TECHNISCHE UNIVERSITÄT DRESDEN

Faculty of Environmental Sciences

Methodical basis for landscape structure analysis and monitoring: inclusion of ecotones and small landscape elements

Dissertation for awarding the academic degree

Doctor rerum naturalium (Dr. rer.net)

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List of abbreviations

2D	Two-dimensional – two dimensions
3D	Three-dimensional – three dimensions
ATKIS	Authoritative Topographic Cartographic Information System (German: Amtiches Topographisch-Kartographisches Informationssystem)
AWEC	Area-Weighted Edge Contrast
BfN	Federal Office for Nature Conservation (German: Bundesamt für Naturschutz)
BKG	German Federal Agency for Cartography and Geodesy (German: Bundesamt für Kartographie und Geodäsie)
BMU	Federal Ministry for the Environment, Nature Conservation and Nuclear Safety (German: Bundesministerium für Umwelt, Naturschutz und Reaktorsicherheit)
CAPE	Corridor Area Percentage of Econet
CBD	Convention on Biological Diversity
CIR	Color Infrared
CORINE	Coordination of Information on the Environment
CLC	CORINE Land Cover
DEM	Digital Elevation Model
dCAPE	Change rate of CAPE between two dispersal distances
DTM	Digital Terrain Model
DLM	Digital Landscape Model
DLM-DE	Digital Landscape Model for Germany (German: Digitales Landbedeckungsmodell für Deutschland)
DLR	German Aerospace Center (German: Forschungszentrum der Bundesrepublik Deutschland für Luft- und Raumfahrt)
DSM	Digital Surface Model
ECMS	Effective Connected Mesh Size
Econets	Ecological networks
ECON	Edge Contrast Index
EU	European Union
ESP	Estimation of Scale Parameters
GIS	Geographic Information System
HNV	High Nature Value
IIC	Integral Index of Connectivity

KIS	Environmental Key Indicator System (German: Umwelt-Kernindikatorensystem)
Lidar	Light detection and ranging
LIKI	State Initiative on Core Indicators (German: Länderinitiative Kernindikatoren)
MESH	Effective Mesh Size
MLR	Ministry of Land and Resources
MMU	Minimum Mapping Unit
MRIS	Multi-Resolution Image Segmentation
MS	Multispectral bands
NCAs	Nature Conservation Areas
NDSM	Normalized Digital Surface Model
NHS	Indicator System for National Sustainable Development (German: Indikatorenberichte zur Nationalen Nachhaltigkeitsstrategie)
NLPs	National Parks
NDVI	Normalized Difference Vegetation Index
NDVI-RE	Normalized Difference Vegetation Index-Red Edge
NIR	Near Infrared
OBIA	Object-Based Image Analysis
Pan	Panchromatic band
PBIA	Pixel-Based Image Analysis
PC	Probability of Connectivity
RE	Red Edge
REVI	Red Edge Vegetation Index
SEBI	Streamlining European Biodiversity Indicators
SHDI	Shannon’s Diversity Index
SIDI	Simpson’s Diversity Index
SWIR	Short Wave Infrared
SRTM	Shuttle Radar Topography Mission
TECI	Total Edge Contrast Index
TIR	Thermal Infrared
UBA	Federal Environmental Agency (German: Umweltbundesamt)
ULTA	Undissected, Low-Traffic Areas

Abstract

Habitat variation is considered as an expression of biodiversity at landscape level in addition to genetic variation and species variation. Thus, effective methods for measuring habitat pattern at landscape level can be used to evaluate the status of biological conservation. However, the commonly used model (i.e. patch-corridor-matrix) for spatial pattern analysis has deficiencies. This model assumes discrete structures within the landscape without explicit consideration of “transitional zones” or “gradients” between patches. The transitional zones, often called “ecotones”, are dynamic and have a profound influence on adjacent ecosystems. Besides, this model takes landscape as a flat surface without consideration of the third spatial dimension (elevation). This will underestimate the patches’ size and perimeter as well as distances between patches especially in mountainous regions. Thus, the mosaic model needs to be adapted for more realistic and more precise representation of habitat pattern regarding to biodiversity assessment. Another part of information that has often been ignored is “small biotopes” inside patches (e.g. hedgerows, tree rows, copse, and scattered trees), which leads to within-patch heterogeneity being underestimated.

The present work originates from the integration of the third spatial dimension in land-cover classification and landscape structure analysis. From the aspect of data processing, an integrated approach of Object-Based Image Analysis (OBIA) and Pixel-Based Image Analysis (PBIA) is developed and applied on multi-source data set (RapidEye images and Lidar data). At first, a general OBIA procedure is developed according to spectral object features based on RapidEye images for producing land-cover maps. Then, based on the classified maps, pixel-based algorithms are designed for detection of the small biotopes and ecotones using a Normalized Digital Surface Model (NDSM) which is derived from Lidar data. For describing habitat pattern under three-dimensional condition, several 3D-metrics (measuring e.g. landscape diversity, fragmentation/connectivity, and contrast) are proposed with spatial consideration of the ecological functions of small biotopes and ecotones.

The proposed methodology is applied in two real-world examples in Germany and China. The results are twofold. First, it shows that the integrated approach of object-based and pixel-based image processing is effective for land-cover classification on different spatial scales. The overall classification accuracies of the main land-cover maps are 92 % in the German test site and 87 % in the Chinese test site. The developed Red Edge Vegetation Index (REVI) which is calculated from RapidEye images has been proved more efficient than the traditionally used Normalized Differenced Vegetation Index (NDVI) for vegetation classification, especially for the extraction of the forest mask. Using NDSM data, the third dimension is helpful for the identification of small biotopes and height gradient on forest boundary. The pixel-based algorithm so-called “buffering and shrinking” is developed for the detection of tree rows and ecotones on forest/field boundary. As a result the accuracy of detecting small biotopes is 80 % and four different types of ecotones are detected in the test site. Second, applications of 3D-metrics in two varied test sites show the frequently-used landscape diversity indices (i.e. Shannon’s diversity (SHDI) and Simpson’s diversity (SIDI)) are not sufficient for describing the habitats diversity, as they quantify only the habitats composition without consideration on habitats spatial distribution. The modified 3D-version of Effective Mesh Size (MESH) that takes ecotones into account leads to a realistic quantification of habitat fragmentation. In addition, two elevation-based contrast indices (i.e. Area-Weighted Edge Contrast (AWEC) and Total Edge Contrast Index (TECI)) are used as supplement to fragmentation metrics. Both ecotones and small biotopes are incorporated into the contrast metrics to take into account their edge effect in habitat pattern. This can be considered as a further step after fragmentation analysis with additional consideration of the edge permeability in the landscape structure analysis.

Furthermore, a vector-based algorithm called “multi-buffer” approach is suggested for analyzing ecological networks based on land-cover maps. It considers small biotopes as stepping stones to establish connections between patches. Then, corresponding metrics (e.g. Effective Connected Mesh Size (ECMS)) are proposed based on the ecological networks. The network analysis shows the response of habitat connectivity to different dispersal distances in a simple way. Those connections through stepping stones act as ecological indicators of the “health” of the system, indicating the interpatch communications among habitats.

In summary, it can be stated that habitat diversity is an essential level of biodiversity and methods for quantifying habitat pattern need to be improved and adapted to meet the demands for landscape monitoring and biodiversity conservation. The approaches presented in this work serve as possible methodical solution for fine-scale landscape structure analysis and function as “stepping stones” for further methodical developments to gain more insights into the habitat pattern.

Zusammenfassung

Die Lebensraumvielfalt ist neben der genetischen Vielfalt und der Artenvielfalt eine wesentliche Ebene der Biodiversität. Da diese Ebenen miteinander verknüpft sind, können Methoden zur Messung der Muster von Lebensräumen auf Landschaftsebene erfolgreich angewandt werden, um den Zustand der Biodiversität zu bewerten. Das zur räumlichen Musteranalyse auf Landschaftsebene häufig verwendete Patch-Korridor-Matrix-Modell weist allerdings einige Defizite auf. Dieses Modell geht von diskreten Strukturen in der Landschaft aus, ohne explizite Berücksichtigung von „Übergangszonen“ oder „Gradienten“ zwischen den einzelnen Landschaftselementen („Patches“). Diese Übergangszonen, welche auch als „Ökotone“ bezeichnet werden, sind dynamisch und haben einen starken Einfluss auf benachbarte Ökosysteme. Außerdem wird die Landschaft in diesem Modell als ebene Fläche ohne Berücksichtigung der dritten räumlichen Dimension (Höhe) betrachtet. Das führt dazu, dass die Flächengrößen und Umfänge der Patches sowie Distanzen zwischen den Patches besonders in reliefreichen Regionen unterschätzt werden. Daher muss das Patch-Korridor-Matrix-Modell für eine realistische und präzise Darstellung der Lebensraummuster für die Bewertung der biologischen Vielfalt angepasst werden. Ein weiterer Teil der Informationen, die häufig in Untersuchungen ignoriert werden, sind „Kleinbiotope“ innerhalb größerer Patches (z. B. Feldhecken, Baumreihen, Feldgehölze oder Einzelbäume). Dadurch wird die Heterogenität innerhalb von Patches unterschätzt.

Die vorliegende Arbeit basiert auf der Integration der dritten räumlichen Dimension in die Landbedeckungsklassifikation und die Landschaftsstrukturanalyse. Mit Methoden der räumlichen Datenverarbeitung wurde ein integrierter Ansatz von objektbasierter Bildanalyse (OBIA) und pixelbasierter Bildanalyse (PBIA) entwickelt und auf einen Datensatz aus verschiedenen Quellen (RapidEye-Satellitenbilder und Lidar-Daten) angewendet. Dazu wird zunächst ein OBIA-Verfahren für die Ableitung von Hauptlandbedeckungsklassen entsprechend spektraler Objekteigenschaften basierend auf RapidEye-Bilddaten angewandt. Anschließend wurde basierend auf den klassifizierten Karten, ein pixelbasierter Algorithmus für die Erkennung von kleinen Biotopen und Ökotonen mit Hilfe eines normalisierten digitalen Oberflächenmodells (NDSM), welches das aus LIDAR-Daten abgeleitet wurde, entwickelt. Zur Beschreibung der dreidimensionalen Charakteristika der Lebensraummuster unter der räumlichen Betrachtung der ökologischen Funktionen von kleinen Biotopen und Ökotonen, werden mehrere 3D-Maße (z. B. Maße zur landschaftlichen Vielfalt, zur Fragmentierung bzw. Konnektivität und zum Kontrast) vorgeschlagen.

Die vorgeschlagene Methodik wird an zwei realen Beispielen in Deutschland und China angewandt. Die Ergebnisse zeigen zweierlei. Erstens zeigt es sich, dass der integrierte Ansatz der objektbasierten und pixelbasierten Bildverarbeitung effektiv für die Landbedeckungsklassifikation auf unterschiedlichen räumlichen Skalen ist. Die Klassifikationsgüte insgesamt für die Hauptlandbedeckungstypen beträgt 92 % im deutschen und 87 % im chinesischen Testgebiet. Der eigens entwickelte Red Edge-Vegetationsindex (REVI), der sich aus RapidEye-Bilddaten berechnen lässt, erwies sich für die Vegetationsklassifizierung als effizienter verglichen mit dem traditionell verwendeten Normalized Differenced Vegetation Index (NDVI), insbesondere für die Gewinnung der Waldmaske. Im Rahmen der Verwendung von NDSM-Daten erwies sich die dritte Dimension als hilfreich für die Identifizierung von kleinen Biotopen und dem Höhengradienten, beispielsweise an der Wald/Feld-Grenze. Für den Nachweis von Baumreihen und Ökotonen an der Wald/Feld-Grenze wurde der sogenannte pixelbasierte Algorithmus „Pufferung und Schrumpfung“ entwickelt. Im Ergebnis konnten kleine Biotope mit einer Genauigkeit von 80 % und vier verschiedene Ökotontypen im Testgebiet detektiert werden. Zweitens zeigen die Ergebnisse der Anwendung der 3D-Maße in den zwei unterschiedlichen Testgebieten, dass die häufig genutzten Landschaftsstrukturmaße Shannon-Diversität (SHDI) und Simpson-Diversität (SIDI) nicht ausreichend für die Beschreibung der Lebensraumvielfalt sind. Sie quantifizieren lediglich die Zusammensetzung der Lebensräume, ohne Berücksichtigung der räumlichen Verteilung und Anordnung. Eine modifizierte 3D-Version der Effektiven Maschenweite (MESH), welche die Ökotone integriert, führt zu einer realistischen Quantifizierung der Fragmentierung von Lebensräumen. Darüber hinaus wurden zwei höhenbasierte Kontrastindizes, der flächengewichtete Kantenkontrast (AWEC) und der Gesamt-Kantenkontrast Index (TECI), als Ergänzung der Fragmentierungsmaße entwickelt. Sowohl Ökotone als auch Kleinbiotope wurden in den Berechnungen der Kontrastmaße integriert, um deren Randeffekte im Lebensraummuster zu berücksichtigen. Damit kann als ein weiterer Schritt nach der Fragmentierungsanalyse die Randdurchlässigkeit zusätzlich in die Landschaftsstrukturanalyse einbezogen werden.

Außerdem wird ein vektorbasierter Algorithmus namens „Multi-Puffer“-Ansatz für die Analyse von ökologischen Netzwerken auf Basis von Landbedeckungskarten vorgeschlagen. Er berücksichtigt Kleinbiotope als Trittsteine, um Verbindungen zwischen Patches herzustellen. Weiterhin werden entsprechende Maße, z. B. die Effective Connected Mesh Size (ECMS), für die Analyse der ökologischen Netzwerke vorgeschlagen. Diese zeigen die Auswirkungen unterschiedlicher angenommener Ausbreitungsdistanzen von Organismen bei der Ableitung von Biotopverbundnetzen in einfacher Weise. Diese Verbindungen zwischen Lebensräumen über Trittsteine hinweg dienen als ökologische Indikatoren für den „gesunden Zustand“ des Systems und zeigen die gegenseitigen Verbindungen zwischen den Lebensräumen.

Zusammenfassend kann gesagt werden, dass die Vielfalt der Lebensräume eine wesentliche Ebene der Biodiversität ist. Die Methoden zur Quantifizierung der Lebensraummuster müssen verbessert und angepasst werden, um den Anforderungen an ein Landschaftsmonitoring und die Erhaltung der biologischen Vielfalt gerecht zu werden. Die in dieser Arbeit vorgestellten Ansätze dienen als mögliche methodische Lösung für eine feinteilige Landschaftsstrukturanalyse und fungieren als ein „Trittsteine” auf dem Weg zu weiteren methodischen Entwicklungen für einen tieferen Einblick in die Muster von Lebensräumen.

1 Introduction

The motivation of this research is awareness of the linkage between biodiversity and landscape structure. A crucial key to the problem of biodiversity loss is consideration of changes in land use and in landscape structure. On a higher organizational level of landscapes or ecosystems, biodiversity can be evaluated by habitat diversity. The first chapter of this work is to illustrate the general relationship between landscape structure and biodiversity, and the current issues for methods used in landscape structure analysis. Detecting and analyzing the landscape structure from the perspective of conservation on biodiversity serve as guideline throughout this text.

1.1 Starting point of this work: biodiversity on landscape level

The rate of biodiversity loss, as a global issue, has been considered as one of the nine planetary boundaries that could help prevent human activities from causing unacceptable environmental change (Rockstrom et al., 2009). Recent research shows that climate change and human-driven land cover change, e.g. urban sprawl, increasing of transport infrastructures, the intensification of agriculture, and forest logging, are the main causes of the increasing species extinction (Giam et al., 2010); in fact changes in land use and landscape fragmentation by infrastructure development are expected to have the most significant effect on biodiversity (Sala et al., 2000). Although biodiversity loss occurs at the local to regional scale, it can have pervasive effects from continental to global level. For example, declining diversity of plants and algae will decrease the biomass of plants in natural ecosystems, and degrade their ability to use biologically essential nutrients from soil and water, moreover reduce the ability of natural ecosystems to produce oxygen, and to remove carbon dioxide from the atmosphere (Cardinale et al., 2011). According to the estimation of Rockstrom et al. (2009), the rate of biodiversity loss has already transgressed its boundaries that Earth can sustain. In order to reduce the rate of extinction and the loss of habitats, biodiversity considerations have to be integrated into spatial development planning (Walz and Syrbe, 2013). However, little is known quantitatively about how much and what kinds of biodiversity should be considered to maintain the resilience of the local ecosystem. This is particularly true at a higher level of large-extent scale.

The 1992 United Nations Earth Summit in Rio de Janeiro defined “biological diversity” as “the variability among living organisms from all sources including, inter alia, marine and other aquatic ecosystems and the ecological complexes of which they are a part of: this includes diversity within species and of ecosystems”(United Nations, 1992, page 146). This means the concept of biodiversity should not be limited to stand only for the species diversity, but in a broad sense, cover three levels: genetic, species, and of ecosystems and landscapes (Figure 1.1). The different levels of biodiversity are built upon one another, and at all levels biodiversity is influenced by temporal and spatial processes (Gaines et al., 1999). More and more ecologists (Blab et al., 1995; Duelli, 1997; Gaines et al., 1999; Noss, 1990; Otte et al., 2007) argue that biodiversity should be surveyed at different organizational levels: regional landscape, community-ecosystem, species-population, and genetic level (Gaines et al., 1999; Gosz, 1993). Since many species depend strongly on specific habitat conditions such as food, shelter, climate etc., it can be assumed that species diversity is determined by landscape structure as an expression of natural conditions and land use (Walz and Syrbe, 2013). As a consequence, the protection of high landscape heterogeneity is important for preserving the greatest possible biodiversity.

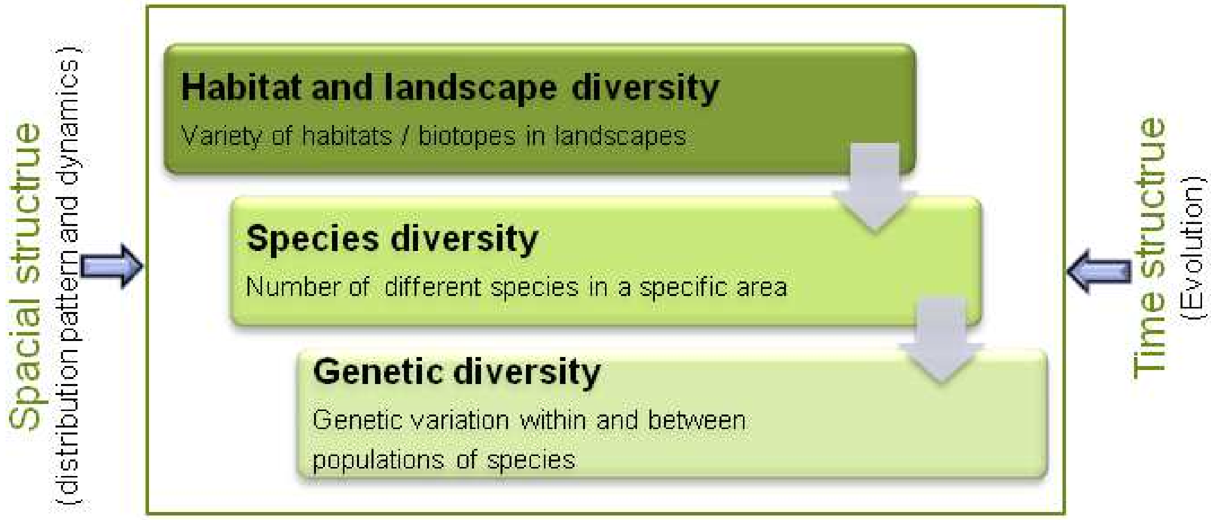

Figure 1.1: Levels of biological diversity (adapted from Blab et al., 1995; Walz, 2011).

1.2 Modern landscape ecology and its shortcomings

Landscapes are complex systems composed of a large number of heterogeneous components which are spatially correlated and scale-dependent (Hay et al., 2003; Wu, 2004). Spatial heterogeneity is considered ubiquitous across all scales and forms the basis for the structure and functioning of landscape (Wu, 2004). The goal of landscape ecology is to determine where and when spatial and temporal heterogeneity matter, and how they influence ecological processes (Turner, 1989). A fundamental issue is how to depict and measure heterogeneity. Spatial heterogeneity occurs in two forms: discrete patches and continuous gradients (Forman, 1995). A gradient works like a continuous surface including the underlying heterogeneity, but without boundaries, e.g. the different height structure of trees in a forest patch. However, the gradient landscape is considered as a rare situation in cultural landscapes and the mosaic pattern has been recognized as a universal form at all spatial scales, including landscapes, regions, and continents. Therefore, the patch-corridor-matrix model and their characterization by means of landscape metrics have been largely adopted to describe and analyze the ground surface. In addition, a variety of software (Baker and Cai, 1992; McGarigal and Marks, 1995; Rempel, 2008) based on this model has emerged and facilitated the knowledge transfer from theoretical model to practice. Indeed, the mosaic pattern is an effective and well conceptualized model that facilitates experimental design, analysis, and management and it has the advantage of computer simulation, calculation, and visualization. There is also criticism (Li and Wu, 2004) that the categorical model poorly represents the true heterogeneity of the landscape, which often consists of continuous multi-dimensional gradients (McGarigal and Cushman, 2005); and it is an oversimplification of realistic conditions without the consideration of the relief (Hoechstetter et al., 2006).

Many studies have drawn attention to the ecological value of small and linear vegetation patches (Lindenmayer and Hobbs, 2008; Lumsden and Bennett, 2005b; Manning et al., 2006) and ecological gradient (di Castri and Hansen, 1992; Hufkens et al., 2009; Risser, 1993). These small landscape patches, such as hedgerows, tree rows and groves, are important for species migration and dispersal on a small scale and are closely related to species richness, e.g. birds (Schifferli, 2000) or arthropods (Duelli and Obrist, 2003). Ecological gradients are often recognized as “ecotones” to indicate the zone of transition between adjacent ecological systems, having a set of characteristics uniquely defined by the strength of interaction between adjacent ecosystems (di Castri and Hansen, 1992). The ecotones which have “functional combination” of habitats in the landscape mosaic are vital to animals that utilize multiple habitat types and have a profound influence on adjacent ecosystems (Cadenasso et al., 1997; Fagan et al., 2003; Senft, 2009; Strayer et al., 2003), for example, ecotones control the flux of materials and energy between ecosystems (Fortin et al., 2000), harboring a rich, specialized fauna and flora (Duelli, 1997; Hoffmann and Greef, 2003; Kumar et al., 2006).

Efforts have been made for using remote sensing images to quantify fine-scale landscape heterogeneity for biodiversity evaluation (Levin et al., 2009; Rocchini, 2007). However, small biotopes and transition zones (or “ecotones”) are often ignored in the mosaic model for landscape monitoring. Commonly, map products offer either extensive geographic coverage at the expense of detail, or are comprehensive in detail but cover only small areas (Farmer et al., 2011). The biotope maps (scale 1:10,000) contain most detail small landscape elements, which are manually delineated based on high resolution imageries. In Germany, the biotope maps are not available for all federal states and they are not regularly updated. For example, the latest biotope map for the state of Saxon is from 2005.

It is stressed that the monitoring scale of landscape depends strongly on the purpose of analysis. In order to fully understand the spatial dimension of ecological patterns and processes with respect to biodiversity, it is necessary to consider the whole landscape matrix, including both larger patches and small biotopes (Walz, 2011).

1.3 Research objectives and key questions

Despite the limitations of the mosaic model, landscape metrics are widely used and useful (Turner, 2005). The question is which degree of simplification can be regarded as acceptable and how detailed information about the landscape structure this model appears not enough to represent. In the following the research objectives and key questions will be given in the background of complementing the mosaic model.

1.3.1 Research objectives

The main objective of this thesis is to develop methods for data analysis as a basis for regular monitoring of landscape structure. The focus is on data evaluation and extraction of small-scale landscape elements from remote sensing images and elevation models; and integration of these elements into landscape structure analysis in three-dimensional space. In line with the main objective of this thesis three sub-objectives are settled:

- Research objective 1: Establishing a model for detecting small biotopes and ecotones on the basis of the spectral and spatial features from remote sensing data and the high resolution Normalized Digital Surface Model (NDSM). Because some of these habitats are not only spectrally but also spatially similar, this gives a big challenge for a standard approach to habitat pattern detection for a regular landscape monitoring.

- Research objective 2: Incorporating these fine-scale biotopes into landscape structure analysis. The question is that these small biotopes cannot be treated simply as patches in the mosaic model, but as inner heterogeneity of patches that may affect the whole landscape. Not only the ecological function of every single small biotopes should be considered, but also the network connected by them.

- Research objective 3: Ecotones or transitional areas between adjacent patches are another part of information which should be integrated in the landscape mosaic model. The ecological functions of ecotones have been studied extensively by many authors. However, quantification and evaluation of ecological functions of ecotone by landscape metrics remains a question to be clarified.

1.3.2 Key questions

In this context, the main challenge of this research is to analyze the landscape structure and habitat pattern in a detailed level integrating small biotopes and ecotones with the existing methods. Under this challenge the following questions are raised and need to be answered:

- What roles do ecotones and small biotopes play in maintaining the ecological functions of the landscape? And how to define them across scales in heterogeneous landscape?

- How can these landscape elements, which are not contained in official / regularly updated land use data, be detected / selected?

- How to incorporate small biotopes and ecotones in existing evaluation methods of landscape structure based on the patch-corridor-matrix model?

The importance of functional roles of ecotones and small biotopes in landscape has been partly explained in this chapter and the detailed features of these landscape elements are given in chapter 2, since it serves as both the motivation and theoretical background for the work. A detail examination of the ecological roles of these landscape elements is necessary to support the argument of integrating them in landscape structure analysis. Question 2 and question 3 are mainly concerning the methodical work which is presented in chapter 3. It is the main innovative part of this work. The attempt is to develop a general approach for landscape monitoring at fine-scale level where the ecological functions of small biotopes and ecotones will be represented by quantitive indicators. After answering these three key questions, two real-world examples are used for testing the proposed methods in chapter 4. The results in two different study areas show whether these small biotopes and ecotones can be effectively detected and more meaningful and precise measurements can be obtained for landscape heterogeneity. Chapter 5 evaluates the applicability of the respective methods for their intended use and gives some additional possible fields for further applications. The main findings are summed up in chapter 6 and the answers to these three questions are finally reconciled and given.

2 Theoretical basis and background

The emphasis of this work is the integration of small biotopes and ecotones for landscape monitoring. This chapter firstly provides in detail about the ecological functions of small biotopes and ecotones, and the important terms are explained. Then, the landscape monitoring situation in Germany and China is presented to give a general impression about different monitoring systems in the context of biodiversity.

2.1 Small biotopes and ecotones as components of landscape pattern

A number of small landscape elements (e.g. hedges, tree rows, etc.) and ecotones have been recognized with high conservation values for biotope connectivity and as important habitats of a diverse and heterogeneous landscape (Driscoll, 2005; Jaeger, 2000; Walz, 2011). Habitat loss, in particular, is a serious consequence of fragmentation processes and has become an important field in conservation biology (Turner, 2005). On the other hand, fragmentation effects on biodiversity may not always be negative (Fahrig, 2003). What is decisive is, whether fragmentation describes the dissection of landscapes by barriers like roads or if it simply characterizes the degree of segmentation of a landscape into small components (Walz and Schumacher, 2005). In the following sections the characteristics of small biotopes and ecotones are reviewed as components of landscape mosaic.

2.1.1 Landscape fragmentation as a result of disappearing small biotopes

Fragmentation is a very manifold concept in ecology. It is comprised of several broad themes of work: biological organization, land cover and habitat, and connectivity (Lindenmayer and Fischer, 2007). ‘Biological organization’ refers to which perspective is used, either a perception of the landscape by a single species or a human perspective for multiple species. ‘Land cover and habitat’ corresponds to the landscape pattern and habitat loss (e.g. amount and configuration of vegetation). ‘Connectivity’ is a highly controversial topic that can be interpreted differently. It can be broken down into ‘structural connectivity’ and ‘functional connectivity’ (Baguette and Dyck, 2007). Structural connectivity refers to the physical connectedness among landscape elements, which is related to the landscape pattern or habitat configuration. Functional connectivity is a combination of both landscape structure and the response of organisms and processes to this structure. It reflects the connectedness of habitat patches for a given taxon or of ecological process (e.g. seed dispersal). Fragmentation and connectivity represent the same characteristic of landscape pattern from two different perspectives. They can be measured in the same way as fragmentation is on the opposite of connectivity. The structural connectivity also relates to the small biotopes which offer potential stepping stones for species movement. These interpatch connections are dependent on some local factors such as vegetation type and dispersal distance (Di Giulio et al., 2009). Jongman (2004) stated further that fragmentation is caused not only by barriers such as roads, urban areas and inaccessible agricultural land, but also by the continuing decrease of landscape elements (small forests, hedgerows, riparian zones).

Since different species require different types of habitat, and different amounts of habitat for persistence, a suitable configuration of landscape is having the required habitat amounts, with interspersed different habitat types as much as possible. A schematic example (Figure 2.1) from Schifferli (1987) shows the number of birds' species declines as the landscape pattern becomes simplified. In other words, large-scale intensively land utilization and removal of small biotopes make the landscape monofunctional and homogenized. Losing small biotopes can significantly influence the ecological functions of a whole landscape (Norderhaug et al., 2000; Oliver et al., 2006; Walz, 2011). Several studies have shown that small biotopes as important spatial elements need to be incorporated in landscape pattern for providing information on the effects of fragmentation and assessing ecological sustainability (Löfvenhaft et al., 2002; Peterseil et al., 2004; Renetzeder et al., 2010). For a holistic understanding of the dynamics of landscape processes, a land-cover map with the smallest distinguishable functional and structural homogenous elements is needed (Farmer et al., 2011). For this purpose, four types of small biotopes (area < 1 ha) including scattered trees, tree rows, hedges, and copses will be detected and incorporated in the landscape structure analysis in this work.

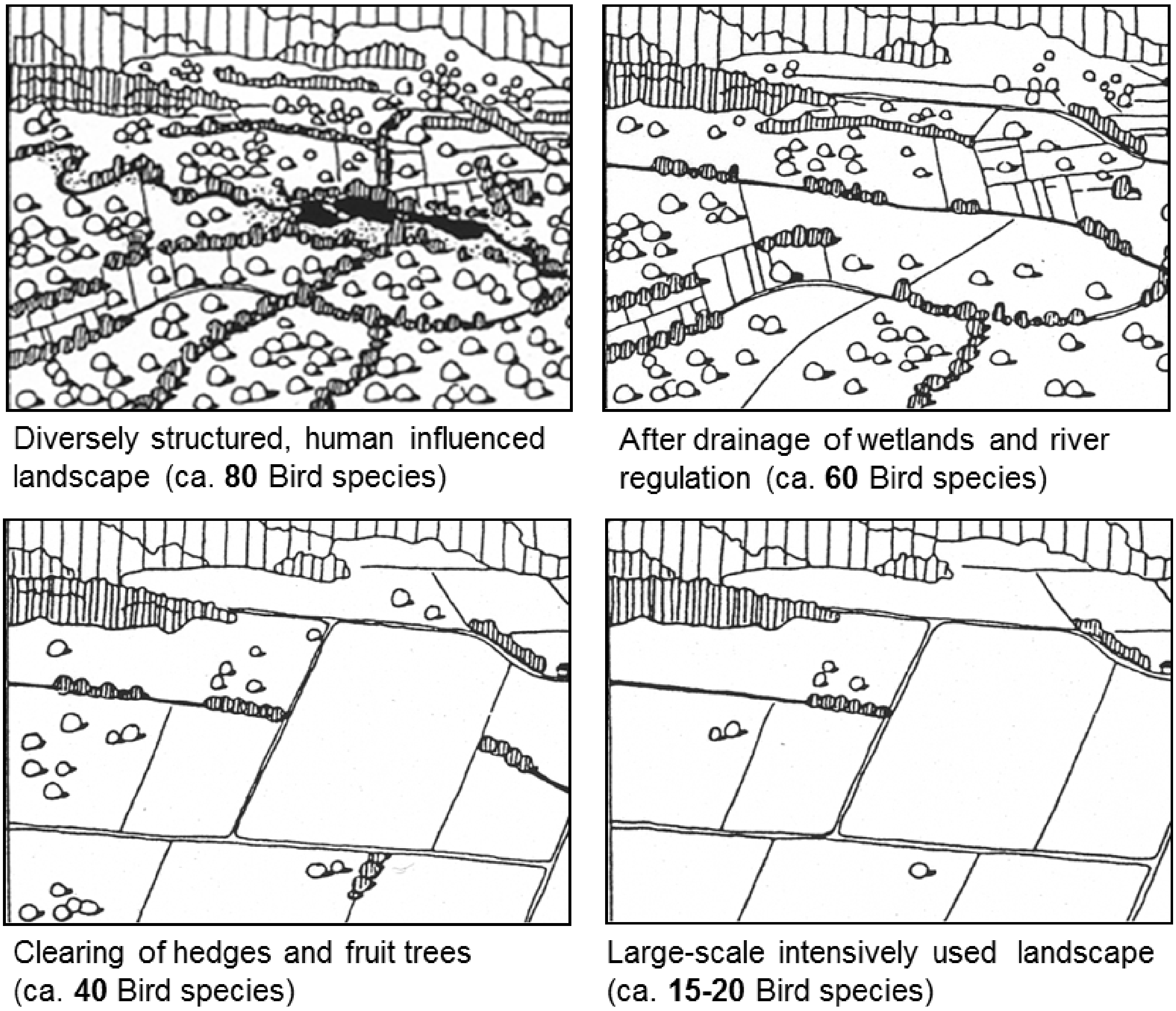

Figure 2.1: An example of effects of landscape structure change on biodiversity (Source: Schifferli, 1987).

2.1.2 A "soft" boundary: ecotones as transitional area between habitats

If the term "fragmentation" is only limited to "the breaking apart of habitat" (Fahrig, 2003), a more fragmented landscape (more, smaller patches and edges) will enhance the interactivity among different habitat types, which should increase habitat complementation and positively affect on biodiversity (Law and Dickman, 1998). In this sense, "habitat fragmentation" has similar meaning of "habitat diversity". The key difference between these two concepts lies upon the boundaries which decide how the landscape may be divided (into more and different land-use classes). Considering from the landscape scale, more types of habitats constituted landscape pattern, more chances the landscape hold different species inside. However, if plenty habitats are separated by sharp border, like railways or urban areas, it actually reduces the effective habitat size and results in isolated and smaller habitats.

2.1.2.1 The model of patch boundary

Each landscape element contains an edge, the outer area exhibiting the edge effect. Two edges combined from adjacent patches compose the boundary or boundary zone (Forman, 1995). Boundaries are defined as a zone between contrasting habitat patches that delimit the spatial heterogeneity of a landscape (Strayer et al., 2003). Figure 2.2 shows a general model of boundary, which is an abstraction of the intervening boundary for two patches within a landscape. It indicates that two individual patches are connected by a gradually changing boundary which stands for a gradient of spatial heterogeneity (Figure 2.2 c). Specific models could be derived from different research questions, but have the same structure as the general model.

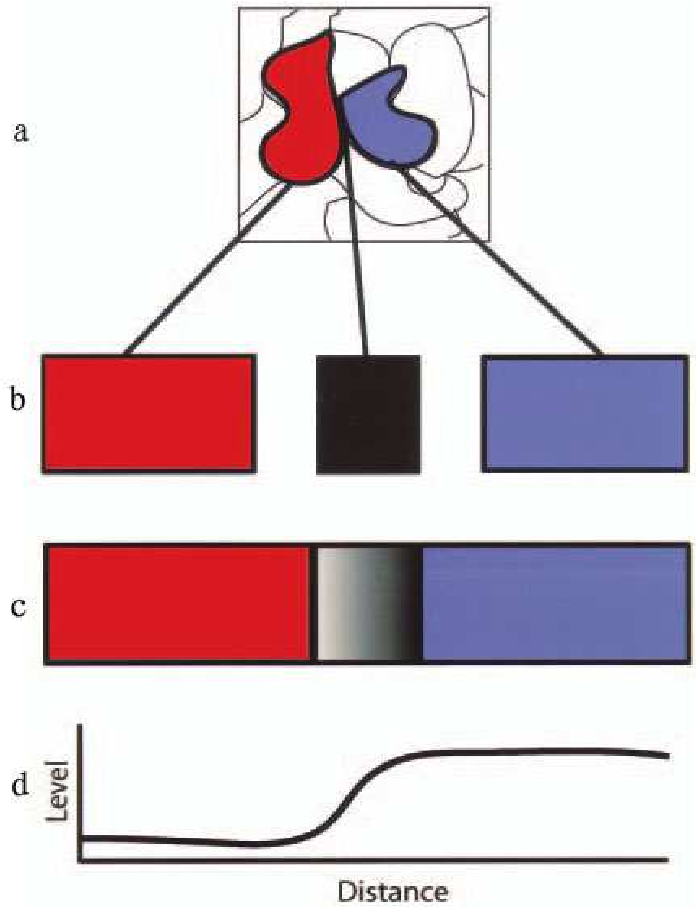

Figure 2.2: A general model for the patch boundary in landscape mosaic (a); (b) shows two patches (red and blue) are isolated by the boundary (black) between them; (c) shows a continuous structure between patches as the gradient from white to black in the boundary; (d) illustrates that the gradient is steeper in the boundary than in either of the neighboring patches (Source: Cadenasso et al., 2003).

The detailed geometry of adjacent patches can result in several kinds of boundaries (Strayer et al., 2003). The simplest case is two patches physically adjoin each other (Figure 2.3 a). The boundary may have thickness, which stands for a gradual change of the environment condition (Figure 2.3 b), as the case of forest edge extends to the field. Patches could be separated by a third structure (Figure 2.3 c), like a road or stream. The boundary geometry is decided by grain, dimensionality, and sharpness. It is important to first consider the grain, while on different grain size the interface between two patches may be different (Figure 2.3 d). Not only the boundary interface, but the dimensionality is also affected by grain size. Boundary may be considered as a thin line or a two dimensional zone between patches (Figure 2.3 e). The dimensionality as an important factor to boundary morphology and distribution is highly related to the grain size. The choice of boundary dimensionality is dependent on the research question and the features of the boundary itself may be involved. For example the sharpness (Figure 2.3 f) is an important feature for the boundary zone, which indicates the degree of the interactivity between patches. There are more spatial features of boundary, such as curvilinearity, edge contrast, that could regulate the exchange of materials, energy, and organisms across boundaries (Cadenasso et al., 2003; Forman, 1995; Hoechstetter et al., 2008).

