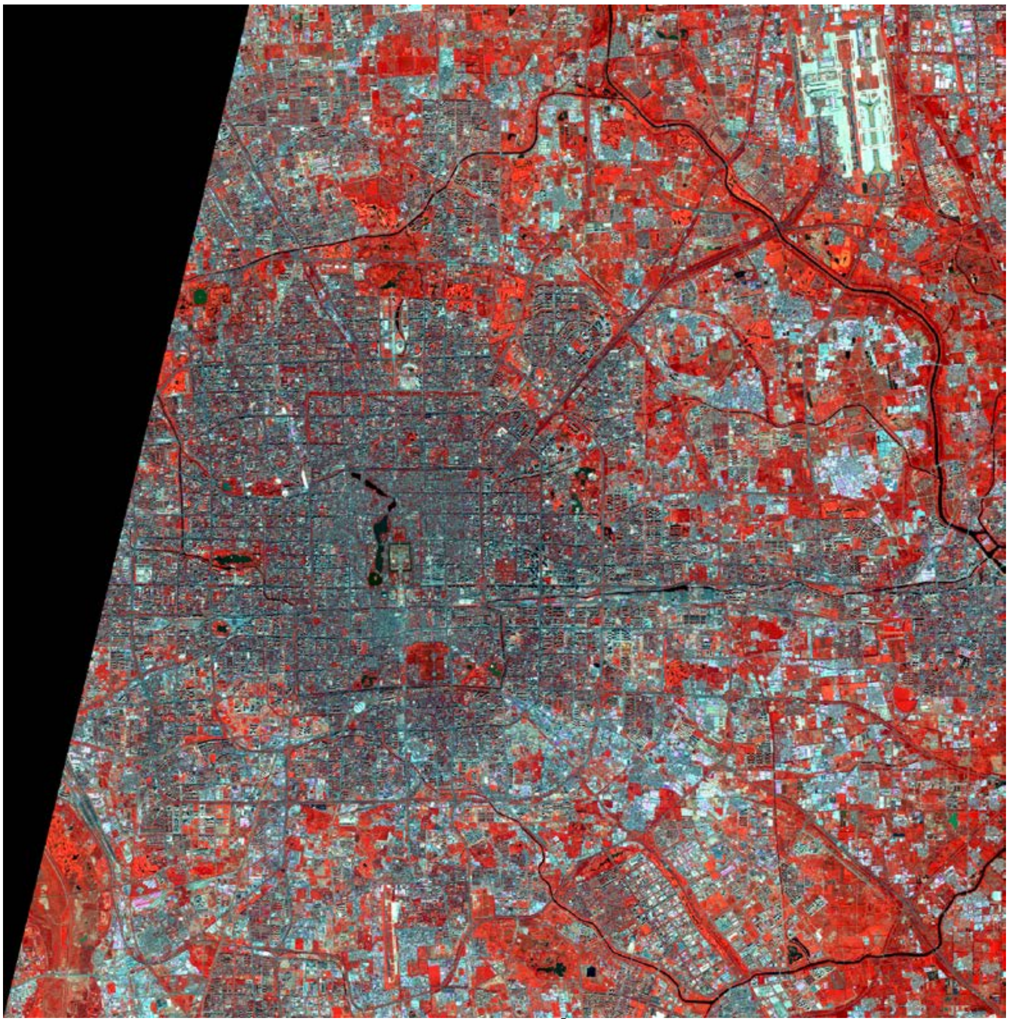

Figure 1. Sentinel-2A FCC image over the 1,370 km^2 comprising study area of Beijing

For 2015, a Sentinel-2A level 1c product acquired on 2015-09-13 was used. A spectral subset of the Sentinel-2A image was chosen excluding the three bands at 60m resolution. For the 2005 dataset, the visible and IR bands of a Landsat 5 TM scene from 2005-07-09 were used.

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 with 13 spectral bands at wavelengths from 443 nm to 2190 nm in 12-bit radiometric resolution with a swath width of 290 km and spatial resolutions of 10, 20 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. 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. The following Table summarizes the Figure 3 depicts all 13 Sentinel-2 bands and resolutions.

Table 1 Senitnel-2A sensor specifications

Spectral bands	Spatial resolution (m)	Spectral wavelength (nm)	Spectrum
1	60	443	visible
2	10	490	visible
3	10	560	visible
4	10	665	visible
5	20	705	VNIR
6	20	740	VNIR
7	20	783	VNIR
8	10	842	VNIR
8a	20	865	VNIR/SWIR
9	60	940	VNIR/SWIR
10	60	1375	SWIR
11	20	1610	SWIR
12	20	2190	SWIR

METHODOLOGY

The methodology displayed in the flowchart in Figure 2 covers all major analytical stages of the analysis including image pre-processing and coregistration, image segmentation and classification, accuracy assessment, post-classification aggregations, landscape metric and proximity analysis, quantification of spatial influences on ecosystem service provision and observation of changes from 2005 to 2015.

