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Monitoring of forest cover change and modeling biophysical forest parameters in the Western Carpathians

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In our technology-heave and complicated globalised world we need at least a part of nature in its original form so as not to lose the meaning of life.

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Abstract

Human-induced environmental change is evident across the globe. Deforestation and forest degradation are among the most critical impacts of humanity on the Earth system, as forests provide crucial ecosystem services, and are a key element in the global climate change discussion, specifically considering the global carbon balance. Therefore, monitoring and quantifying forest changes are of prime scientific interest. The main goals of this thesis were to monitor forest change across country borders in the Western Carpathians, and to assess coniferous forest biomass dynamics and their impact on aboveground forest carbon storage. Generally, Carpathian forests provide outstanding biodiversity levels, high growing stocks, and an important European carbon sink. However, the Western Carpathian forests are exceptional, with a turbulent land-use history, high airborne pollution loads, and ongoing forest decline. Forest change between 1985 and 2010 was quantified using remote sensing techniques. Results show that the synergistic effect of unsustainable forest management in the past and high pollution levels during communist times significantly damaged coniferous forests. Spruce-dominated stands exhibit lower resistance against biotic and abiotic impacts, and are more susceptible to pests and extreme weather events. Widespread biomass loss since 2005 has converted coniferous forests from a net carbon sink into a net carbon source. Cross-border analysis emphasized the role of site characteristics such as forest type, predominant species, topographic conditions, pollution hotspots, microclimate, and their interactions for forest decline. Summarizing, this thesis tells a complex socio-ecological story and provides estimates of aboveground carbon stock changes in Western Carpathian forests.

Zusammenfassung

Die Umweltveränderungen durch den Menschen sind auf unserer Erde allgegenwärtig. Entwaldung und Waldschädigung beeinflussen das System Erde entscheidend, denn Wälder bieten wichtige Ökosystemleistungen und sind Kernelement der Debatte um den Klimawandel, speziell hinsichtlich der globalen Kohlenstoffbilanz. Veränderungen der Waldbedeckung zu quantifizieren ist daher von herausragendem wissenschaftlichen Interesse. Ziel dieser Arbeit ist es, Waldbedeckungsveränderungen in den Westlichen Karpaten grenzübergreifend zu bestimmen, sowie Dynamiken der Biomasse von Nadelwäldern und deren Auswirkungen auf die oberirdische Kohlenstoffspeicherung abzuleiten. Die Karpatenwälder zeichnen sich durch ein hohes Maß an Biodiversität, einen großen Holzvorrat und als wichtiger Kohlenstoffspeicher für Europa aus. Jedoch sind diese Wälder auch geprägt von einer bewegten Geschichte der Landnutzung, hoher Luftverschmutzung und einer andauernden Waldabnahme. Mittels Methoden der Fernerkundung wurden Veränderungen in der Waldbedeckung für die Jahre 1985 bis 2010 abgeleitet. Die Ergebnisse zeigen, dass insbesondere das frühere Forstmanagement sowie die starke Luftverschmutzung zu Zeiten des Kommunismus gemeinsam die erhebliche Schädigung von Nadelwäldern bedingen. Fichtendominierte Bestände offenbaren dabei eine geringere Widerstandsfähigkeit gegenüber biotischen sowie abiotischen Belastungen, z.B. Schädlingen und Extremwettersituationen. Seit 2005 verwandelten sich die Nadelwälder infolge eines weit verbreiteten Biomasseverlustes von einer Netto-Kohlenstoffsenke in eine Netto-Kohlenstoffquelle. Die Analysen betonen den Einfluss bestimmter Standortfaktoren wie Waldtyp, vorherrschende Baumart, topographische Gegebenheiten, Brennpunkte der Umweltverschmutzung, Mikroklima und deren Interaktion auf die Waldabnahme. Die Arbeit legt eine komplexe sozio-ökologische Geschichte dar und erbringt Schätzungen über die Veränderung des oberirdischen Kohlenstoffvorrates der Wälder der Westlichen Karpaten.

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Chapter I:
Introduction

1 The Earth of nature and humans

Our planet has existed and has been constantly changing for over 3.8 billion years. Natural evolution and extinction patterns have shaped biodiversity, and nature has always been in flux (Rull 2009). Humans – as *Homo sapiens* and the result of natural evolution – appeared only around 200,000 years ago, which means that the Earth has evolved without human intervention for its almost entire history (Rull 2011). About 12,000 years ago, with the invention of agriculture, humans began to change the Earth more dramatically (Kluever 2008). While initially these changes influenced only the local environment, over time, humans have begun to *shape* the environment at a global scale. Nowadays this has shifted towards an unsustainable exploitation of the Earth and results in *environmental changes* that can be witnessed almost everywhere around the globe. Moreover, it is expected that the effects of *human-induced environmental changes* will continue for the next centuries and millennia, as there is a lag between reaction and effect (Underdal 2010).

Human-induced environmental changes manifest themselves in the accumulation of greenhouse gases (GHG) - such as carbon dioxide and methane -, a changing climate, as well as the degradation of oceans and terrestrial ecosystems (Moran and Ostrom 2005; Zalasiewicz et al. 2010). Degradation of ecosystems is defined as a persistent reduction in the capacity to provide ecosystem services (MA 2005). These are especially threatened by extensive land-use and land-cover changes (LULCC), which cause habitat destruction and subsequent biodiversity loss. These changes are expected to increase in the near future, owing to global climate change and a constantly growing human population, which force changes in agricultural policies and globalization of trade (Schulp et al. 2008; Parker 2011; Rull 2011). Clearly, these processes will increasingly determine the amount of land required for different uses such as agriculture, forestry, industrial, residential and recreational purposes (Schulp et al. 2008).

Yet *degradation of terrestrial ecosystems* has a critical impact on the global carbon cycle balance, as those are the major carbon sinks by sequestering carbon and diminishing the build-up of carbon dioxide in the atmosphere (Zhao and Running 2010). Thus, contemporary global change research aiming to further the understanding of the carbon cycle and the accounting of carbon storage in plants is one of the most critical endeavors of our time (Moran and Ostrom 2005). The capacity of plants to store carbon is defined as the terrestrial Net Primary Production (NNP) and is measured by *biomass increment*.

Evidently, the NNP depends on the investigated scale since there are global, regional, and local differences between ecosystem's capacities. Recent studies at global scale show that carbon uptake by plants could be driven by present climate change, particularly a raising temperature and the availability of water (Zhao and Running 2010). While clearly the same drivers would determine local to regional NNP and *biomass change*, their dimension and significance is different.

Globally speaking, the last decade was the warmest one since the beginning of recorded measurements of temperature (WHO, NOAA, NASA). *Locally and regionally speaking*, however, climate change in terms of weather anomalies has a higher variation, frequency, magnitude and duration as well as a stronger socio-economic impact on the local population. Hence, climate change is likely to be a direct driver for habitat degradation (for example wind-throws, drought, fire), as well as to induce and strengthen other degradation drives (for instance, pest or harvesting regime).

An increasing number of local to regional studies revealed that habitats (as a part of ecosystems) can convert from net carbon sinks to net carbon sources because of their degradation, climate change, or both (Kurz et al. 2008a; Kurz et al. 2008b; Schroeder et al. 2008). The *biomass change under climate-induced stress* differs from habitat to habitat and from species to species (Crookston et al. 2010), as they vary in terms of vulnerability to climate change and ability to withstand and recover from degradation. It is therefore crucial and indispensable to accurately estimate and differentiate habitat productivity and *long-time biomass trends* at a local to regional scale, before applying those to global forecasts.

Finally, by almost any measure, the effects of the *human-induced environmental changes* will continue for centuries and millennia. However, the long-term extent of these effects and following future changes is currently unknown (Zalasiewicz et al. 2010). It is very hard to predict which effects will interplay, and which factors will strengthen or weaken the effects of anthropogenic change. For now, from all above-mentioned human-induced environmental changes, undoubtedly one has the greatest consequence for humans and other species – it is the land-cover change, particularly *the change in forest cover* (Moran and Ostrom 2005).

2 Forest ecosystem role and dynamics

Due to their ecological, economical and spiritual goods and services, *forests* are essential for human life (Bengtsson et al. 2000; Foley et al. 2007b). Indeed, forests improve soil properties, protect hydrological flows, and harbor the majority of the earth's biodiversity (MA 2005). Moreover, forest ecosystems (with their aboveground and belowground dimensions) contain the majority of the terrestrial *carbon stock* (McMahon et al. 2010).

Nonetheless, forest and its management can contribute to both an increase and reduction of future atmospheric greenhouse gases concentration (Kurz et al. 2008b). The most radical contribution is forest logging, when forests are converted *from a net carbon sink to a net carbon source*. Currently, around 13 million ha of forests are converted every year to other uses, or are lost due to natural reasons (FAO 2010). The Food and Agriculture Organization (FAO) of the United Nations reports, that the highest global net loss of *forest biomass* over last 10 years for South America and Africa was related to the *conversion* of tropical forest to agricultural land (Figure I-1). Furthermore, our current global course, particularly in terms of agricultural policies and globalization, will most likely trigger further rapid loss of forests to make room for agriculture (Meyfroidt and Lambin 2011). Although Europe and Asia feature a net gain of forest biomass, climate-related factors like drought, fires and forest pests play a significant and steadily increasing role in *deforestation* and forest degradation (Dale et al. 2001; Kurz et al. 2008b; Allen et al. 2010).