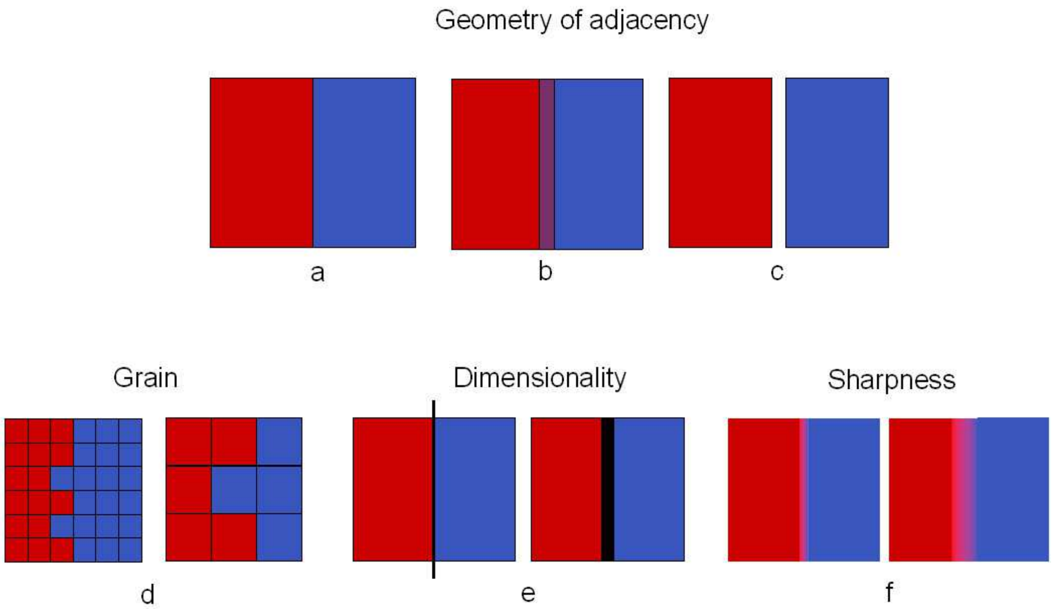

Figure 2.3: Geometry and some spatial features of boundary: (a) A simple boundary between two adjoining patches; (b) a boundary zone (with gradual change in ecological condition) between two patches; (c) a boundary between two disjunct patches; (d) the interface of the boundary is affected by grain size; (e) boundary could be a thin line or a two dimensional zone; (f) a gradient boundary between two patches may be steep or soft (Source: adapted from Strayer et al., 2003).

2.1.2.2 The ecotone concept

At the beginning of the 20^{th} century, an ecotone has been treated as an environmentally unstable zone, which encompasses abrupt or accumulated change (Clements, 1905; Livingston, 1903). With the advent of landscape ecology, it came to think ecotones as ecological boundaries that contribute to the spatial heterogeneity of the landscape

(Cadenasso et al., 2003; Fagan et al., 2003; Fortin et al., 2000; Holland et al., 1991; Senft, 2009). In short words, it is described as "the overlap or transition zone between two plant or animal communities" (Forman, 1995). A set of general characteristics should be considered when applying the ecotone term. First, the term ecotone not only refers to the gradient between different vegetation types, but also some other abiotic elements. It could be a boundary between a forest and field or a river and its estuary. Second, ecotone could be found across a range of scales, from a few centimeters to several kilometers; or in a hierarchical structure from the population level to the biosphere level depending on the research question (Gosz, 1993). Third, the ecotone more often has a multi-dimensional structure (Hufkens et al., 2009). It is not confined to one or two dimensions as a sharp boundary line or an overlapped zone between adjacent patches. The third spatial or temporal dimension could also define an ecotone. For example the forest-field ecotone could be defined by vegetation height (Strayer et al., 2003), or a variable climate as described by Allen and Breshears (1998). Therefore, the definition of ecotone should emphasize the multivariate approach. In case where multiple ecological properties jointly define a transition zone, these properties may be spatially congruent with one another (Strayer et al., 2003). However, the representation of the ecotone is often limited by the dimensionality of the technique used to characterize its multi-dimensional properties (Hufkens et al., 2009). Furthermore, ecotones have a set of characteristics defined by the magnitudes of ecological exchange like energy or material flow between ecological systems. Often multiple processes are driving this exchange and forming a transition zone between adjacent patches.

Since the ecotone is a multi-dimensional and multi-scale concept, it is necessary to specify the ecotone in the research context. For the work at hand, the ecotone is defined at the local level as a "soft" boundary between vegetation communities (forest-field boundary). It has a three dimensional structure appearing as gradual blending of the two vegetation communities on the boundary area, where the third spatial dimension (vegetation height) is used to constrain the transition zone on forest-field boundary. The boundary model in Figure 2.3 (b) represents the gradient which combines both the edges of adjacent forest and field. This context defined boundary, along with small biotopes, are both influential in the interactions between patches and ultimately affect landscape-level dynamics. The ecological functions of small biotopes and ecotones are discussed in the following chapter.

2.1.3 Ecological functions of small biotopes and ecotones

Scientists have long been aware of the important role of small biotopes and ecotones in ecosystems. Consequently, a lot of researches have been conducted to reveal the importance of the small elements for reconstructing the linkage inside a landscape (van der

Ree et al. 2004, Herrera and García 2009, Lander et al. 2010), and the speciation process in ecotones where ecosystems are dynamic and exchange of genes often take place (Schilthuizen 2000, Smith et al. 2001, Araújo 2002). As the work at hand intends to enhance landscape structure analysis by incorporating these elements, a short review of the ecological functions of small biotopes and eoctones is needed in order to understand their functional roles in landscape.

2.1.3.1 Ecological functions of small biotopes

The loss of small biotopes can decrease the landscape linkages, especially in the densely populated areas. Not only humans use landscape linkages; also plants and animals move through landscapes in their own way. Also they need their landscape linkages to move from one suitable habitat to another, on a short distance along a hedgerow or over a small grove. In this work, the ecological functions of small biotopes (including scattered trees, tree rows, (field) hedges, and (field) copses) are examined from literatures and concluded in table 2.1.

Table 2.1: Summary of the ecological functions of small biotopes in promoting biodiversity.

Small biotope	Ecological functions	Sources
Scattered tree	Provision of habitats (for birds, bats, etc.)	(Fischer and Lindenmayer, 2002a; Galindo-González et al., 2000; Luck and Daily, 2003; Lumsden and Bennett, 2005a; Oliver et al., 2006)
	Enhancement of ecological connectivity as stepping stone (seed dispersal, bird migration)	(Cascante et al., 2002; Fischer and Lindenmayer, 2002b; Graham, 2001; Guevara and Laborde, 1993; Herrera and García, 2009; Lander et al., 2010; van der Ree et al., 2004)
	Biological legacies after a disturbance (providing assistance for other species to persist; habitat for recolonization; source of energy and nutrients)	(Dorrough and Moxham, 2005; Lindenmayer and Franklin, 2002; Toh et al., 1999)
	Influences on abiotic environment (such as mineralization of nutrients, infiltration of	(Eldridge and Freudenberger, 2005; Tiessen et al., 2003; Wilson, 2002; Yates et al.,

	rainfall)	2000)
(field) hedges / tree row	Provision of habitats or refuges (most forest edge species).	(Gelling et al., 2007; Hannon and Sisk, 2009; McCollin et al., 2000)
	Control on many major abiotic fluxes, such as fluxes soil desiccation, soil erosion and nutrient runoff.	(Baudry et al., 2000; Bu et al., 2008; Burel and Baudry, 1995; Hairiah et al., 2000)
	Function as corridors for movement of many plants and animals across a landscape	(Campagne et al., 2009; Forman and Baudry, 1984; Gelling et al., 2007; Petit and Burel, 1998; Wehling and Diekmann, 2009)
	Regulation of microclimate (wind speed, evaporation)	(Burel and Baudry, 1995; Forman and Baudry, 1984; Sánchez et al., 2010)
(field) copses / shrub	Provision of habitats and improvement of food-web.	(Beschta and Ripple, 2012; Inglis et al., 1994)
	Contribution to species distribution (e.g. seed, ants, scorpion, cicada, reptiles, small mammals).	(Daryanto and Eldridge, 2012; Li et al., 2009)
	Influence on abiotic environment (soil stabilizer and prevent water and soil erosion)	(Martínez-García et al., 2011; Wezel et al., 2000)

The review of the literature shows that small biotopes are of high natural value for the conservation of biodiversity (Ernoult and Alard, 2011; Forman, 1995; Morelli, 2013). The main functions of these small biotopes in ecosystem are either providing habitat for some edge species or forming a network to strength the species movement, such as hedgerow network (Burel and Baudry, 1995; Forman and Baudry, 1984). Except the ecological functions, the small biotopes also have influence on humans, such as: recreational value, shade and sheltered grazing for livestock, wood products (Manning et al., 2006). Hedgerows and copses perform diverse functions for society and the farmer that are both economically and ecologically significant (Forman and Baudry, 1984).

2.1.3.2 Ecological functions of ecotones

Ecotones, as zone which may conceive both characteristics of adjoining ecosystems, are widely considered to harbor higher biological diversity than each neighboring area. As unique habitat it may be optimal for some species and inhospitable for others (di Castri et al., 1988). As ecological boundary it may act as barrier or corridor for the transit of disturbance, nutrients, or organisms. From the view of patch dynamic, they are regarded as dynamic components of a landscape which enhance the strength of landscape interactions and provide habitat for many transient organisms (Senft, 2009). However, they are more or less a conceptual view, more evidences and field investigation need to be conducted to explain the mechanisms behind the underlying processes which control changes in richness.

Ecotone as part of habitat diversity

Biodiversity could be observed on different levels of genes, species, and habitats. Two manifestations of diversity are addressed here: (1) diversity of patches, and (2) diversity of species. Patch diversity here refers to both the vegetation forms that are used to characterize biomes and vegetation structure within a biome (e.g. the distribution of overstory and understory life forms). Species diversity indicates both richness and evenness. Here it is restricted to species richness.

When ecotones serve as habitat, they can strongly influence local and regional species density and diversity (di Castri et al., 1988). One reason is due to the “edge effect” (Odum, 1971) in ecotone where species from each of the adjacent communities plus species inhabiting only ecotone (ecotonal species) and multihabitat species exist (Forman, 1995). The edge effect can be visualized like in figure 2.4, which shows the species distribution along forest/field boundary. In the case of individually examining the species in forest, ecotone, and field, the number of forest species would decline from ecotone to field, and for grass species decreasing trend can also be observed from ecotone to forest. Between forest and field ecotonal and multihabitat species will reach the peak abundance. If we add the three curves of species distributed in these three habitats, the cumulated species diversity along forest/field boundary can be concluded as the curve on the top in figure 2.4. It shows a higher species diversity from adding the “edges” of both adjoining communities.

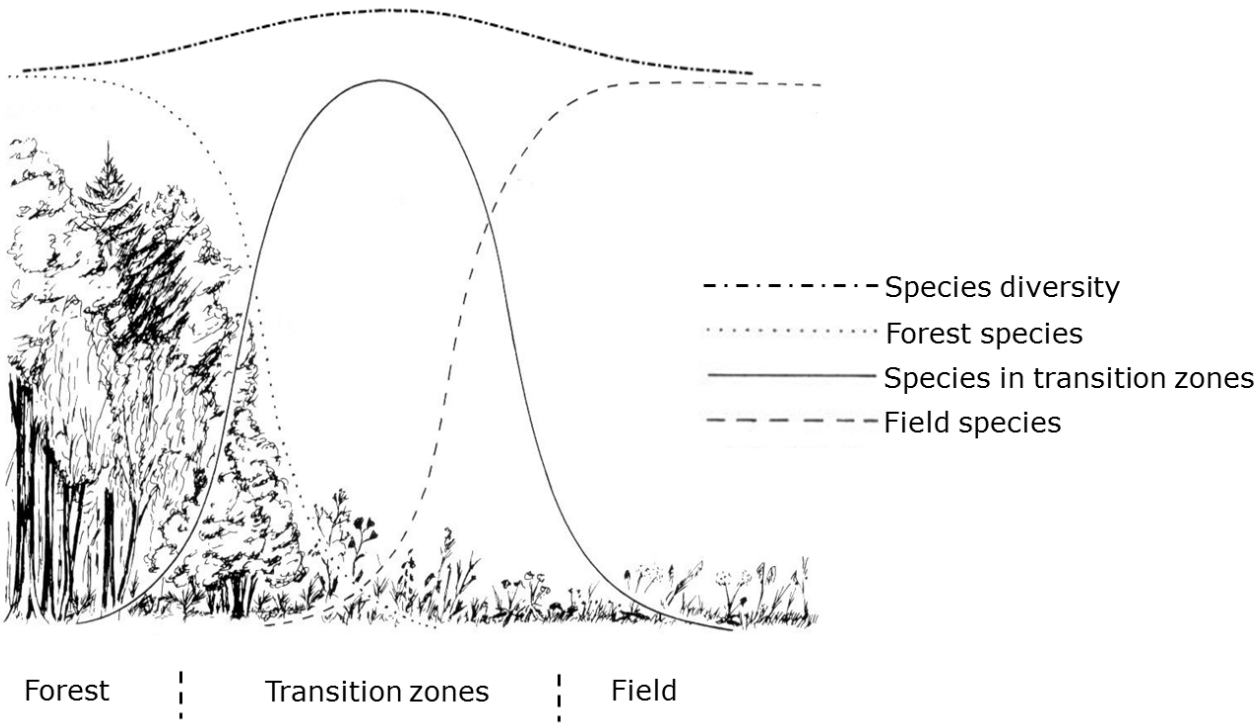

Figure 2.4: Species distribution along forest/field boundary (Source: adapted from Wolff-Straub 1984, Jedicke 1990).

However, in practice there are seldom evidences which support this biological edge effect. Some empirical studies are even contradictory. Baker et al. (2002) has studied the patterns of bird densities across heath–wood edges in southeastern Australia and found the bird density and species richness were much higher in wood habitat than in heath habitat, and no bird species could be categorized as ecotonal. Kotze and Samways (2001) investigated epigaeic amphipod, carabid and ant distribution patterns across Afromontane forest/grassland ecotones in South Africa. They found little evidence to support the edge effect, but the grassland habitats were strongly recommended to be incorporated into forest conservation strategy. Lloyd et al. (2000) examined three different types of ecotones and found that ecotonal species were significantly more frequent in two of the four investigated ecotones, but species richness was intermediate between that of adjacent communities. There are also studies that show clear edge effects at ecotones. Helle and Helle (1982) found more bird species on forest edge in Gulf of Bothnia due to more diverse resources in edge zone, e.g. food and shelter, than in the central forest. Harper and Macdonald (2002) investigated the spatial and temporal pattern at forest edge in Alberta (Canada) and detected significant edge effects. Rusek (1992) studied the distribution and function of soil organisms in three different types of ecotones in South Moravia (former Czechoslovakia) and found that some species showed an increase in the ecotones, but different group of organisms were affected not in the same way by edge effects. Empirical studies showed three possibilities of species diversity in ecotone: less than either adjacent patch; intermediate between the patches; or higher than in adjacent patches. More literatures could be found which concerned on one or several kind of species in ecotones, primarily birds. It is necessary to fully examine different categories of species along ecotone to understand the edge effect. This is not easy, because ecotone occurs at a variety of spatial and temporal scales that may be thousands of kilometers long; and organisms have also scale, from large mammals to smaller insects. Thus, a general relationship between ecotone and species diversity may not be concluded. The species diversity depends on the properties of the ecotone where it is studied. Nevertheless, ecotones as special habitats could contribute to landscape pattern diversity and influence the ecological function of landscape. With changing climate threatening on species distributions and the habitats on which they depend, more emphases have aroused on the conservation of ecological gradients which are important in diversification and speciation (Araújo, 2002; Schilthuizen, 2000; Smith et al., 2001; Smith et al., 1997).

Ecotone as boundary for regulating ecological flow

Boundaries led to heterogeneous pattern, where physical and ecological flows occur (Forman, 1995). Ecotone can be considered as a specific type of boundary which has important effects on movements of animals and materials, rates of nutrient cycling, and levels of biodiversity (Cadenasso et al., 2003; Peters et al., 2006; Shaw and Harte, 2001). In nature no absolute barriers or boundaries exist, only filters (Forman, 1995). To understand the “filter function” of ectones, a framework including three components is suggested: type of flow, patch contrast, ecotone structure (Cadenasso et al., 2003).

Four types of flow including materials, energy, organisms, and information are related to ecological system. Materials such as seeds, silt, wood, dead organic, and pollutant are carried across landscape boundaries by water, wind, flying animals, terrestrial animals, and humans. Wind, water as material flow passages require external thermal gradients from the environment; in contrast, animals and humans as material carriers need internal energy (Forman, 1995). The energy flow through landscape boundaries are in various forms: light, heat, or transformation of stored energy in biological forms (Cadenasso et al., 2003). Energy transformation often controls the material flux. Ryszkowski and Kędziora (1993) demonstrated that the horizontal passage of heat energy between cultivated fields and ecotones enhanced evaporation in shelterbelts and resulted in reduction of water flux. The thermodynamically open heterogeneous system is a requisite for the fluxes observed in a landscape (Forman and Moore, 1992). The flow of organisms and information are higher levels of organization than the flow of either material or energy. Mammals commonly move along the boundary both inside and outside the mantel, sometimes forming migration paths.

Within the boundary area, there are maybe intensive interactions among animals, for example the so called “ecological traps” (Gates and Gysel, 1978), which means predators focus on edge region for food searching where herbivores usually have a higher density. Information flow, like the sound of a lion roaring is information for potential prey concerning the whereabouts of the predator. Or genetic information can be exchanged by hybridization between subspecies from different habitats in ecotone (Leaché and Cole, 2007; Yanchukov et al., 2006).

Patch contrast is the feature that is used to differentiate patches and defines the characteristics of boundaries. Patches can differ in architecture, composition, or process (Cadenasso et al., 2003). There are several features which could define patch contrast, such as population density in the edge, the chemistry of adjacent soils, the vertical vegetation structure of the edge, or landform. For example, according to height contrast the field edge width based on illumination is approximately equal to the height of the trees in forest edge (Forman, 1995). Due to the sudden drop of the wind speed in forest/field boundary sand, seeds, or mineral nutrients from fertilizer, pesticides can accumulate; consequently the composition of boundary will be changed as well.

The architecture of a boundary is its three-dimensional structure composed of biological or physical features (Cadenasso et al., 2003). Moreover, the internal structural characteristics of the boundary play a key role in determining its ecological functions. The experiment from Ryszkowski (1992) shows that the amount of absorbed radiation energy is relatively high when the area receiving solar radiation has a high moisture content, a rough surface, and dark coloration. For instance, shelterbelts intercept more light than meadows. Jordana et al. (2000) has found that across ecotones between pine forests and shrublands in Navarra (Spain) and Sicily (Italy), soil is being actively created by certain Mediterranean shrubs which seem to play a most important role in providing adequate microclimatic and energy input conditions for the soil engineers. Moreover, the boundary structure can enhance the contrast between patch interior and patch edge. Within forest/field boundary, due to the presence of a greater surface exposed in forest edges, this may lead to lower live tree density and canopy cover, higher mortality and windthrow than interior forest (Mascarúa López et al., 2006).

Patch, ecotone, and heterogeneity are scale dependent (di Castri et al., 1988; Gosz, 1993; Wiens, 1992). According to the space-time principle, spatial scale and temporal scale are common bound each other. The larger a studied area is, the longer the relevant time scale (Forman, 1995). The effects of ecological and evolutionary processes in shaping biodiversity patterns and processes in ecotones differ among spatial scales (Karka and Rensburg, 2006). The spatial scale of a particular investigation is determined by its grain size (the limit of resolution of measurements or sampling) and its extent (the limit of the area within which samples are taken) (Wiens, 1992). As figure 2.3 (d) described, the boundary will become blurred on a coarse grain, and may even not be detected because the discontinuities that separate adjoining patches are leveled out within the large grain size. The ecotones that fall beyond the extent of investigation will likely not be detected. In this study the focus is on the forest/field boundary (ecotone) at a fine spatial scale. A conceptual framework for ecotone detection is developed and a specification of ecotonal characteristics is applied in landscape monitoring.

2.2 Landscape monitoring in Germany and China

Landscape monitoring is important for the protection of environment and insurance of sustainable development (Cassatella et al., 2011). Besides, a set of indicators based on landscape monitoring is necessary to fulfill a country's obligation for CBD (Convention on Biological Diversity) targets. According to the report for the project "National indicators, monitoring and reporting for CBD targets" (Bubb et al., 2011), 121 of the 193 CBD Parties has reported or referenced at least one biodiversity indicator in their 4th national report, but only 58 had evidenced indicators (e.g. with results or figures) in their report. "Coverage of protected area" and "Extent of forests and forest types" are the first and second most reported indicators. On one hand, habitat deterioration and land use change are important causes of known extinctions; on the other hand, monitoring on landscape degradation is a relative cost-efficient approach for biodiversity evaluation. Biodiversity is a broad issue which involves many sectors, such as forestry, fishery, and agriculture. It is necessary for a country to have a national office or institution with the responsibility for the coordination, analysis and communication of different information. In the following sections around biodiversity conservation the landscape monitoring system in both Germany and China will be shortly reviewed.

2.2.1 Landscape monitoring in Germany

Preserving nature has a long tradition in Germany. Particularly since the mid-eighties, nature conservation has constituted a central element of the German Government's environmental policy (BMU, 2007). In 1986 the Federal Ministry for the Environment, Nature Conservation and Nuclear Safety (Bundesministerium für Umwelt, Naturschutz und Reaktorsicherheit, BMU) was founded, followed in 1993 by the creation of the Federal Office for Nature Conservation (Bundesamt für Naturschutz, BfN). Some achievements in the conservation of biological diversity have appeared, e.g. water quality has improved and once-endangered plant and animal species are now on the increase (BMU, 2007), but more concrete efforts, e.g. building landscape monitoring systems for nature conservation, are needed to meet the targets of CBD internationally and its own national objectives on biological diversity.

2.2.1.1 Current situation of biological diversity in Germany

Germany has around 9,500 species of plant, 14,400 species of fungi and 48,000 species of animal (around 4 % of the world population of known living fauna) (BMU, 2007). The first volume of the updated version of the Red Lists for vertebrate groups in Germany (BfN, 2009) was published in 2009, including the mammals, breeding birds, reptiles, and amphibians as well as the freshwater lampreys and fish. 478 taxa, which covered the best-known taxa and all large land animals, are assessed in this volume. According to the Red Lists, a substantial number (132 taxa, just fewer than 28 % of the total) are under threat. *These* plus the 37 species (7 %) already extinct in the wild make up over a third (35 %) of assessed vertebrates. 44 taxa (9.2 %) are 'near threatened' and call for special attention because they are at risk of sliding into one of the threat categories. Reptiles are the most highly endangered vertebrate group with more than 60 % of taxa under threat. In all other vertebrate groups, less than 40 % of taxa are under threat. In the case of habitat types, over two thirds (72.5 %) of all habitat types found in Germany (the edition of the Red List (Riecken, 2006) distinguishes 690 habitat types) are classified as threatened. Two habitat types have been completely destroyed since only one type was extinct in 1994. The proportion of "critically endangered" habitat types has dropped to 13.8 %. In contrast, the proportions of endangered and vulnerable habitat types both increased. Some habitats types classified as not endangered (least concern) in 1994 have thus become endangered. This shows that some protection measures taken for "critically endangered" habitats have already had some effects, but the other habitats are facing increasing threats, even extinct risk.

From the perspective of landscape development, there have been two trends since the industrial revolution, homogenization and fragmentation, which have been evident for decades in the European landscape (Jongman and Pungetti, 2004). Large and intensifying agriculture modifies habitat diversity, field size, and crop availability (Schifferli, 2000) while rendering land monofunctional. In Germany, landscape fragmentation has increased since the end of the 19th century owing to increasing mobility and the settlement growth (Haase et al., 2007; Walz and Schumacher, 2005). For example, a research of landscape monitoring for the whole Federal State of Saxony (time span from 1780 to 2000) shows a significant decline in small quasi-linear structures (such as hedges and tree rows) and increasing fragmentation of open space by transport infrastructure (Walz, 2008).

Among the many reasons behind the threats to biodiversity in Germany (e.g. discharge of pollutants and nutrient, climate change, invasive non-native species, etc.), the landscape degradation and land use change accounted for a large proportion (BMU, 2007). Such as the construction of human settlements, transport routes, excavations, farmland consolidation, drainage, backfilling of water bodies, changes of use in agriculture and forestry. Urbanization, agriculture and industry have put increasing pressure on the functioning of landscape and nature.

2.2.1.2 Data used for landscape monitoring

On the level of Europe, the project for Coordination of Information on the Environment (CORINE) was initiated by the European Commission in 1985 for land cover mapping and it was a prototype project working on many different environmental issues (EEA, 1995). The CORINE Land Cover (CLC) map is composed of 44 classes, organized hierarchically in three levels and is available for most areas of Europe. The scale of the land cover map is fixed at 1:100,000; the Minimum Mapping Unit (MMU) is 25 ha. Linear features less than 100 m in width are not considered. The database was firstly established in 1990; afterwards, two updates of the CORINE database in years 2000 and 2006 were accomplished. It was developed to compile information on the environment topics which have priority for all members of European Union (EU). Therefore, the resolution is not sufficient for habitat monitoring at a very detailed level with regard to biodiversity.

ATIKIS Basis-DLM (Digital Landscape Model) is the official German nation-wide digital database for topographic spatial data[1] and is updated annually. ATKIS stands for “Amtliches Topographisch-Kartographisches InformationsSystem”. The Basic-DLM has a scale of 1: 25,000 and its MMU is depending on the feature type 0.1 to 1 ha. The database consists of point, line, and polygon feature types which are thematically categorized into layers, such as built-up areas, vegetation, water, traffic, etc. It allows geometry overlapping of multiple layers, which means that one single landscape element may belong to multiple ATKIS layers, for example, a “forest” patch can also belong to “national park”. This database contains detailed land surface information, especially on land use types from human perspective.

To improve the interoperability between national and pan-European geoinformation data sets, the Digital Landscape Model for Federal Purpose (DLM-DE) was established by the German Federal Agency for Cartography and Geodesy (Bundesamt für Kartographie und Geodäsie, BKG) in corporation with the Federal Environmental Agency (Umweltbundesamt, UBA). It contains areal information on land cover and land use in the sense of European nomenclature of CORINE Land Cover (CLC) at the scale 1: 50,000. The polygon layers of the ATKIS categories built-up areas, water, traffic, and vegetation have been adapted in

[1] http://www.adv-online.de/Geotopography/ATKIS/ (Accessed October 13, 2014)

modified form to the specific requirements of the DLM-DE. Some CLC-classes which are not included in ATKIS should be integrated in the DLM-DE, like sparsely vegetated areas, transitional woodland-shrub, natural grassland etc. The MMU for DLM-DE is 1 ha, meaning that every feature smaller than 1 ha will not be updated but only generalized to its neighboring features. DLM-DE can be seen as a mixed product between CORINE and ATKIS. It has more land cover classes than CORINE, and a higher resolution. Comparing to ATKIS, it contains additional land cover types integrated from CORINE concerning on natural area in landscape, but with a coarser resolution. The first edition of the DLM-DE was generated for the reference year 2009 and an update for the reference year 2012 is in plan.

The nation-wide land-cover databases are used not only for environmental monitoring; they serve as the basic data for various needs and concerns, such as spatial planning, security, etc. Besides the nation-wide land cover database, there are other databases which can be used for landscape monitoring, for instance, the biotope maps made by the state offices or local institutions.

2.2.1.3 Landscape indicators for biodiversity conservation

In Germany, the indicator set for the National Strategy on Biological Diversity has been revised since the end of 2007 and was firstly presented in a standardized format in the German federal government report in 2010 (BMU, 2010). For the National Strategy's indicators, existing indicator systems at the international, European and national levels were taken into account, such as CBD's headline indicators. Some of the National Strategy's indicators refer to the "Streamlining European biodiversity indicators (SEBI 2010 indicators[2])" which has been undertaken by a Coordination Team with representatives from several organizations, such as EEA (the European Environment Agency), ECNC (the European Centre for Nature Conservation), UNEP-WCMC (the World Conservation Monitoring Centre) and others. It also makes use of reliable indicators which are proved to be useful in Germany or states of Germany. For example, the Indicator System for National Sustainable Development (German: Indikatorenberichte zur Nationalen Nachhaltigkeitsstrategie-NHS[3]), the Environmental Key Indicator System (German: Umwelt-Kernindikatorensystem-KIS[4]), and the State Initiative on Core Indicators (German: Länderinitiative Kernindikatoren-LIKI[5]). These indicator systems were founded by different federal departments concerning on environment protection and sustainability form different perspectives. NHS contains 21 key

[2] http://biodiversity.europa.eu/topics/sebi-indicators (Accessed October 13, 2014)
[3] http://www.bmu.de/themen/strategien-bilanzen-gesetze/nachhaltige-entwicklung/ (Accessed October 13, 2014)
[4] http://www.umweltbundesamt.de/en/press/pressinformation/what-is-state-of-environmental-protection-in (Accessed October 13, 2014)
[5] http://www.lanuv.nrw.de/liki-newsletter/ (Accessed October 13, 2014)

indicators which cover all areas of society for ensuring sustainable development, e.g. resource conservation, climate protection, renewable energy, land consumption, biodiversity, economic performance, air quality, health, education and so on. KIS comprises 58 indicators concerning on climate change, biodiversity, nature and landscape, health, quality of life, resource use and waste management. Within LIKI, a set of 24 environmental core indicators was developed to ensure a standard use of these indicators at a federal and state level. Biodiversity conservation is not only about protection, but also sustainable development. Parts of these indicator systems are highly related or identical to each other, and some environment-related indicators were also adopted by National Strategy on Biological Diversity.

The National Strategy contains 19 indicators assessing the environment form various aspects, including components of biological diversity (7 indicators), Settlement and transport (2 indicators), economic activity (8 indicators), climate change (1 indicator), public awareness (1 indicator). Since the research focus is on spatial analysis at landscape level, only the indicators related to habitat monitoring and land-use change are presented below.

Conservation status of Habitats Directive habitats and species

As an EU member Germany is obligated to monitor/observe the conservation status of natural habitats and species according to the Article 11of the Habitats Directive[6] of European Commission. In Germany, the responsibility for implementing the monitoring concept falls to the states. National government (acting through the Federal Agency for Nature Conservation) is solely responsible for monitoring in the North Sea and Baltic Sea Exclusive Economic Zone. The Federal Agency for Nature Conservation (BfN) is responsible for data aggregation and the final assessment of conservation status at national level. The assessment of conservation status is classified into three levels shown as the colors of a traffic light: ‘Favorable’ (green), ‘Unfavorable – inadequate’ (yellow) and ‘Unfavorable – bad’ (red). An extra ‘Unknown’ category is used where assessment is not possible due to deficient data. The habitat assessment is based on the expertise, not from spatial analysis; but the habitat distribution data and maps will inevitably have impact on the assessment. To compile the index, habitats and species are weighted by the assessment result and the size of their range in each biogeographical region as a percentage of the total range in Germany. The indicator stands at 48 % for the reporting period 2001-2006. Target is 80 % in 2020 formulated in the National Strategy on Biological Diversity (BMU, 2007).

[6] Council Directive 92/43/EEC, http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=CONSLEG:1992L0043:20070101:EN:HTML (Accessed October 13, 2014)

Protected areas

This indicator assesses the total size of strictly protected areas in Germany. The Nature Conservation Areas (NCAs) and National Parks (NLPs) are used in this purpose as a percentage of the German land surface. They are vital instruments in the conservation of biodiversity in Germany. Attention must also be paid to ensuring that protected areas are properly linked in an ecological network. The qualitative target is to secure the national habitat network and put Nature 2000 sites[7] under protection. A further target is to have 2 % of the German territory entirely out of human disturbance by 2020.

High nature value farmland

This indicator is used on both the Europe and the Germany level and it reports the area of High Nature Value farmland (HNV farmland) as a percentage of the total farmland area. HNV farmland is classified into three types: (1) farmland with a high proportion of semi-natural features; (2) farmland dominated by low intensity farming or a mosaic of semi-natural and cultivated land and small-scale features; (3) farmland supporting rare species or a high proportion of European or world populations of species (Andersen et al., 2003). In Germany, HVN farmland comprises species rich grassland, fallow land, species rich arable land, sparse orchards, and vineyards. Structurally rich landscape elements such as hedges, field margins, field copses and small water bodies that form part of the farmed cultural landscape are also given the status of HVN (BMU, 2010). The 2009 survey returns an indicator of 13 % for the proportion of HNV farmland area relative to the total farmland area of Germany. The target is to increase the area proportion of HNV farmland to 19 % by 2015 (BMU, 2010).

Increase in land use for settlement and transport

The increasing settlement and transport have direct environment impacts: loss of habitats, loss of fertile farmland, and loss of ecological soil services caused by surface sealing. This indicator tracks the average increase in land use for settlement and transport in Germany, measured in hectares per day. It covers land use including buildings and green spaces, recreation and cemeteries, and transport. The target was set for new land use for settlement and transport of an average daily maximum of 30 ha by 2020.

Landscape dissection

The indicator measures the degree of landscape fragmentation in Germany by transport networks at landscape level. It looks at the main elements of transport including roads

[7] EU wide network of nature protection areas under Habitat Directive, http://ec.europa.eu/environment/nature/natura2000/index_en.htm (Accessed October 13, 2014)

(federal motorways, federal roads, state roads and district roads), railway lines, and canals. The assessment of the landscape dissection impact of roads also considers traffic volume, as roads with heavier traffic pose greater barriers to wildlife. Besides transport network, settlements and airports with an area in excess of 93 ha are also considered as ecological barriers (BMU, 2010). The Undissected, Low-Traffic Areas (ULTA) are defined as areas of at least 100 km^2 in size that are not fragmented by transport networks. There are two approaches to measure landscape dissection: (1) the proportion of total area of ULTA in Germany; (2) Effective Mesh Size (MESH), used for describing average connected area within the landscape (Jaeger, 2000). According to the statistics in 2000 and 2005, the proportion of ULTA declined from 26.5 % to 25.4 %, and MESH declined from 84 km^2 to 81 km^2 in Germany. In the National Strategy on Biological Diversity (BMU, 2007), the German federal government has set a target of holding constant the current proportion of ULTA as it is in 2005 (25.4 %).

In addition, the German government has developed a federal re-crosslinking program to complement the ecological network. The main aim of this program is to build Wildlife Bridges at key points in the network of ecological corridors (Fig. 2.5). A sub-indicator for evaluating the reverse effects of dissection (such as Wildlife Bridges) should be developed in the future.

Figure 2.5. Wildlife Bridge over a federal motorway in Germany (Photo: Sarah. Walz)

2.2.2 Landscape monitoring in China

The relationship between nature and human is the basic question of Chinese philosophy. It is about harmony with nature – the “Unity of Man and Nature” – a concept with ancient roots in Chinese thought. In the long history of China, both governmental and nongovernmental limitations were set for firewood collection and fishing, which have played a role in the protection of nature. Some simple conservation ideas have emerged in the past. Although with superstitious meaning, some concepts could be recognized as the prototype as nature reserve, like “Fengshui forest” (Coggins et al., 2012) or “Dragon mountain”. Another example is the evolution of greenway in China, which dates back to the Zhou Dynasty (1100-770 B.C.). It was written in the ritual that trees should be planted along moats outside each city’s wall and water channels in the countryside (Yu et al., 2006). This ritual is well adhered in later dynasties and affects the country’s landscape until today. Nowadays, with the speeding up process of industrialization and urbanization China is facing unprecedented pressure for nature conservation.

2.2.2.1 Current situation of biological diversity in China

According to the Fourth National Report for CBD (MEP, 2008), China has more than 35,000 species of higher plants, 6,347 species of vertebrates, 2,200 species of bryophytes, 2,600 species of ferns, 250 species of gymnosperms, and over 30,000 species of angiosperms. But around 15-20 % higher plants are under threat, 233 vertebrates are facing extinction, around 44 % of wild animals declined in their numbers, particularly non-national protected wild animals. Habitats conservation also face degrading situation. About 90 % of the grasslands are experiencing various degrees of salinization and desertification. It is estimated that 40 % of the major wetlands are facing threats of severe degradation, and coastal mudflats and mangroves particularly have suffered serious damage. On the contrary, forest coverage has maintained a sustainable growth since 1950s as a result of implementing several forestry projects and establishing national nature reserves. By the end of 2011, 2,640 nature protection sites were founded, which distributed disproportionally in mainland China and more than 50 % located in western provinces. The total area of the nature reserve is 1.49 million km^2, which accounts for about 15 % of the land territory (MEP, 2011).

In China, the structural degradation of landscape is due largely to intensive, ongoing industrialization and urbanization (MEP, 2008). Excessive reclamation, resource exploitation and overgrazing destroyed the habitats of many wild animals and plants. Massive water conservancy projects and dam constructions blocked lakes and rivers as well as the migrating channels of fish populations. Railway and highway constructions dissect the landscape and cause immediate threats to population multiplication (Li et al., 2010b).

Pollution from industry and farming activities results in the extinction or reduction in the population of many species. In addition, climate change and invasion of alien species will continually threat the conservation of biodiversity.

In short, conservation of species and habitats in China is in a severe situation. The weak public awareness of sustainable consumption and lack of efficient government measurements are the main constraints on nature conservation in China.

2.2.2.2 Data used for landscape monitoring

The ecological value of China's nature reserves has been mainly under studied by the scientists from a regional perspective (Cao et al., 2013; Wang et al., 2013) or a national perspective (Li et al., 2010a; Quan et al., 2011; Wu et al., 2011). According to China's "National Biodiversity Strategy and Action Plan (v.2) (2011-2030)", a ten year project of nationwide biodiversity monitoring system has been announced including species types and populations, ecosystem types, area and the protection status (MEP, 2011). At present, there is no specific nationwide database for landscape monitoring in China. This does not necessarily mean that there is no relevant data to support the landscape monitoring, for example, the land survey data from the Ministry of Land and Resources (MLR). The first nationwide land survey in China began in May 1984 and ended in 1997, which took thirteen years. The second land survey began in July 2007, and finished in 2009. According to the requests of the overall program (MLR, 2007), a mapping scale of 1: 10,000 is used as the main scale; for parts of the mountains, grasslands, deserts and other regions mapping scale can reach 1:50,000; in economically developed regions and cities of the urban fringe the mapping scale can be 1:5,000 or 1:2,000. The land survey databases contain a set of results of maps and text, and other content of the outcome. The final databases contain land-use information on four levels (state-province-city-county), which include: land-use data at all four levels; land ownership at all levels; multi-source, multi-resolution remote sensing images; basic farmland information at all levels; city (county) level cadastral information (MLR, 2007).

Besides the land survey database, China would conduct its first national geographic condition census. This project was launched in January 2013 and scheduled to be completed at the end of 2015. "Geographic condition" means natural and human geographic elements on land surface. Natural elements concern on the spatial distribution of vegetation, water, desert and bare soil and other land cover types. Human geographic elements include transportation networks, residential areas and facilities, which are closely related to human activities. This nationwide database mainly serves for the country's economic development and environment monitoring. After the census, the information of geographic condition on land surface will be regularly collected and open to relevant departments.

2.2.2.3 Landscape indicators for biodiversity conservation

To meet the CBD target set at the 6th Conference of the Parties – "significantly reduce the current rate of biodiversity loss by the year 2010" (MEP, 2008), China has established 17 indicators in the 4th national report from seven aspects of the status and changes of biodiversity, ecosystem integrity and services, threats to biodiversity, sustainable development, genetic resources, financial support, and public awareness. In 2011 China has published its national biodiversity strategy and action plan (2011-2030) (MEP, 2011), which expressed its strategic goals for next twenty years, including the short term goal: by 2015 the trend of biodiversity losing can be significantly curbed in hotspot areas; the interim goal: by 2020 the loss of biodiversity will be basically under control; and a long term goal: by 2030 the biodiversity will be effectively protected. On other hand, because of the uncompleted biodiversity monitoring system in China, only limited data can be used for the assessment of the CBD targets[8] and national strategic goals (Xu et al., 2012). Since China has a large territory covering distinct biogeographic regions, establishing the indicators at landscape level would be an effective approach for nationwide biodiversity evaluation. Table 2.2 concluded the possible indicators for landscape monitoring towards the Aichi targets and national goals of China.