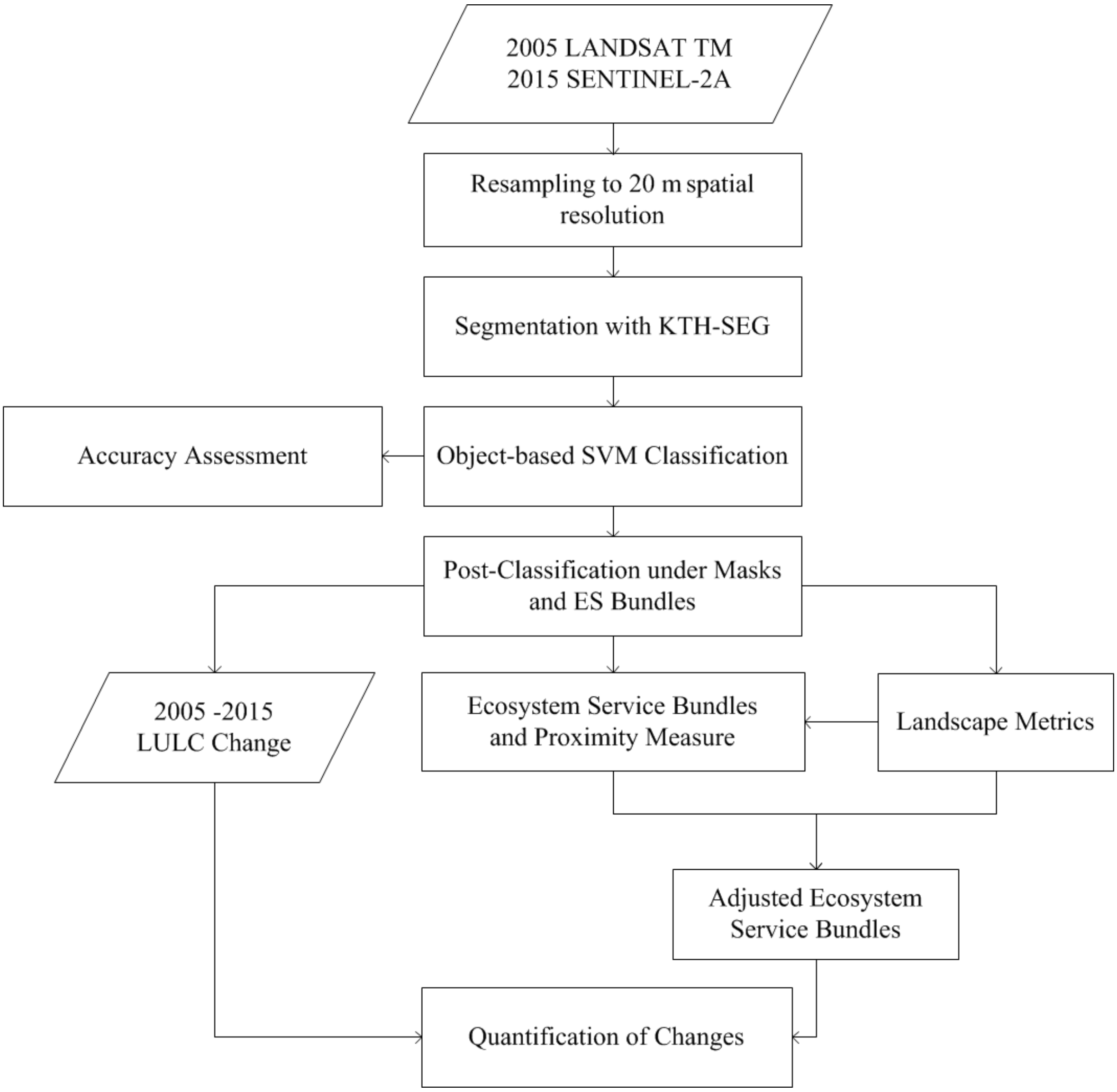

Figure 2. Methodology flowchart

Urban Land Cover Classification

Object-Based Image Analysis (OBIA) techniques have grown in popularity over the past years due to their often superior performance over traditional pixel-based classifiers (Myint et al., 2011) and they are recommended for classification of ecologically relevant space, e.g. through habitat (Corbane et al., 2015) or biotope mapping applications (Tiede et al., 2010). An OBIA approach was adapted in this study through image segmentation that was performed by the KTH-SEG software package (Ban and Jacob, 2013). KTH-SEG features 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 into 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 then 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. For the segmentations performed in this study, the most suitable parameters were empirically determined as follows: Canny threshold: 0.07-0.14 (2005 dataset) and 0.05-0.1 (2015 dataset); grow 0.5/0.5, merge 0.5/0.5, minimum and maximum segment sizes were chosen from 2 to 500 pixels. The segments for the 2005 and 2015 classifications were then classified with an implementation of the java libSVM library (Chang and Lin, 2011) in KTH-SEG into 13 spectrally different classes that were aggregated into 6 contextually coherent land use and land cover classes. SVM is an effective classifier that originated from the field of machine learning. 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 base function (RBF) kernel was used. The required parameters were automatically determined through a grid-search approach. Both mean and standard deviation of the digital numbers from the MSI bands were chosen as input features to the classifier. Classification accuracy assessment was performed by selecting a minimum of 1,000 validation pixels per class homogeneously distributed across the images. Validation site selection was performed under two premises, i.e. 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 assessment was performed on the final classifications after aggregation of subclasses. The validation sites do not coincide with the training sites and were chosen manually all over the scene. As measures of accuracy, kappa coefficient, overall, average, user's and producer's accuracies were chosen. As major post-classification procedure, urban green spaces and golf courses were delimited through reclassification of agricultural land under urban and golf course masks. Thus, eight classes are derived as agriculture, forest, water bodies, high density built-up, low density built-up, roads/impervious surfaces, urban green spaces.