Apart from abrupt *deforestation* induced by nature, humans, or both, an increasing number of studies report *long-term gradual forest biomass changes* in many regions of the world (Josefsson et al. 2009; Dale et al. 2010; Pan et al. 2011). To what extend these changes are positive or negative, and what their exact drivers are, is still under scientific investigation. On the one hand, Zhao and Running (2010) documented a decreasing plant *productivity*, particularly in the Southern Hemisphere over the last decade, although this one was the warmest in the recorded history. Moreover, other studies report forest dieback related to increasing *insects activity*, and warn about the unprecedented extent and severity of insect outbreaks in the near future (Kurz et al. 2008a; Hlásny et al. 2010a). On the other hand, McMahon et al. (2010) showed that forest biomass recently increased across forest types mainly due to climate change (higher temperatures and longer growing season). Furthermore, they argue that this growth after stand-replacing events is greater than expected. Additionally, an increasing number of studies underline interdependencies

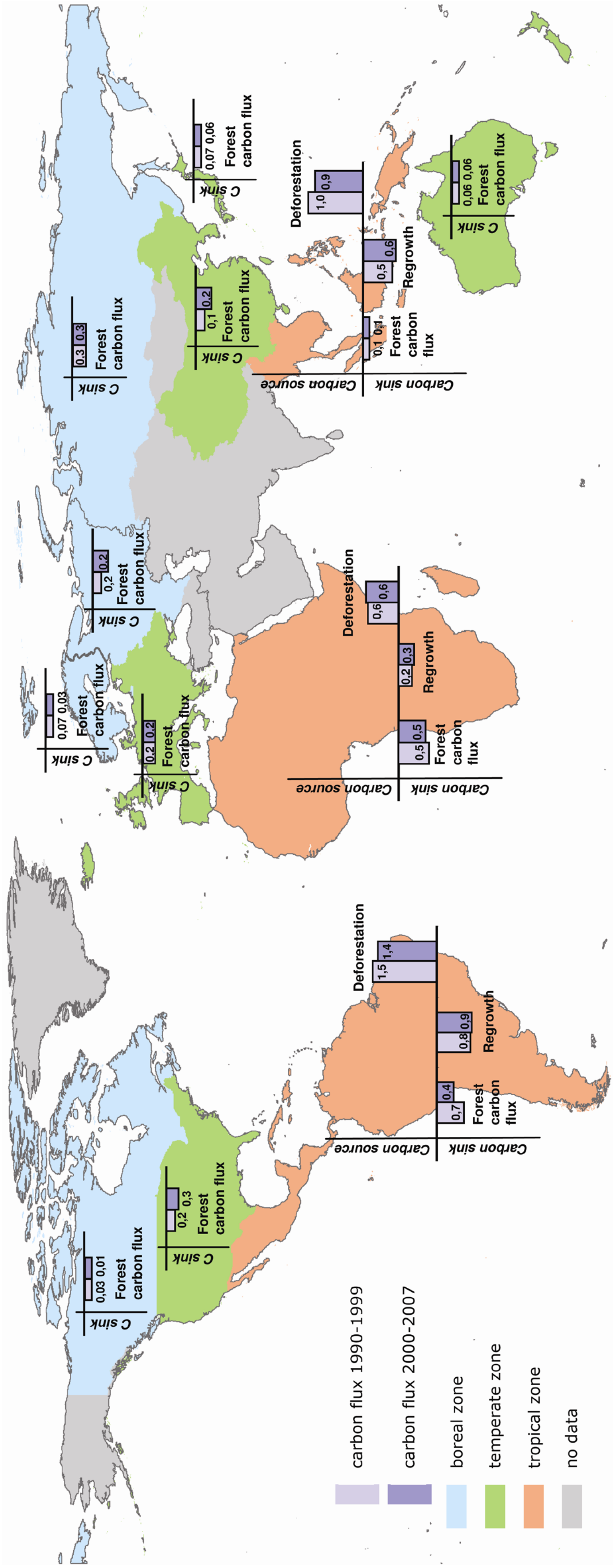

Figure I-1: Forest carbon sinks and sources (Pg C year-1) for 1990-1999 and 2000-2007. Forest carbon flux for global established forests in three ecosystem zones; regrowth carbon flux for tropical forests after anthropogenic disturbances; and deforestation tropical gross carbon emissions; adopted from Pan et al., 2011.

among biotic and abiotic factors (Dale et al. 2001; Thomas et al. 2002; Bytnerowicz et al. 2007; Brook et al. 2008; McDowell et al. 2011). These interactions as synergistic processes amplify vegetation feedbacks and cause cascading effects (Brook et al. 2008). However, their widespread and multidimensional impact still remains unpredictable to future forest change. Therefore, even if globally decreasing trends in forest carbon storage is presumed, no single trend and thus single expectation for regional and local carbon balance can be determined.

Forest ecosystems are complex and dynamic, and their *management* is very challenging (Wulder 2006). However, knowledge limits and unsustainable management decisions generate even more complexities due to interactions between natural and human-induced factors. In the light of the *long-term forest dynamics*, cyclical destruction (disturbance) and creation (recovery) ensue each other, making it impossible to define one single natural state of the forest (Rull 2011). Once these periodic dynamics are interrupted and unsustainable silviculture follows, subsequent degradation and species endangerment occur. One well-known example of historical management failure took place in Europe during the Austro-Hungarian time, and was related to a rapid increase in the demand for energy and fuel. In this case, natural forests were overexploited and large-scale artificial deforestation and reforestation periods followed each other (Luyssaert et al. 2010). Natural silver fir (*Abies alba*) and beech (*Fagus sylvatica*) forests were largely replaced by *monocultures of Norway spruce* (*Picea abies*), particularly in Central Europe. This caused a widespread biodiversity loss and ongoing depletion of forest ecosystem functions.

2.1 The Carpathian forests

The Carpathian Mountains sustain Europe’s largest continuous mountain forest ecosystem. Extending from Austria to Serbia, the Carpathians cover most of Slovakia and Romania as well as parts of the Czech Republic, Hungary, Poland and Ukraine (Turnock 2002; Witkowski et al. 2003; UNEP 2004). Along with the Carpathian Ecoregion Initiative (CERI) created in 1999, the outlines of *the Carpathian Ecoregion* (approx. 210,000 km^2) were defined based on ecological and geo-morphological criteria (Figure I-2). The aim of CERI is to unite people, development, and conservation efforts across political and social boundaries (Ruffini et al. 2006).

The Carpathian forests cover about half of the Carpathian Ecoregion and consist of deciduous, coniferous and mixed stands, dominated by beech, spruce and fir. Globally, the Carpathian forests are an important carbon sink due to their high productivity, and the high proportion of natural and semi-natural old stands (Nijnik and Van Kooten 2006; Luyssaert et al. 2008). At the continental scale, the Carpathians are a key element of the European carbon cycle (Schulp et al. 2008), and a bridge between Europe's southern and northern forests. They thus serve as an important refuge and corridor for flora and fauna. Providing a high biodiversity and also constituting an important habitat for threatened species, the Carpathian forests are of great scientific interest and of extraordinary conservation value. They harbor Europe's largest population of brown bear (*Ursus arctos*), wolf (*Canis lupus*), Eurasian lynx (*Lynx lynx*), wildcat (*Felis silvestris*), and European bison (*Bison bonasus*) (Webster et al. 2001; Oszlanyi et al. 2004; KEO 2007).