Table 2.2: Possible indicators at landscape level for biodiversity assessment in China.

Indicators	Meaning	References
Area and proportion of land cover	Refers to a variety of land cover types and proportions in different periods and indicates status and trends of ecosystems.	China 4th national report (MEP, 2008)
Number and coverage of nature reserves	Coverage refers to the percentage of the area of terrestrial nature reserves to the national terrestrial area and reflects the status of in-situ conservation of biodiversity.	China 4th national report (MEP, 2008)
Area of natural ecosystems	Including forest, grassland, wetland, and desert.	(Li et al., 2011)
Integrity of natural ecosystems	Including following sub-indicators: area of desertified land and density of railways and highways.	China 4th national report (MEP, 2008)
Connectivity and	Indicates the dissection of China's landscape by	(BMU, 2010; Li et al.,

[8] CBD targets for the period 2011-2020 set in the 10th Conference of the Parties. http://www.cbd.int/sp/targets/ (Accessed October 13, 2014)

dissection of landscape	roads and urban areas, e.g. effective mesh size.	2011; Li et al., 2010b)
Area and habitat quality of important ecosystems	Habitat quality can be described using the “traffic light” approach which is used in Europe (see detailed method in references).	(BMU, 2010; Defra, 2012; Li et al., 2011)
City expansion and road construction	Refers to the average increase in land use for settlement and transport.	(BMU, 2010; Li et al., 2011)
High nature value farmland	Defined as the area of high nature value farmland (HNV farmland) as a percentage of the total farmland area (see in references).	(Andersen et al., 2003; BMU, 2010; Paracchini et al., 2008; Pointereau et al., 2007)
Grassland affected by overgrazing	Overgrazing is the main driving force for grassland degradation in China. This indicator measures how overgrazing directly affect grassland, for example sheep density in pasture land.	(Li et al., 2011)

Some of the presented indicators in Table 2.2 have already been included in the 4th national report of China, and analyzed in the report based on the existing data. Other recommended indicators which have been used at the European or state levels can be the potential indicators incorporated in the landscape monitoring system for China, for example, the conservation status of habitats which is used in Germany under the Habitat Directive of Europe (BMU, 2010). The indicator “effective mesh size”, which is a well-established indicator mostly used for assessing landscape fragmentation, has also been tested at the national level in China (Li et al., 2010a). For the national HNV farmland indicator, China may refer to the method using land cover data with relatively low resolution as it is calculated for Europe based on CORINE land cover data (Paracchini et al., 2008). For the region densely covered by agriculture, the monitoring method for HNV farmland applied in Germany (BMU, 2010) or France (Pointereau et al., 2007) would be appropriate at a detailed level. As 90 % of grassland in China is experiencing degradation, an indicator for assessing grassland status is necessary, such as grassland affected by overgrazing. The targets for these indicators should be set considering both the CBD targets and China’s national objectives based on the current situation from the social and economic development.

2.3 Summary

Biodiversity loss as a global issue refers to every scale levels. Habitat diversity is an essential level of biological diversity, because it determines the species diversity and genetic diversity. In order to meet the targets for biodiversity conservation, it is necessary to establish the monitoring system and relative indicators at landscape level. As concluded in this chapter small biotopes and ecotones supply important ecological functions for landscape integrity, thus they should also be monitored and integrated in the landscape metrics for describing the landscape composition and structure. For example, the small biotopes are considered as key factors for the indicator of HNV farmland. In chapter 3 the proposed method of integrating small biotopes and ecotones for landscape structure analysis will be presented.

3 An enhanced approach for landscape structure analysis

In the previous chapters, the shortcomings of the traditional mosaic model were provided. In particular, the small biotopes and ecotones which are ecologically meaningful are normally absent in landscape structure analysis. The approach proposed in this chapter for dealing with these shortcomings mainly contains two parts. In chapter 3.2 a general land-cover classification procedure is described, which integrates both Object-Based Image Analysis (OBIA) and Pixel-Based Image Analysis (PBIA) using the high resolution lidar (light detection and ranging) data and multispectral images (RapidEye data). It demonstrates a data fusion concept for land use classification and the detection of fine-scale landscape elements. Chapter 3.3 presents several modified 3D-Metrics that can incorporate the small biotopes and ecotones in the landscape structure analysis. The ecological functions of these fine-scale landscape elements are measured from three aspects: landscape diversity, landscape fragmentation/connectivity, and landscape contrast.

3.1 Data basis

Using aerial photographs, Carl Troll (1939) has mapped the patterns and arrangements of landscape units for the first time, which means that he conducted ecological investigations on a landscape level. Subsequently he originally coined the term “landscape ecology” (in German “Landschaftsökologie” (Troll, 1950, 1963)). From the birth of landscape ecology we can see, remote sensing has been an important tool for recognizing the landscape pattern. The development of the remote sensing technology, particularly with the wide spread of high resolution remote sensing imagery, makes the Earth observation more extensive and more accurate. It is the basis of image understanding to extract and recognize geographic object information from remotely sensed images. In high spatial resolution images, the information about land surface is extremely rich and textural feature is prominent (Neubert, 2006). In addition, the availability of high resolution digital elevation data gives new possibilities to understand the landscape structure in a three dimensional perspective (Hoechstetter, 2009). As the data basis for landscape monitoring, only regularly collected data is considered in this thesis. Therefore the focus is laid on the extraction of landscape elements from remote sensing data, land-use maps and digital surface models from official land survey.

3.1.1 RapidEye images

Since 2009, new remote sensing data from the RapidEye satellite has become available. RapidEye is a German, five satellite constellation; each satellite has five spectral bands (blue, green, red, red edge and near infrared) with a 6.5 meter nominal ground resolution (resampled to 5 m pixel size). It offers different levels (e.g. 1B and 3A) of standard image products in a format that can be easily integrated into any Geographic Information System (GIS). For the RapidEye basic product (1B) delivered with radiometric and sensor correction but without any further corrections for any terrain distortions. The RapidEye ortho product (3A) is subject to radiometric, sensor and geometric corrections and the images are rectified using a SRTM (Shuttle Radar Topography Mission) DEM (level 1) or better.

A comparison between RapidEye data and other available satellite imagery of medium-resolution (1 m to 30 m) is shown in Table 3.1. Comparing to other satellites, RapidEye can quickly and reliably deliver multi-temporal data sets in relatively high resolution. It has a large collection capacity (the system records a 77 km wide swath and produces data of more than five million square kilometers of the Earth every day) and quick revisit time to any place on Earth[9]. This makes RapidEye unique in providing multi-temporal datasets over large areas. It is the first commercial satellite system offering a Red-Edge band (690nm-730nm), which measures variance in vegetation, allowing, e.g. species separation and monitoring vegetation health. Due to the short revisit time span of RapidEye data, it offers great potential to support a multi-temporal classification progress, which is especially useful for vegetation monitoring. Considering the task at hand, RapidEye ortho product (3A) is selected as a main image source.

Table 3.1: Satellite image products comparison (information is collected from following sources: BlackBridge[10], Satellite Imaging[11], esa Earth Online[12])

Satellite Sensors	Resolution*	Spectral Bands	Revisit Time	Swath Width
RapidEye	MS: 6.5 m (resampled to 5 m pixel size)	Blue: 440-510 nm Green: 520-590 nm Red: 630-685 nm Red Edge: 690-730 nm NIR: 760-850 nm	Daily (off-nadir) / 5.5 days (at nadir)	77 km
SPOT-5	Pan: 5 m (2.5 m by interpolation)	Pan: 480-710 nm Green: 500-590 nm	2-3 days (varies with	60 km

[9] http://www.blackbridge.com/rapideye/products/images.htm (Accessed October 13, 2014)
[10] http://www.blackbridge.com/rapideye/index.html (Accessed October 13, 2014)
[11] http://www.satimagingcorp.com/ (Accessed October 13, 2014)
[12] https://earth.esa.int/web/guest/missions (Accessed October 13, 2014)

	MS: 10 m SWIR: 20 m	Red: 610-680 nm NIR: 780-890 nm SWIR: 1,580-1,750 nm	latitude)	
SPOT-6	Pan: 1.5 m MS: 6.0 m	Pan: 450-745 nm Blue: 450-520 nm Green: 530-590 nm Red: 623-695 nm NIR: 760-890 nm	1 to 5 days (varies with latitude)	60 km
FORMOSAT-2	Pan: 2 m MS: 8 m	Pan: 450-900 nm Blue: 450-520 nm Green: 520-600 nm Red: 630-690 nm NIR: 760-900 nm	Daily	24 km
ALOS	Pan: 2.5 m MS: 10 m	Pan: 520-770 nm Blue: 450-500 nm Green: 520-600 nm Red: 610-690 nm NIR: 760-890 nm	46 days	35km (triplet stereo observations), 70km (at nadir)
Landsat 8	Pan: 15 m MS:30 m TIR: 100 m	Coastal: 435-451 nm Blue: 452-512 nm Green: 533-590 nm Red: 636-673 nm NIR: 851-879 nm SWIR-1: 1,566-1,651 nm SWIR-2: 2,107-2,294 nm Pan:503-676 nm Cirrus: 1,363-1,384 nm TIR-1: 10,600-11,190 nm TIR-2: 11,500-15,510 nm	16 days	185 km

*Pan: Panchromatic band; MS: Multispectral bands; NIR: Near Infrared; SWIR: Short Wave Infrared; TIR: Thermal Infrared.

3.1.2 High resolution elevation data

The sensitivity and accuracy of conventional sensors have significant limitations for ecological applications, and they produce only two-dimensional images, which cannot fully represent the tree-dimensional structure of, e.g. forest canopy (Lefsky et al., 2002). Alternatively, lidar (light detection and ranging) is a promising approach to both increase the accuracy of biophysical measurements and extend spatial analysis into the third dimension.

The lidar device measures the distance through laser pulses that strike and reflect from features on the surface of the earth. The distance is determined by the elapsed time between the emission of a laser pulse and the arrival of the reflection of that pulse at the sensor's receiver. The return signals are generally collected in two ways: either as discrete signals, which measure reflected energy quantified at amplitude intervals and recorded at precisely referenced points in time and space, or as continuous wave (Lefsky et al., 2002). The "discrete return" lidar device converts scanning angle and distance from sensor information into georeferenced data points. The high point density of laser mapping systems enables achieving a detailed description of geographic objects and of the terrain.

The uses of lidar data in ecological application are numerous, especially for forested inventory. Stephens et al. (2012), for example, used airborne lidar data to estimate forest carbon stocks and proved that lidar improved the precision of stock estimates compared to ground plots alone. Tonolli et al. (2011) presented a method combining airborne lidar and multispectral data for the estimation of timber volume and found that lidar variables provided the majority of the explanative contribution for the estimation. Other applications of using lidar data for aboveground forest biomass or leaf area estimation have been studied frequently (Clark et al., 2011; Korhonen et al., 2011; Naesset et al., 2013; Zhao et al., 2009). In addition, the lidar data has also been used to characterize the forest structure (Korhonen et al., 2011; Latifi et al., 2012). The capacity to do individual tree level analysis depends on the spacing of the lidar data and the size of the trees (Richardson and Moskal, 2011; Zimble et al., 2003), because the points sampling density will have a strong influence on crown area estimation (Roberts et al., 2005). However, for a plot level analysis the tree heights can be accurately estimated and lidar-derived tree heights could be useful in the detection of differences in the continuous, nonthematic nature of vertical forest structure (Roberts et al., 2005; Zimble et al., 2003).

In this research, the lidar data was acquired by TopoSys GmbH[13] (Biberach, Germany) in the spring 2005 using the Falcon II sensor system. The sensor has an effective scan rate of 83 kHz, and laser wavelength of 1,560 nm. The system measurement accuracy is 15 cm in the vertical direction and 50 cm in the horizontal direction. Data recording of the first and last echo can produce a Digital Surface Model (DSM) that includes man-made features and vegetation superimposed on the terrain with 1 meter resolution. The digital camera associated with the lidar device provides digital RGB and CIR (Color Infrared) ortho images of 50 cm resolution. See examples in Figure 3.1.

[13] http://lidarcomm.com/id17.html (Accessed October 13, 2014)

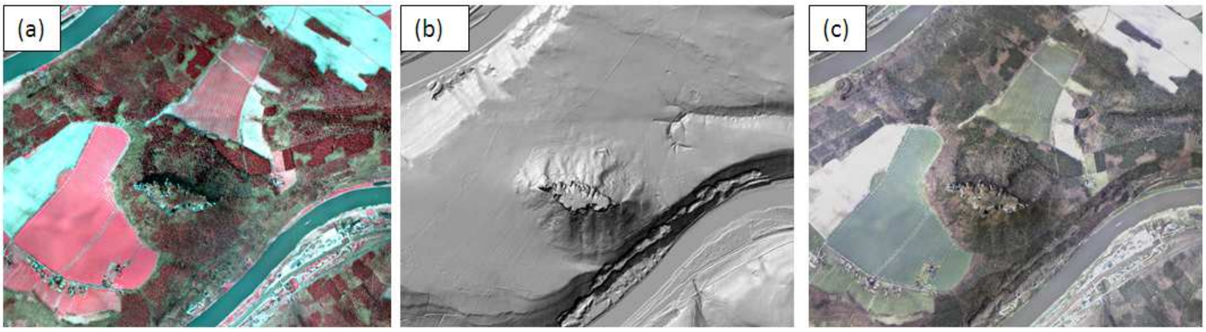

Figure 3.1: A sample of data acquired from lidar device in this study (Lilienstein in Saxon Switzerland, see detailed description in chapter 4.1). (a) Digital CIR ortho image. (b) Hillshade visualization of digital surface model. (c) The overlaying of both digital RGB ortho image and the terrain model.

The DSM can be processed to eliminate the man-made features and vegetation to derive the associated DEM (Csaplovics and Wagenknecht, 2000). While the DEM shows the height of the ground surface, the DSM also contains vegetation and human artefacts like buildings. To obtain object height information, the Normalized Digital Surface Model (NDSM) was calculated simply by subtracting DEM from DSM. Based on the high resolution NDSM data, detailed landscape elements (e.g. single trees, hedges or copses) can be observed (see Figure 3.2). Moreover, NDSM can also be used for the determination of transition zones created by the elevation gradient on forest boundary (Hou and Walz, 2013a). For characterizing landscape structure, the high resolution elevation model enables the analysis in a realistic way, for example the calculation of true surface area of patches or distances between patches (Hoechstetter et al., 2006; Hoechstetter et al., 2008). Therefore, incorporation of the high resolution elevation data can give an insight into the landscape structure on the vertical dimension and result in realistic descriptions of the land surface.

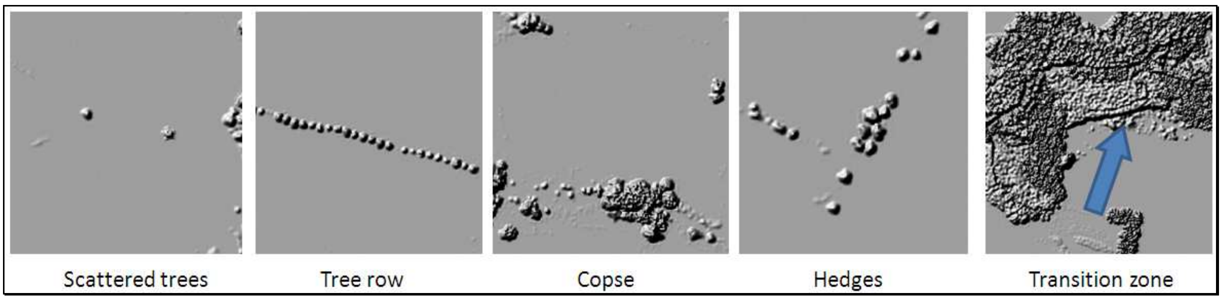

Figure 3.2: Visualization of different small biotopes and transition zones from a high resolution normalized digital surface model (NDSM).

3.1.3 Other data

Besides the raster data, some existing vector data can be integrated to produce the land-cover map for landscape structure analysis. The official land-use data, such as ATKIS in Germany, normally don’t have the detailed land-cover information of small biotopes, but it can be used as ancillary data for the classification of the main land-cover classes or used as reference data to confirm the classification result. Other data source, like biotope maps or topographic maps, may also be adopted as reference data. It is dependent on the availability of the data for the investigated area.

3.2 Mapping landscape pattern by integration of an object- and pixel-based classification approach

This chapter deals with the methodology of image processing for data preparation for landscape structure analysis. Both Object-Based Image Analysis (OBIA) and Pixel-Based Image Analysis (PBIA) are adopted to delineate tangible objects from different image sources while at the same time bringing image processing into correspondence with the landscape pattern (Blaschke, 2010; Burnett and Blaschke, 2003). The strategy is to combine different data sources to characterize landscape pattern at multiple scales for landscape monitoring. It mainly contains two steps (OBIA and PBIA, Figure 3.3) which are respectively applied on RapidEye images of relatively high resolution (5 m * 5 m) and on NDSM of fine resolution (1 m * 1 m). First, an object-based classification process is implemented based on the Rapideye images to produce a land-cover map including main classes. Since some small biotopes don't appear on this map of coarse resolution, in the next step the high resolution NDSM is integrated with the vegetation classes derived from the map in the first step. Then pixel-based image processing steps are adopted to delineate the small biotopes (tree rows, hedges, copses, and scattered trees inside open fields) and ecotones between forest and field. Chapter 3.2.1 and 3.2.2 will explain the two steps in detail.

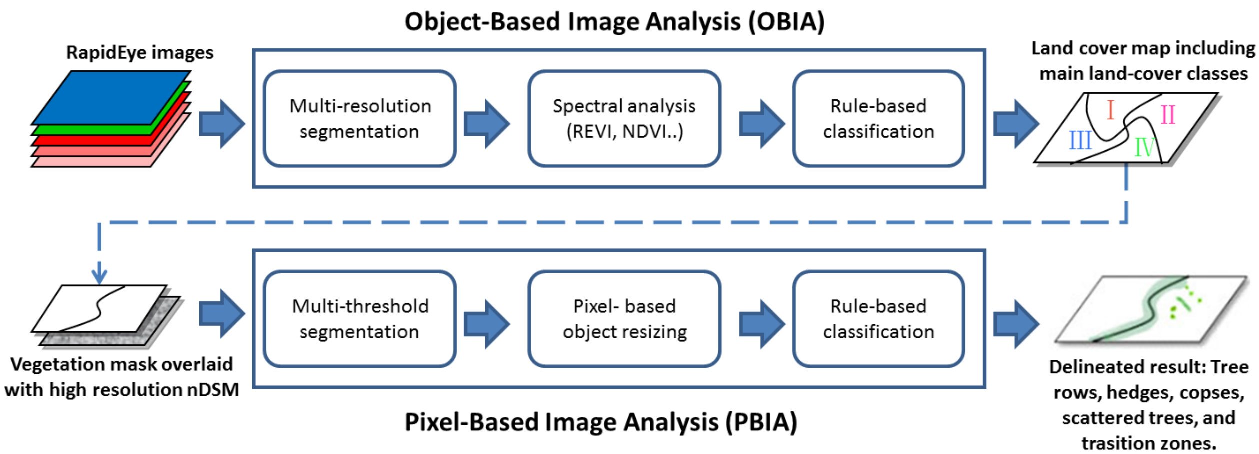

Figure 3.3: Workflow of the proposed method for land-cover mapping and extraction of small biotopes and transition zones.

3.2.1 Object-based image analysis (OBIA): land-use classification based on multi-temporal RapidEye images

The concept of OBIA has emerged along with the advent of high resolution imagery. Since the pixel size of high resolution images is much smaller than the target, it is necessary to group the pixels as an “object”. Further classifications are implemented on these image objects. They are created by a multi-level image segmentation process and are organized in a hierarchical structure, which allows more than one level of image objects classification. In addition, landscape structure analysis requires multiple levels of classification fitting to the landscape hierarchy. Thus OBIA is considered as a suitable approach and often applied for mapping landscape pattern (Buck et al., 2011; Farmer et al., 2011; Townsend et al., 2009).

In the following, the proposed method based on RapidEye images for land-cover classification are presented and described in detail. The software used in this work is eCognition (Definiens AG, 2009b).

3.2.1.1 Spectral feature of RapidEye image

Spectral information that an image can supply is an important factor on classification accuracy. Compared to other satellite images, RapidEye satellites include a Red Edge band, which is sensitive to changes in chlorophyll content (Munden et al., 1994). To analyze the function of the Red Edge band in land cover classification an atmospheric correction has been firstly applied to the images. Then a vegetation index considering the Red Edge band is proposed and the spectral pattern analysis for this index has been conducted using some sample data.

3.2.1.1.1 Atmospheric correction for RapidEye data

The main reason for atmospheric correction is making multi-temporal scenes from RapidEye become comparable, because digital numbers are substituted by surface reflectances. For the work at hand, the software ATCOR is used for atmospheric correction. It was originally developed at the German Aerospace Center (DLR), and integrated in ERDAS IMAGINE software. The satellite version of ATCOR supports all major commercially available small-to-medium sensors with a sensor-specific atmospheric database of look-up tables containing the results of pre-calculated radiative transfer calculations (Richter and Schläpfer, 2013).

ATCOR supports atmospheric correction including water vapor, aerosol, and visibility. As the RapidEye sensor does not possess spectral bands in water vapor regions (bands around 940 or 1130 nm), an estimate of the water vapor column based on the season (summer or winter) is necessary, such as middle latitude summer, tropical conditions, dry desert or winter. The aerosol type includes the absorption and scattering properties of the particles.

ATCOR supports four basic aerosol types: rural, urban, maritime, and desert. Usually the user can choose the aerosol type based on the geographic location. For example, for an area close to the sea, the maritime aerosol would be a logical choice if the wind is coming from the sea. Visibility can be automatically calculated from Red/NIR bands, if the scene contains dense dark vegetation (e.g. coniferous forest). Detailed explanation about the atmospheric parameters can be found in the user's guide of ATCOR (Richter and Schläpfer, 2013). Figure 3.4 shows the window of ATCOR for processing the RapideEye image acquired on September 25th 2009. For RapidEye data the sensor geometry parameters can be found in the metadata file of the image, including solar (zenith angle), solar azimuth, sensor tilt, satellite azimuth.

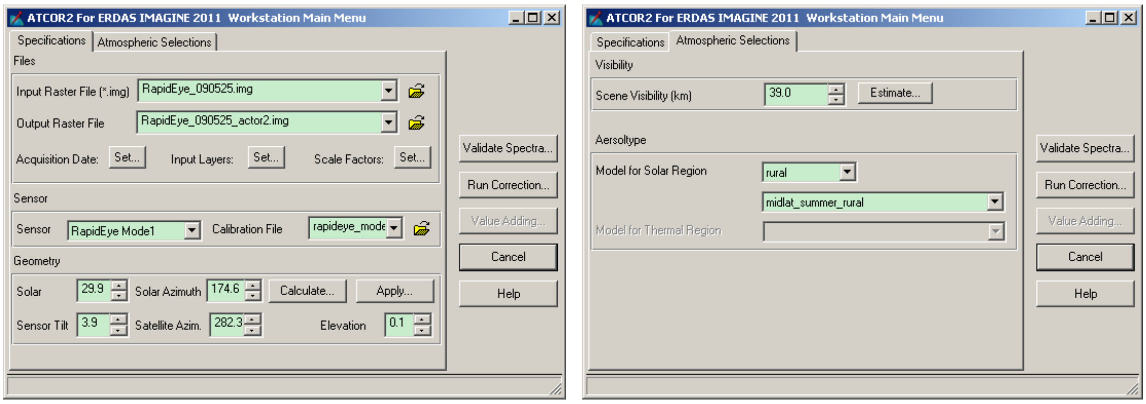

Figure 3.4: The window of ATCOR2 for the atmospheric correction of the RapideEye image of Rathen, Germany

3.2.1.1.2 The use of Red Edge band in vegetation classification

As mentioned before, RapidEye is the first commercial satellite that offers a Red Edge band (690nm-730nm). Previous studies have proved this Red Edge band is sensitive for the chlorophyll content of vegetation (Gitelson et al., 1996; Munden et al., 1994). Related vegetation indices have been proposed based on the Red Edge, for example the NDVI-RE, which is derived from NDVI (Normalized Difference Vegetation Index, Equation 1) by replacing the NIR band with Red Edge band (Schuster et al., 2012) or replacing the Red band with Red Edge band (Tapsall et al., 2010). Several tests have been conducted to demonstrate the improved variance measurement in vegetation using the Red Edge band, e.g. species separation and land-cover classification (Bindel et al. 2011; Schuster et al. 2012). However, the experimental results show two formations of NDVI-RE have no significant difference from NDVI for vegetation classification (Schuster et al., 2012; Tapsall et al., 2010). In order to exploit the potential of Red Edge band for vegetation classification, different formulations of vegetation index incorporated with the Red Edge band have been tested in this work. As a result, a modified vegetation index is formulated (Equation 2), named as REVI (Red Edge Vegetation Index).

Equation 1: $NDVI = \frac{NIR - RED}{NIR + RED}$

Equation 2: $REVI = \frac{\rho NIR}{\rho RE^2} \times 100$; where ρ= reflectance value

In order to explain the use of REVI and NDVI in vegetation classification, RapidEye images of Rathen in Germany on May 25th, August 1st, and August 31st 2009 (see details in chapter 4.1) are chosen as test data. The main vegetation in this region is forest (coniferous and broad-leaved), grassland, and farmland. Because of farmland cultivation, a multi-temporal approach is useful to classify crops according to seasonal changes in spectral signals. Since different crops would be planted each year in this region, the detailed crop content is not the focus in this work. From the color-infrared images (Figure 3.5), three types of crops can be visually identified according to their color difference. From each crop typical samples are selected for the calculation of average and standard deviation of NDVI and REVI based on a multi-temporal layerstack from three RapidEye images. Standard deviation values are shown as error bar to the average values (see Figure 3.6). The signal pattern comparison shows both NDVI and REVI indicate the seasonal changes in different crops. From May to August the NDVI and REVI values for crop1 show an increasing trend contrary to the decreasing trends for crop2 and crop3, which makes crop1 easier to differentiate. In the case of crops 2 and crop 3, there is more significant difference on REVI than NDVI in May, which makes the varying REVI a significant feature enabling farmland plots to be distinguished.

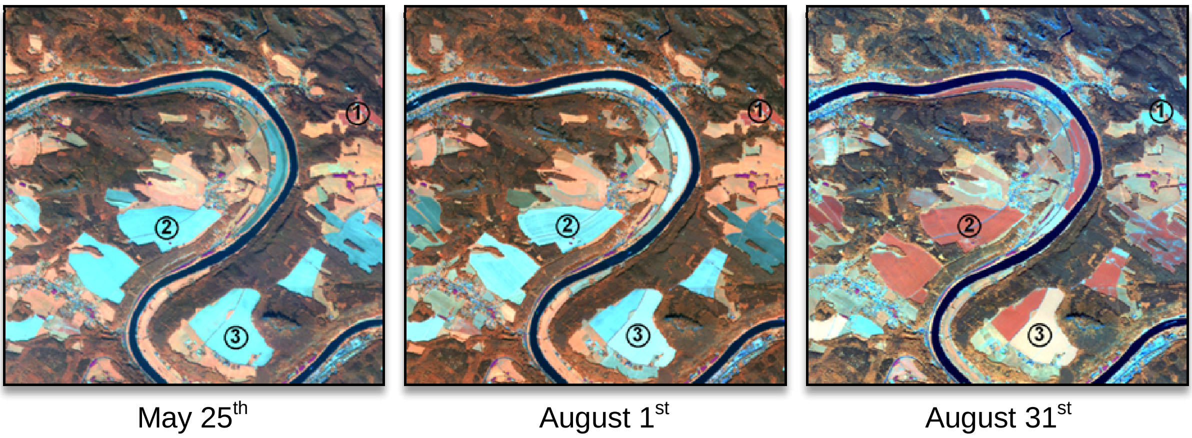

Figure 3.5: Color-infrared images composed of RapidEye band 5, 4, 2; three types of crop can be visually identified from the time series images.

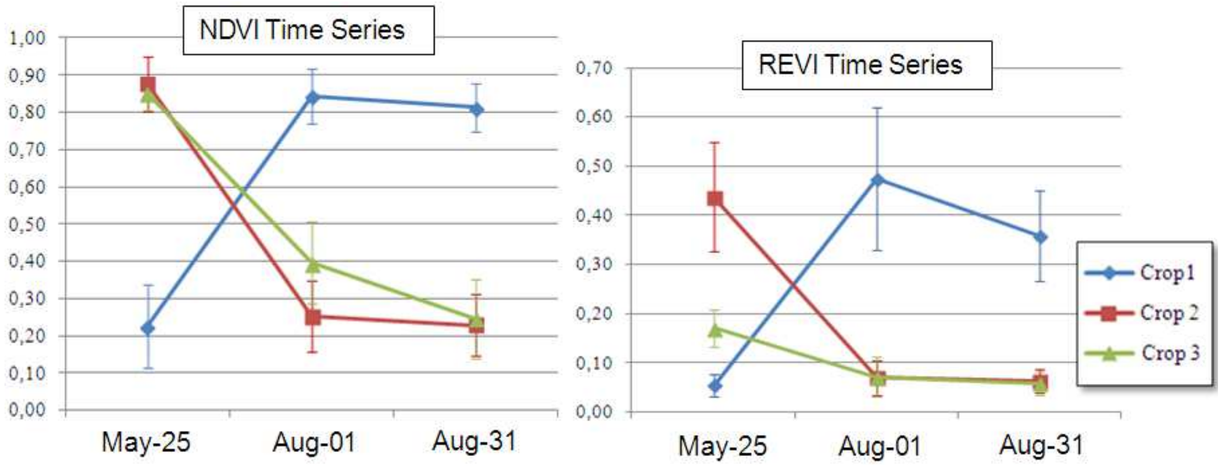

Figure 3.6: Comparison between NDVI and REVI values for crop classes based on multi-temporal RapidEye images.

Likewise, samples of forest and grassland are selected for the calculation of the average and standard deviation values of REVI and NDVI for the time series images. Figure 3.7 shows the signal patterns of NDVI and REVI with respect to the acquisition dates. It reveals that there is a significant difference on REVI between forest and grassland, especially on August 1st. On the other hand, the NDVI value of grassland is not as stable as REVI, and partly mixed with forest. However, the REVI values of forest sub-classes (broad-leaved forest, coniferous forest, and mixed forest) are almost completely overlapped on multi-temporal images (see Figure 3.8). It seems that the REVI can minimize the signal difference among the forest sub-classes and allows classifying the forest as a whole. Thus the optimal solution is to use REVI firstly to differentiate forest and grassland, and then to use NDVI to classify forest sub-classes.

From the spectral analysis, it can be seen that the ability of RapidEye satellite to capture multi-temporal images within a brief interval of time combined with its Red Edge band capability can significantly improve the accuracy of vegetation classification. This is a big advantage and especially useful for farmland monitoring (Tapsall et al. 2010).

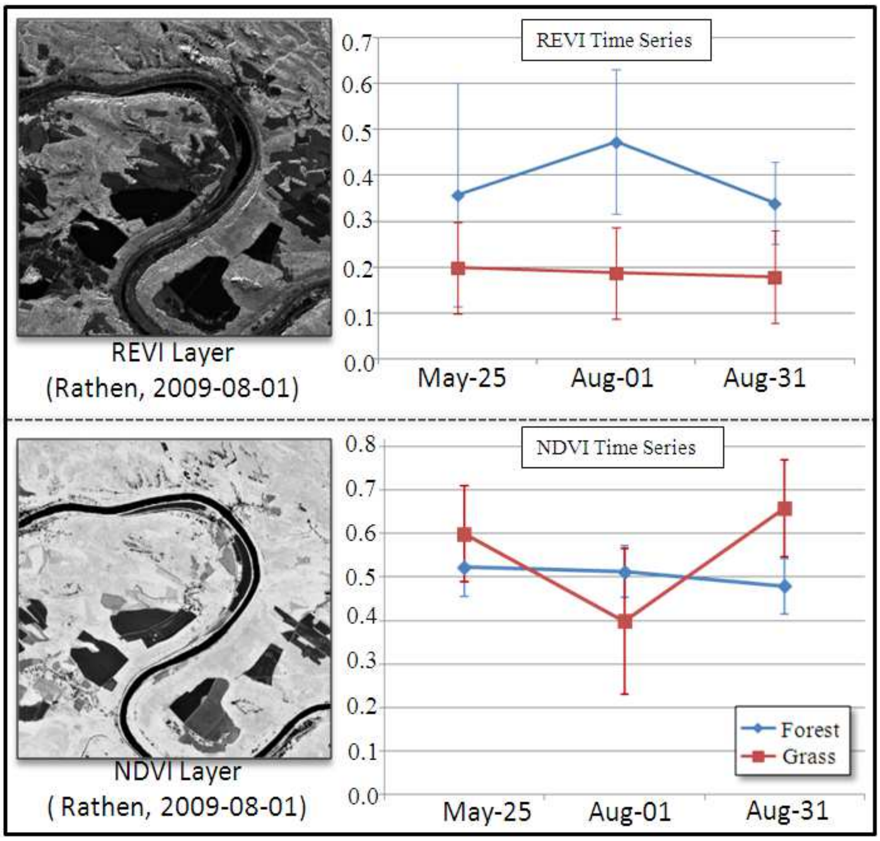

Figure 3.7: Comparison between NDVI and REVI values for forest and grassland based on multi-temporal RapidEye images.

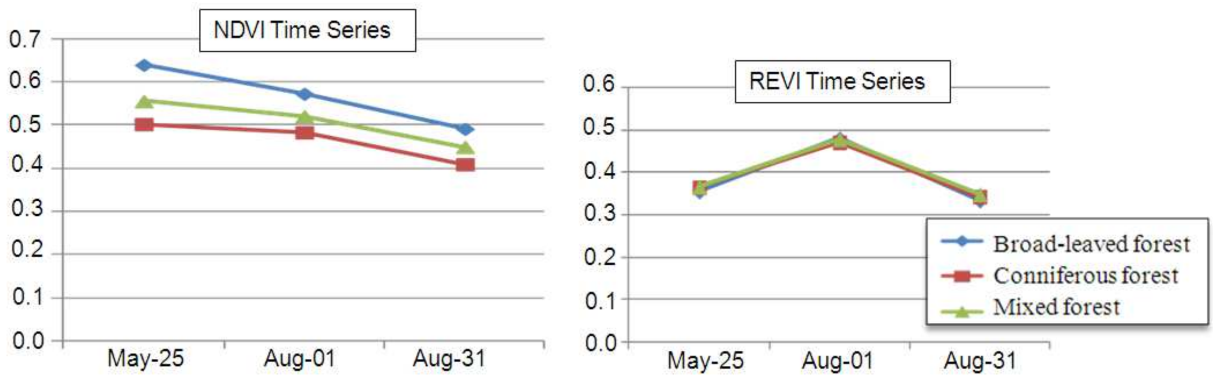

Figure 3.8: Comparison between NDVI and REVI values for forest sub-classes (broad-leaved, coniferous, and mixed forest) based on multi-temporal RapidEye images.

Besides the vegetation index layers, NDWI (Normalized Difference Water Index, Equation 3) (McFeeters, 1996) can also be derived from RapidEye data. This index is useful for water classification and together with REVI and NDVI used as the main features for the classification of RapidEye images.

Equation 3: $$NDWI = \frac{GREEN - RED}{GREEN + RED}$$

3.2.1.2 Class hierarchy

The landscape system is considered as a nested hierarchy with each level containing the levels below it (Forman, 1995). It refers to how a system of distributed functional elements is linked at two or more levels (Wu, 1999). For example, a forested landscape might be hierarchically structured and it comprises several sub-ecosystems (e.g. coniferous forest, broad-leaved forest), which in turn are composed of individual trees. Correspondingly mapping landscape pattern should also be conducted at multi-spatial scales, beginning with a coarse-scale inventory of vegetation, habitat structure, then at a fine-scale including biologically significant areas, such as small biotopes and ecotones (Duelli, 1997; Honnay et al., 2003; Noss, 1990; Uuemaa et al., 2009).

In the object-based environment, all image objects are organized in a class tree according to the simulated hierarchical levels for classification (Hay et al., 2001; Wu and David, 2002). There are two ways to represent the relationship among classes in eCognition: group view and inheritance view. Group view allows the user to assign a logical structure to the classes. This originates from human cognition of the landscape focusing on land uses of the patches. For example different crops are recognized as farmland class, although they are covered by different types of vegetation. Inheritance view of class hierarchy allows class descriptions to be passed down from parent to child classes. This means that the child classes inherit at least one common feature from their parent class. Classes are categorized by their surface cover. For example coniferous forest and broad-leaved forest are considered as child classes of forest because they both possess the characteristics of trees, which are the common features for them to be classified as forest. Sometimes the group view and inheritance view are the same for the class hierarchy, like the example of forest. In the case of farmland, the crops logically belong to farmland class, but they need to be classified separately because of their different spectral features and growing period.

Considering the work at hand, a general class hierarchy needs to be established in group view for landscape structure analysis, which is described in Figure 3.9. From the entire image, the land surface is divided into four parts: settlement, traffic, vegetation, and non-vegetation. The next two class levels are used for producing land-cover maps including main classes and sub-classes for landscape structure analysis. The main land-cover map, which has a spatial scale similar to the ATKIS data (1:25.000), includes major land-cover types (settlement, traffic, farmland, forest, grass, water, and bare area). The main land-cover map will level out the particularities of individual areas and hence is often remote from the practical requirements of nature conservation. For that reason, a more detailed land-cover map is desirable, containing sub-classes at a lower hierarchical level. On this detailed land-cover map, settlements are differentiated as sealed areas and unsealed areas; forest is divided into three sub-classes: coniferous, broad-leaved, and mixed; farmland is delineated into different plots according to crop type. The affiliation among the classes (shown in Figure 3.9) is from a logical view, and will not affect the image classification process.

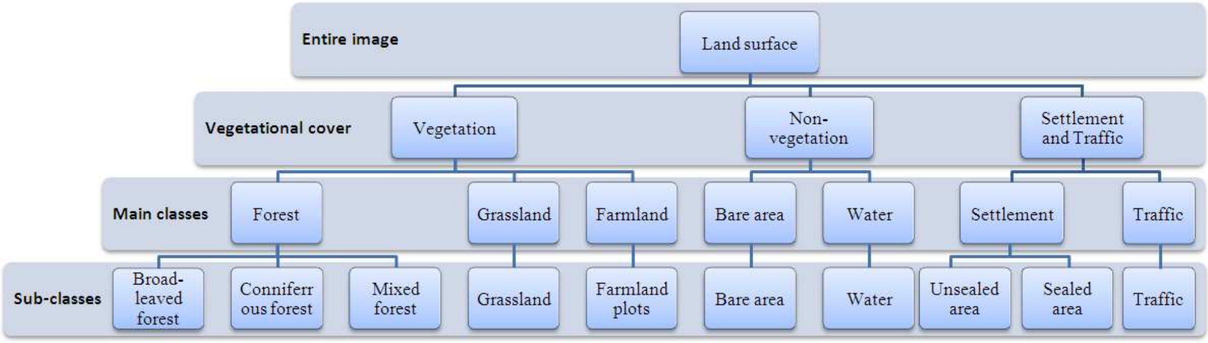

Figure 3.9: Class hierarchy in group view applied in eCognition.