Landscape Metrics and Ecosystem Services

The choice of classes in this study is motivated by two factors. The first one is the detection of major ecosystem service providing land cover classes and the second one is their relation to different man-made features that influence ecosystem importance and quality. Provisional classes were selected based on the urban ecosystem service summary provided by Gómez-Baggethun et al. (2013), artificial classes were chosen as high-density and low-density built-up areas and roads/other impervious areas such as parking lots, public squares or airport runways. It is understood that low-density built-up classes can provide some ecosystem services but as they are not explicitly targeted in the abovementioned summary and as the share and distribution of green space in the direct proximity to built-up space and their use is not known, quantification is difficult. Hence, low density areas have been excluded as service providers but they should be considered if more detailed land cover data is available and if the actual land use is known.

The dependencies of service provision on spatial attributes are defined as follows:

- Area: Larger areas provide more services
- Connectivity: Connected landscapes increase service provision through enhanced movement corridors and material flows
- Core: Core patch areas with no edge influence are important for species through provision of a more unaltered habitat.
- Diversity: Diverse landscapes increase the services through being more visually appealing, offering more possibilities for social and recreational activities and through being more species rich.
- Edge: Edge contamination of natural blue and green spaces through built-up space affects service quality though pollution and decreased species movement
- Proximity: Closeness to built-up areas increases importance.

Landscape metrics in this study are used to quantify the overall changes in the study area as a whole and to evaluate the spatial effects on service class bundle provision. Therefore, metrics at the patch level are not considered here. The landscape metrics to quantify these effects are chosen and described according to McGarigal et al. (2012) as follows:

- CA: Class area is a measure of landscape composition; specifically, how much of the landscape is comprised of a particular patch type. In addition to its direct interpretive value, class area is used in the computations for many of the class and landscape metrics.
- COHESION: The patch cohesion index measures the physical connectedness of the corresponding patch type. Patch cohesion increases as the patch type becomes more clumped or aggregated in its distribution; hence, more physically connected.
- CWED: Contrast-weighted edge density is an index that incorporates both edge density and edge contrast. It standardizes edge to a per unit area basis that facilitates comparison among landscapes of varying size. Edge contrast is defined on a scale from 0 to 1, where 0 indicates no edge contrast and 1 the largest difference between two classes. In this study 0 contrast in-between green and blue classes and 0 contrast in-between built-up classes was chosen. The contrast values between natural green and blue spaces and built-up classes were defined as follows: natural versus low density built-up (0.4), versus high density built-up (0.7) and versus roads/impervious surfaces (0.9).
- PLAND: The percentage of landscape quantifies the proportional abundance of each patch type in the landscape. Like total class area, it is a measure of landscape composition important in many ecological applications.
- TCA: Total core area represents the area in the patch greater than the specified depth-of-edge distance from the perimeter. TCA was chosen to quantify service provision classes where a negative effect of adjacent other patch types is expected. A depth-of-edge distance of 10 m was chosen here since no particular ecological profile is considered and edge effects differ for organisms and ecological processes (Hansen and di Castri, 1992). TCA is aggregated (summed) over all patches of the corresponding patch type.
- SHDI: Shannon's diversity index is a popular measure of diversity in community ecology, applied here to the complete landscape. Shannon's index is somewhat more sensitive to rare patch types than Simpson's diversity index.

CA, COHESION, CWED, PLAND and TCA are considered at class and SHDI at landscape level. For more comprehensive explanations and descriptions of the metrics, reference is given in McGarigal et al. (2012). The proximity criterion was implemented by creating a 200m buffer between high density and low density built-up areas. Whatever green and blue space falls into the buffer is believed to be of higher importance to the close-by population than corresponding areas further away. To better relate the proximity criteria to an increasing urban population the ratio between provisioning classes that lie within 200 m of low- and high density built-up areas and the simultaneous increase in high and low density built-up areas was created. The following table summarizes important ecosystem services for urban areas, the land use/land cover classes that provide these services, considerations about what spatial characteristics are important for service provision and quality alongside appropriate landscape metrics to express those.

Table 2 Summary of ecosystem services, provisional land cover classes according to Gómez-Baggethun et al. (2013), influential spatial attributes and suggested landscape metrics to quantify these spatial attributes.

Ecosystem Service	*Provided by LULC*	*Service dependent on*	*Metric*
Food supply	Agriculture Forest Water bodies	Area	CA PLAND
Water supply	Forest Golf courses Urban green spaces Water bodies	Area Edge	CA CWED PLAND
Temperature regulation	Forest Golf courses Urban green spaces Water bodies	Area Proximity	CA PLAND
Noise reduction	Agriculture Forest Golf courses Urban green spaces	Area Proximity	CA PLAND
Air purification	Forest Golf courses Urban green spaces	Area Proximity	CA PLAND
Moderation of climate extremes	Forest Golf courses Urban green spaces Water bodies	Area Proximity	CA PLAND
Runoff mitigation	Agriculture Forest Golf courses Urban green spaces Water bodies	Area	CA PLAND
Waste treatment	Agriculture Water bodies	Area	CA PLAND
Pollination, pest regulation and seed dispersal	Agriculture Forests Urban green spaces	Area Connectivity Core Diversity Edge	CA COHESION CWED PLAND SHDI TCA
Global climate regulation	Agriculture Forest	Area	CA PLAND
Recreation	Forest Golf courses Urban green spaces Water bodies	Area Diversity Proximity	CA PLAND SHDI
Aesthetic benefits	Forest Urban green spaces Water bodies	Area Diversity Proximity	CA PLAND SHDI
Cognitive development	Forest Urban green spaces Water bodies	Area Diversity Proximity	CA PLAND SHDI
Place values and social cohesion	Forests Golf courses Urban green spaces Water bodies	Area Diversity Proximity	CA PLAND SHDI
Habitat for biodiversity	Agriculture Forest Urban green spaces	Area Connectivity Core Diversity Edge	CA COHESION CWED PLAND SHDI, TCA