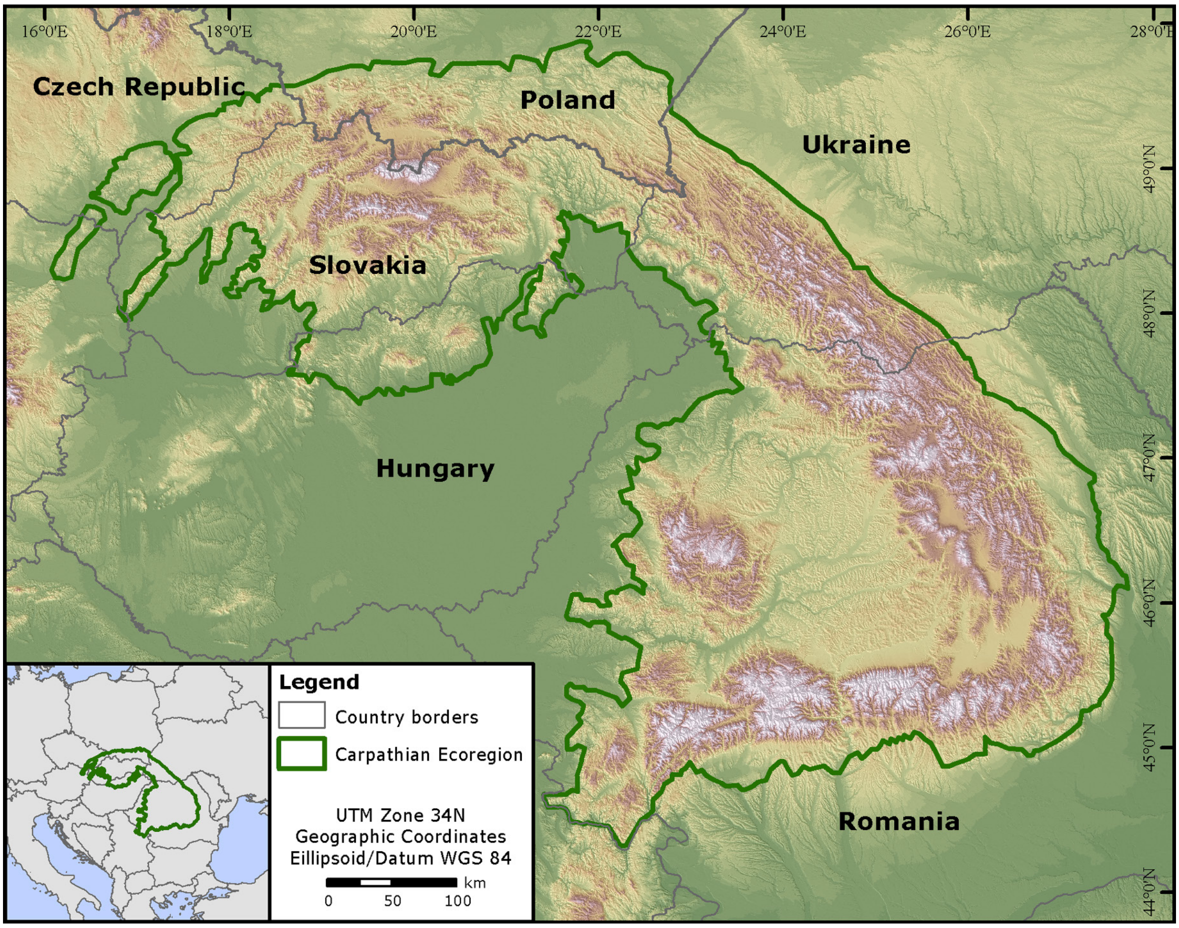

Figure I-2: The Carpathians (Data: SRTM digital elevation model, ESRI Data and Maps Kit, Carpthian Ecoregion Initiative).

According to political circumstances, trade requirements, forest management policies, as well as industrial conditions, the high value of the Carpathian forests has over time been differently understood and accounted for. In particular, during the Austro-Hungarian Empire and the expansion of the industrial revolution in mid-19th century, the demand for energy exploded. As a consequence, the exponentially increasing demand for softwood and its products trigged the beginning of regular forest management practices. Certain tree species, in particular the Norway spruce, were propagated as they ensured high productivity, short harvesting cycles and quick revenues. Hence, natural fir and beech forests were largely replaced by spruce monocultures of foreign provenience, particularly in *the Western Carpathians*, extending far beyond their physiological limits. In addition, the established tradition of spruce-based timber production required stable, low risk forest management, preventing and minimizing large-scale disturbances. Thus, *disturbances* were seen as a threat to timber production rather than as a natural forest dynamic (Svoboda and Pouska 2008). The subsequent forest practices in the 20th century followed that tradition and took extensive benefit from spruce monocultures.

Apart from forest *management practices*, rapid industrialization after World War II, along with inadequate environmental standards, led to increased *environmental pollution* during communism in Central European countries (Cerny 1969; Dovland 1987; Ellsworth 1997; Bytnerowicz et al. 1999). Long-term atmospheric *deposition of sulphur* and *nitrogen* reached critical concentrations, causing an acidification and eutrophication of ecosystems and hampering their functions. In particular, the impact on the chemical composition of ground water and soils was enormous (Cerny 1969; Dovland 1987), thereby resulting in widespread deterioration of forest health and resistance to diverse stress factors (Materna 1989; Schulze 1989; Kubikova 1991). Although, heavy industry in Central Europe was drastically reduced with the fall of communism in 1989 and the dawn of industrial transformation, the overall environmental situation in the Carpathian forests has not improved. This is mainly due to high levels of atmospheric depositions and the buffering processes of forest soil, causing delayed forest restoration (Posch 2001).

3 The Western Carpathian case study

3.1 Motivation and the study area

The Western Carpathians were selected as a study site, because the region has been strongly influenced by highly *dynamic changes* in politics and socio-economic patterns. Already during the Austro-Hungarian Empire, local properties, demands and interests were divided between three nations - Czech, Polish and Slovak - although they were united and ruled by the Habsburg Monarchy. According to the political situation, the Habsburg possessions had grown since 1282 by acquiring new land and shifting the borders, thereby strengthening their sphere of influence in the socio-economic domain. To cope with the economic demands of the rapid industrialization in the 19th century, *productive forestry* - oriented on fast growing Norway spruce - was established (Hlásny et al. 2010b).

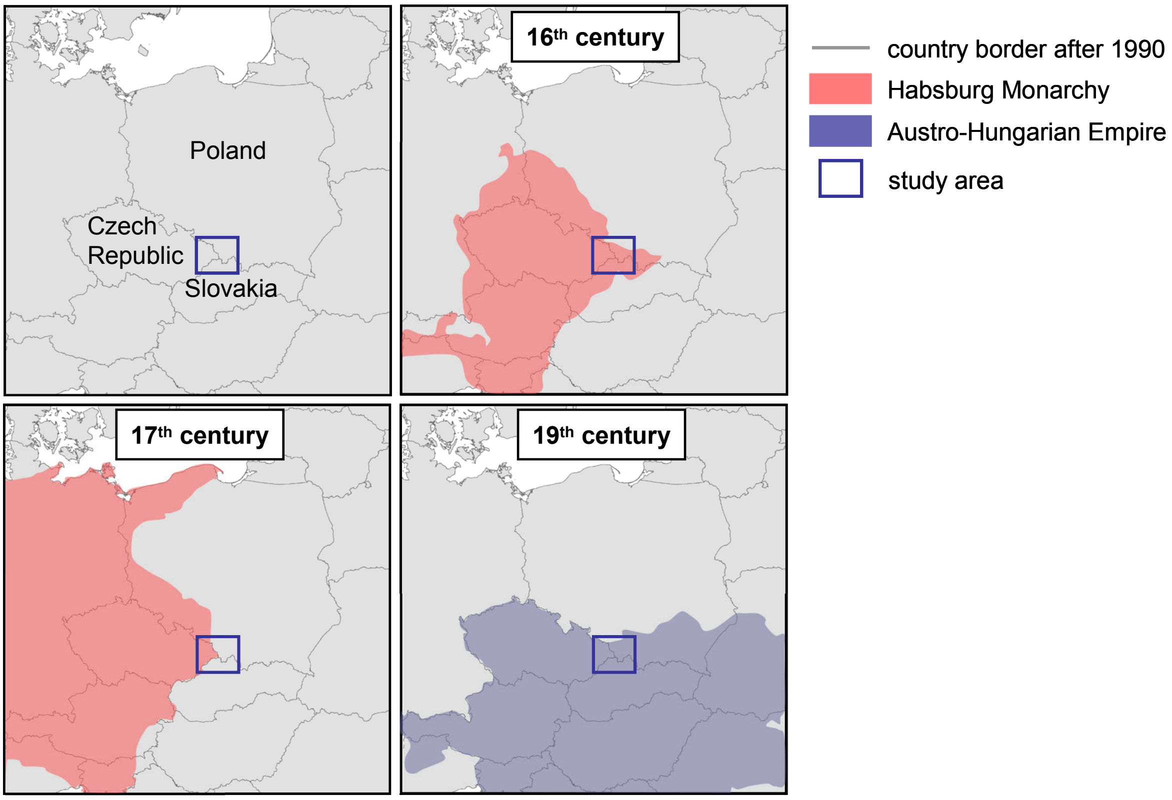

Figure I-3: Habsburg Monarchy and Austro-Hungary possessions between 16th and 19th century. Maps were adopted from: A School Atlas of English History by Samuel Rawson Gardiner 1892, Becker et al. (2011), and the WIKIMEDIA COMMONS Atlas of the World.

With the expectation of steadily increasing economic profits in the 20th century, the region experienced a "second industrialization". Large production centers in the Ostrava and the Katowice coal basin (the Upper Silesia) were expanding and flourishing. During communism, rapid *industrial development* continued (seen also as a competition between capitalist and socialist political systems), and environmental standards were largely disregarded. In consequence, high and long-term pollution loads of sulphur dioxide (SO_2) (Figure I-4) and nitrogen oxides (NO_x) affected the environment in Central Europe, including especially the Ostrava, Karvina and Katowice regions.

Beyond a tremendous impact on human health, these large-scale pollutions had significant consequences on *forest conditions*. Since the late 1990s, increasing *degradation and mortality of spruce stands* in the Western Carpathians have been reported (Kozak 1996; Badea et al. 2004; Grodzki et al. 2004), leading to forest decline at present (Ditmarová et al. 2007; Šrámek et al. 2008; Grodzki 2010). Nowadays, the majority of disturbances result predominantly from *the synergistic effect* of fungal pathogens activity (*Armillaria* sp.), unfavorable weather conditions, extreme storm events and subsequent bark beetle outbreaks (e.g., *Ips typographus*). However, the extent and the precise mechanism of the ongoing decline of Western Carpathian forests are still not fully understood.