3.2.1.3 The concept of image segmentation

Segmentation is a process of grouping pixels, which provides the building blocks of Object Based Image Analysis (Blaschke et al., 2008; Lang et al., 2009); thus, it is the first step in OBIA. Segmentation is not only to cut something big into smaller pieces, but any operation that creates new image objects or alters the morphology of existing image objects according to specific criteria (Definiens AG 2009). This means segmentation can be a subdividing operation, a merging operation, or a reshaping operation. The basic segmentation strategy is either following a “top-down” or “bottom-up” process. “Top-down” segmentation means cutting objects into smaller objects. It can initiate either from the entire image or specific objects. “Bottom-up” segmentation means assembling objects to create larger objects. Similarly, it can either start with the pixels of the image or particular image objects.

eCognition Developer 8 offers three “top-down” segmentation methods: chessboard segmentation, quadtree-based segmentation; and multi-threshold segmentation (Definiens AG, 2009b). Chessboard and quadtree-based segmentation are generally useful for tiling and dividing objects into equal regions. Multi-threshold segmentation is applied only on single layer and has also the function of objects classification. This algorithm contains two steps. Firstly it splits the image object domain according to the pixel thresholds, and then pixels belonging to the same object domain will be classified as the same type. The thresholds should be set in the range of the pixel values of this applied layer.

A “bottom-up” segmentation algorithm frequently used in the earth sciences is Multi-Resolution Image Segmentation (MRIS) (Baatz and Schäpe, 2000). It is applicable to multiple layers. In this segmentation process, two cells are merged to form segments if the merged segments do not exceed a user-defined heterogeneity threshold. This heterogeneity is fixed by the “scale parameter” including both spectral and spatial criteria. The spectral criterion is calculated from the spectral values on each band. The spatial criterion contains two parts: smoothness and compactness which are related to the shape of segments. Distinct weights (determining the proportions in the heterogeneity threshold) can be assigned to each criterion in MRIS. Normally spectral criterion has a larger weight than spatial criterion. However, especially in strongly textured image data the shape criteria can help to maintain smooth edges or a more or less compact shape (Baatz and Schäpe, 2000).

In practice, the segmentation algorithms are often used together with classification in an iterative process. The aim is to segment image objects close to real-world entities. The use of the segmentation algorithms is dependent on the target objects and the available data. For example, chessboard segmentation is often used together with the thematic layer to do a quick segmentation for creating identical image objects as in the thematic layer. Multi-threshold segmentation is used on a single layer which exhibits distinct value for the target objects. MRIS uses multi-layer information and results in the general objects for all classes based on a comprehensive consideration from spectral and spatial aspects. However, it is often not possible to determine the optimal segmentation parameter of analysis in advance (Blaschke 2010) and the segmented methods are not fully operational and transferable to another image without major corrections. From general to specific objects, the selection of appropriate scale parameters for MRIS has depended heavily on trial and error. A plug-in tool for eCognition named “Estimation of Scale Parameters (ESP)” (Drăguţ et al., 2010) may help to estimate the scale parameters for image segmentation (see details in chapter 4.2.1.2).

3.2.1.4 Segmentation and classification strategy

Because this research is to establish a regular monitoring approach, a general segmentation strategy applied on RapidEye data is necessary. According to the class hierarchy (see in Figure 3.9), both bottom-up and top-down segmentation processes are adopted to produce the main land-cover map and detailed land-cover map (Figure 3.10). Starting from the RapidEye image, the segmentation level1 is typical for detecting settlements and traffic classes. The chessboard segmentation is adopted in this step to segment the artificial area and official land-use data (i.e. ATKIS) used as thematic layer in the segmentation process. Then a lower level (level 2) is created by the MRIS algorithm. It is important to note that this level is not very sensitive to the scale parameter defined in MRIS. The scale parameter should be set small enough to separate pixels belonging to different classes. Segmentation on level 2 is used as a pre-classification for aggregating pixels into small homogeneous objects which will be used as the base for classification. For the image object classification a membership function can be assigned to each class. It defines the relationship between feature values and the degree of membership to a class using fuzzy logic (i.e. any value between one (true) and zero (not true)). The membership functions can be user-defined or generated based on the sample objects. In the latter case, the spectral features are used for the membership definition of the main classes. For creating the main land-cover map, the segmented image objects on level 2 will be classified and merged if they belong to the same class.

Based on the main map, a top-down segmentation process is conducted to create three sub-levels, respectively on forest, settlement, and farmland classes. The segmentation on sub-levels is used for further classification of subclasses which are mainly vegetation covers. Therefore, the vegetation index layer (i.e. NDVI and REVI) should be incorporated during the segmentation and classification on sub-levels. As NDVI is sensitive to forest subclasses, it will be the main input data source for the forest classification. The REVI layer is used to segment the farmland plots, as REVI is more sensitive to crops than NDVI (see chapter 3.2.1.1.2).

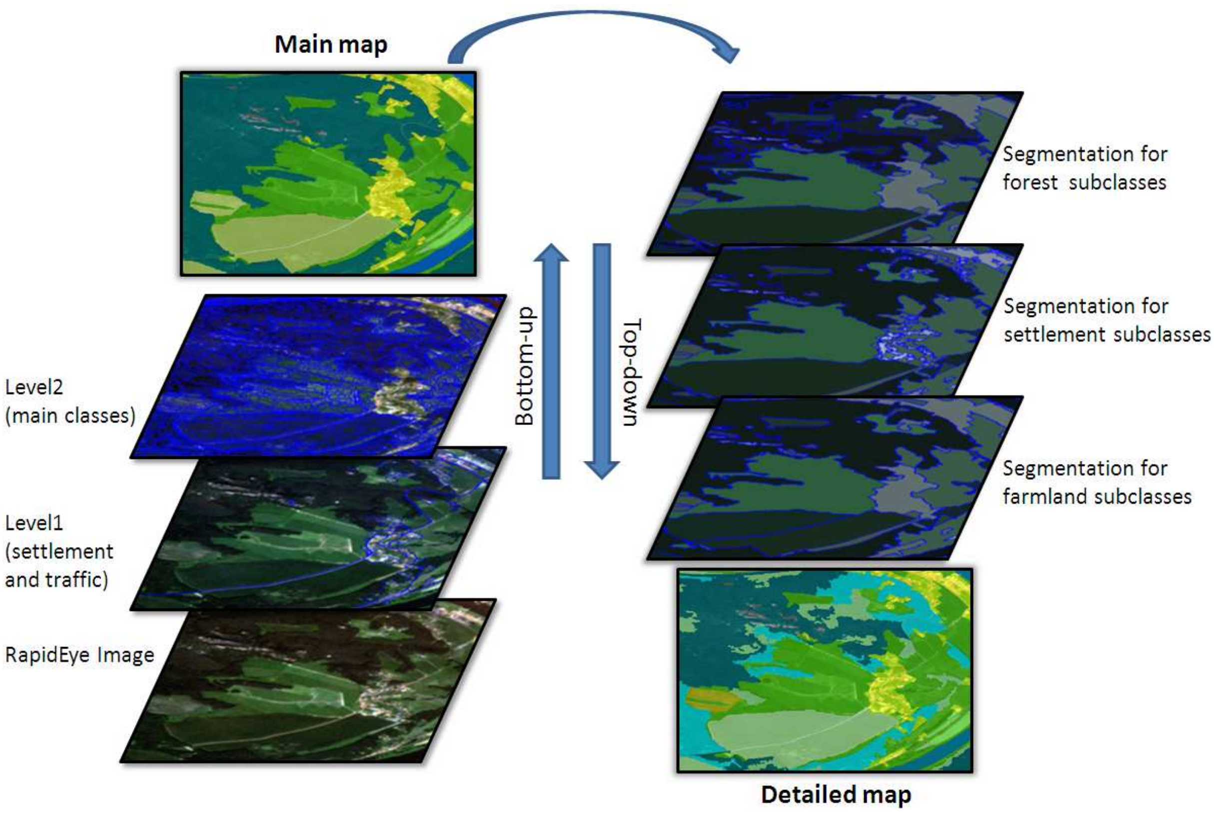

Figure 3.10: Segmentation strategy for main and detailed maps.

There is no “perfect” segmentation which can directly segment the whole image into geographically meaningful objects. It is useful to consider the objects in a class hierarchy and to choose a suitable segmentation algorithm. On the level of the main map, all RapidEye bands are used as input data for the MRIS segmentation to create general objects for classification. The further segmentation then is conducted on particular classes at a sub-level. Some specific layers (i.e. NDVI, REVI) can be chosen as input data according to the spectral feature of the target classes.

The classification process is implemented on the segmentation levels for main and detailed land covers. The multi-temporal approach can result in higher accuracy especially for farmland classification. The changes of the spectral signal within the time span can strongly support the vegetation classification. Besides the spectral features (e.g. NDVI, REVI) object shape features and its relation to neighborhood can also be used in object classification. As more accurate image objects are segmented, more features can be used in the classes' description. This OBIA strategy starts with rather simple or general segmentation, and then the classification result will be improved as more context knowledge can be incorporated at detailed level.

3.2.2 Pixel-based image analysis: detection of ecotones and small biotopes using high resolution NDSM data

Using the classification result of RapidEye data as a base map, a special effort is made by taking the "third dimension" into consideration for the next step. Due to the small size of the target objects (e.g. single trees, hedges, copses, and tree rows) and the structure of ecotones, the pixel is chosen as the operational unit for detecting them. In the following, firstly the definitions of the small biotopes and ecotones are given; then, the corresponding features and algorithms used in this research will be explained in detail; lastly, the detection process is presented.

3.2.2.1 Ecotone model and definition of small biotopes

Ecotones can be defined at many spatial scales, depending on the question of interest. Gosz (1993) defined an ecotone hierarchy of five levels: Biome ecotone, landscape ecotone, patch ecotone, population ecotone, and plant ecotone. Each level has a range of constraints and interactions between constraints. The primary constraints vary with the scale of the ecotone. At the landscape level ecotones are gradients between more homogenous patches of vegetation (Fortin et al., 2000; Risser, 1993). The gradient constraints could be certain abiotic parameters, like temperature, light, and moisture, even some belowground conditions (Cadenasso et al., 1997; Chen et al., 1992). The variable and the non-exclusive use of the term "ecotone" can be a source of confusion when interpreting and comparing studies (Hufkens et al., 2009). In this research, the ecotones between forest and field refers to mixed vegetation above the field layer but below the overstory formed by a combination of side branches of canopy trees, small trees, lianas, and shrubs. In this case, the difference in elevation is a good alternative to represent the gradient on forest boundary. Such differences have obvious ecological consequences. For example, ecotones can act as “terrain barriers” for the movement of certain species to enter the interior patch, or as a wind shield from adverse climatic conditions (Hoechstetter, 2009).

Figure 3.11 shows the height difference model of transitions between forest and field (including grassland and farmland), which provides a meaningful result in this case and can be used to characterize the landscape in a three-dimensional perspective. P_t stands for the transition zone or ecotone between P_f (interior forest patch) and P_g (interior field patch). The mixed vegetation area can act as a buffer between forest and field, which is located on the forest/field boundary and has the height between H_f (height limit of forest canopy) and H_g (height limit of field).

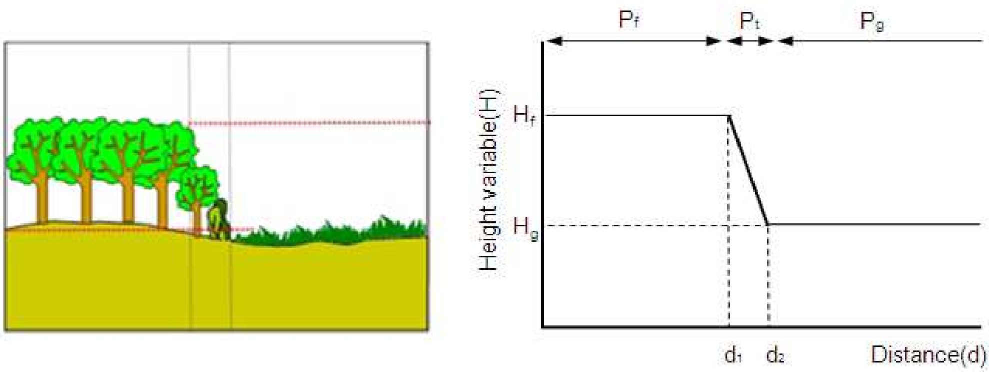

Figure 3.11: Simplified conceptual model of the spatial relationship of the forest transition to adjacent field (adapted from Walz et al., 2007).

Small biotopes like hedges, copses, tree rows, and scattered trees are considered as important components in landscapes. The previous chapter shows that these detailed landscape structures are closely related to species richness and the ecological functions of the whole landscape. They are defined by an area less than 0.5-1 hectare, a minimum width of 5 m and the occurrence in the open landscape, isolated from forest (BfN, 2002). Hedges are defined as shrub-dominated structures in crop fields or meadows/pastures, while a copse is characterized by several or dominating trees in the vegetation stand and the covering of trees exceeds 40 %. If the average height of forest crown in this region is H_f, the height threshold between shrub-dominated structures and tree-dominated structures is (40 % * H_f). Hedges are shorter or equal to this threshold; and the other small vegetation habitats are taller than this value. The definition of a tree row is a line of trees outside closed wood stock. From the definitions we see that their spectral characteristics are very similar, because they are all vegetation stocks with differing inner structures. They can be differentiated in terms of shape and height. Normally a single tree's canopy is smaller than 15-20 m^2. Hedges are relatively lower than other habitats because they consist mostly of shrubs, while copses contain trees and shrubs, tree rows consist only of trees. The tree interval along the tree row is considered smaller than 10 m, and the form of a tree row is long and narrow, so that this characteristic can be used to distinguish it from copse. According to the definitions and experience in field, the distinguishing features for these small biotopes can be summed up in Table 3.2:

Table 3.2: Concluded description of small-scale biotopes (H_f: average height of tree canopy in this region).

Habitat type	Hedge	Single tree	Copse	Tree row
Area	< (0.5-)1 ha	< (15-)20 m^2	20 m^2 < area < (0.5-)1 ha;	< (0.5-)1 ha
Average Height	=< 40 %*H_f	> 40 %* H_f	> 40 %* H_f	> 40 %* H_f
Shape				length/width ratio > 3 length >25 m width < 4 m tree interval distance < 10m;

3.2.2.2 Applied features and algorithms

The detection methods of small biotopes and ecotones are also implemented in eCognition. One of the advantages in the object-based environment is the additional shape features (e.g. length, width or length/width) which can be used in an iteration process of pixel-based segmentation and object-based classification. When the shape of the object approaches to real geographical entities, the shape-related features can better be applied for the object classification. Therefore, the reshaping process has the potential to improve the classification accuracy, especially on object boundary. In the following text a brief introduction about the applied features and algorithms used in this work is given.

An important feature that would be used for habitats detection is the ratio of length to width of image objects. It can be approximated in two ways, either using the bounding box of the image object or using the elliptic approximation. The bounding box is the smallest rectangular area that encloses all pixels of the object along x and y axes. It is defined by the minimum and maximum values of the x and y coordinates of an image object (Figure 3.12). Elliptic approximation based on eigenvalues measures the statistical distribution of the coordinates (x, y) in an image object. It computes an ellipsis with axis along the eigenvector e_1 with length a, and along the eigenvector e_2 with length b (Figure 3.12). The ratio of length

(a) to width (b) is identical to the ratio of the eigenvalues of the covariance matrix derived from the coordinates of the pixels in an image object, with the larger eigenvalue being the numerator of the fraction. In eCognition, both calculations are compared; the smaller of both results is returned as the feature value. Detailed explanation can be found in the reference book of eCognition (Definiens AG, 2009a). Other shape-related features based on the feature of length/width are listed in Table 3.3.

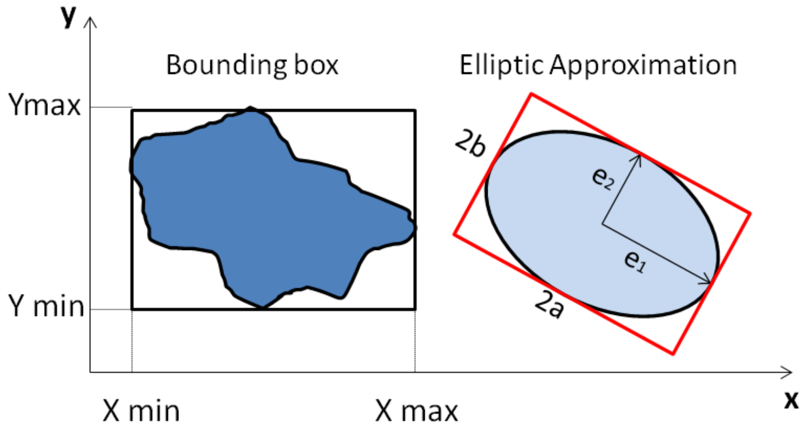

Figure 3.12: Shape approximations based on bounding box or Eigenvalues (adapted from Definiens AG, 2009a).

Table 3.3: Shape related features used in this research (source: reference book of eCognition8).

Object features	Formula	Remarks
Area	#P ∗ u2 # P: total number of pixels contained in an image objet; u: pixel size in coordinate system units.	One pixel area multiplied by the number of pixels contained in an image object. In scenes that provide no unit information, the area is simply the number of pixels that form it.
Length	$\sqrt{\#P * \gamma}$ γ: Length/Width ratio of the image object	Length/Width ratio multiplies the pixel number of an image object equals to Length squared.
Width	$\frac{\#P}{\gamma}$	The total number of pixels contained in an image object divide by the Length/Width ratio.

Apart from the object features, pixel-based algorithms are important in the detection process. Such as the multi-threshold segmentation which allows to segment the NDSM layer into elevated and non-elevated objects according to the height threshold set by user. More important is the pixel-based object resizing algorithm which is used for reshaping the elevated object to finally get the accurate form of small biotopes and ecotones. This algorithm has the basic function to create buffers around objects based on pixel criteria and it can grow or shrink the object outline by setting an outer or inner buffer range (Definiens AG, 2009a).

3.2.2.3 Detailed landscape structure detection based on NDSM

In order to extract the detailed landscape structure accurately, the spatial resolution of the grid should be many times finer than the size of targets (Lechner et al., 2009). The resolution of RapidEye data is fine enough for mapping the main vegetation classes (e.g. forest, grassland, and farmland), but cannot fulfill the needs of small biotopes detection (e.g. single trees). In this case the high resolution NDSM data derived from the lidar system is adopted as data source. A vegetation mask including forest, field (combined by grassland and farmland derived from the land-cover map) is used as base map for the next step of work. This combination can give an additional view on the landscape pattern from the third dimensional perspective.

3.2.2.3.1 Ecotone detection

Based on the ecotone model (Figure 3.11), the detection process is concentrated along the boundary between forest and field. Not only the height difference is used as a criterion of ecotone, but also the surrounding pixels of ecotone are also taken into account. According to the model by Riitters et al (2000), the proportion of non-transition pixels within a fixed-area is assumed to be between 40 % and 60 %. This means that the proportion of both forest and field pixels should be less than 60 % around the ecotone pixels. In this work, a fixed window (15 by 15 pixels) is used moving along the border between forest and field. Considering on the forest boundary structure, it is necessary to set a height limit in the moving window to constrain the extended distance of ecotone edge. The height limits on the sides of forest (H_f) and field (H_g) should be set according to the study area. The detection method can be concluded as a “growing and shrinking” process:

(1) Growing process: refining the border between forest and field. Overlaying NDSM (1 meter resolution) with forest class and the field class from the land-cover map. Due to the coarser resolution of RapidEye data (5 meter resolution), the border between forest and field may not match to the NDSM. Therefore, the first step is to optimize the border in a midline of certain height between the two sides. H_m is assumed as the height of optimized border between forest and field. This refining process contain following steps (see in Figure 3.13 ①):

- Grow forest pixels into field where NDSM > H_m and relative area of forest pixels in window (15 by 15) >= 40 %;

- Grow field pixels into forest where NDSM <= H_m and relative area of field pixels in window (15 by 15) >= 40 %.

(2) Shrinking process: from the midline between forest and field, shrinking both forest and field to meet their height limits. Meanwhile the proportion of forest or field in this fixed window should also be below 60%. The height limits of ecotone are decided by user according to the ecotone structure in the study area. Normally they should be set between the average height of forest and field (see in Figure 3.13 ②):

- Using ecotone class, shrink field pixels which are higher than H_g, and the proportion of field pixels in window (15 by 15) < 60 %;
- Using ecotone class, shrink forest pixels which are lower than H_f , and the proportion of forest pixels in window (15 by 15) < 60 %.

(3) Eliminate impurities inside the transition area to avoid some variation pixels (Figure 3.13 ③).

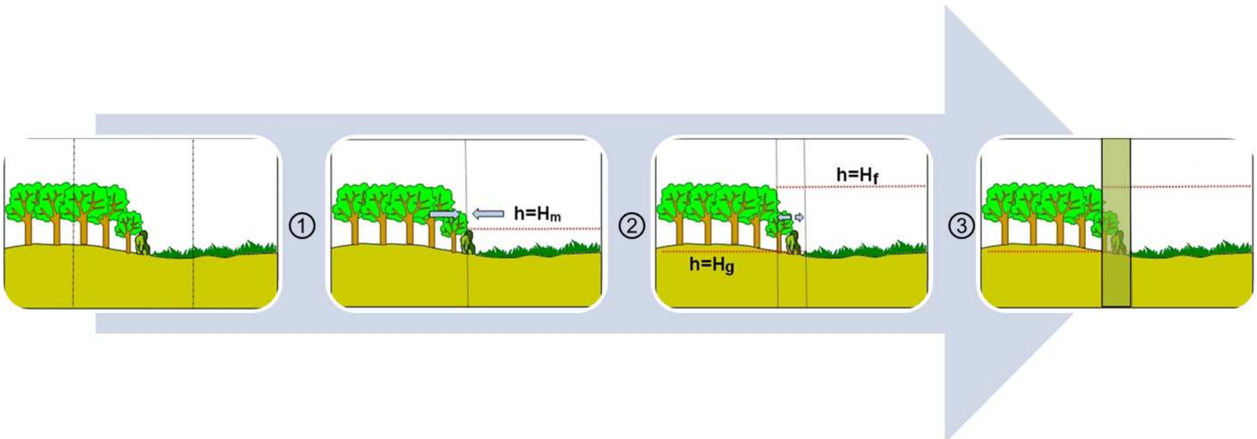

Figure 3.13: Ecotone detection process: (1) Growing the borders of forest and field to meet a midline between them. (2) From the midline shrinking back to the inner forest and field. (3) Eliminating process (H_f: the height limit of ecotone on forest side; H_g: the height limit of ecotone on field side; H_m: the height of border between forest and field).

3.2.2.3.2 Small biotopes detection

Before detecting the small biotopes, all pixels of NDSM have been classified as field and non-field classes using the field mask derived from the land-cover map. The detection process is implemented on pixel level using NDSM layer, and the threshold H_m is set in the algorithm to differentiate grass and woody habitats. Within the extent of field all elevated pixels (higher than H_m) are segmented as candidates for small biotopes (see in Figure 3.14 a). However, the NDSM data allows tree rows to be delineated only in the form of single trees. From Table 3.2 we see that it is not possible to distinguish between copse and tree row only using area and height features. This being the case, the linearity of tree rows cannot be used to distinguish them. For this reason, the pixel-based object resizing algorithm

(Definiens AG 2009) is used to create buffers according to the assumed interval distance of tree row (see Table 3.2) for all candidates. Afterwards all candidates' pixels and the buffer around them are merged to connect single trees (Figure 3.14 b). The length, width, and length/width ratio of features (see Table 3.2) are then used to differentiate tree rows (Figure 3.14 c). After that, the border of tree rows can be smoothed and all objects are shrunk back to the original size (Figure 3.14 d). Finally, the rest candidates are classified according to the shape features concluded in Table 3.2 (Figure 3.14 e).

It is important to note that the thresholds set for the features (as shown in Table 3.2) need to be adjusted. Because of the buffering process for the objects and the bias inherent to NDSM data, the boundary of an image object is always fuzzy. The actual area threshold between single tree and copse could be a little larger than 20 m^2; the height threshold between trees and hedge may be lower than 40 % of canopy height. These parameters have to be adapted when applying this method in different regions.

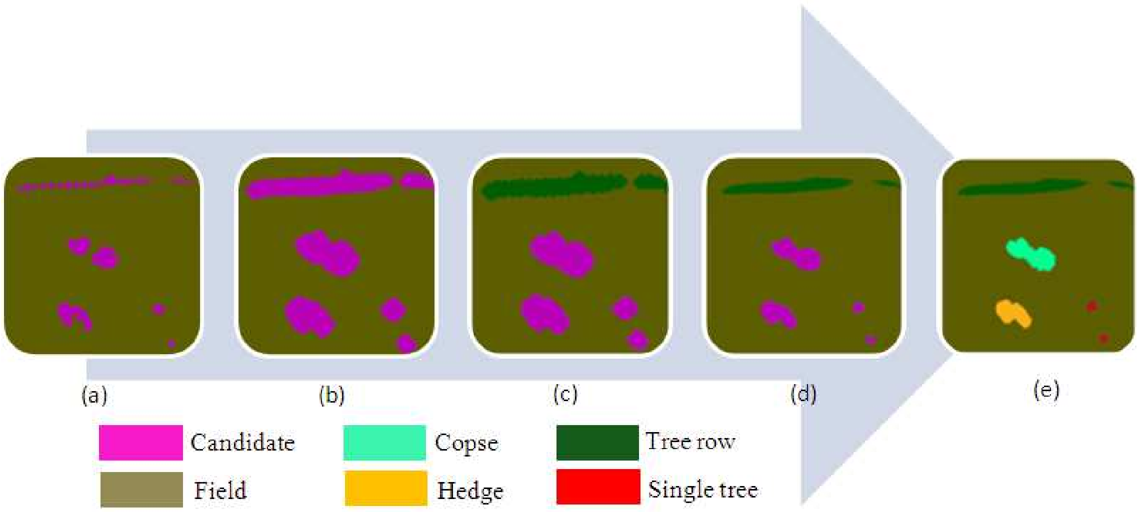

Figure 3.14: The detection process of small biotope: (a) Object-candidates higher than 2 m within the extent of field. (b) Buffer all candidates to merge the objects to be considered as constituting a row. (c) Classify tree rows based on shape features. (d) Smooth the border of tree row and shrink all objects. (e) Classify the rest candidates using rule-based classification.

3.3 Landscape structures analysis

Landscape metrics based on the mosaic model are often used in landscape structure analysis. In practice the application of this model may be over simplified by losing valuable information on the landscape structure, such as the terrain characteristics of landscape (Hoechstetter et al., 2008; Walz et al., 2007), ecological gradient (ecotones) between patches (McGarigal and Cushman, 2005), and small elements within patches (Hou and Walz, 2013a). For biodiversity evaluation on landscape level, it is important to incorporate these elements into landscape structure analysis, because the small biotopes and ecotones supply specific habitats, and affect species dispersal or interactions. Through their effects on neighboring patches, the whole landscape function analysis results could be affected as well.

In the following the focus is on developing suitable techniques to incorporate the small biotopes and ecotones in the landscape structure analysis. This section is subdivided into two main parts. In the first part (chapter 3.3.1), landscape structure is mainly analyzed from three perspectives: diversity, fragmentation, and contrast. The developed metrics on fragmentation and contrast consider ecotones as the buffering area or gradient for increasing the effective area of both forest and open field and reducing the edge contrast between them. In the second part (chapter 3.3.2), the ecological network of woody habitats is established using the small biotopes as conjunctions for forest patches and indicators derived from this ecological network are presented for assessing the habitat connectivity.

3.3.1 Metrics for describing landscape structure

Landscape diversity, landscape fragmentation, and landscape contrast have been considered as crucial factors for assessing biodiversity across different scales (Schindler et al., 2008). The metrics used for analyzing landscape structure are dependent on the conceptual model for representing the landscape. Landscape diversity describes the composition of landscape which focus on how many types of habitats and what is the proportion for each type without explicit consideration on the spatial configuration among the patches. Landscape fragmentation can be calculated using mosaic model or binary model. This index considers both the composition and spatial pattern of landscape, but the borders between patches are either regarded as no permeable (high contrast) or as full permeable (no contrast). In other words, the patch borders are abrupt in the use of fragmentation concept. In this thesis the index of landscape contrast is based on the model which considers the landscape as a mosaic with discrete patches and permeable boundaries between them (intermediate edge contrast). It describes the landscape spatial heterogeneity from a comprehensive view including the aspects of patchiness and gradient. However, the interpretation of this index is related to the definition of dissimilarity between patches.

3.3.1.1 Landscape diversity

The actual loss of biodiversity is not only in terms of the decline in species number, but also by the disappearing habitats or ecosystems. In landscape ecology, patches are defined as relatively homogeneous spatial units that are often categorized by vegetation covers, e.g. forest and field patches. This diversity of spatial units is generally recognized as a level of biological diversity (Walz, 2011). The patch model-based indices “Shannon’s diversity

(SHDI)" and "Simpson's diversity (SIDI)" are widely used in practice. They are not uncontroversial because they take no account of the uniqueness or potential ecological importance of individual patches or ecosystems (McGarigal, 2002). But their output can serve as a valuable mean of comparing the relative diversity of two landscape sections (Hoechstetter, 2009). In this research both metrics are tested (Equation 4 and Equation 5). The two indices depend on the richness of patch classes and area proportions for each class. Since an area can be affected by the underlying terrain, diversity metrics are likely to respond to terrain effects. When certain patch classes are predominantly located in steep terrain, it will lead to an underestimation in terms of area proportion. This may result in misleading diversity analysis when true surface area is a significant variable. It is therefore ecologically meaningful to incorporate the third dimension in diversity measures, particularly in mountainous areas.

Equation 4: $$\text{Shannon's Diversity (SHDI)} = -\sum_{k=1}^{n} P_k \ln(P_k)$$

Equation 5: $$\text{Simpson's Diversity (SIDI)} = 1 - \sum_{k=1}^{n} P_k^2$$

P_k: area proportion of the landscape occupied by patch type (class) k;

n: the number of patch types (classes) in the landscape.

Normally, the values of the diversity indices increase with the complexity of the landscape structure. For a fixed class number, the diversity indices would achieve their maximum values when the area proportions for all classes are the same, where $SHDI_{max}$ = ln (n) and $SIDI_{max}$ = 1-(1/n). Consequently the landscape evenness index can be derived as following:

Equation 6: $$\mathit{Shannon's\ Evenness\ (SHEI)} = \frac{SHDI}{SHDI_{max}} = \frac{-\sum_{k=1}^{n} P_k \ln(P_k)}{\ln(n)}$$

Equation 7: $$\mathit{Simpson's\ Evenness\ (SIEI)} = \frac{SIDI}{SIDI_{max}} = \frac{1-\sum_{k=1}^{n} P_k^2}{1-(\frac{1}{n})}$$

3.3.1.2 Landscape fragmentation

The concept of fragmentation has often been used to describe the breaking of a large habitat into smaller, more isolated fragments (Forman, 1995; Jaeger et al., 2011). For fragmentation assessment, specifying the research focus is important. In this thesis fragmentation has been understood in two ways: first, it is used as the synonyms for landscape dissection which refers to the obstacles (lines and areas) that block the movement of animals, often including artificial structures, e.g. transportation networks, residential areas and facilities. Second, fragmentation is applied on specific habitat types, such as forest. In this case, it describes the discontinuity of the habitat distributed in the landscape.

In a narrower sense, the landscape fragmentation is considered as the combination of ‘habitat loss’ and ‘isolation’ (Forman, 1995). Accordingly the measurements of habitat fragmentation can also be separated into two parts: habitat loss and fragmentation per se (e.g. the breaking apart of habitat, controlling for changes in habitat amount) (Fahrig, 2003). Resulting from this interest in habitats fragmentation, the landscape metric “Effective Mesh Size” (MESH, Equation 8) is found to be useful for measuring and comparing this effect and it can also be applied in landscapes differing in total size and with differing proportions of habitat patches (Jaeger, 2000). This index has a practical meaning and can be applied for describing both landscape dissection and habitat discontinuity. First, it calculates the probability that two randomly placed animals within the landscape are reachable from each other. Then, the effective mesh size can be described by multiplying this probability by the total landscape area. For example, in the calculation of landscape dissection, the landscape is perceived as a binary map, which means the patches are either natural area (vegetation covers) or barriers (traffic network, human settlement). Because the barriers are considered as impermeable lines, only the natural area will be incorporated in the calculation. The result indicates the effective mesh area of the natural area in the landscape. MESH can also be applied on a specific habitat type (class level), which measures the effective mesh area of this habitat. The value of MESH for habitat is dependent on the habitat distribution and area proportion of the habitat taken in the whole landscape.

Equation 8: $$MESH = \left(\frac{a_1^2}{A^2} + \frac{a_2^2}{A^2} + \cdots + \frac{a_n^2}{A^2}\right) \times A$$

$a_1 \ldots a_n$: area of the patches belonging to the habitat analyzed;

A: total area of the landscape (matrix area).

Specifically for vegetation cover (including forest and field), the ecotones between forest and field are considered as a mixed habitat where the species interactions are enhanced by supporting both edge species of forest and field. The ecotones are assumed that they have both the characteristics of forest and field; thus, they will be incorporated for the MESH calculation of both field (Equation 9) and forest (Equation 10). The modified formulas of MESH take special consideration of the ecological function of ecotones which can increase the effective mesh area and reduce the discontinuity for both forest and field. If the vegetation cover is considered as a whole class including forest, field and ecotones, then the function of ecotone will be neglected (Equation 11).

Equation 9: $$MESH_g = \left(\frac{\sum_{i=1}^{m} \left(a_i + a_{ti}\right)^2}{A} \right)$$

m: number of field patches;

a_i: area of field patch i;

a_{ti}: area of transitions which share the same border with grass patch i;

A: total area of landscape.

Equation 10: $$MESH_f = \left(\frac{\sum_{j=1}^{m} \left(a_j + a_{tj}\right)^2}{A} \right)$$

n: number of forest patches;

a_j: area of forest patch j;

a_{tj}: area of transitions which share the same border with forest patch j;

A: total area of landscape.

Equation 11: $$MESH_V = \frac{\sum_{k=1}^{h} \left(a_k\right)^2}{A}$$

h: number of vegetation patches ;

a_k: area of vegetation patch k including forest, field, and ecotones between them;

A: total area of landscape.

3.3.1.3 Landscape contrast

The patch contrast is used to describe the relative difference between patches or patch classes; for example “edges” have a kind of “contrast effect”. A strong contrast value means that adjacent patches differ strongly and the transitions between them are narrow or even absent (Forman and Godron, 1986). In practice, the contrast value is highly related to the conceptual model used for simulating the landscape. Categorical landscape models ignore within-patch heterogeneity and emphasize contrast between adjacent patches. Figure 3.15 shows how the landscape can be represented from low to high contrast as: homogeneous, gradient, mosaic, and binary. The choice of the model for representing landscape heterogeneity depends on the ecological processes under consideration and organisms involved (Wiens, 1989). Specifically in this research, ecotones between forest and field are defined as height gradient and the boundary behavior is related to the transition forms, such as a thin border or a broad transition zone with mixed vegetation. In this case, the vertical structure is used as a means that integrates discrete and gradient forms of spatial heterogeneity.

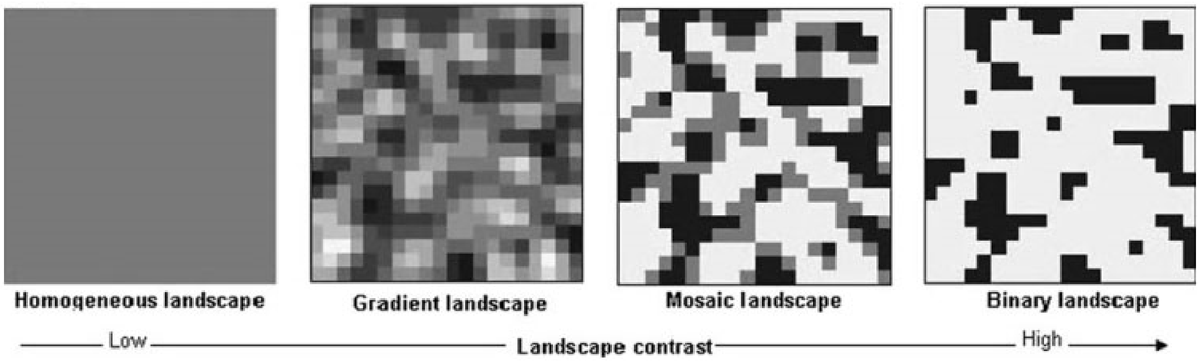

Figure 3.15: Four landscape models (homogeneous, gradient, mosaic and binary model) along the dimension of landscape contrast (source: Biswas and Wagner, 2012).

Of relevance to the contrast of vegetation cover, the "dissimilarity" or "edge contrast weight" is derived from the difference in height among habitats. Such differences have rather easily deducible ecological consequences. For example, in the form of passive dispersal, seeds will accumulate on the forest boundary as plants dispersed by wind; or the "terrain barriers" can act as obstacles for the movement of certain species. The ecotones can reduce the edge contrast value on both forest and field edges. Human facilities, such as traffic roads, are considered as barriers which present high contrast and may be assigned with the highest edge contrast value. In particular, the degree of patch contrast may influence species dispersal patterns, and thus indirectly affect the degree of patch isolation. The forest along a transition zone is less isolated than along the bare soil (agriculture land) (see Figure 3.6).

Figure 3.16: Contrast magnitude along patch edges (Photos: Wei Hou).

In this context, a height-based variant of the Edge Contrast Index (ECON) (Hoechstetter, 2009) has been used for characterizing patch contrast (Equation 12). ECON equals the sum of the patch perimeter segment lengths p_k multiplied by their corresponding contrast weights (d_k), divided by the total patch perimeter (p), then converted into a percentage value (multiplied by 100). The dissimilarity value d_k assigns values between 0 and 1, with a value of 0 being assigned to the minimum difference in mean elevation between two adjacent patches. Conversely, a value of 1 is assigned to the maximum mean elevation between two adjacent patches, edge segments along the landscape boundary are assigned d_k =0. Afterward, on a higher level (class level or landscape level) the edge effect can be measured by Total Edge Contrast Index (TECI). Like its patch-level counterpart, this index quantifies edge contrast as a percentage of the possible maximum (McGarigal et al., 2012). However, this index ignores patch distinctions; it quantifies edge contrast for the landscape as a whole. Therefore, it is helpful to quantify the edge contrast from the perspective of landscape configuration. On the landscape level, the Area-Weighted Edge Contrast (AWEC) can be defined as average dissimilarity in vertical structure of habitats (Equation 13). It is not only an accumulation of the edges' contrast value; meanwhile the area proportion of each patch is also incorporated. This area-weighted index may be more appropriate than the unweighted mean index, since larger patches play a dominant role in the landscape dynamics. Otherwise, small patches will have an equal effect on the average edge contrast index, when in fact they play a disproportionately role in the overall landscape contrast. This index can also be applied in landscapes differing in total size and with differing proportions of habitat patches. The lowest value of AWEC is 0 when the whole landscape is considered as one patch (landscape boundary is assigned with dissimilarity of 0), and the highest value is 1 as all patches have hard edges (maximum dissimilarity). Generally, lower landscape contrast are more conducive to animal dispersal; but it depends on the species, for example, the field rat is known to invade disturbed habitats, e.g. fragmented forests (Gibson et al., 2013).