Considering the contextual split between land cover and land use in relation to ecosystem services it should be noted that land cover is more indicative for regulating, supporting and habitat services since their functions are directly related to the presence of a land cover class that fulfils an ecosystem function. Provisioning and cultural services are more dependent on how the land that holds the potential to provide these services is actually used. Since one objective of this study is to only use remotely sensed data, land cover classes as a proxy for ecosystem services are considered here since the actual land use of a land cover class is difficult to determine without ancillary data. The original summary of Gómez-Baggethun et al. (2013) features more urban ecosystem service providing classes that are identified through literature. Not all of these areas were however considered in this study. The classes that were omitted here are green rooftops, cemeteries, private and community gardens and backyards since they only make up a small part of the study area and since their classification is difficult with the underlying data. These urban classes play a minor role at the scale under consideration but could be considered when high-resolution data is used. Wetlands that play an important role in ecosystem service provision are not present in the study area. Water bodies were note explicitly mentioned as urban features that contribute to runoff mitigation but it is understood that they also provide this service and are hence included. Neither were they considered to contribute to social ecosystem services, i.e. recreation, cognitive development, sense of place and aesthetic benefits but are believed to provide such services, e.g. in form of the centrally located Beihai park or the Yuyuan pond. The urban green space class was integrated to distinguish ground-layer vegetation within the urban boundary from agriculture since urban vegetation is predominately not used for food production. Other features that can be included in urban green spaces by definition, i.e. trees and water bodies were not considered as urban green spaces but were kept as land cover class forest and water bodies due to the different ecosystem functions they fulfil as opposed to ground-layer vegetation. Highly managed golf courses are composed trees, open soil water and lawn. The open soil and lawn parts of golf courses were classified as such but trees and water bodies were kept as own land cover class as a result of their distinct functions. Some research has shown that golf courses provide also habitat functions and foster biodiversity (Colding and Folke, 2009) but the biodiversity function is a) more related to trees than lawns that are separated here and b) falls usually short of other more natural and remnant vegetation. Hence, golf courses were not attributed habitat function in this study. Agricultural areas in form of vegetated fields or bare soil were aggregated into the agriculture class. Both bare and vegetated fields provide at some point in time food supply services in form of crops but provide the services permeable soils do at all time.

As can be seen from Table 2 above, land cover classes that serve as proxies for ecosystem services were bundled according to their similar service provision capacities and landscape metrics that are used to evaluate spatial influence on service provision.

The following services were aggregated into the same service category:

- Recreation/Place values and social cohesion
- Aesthetic benefits/Cognitive development
- Temperature regulation/Moderation of climate extremes
- Pollination, pest regulation and seed dispersal/Habitat for biodiversity

Other services that neither share the same classes nor are equally influenced by spatial characteristics are:

- Food supply
- Water supply

- Noise reduction
- Air purification
- Runoff mitigation
- Waste treatment
- Global climate regulation

Landscape metrics were generated for the landscape as a whole (SHDI) and for each land cover class individually. The resulting values were normalized and summed up 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.

RESULTS

Figure 3 below shows the classification results after class aggregation and post-classification. Land cover over Beijing in 2005 is displayed at the left hand side and over Beijing 2015 to the right.

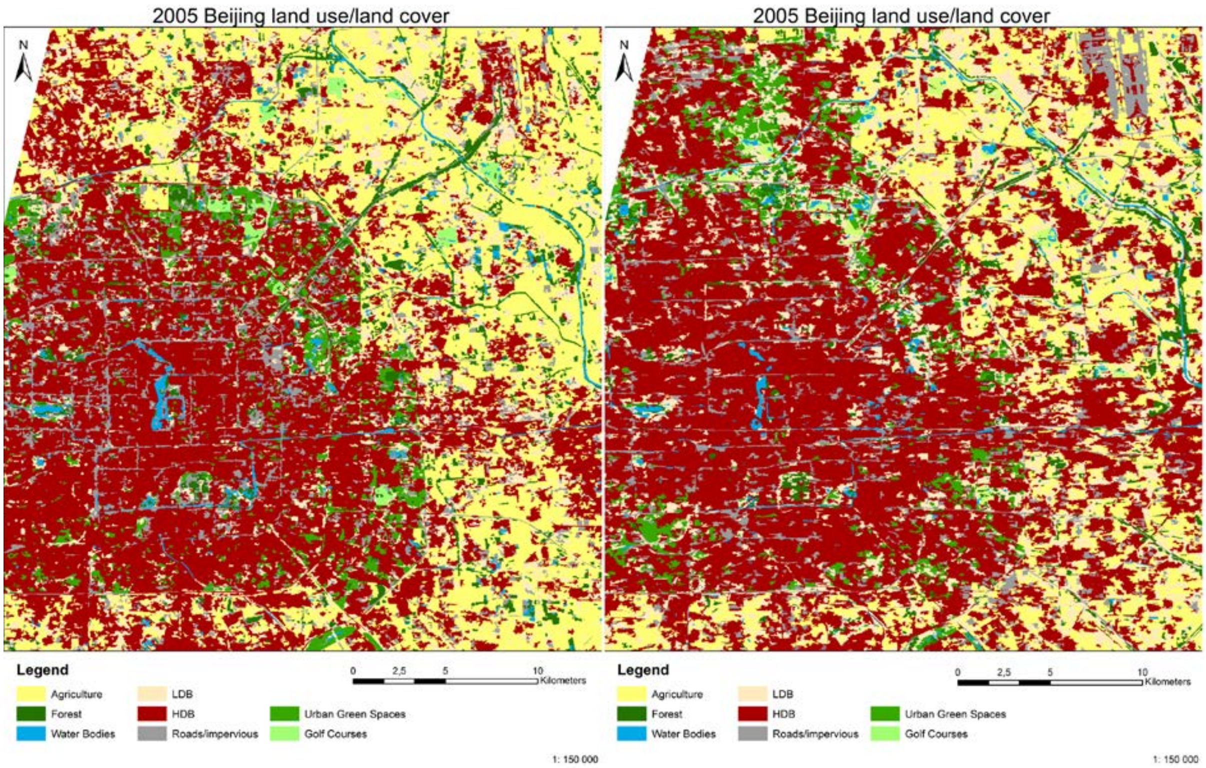

Figure 3. Land cover classification result for Beijing in 2005 (left) and for 2015 (right)