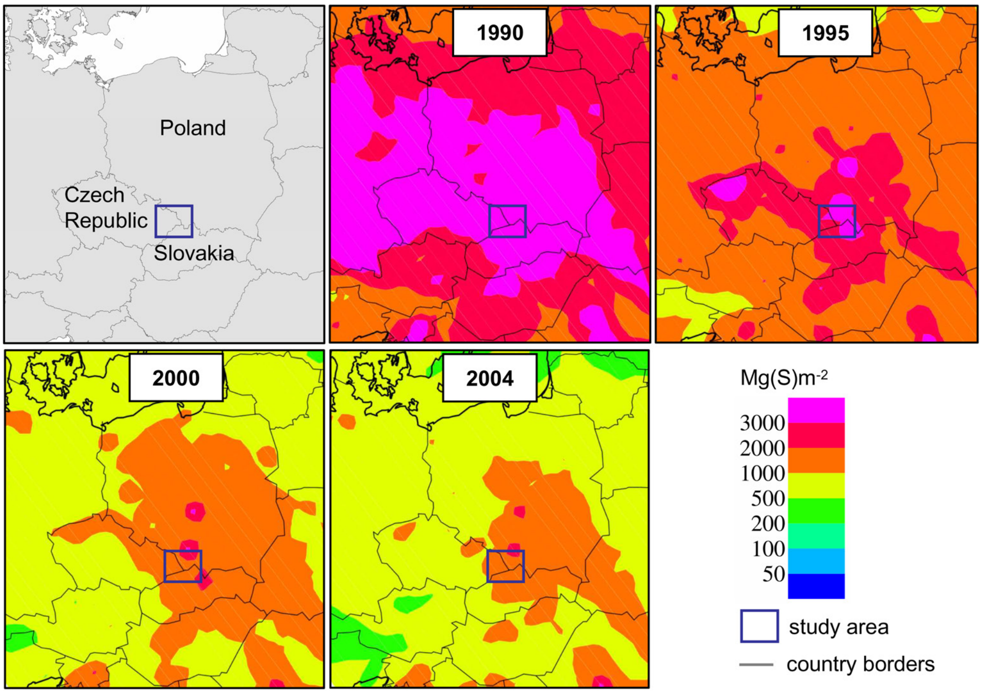

Figure I-4: Deposition of sulphur between 1990-2004 in Central Europe (adopted from EMEP Report 2006).

What is the actual range, magnitude and importance of this decline? How does it affect local and regional forest carbon storage, and the future sequestration potential? Answering these and many other related questions is critical but unthinkable without knowing the regional long-term forest ecosystem dynamics, particularly the disturbance and recovery extent and rates.

A further motivation concerns the opportunity to explore the effectiveness of a *remote sensing-based approach* to complement state-of-the-art forest change detection analysis. The feasibility of our approach was moreover facilitated by the availability of stand-specific field data, survey data and expert knowledge for the region, based on earlier studies (Grodzińska and Szarek-Łukaszewska 1997; Kozak 2003; Bytnerowicz et al. 2004; Ditmarová et al. 2007).

Last but not least, since the entire Carpathian Ecoregion has been affected by turbulent political and socio-economical changes, also within the field of forestry policies, there is a strong belief in possible implications of the outcomes of this thesis. This includes a better understanding of ongoing processes in other spruce-dominated regions, as well as raising awareness about consequences in the future.

3.2 Objectives

The core contribution of this work is to monitor forest change in the Western Carpathians with respect to land-use and pollution legacies, and to assess coniferous forest dynamics and their impact on local forest carbon storage. The following three central research questions and related specific objectives were formulated:

<u>Research question I:</u> *How do pollution legacies from communist times, in the context of historic and contemporary forest management, affect forest ecosystems across Polish, Czech and Slovak border?*

Quantifying the *status quo* of forest cover change among countries can improve the understanding of political and socio-economic driving forces on land-use change. Moreover, since these driving forces trigger profit-oriented development over time, economic sectors such as industry were exposed to production pressure. Thus, during the Austro-Hungarian Empire, productive spruce-oriented forestry was introduced, and during communism, high and long-term pollution loads were released, completely disregarding environmental standards. Given this past, how do these legacies affect the current forest status in the Western Carpathians, and what are possible differences among countries? While field-based evidence across the Carpathians is abundant, it appears that only few studies as yet have compared related forest cover change at landscape scale and across country borders. Kuemmerle et al. (2006) quantified differences in land cover and landscape pattern in the border region of Poland, Slovakia, and Ukraine. They found marked discrepancies in forest cover and composition across countries. Kozak et al. (2007a) investigated forest transition between the 1930s and the 1990s across the Czech, Polish, Slovakian, and Ukrainian part of the Carpathians. They noted that in particular socio-economic polices were a driving force for the observed differences. Clearly, both studies underline the high significance and potential of such comparative research.

Based on the above mentioned issues, this work investigates forest decline and subsequent forest regeneration in the border region of the Czech Republic, Poland, and Slovakia, an area close to several centers of heavy industry during communist times. The specific objectives were:

(1) to map forest cover for 1987 and 2005 using satellite data and a state-of-the-art analysis strategy, and

(2) to assess change rates and spatial patterns in relation to topographic factors and forest composition for different countries.

<u>Research question II:</u> *What are the spatial patterns of coniferous forest productivity in the Western Carpathians and which methodological approach enables its comprehensive investigation?*

Understanding the potential of forest ecosystems as carbon sinks requires a thorough knowledge of forest productivity. Since the latter is primarily quantified as forest biomass, its accurate estimation is recognized as one of the most important parameters for carbon modeling. For applications in a local context, biomass is often derived from stand-based forest inventory. However, in a dynamic region with high forest disturbance rates, stand-based inventories quickly become outdated. Thus, remote sensing offers great opportunities for substituting stand-based input variables in biomass models. Indeed, for regional to global carbon modeling, tree biomass is typically assessed from remote sensing data (Kimball et al. 2000; Mickler et al. 2002; Schroeder et al. 2008). While a number of studies revealed the great potential of both stand-based and remote sensing-based approaches for estimating aboveground biomass, little research has been dedicated towards their integration. Therefore, the specific objectives related to the second research question were:

(3) to estimate aboveground coniferous forest biomass (AGB) at local to regional scales, using solely inventory-, and remote sensing-based approaches, and

(4) to evaluate the prediction utility of an integrated approach by combining inventory data, remotely-sensed information and derivatives from topography data.

Beyond forest biomass, the leaf area index (LAI) is also recognized as one of the most important parameters for carbon modeling (Hall et al. 1995). Strongly correlating with aboveground carbon, LAI is also widely used as a key parameter for characterizing forest productivity. Direct LAI measurements include harvesting, litter collection, and allometry – clearly a destructive and time-consuming process. Indirect LAI estimates, in turn, can be gathered through optical devices such as the LAI-2000 Plant Canopy Analyzer or hemispherical photography. They are based on measuring canopy transmittance, canopy gap fractions and leaf-angle distribution (Breda 2003). For over two decades now, direct and indirect LAI measurements have been used as a reference for modeling and validating forest LAI from either inventory or remotely sensed data. However, it appears little research has been carried out on integrating both types of data, and comparing their modeling potential, either alone or combined. Therefore, a supplementary specific objective was:

(5) to investigate the potential of inventory-, remote sensing- and combined approach to estimate the LAI of coniferous forests in the study area.

Research question III: *How do forest dynamics affect coniferous productivity in the Western Carpathians and what are the main driving forces?*

Forest dynamics are characterized by disturbances and recovery, the key-processes affecting forest productivity. Thus, spatially and temporally accurate knowledge of these processes and their drivers are critical for understanding regional carbon cycles. Since forest biomass is used to describe forest productivity, the quantification of biomass variability over space and time is crucial for an accurate carbon accounting.

The magnitude of carbon loss and uptake is determined by the rate of biomass reduction and accumulation at fine spatial and temporal scales. Hence, satellite data has great potential to adequately capture its dynamics (Wulder et al. 2008b; Huang et al. 2010; Powell et al. 2010). Moreover, using remote sensing data, forest change phenomena both continuous and subtle (associated with thinning, forest degradation or recovery), as well as discontinuous and sudden (e.g., clear-cuts, wind-throws) can be assessed (Kennedy et al. 2007). Therefore, the specific objectives here were:

(6) to distinguish and compare abrupt and gradual forest biomass changes, and to

(7) to derive biomass trajectories and quantify the net change between 1985 and 2010.

Additionally, to better understand the spatial and temporal patterns of changes, the relationship of disturbances and gradual biomass changes against topographic factors and forest stand age were analyzed.

3.3 Methods design

Answering the specified research questions requires comprehensive datasets and adequate methods. This includes satellite imagery, forest inventory, and field survey data, as well as the support of a geographic information system (GIS) and advanced remote sensing and modeling approaches.

Stand-specific forest inventory data was provided by the Polish State Forest Holding, covering about 14% of the study area. Despite the high precision of the inventory data, its application is constrained spatially as well as temporally, limited to 10-year intervals (Houghton 2005). In contrary to this, the synoptic nature of satellite-based earth observations enables a consistent monitoring of forest cover and its dynamics across space and time (Hansen et al. 2010). In consequence, remote sensing analysis became a universal tool and is likely to evolve into a standard instrument in professional forest management (Smith et al. 2003).