Equation 12: $$ECON = \frac{\sum_{k=1}^{m}(p_k \times d_k)}{P} \times 100,$$

p_k : edge length of segment k;

d_k : contrast weight of segment k;

P : total patch perimeter;

m: number of patch segments.

Equation 13: $$AWEC = \frac{\sum_{i=1}^{n}(a_i \times ECON_i)}{A}$$

n: number of patches in the landscape;

a_i: area of patch i;

$ECON_i$: the edge contrast value of patch k, see Equation 12.

A: area of the total landscape.

3.3.2 Habitat connectivity analysis considering small biotopes as stepping stones

As concluded in chapter 2.1.3.1 the common ecological function of all small biotopes (scattered trees, tree rows, hedges, and copses) is to enhance the landscape connectivity either as a stepping stone or as a corridor. In general many small, less mobile species require corridors at a small scale where migration and commuting movements are measured in hundreds of meters. Within the ecological network, connectivity can be measured by interpatch connectivity and intrapatch connectivity. The concept of intrapatch connectivity takes the patch itself as the place where the species interactions happen and it actually has the same meaning of effective mesh size. Thus, intrapatch connectivity can be measured in the same way as habitat fragmentation (see chapter 3.3.1.2). The connection among patches is defined as interpatch connectivity, which is concerning on the linkages among habitats or the different components of landscape (e.g. amount and configuration of vegetation). The size of connected patches indicates the availability of the habitat within a reachable distance (Saura et al., 2011; Saura and Pascual-Hortal, 2007). In the following, the ecological network (econet) for woody habitats is firstly established using small biotopes as stepping stones. In the next step, the relevant metrics will be developed based on the econet for describing landscape connectivity including both the interpatch and intrapatch connectivity.

3.3.2.1 Mapping ecological network

There are several models available for mapping landscape connectivity, such as the Morphological Spatial Pattern Application (MSPA) of the GUIDOS software for mapping the morphological shapes of forest (Vogt et al., 2007a). GUIDOS can be applied either on a forest map (Vogt et al., 2007b), or on the simulation of a species movement map (Vogt et al., 2009). The limitation of this algorithm is that it can only be used for binary land-cover maps without consideration of the effects of other components of the econets, e.g. stepping stones and barriers. Graph theory has frequently been used for corridor design and nature conservation planning (Erős et al., 2012; Galpern et al., 2011; Luque et al., 2012; Minor and Urban, 2007), simplifying landscape structure as a graph consisting of a set of nodes (habitats) and links (connections). The links between each pair of patches are defined as landscape permeability that describes the probability of species migration within landscape. A problematic aspect of applying graph theory is the uncertainty to calculate functional links (Awade et al., 2012), because they are dependent not only on species movement but also habitats spatial distribution.

An econet can be geared towards either habitats or species (Jongman, 2007). For the work at hand, the intention is not on any particular species but the entire habitat pattern, typically on woodland habitats. Besides forest patches as the main component of this econet, the small biotopes (tree row, hedge, copse, scattered tree) are considered as stepping stones and open field (including grassland and farmland) are considered as permeable area for species dispersal. A method called "multi-buffer" algorithm developed by Hänel (2007) is adopted for mapping connections among woody habitats through stepping stones. The conceptual model (see in Figure 3.17) shows that the connections between patches are created in a "buffer and shrink" process. It is necessary to incorporate the small biotopes for mapping the econets, since they can act as stepping stones to build the connections between the large patches that are far from each other. Moreover, the connected patches can be treated as patch clusters for the next buffering process using a further buffer range. This "multi-buffer" process is implemented in ArcGIS 9.2 software as following:

(1) Buffering all woody patches including forest and small-scale biotopes with an outer or positive buffer range;

(2) Shrinking the buffered elements (see step one) with an inner or negative buffer range (same as the buffer range in step one). Connections are kept among patches if they are in close proximity or with small biotopes between them;

(3) Using the connections to identify connected woody habitats. If they are adjacent to the same connection, then they belong to the same forest cluster. The connection is considered as designated corridor and the identified small biotope inside forest cluster is considered as stepping stone;

(4) Using barriers to intersect the connections established in step 3. If the connections are not overlapping with barriers, they can be considered as a forest cluster. Otherwise, the connection will be cut by the barriers.

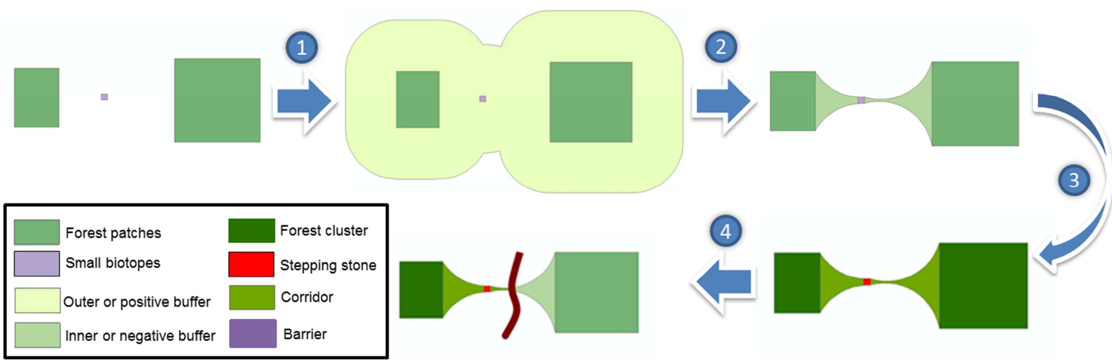

Figure 3.17: Conceptual schema for mapping the designated forest econet (Reproduced and altered according to Hänel, 2007).

Comparing to the graph theory the multi-buffer approach considers habitat connectivity from the perspective of habitat spatial pattern and doesn't refer directly to species (without the assumptions on species movement for estimating the permeability among patches). In this case spatial connections are dependent on the smallest distance between the patches and the patches topology, e.g. the ratio of opposite edge lengths of patches. The form of the connections has also ecological meaning for representing the flux among the patches (Figure 3.18). As a result, it gives a visualized econet maps based on the buffer ranges.

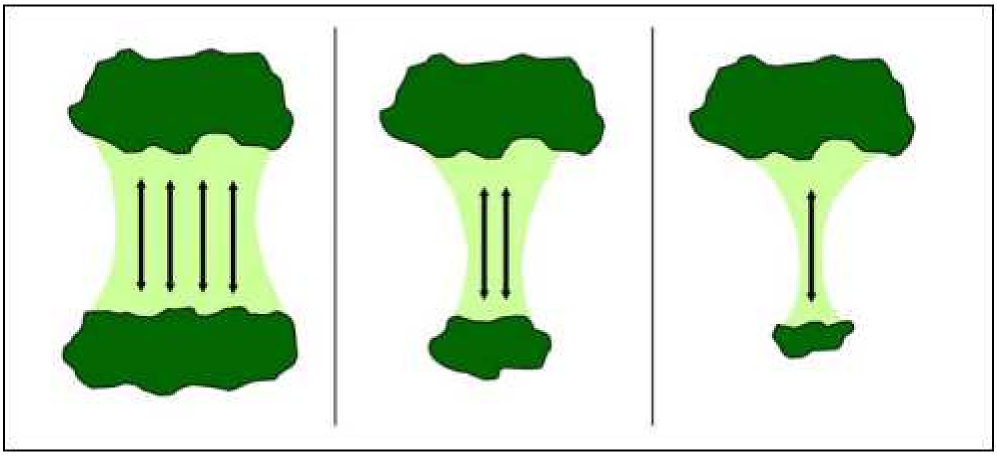

Figure 3.18: Influence of different shapes of patches within same distance on the potential corridor form: larger shapes result in wider corridors (adapted from Hänel, 2007).

3.3.2.2 Indicators for assessing ecological networks

Based on the econet map valuable information can be derived, for example the gaps in ecological network (Bianchin and Neubert, 2013). In addition to the visualized result, also quantitative indicators can be derived from the econets map. In the following, three indicators are developed from the perspective of structural connectivity.

The simple spatial metrics counting the number of connections, e.g. connectance index (McGarigal et al., 2012), are not sufficient for landscape connectivity analysis, sometimes even misleading. A fragmented landscape could have more connections than a homogeneous landscape, but it does not mean better habitat connectivity. The key is to measure the habitat area that is reachable for species, which means not only connections between patches (interpatch connectivity), but also the area within habitat patches (intrapatch connectivity) has to be taken into account (Saura and Pascual-Hortal, 2007).

The second indicator of the City Biodiversity Index (CBI) was formulated based on Effective Mesh Size (Jaeger, 2000) at the First Expert Workshop on the Development of the CBI in

February 2009, Singapore[14]. This indicator is designed specifically for monitoring and measuring connectivity in cities, but without the consideration of corridor areas. Applying this indicator on the econet map, the result can be interpreted as effective connected mesh size, containing both intra- and inter-patch connectivity. To differentiate the use of this indicator on econets, it is named as Effective Connected Mesh Size (ECMS). Calculation of this metric is relatively simple, see Equation 14. It was assumed that the woody patches connected by corridors constituted an integrated patch cluster. In this case, the patch cluster is considered to be one patch in the established econet. ECMS equals the sum of cluster area squared, summed across all forest patches and corridors within the cluster, divided by the total landscape area, then divided by 10,000 (to convert to hectares). The value of ECMS for habitat is dependent on two conditions: how well are the habitat patches connected and how big is the area proportion of the connected habitat taken in the whole landscape.

Equation 14: $$ECMS = \left(\frac{\sum_{k=1}^{n} a_k^{\,2}}{A} \right) \times \frac{1}{10000}$$

n: number of forest clusters (connected forest patches including corridors) within the ecological network;

a_k: area of the integrated woody patch k;

A: total area of whole landscape.

Range: ratio of cell size to landscape area < ECMS < total landscape area (A)

For a specified buffer range the areas of connections imply the flux between the patches (see Figure 3.18). Therefore, the Corridor Area Percentage of Econet (CAPE) can be considered as an indicator for estimating the intensity of interactions among habitats (interpatch connectivity). This index is calculated simply as the ratio of corridor area and the area of habitats in the analysis (see Equation 15). Using the “multi-buffer” process, the econet could be established on different buffer ranges. The change rate of CAPE between two buffer ranges (k, k-1) shows the econet inner structure in terms of the distance among forest patches (Equation 16).

Equation 15: $$CAPE = \frac{\sum_{j=1}^{m} a_j}{A_{econet}} \times 100\%$$

m: number of corridors

[14] http://www.cbd.int/authorities/gettinginvolved/cbi.shtml (Accessed October 13, 2014)

a_j: area (m^2) of corridor i based on specified buffer range;

A_{econet} : total econet area (m^2).

Range: 0=<CAPE<100

Equation 16: $$dCAPE_k = \frac{CAPE_k - CAPE_{k-1}}{CAPE_{k-1}} \times 100\%$$

3.4 Summary

The enhancement for landscape structure analysis comes from two aspects. First is to tap into the potentials of available data to further explore the detailed landscape structure. The combination of RapidEye images and lidar data can fulfill the needs of both spectral and spatial resolution for landscape monitoring and yield valuable information of landscape composition on different spatial scales. In addition, the lidar data offers the possibility to get the features of landscape elements in three dimensional perspectives. After that, these detailed landscape elements (small sized habitats and ecotones) are incorporated into the modified landscape metrics or newly developed indicators. These detailed structures serve as complementary components which may affect the whole ecological functions of landscape. Therefore, the method developed in this chapter can result in a more realistic simulation of the landscape structure

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4 Examples of use and results: application of the proposed methodology in test sites of Germany and China

In the previous chapters, the importance of small biotopes and ecotones for the ecological functions of the landscape and how they can be incorporated in existing methods for landscape structure analysis have been demonstrated. In order to give an insight into the applicability of the proposed methods described in chapter 3, they have been tested in various situations and at different spatial scales based on the available data.

4.1 Study areas and data basis

Two test sites in Germany and China are chosen for the application of the proposed method. The German test site is located in eastern Germany, around the village of Rathen, forming part of the German national park “Saxon Switzerland”. It is a mountainous area largely covered by forest, encompassing several types of land use structures and classes, mainly including rural settlements and surrounding agricultural land, and the river Elbe (Figure 4.1).

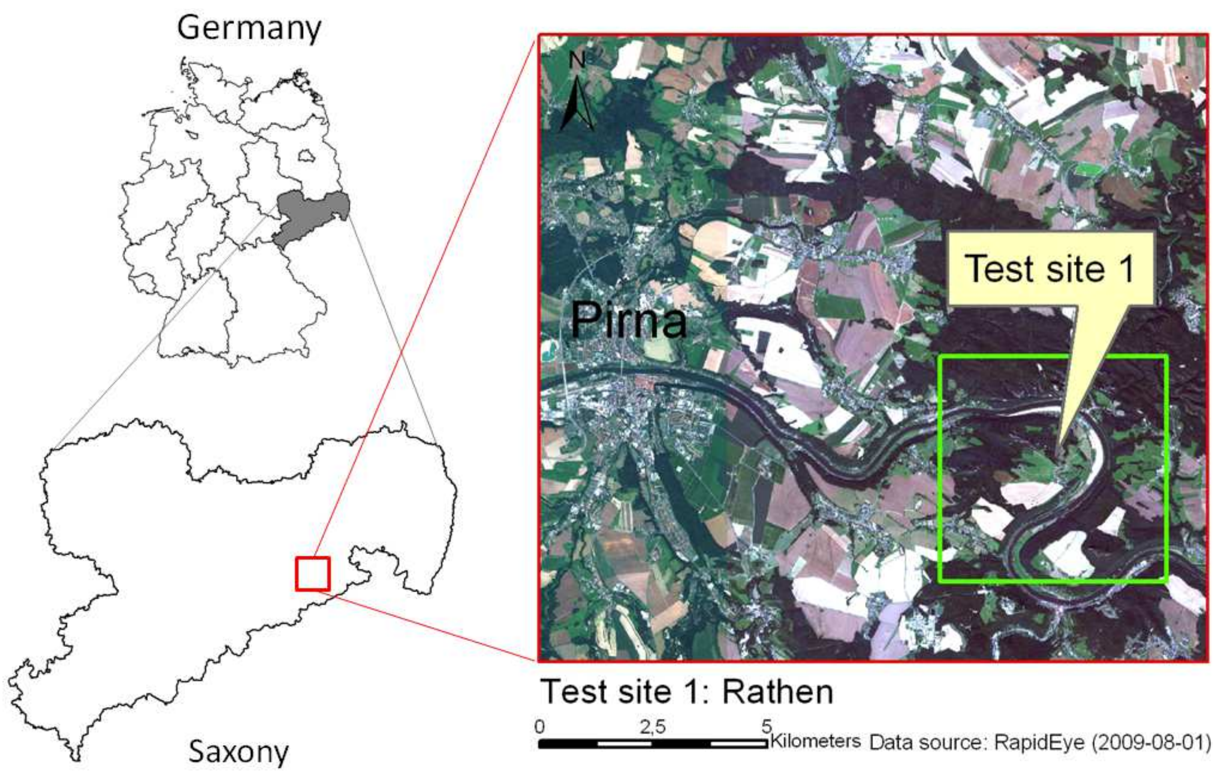


Figure 4.1: Location of the test site Rathen. Left: sketch maps of Germany and the Free State of Saxony locating the test site; right: true color composition of the RapidEye image.

The Chinese test site is located in the suburban area Jiawang district in Jiangsu province, which is a post mining area, barely forested and largely used for agriculture. The terrain in this region extends from low hills in the north to plains in the south, with a branch of the Beijing-Hangzhou Grand Canal crossing the area from west to east. Long and intensive mining has had a tremendous impact on the environment, causing ground subsidence and destroying arable land. From the beginning of this century, the closure of coal mines has given greater scope for environment restoration such as farmland reclamation and fish pond construction in subsidence areas. The intensive anthropic activities have greatly changed the landscape structure in this region (Figure 4.2).

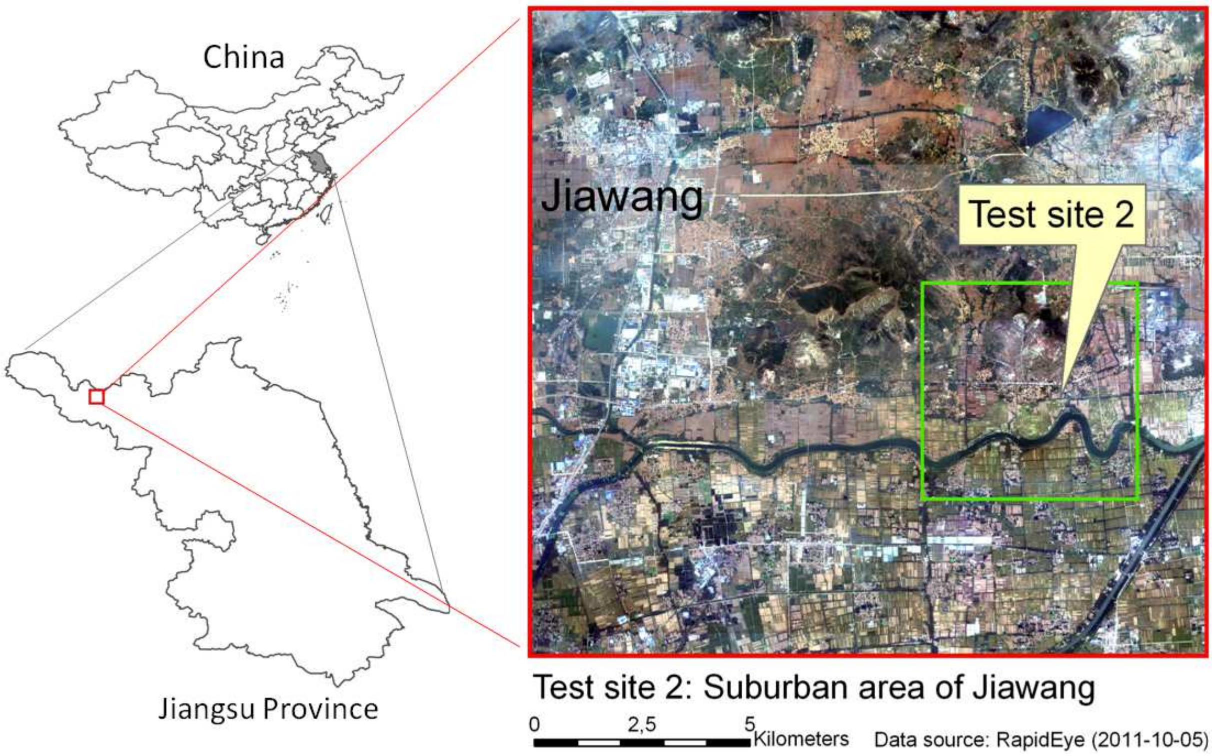


Figure 4.2: Location of the test site Jiawang. Left: sketch maps of China and Jiangsu province locating the test site; right: true color composition of the RapidEye image.

Both of the two test sites cover the same extent (5km × 5km) and possess similar land-cover types, but great differences in proportion. In the two test sites RapidEye images are collected, but the lidar data is only available in the German test site. Therefore, the detailed landscape structure analysis considering small biotopes and ecotones is only conducted in test site 1. The object-based image classification is applied on RapidEye images in both test sites and their landscape pattern are compared at the same spatial scale. For extraction of settlements and traffic roads the official land-use data are adopted. For spectral testing samples and classification training, ancillary data are used, such as a digital biotope map, high resolution satellite images or aerial photos. An overview of the data used in the two test sites is shown in Table 4.1.

Table 4.1: Overview of the data used for the test sites

	Test site 1 (Rathen)	Test site 2 (Jiawang)
RapidEye images	Acquired on dates of 2009-05-25; 2009-08-01; 2009-08-31; resolution 5 m.	Acquired on dates of 2011-05-14; 2011-06-01; 2011-10-05; resolution 5 m.
Digital elevation model (DEM)	Extracted from last pulse of lidar data (collected during April to May in 2005); resolution 1 m.	Calculated from official topographic map (2004); resolution 5 m.
Digital surface model (DSM)	Extracted from first pulse of lidar data (April to May in 2005); resolution 1 m.	n/a
Land-use data	ATKIS land-use data (2009); scale 1:25.000.	Land-use map (2004) available from Jiawang District Planning Bureau.
Auxiliary data	Aerial images (April to May in 2005) acquired from lidar system; resolution 0.5 m. Biotope map (2005); scale 1:10 000.	QuickBird image (2009); resolution 0.6 m.

4.2 Object-based image classification

Image classification is the first step of the analysis of landscape structure, as it converts the raw pixels into patches. In the following chapters the RapidEye data of both test sites is classified according to the procedures outlined in chapter 3.2.1. Since the landscape composition is similar in two test sites, the established classification rules on one test site can also be applied on the other one with minor adjustments.

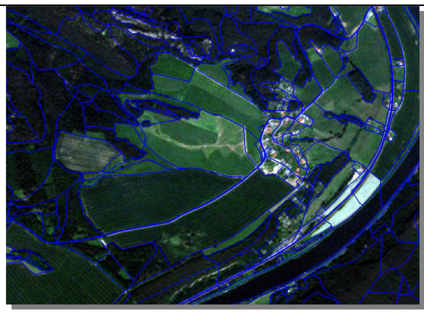
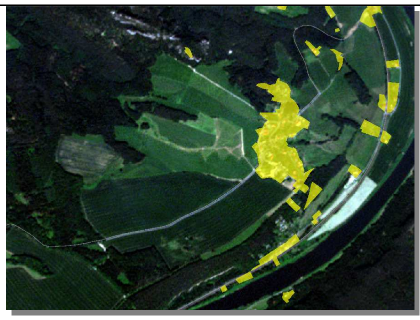
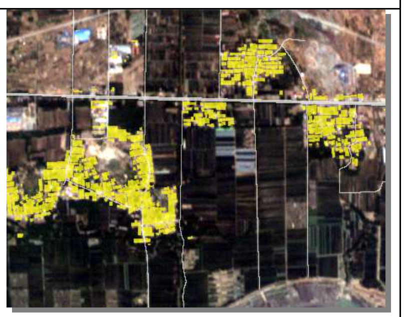
4.2.1 Classification of main classes

The first aim of this work is to classify the main land-use classes shown in the class hierarchy (see Figure 3.9). The classification strategy also follows the class hierarchy, which begins with the land uses on a higher level. The result has a similar spatial scale like ATKIS data and will be used as a base map for further detection for the detailed landscape elements.

4.2.1.1 Settlement and traffic extraction

It is often the case that rural settlements show no distinct border with their surrounding area and traffic areas are covered by roadside trees in the Remote Sensing image. A sound solution for the artificial area extraction is to use the existing land-use maps which are manually produced. In the first step of work the official land-use maps in both test sites are incorporated as thematic layers for image segmentation and classification. The chessboard segmentation algorithm is used to produce segmentation level1. In this algorithm the parameter “object size”, which determines the size of segments, should be set sufficiently high to constrain the border of segments identical to the settlement class and traffic class in land-use maps. Then the image objects are classified according to the attribute from the land-use maps (Table 4.2), e.g. in test site1 objects are classified as settlement where the attribute from ATKIS is “2101”.

Table 4.2: Exemplified results of segmentation and classification for the artificial areas in the two test sites.

Segmentation and classification results (level1)		
	Test site1 (Rathen)	Test site 2 (Jiawang)
Chessboard segmentation: land use map as thematic layer; object size 10000		
Settlements and traffic roads classification according to the land-use type in thematic layers		

4.2.1.2 Assessing scale parameter for segmentation

For classifying the main classes, a lower segmentation level2 is created by means of Multi-Resolution Image Segmentation (MRIS) which aims to supply the “building” objects for all classes (see in chapter 3.2.1.3). It means the scale parameter in MRIS should be small enough to separate the pixels belonging to different classes. The tool Estimation of Scale Parameters (ESP) (Drăguţ et al., 2010) is employed for capturing the finest scale parameter. It uses local variance (LV) graphs to reveal the multi-scale structure of images. LV equals to the average value of standard deviation of image segments. To observe the optimal scale parameter of the inflection point of LV, rate of LV-change (ROC=rate of change in local variance between the scale level of interest and previous one) will be graphed. This graph describes the LV value changing along a given scale array. The inflection points on LV graph indicate the potential scale parameter for the image segmentation. However, this tool only applies on a single spectral band. The scale parameter calculated from one band will neglect the spectral information of the others. In practice, the estimation result of ESP can be used as a reference value for the parameter set in MRIS. In test site1, all bands from the RapidEye image of May 25th have been individually tested in ESP. All other parameters are held constant (shape 0.1 and compactness 0.5). Figure 4.3 shows the values of LV and ROC against scale levels. The smallest scale parameter is defined as the first break in the ROC-LV curve after continuous and abrupt decay. Such a threshold can appear as a small peak. For test site1, the finest scale 22 obtained from the blue and red edge band is set in MRIS (Figure 4.3 c, d). In the case of test site2, the same procedure has been applied on the image of May 14th and the finest scale 12 is observed. Table 4.3 gives an impression of segmentation results after applying MRIS in the two test sites with the parameters estimated from ESP.

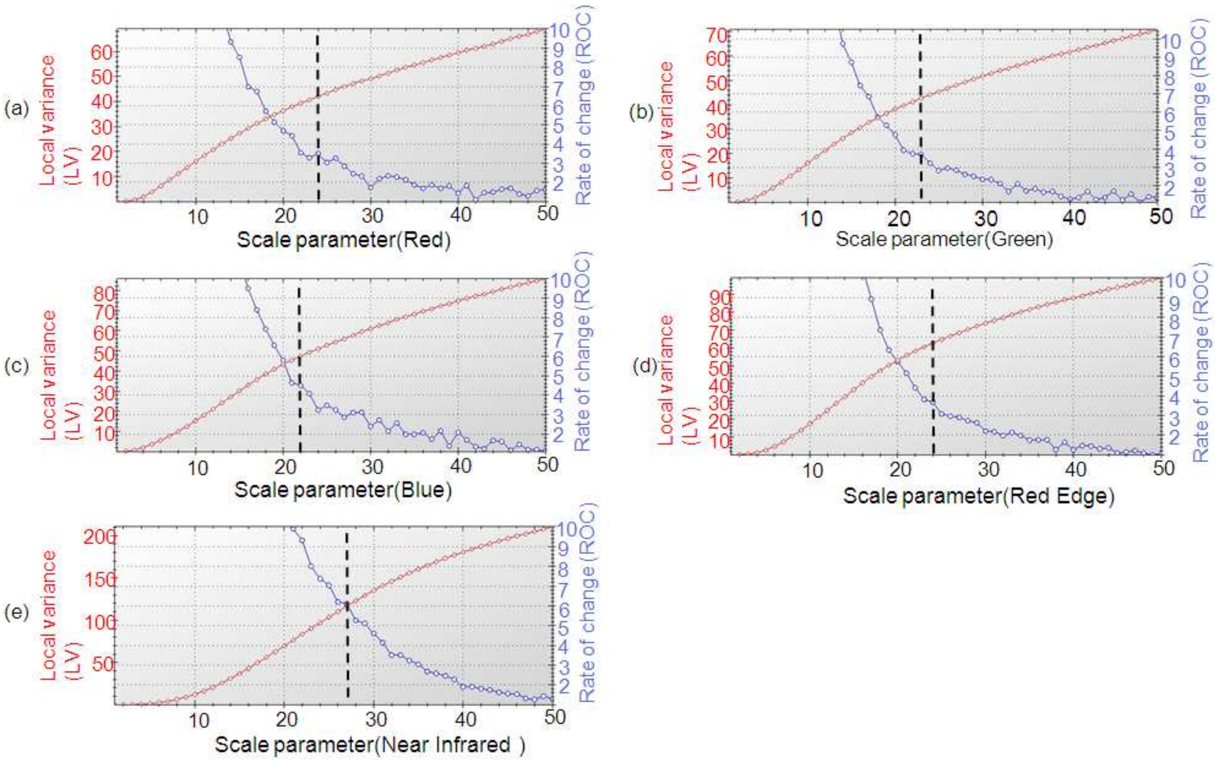
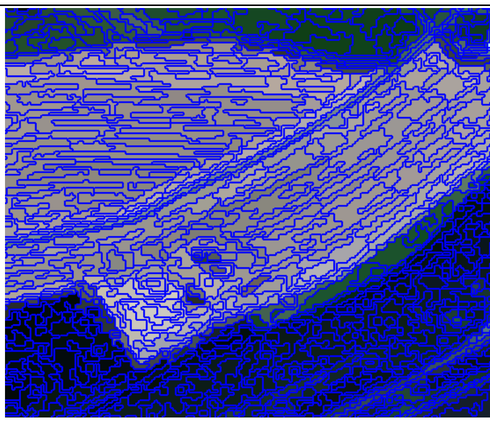
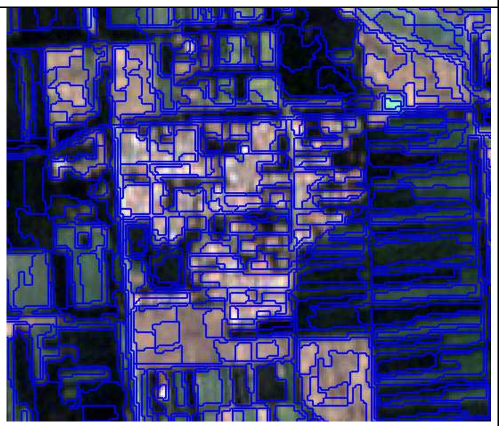


Figure 4.3: Outputs of scale parameter estimation of ESP tool: (a) on red band: scale ≈ 24; (b) on green band: scale ≈ 23; (c) on blue band: scale ≈ 22; (d) on red edge band: scale ≈ 22; (e) on near infrared band: scale ≈ 27.

Table 4.3: Parameter sets and exemplified results of applying MRIS for RapidEye images on level 2.

Segmentation on level2		
	Test site1 (Rathen)	Test site2 (Jiawang)
MRIS parameter	Scale=22; Shape=0.1; Color=0.9; Compactness=0.5; Smoothness=0.5	Scale=12; Shape=0.1; Color=0.9; Compactness=0.5; Smoothness=0.5
Segmentation result examples		

4.2.1.3 Classification process

Figure 4.4 shows the applied processing chain in test site 1, which follows “left-right”, “top-down” sequence. For both test sites the settlement will be firstly classified on the segmentation level1. Then the rest main land-covers are classified on level2. The classification follows the class hierarchy from top to down (Figure 3.9). After the extraction of settlement on segmentation level1, rule-based classification is carried out at two segmentation levels and detailed rule sets are shown under each class. Firstly the land-covers are easily identified, for example the water area can be classified by NDWI (McFeeters 1996) and other land surface is divided as non-vegetation and vegetation by NDVI. Next, the vegetation objects will be further classified into sub-classes (forest, grassland, crops) based on the changing REVI value in May and August. In the end, all adjacent objects of the same classes are merged to form land-cover polygons and the three crops are merged as one farmland class.

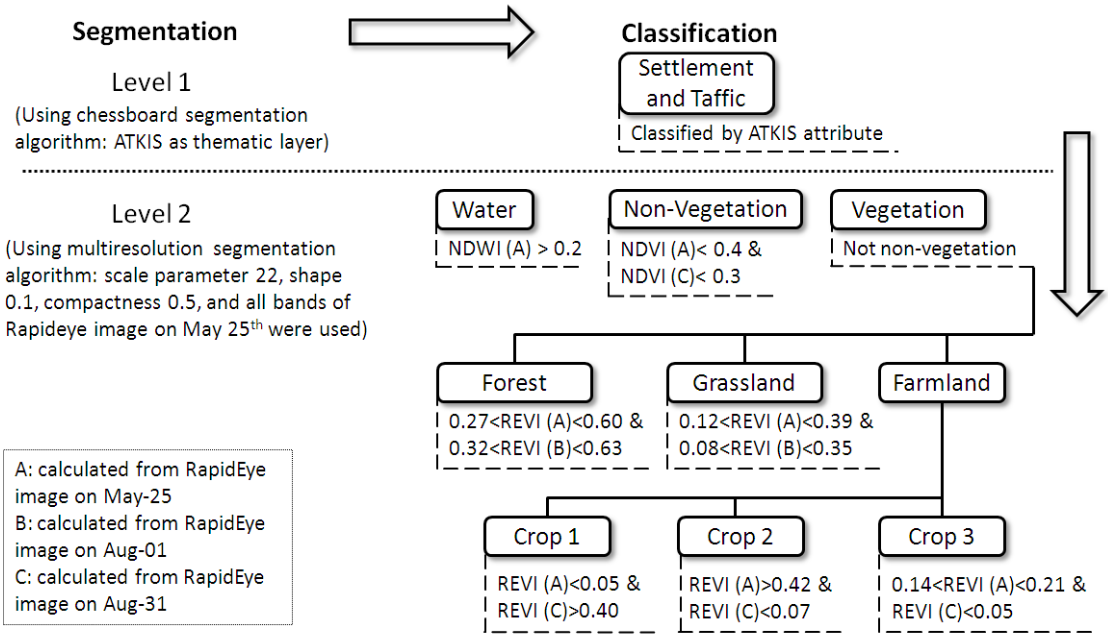


Figure 4.4: Process for the classification of the main land-covers in test site Rathen.

Since the main land-cover types are similar in the two test sites, the same classification procedure can be applied for test site2, but the parameters for class memberships should be adapted to the local situation. Using the same segmentation strategy and multi-temporal classification approach, main land-cover maps for both test sites can be produced (see Figure 4.5).

However, the landscape configuration in two test sites remains quite different. In test site Jiawang, there are four types of crops which account for the largest proportion of the landscape. Sparse vegetation covers the north hilly area and many scatted woody patches are distributed in the agriculture area. Compared to the test area of Rathen, the landscape of Jiawang is more affected by human activities.

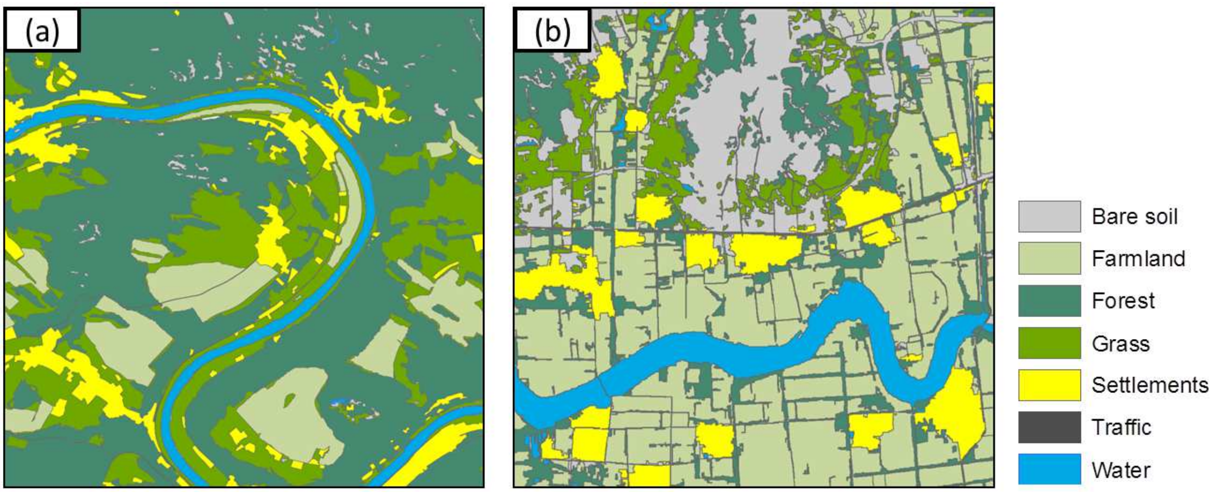


Figure 4.5: Main land-cover maps for Rathen (a) and Jiawang (b) test sites.

4.2.2 Further classification of detailed land-cover classes

The further classification is mainly applied on vegetation covers. Based on the previous classification result, the very specific measurements can be performed on the chosen object domain. In this detailed land-cover map, forest is classified as coniferous, broad-leaved, and mixed forest; farmland plots are delineated according to crop types; and settlements are divided into sealed and unsealed area. The classification processes for these sub-classes are presented in the following.

4.2.2.1 Detailed classification within settlements

Within settlement area all pixels are segmented and classified by the multi-threshold segmentation algorithm which is applied on the NDVI layer. For example, in test site of Rathen pixels which have a NDVI value greater than 0.38 (calculated from the image of May 25th based on the test samples of settlements) will be segmented and classified as unsealed area (Vegetated covers) and the rest part within rural settlement is classified as sealed area (e.g. house roof, bare soil, and road) (see Figure 4.6 (a)). Similar approach is also applied in test site of Jiawang (Figure 4.6 (b)). This step is simply used for describing the land covers inside the settlement and the result will be used in the step of econets analysis.

Figure 4.6: Examples of classification within settlements in the test site Rathen (a) and Jiawang (b).

4.2.2.2 Farmland plots delineation

In the process of main land-cover classification, the crop plots have been classified (see Figure 4.7 a), and then combined to form the farmland class. However, in order to extract the accurate border of farmland plots, more detailed measurement could be applied within the farmland area. In this case, the sobel filter is used on the NDVI layer (Figure 4.7 b) for edge extraction. The result highlights the edges between farmland plots (Figure 4.7 c). Using this filtered result, the edges between plots can be segmented by means of multi-threshold segmentation (Figure 4.7 d). Then the rest farmland objects will be segmented again using multi-resolution image segmentation for creation of the sub-level of farmland (Figure 4.7 e). In this segmentation, REVI layers are set as the input data and scale parameter could be estimated by ESP tool. Finally, all objects within farmland including edges will be classified again by the multi-temporal approach. The result (Figure 4.7 f) after edge extraction shows the borders between farmland plots smoothed and more accurate than before (Figure 4.7 a). In the case of test site Jiawang, it contains four crop types and the farmland plots are smaller than in Rathen, but the same delineation method can be applied in this region for detailed farmland classification.