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. Overall classification accuracies and kappa coefficients are presented in Table 3 below.

Table 3. Summary of classification accuracies

Classification	**Overall accuracy**	**Kappa**
2005 Landsat	84.7	0.82
2015 Sentinel-2A	90.2	0.89

Further information on individual class confusions and producer's and user's accuracies is given in the confusion matrices in Tables 4 and 5 below.

Table 4. 2005 classification confusion matrix

Class	HDB	LDB	Roads	Agriculture	Forest	Water	**UA**
HDB	**70.5**	1.2	2.7	25.6	0	0	**70.5**
LDB	4.1	**81.2**	11	3.6	0.1	0	**81.2**
Roads/impervious	14.3	4.6	**78.7**	0.8	0.4	1.3	**78.7**
Agriculture/open	0	5.1	0	**94.9**	0	0	**94.9**
Forest	0.1	0.5	8.0	4.5	**86.9**	0	**86.9**
Water	0	0.1	0.4	0.1	3.3	**94.1**	**96.2**
PA	**78.7**	**87.2**	**79.0**	**73.6**	**95.7**	**98.6**	

The confusion between high density built-up areas and agriculture 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 as shown in Table 5.

Table 5. 2015 Sentinel-2A classification confusion matrix

Class	HDB	LDB	Roads	Agriculture	Forest	Water	**UA**
HDB	**92.2**	2.2	4.7	0.9	0	0	**92.2**
LDB	13.5	**85.5**	0	1	0	0	**85.5**
Roads/impervious	6.7	1	**83.0**	9.3	0	0	**83.0**
Agriculture/open	2.8	0.8	3.1	**90.6**	2.8	0	**90.6**
Forest	3.0	6.5	0.1	0.2	**90.2**	0	**90.2**
Water	0	0	0	0	0	**100**	**100**
PA	**77.8**	**89.2**	**91.6**	**88.6**	**97.0**	**100**	

The decrease in agricultural land in favour of built-up areas, urban green spaces, golf courses and water can be confirmed when looking at the bar chart in Figure 4 below that shows the percentage of landscape in 2005 and 2015. 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%.

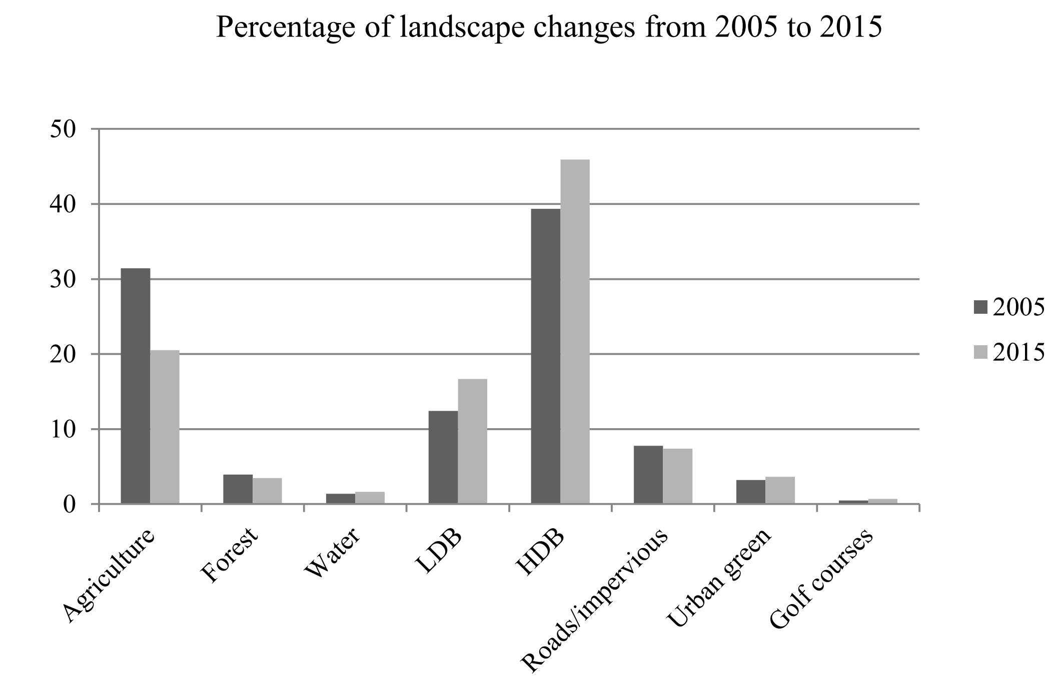

Figure 4 Changes in PLAND from 2005 to 2015

Table 6 below summarizes the original landscape metrics before scaling for 2005 and 2015 and Figure 5 visualizes the relation among the metrics.