Passive sensors, such as Landsat, SPOT (Satellite Pour l'Observation de la Terre), or MODIS (Moderate Resolution Imaging Spectroradiometer), have been widely used to assess forest cover and forest cover changes (Kuemmerle et al. 2009; Hansen et al. 2010). These systems differ in terms of their spatial, spectral and temporal resolution, as well as data access policies and associated costs. They have been applied in the forestry sector at different scales and for various research questions. MODIS, for instance, has been used for large-scale global forest monitoring and mapping (Blackard et al. 2008; Coops et al. 2009), while Landsat or SPOT have been used for local to regional forest assessments (Bartalev et al. 2003; Townsend et al. 2009; Knorn et al. 2012). However, passive sensors have, for example, a limited sensitivity for reproducing forest productivity in the closed canopy structure within dense forests. An alternative approach is taken by active sensors. They emit and record energy in e.g., the microwave (radar) or near-infrared (lidar) portions of the electromagnetic spectrum. Both systems have been studied in terms of their capacity to estimate forest biomass (Lefsky et al. 2002; Treuhaft et al. 2004; Pflugmacher et al. 2008). However, it seems that to-date the latter provides the most accurate estimates overall. Nevertheless, the applicability of active sensors is spatially and temporally constrained, and additionally limited by high costs. Therefore, it is unlikely that these sensors will be able to play a large role in sufficient continuous monitoring of forest biomass.

To-date, the most widely used and, since recently, freely available data type for forest monitoring and mapping is Landsat imagery. The Landsat system offers a good compromise between spatial resolution, aerial coverage, and spectral sensitivity. Hence, Landsat data has been used regularly to predict forest biomass, e.g., for dominating tree species in Newfoundland, Canada (Luther et al. 2006), or a national-level biomass assessment across North America (Powell et al. 2010). Moreover, since the Landsat satellite system recorded data for over 35 years, it is predisposed to determine forest cover change and biomass dynamics consistently across space and time (Cohen and Goward 2004; Huang et al. 2010; Kennedy et al. 2010). Consequently, Landsat data provide the requirements to accomplish all objectives of this thesis.

Beyond forest inventory and satellite imagery, field survey data provides crucial supplementing information. On the one hand, it allows for the verification of statistics compiled by the national forest inventories, on the other, it provides unique datasets for calibration and validation purposes. Not to be underestimated, *in situ* impressions are also key to gaining a better understanding of existent processes. Therefore, three field campaigns were undertaken (2005, 2006 and 2007) and spruce-dominated stands with dominant cohort ages ranging between 40 and 150 years were sampled. The sampling design was adopted from the official Polish Forest Inventory to ensure compatibility with stand-based estimates from official data sources. Apart from the standard data collection (stem density, diameter at the breast high, and tree height), descriptive information such as canopy closure, defoliation, discoloration, and presence of understory, insects or fungi, was gathered. Additionally, LAI was estimated using the LAI-2000 Plant Canopy Analyzer, as well as hemispherical photography.

A methodological cornerstone of this work was to investigate forest change and to estimate forest productivity. In order to carry this out, sufficient change detection techniques and modeling approaches were required. Concerning the change detection, first a Support Vector Machine (SVM) classifier, and later the Landsat-based detection of Trends in Disturbance and Recovery (LandTrendr) were applied. The SVM classifier is a non-statistical binary approach developed in the field of machine learning, capable of fitting complex (non-linear) responses (Vapnik 1999). In comparison to other classification algorithms, SVM outperforms or is at least as accurate as other parametric or non-parametric classifiers (Huang et al. 2002; Pal and Mather 2005; Dixon and Candade 2008). In Huang et al. (2002) and Foody and Mathur (2004), a detailed descriptions of SVM is provided in a remote sensing context.

The LandTrendr approach (Kennedy et al. 2010) is a newly developed powerful technique, which makes use of the Landsat temporal depth. It provides an opportunity for reconstructing forest disturbance histories with annual resolution, as well as for mapping long-term trends. While LandTrendr has been applied by Powell et al. (2010), Meigs et al. (2011), Pflugmacher et al. (2012), and Griffiths et al. (2012), only the first study focused on quantifying live aboveground forest biomass dynamics. In this thesis, LandTrendr was applied to derive biomass trajectories, and to quantify the net biomass change between 1985 and 2010.

Hitherto, numerous algorithms have been tested for modeling forest structure and biomass estimation. The vast methodological range spans from simple and multiple linear regression models (Nilson et al. 1999; Shvidenko et al. 2007), over vegetation canopy models (Wu and Strahler 1994; Eklundh et al. 2001), classification and regression trees (CART) (Chojnacky and Heath 2002; Keeton et al. 2011), to artificial neural networks (Atzberger 2004; Schlerf and Atzberger 2006; Jung et al. 2008). A comparative study explored that for forest structure prediction, the simplest linear models were equally as efficient as, for example, CART or generalized additive models (GAM), although sometimes variables with predictive strength were excluded (Moisen and Frescino 2002). Thus, more flexible modeling methods might have greater capacity, such as, for instance, incorporating correlated variables or both categorical and continuous variables. The Random Forests (RF) approach (Breiman 2001) captures this modeling flexibility. RF is a non-parametric ensemble method of the CART algorithm (Morgan and Sonquist 1963; Breiman et al. 1984). Due its ability to rank the relative predictive strength of multiple independent variables and its robustness to over-fitting, RF received considerable attention in the ecological and remote sensing literature (Breiman 2001; Cutler et al. 2007). Hence, for the biomass estimates in the presented thesis, the RF-based modeling approach was employed.

4 Structure of this thesis

This work is structured in three main sections (Chapter II-IV), which relates to one of the outlined research questions, respectively, and thus forms the core of this thesis. In Chapter II, differences in forest cover between 1987 and 2005 among the Polish, Slovak, and Czech part of the study area are assessed and quantified. Change rates and spatial patterns in relation to topographic factors and forest composition are also investigated. This is done using Landsat TM (Thematic Mapper) imagery, a digital elevation model (DEM), forest inventory and climate data. The change detection procedure is divided into the actual classification stage using a SVM classifier, and a post-classification analysis of the change classes. The following chapter (Chapter III) evaluates the prediction strength of solely inventory-, and remote sensing data, as well as that of an integrated approach. In particular, its capacity to describe coniferous forest productivity and its patterns in the Western Carpathians are studied. Here, Landsat TM imagery from 2005, DEM, stand-based inventory, and field measurements are used, and a RF approach is applied to estimate coniferous forest biomass. In the last core chapter (Chapter IV), a comprehensive analysis on forest dynamics affecting coniferous productivity in the Western Carpathians is undertaken, and the main driving forces are discussed. For doing so, Landsat TM and

Enhanced Thematic Mapper Plus (ETM+) images, a SPOT 1 image and an Indian Remote Sensing Satellite with the Linear Imaging Self-Scanning Sensor (IRS-C1 LISS III) image for the period between 1985 and 2010 were used. SVM classifier, RF biomass modeling and the LandTrendr trajectory-based change detection approach complement the methodological core of this chapter. Chapter V finally synthesizes the main outcomes of the preceding chapters, draws more general conclusions, and discusses application possibilities and future research directions.

Chapters II – IV are written as stand-alone manuscripts to be published in internationally recognized, peer-reviewed journals. They thus fulfill the formal requirements of a cumulative doctoral dissertation. Since, each chapter is structured into sections such as background information, study area, data and methods, results, discussion, and conclusions, a certain amount of recurring material throughout the thesis is unavoidable. The three core chapters were published or prepared as follows:

Chapter II: Main-Knorn, M., Hostert, P., Kozak, J., & Kuemmerle, T., (2009). How pollution legacies and land use histories shape post-communist forest cover trends in the Western Carpathians. *Forest Ecology and Management, 258*, 60-70.

Chapter III: Main-Knorn, M., Moisen, G., Healey, S., Keeton, W. S., Freeman, E., & Hostert, P., (2011). Evaluating the remote sensing and inventory-based estimation of biomass in the Western Carpathians. *Remote Sensing, 3*, 1427-1446.

Chapter IV: Main-Knorn, M., Cohen, W.B., Kennedy, R.E., Grodzki, W., Pflugmacher, D., Griffiths, P., & Hostert, P., (in preparation). Monitoring coniferous forest biomass change using a Landsat trajectory-based approach.

Two appendices supplement this thesis. Appendix A extends the analysis described in Chapter III by investigating the potential of inventory-based and remote sensing-based approaches – as well as a combination thereof - to estimate LAI of coniferous forests in the study area. Appendix B complements the findings of Chapter IV by analyzing the relationship of forest biomass loss (abrupt and gradual biomass changes) against topographic factors and forest stand age. Both appendices were written as independent pieces of research. The first appendix (Appendix A) is written as stand-alone manuscript to be published in an internationally recognized, peer-reviewed journal. The second appendix (Appendix B) has the form of short research communication.

Chapter II:
How pollution legacies and land use histories shape post-communist forest cover trends in the Western Carpathians

Forest Ecology and Management 258 (2009) 60-70

Magdalena Main-Knorn, Patrick Hostert, Jacek Kozak,
and Tobias Kuemmerle

Abstract

Forests that encompass the border triangle of Poland, the Czech Republic and Slovakia currently suffer from centuries of inadequate forest management strategies, including overexploitation during the countries' respective communist regimes and high stress levels due to airborne emissions from heavy industry. Since the fall of the Iron Curtain, each country has approached forest monitoring, protection and the improvement of forest conditions in its own way. Spaceborne remote sensing of forest changes across country borders offers great potential for better understanding the underlying drivers of change and for developing comparable indicators between countries.