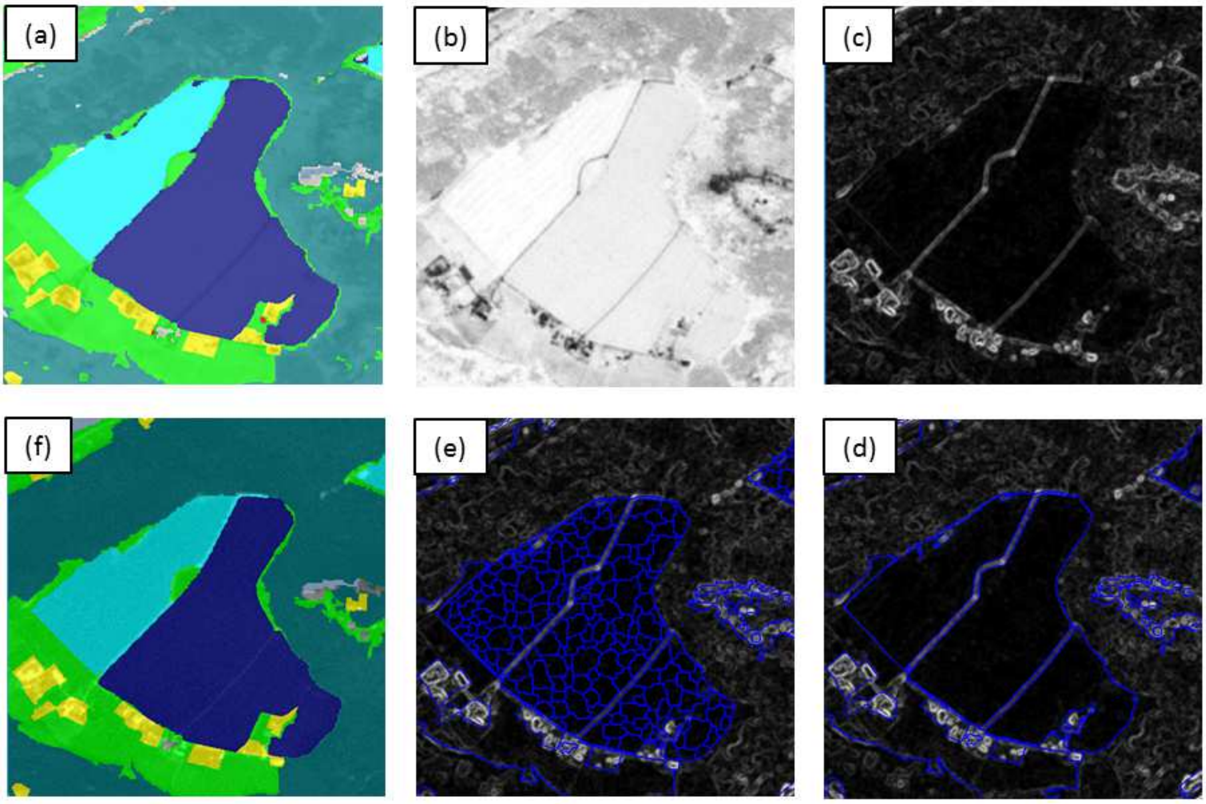


Figure 4.7: Delineation of farmland plots exemplified in the test site Rathen: (a) classification of farmland plots without edge detection process; (b) NDVI layer calculated from RapidEye image on May 25th; (c) the result of applying sobel filter on NDVI layer; (d) edge extraction of farmland plots using multi-threshold segmentation; (e)

segmentation on farmland plots except edges; (f) classification of farmland plots after edge extraction.

4.2.2.3 Detailed classification within forests

In the previous steps, the classification approaches are basically the same for the two test sites. But the processes for further classification in forested areas are different, since the forest patterns of the two test sites are different from each other. In the test site of Rathen forest is relatively compact which is composed of different sub-classes, e.g. coniferous, broad-leaved, or mixed forest. In the test site of Jiawang the forest cover is mainly coniferous forest which is dispersed widely in the field. In addition, the high resolution lidar data for small biotopes detection is only available for the test site of Rathen. Therefore, the attempt of further forest classification in Jiawang is to identify the small woody habitats based on the RapidEye data.

Within the Rathen area all forest patches smaller than 1 ha will be dissolved to the surrounding patches and the rest forest patches are aimed to be classified into the forest sub-classes. Spectral analysis in previous chapter has shown that NDVI is more suitable for classifying the forest sub-classes than REVI (see Figure 3.8). Before classification, a sub-level of image objects is created by MRIS which is applied on the forest cover. NDVI layers are mainly used as the input data in MRIS and the scale parameter should be set relatively small for separating the pixels belonging to different forest sub-classes. To differentiate the forest sub-classes, the fuzzy classification approach is adopted and NDVI is used as the key feature for defining the membership functions of the sub-classes. Samples from each class are selected from the biotope map and used for the estimation of membership functions in each class. Figure 4.8 shows the estimation result of membership functions of each class. Horizontal axis stands for the NDVI value and vertical axis describes the membership value: 0 means not a member of the corresponding class; 1 means totally belonging to the class. This figure indicates that from May to August the NDVI difference among the three sub-classes decreases as the overlapped area of their membership functions increases. At the end of August the mixed forest is hard to distinguish from other two classes. Thus, the NDVI features acquired on May 25th and August 1st are used to define the membership function of forest sub-classes. This fuzzy classification approach may result in uncertain boundary among these sub-classes.

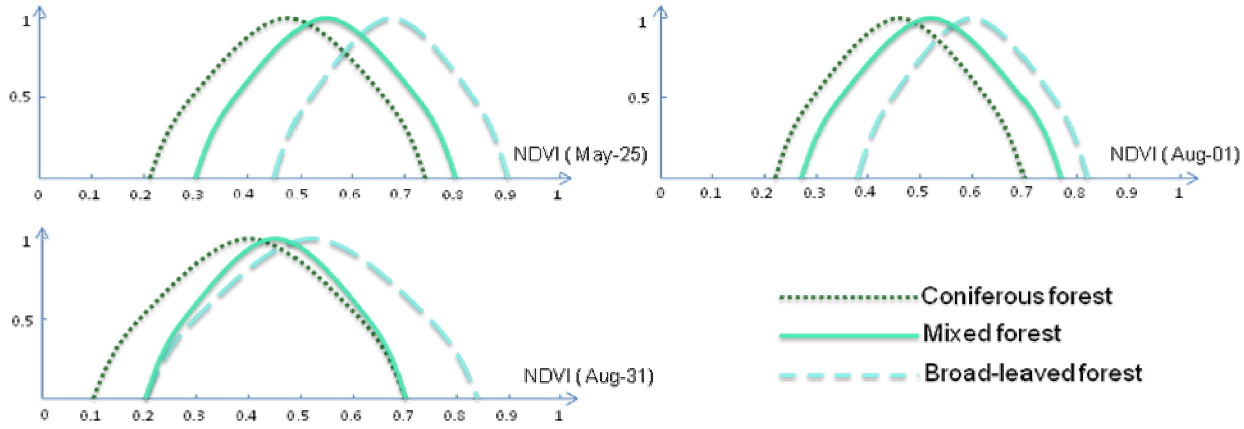


Figure 4.8: Definitions of membership functions (using NDVI feature) for forest sub-classes for the Rathen test site using three acquisition dates.

On the other hand, the forest in Jiawang will be further classified according to their areas and neighborhood. The small woody patches located near to settlement or within farmland are classified as groves; patches within the groves smaller than 1 ha are classified as copse; the rest mainly covering the hilly area is considered as native forest habitat. The final results of the detailed forest classification in the two test sites are shown in Figure 4.9.

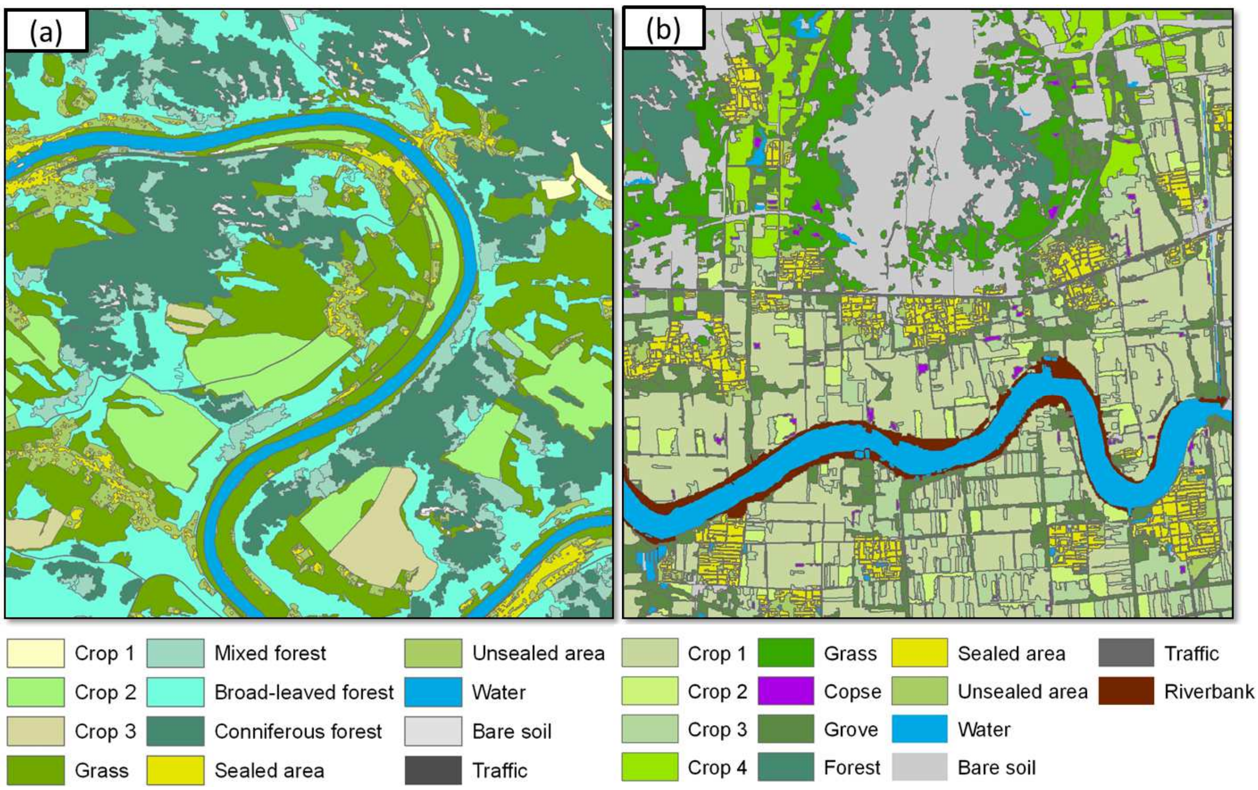


Figure 4.9: Detailed land-cover maps for Rathen (a) and Jiawang (b) test sites.

4.2.3 Accuracy assessment

4.2.3.1 Classification accuracy in test site Rathen

For the main land-cover map, the ATKIS data is used as a reference to assess the accuracy of classification. Since settlements and traffic are extracted from ATKIS layer, there is no need to assess their classification accuracy. A symmetrical difference analysis between the classification result of the main classes and ATKIS (Figure 4.10) shows that most of the different areas between the classification results and ATKIS are located at vegetation borders. The ATKIS data is mainly based on manual delineation; the boundaries between patches are regular and sharp. Transition zones are sensitive to the location of boundaries; so the sharp ATKIS boundaries may not be suitable for detecting transition zones. In a next step, confusion regions in vegetation classes can be identified by intersecting the differences from the last step (red circle areas in Figure 4.10). For these confusion regions, an onsite investigation confirmed that there are some misclassified areas, and also areas where official ATKIS data is not up to date.

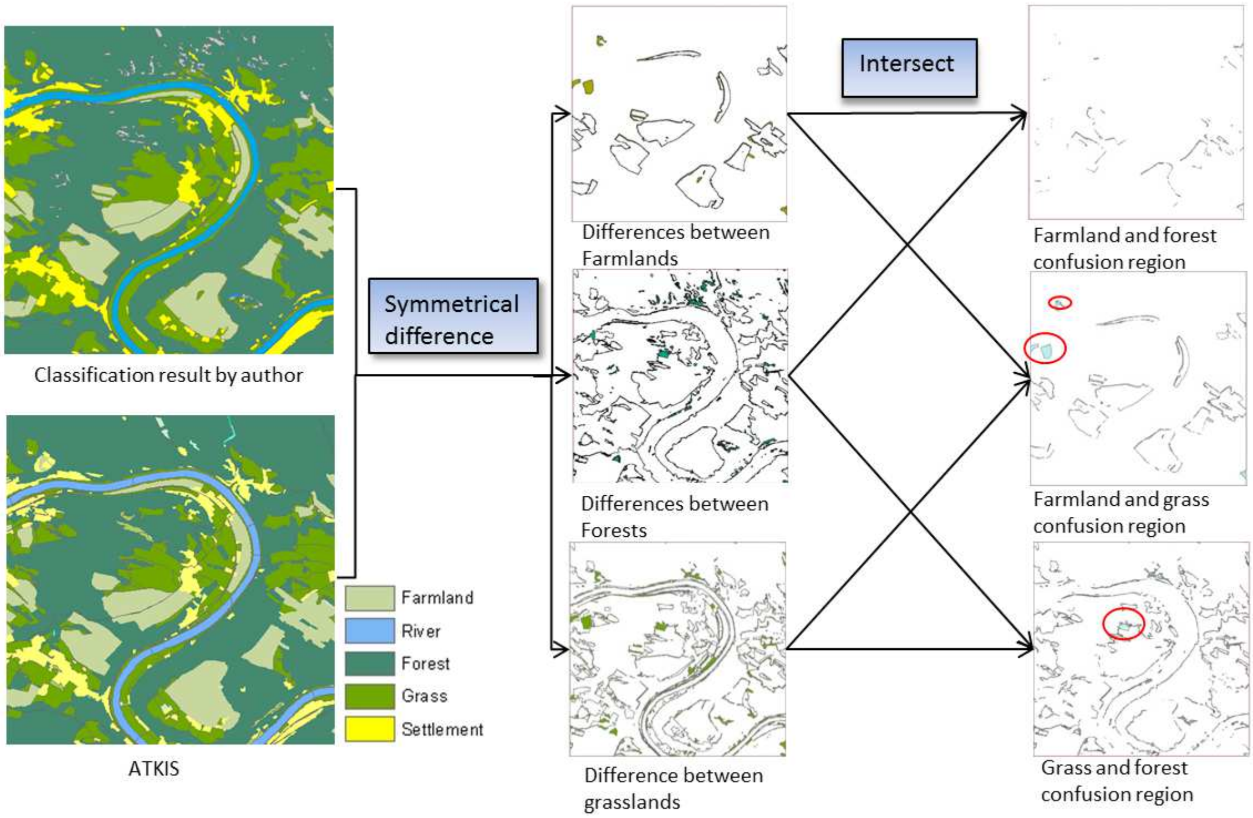


Figure 4.10: Comparison between ATKIS data and classification results on the main level based on RapidEye imagery (symmetrical analysis for each vegetation class between ATKIS and classification result; then, intersection of these differences for each two classes to obtain the confusion regions between them).

In order to assess the classification result on the detailed level, 500 stratified random points were selected as reference confirmed by a high resolution aerial image and a biotope map. Table 4.4 shows the accuracy assessment. The overall accuracy on the main level is 0.92, which is higher than the accuracy on detailed level. The multi-temporal approach allows precise classification of farmland plots and forest, but the accuracy of grassland classification is lower than for other vegetation types (grassland has the most confusion regions with other vegetation, see Figure 4.10). This may be because the classification process treats grassland as consistent vegetation without significant seasonal change. In reality, however, some grass plots were mowed or changed their color due to dehydration during summer, which may lead to misclassification between grassland and farmland. The classification accuracy on detailed level indicates that the resolution of RapidEye imagery maybe not enough for the detection of rural settlement structure and the fuzzy classification approach for forest sub-classes can result in some uncertainty, especially for mixed forest and broad-leaved forest.

Table 4.4: Accuracy assessment for classification on the main and detailed levels in Rathen.

On main level	Bare soil	Grassland	Farmland	Water	Forest
Producer accuracy	0.63	0.83	0.97	0.97	0.96
User accuracy	0.83	0.87	1	0.85	0.95
Overall accuracy	0.92				

On detailed level	Unsealed area	Sealed area	Crop1	Crop2	Crop3	Coniferous forest	Broad-leaved forest	Mixed forest
Producer accuracy	0.96	0.62	1	0.95	0.98	0.88	0.89	0.79
User accuracy	0.86	0.80	1	1	1	0.96	0.76	0.87
Overall accuracy	0.89							

4.2.3.2 Classification accuracy in test site Jiawang

In the test site Jiawang, 500 stratified random points were selected as reference for the accuracy assessment. Since the existing land-use data and QuickBird image are comparatively older than the RapidEye images, Google Map is also employed for the confirmation of the reference points. Because the settlement is extracted directly from the official land-use data, the classification accuracy of settlement is not assessed. Table 4.5 shows the result of the accuracy assessment on both main and detailed classification levels. In this region the bare soil is located between forest and grassland. For the main land-cover classes, the confusion regions are mostly among forest, grassland, and bare soil. On the detailed level, the farmland plots are much smaller than in Rathen. The small groves and copse are densely distributed among the plots, which can cause misclassification between the crops and the small biotopes. This non-uniform farmland pattern results in low classification accuracy for farmland plots (see Table 4.5).

Table 4.5: Accuracy assessment for classification on the main and detailed levels in Jiawang.

On main level	Bare soil	Grassland	Farmland	Water		Forest		
Producer accuracy	0.90	0.90	0.81	1		0.85		
User accuracy	0.82	0.86	0.92	1		0.85		
Overall accuracy	0.87							
On detailed level	Unsealed area	Sealed area	Crop1	Crop2	Crop3	Crop4	Grove	Copse
Producer accuracy	0.80	0.80	1	0.67	0.67	1	0.85	1
User accuracy	1	0.67	0.76	0.80	0.86	0.80	0.92	0.81
Overall accuracy	0.85							

4.3 Fine-scale landscape structure detection

This step is applied on a fine spatial scale for the analysis of the vertical structure of vegetation. As input data source the NDSM data derived from lidar is used. Since this data is only available in the test site Rathen, the detection of ecotones and small biotopes are only applied in the German test site Rathen.

4.3.1 Detection results

The ecotone in this research is defined as the boundary with height gradient between forest and field, and the small biotopes are mainly woody elements distributed within the extent of field area (see detailed definition in chapter 3.2.2.1). The detection process is conducted on the NDSM data overlaid with vegetation cover extracted from the RapidEye data (Figure 4.11 a). Generally the NDSM value of ecotonal pixels should be between the average heights of forest canopy (16.21m) and field cover (0.27m). However, along the forest/field boundary the vegetation structure varies from the inner patches and the forest canopy on the boundary is actually lower than the average value. For this reason an upper height limit of ecotone pixels in a window (15 by 15 pixels) is defined as 6.5 m. As lower limit 1m is defined. Ecotone detection contains two steps: growing and shrinking. Growing is the process of optimizing the coarse border between forest and field based on the NDSM data. The adjacent forest and field will simultaneously grow into each other to meet an intermediate height of vegetation cover. In this study area, it is assumed to be 2 m (a value between the upper and lower height limit). The growing processes can result in a refined border between forest and field fitting to NDSM data (Figure 4.11 b). In a next step, from the optimized border both forest and field are shrunk until they meet their height limits. At the same time, the pixels in a moving window (15 by 15 pixels) must fulfill the proportion limits of ecotone (see Figure 4.11 c). Lastly, impurities inside shrinking area will be removed within the transitions. The left shrinking area connecting forest and field is considered as ecotone between forest and field. After the detection of ecotones, within the field all elevated objects (higher than 2m, smaller than 1 ha) will be segmented as candidates for small biotopes (Figure 4.11 d). For the detection of tree rows, a "buffering and shrinking" process is applied to connect the neighboring trees in the form of the tree line, and then it can be classified by the linear features, such as length, width, and length/width ratio (Figure 4.11 e). Then, all other candidates will be classified according to their shape and height (Figure 4.11 f), for example hedges are lower than copses and single trees; the area of single tree is smaller than copse (see detailed definition in Table 3.2). In the end, 244 single trees, 160 hedges, 193 copses, and 63 tree rows were detected in this test site. Figure 4.12 shows the detection results of small biotopes overlaid with an aerial photo.

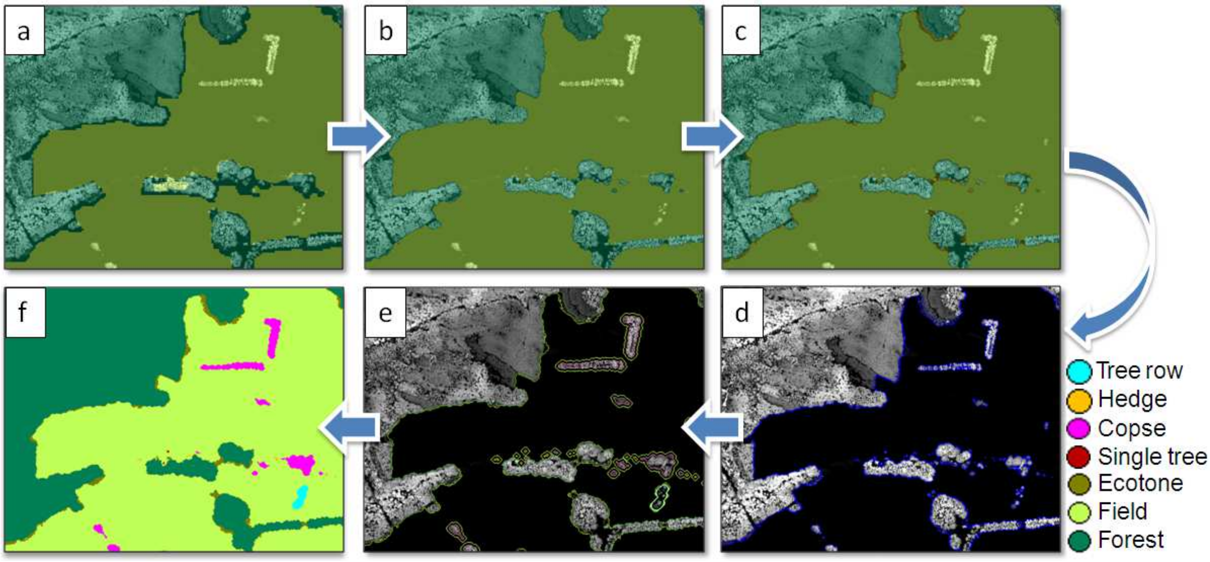


Figure 4.11: Example of ecotone and small biotopes detection in Rathen: a) vegetation cover overlaid with NDSM; b) refining forest/field border; c) shrinking forest and field; d): segments for small biotopes detection; e): buffering and shrinking for tree row detection; f): detection result of small biotopes and ecotones.

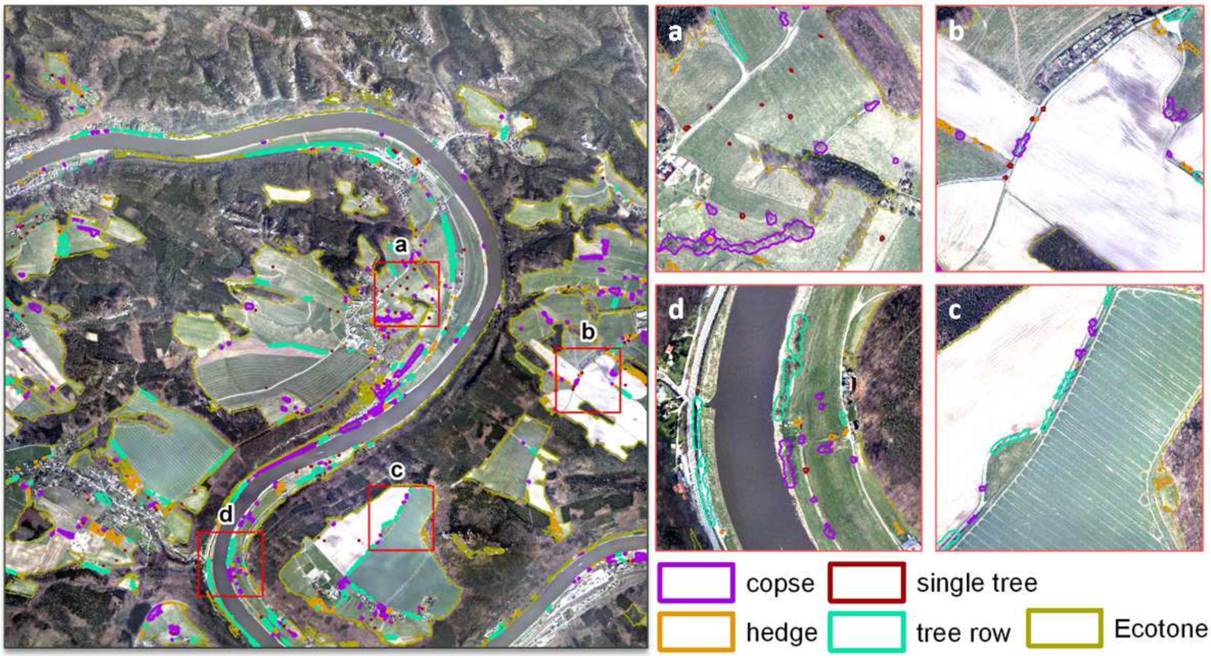


Figure 4.12: Detection result overlaid with aerial photo and four sample areas with small biotopes and ecotones in test site Rathen.

Because of the reclamation and intensification of farmland within last decades and forest management in Rathen, forest boundaries have lost their gradient structure and the width of forest edges become increasingly narrow. The detected ecotones in this region take only about 2.0 % of the whole area of forest. There are about 40 ecotones which are larger than 0.1 ha and the average size of these ecotones is 0.3 ha. Using the method developed in this thesis, the ecotones in this region are detected mainly in three forms: the thin transitions along the forest/field border (Figure 4.13 a); small copses connecting two forest patches (Figure 4.13 b); and wide forest edges with convex or concave shape (Figure 4.13 c, d). All three forms of ecotones have an inner structure with high elevation differences, which indicates higher heterogeneity than forest and field interiors.

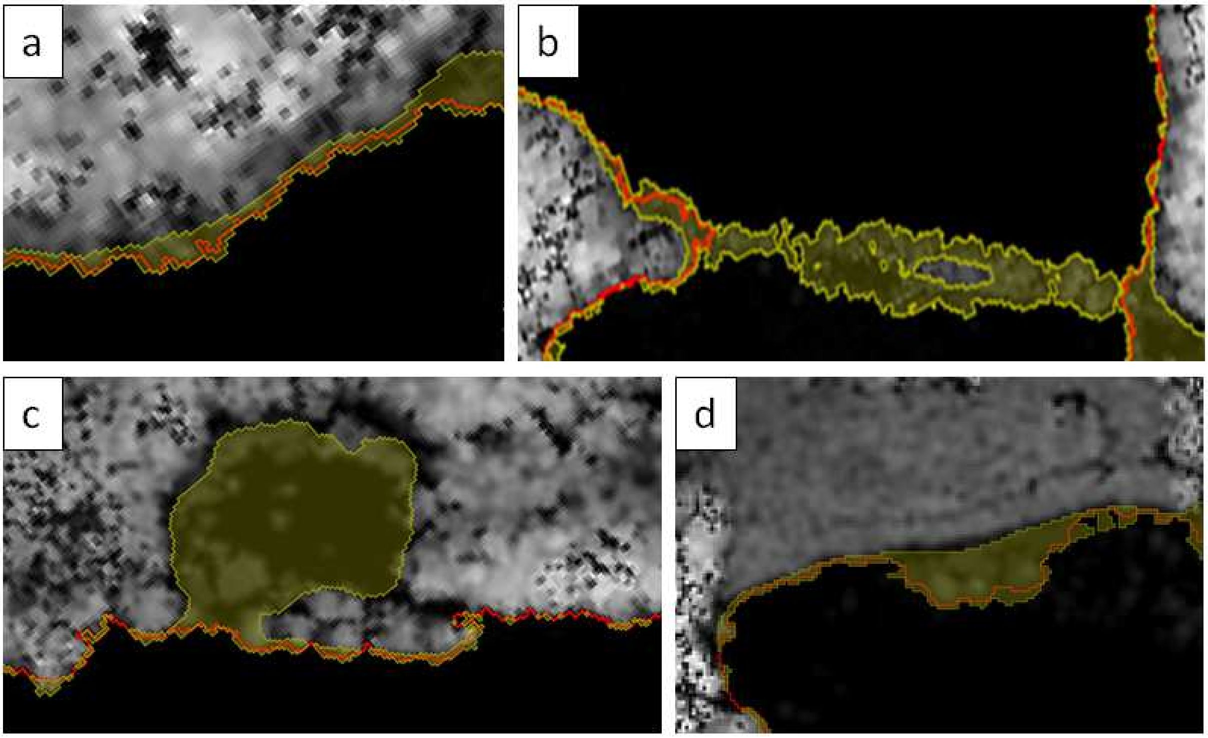


Figure 4.13: The forms of ecotones in Rathen: (a) thin transition along forest/field border; (b) copse connecting two forest patches; (c) concave ecotone on forest edge; (d) convex ecotone on forest edge (red line represents the border between forest and field and gray region represents the ecotone).

4.3.2 Accuracy assessment

For verifying the results, on-site investigations are conducted in four samples (500 m * 500 m) which are selected in this region (Figure 4.12). Table 4.6 shows the accuracy assessment based on the four samples. The detection method of small biotopes treats all elevated elements inside fields as woody habitats, but in reality there are also other elevated objects distributed in the field, such as telegraph poles or hunter cabins. Since the distance between telegraph poles is longer than the interval distance in a tree row, the telegraph poles are all classified as single trees (see Figure 4.14). This would lower the accuracy of single tree detection. Hedges normally are lower than the other small biotopes, but some newly planted trees in this region can be misclassified as hedges. Copses and tree rows also could be misclassified, because some copses have the same shape in long and narrow as tree lines. A copse or tree row may also have the function of ecotone when it is located between two forest patches and has a gradient boundary on both sides. Therefore, copses can also be classified as ecotones (see Figure 4.13(b)). Because the NDSM data was acquired in 2005, the small biotopes may be changed during past few years (the field survey was conducted in 2013). This may lead to underestimation of the accuracy for small biotopes delineation.

Table 4.6: Accuracy assessment on small biotopes detection.

Biotope types	Reference totals	Classified totals	Number correct	Producer accuracy	User accuracy
Single tree	31	33	28	0.90	0.85
Hedge	11	10	9	0.82	0.90
Copse	19	20	14	0.74	0.70
Tree row	18	16	12	0.67	0.75
Totals	79	79	63		
Overall accuracy	0.80				

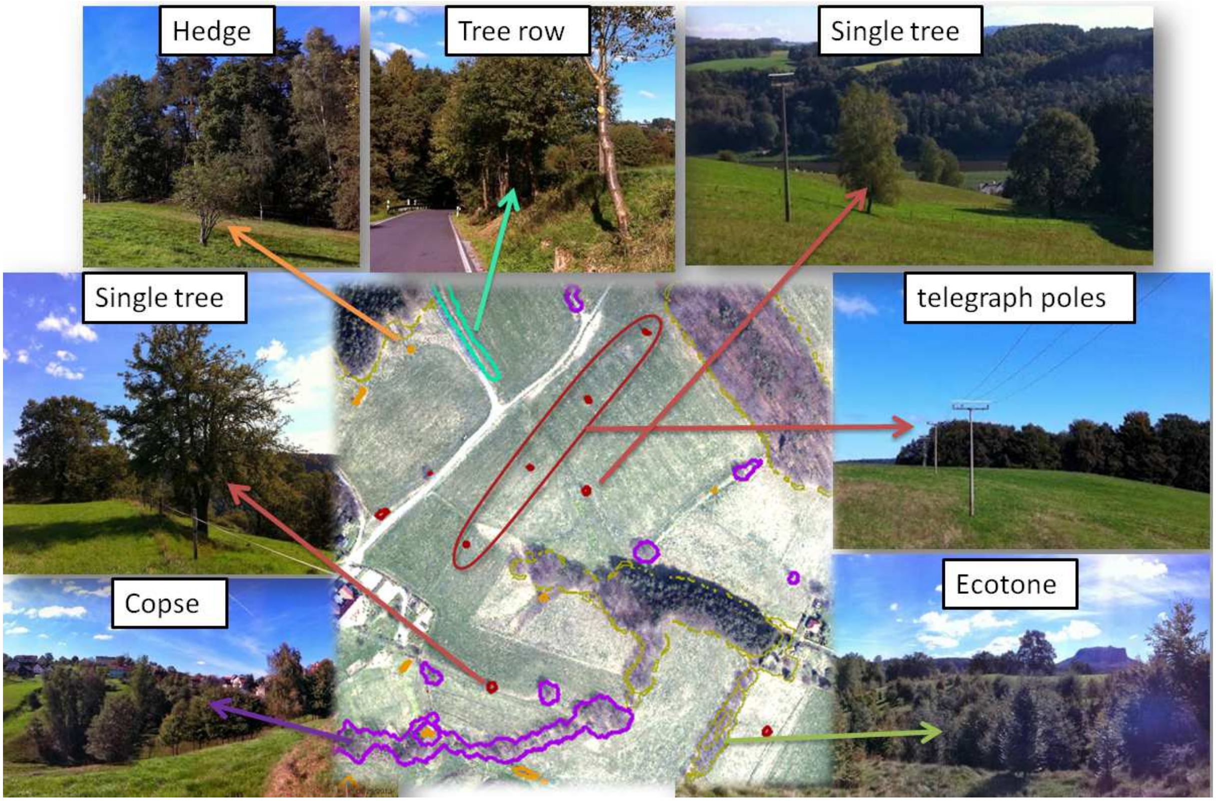


Figure 4.14: Verification of the detection of small biotopes and ecotones in sample (a).

4.4 Landscape structure analysis

After the classification and detection processes the pixels of remote sensing images and lidar data have been converted to the land-cover/land-use patches which can be directly exported into GIS software for further spatial analysis. In the next step, three landscape metrics (diversity, fragmentation, contrast) are adopted for describing the landscape composition and spatial configuration. Furthermore, the ecological network analysis is applied on the test sites for describing the landscape connectivity with particular consideration on the small biotopes. The aim is to analyze the landscape structure in a detailed and realistic way by incorporating the third spatial dimension, the small biotopes and ecotones.

4.4.1 Comparing “2D” and “3D” metrics in practice

The third spatial dimension is used not only for detecting landscape elements but can also be applied for landscape metrics calculation, for example the surface area, perimeter, and distance between patches. Most of the landscape metrics are calculated from these basic geometrical features, such as shape metrics, edge metrics, or diversity metrics. In this study, the ArcGIS-Extension ‘LandMetrics-3D’ (Walz and Hoechstetter, 2008) is employed to take relief into account for the metrics calculation.

4.4.1.1 Basic patch geometry

In the first step of the analysis of landscape structures in the two test sites, the basic geometry of each class is calculated and compared to their standard 2D-equivalents. For the calculation of 3D landscape metrics, the DEMs with a horizontal resolution of 5 m have been used in combination with the corresponding land-use layers derived from RapidEye data.

It is obvious that incorporation of the relief in the calculation of patch geometry can result in an increase of both patch area and perimeter. Table 4.7 shows the area and perimeter of the main land-cover classes calculated by the standard planimetric approach (2D) and the method using true surface geometry (3D) in two test sites. Basically form 2D to 3D conditions, the area and perimeter for all classes will increase because of the relief effect. In the test site Rathen this kind of increase is more significant than in Jiawang, which means Rathen has a steeper terrain. In both test sites, the area of forest and bare soil increases from the 2D- to the 3D-version comparatively more than other land cover classes. This shows that forest and bare soil are located in rougher area in the test sites. Especially in Rathen the discrepancy of forest area between 3D- and 2D-version is more than 160 ha. The perimeter of forest has also increased about 14 km from 2D to 3D conditions. Due to the terrain effect, the total area of the land cover classes in Rathen has increased 8.1% and the total area of the land cover classes in Jiawang has increased 0.5%. As an intermediate result, it can be stated that considerable differences between the 2D and 3D patch geometries can be observed in steep and rough terrain. Consequently, the general approach to integrate terrain effects into common landscape metrics can be assumed to be appropriate for analyzing the landscape structure in a realistic way.

Table 4.7: Comparison of the basic geometry calculated in 2D- and 3D-versions.

Basic geometry	Rathen				Jiawang			
	Area (ha)		Perimeter (km)		Area (ha)		Perimeter (km)	
	2D	3D	2D	3D	2D	3D	2D	3D
Forest	1355.97	1518.37	175.62	189.50	403.90	409.66	259.87	260.61
Grassland	528.83	543.36	191.68	196.20	218.54	219.54	133.65	133.92
Farmland	288.22	289.15	44.42	44.60	994.23	994.32	241.67	241.69
Water	101.49	102.51	28.70	28.97	190.15	190.17	35.91	35.92
Settlement	192.12	199.26	74.54	76.84	241.78	241.95	66.72	66.73
Bare soil	26.36	43.40	38.52	47.04	404.74	410.19	178.66	179.41

4.4.1.2 Diversity metrics

The diversity metrics are related to number of classes and proportion of classes, which means they may also be affected by the relief effect. Table 4.8 shows the corresponding results for both test sites on main and detailed land-cover maps. As one could expect, landscape diversity metrics (Shannon's and Simpson's diversity) show higher values on the detailed land-cover maps than the main maps in both test sites. The 3D-version of diversity metrics in Jiawang exhibits no difference comparing to their 2D-equivalents, as the underlying terrain is not steep enough to affect the metrics. In the test site Rathen, only slight differences between the standard planimetric approach (2D) and the method using true surface geometries (3D) are observed. At the same classification level, the results of 3D diversity metrics are lower than of 2D diversity metrics. Because forests are the dominating land cover class in this region and are located in steeper areas; thus, the increase of forest area from 2D to 3D condition is greater than the average increase in the landscape, which leads to lower evenness and diversity. Nevertheless, the results on both test sites reveal that the diversity metrics may hardly be affected by the terrain effect.

Moreover, the diversity metrics in Jiawang are higher than in Rathen either calculated in main or detailed land-use maps. But this doesn't mean Jiawang has a higher biodiversity status. In reality, Rathen is largely covered by forest and is located in the nature protection area. On the contrary Jiawang there is a post mining area where forest is largely replaced by bare soil. Forest as an important habitat exhibits high value for biodiversity conservation. Neither Shannon's nor Simpson's diversity indices differentiates the habitat types in keeping biodiversity. In addition, the landscape diversity indices only take the landscape composition into account without consideration on the spatial pattern. Therefore, considering only Shannon's or Simpson's indices to describe habitats status could be misleading.

Table 4.8: Statistical summary of the diversity metrics calculated for the two test sites, referring to the main and detailed classes.

Diversity metrics		Rathen		Jiawang	
		Main classes	Detailed classes	Main classes	Detailed classes
Shannon‘s Diversity Index (SHDI)	2D	1.30	2.06	1,61	2.21
	3D	1.28	2.05	1.61	2.21
Shannon‘s Evenness Index (SHEI)	2D	0.63	0.80	0.90	0.90
	3D	0.61	0.79	0.90	0.90
Simpson‘s Diversity Index (SIDI)	2D	0.64	0.84	0.76	0.87
	3D	0.62	0.84	0.76	0.87
Simpson‘s Evenness Index (SIEI)	2D	0.77	0.91	0.91	0.95
	3D	0.75	0.91	0.91	0.95

4.4.1.3 Effective mesh size (MESH)

Table 4.9 shows the calculation of effective mesh size for forest, field, and the vegetation covers in two test sites under 2D and 3D conditions. Under 3D conditions the values of MESH for forest in both test sites are higher than under 2D conditions, but for field they are lower. The reason is the same as in the case of the diversity indices. Since the forest is located on rough terrain in the test sites, from 2D to 3D conditions the area of the forest class increases more than field, which changes the proportions of classes in the landscape. In Rathen, the ecotones between forest and field are additionally incorporated for MESH calculation. In this case the ecotones act as a “buffer region” and can be used as a common area for MESH calculation of both forest and field. As a result, the values of MESH for forest and field increased. This increased MESH areas are vital for edge species, because ecotones can improve opportunities for multiple environmental and biological benefits, and the varied vegetation distribution on the forest/field boundary can also enlarge the inner species’ living area as well as increase the possibility for inter-species communication.