Table 6. Metrics based on 2005 and 2015 classifications (Units are as follows: CA, TCA and PROX in hectare, CWED in meters per hectare, PLAND in percentage, COHESION, SHDI and PROXrel are unitless)

2005								
Class	*CA*	*PLAND*	*CWED*	*TCA*	*COHESION*	*SHDI*	*PROX*	*PROXrel*
Agriculture/open	43067	31.42	26.83	37026	99.79	1.51	40567	0.571
Forest	5404	3.94	3.56	3765	96.85	1.51	4985	0.070
Water	1905	1.39	2.17	1275	96.26	1.51	1792	0.025
LDB	17035	12.43	9.59	11615	97.03	1.51	17036	-
HDB	53977	39.38	18.65	47024	99.93	1.51	53971	-
Roads/impervious	10658	7.78	11.00	6878	96.68	1.51	10572	-
UGS	4388	3.20	6.53	3191	96.92	1.51	4386	0.062
Golf courses	642	0.47	0.15	568	98.72	1.51	600	0.008
2015								
Class	*CA*	*PLAND*	*CWED*	*TCA*	*COHESION*	*SHDI*	*PROX*	*PROXrel*
Agriculture/open	28126	20.52	24.99	22711	99.14	1.54	27888	0.325
Forest	4782	3.49	3.96	3318	96.83	1.54	4778	0.056
Water	2262	1.65	3.27	1379	95.81	1.54	2255	0.026
LDB	22899	16.71	12.84	16080	97.73	1.54	22897	
HDB	62926	45.91	20.13	54845	99.94	1.54	62924	
Roads/impervious	10150	7.40	6.41	6564	97.46	1.54	10108	
UGS	4968	3.62	6.78	3606	97.76	1.54	4963	0.058
Golf courses	965	0.70	0.37	747	98.42	1.54	955	0.011

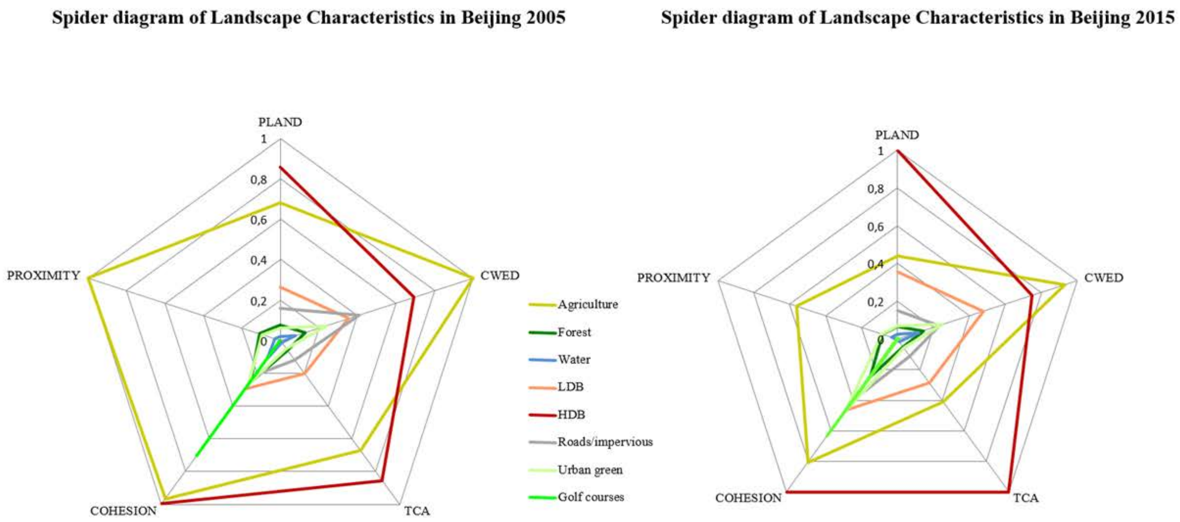

Figure 5 Landscape characteristics in Beijing 2005 and 2015

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. 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. Urban growth that is observed in the study takes form in increases of surface sealing, e.g. in the extension of Beijing Capital International Airport and in newly built-up high density and low density 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 urban green spaces 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. The effects of urban land cover change quantified through ecosystem services are summarized in Table 7 below.

Table 7. The effect of landscape composition and configuration on ecosystem service bundles

Service Bundles 2005	*CA*	*COHESION*	*CWED*	*SHDI*	*TCA*	*Proximity*
Food supply	50376	-	-	-	-	-
Water supply	12339	-	12.42	-	-	-
Temperature regulation	12339	-	-	-	-	0.166

Moderation of climate extremes						
Noise reduction	53501	-	-	-	-	0.712
Air purification	10434	-	-	-	-	0.140
Runoff mitigation	55406	-	-	-	-	-
Waste treatment	44972	-	-	-	-	-
Pollination. pest regulation and seed dispersal/Habitat for biodiversity	52859	293.56	36.92	1.511	43982	-
Global climate regulation	48471	-	-	-	-	-
Recreation/Place values and social cohesion/	12339	-	-	1.511	-	0.166
Cognitive development/Aesthetic benefits	11697	-	-	-	-	0.157
Service Bundles 2015	*CA*	*COHESION*	*CWED*	*SHDI*	*TCA*	*Proximity*
Food supply	35170	-	-	-	-	-
Water supply	12977	-	14.39	-	-	-
Temperature regulation Moderation of climate extremes	12977	-	-	-	-	0.151
Noise reduction	38841	-	-	-	-	0.450
Air purification	10715	-	-	-	-	0.125
Runoff mitigation	41103	-	-	-	-	-
Waste treatment	30388	-	-	-	-	-
Pollination. pest regulation and seed dispersal/Habitat for biodiversity	37876	293.72	35.73	1.540	29635	-
Global climate regulation	32908	-	-	-	-	-
Recreation/Place values and social cohesion/	12977	-	-	1.540	-	0.151
Cognitive development/Aesthetic benefits	12012	-	-	-	-	0.140