For this paper we evaluated how forests changed in the border region of Poland, the Czech Republic and Slovakia between 1987 and 2005 and how these changes depended on industrial transformations before and after 1989. We used Landsat Thematic Mapper imagery and a Support Vector Machine (SVM) classifier to assess forest cover change between 1987 and 2005. Our results showed that 8.12% of the forest stands in our study region were degraded either partially or completely during that time period, a percentage that equals 14,972 ha of the area's total forest cover. At the same time, 7.57% (13,951 ha) of the area was reforested or regenerated on previously damaged forest stands. Forest changes were similar in the Czech Republic and Slovakia, but differed in Poland. Comparing forest composition, topography, and aspect with forest decline revealed the importance of forest management and pollution legacies from communist times when explaining today's forest disturbance patterns.

1 Introduction

Forests, through ecological, economic and spiritual functions, play an important role for human life (Bengtsson et al. 2000; Foley et al. 2007a; Chazdon 2008). Indeed, forests protect water resources, prevent soil erosion, store large amounts of carbon, and harbor the majority of the world's biodiversity (Norton 1996; Fuhrer 2000; MA 2005; Bonan 2008). Disturbances in forest ecosystems caused by both natural and human impacts lead to changes in species composition, forest structure or function. Eastern and Central Europe still have vast and relatively undisturbed forests compared to Western European countries. Yet these forests were often under considerable stress. First, forest management during Austro-Hungarian rule introduced inappropriate planting strategies. Second, rapid industrialization after WW II, along with inadequate environmental standards, led to increased environmental pollution during communism, thereby weakening the resistance of trees to natural disturbances. Several studies have shown that air pollution had an enormous impact on the chemical composition of ground water and soils in Central European countries during that period (Cerny 1969; Dovland 1987), which resulted in widespread deterioration of forest health. Schulze (1989) identified a wide variety of natural and human stress factors (air pollution, pathogens, short acute weather events, etc.) that cause forest damage across Central Europe. For example, Materna (1989) and Kubikova (1991) described the relation between air pollution, wet deposition and forest decline in Czechoslovakia. The question is how these pollution legacies from communist times, against the background of historic and contemporary forest management, affect forest ecosystems in Central European countries today.

With the fall of communism, heavy industry in Central Europe was drastically reduced and the resulting industrial transformation improved the overall environmental situation. Between 1990 and 1995, emissions decreased considerably. The baseline scenario for 2010 (compared with emission levels from 1990) forecasted decreases of CO_2 emissions by 10%, SO_2 emissions by 68%, NO_x emissions by 42% and particulate matter under 10 µm by 67% (PM_{10}) (van Vuuren et al. 2006). Moreover, introducing EU environmental standards and implementing EU policies has improved environmental quality and protection since the accession of Central European countries to the European Union (EU) in 2004 and 2007 (Andonova 2003; Zellei et al. 2005; Mill 2006).

Dwindling pollution levels in post-communist times and positive changes in environmental conditions suggest a general improvement in vegetation health. However, Ellsworth and Oleksyn (1997), as well as Klimo et al. (2000) found a considerable loss in forest productivity and stability, specifically for spruce monocultures, and Oszlanyi (Oszlanyi 1997) and Vacek et al. (1999) discussed a loss of canopy foliage due to air pollution stress in Slovakia and the Czech Republic. Several authors discussed high levels of forest damage and defoliation in Polish forests due to high concentrations of toxic air pollutants and elevated deposition of sulphurous and nitrogenous compounds resulting in the accumulation of toxic compounds in tree foliage (Dmuchowski and Bytnerowicz 1995; Bochenek et al. 1997; Grodzińska and Szarek-Łukaszewska 1997). The International Co-operative Programme on Assessment and Monitoring of Air Pollution Effects on Forests (ICP Forest) conducts an annual monitoring of forest conditions at the European level. However, none of these studies provide figures that are comparable across country borders on the regional level.

The Carpathian Mountains sustain Europe's largest continuous mountain forest ecosystem. Extending from Austria to Serbia, the Carpathians cover most of Slovakia and Romania and parts of the Czech Republic, Hungary, Poland and Ukraine (Turnock 2002; Witkowski et al. 2003; UNEP 2004). Carpathian forests are an important carbon storage area due to the high proportion of old stands and its high productivity (Nijnik and Van Kooten 2006; Luyssaert et al. 2008). Moreover, the Carpathians bridge Europe's southern and northern forests, serving as an important refuge and corridor for flora and fauna, including Europe's largest population of brown bear (*Ursus arctos*), wolf (*Canis lupus*), lynx (*Lynx lynx*), wildcat (*Felis sylvestris*), and European bison (*Bison bonasus*) (Webster et al. 2001; Oszlanyi et al. 2004; KEO 2007).

Focusing on the Carpathian Mountains, we observe ongoing forest damage due to biotic stress factors like insects and diseases, which eventually lead to heavy spruce dieback and increasing damage in the case of storm events. Badea et al. (2004) reported between 29.7% and 34.9% of forests in the Carpathians were severely affected by air pollution and natural stress factors from 1997-2001. A few other authors pointed out both anthropogenic and natural stress factors such as synergetic drivers, describing forest health decline in the Carpathian range (Kozak 1996; Grodzki et al. 2004; Longauer et al. 2004).

The impact of environmental pressure on mountain forest ecosystems in the Carpathians, particularly from high concentrations of air pollutants, contamination by heavy metals in soil and foliage, insect pests or extreme weather events, has been analyzed using traditional field-based methods (Bytnerowicz et al. 1999; Zwoliński et al. 2001; Bytnerowicz et al. 2003; Mankovska et al. 2004; Grodzki 2006). Due to the lack (or inconsistency) of field monitoring data, only few studies have as yet compared rates of past forest status or forest cover change with its drivers for different countries, i.e., across borders. This kind of large-area forest mapping requires the use of remote sensing and geoinformation techniques (Moran and Ostrom 2005). However, few studies have so far used remote sensing to map forest cover changes in the Carpathians. Kozak et al. (2007b) showed that, simultaneously with forest decline and reforestation, forest degradation and regeneration in the late 20th century occurred in various ranges in the northern Carpathians, resulting in a net forest increase of 0.4% annually. Kuemmerle et al. (2007) analyzed forest change in the border region of Poland, Slovakia and Ukraine and found increased forest disturbance rates after the breakdown of communism, as well as substantial differences in harvesting rates and spatial patterns among countries.

A dramatic increase in forest damage and spruce forest dieback has recently been reported from field-based assessments in the Western Carpathians (Ditmarová et al. 2007; Grodzki 2007; Fiala et al. 2008; Šrámek et al. 2008). While field-based evidence across the Carpathians is abundant, no study has yet compared related forest cover change at landscape scales and across country borders. We therefore decided to use remote sensing and forest inventory data to assess forest decline and subsequent forest regeneration in the border region of the Czech Republic, Poland, and Slovakia, an area close to several centers of heavy industry during communism. Our specific objectives were:

1. to map forest cover for 1987 and 2005 using Landsat data and a state-of-the-art analysis strategy, and
2. to assess change rates and spatial patterns in relation to topographic factors and forest composition for different countries.

2 Study area

Our study area covers approximately 5900 km^2, of which 2500 km^2 are mountain forest ecosystems that are shared between six landscape parks in the Beskid Mountains of the northwestern Carpathians (Figure II-1). Large industrial centers surround the Beskid Mountains in the north and west, especially around Katowice, Ostrava, and Bielsko-Biała.

While many enterprises from communist times have collapsed or were terminated and the remaining industries have largely adapted to European standards, the concentration of production centers in the region is still high, specifically in Poland and the Czech Republic.

The climate in this region is typical for moderate continental mountain zones, with rainfall increasing with altitude from 800 to 1400 mm (Obrębska-Starklowa *et al.*, 1995). Winters are usually long and snow cover persists over 130 days a year in some mountain valleys. The mean temperature is about 7°C below 700 m above sea level (asl), dropping to about 4°C at a height of 1100 m asl. Temperature inversion is frequently observed in valleys (RDLP-Katowice 1997), especially in the winter. Warm foehn winds from the south and south-west are an important aspect of the regional climate.

Forests in the study region mostly cover the lower montane zone (Figure II-2). Natural vegetation there mainly consists of fir (*Abies alba*) and beech (*Fagus sylvatica*). The present species composition was significantly altered because of centuries of forest management, i.e., promoting spruce (*Picea abies*) monoculture plantations, the lack of natural tree regeneration, and unsustainable logging practices (Fabijanowski and Jaworski 1995; Oszlanyi 1998; Holusa et al. 2005).