The vegetation cover (including forest, field, and ecotones classes) is considered as natural areas which are rarely affected by human infrastructures. The effective mesh size of vegetation cover is often used as an indicator of landscape fragmentation. The MESH value of vegetation cover depends on its area proportion in the whole landscape. Because forest is the dominating class in Rathen, the MESH for vegetation cover is higher in 3D condition than in 2D condition. In the case of Jiawang, the 3D version of MESH for vegetation cover is lower than its 2D version, since field is the dominating class in Jiawang.

Table 4.9: Statistical summary of the fragmentation metrics (MESH) calculated for the two test sites.

Fragmentation metrics	Rathen				Jiawang	
	MESH (ha) without ecotones		MESH (ha) with ecotones		MESH (ha) without ecotones	
	2D	3D	2D	3D	2D	3D
Forest	329.31	396.11	341.10	413.67	3.08	3.26
Field	24.69	23.35	25.86	24.52	28.16	28.04
Vegetation cover	929.57	1013.89	929.57	1013.89	162.86	162.77

Effective Mesh Size (MESH) is an effective indicator for the measurement of vegetation fragmentation. Larger MESH value means less fragmented. The 3D version of MESH using true surface geometry can reflect the vegetation fragmentation in a realistic way. The comparison of 3D-MESH values in two test sites shows that the vegetation in Jiawang is highly fragmented; especially the forest patches are under severe situation. In contrast, Rathen has a less fragmented vegetation pattern. Furthermore, the incorporation of ecotones into the calculation of MESH can be used to analyze the function of ecotones for alleviating vegetation fragmentation. In the test site of Rathen, the MESH values of forest and field increased by 4.4 % and 5.0 % respectively when considering ecotones. The results in Rathen show also little effect of ecotones for alleviating fragmentation for both forest and field habitats, since the forest boundaries have been managed manually for a long time and the boundary structures have become more artificial.

4.4.2 Landscape contrast analysis

The contrast indices were calculated exemplarily for a 500 m * 500 m section from the test site of Rathen (using the NDSM with horizontal resolution of 1 m and the land cover data). The results of landscape contrast analysis are shown in Figure 4.15.

Having a look at the first case form Figure 4.15, the land cover classes are obtained from the RapidEye images and some small biotopes and ecotones are ignored. In the second case, the land covers are at a much more detailed scale with special consideration of small biotopes and ecotones. In the outcome of the calculation of Edge Contrast Index (ECON), patch A in case 1 is considered as a whole forest patch adjacent to the field and has an edge contrast value of 55.01 %. In fact, it is an assembly of several small patches. In case 2 patch

A is further divided into corresponding parts. One of the corresponding patches shows a higher ECON of 70.90 %. In the first case the ECON value of patch A represents an average elevation contrast of a combined patch and the height difference within patch A is smoothed. The form of patch B in case 2 has changed little from case 1, but the ECON value of patch B declines from 63.10 % to 61.21 %. The reason is the existing ecotone around patch B that act as a buffer between forest and field, resulting in a lower average height contrast of patch B with its surrounding patches. Although more patches are delineated in the second case, the Total Edge Contrast Index (TECI) is still lower than in the first case. It shows that both ecotones and small biotopes possess low edge contrast values that can alleviate the total edge contrast of the whole landscape. Accordingly, the Area-Weighted Edge Contrast (AWEC) declines as well from case 1 to case 2. Compared to TECI, AWEC is a more sensitive indicator for describing the average height dissimilarity on landscape level, as it highlights the contributions of small biotopes and ecotones to the whole landscape contrast.

Landscape contrast is highly related to species distribution and habitat fragmentation (Kuefler et al., 2010). And within the landscape it can be viewed as average dissimilarity in habitat quality (Biswas and Wagner, 2012), e.g. elevation difference of habitats. The simulation of habitat dissimilarity depends on the question in practice or the taxon examined. Also the spatial scale can affect the result of contrast analysis. A coarse classification may neglect the inner patch heterogeneity and the edge effects, like in case 1.

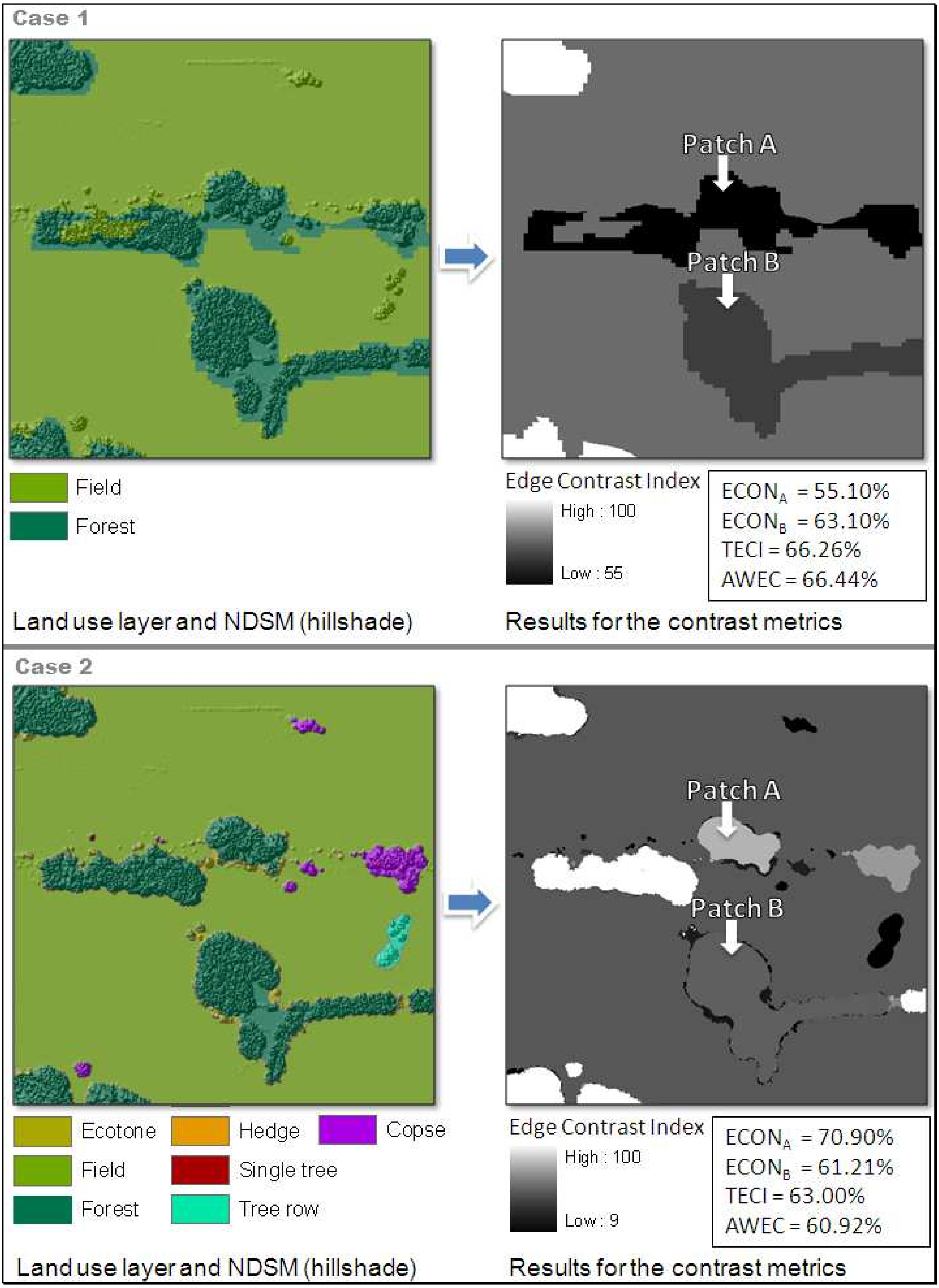


Figure 4.15: Two cases of the application of the adjusted Edge Contrast Index (ECON) based on the NDSM layer. Case1 shows the results of contrast metrics using the coarse resolution land use layer from the classification of RapidEye data and case 2 shows the results of contrast metrics using the detailed detection results from lidar data.

4.4.3 Ecological network analysis using small biotopes as stepping stones

Differing from habitat fragmentation, the econet analysis is used in terms of habitat availability for measuring both intrapatch connectivity and interpatch connectivity according to the distance between patches (see chapter 3.3.2). In the work, the econet analysis is applied in the exemplified test sites. Using small biotopes as stepping stones, the connectivity of woody habitats of two test sites will be compared.

4.4.3.1 Selection of buffer ranges

The econets can be established on different dispersal distances, which relates to the movement capacity of the species. Considering the small size of the stepping stones (< 1 ha) in this research, the buffer radius is set in maximum 200 m, which means the maximum dispersal distance of the species is 400 m. This includes a wide range of spiders and beetles, fungi and insects that feed off dead wood and worms. According to the existing surveys (Bastian and Schreiber, 1999; PAN, 2006), the potential dispersal distances and stepping stones for animal migration are shown in Table 4.10.

Table 4.10: Selection of buffer ranges and stepping stones (Source: Bastian and Schreiber, 1999; PAN, 2006).

Maximum dispersal distance (m)	Species	Potential stepping stone	Buffer range (m)
50-100	Ants, ground beetles, deadwood insects	Single tree, tree row, hedge, copse, grove	50
100-200	Weasel, shrew mouse	Tree row, hedge, copse, grove	100
200-400	Hedgehog, ermine, dormice	Hedge, copse, grove	200

4.4.3.2 Mapping ecological networks

Figure 4.16 shows the maps of econets in both of Rathen and Jiawang test sites for different dispersal distances using the “multi-buffer” approach (as outlined in chapter 3.3.2.1). The econet is composed of five components. Taking Rathen as an example, the forest patches are considered as the core habitats that need to be connected. The small woody habitats are the potential stepping stones among the forest patches. The Elbe River, impervious areas in settlement, and traffic infrastructure (e.g. highway, state road, county road, and railway) are treated as barriers. Pervious areas in settlement and open field (i.e. grassland and farmland) are used as permeable area where connections could be established between the core patches. The econet in Jiawang has a similar composition like Rathen, except the habitats for stepping stones. Due to lack of lidar data in Jiawang, the small biotopes have not been detected as in the case of Rathen. As a result, groves and copses have been classified from RapidEye images and used as potential stepping stones in econet analysis. It is assumed that connections could be established, if the distance between woody habitats (forest patches and small biotopes) is closer than two times of the buffer range. As the buffer range increases, small stepping stones may be omitted and more corridors could be established directly between forest patches. In general, a greater buffer range results in more connected patches.

From the outcome of the econet maps, the function of small biotopes can be directly recognized. Some of them may be used as stepping stones at a long dispersal distance, but not for a short one. The econet maps also show that the vegetation pattern in the two test sites varies significantly. Rathen is covered by large forest patches with small woody biotopes used in econet. Jiawang shows a more fragmented structure that dispersed groves form lots of connections among the woodlands.

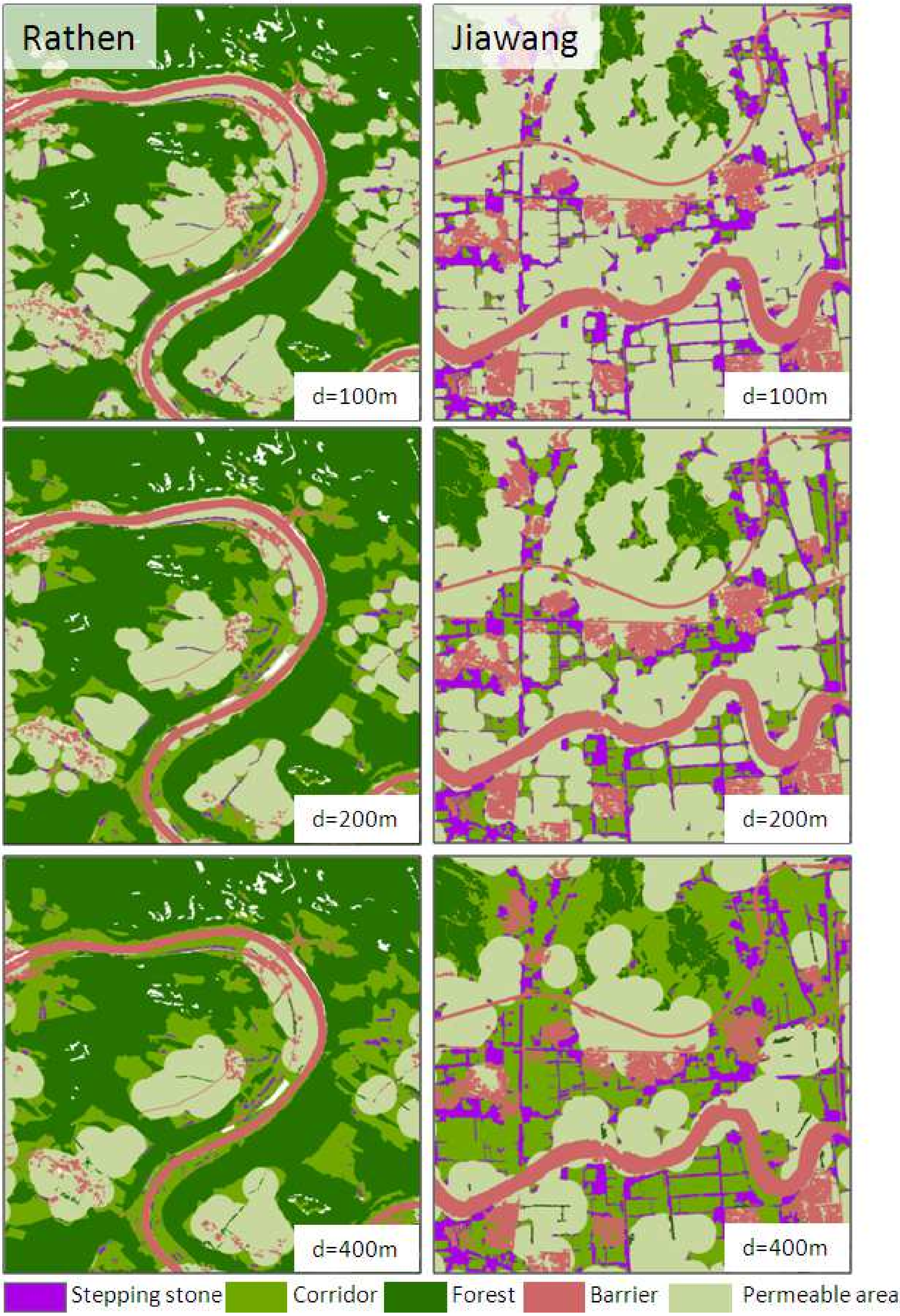


Figure 4.16: Ecological networks of woody habitats in the test sites Rathen and Jiawang for three dispersal distances (d) of 100 m, 200 m, and 400 m.

4.4.3.3 Analysis of connectivity for the test sites

In the test site of Jiawang, due to long-term mining exploitation and farmland cultivation, the hills had little forest cover and the local landscape is significantly fragmented. Figure 4.17 shows that forest patches constitute a large part of the econet in Rathen (more than 70 %), and the percentage of forest in the econet of Jiawang is below 50 %. In the test site Jiawang the proportion of stepping stones is much higher than in Rathen, and the proportion of corridors correlates strongly with dispersal distance. This can be explained by the indicator of Effective Connected Mesh Size (ECMS, see in Table 4.11). As expected, ECMS values increases with dispersal distance in both test sites. In Rathen, ECMS values are much higher than in Jiawang at all three dispersal distances. This means larger connected forest patches are available for animals as habitats and to move within the test site Rathen. The ECMS index in Rathen also exhibits relatively stable values with increasing dispersal distance, whereas in Jiawang this index is highly sensitive to dispersal distance. As mentioned in chapter 3.3.2.2, ECMS metrics takes both intrapatch and interpatch connectivity into account. In a less fragmented landscape intrapatch connections are the dominant factor of habitat availability, which gives more weight to larger patches in the overall metrics value. In Jiawang, interpatch connections take a higher proportion of habitat availability than Rathen, which makes its ECMS index being more sensitive to the dispersal distance.

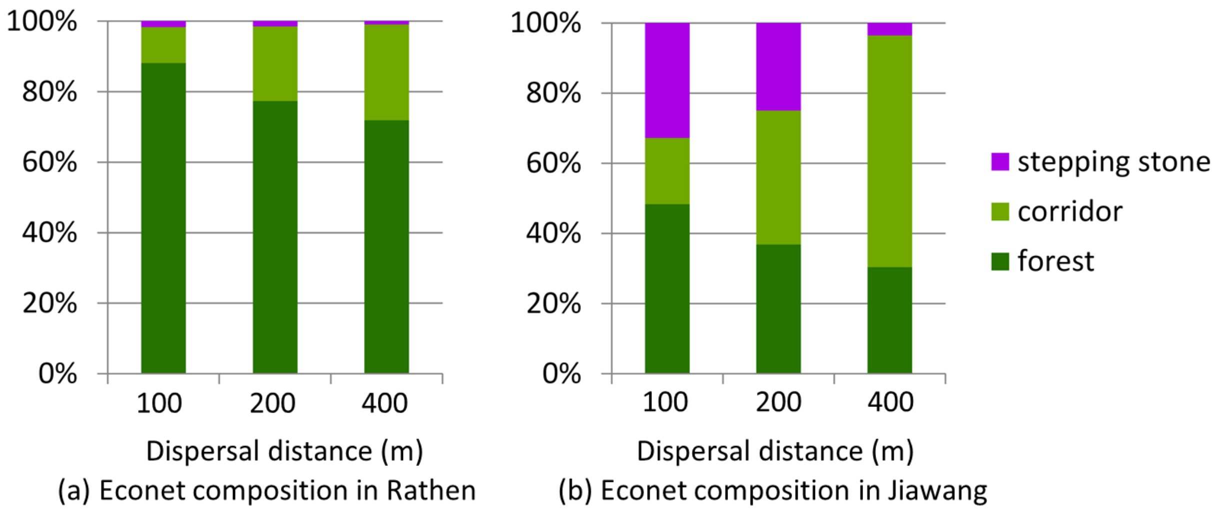


Figure 4.17: Comparison of econet composition for three dispersal distances in Rathen (a) and Jiawang (b).

For describing the interpatch connectivity, the index "Corridor Area Percentage of Econet (CAPE)" is used for both test sites. As shown in Table 4.11, this index in Jiawang shows higher values on all buffer ranges than in Rathen. This means that the interactions between woody habitats in Jiawang potentially happen more than in Rathen. Having a look at the change rate of CAPE (dCAPE), a clear increasing trend of CAPE value can be seen as the dispersal distance is varying from 100 m to 200 m in both test sites. As dispersal distance changes from 200 m to 400 m, the CAPE index for Rathen increases by 28.19 % and for Jiawang by 73.09 %. This means more interpatch connections have been established in Jiawang at the dispersal distance 400 m. The increasing rate of corridor proportion implies that there are more woody habitats that are located farther than 200 m apart from each other in Jiawang than in Rathen. In other words, Jiawang shows a more fragmented habitat pattern. Forest patches and small woody habitats are distributed farther from each other than the habitats in Rathen. In contrast, Rathen shows a relatively compact landscape pattern and most forest patches and small woody habitats are within 200 m of each other.

Table 4.11: Results of ecological indicators for woody habitats connectivity on three dispersal distances in Rathen and Jiawang.

	Rathen			Jiangwang		
Dispersal distance (m)	ECMS (ha)	CAPE (%)	dCAPE (%)	ECMS (ha)	CAPE (%)	dCAPE (%)
100	537.98	10.23	-	9.29	18.88	-
200	699.89	21.18	107.04	38.97	38.16	102.12
400	794.76	27.15	28.19	218.19	66.05	73.09

4.5 Summary

In this chapter, the proposed methodology from chapter 3 has been applied in two real-world examples. In the test site of Rathen, the landscape structure analysis was conducted at a very detailed level with the help of high resolution lidar data. Specifically, the small biotopes and ecotones have been incorporated in the analysis of habitat fragmentation, contrast, and connectivity analysis. The results have shown that they are valuable information for assessing the habitat pattern. In the test site of Jiawang, the landscape structure analysis was applied on a relatively coarse level. The comparison between the two test sites shows the applicability of the proposed method on distinct landscape pattern. In addition, incorporation of the third spatial dimension can help to calculate the patch geometry under a realistic condition and results in more accurate values of the landscape metrics.

5 Discussion and evaluation

This thesis has been structured as follows: chapter 2 outlines the ecological functions of small biotopes and ecotones. Besides, possible methodical approaches for the detection and incorporation of these elements in landscape structure analysis are demonstrated in chapter 3 as well as the results obtained by applying these methods in two real-world examples illustrated in chapter 4. Specifically, the proposed methodology for landscape structure analysis will be discussed as a whole and evaluated in details in this chapter.

5.1 Evaluation of the proposed methods for image processing

Scale (including grain size and extent) is a key question for landscape structure analysis and can affect the interpretation of the landscape metrics (Cadenasso et al., 2003; Fagan et al., 2003; Fortin et al., 2000; Gosz, 1993; Hay et al., 2003; Schindler et al., 2012). The hierarchical approach of land-cover classification can reflect multi-scale landscape structure. In fact, the relevant pattern is revealed only when the grain size of analysis fits to the scale of the phenomenon under study (Wu, 2004). The scale is related to the pixel size of the imagery used. RapidEye images can supply multi-spectral reflectance values of the ground surface within a relative coarse resolution (5 m * 5 m); NDSM derived from lidar system contains the information of objects height on the ground surface in very high resolution (1 m * 1 m). The combination of both data sources enables us to monitor the landscape pattern at different spatial scales and map different elevated objects over a larger area. The incorporation of NDSM not only provides a detailed monitoring scale, but also changes the monitoring view from 2D to 3D. This results in a more realistic representation of the landscape pattern. For processing the images of different sources, both object-based and pixel-based image analysis have been used for land-cover/land-use classification and detailed landscape elements detection. A brief evaluation of the methods used for image processing within the scope of landscape analysis is provided in the following sections.

5.1.1 Applying Object-Based Image Analysis (OBIA) on RapidEye data

The object-based image analysis has been shown to be effective and efficient for high resolution image classification by many authors (Walter 2004, Bock et al. 2005, Radoux and Defourny 2007, Blaschke 2010, Förster et al. 2010). The main advantages of this method can be concluded in several aspects. First, it generates homogenous objects rather than a “salt and pepper” structure which is often the case in pixel-based image classification. Second, comparing to pixels, image objects have more attributes, such as shape, neighborhood, texture, and user-defined features. The process of OBIA is an iterative loop of segmentation and classification based on the class hierarchy. Segmentations are the operations that alter the shape of image objects as close as possible to the objects of interest; then more distinguishing features can be used for image object classification. Third, the capacity to integrate additional knowledge (e.g. vector land-use maps like ATKIS) and the application of fuzzy rules allows the classification process to incorporate assistant data and user experience. All image objects can be organized on different hierarchical levels in line with the strategy of multi-scale analysis of landscape structure. Finally, the output of OBIA is usually a classified image, which often becomes part of a map used, for example, to illustrate different vegetation types in an area. The segmentation result can be an output, and is often imported into a GIS software as a polygon vector layer (e.g. shapefile), for statistical analysis.

In this thesis, the classification process was developed based on the advantages of both OBIA concept and RapidEye images. A hierarchical approach has been adopted; and then, two land-cover maps on different spatial patterns are derived from multi-temporal RapidEye images. The main land-use classes from class hierarchy (Figure 3.9) constitute the first map which has similar classes as ATKIS data. On a detailed level, the sub-classes will be further classified based on the main map. Specific rules have been set for classification of each land-use class according to the spectral features of RapidEye data. For example, based on the Red Edge band the developed REVI is proved to be more effective than NDVI-RE for different vegetation classification (see chapter 3.2.1.1.2). In the following, the characteristics of the proposed classification method will be discussed.

According to the classification strategy settlements and traffic lines are initially extracted based on the existing land-use data, since the borders of the artificial land uses are often mixed with surrounding land covers on remote sensing images. Within the settlement area, the ground surface is simply classified as sealed and unsealed area based on NDVI layer derived from the RapidEye images. Traffic areas and sealed areas are treated as ecological barriers in the econet analysis. This classification approach can ensure that the settlement structures derived from RapidEye images from two test sites are comparable. Nevertheless, with the help of the high resolution NDSM and ATKIS data, the rural settlement in test site Rathen can be classified into more detailed classes, such as buildings, elevated vegetation, ground vegetation, and bare soil (see Figure 5.1). Buildings can be extracted from ATKIS data; and elevated vegetation can be classified by NDSM. Then, ground vegetation and bare soil can be differentiated by NDVI derived from spectral layers of RapidEye images. The detailed settlement structure has the potential to improve the result of econet analysis. But the settlement is not the focus in this thesis and the developed classification rules for the land-cover maps are intent to apply on the regularly collected data source, like RapidEye images.

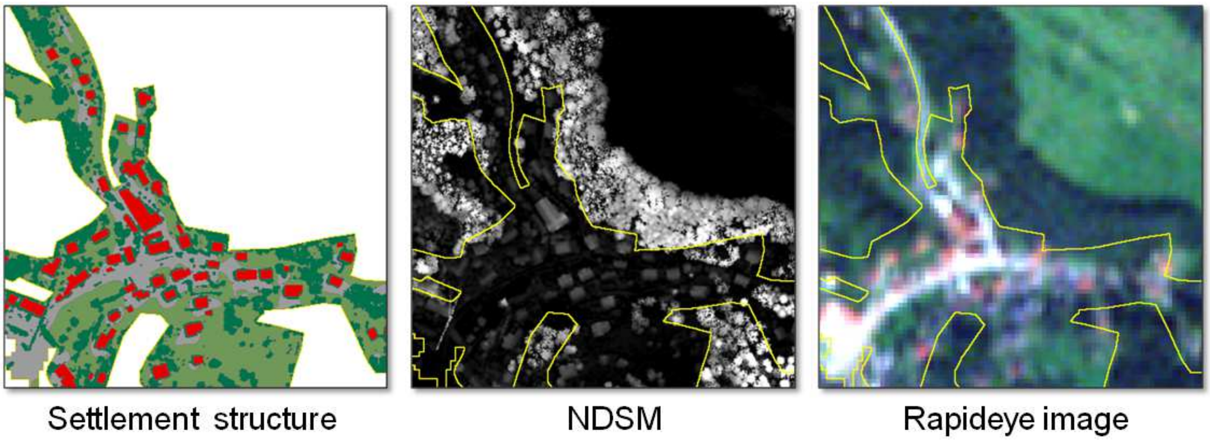


Figure 5.1: Detailed settlement structure classification based on NDSM and RapidEye image.

The symmetrical difference analysis between the vegetation classification result and ATKIS data (chapter 4.2.3.1) have proved that the introduced vegetation index (REVI) derived from Red Edge band is useful for vegetation classification and the results fit ATKIS layer quite well, especially the forest coverage (accuracy higher than 95 %). The use of REVI in both Rathen and Jiawang test sites shows that this index can be applied for either largely forested area or barely forested area. The comparison of the signal patterns between REVI and NDVI (chapter 3.2.1.1.2) demonstrates that REVI is more suitable than NDVI to differentiate forest and grassland. However, for the forest sub-classes NDVI works better than REVI. This means that the introduced REVI should be applied on a higher class level, such as the main classes of vegetation (Hou and Walz, 2013b). Besides the vegetation indices, the Normalized Difference Water Index (NDWI) is used for water classification and the result of applying this index on RapidEye images shows high accuracy (higher than 85 %).

The multi-temporal RapidEye images are useful for monitoring on the growth period of various crops. Using the edge detection algorithm (e.g. sobel filter) and the segmentation technique crop plots can be delineated based on their spectral features (e.g. REVI, see chapter 4.2.2.2). The accuracy assessment of classification results in the test sites reveal that the multi-temporal approach is an effective means for farmland classification and the crop plots will be better delineated when they are in relatively large size. Since different crops may be planted from year to year in the same region, the crop types are not the focus of this research. The plots information can help the management of agriculture resources and contribute to the monitoring of High Nature Value farmland (HNV) as the base map.

During the classification process, the calibration of fuzzy membership functions of the classes and the estimation of parameters used in the segmentation could be very time-consuming. In practice, the class membership functions are often calculated from the samples in the study area and the segmentation parameters may be achieved by the assistant tools, such as Estimation of Scale Parameters (ESP). Although the concrete parameters of the rule sets are dependent on the study area, the segmentation and classification strategies and the features used in class description are applicable for RapidEye data in different regions, such as the exemplified cases of the classification in German and Chinese test sites.

In this work, both test sites are in small size (5 km * 5 km). The classification accuracy is decisive for the detection of small landscape elements in the next step. For further application of this method, it is necessary to ensure the applicability of the classification rules on a larger area, especially the accuracy of vegetation classification. Figure 5.2 shows the comparisons between ATKIS layer and vegetation classes of applying the same classification rules in a larger area (24 km * 19 km) in “Saxon Switzerland”. The intersected areas of forest and field (including farmland and grassland) are the identical regions between ATKIS and classification results. Using ATKINS as reference data, the user and producer accuracy for forest class is respectively 94 % and 93 %; and for field class is 95 % and 94 %. From the comparison, we see that most large forest and field patches can be identified by this OBIA approach. The classification results is similar to the test site Rathen (see Figure 4.10), the confusion areas differing from ATKIS are mainly some small patches and the patch boundaries, which can be clarified in the next step of detailed landscape elements detection.

Through the discussion above, this proposed OBIA procedure appears: (1) *reproducible*: the rule-based classification process is corresponding to the class tree and all rules could be refined by the user at any time in the classification process, such as the further classification within settlement in Rathen; (2) *scalable*, this method can organize all image objects in a multi-scale structure and it can produce land-cove maps on different levels (e.g. main classes and sub classes);(3) *easily transferable*: on the level of main land-use classification, the rule sets can be applied in two different test sites (Rathen and Jiawang) with necessary adjustment of rules parameters and the results are in high accuracy; (4) *quickly applicable over broad areas*: the classification rule sets used in a small area (Rathen) can be easily used in a larger area in the same region (see Figure 4.10) without changing the classification parameters. Such reliable spatial information of vegetation distribution over broad territory has the potential for the further detection of detailed landscape elements in a large landscape extent.

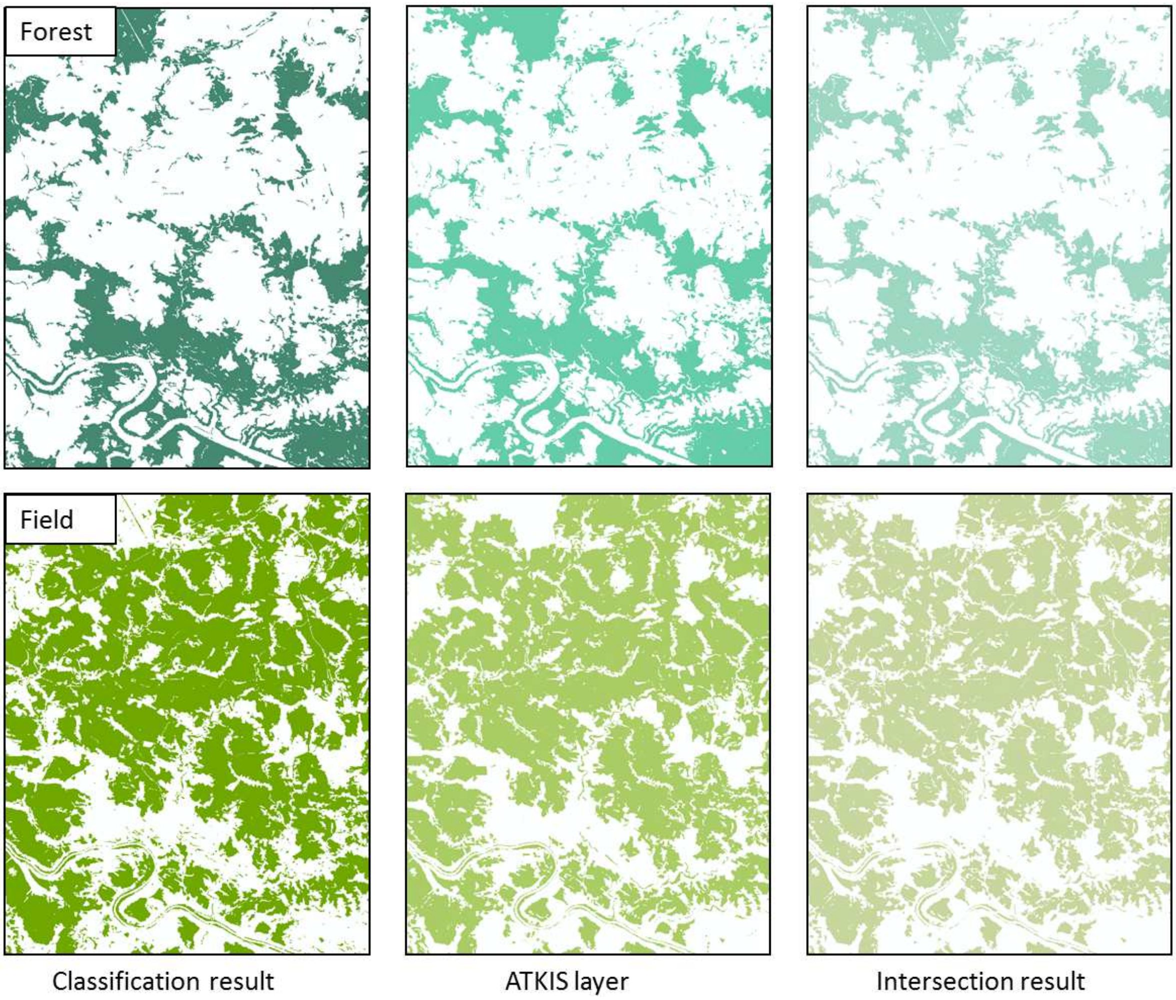


Figure 5.2: Comparisons of the classification results with ATKIS layers in a large area in “Saxon Switzerland”.

5.1.2 Applying pixel-based object detection on high resolution NDSM

The detection of small biotopes or ecotones has been extensively studied. Current methods for detecting small biotopes rely mostly on very high spatial resolution images (Bunting and Lucas, 2006; Cousins and Ihse, 1998; Hirschmugl et al., 2007; Pouliot et al., 2002). Cousins and Ihse (1998) made a first step towards a national landscape monitoring system including small biotopes and linear elements based on color infrared (CIR) aerial photographs. However, the CIR aerial photographs needs manual interpretation and this is time-consuming. Levin et al. (2009) mapped scattered trees using a combination of spectral and segmentation based methods from Landsat and SPOT images. This procedure is applicable only for a limited size of trees, and tree groups may appear as single trees on satellite images. As more fine spatial resolution remote sensing data becomes available, more advanced procedures and spectral measures have been developed for tree delineation. However these methods are mostly applied to specific spectral information and the application processes are complicated and time-consuming (Bunting and Lucas 2006, Sheeren et al. 2009, Larsen et al. 2011). Lechner et al. (2009) showed the limitations of the use of remote sensing images without additional data for the accurate detection of small and linear landscape elements. Only using high-resolution images, the segmentation of the small biotopes is problematic because of the varying reflectance characteristics of the small biotopes and the existence of surrounding pixels with similar reflectance value. In this sense the combination of other data with remote sensing images may supply a solution for this problem, such as lidar data which has been often used in mapping tree crowns and measuring individual tree structure (Brandtberg et al., 2003; Holmgren et al., 2008; Lee et al., 2010; Morsdorf et al., 2004).

In this research, a methodology combing object-based and pixel-based image analysis is proposed using the high resolution NDSM (derived from lidar system) and multispectral images (RapidEye data). It demonstrates a data fusion aspect for land use classification and fine-scale landscape elements detection. Two steps are separately implemented on different data sources. First, the RapidEye images have been used in the object–based classification of the vegetation mask. Second, overlaying the vegetation mask with NDSM small biotopes have been detected within the field area based on their morphological features. Using the high resolution NDSM (1 m) the morphological features can be measured at the level of pixel size. Therefore, the pixels are chosen as the basic unit for further detection. It is assumed that these small woody biotopes are the only elevated objects existing in the field. In this case, object height is used as the only factor for the preliminary segmentation of small biotopes. A pixel-based “buffering and shrinking” procedure is developed specially for modifying the outline of the linear elements (i.e. tree row). The differentiation of the small biotopes is based on their height and shape attributions (see Table 3.2) and the overall accuracy is 80 % (see Table 4.6). The proposed hybrid method allows spectral and shape information to be successively used to extract the small biotopes. This improves the applicability of the approach, as it is not limited to the combination of data sources. But it also has limitations. For example, the accuracy of the base map (land uses derived from RapidEye images) will affect the detection results; and some other elevated elements inside the field area (e.g. telegraph poles, hunter cabins) can be misclassified as small biotopes. . The correction of such elements may be achieved by incorporation of very high resolution aerial images or on site field investigation. As a result, the detected small biotopes and the land-use maps classified from RapidEye data show that it is possible to update official land-use data like the German digital landscape model (ATKIS) partly by using multispectral data from sensors like RapidEye in combination with high resolution elevation data.

For the ecotone analysis different methods have been developed depending on the focus of ecotone research, such as moving split window (Senft, 2009), probability mapping (Hill et al., 2007), or wombling techniques (Fortin et al., 2000). But the variable and the non-exclusive use of the term “ecotone” can be a source of confusion when interpreting and comparing studies (Hufkens et al., 2009). In this work, the difference in height is chosen to represent the environmental gradient between forest and field at a fine spatial scale. This enables the ecotone to be explored in three dimensional space, not treating height as the only variable but also taking surrounding patches into account using the moving window analysis. A pixel-based ecotone detection method based on NDSM has been introduced in chapter 3.2.2. And the result of applying this method in Rathen shows ecotones in this region are mostly in the form of transitional boundary between forest and field (Figure 4.12). But there are also other forms of ecotones that could be mixed with small biotopes. For example, a copse or hedge located closely to forest patches may have the ecotonal feature as elevation gradient on forest/field boundary (see in Figure 4.13). In this case, the small biotopes with ecotonal feature will be classified as ecotones since ecotones are considered more influential than individual biotopes in landscape connectivity analysis (see detail explanation in chapter 5.2.2.2). Within the object-based environment, some meaningful attributes can be directly calculated for the transitional boundary between forest and field, e.g. length, width, average height, standard deviation of height, and curvilinearity (Figure 5.3). These attributes have particular ecological meaning and can be used in further landscape structure analysis, for example the curvilinearity of the transitional boundary strongly influences wildlife usage and movement (Forman, 1995).