The land cover classes that are the basis for ecosystem service bundles were evaluated according to their spatial characteristics that influence service provision in 2005 and 2015. Positive development trends, e.g. an increase in provisional area by 100% would result in a 100% increase in service provision. If the same class however shows a 50% decreased cohesion value, the total combined increase in service provision would only amount to 75% ((100 + 50)/2). In order to just express purely relative changes to ecosystem service provision from 2005 to 2015, the spatial attributes as of 2005 were used as a baseline scenario. The spatial changes in all land cover classes contributing to a service bundle as presented in Table 1 were aggregated. Both positive and detrimental influences on ecosystem services were summed up and averaged for each bundle. The overall changes in percent are displayed in Table 8 below.

Table 8 Ecosystem Service bundle changes in percent

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

All ecosystem service bundles have decreased in service provisional value over the past 10 years. Decreases of more than 30% are noted in the bundles that represent food supply, noise reduction, waste treatment, global climate regulation. 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.

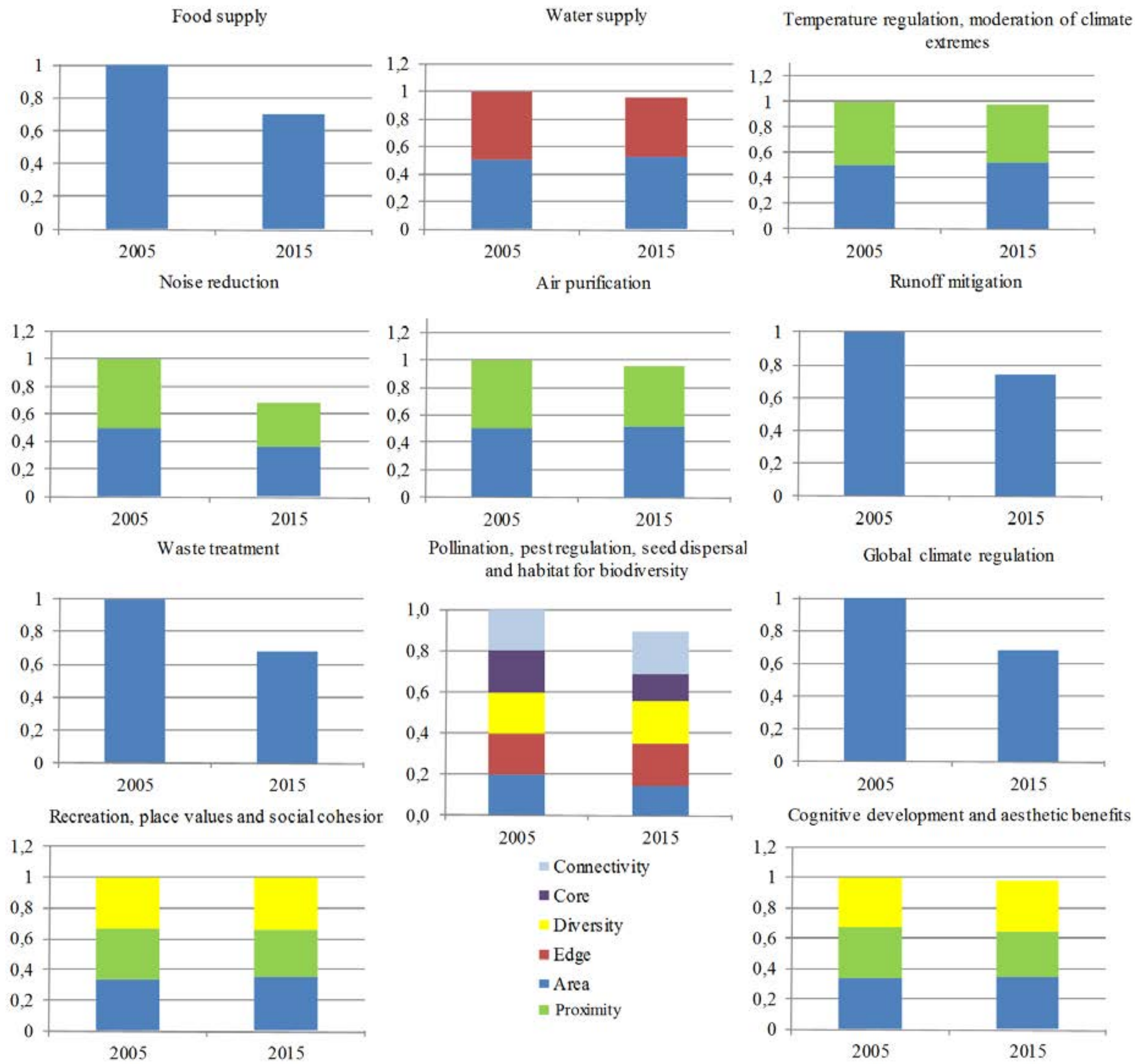

Figure 6. Ecosystem service bundle changes and share of spatial influence

DISCUSSION

Higher classification accuracies in the 2015 classification could be achieved than for the 2005 classification where 30m resolution data was used. However, 20m resolution data that was classified in 2015 is believed to be too coarse to grasp small scale changes in urban green spaces in the inner city and here the use of high-resolution data is advised (Qian et al. 2015b). Improvements for the reduction of class confusions could be achieved through the integration of additional features or texture measures in the segmentation and classification approach in the future. Roads, whose classification at 30m resolutions is difficult, are believed to be more easily distinguished from other built-up areas through their linearity. Especially here, shape and topological information could be integrated as additional features.