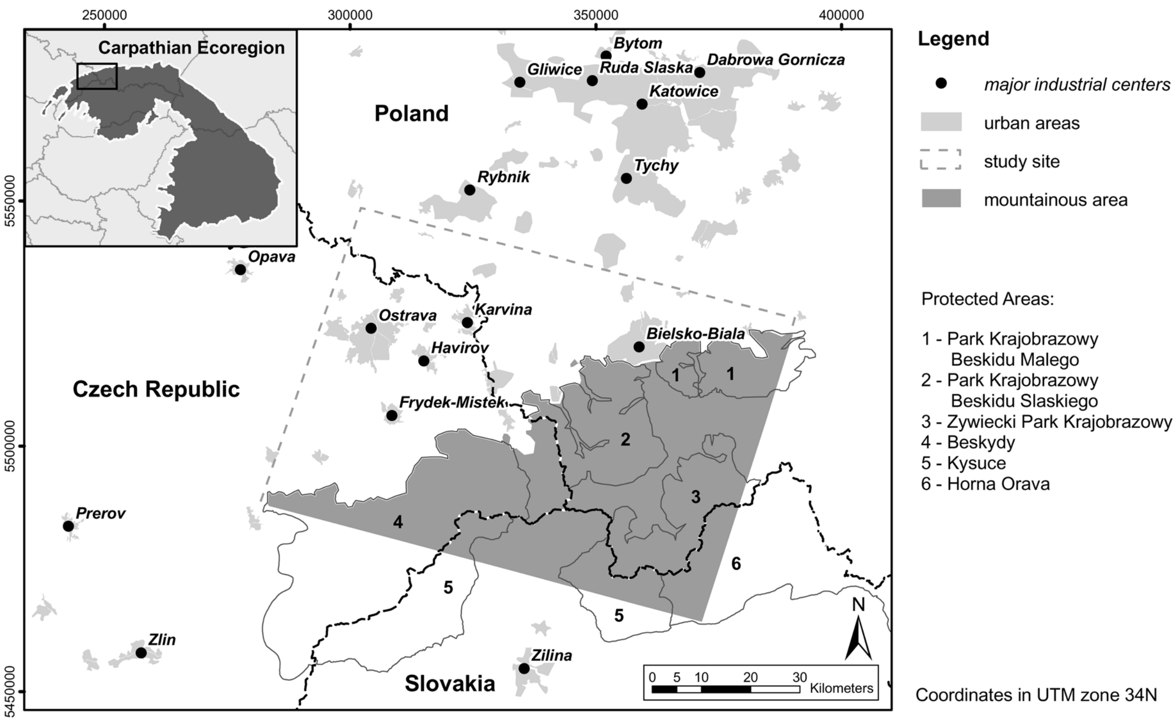

Figure II-1: Study area and large industrial centers in the Western Carpathians and surrounding areas.

3 Data and methods

We used satellite images, a digital elevation model (DEM), forest inventory data and climate data to analyze forest cover change between 1987 and 2005. We incorporated forest inventory data from 2003, 2004, and 2007 from the Polish state forest service; this data covered 14% of the study area and included stand information such as: dominant species, tree age, diameter at breast height (dbh), tree height and stand density. Climate data, including wind speed, prevailing wind direction and information on extreme weather events, were obtained from the Czech Hydrometeorological Institute (CHMI).

We acquired Landsat Thematic Mapper (TM) images (path/row 189/025) from 23rd August 1987 and 9th September 2005. Thermal bands were excluded from the analysis. The Landsat TM image covered part of the Western Carpathians, in the proportion of 53% (97,542 ha) of the study area situated in Poland, 27% (50,552 ha) in the Czech Republic and 20% (36,226 ha) in Slovakia. In general, the area selected for the analysis shows typical landscape features of the Western Beskid Mountains in the Czech Republic, Poland and Slovakia, although the occurrence of spruce plantations is higher here than elsewhere in the northern Carpathians. Hence, the area is heavily affected by spruce decline.

Because spruce forests are characterized by relatively little phenological variability, we used single date imagery per monitoring period to identify relevant changes. The Space Shuttle Radar Topography Mission (SRTM) (Slater et al. 2006) DEM was resampled to 30 m using bilinear interpolation to match the spatial resolution of Landsat TM data.

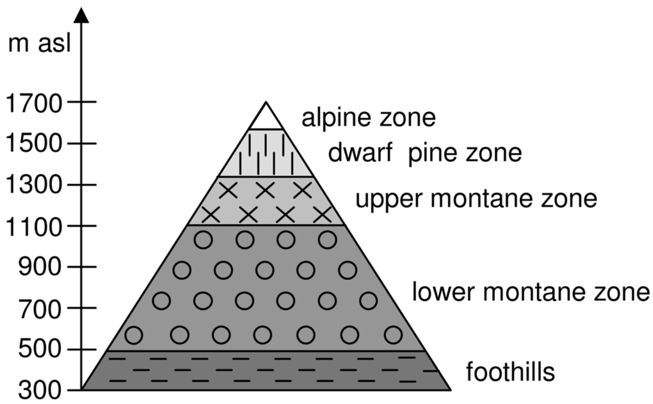

Figure II-2: Zones in the Western Beskids (after Fabijanowski and Jaworski 1995).

Bi-temporal forest change detection requires accurate image co-registration and radiometric normalization (Coppin et al. 2004). We therefore ortho-corrected the imagery to Universal Transverse Mercator (UTM) coordinates (World Geodetic System [WGS] 1984 datum and ellipsoid). First, we registered the 2005 image based on ground reference points gathered in the field and using the semiautomatic image registration software FindGCP (Hill and Mehl 2003). FindGCP requires few interactively selected initial control points and finds additional GCPs automatically based on image correlation. The ortho-rectified 2005 image was the basis for co-registering the 1987 image. We used 278 registration points generated in FindGCP and confirmed sub-pixel accuracy below 0.5 pixel based on independent check points. Finally, we stacked the spectral bands and a simulated illumination layer based on DEM illumination according to the respective date of image acquisition to compensate for varyingly illuminated forest types (Huang et al. 2008). Only a few clouds and cloud shadows occurred in the 2005 image and were digitized and masked.

Change detection was divided into the actual classification stage, a post-classification analysis of change classes (Figure II-3), followed by an accuracy assessment. We applied a Support Vector Machine (SVM) classifier to produce forest type maps for both years based on the classes coniferous, deciduous, mixed forest, and non-forest. SVM is a non-statistical binary classifier developed in the field of machine learning (Vapnik 1999). Comparisons with other classification algorithms show that SVMs outperform or are at least as accurate as other parametric or non-parametric classifiers (Huang et al. 2002; Pal and Mather 2005; Dixon and Candade 2008). Classification is based on separating two classes by fitting an optimal hyperplane to the training samples in a multi-dimensional feature space. The hyperplane is constructed by maximizing the distance between class boundaries (Huang et al. 2002; Pal and Mather 2005; Foody et al. 2007). Huang et al. (2002) and Foody and Mathur (2004) provide detailed descriptions of SVM in the remote sensing context.

Training data were selected based on a stratified random sampling scheme and assigned to the four classes. Only four aggregated sets of point training data were needed to represent coniferous, deciduous, mixed forest, and non-forest, as SVMs are capable of mapping multimodal classes in spectral feature space. Labeling training points for 2005 was based on Quickbird and Ikonos satellite images from 2004 and 2005 covering 11.4% of study area. The assignment for 1987 was guided by the forest inventory data and a visual interpretation of the Landsat image. We classified a forest stand to be “coniferous” or “deciduous” when 70% coniferous or deciduous species, respectively, occurred. All other forests were defined as mixed stands.

Next, we calculated change statistics by summarizing areas of forest decrease, increase, or areas with largely unchanged forest cover between 1987 and 2005.

Further, areas without net-changes in forest cover potentially represent changes in environmental quality, depending upon transitions between forest types. We therefore quantify all forest type changes, resulting in 12 transition classes between different forest types and the no-change class. Forest type transition from coniferous to other forests must largely be interpreted as earlier forest degradation. Spruce monocultures have then been substituted by more appropriate forest compositions between 1987 and 2005.