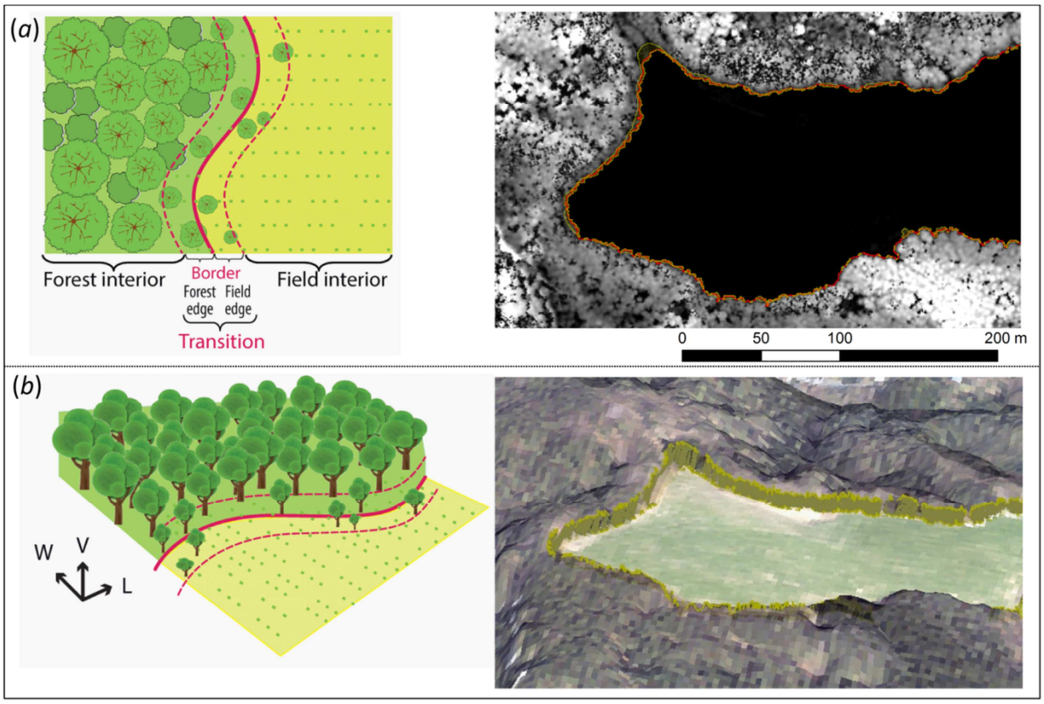


Figure 5.3: Comparison between the conceptual model and the detection result for the transitional boundary in 2D (a) and 3D (b) (reproduced according to Forman, 1995).

In summary, the incorporation of the third dimension for detailed landscape elements detection has proved to be promising and practicable. Using the pixel-based algorithm small biotopes can accurately be delineated and their outline can be adjusted. This would ensure that they can be detected based on the shape features. In terms of ecotone, the height gradient model enables the ecotone to be explored from the third spatial dimension and yields valuable information on forest/field boundary. It can be expected that this detailed representation of the landscape pattern will enhance the landscape structure analysis and result in a more realistic simulation of landscape pattern.

5.2 Evaluation of the metrics for landscape structure analysis

The findings by incorporating the third dimension in landscape structure analysis suggest that landscape metrics relate closely to the variability of the underlying terrain and patch surface properties. The basic effect of switching from 2D to 3D metrics is the increase of patch area and perimeter, especially in steeper areas. This will affect a series of landscape metrics, such as diversity or fragmentation metrics. In the following section, the metrics describing landscape diversity, landscape fragmentation/connectivity, and landscape contrast will be evaluated with special consideration on the small biotopes and ecotones.

5.2.1 The application of landscape diversity metrics

Landscape diversity gives an overall description of landscape composition which is related to the class number and class proportion. The results of applying Shannon’s diversity (SHDI) metric and Simpson’s diversity (SIDI) metric in 2D and 3D versions for the test sites show that they are slightly affected by the terrain effect (see chapter 4.4.1.2). If the predominant patch type in the landscape (e.g. forest) is located in the mountain area, its true surface area will be much larger than the planimetric area which leads to the disproportionate increases of area among classes. This means a lower Evenness index under 3D conditions and correspondingly there will be a lower diversity index, like the case in the test site Rathen. But there is no general principle for landscape diversity metrics in corresponding to the terrain effect. This is due to the fact that common diversity metrics are mainly based on area proportions of classes which have an uncertain response to the “true surface effects”. What can be confirmed from the test sites is that the terrain impact on landscape diversity indices will decrease as the land cover is classified in more detail. It seems that the “true surface effects” tend to level each other out for the detailed patch classes.

The Shannon’s and Simpson’s diversity metrics have the capacity to measure the degree of concentration when patches are classified into types, but without differentiating the ecological function of patch types. Besides, the spatial distribution of patches has been ignored in these indices. This makes the landscape diversity metrics less applicable in evaluation of habitat status at landscape level.

5.2.2 The application of the metrics for describing landscape fragmentation/connectivity

Landscape connectivity can be measured in two aspects: structural and functional connectivity. Structural connectivity refers to the degree of habitat connectedness, while functional connectivity starts from a species-specific view (Kindlmann and Burel, 2008). For assessing the functional connectivity, it is hard to find a single landscape surrogate measure (or even an extensive suite of surrogate measures) to adequately reflect the landscape connectivity for biota per se (Lindenmayer et al., 2002). Structural connectivity, on the other hand, is essential for landscape management even if the functional role for species dispersal and immigration remains an open issue (Lindenmayer et al., 2002; Vos et al., 2001). In the following the metrics for describing structural connectivity under fixed dispersal distances will be discussed with special consideration of the functions of ecotones and small biotopes.

5.2.2.1 Unification of landscape fragmentation and connectivity

The term of fragmentation has been used in this thesis in two aspects: habitat loss and habitat isolation. These two aspects are related to the same ecological process of intrapatch connectivity which only takes the patch areas as the input for the calculation of connectivity, but without considering the connections between patches. Therefore, the concept of intrapatch connectivity is an opposite expression of fragmentation. The indicator Effective Mesh Size (MESH) is actually a measurement of intrapatch connectivity.

In addition to the intrapatch connectivity, interpatch connectivity should also be considered in the landscape structure analysis. The interpatch connectivity depends on the patch distribution or topology, dispersal ability of the species (dispersal distance) and their response to the nature of the matrix. In this thesis the “multi-buffer” approach is adopted to establish the interpatch connections among forest patches (see chapter 3.3.2.1). The form of connections is related not only to the distance between patches, but also the patch shape and topology, e.g., ratio of opposite edge lengths of patches. The buffer ranges have been concluded according to the dispersal ability from a number of generalist species. Regarding the landscape matrix, agricultural fields and unsealed areas in settlements are considered as permeable area for species dispersal; and the traffic, river, and sealed area in settlements are taken as barriers. Using this methodology, econets can be built on different dispersal distances. Then, Effective Connected Mesh Size (ECMS) is applied on the econet maps for calculating both intra- and interpatch connectivity. This ECMS is actually equivalent to apply

MESH on all connected forest clusters including connections. MESH can be understood as the case of ECMS in a dispersal distance of 0 m. The interpatch connectivity is incorporated in ECMS by the area of corridors which stands for the available area for species dispersal but not belonging to forest patches. One thing should be noticed is, that the ECMS index measures intrapatch and interpatch connectivity on the same weight for landscape connectivity. It is assumed that within a patch or connected patches the connection possibility is 1, but in reality the connection among different patches could be weaker as they are indirectly connected. Generally speaking intrapatch connection has more influence on ecological connectivity than interpatch connection. However, this is still dependent on species, for example, some edge species more likely dispersed among habitats (Jaeger et al., 2011).

In summary, the concept of landscape fragmentation and connectivity can be unified in the landscape structure analysis and measured by the metrics of Effective (Connected) Mesh Size, which combines both intra- and interpatch connectivity.

5.2.2.2 Functional roles of ecotones and small biotopes in econets

In previous chapters, forest fragmentation and econets connectivity have been analyzed in the test sites where ecotones and small biotopes are incorporated in the analysis as functional parts (chapter 4.4.1.3 and chapter 4.4.3.3). The isolation effects on forest patches depend on the permeability of adjacent land-cover types. Ecotones between forest and field are considered as a mixed habitat which can support edge species on both sides. They play a functional role of enhancing intrapatch connectivity for both forest and field. Therefore, ecotones are incorporated in the calculation of MESH for forest and field as common area and the alleviation effect on fragmentation depends on the area proportion of ecotones. In the case of Rathen, the ecotones can slightly increase the MESH value as shown in Figure 5.4 (left diagram, the MESH value including ecotones corresponds to dispersal distance labeled as “0+”).

Small biotopes are considered as stepping stones for mapping econets and play a functional role of enhancing interpatch connectivity among forest patches. For the calculation of ECMS index patch connections established through stepping stones are considered as the proportion of interpatch connectivity. The results of metrics for forest connectivity in the test sites are shown in Figure 5.4. The metrics pattern can reflect the spatial distribution of forest patches. The MESH value measures the intrapatch connectivity of forest patches under a dispersal distance 0 m. Intrapatch connectivity is an intrinsic feature which is not affected by the dispersal distance. As the dispersal distance increases, the ECMS value is more like dependent on the interpatch connectivity. The function of small biotopes as conjunctions is related to their distance away from the forest patches and their topological feature in the econets. Compared to Rathen, Jiawang shows much lower intrapatch connectivity and its interpatch connectivity is highly related to dispersal distance. This fits to the fact that little forest patches dispersedly distributed within Jiawang. For species with low mobility, the forest area (intrapatch connectivity) where they dwell is much more important than the area made available through dispersal to other patches (interpatch connectivity). For species with strong dispersal abilities the amount of forest patches is irrelevant to determine the total available habitat. Because the species can reach many habitats through stepping stones or directly disperse among forest patches.

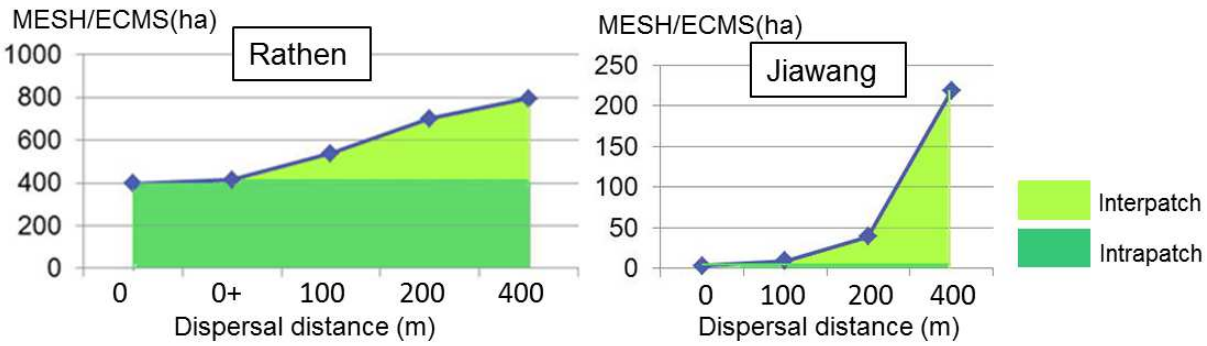


Figure 5.4: Forest connectivity analysis concerning on both intra- and interpatch connectivity in test sites of Rathen and Jiawang (dispersal distance “0+” means incorporation of the ecotones that directly adjacent to forest patches).

5.2.2.3 General applicability in econets analysis

In chapter 3.3.2, a general approach for econets analysis has been developed. It contains a “multi-buffer” procedure for econets mapping and metrics for evaluating the connectivity of econets. The use of these metrics in monitoring and comparing landscape connectivity has been proved to be applicable in both examples in Germany and China.

This “multi-buffer” mapping process is based on a vector-based GIS algorithm. The selection of buffer range could be interpreted as a scale effect on landscape structure analysis. The home range size is proportional to dispersal distance (Bowman et al., 2002). In a large dispersal distance some small biotopes may not be identified for the conservation of econets, such as scattered trees or tree rows. It is assumed that potential stepping stones should increase in size as the species dispersal distance increases. For example, a single tree can be a stepping stone for deadwood insects at a dispersal distance of 100 m, but not for dormice at 400 m dispersal distance (Table 4.10). As the buffer range increases, the large forest patches will be directly connected without small stepping stones. The mapping process is different from MSPA (Morphological Spatial Pattern Application, Vogt et al., 2007a), which is applied for mapping the structural components of forest according to their morphological feature. It results in physical pathways between different core areas (Vogt et al., 2007b). However, the effects of other components of the econets, e.g., stepping stones and barriers, are not included in MSPA. An advantage of this “multi-buffer” approach is that it can easily incorporate stepping stones and barriers in the mapping process. The interpatch connection in the econet can be considered as the shortest path between patches.

In reality conservation plans limited to one scale will neglect the biodiversity pattern and ecological processes that are important at other scales (Huber et al., 2010). To fully understand landscape connectivity, it is necessary to simulate ecological networks at multiple dispersal distances. Considering on the small size of potential stepping stones in this work, dispersal distances are set to 100, 200, and 400 m for the test sites. In the mapping processes, impermeable areas are used to intersect connections between woody patches. By this way, the interpatch connections that are overlaid with landscape barriers will be simultaneously cut off from the barrier’s border, and the forest patches belonging to the same cluster will be identified. But the intersected corridors may contain redundant part along barriers, as there maybe corridors including only stepping stones without connecting to large forest patches. This bias could be tolerant for a fine-scale network, but would not be applicable for very large buffer ranges. This leads to the conclusion that this “multi-buffer” approach is generally applicable on fine spatial scale when the position of landscape barriers has been incorporated into the mapping process. As the buffer range enlarges, more connection bias may happen in econets. Despite of this limitation, the vector-based approach allows a convenient and rapid simulation of econets analysis as well as corresponding structural indicators can be calculated directly from this established network.

Recently improved graph-based metrics have been developed to measure habitat availability at the landscape scale (Pascual-Hortal and Saura, 2006; Saura and Pascual-Hortal, 2007; Saura and Rubio, 2010). The concept of habitat availability measures reachability for species in the extent of integrating both habitat size (intrapatch connectivity) and the area made available by the connections between habitat patches (interpatch connectivity) (Luque et al., 2012; Saura et al., 2011). The index of Effective Connected Mesh Size (ECMS) has the sense of habitat availability, because it measures both intra- and interpatch connectivity. Differing from the other metrics based on the probabilistic approach, e.g. Probability of Connectivity (PC, Saura and Pascual-Hortal, 2007), Integral Index of Connectivity (IIC, Pascual-Hortal and Saura, 2006), and Power Weighted Probability of Dispersal (PWPD, Estreguil et al., 2012), the computational effort of ECMS is relatively lower. It measures landscape connectivity directly from the econets map without specific assumptions about the feasibility between patches. The ECMS measures interpatch connections based on the area of connections mapped from the “multi-buffer” process. However, the connections may not be the actual dispersal route of animals. Therefore, the result of ECMS has no absolute meaning and should be interpreted in relative terms and used only in a comparison process.

To further examine the interpatch connectivity, two metrics CAPE and d CAPE have been calculated. CAPE measures the proportion of connections within the econets. It implies the proportion of interpatch connectivity in habitat availability. A higher CAPE value means more connections among forest patches. As dispersal distance increases, this indictor will be correspondingly larger. Applying CAPE in a multiple buffer process the dCAPE (change rate of CAPE between two buffer ranges) can be used to identify the gap ranges among habitat patches or interpreted as the degree of habitat fragmentation.

In summary, the model using the “multi-buffer” approach in combination with the proposed metrics is effective and easy-to-use in econets analysis. However, it is scale-dependent and should be applied in corresponding research at fine-scale level.

5.2.3 The application of the metrics for describing landscape contrast

Patchiness and gradients are the concentrated expressions of spatial heterogeneity in the landscape (Wu, 2007). For analyzing the ecological gradients, McGarigal (2009) introduced surface metrics as an alternative to patch metrics for the quantification of landscape structure. Hoechstetter et al (2011) used lacunarity analysis to analyze gradual value progressions in landscape systems. Both methods interpret the landscape as a continuous surface instead of the patch model. In this thesis ecotones are defined as elevation gradient and detected in the form of a patch class. At the landscape level, ecotones can be regarded as transitional area between forest and field exhibiting the characteristic of gradient. Accurate height information not only can be used for ecotone detection but also help to determine the spatial heterogeneity in vertical dimension, e.g. by applying the modified landscape contrast indices (chapter 3.3.1.3). At a fine spatial scale the results might be considered as a surface representation of patch dissimilarity.

At the patch level, the modified edge contrast index (ECON) measures the degree of elevation contrast between a patch and its immediate neighborhood. It is calculated based on the difference of mean height between the patches. The mosaic model can highly affect the contrast value, since the patch interior and its exterior may exhibit different elevation. In addition, some small patches which are normally neglected in landscape structure analysis may also be counted in the average height of matrix. This could result in an underestimation of the contrast value between the patches and matrix. For this reason, it is necessary to detect these small patches and differentiate the patch interior and its exterior, such as ecotones. At a fine spatial scale, a big patch may be separated into several parts which can exhibit either higher or lower contrast than the average value. The ecotone shows a relatively lower contrast value than the patch interior. It functions as a buffer area that allows its surroundings to be easily accessed.

ECON is a relative measure at patch level and stands for the degree of contrast in patch edge regardless of how big the patch is. It could be misleading to calculate the mean edge contrast which quantifies the average edge contrast for a particular patch type (class level) or for all patches in the landscape (landscape level). In this case two metrics that treat the landscape as a whole or refer to the patch proportions have been developed at the landscape level: Total Edge Contrast Index (TECI) and Area-Weighted Edge Contrast (AWEC). The example shown in chapter 4.4.2 demonstrates that the existence of small biotopes and ecotones can reduce the landscape contrast (of both TECI and AWEC) as they possess the characteristic of lower edge contrast than the patch interior. The TECI counts only the total edges within the landscape and ignores patch distinctions. AWEC is a more suitable indicator than TECI for incorporation of small biotopes and ecotones in landscape contrast analysis. In addition AWEC is insensitive to the omission or addition of very small patches. In practice, this makes the results more reproducible as it has no specific requirement of patch size.

From the third dimension, the concept of landscape contrast can bring the ecological function of ecotones and small biotopes together. If the height difference among patches is considered as "terrain barrier", the ecotones or small biotopes can be recognized as shift areas that may influence transboundary movements. The concept of landscape contrast can be regarded as a further step after landscape fragmentation with additional consideration of the edge permeability in the landscape structure analysis.

5.3 Possible fields of application

As important landscape components, ecotones and small biotopes are crucial to be incorporated in the landscape structure analysis especially with respect to biodiversity conservation. Throughout this work, the goal has been pursued to develop methods that can support land-cover/land-use classification as well as landscape structure analysis to include ecotones and small biotopes. The novel methods have considerable potential for application. Apart from the examples of application presented in the last chapters, there are other possible fields in which the proposed methods can be applied:

- *Forest resources management*: The ability of acquiring multi-temporal images in a short interval is an advantage for applying RapidEye images for landscape monitoring. Using the vegetation index REVI can precisely extract the extent of forest resources and the forest composition (coniferous, broad-leaved, and mixed forest). With the help of high resolution lidar data, the distribution of forest boundary can be detected using the approach of “growing and shrinking” developed in this thesis and some additional features on forest boundary can also be calculated (see in Figure 5.3). Such information would be useful to plan forest activities, such as silviculture, crown forest management, harvesting programs, and more.

- *Farmland monitoring*: The plots distribution within farmland can be achieved from multi-temporal classification on RapidEye images. The produced maps and statistical data are useful for evaluating the agricultural resources and regular monitoring on plots can conduct the agriculture activities. Since the farmlands with structurally rich landscape elements (e.g. hedges, field margins, and field copses) are recognized as High Nature Value (HNV, see chapter 2.2.1.3), the proposed method for small biotopes detection will help to identify the farmland status of HNV.

- *Econets gap analysis*: Having a second thought on the econets mapping process (see detail in chapter 3.3.2.1), in the third step the landscape barriers (traffic, river, etc.) could be used to intersect the connection between patches. This can help to find the blocks where connections potentially should be strengthened. Furthermore, this would be also useful for landscape planners to fix the location for building Wildlife Bridges at key points of the econets.

- Assessing the function of *Wildlife Bridges*: As introduced in chapter 2.2.1.3, Wildlife Bridges have been built for alleviating the fragmentation effects of traffic routes. But it is not easy to incorporate them into the fragmentation metrics of MESH. As shown in Figure 5.5, case (a) is totally fragmented by the traffic and has a MESH value of 26 km^2. Since patch A and patch B are considered as connected by Wildlife Bridges in case (b) and (c), they show relatively bigger, but the same MESH value of 50 km^2. No matter how many bridges will be built between patch A and B, it won’t affect the MESH value. The latter two MESH values of case (b) and (c) certainly do not fit the reality. To solve the problem, the concept of landscape contrast can be a simple solution. In addition to MESH, using landscape contrast (e.g. AWEC) as a second level indicator to describe the functions of Wildlife Bridges. If the traffic is assumed as absolute linear barrier, the AWEC value of case (a) will be 1 and in case (b) and (c) the AWEC value will be lower than 1. Their AWEC values depend on how Wildlife Bridges can decrease the edge contrast between patch A and B. This edge contrast degree may relate to the breadth and length of Wildlife Bridge. There is no doubt that the landscape contrast value of case (c) is lower than case (b), since two Wildlife Bridges have a greater effect on alleviating the edge contrast degree. The combination of fragmentation and contrast metrics can be used as an integrated indicator for the evaluation of the effects of both traffic and Wildlife Bridges on natural landscape.

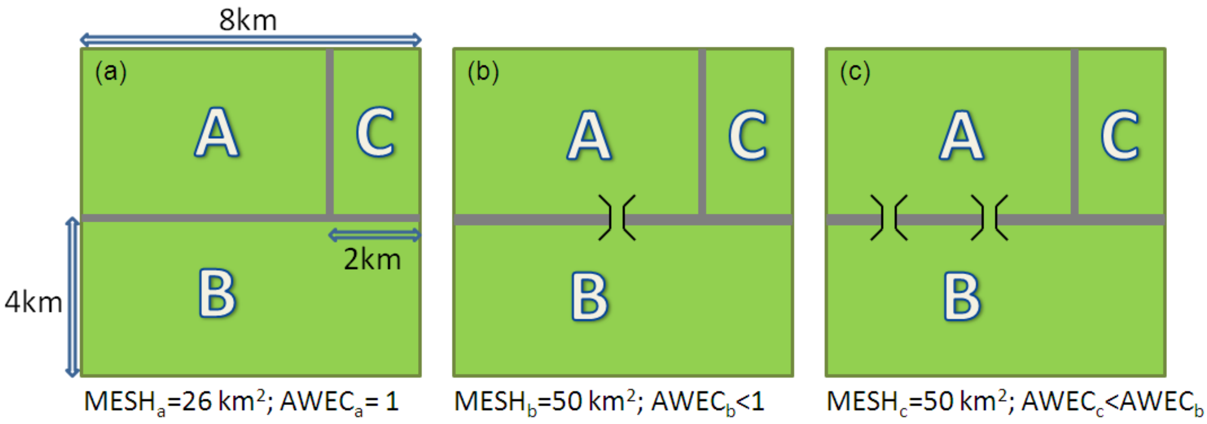


Figure 5.5: Conceptual models of Wildlife Bridges in fragmented landscape:(a) patch A, B, C are totally fragmented by traffic; b) Patch A and B is connected by a Wildlife Bridge; c) Patch A and B is connected by two Wildlife Bridges).

6 Conclusion and outlook

The work starts from the integration of the third dimension into the land-cover classification and landscape structure analysis. It leads to a further detailed level for landscape monitoring. With the help of the high resolution NDSM (derived from lidar system) in combination with multispectral data (RapidEye images), fine-scale landscape elements can be automatically delineated. The enhancement for landscape structure analysis is due to the incorporation of these detailed landscape elements with modified 3D-Metrics.

In chapter 2 the details of the ecological roles of small biotopes and ecotone are outlined based on the existing literature. Furthermore, the official landscape monitoring systems used in Germany and China were also presented to give an impression of the common used data and the official indicators concerning on biodiversity at landscape level. As concluded in chapter 2.2, either in Germany or in China the landscape monitoring is focusing on large spatial scale and the gap of incorporating fine-scale landscape elements still needs to be filled. Chapter 2 serves as a background knowledge that shows the possible aspects that the ecotones and small biotopes could be integrated in the assessment of landscape structure. This part of work, at the same time, provides an answer to the first of the three questions raised in chapter 1.3.2.

- *What roles do small biotopes and ecotones play in maintaining the ecological functions of the whole landscape? And how to define them across scales in heterogeneous landscapes?*

  Besides providing habitats for some small-sized animals, the small woody biotopes are commonly viewed as key elements for the linkages among forest patches. Losing these elements can decrease landscape connectivity and result in a more fragmented structure. In addition, abiotic processes can also be affected by these small elements, such as mineralization of nutrients, infiltration of rainfall, water and soil erosion etc. The materials and energy flows are both affected by them. In other words, these small biotopes as important parts of the landscape pattern strengthen the overall landscape diversity and thus the resilience of the ecosystem. For the work at hand, four types of small biotopes are considered including scattered trees, tree rows, (field) hedges, and (field) copses. They are defined at a detailed spatial scale (< 1 ha) and can be differentiated by shape features (e.g. height, length, and length/width) as concluded in chapter 3.2.2.1. In this thesis, ecotones are defined as a transitional area with mixed vegetation and specified as elevation gradient between forest and field. As mixed habitat, ecotone may serve as the hot spot area for species diversity. Because an ecotone is the zone in which two communities overlap, many different forms of life will live together and compete for space. As ecological gradient, the ecotones function as buffer zones or filters that would alleviate the landscape fragmentation and increase the permeability on patch edges. It regulates the ecological flows among landscape including materials, energy, organisms, and information that are related to ecological system. In brief, the ecological functions of the small biotopes and ecotones are concluded mainly from three aspects: increasing habitats for small-sized animals and ecotonal species, enhancing landscape connectivity and reducing landscape contrast.

Therefore, methods for delineating small biotopes and ecotones in the format which is applicable for landscape metrics calculation are needed. Accordingly new or modified metrics for incorporating these elements in the analysis of landscape structure should be developed. In the next step, chapter 3 provides a methodical solution to the second and third research questions and chapter 4 gives two real-world examples for the application of the proposed methods. These chapters are the main innovative and practical parts in this work.

- *How can these landscape elements, which are not contained in official land-use data, be detected / selected?*

An integrated approach for landscape monitoring is presented based on the multi-spectral data (RapidEye images) and high resolution NDSM. It contains two steps. Firstly an OBIA (Object-Based Image Analysis) process is applied on the RapidEye images for generating land-cover maps including main and sub classes. Then, based on the existing land-cover maps, a further PBIA (Pixel-Based Image Analysis) is adopted for the detection of the fine-scale landscape elements using high resolution NDSM data. The strategy of image analysis is to apply different classification approaches on the proper data sources according to the image resolution and targets. The integration of OBIA and PBIA turns out to be a suitable method for obtaining more detailed description of landscape pattern.

The examples of image processing presented in chapter 4 reveal that the proposed OBIA process which is applied on multi-temporal RapidEye images can achieve high accuracy results in both test sites in Germany and China. The image analysis adopts a hierarchical approach combining the “bottom-up” segmentation and “top-down” classification strategy for a refinement of land cover mapping from main classes to sub-classes. Since this OBIA process is developed as a general solution which should be applicable on other similar research areas, the features used in image segmentation and classification should be generated by the common spectral layers, e.g. the spectral indices REVI and NDVI. One thing should be noticed is that the parameters for these indices need to be adapted when applying the rule sets in other research areas. In addition to the abundant spectral information, another advantage for RapidEye data is the ability to acquire images in a short interval that allows a multi-temporal analysis on vegetation pattern which has been proved very useful for farmland classification.

The PBIA is introduced as a further step for detecting more detailed landscape structures (e.g. small biotopes and ecotones). This step is applied on the high resolution NDSM (derived from lidar data) using the land-cover map (derived from RapidEye data by OBIA) as a base map. The results in this step can be regarded as the outcome of the combined data sources of high spectral resolution RapidEye images and high spatial resolution NDSM. In the test site of Rathen, different types of small biotopes were delineated according to their shape features. Thereby the pixel-based “growing and shrinking” process is proved to be effective for the ecotone detection. As a result, four types of ecotones can be identified in this region (Figure 4.13). The result obtained in this process is highly dependent on the parameters used in the algorithm which should be carefully set according to the local conditions. In addition, the data bias should also be considered to set the parameters. For example, the “growing and shrinking” process may change the outline of the small biotopes that could slightly affect the shape parameter. Since the effect from such process is the same on all small biotopes, the detection results will be unaffected. The ecotone is detected based on a categorical land-cover map and a continuous surface model of elevation. Thus, it has the characteristic of both patchiness and gradient. Furthermore, the proposed method for ecotone detection is not restricted to the analysis of elevation gradient but can be also applied to any data representing a non-categorical environmental variable.

The last research question deals with the indices which describe the landscape structure particularly with consideration of these small biotopes and ecotones. The answer to this question is not the measurements for the ecological functions of these fine-scale elements, but the integrated indices which incorporate these elements into the structural analysis of the whole landscape.

- *How to incorporate small biotopes and ecotones in existing landscape structure evaluating methods based on the patch-corridor-matrix model?*

There have been a number of indices used for the analysis of landscape structure. In chapter 3.3, some of them are reformulated to integrate the small biotopes and ecotones in calculation. Referring to research question 1, the related indices could be concluded in three aspects for landscape structure analysis: landscape diversity, landscape fragmentation/connectivity, and landscape contrast.

Small biotopes and ecotones can be simply considered as individual patch types in the calculation of Shannon's diversity (SHDI) and Simpson's diversity (SIDI) that are the most common diversity indices used in landscape ecology. However, these indices may not be suitable for describing habitat heterogeneity. Not only the types of habitats or the number of certain habitat within the landscape, habitat heterogeneity should also consider the spatial distribution of habitats and the key habitats which are more important for species survival. Neither SHDI nor SIDI discovers habitat functions in the calculation of landscape diversity. Comparing the values of diversity metrics in two test sites (Table 4.8), it is concluded that only using Shannon's or Simpson's diversity metrics is not enough for indicating the habitat status with respect to biodiversity conservation. Sometimes they are even misleading, thus the ecological functions of small biotopes and ecotones should be measured not only in landscape composition but also in landscape configuration.

Landscape fragmentation and connectivity can be unified under the concept of habitat availability, which contains the meaning of intra- and interpatch connectivity. The original form of fragmentation index (MESH) measures the intrapatch connectivity of landscape. In chapter 3.3.1.2, the modified index of MESH as an example of the group of fragmentation metrics is proved to be sensitive to ecotones. It is assumed that the ecological role of ecotone is twofold that it can either be a part of forest or a part of field. This leads to an increase of MESH on both forest and field. Chapter 4.4.3 has shown a simple model for mapping and analyzing landscape connectivity at fine spatial levels. This model consists of two parts: the multi-buffer method used for mapping econets; and quantitative indicators for evaluating connectivity. Small biotopes are used as potential stepping stones for establishing the connections among forest patches. The landscape connectivity can be measured by the Effective Connected Mesh Size (ECMS), which is developed in this work. The experimental results on real forest landscape in German and Chinese test sites have shown that this model is efficient for implementation in different landscape patterns. The result of the metrics used in two test sites is consistent with the landscape pattern actually observed. The outcomes of the metrics can be considered as general evaluations of landscape structural connectivity. For species-specific corridor design, this model could also be applied to a specific buffer range. In addition, the use of this model under different buffer ranges can help to reveal the interpatch connectivity by using CAPE and dCAPE (chapter 3.3.2.2).

If the fragmentation concept treats the landscape as a binary model (natural patches and barriers), the contrast index would be useful for describing the inner heterogeneity of natural patch, such as ECON which is developed based on the height difference between the target patch and its surroundings. Like other landscape metrics, this index is also scale-dependent. At the landscape level, the examples shown in chapter 4.4.2 reveal that the contrast indices, e.g. Area-Weighted Edge Contrast (AWEC), have the potential of incorporating the gradients into landscape structure analysis. It allows the analysis of raster data such as digital elevation models over a range of spatial scales. The outcome of AWEC is related to the definition of patch or the model used for landscape simulation. The interpretation of this "contrast effect" depends on the definition of "patch dissimilarity" which is applied in ECON. The concept of landscape contrast gives a detailed description of landscape heterogeneity with "soft" boundaries among patches.

In addition, the proposed indices in this work are calculated under 3D condition. The analysis of using these indices is based on realistic patches' geometry. This results in a detailed description of landscape structure with consideration of fine-scale landscape elements and terrain effect.

The answers to the three research questions constitute the subject of this thesis. The results obtained throughout this research show the value of present work in two aspects: First, an image processing approach integrating remote sensing images and high resolution elevation data is demonstrated for producing land cover maps at two spatial scales. In particular, it offers the solution for automatically delineating small biotopes and transitions at the fine spatial scale. Second, various methodical suggestions to incorporate these fine-scale landscape elements into landscape structure analysis are presented and implemented in two real-world examples.

Biodiversity is a concept too vague and broad for full and direct application in real world regulation and management. Schindler et al (2012) have tested a number of landscape metrics across different extent scales to prove the correlation between landscape metrics and species richness, and have shown that the value of metrics depends strongly on the taxon examined. It is often difficult to postulate a general correlation between species diversity and landscape metrics. The presented work is certainly not the complete solution on this subject. The efforts are made to analyze the landscape structure in a much more detailed and precise way that would enhance understanding of the relationship between landscape pattern and process. When applying the proposed methods in reality, two things should be kept in mind. The first is the spatial scale of investigation. The results of integrating 3D-aspects in landscape structure detection depend strongly on the resolution of the input data. On a coarse level the fine-scale landscape elements are obliterated by making mean values over large areas. The second is interpretation of landscape metrics. Taking account of terrain effect complements landscape structure analysis, but as with 2D metrics the values of 3D metrics do not possess any absolute meaning in themselves. They should be interpreted in relative terms and used, for example, to compare different areas or different time states of landscapes. Nevertheless, the proposed methodology may serve as a stepping stone for further studies dealing with landscape pattern. Future work may focus on refining and improving the methods of pixel-based image analysis on higher resolution data as well as testing them under real-world conditions to gain more accurate and detailed landscape elements. Besides the presented landscape indices, additional information can also be considered in landscape structure analysis, for example, the different forms of ecotones or the shape features of forest/field transitions (average height, standard deviation of height, or curvilinearity). The future work may need to find new alternative landscape models for applying the "gradient concept", such as the surface metrics expressed by McGarigal and Cushman (2005). In addition to the elevation, other variables, e.g. temperature, humidity or other abiotic variables, can also be used for representing environmental gradient. Linking landscape structure and biodiversity, landscape metrics must always be selected based on the tasks or problems, and in accordance with the available resources (Walz, 2011). The introduced indices of landscape diversity, landscape fragmentation/connectivity, and landscape contrast can be used as a basis for general evaluation of natural landscape pattern regarding biodiversity conservation.

In short, the present work provides both conceptual models and practical approaches to landscape monitoring at a fine-scale level. Moreover, it works as an inspiration for further methodical developments to gain more insights into the landscape structure and contributes to the increasing complexity and severity of ecological problems. The last thing that should be fully aware is that biodiversity conservation is a much broader theme which refers to not only the protection of target species or habitat diversity, but also the avoidance of landscape aesthetics loss, protection and improvement of social and economic values, and persistence of culture heritage in landscape (Csaplovics et al., 2003; Walz, 2011).

7 References

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Acknowledgements

Looking back to the past five years I'm very glad that I have done my Ph.D in Germany, although it is not always a "pleasant journey". Without the helps and supports from my supervisors, colleagues, friends, and family it won't be possible that I can finish my study.

I'd like to express my special gratitude to PD. Dr. Ulrich Walz at the Leibniz Institute of Ecological Urban and Regional Development (IOER) who supported me from the very beginning until the end. As my mentor and supervisor he was always guiding me in my scientific work and gave me valuable advices. Many ideas and new thoughts came from our countless discussions. Apart from my work, he was also willing to answer my questions in all aspects, e.g. taking German course, visiting doctors, etc. His help really made me feel secure and comfortable in a foreign country.

I'm very grateful to Prof. Dr. Elmar Csaplovics at the Dresden University of Technology, under whose supervision I began my research. I still remember his warm welcome on the first day I arrived in Dresden. During various stages of my work he offered many valuable suggestions. He has been always supportive and encouraged me to finish this research. My gratitude is also extended to Prof. Dr. Song (University of Chinese Academy of Sciences, Beijing) for agreeing to act as advisor and reviewer and for providing very helpful comments on my dissertation.

I want to thank Prof. Dr. Dr. Berhard Müller (IOER) who was the chairman of my doctoral examination board. I appreciate the assistance that he has supplied for me. Many thanks also go to Prof. Dr. Wolfgang Wende (IOER) for being my examiner of oral test. I did learn a lot about spatial planning system in Germany from his lessons. I owe much to Prof. Dr. Isolde Roch (IOER) who firstly introduced me into the Leibniz Institute of Ecological Urban and Regional Development where I got the support for finishing my study.

I also wish to give my special thanks to Dr. Marco Neubert (IOER), who acted as my additional supervisor and joined all the stages of my work. He has been always helpful and provided me good counsel in many ways. From remote sensing image classification to ecological network analysis, he was the right person to ask for advices and a reliable consultant.

I enjoyed all discussions and "working experience" in the sharing office with Markus Dießelmann, Reinhard Beger, Sebastian Muhs, Holger Oertel, Daniel Eichhorn, Odette Kretschmer. For creating the excellent working conditions, I am very thankful to the following colleagues from IOER: Dr. Gerd Lintz, Dr. Ralf-Uwe Syrbe, Dr. Robert Hecht, Hendrik Herold, Sabine Witschas, Claudia Schwertner, Christina Kraatz. Even though I cannot name them all here, there are many colleagues and fellow doctoral candidates who also played an important role during my work for the last years.

This work was carried out at the Leibniz Institute of Ecological and Regional Development in Dresden. I gratefully acknowledge the funding sources that made my Ph.D wok possible. I was funded by the China Scholarship Council from 2009 to 2013. Further appreciated assistance for accomplishing this study was provided by the Graduate Academy of Dresden University of Technology within the program for young scientists during the completion of the doctorate. This work was supported by the German Aerospace Center for providing RapidEye data from RapidEye Science Archive. The airborne laser scanning data were supplied from the project of “Geographic information networks for cross-border national park region Bohemian-Saxon Switzerland (Dresden University of Technology, Institute of Photogrammetry and Remote Sensing)”.

It is important to have a net of good friends for being abroad. Thank you very much Lars, Carola, Alex, Sebastian Hoechstetter, Kai, René, Judith, Frank, Thomas, and Ralf that you have been so nice for helping me settle down and getting to know the German culture. I have become a very good friend to the family of some mentioned people above. I really enjoyed the time that we have spent together. Thanks also go to Lynn and Fei for proofreading the final manuscript.

I am indebted to my parents, my grandma, and all the other family members, who have been an important and indispensable source of spiritual support. Lastly, I wish to express my profound appreciation to my wife Jingyang. Without her support, encouragement, and tolerance, this study would not have been possible.

Dresden, October 2014
Wei Hou