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 ecosystem services is evaluated by the local population is not drawn into consideration here. In Beijing, local microclimate regulation, noise reduction and air purification may play a more important role than possibly subordinate services such as pollination, pest regulation and seed dispersal services. In other parts of the world, just these services might be crucial for survival. Because of these difficulties, a relative evaluation was performed here, only based on spatial characteristics devoid of subjective human valuations.

The classification results suggest increases of built-up areas in the rural-urban fringe end deconstruction of older suburban agglomerations in favour of urban green spaces. Additionally, decreasing agricultural areas contribute to urban growth and creation of urban green spaces in the urban-rural fringe. The general trend of increases in urban green spaces in Beijing can be confirmed by Qian et al. (2015a), although the study focusses at a different, more detailed scale and uses a different classification scheme. A comprehensive classification scheme for urban ecosystem services is still missing and the choice of classes here is non-exhaustive and motivated by what can be classified with sufficient accuracy without integration of additional data. Other urban features that provide ecosystem services or at least fulfil some ecological functions can be integrated if high-resolution data is used. The idea of linking land use and land cover data to ecosystem service bundles and to evaluate those in terms of spatial influence facilitates interesting new possibilities to investigate and compare ecological developments in another more refined way. As ecosystem services are but one ecological indicator, the establishment of a direct link between land use land cover to actual underlying ecosystem functions would also be an interesting consideration. Not only could be shown how landscape metrics can be used to create a more detailed picture of ecosystem service provision, but also often neglected proximity measures were integrated in the study. If we recall what the essence of ecosystem services are, namely benefits that humans derive from functioning ecosystems, it becomes clear that without any humans to use the services, the concept is meaningless. This is especially true for social ecosystem services. Therefore, accessibility to ecosystem services is of utmost importance. This was expressed by the proximity criterion in this study although a more refined way of dealing with the matter is possible. For example through a more detailed distinction into building types, varying degrees of need for ecosystem services and at the same time the types and magnitudes of stress built-up categories exert on ecosystems could be addressed. A suggested split closer related to land use in different urban categories in environments such as the study area could for example be a distinction into commercial, residential and industrial complexes.

The metrics chosen here are believed to most adequately express the spatial influence on provision of the selected ecosystem services. As services are considered at a landscape and class perspective, patch metrics were not considered. These could be integrated if a particular patch, e.g. an urban park, or a species with a specific landscape dependency is considered. For these special cases, additional and/or other metrics and parameter settings can be chosen. Looking at the changes in ecosystem service provision bundles, increases and decreases are to be interpreted with caution. One should be aware of that all the classes that bundle is composed of do not have equal influence on service provision. For example, air purification that is provided through forests, urban green spaces and golf courses, was found to have decreased by 4 percent in 2015 as compared to 2005. This is a result of increases in urban green spaces and golf courses and decreases in tree cover in the urban fringe. Urban green spaces increased by 580 ha, golf courses by 323 ha and forests decreased by 622 ha. The actual contribution of the individual bundle elements is not obvious here. Maybe, the increase in urban green spaces counteracts the decrease with about 2. In the bundle, all three components are however treated equally. This problem can only be solved by determining more refined shares of individual class contributions. This however requires additional information on the species level and patch composition that was not attempted in this study but could be an interesting future addition to the method. To this means, high resolution and hyperspectral data and a priori information on the presence of species and their individual capacities to provide ecosystem functions could complement the multispectral information used in this study. An interesting continuation of this study would be to explore further links between ecosystem services and landscape metrics when smaller scales with more detailed urban land use and land cover classes are considered and to this means establish a new method using high-resolution data. Another aspect that has recently enjoyed increased attention is ecosystem disservices, i.e. the negatively experienced characteristics of ecosystems that could be analysed in similar ways. This study has focussed exclusively on service provision. Investigations of service demand patterns would also be an interesting extension to the approach pursued here.

CONCLUSION

This study investigated the potential of Sentinel-2A MSI data for urban land cover mapping and ecosystem service analysis. Classification accuracies of 90.2% could be reached that were 5.5% higher than on Landsat TM data. This indicates the suitability of Sentinel-2A data for urban land cover and ecosystem service mapping. Ecosystem services are often used as ecological indicator but spatial characteristics of ecosystem service providing land cover classes are very seldom drawn into consideration. This study presents a systematic approach that through cross-methodological investigations with landscape metrics quantifies the impact of spatial patch characteristics and landscape composition and configuration on ecosystem service provision. Ecosystem service bundles were created based on similar land cover classes that underlie the services and based on similar spatial influences on service provision. Changes in ecosystem service provisions in Beijing from 2005 to 2015 as a result of urban land cover changes were observed and quantified through landscape metrics. The urban development of Beijing over the past ten years is characterized by a decrease in agricultural areas in the rural-urban fringe in favour of new high and low density built-up areas, urban green spaces and golf courses. The planar increase in urban areas is partly counteracted by the creation of managed urban green spaces and urbanization trends in Beijing take mainly place in the third dimension in form of high-rise developments to accommodate an increasing population. Most negatively affected by landscape structural changes through decreases in service area, edge contamination and fragmentation were food supply, noise reduction, waste treatment, global climate regulation. The approach developed in this study extended the ecosystem service concept to including the influence of spatio-temporal characteristics of ecosystem service provisional patches, thus resulting in a more realistic and comprehensive appraisal of ecosystem services than traditional monetary approaches in urban areas.

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