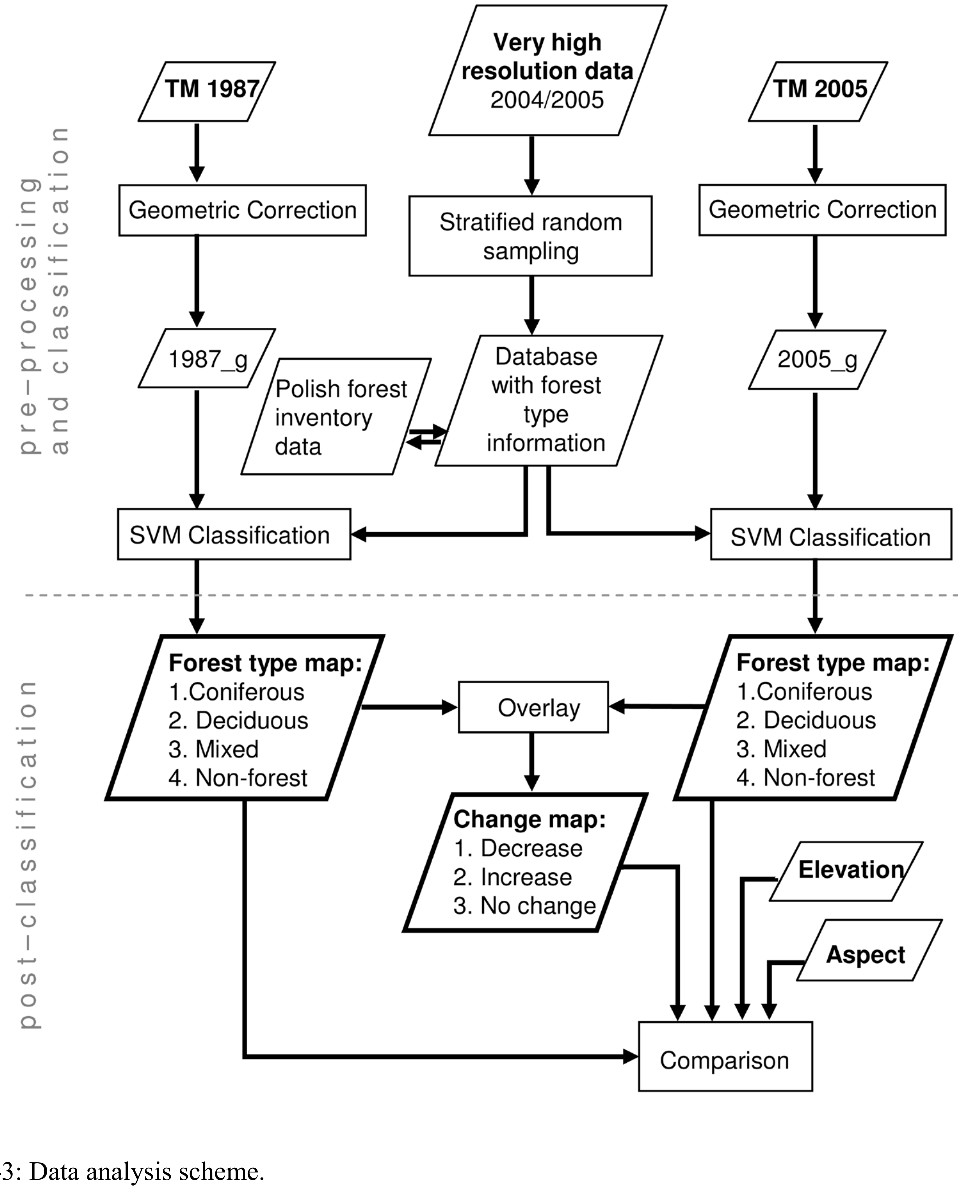

Figure II-3: Data analysis scheme.

We validated accuracies on a forest/non-forest basis from 500 randomly generated reference points within available high resolution Quickbird and Ikonos data for 2005, and Landsat TM data for 1987. Forest type classifications and the change map were validated with 500 randomly sampled reference points in a class-wise stratified manner after eliminating patches of 2 pixels or less. Stratifying reference points allowed us to validate classes independently from their frequency and spatial coverage: we calculated error matrix, overall, user's and producer's accuracies, as well as kappa coefficients (Congalton 1991; Foody 2002).

Forest increase and decrease was assessed for the whole study area. Disturbances older than 10 years are likely not detectable due to management activities and forest regrowth. It is also well known from the field that heavy storms, along with tree infestations, have created vast forest damage during that time period (Grodzki 2007). Forest harvesting beyond salvage logging was therefore an exception and changes need to be interpreted as a consequence of previous damages.

We also analyzed forest changes with respect to forest types, elevation and aspect (with regard to the prevailing wind direction) for the whole study area and for each country to investigate reasons for forest cover changes in post-communist times. The timberline in the Beskid Mountains reaches 1350 to 1400 m, with higher elevations covered mostly by dwarf mountain pine (Towpasz and Zemanek 1995). As dwarf pine is hardly separable from spruce forest stands in Landsat data, and areas above 1200 m are less than 1% of the overall forest area, we excluded elevations above 1200 m from the analysis. Moreover, only marginal forest fractions occurred in lowlands, and we therefore excluded the areas below 400 m in the analysis as well. The DEM was stratified into 20 m elevation zones and the aspect layer into eight 45° zones to summarize forest changes within each zone.

4 Results

Results clearly depict various change regimes in the border region of Poland, the Czech Republic and Slovakia (Table II-1). In total, 8.1% of the forest stands were converted to non-forest (14,972 ha), while 7.6% (13,951 ha) regenerated or were reforested. Cover changes seem to be comparable for the Czech Republic and Slovakia and differ for Poland. In the Czech and Slovakian part of the study area, net forest cover increase amounts to 4.6% (2307 ha) and 1.9% (710 ha), respectively, while areas of forest cover decrease sum up to less than 7.0% (3560 ha) and 7.4% (2662 ha), respectively. In Poland, net forest cover decreased by 4.2% (4038 ha). This results in 9.0% (8750 ha) of forest decrease, while a 4.8% (4713 ha) forest increase occurred.

Table II-1: Overall change statistics.

	Poland		Czech Republic		Slovakia	
	%	ha	%	ha	%	ha
No forest change	86.2	84,078.5	81.4	41,126.2	83.3	30,191.4
Forest decrease	9.0	8750.7	7.0	3559.3	7.4	2662.4
Forest increase	4.8	4712.9	11.6	5866.4	9.3	3372.4
Total	100.0	97,542.0	100.0	50,551.9	100.0	36,226.2

Table II-2: Class-wise change statistics.

Change class	%	ha
Coniferous to Non-forest	8.3	5608.9
Deciduous to Non-forest	3.1	2129.0
Mixed to Non-forest	11.2	7628.1
Non-forest to Coniferous	1.3	874.8
Non-forest to Deciduous	4.8	3275.7
Non-forest to Mixed	16.8	11,425.7
Coniferous to Deciduous	0.3	206.9
Coniferous to Mixed	25.9	17,546.4
Deciduous to Coniferous	0.1	58.1
Deciduous to Mixed	5.1	3457.2
Mixed to Coniferous	17.3	11,717.6
Mixed to Deciduous	5.8	3930.0
Total	100.0	67,858.7

4.1 Forest cover change and forest type

Change statistics for the entire study area show that change from coniferous forest to mixed forest dominated, accounting for about 26% (17,546 ha) of all detected changes (Table II-2). However, reversed transition was observed as well. Reforestation was almost exclusively manifested as mixed forest, while forest decrease occurred in mixed and coniferous stands, with a marginal fraction in deciduous stands only.

Coniferous stands significantly decreased by 11%, or 11,162 ha of the total forest area in Poland, compared to 8% (2705 ha) and 6% (1537 ha) in the Czech Republic and Slovakia, respectively (Figure II-4). Mixed forest stands increased by 9% in Poland (5126 ha), by 8% in the Czech Republic (4572 ha) and by 5% in Slovakia (1975 ha). Deciduous stands increased by 2% (1545 ha and 655 ha) in Poland and Slovakia, while significant changes in deciduous forest cover were not detected in the Czech Republic.

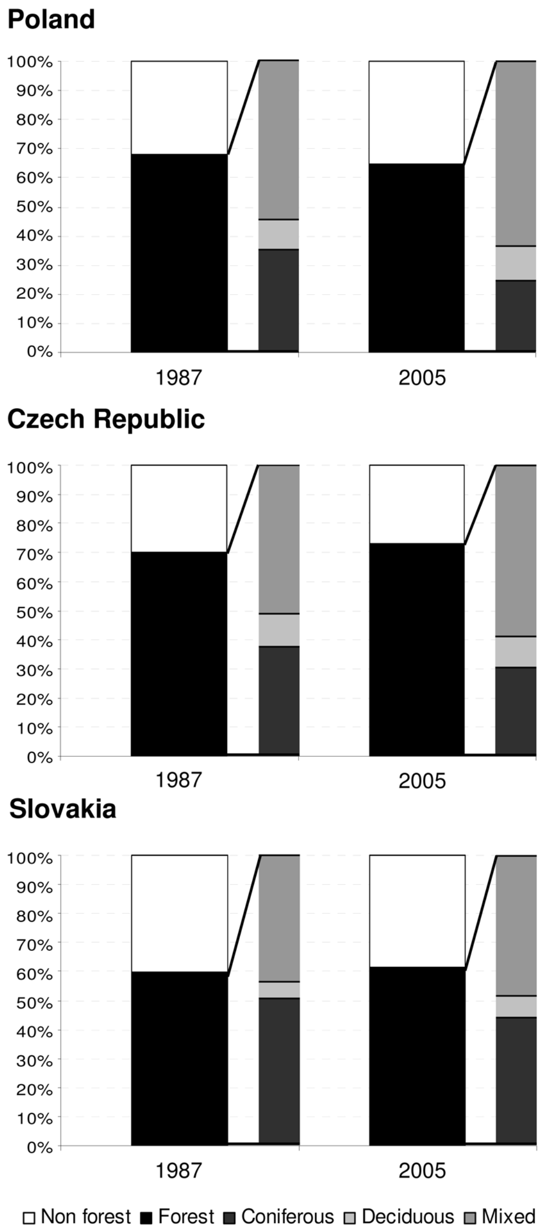

Figure II-4: Forest/non-forest and forest types in 1987 and 2005.

4.2 Forest cover and topography

Forest distribution by elevation is similar for Poland and the Czech Republic, where most of the stands cover heights between 500 and 900 m (Figure II-5). We integrated forest cover per elevation zone for 20 m intervals; relative forest cover decrease for the whole study area showed a maximum of 18% at 400 m, then dropped and stabilized around 8% between 580 and 800 m. Above 1000 m, an increase of forest disturbance to 10% was noticeable. Reforestation and regeneration occurred on the stable level of about 8% between 400 and 1000 m and sank at the mountain top.

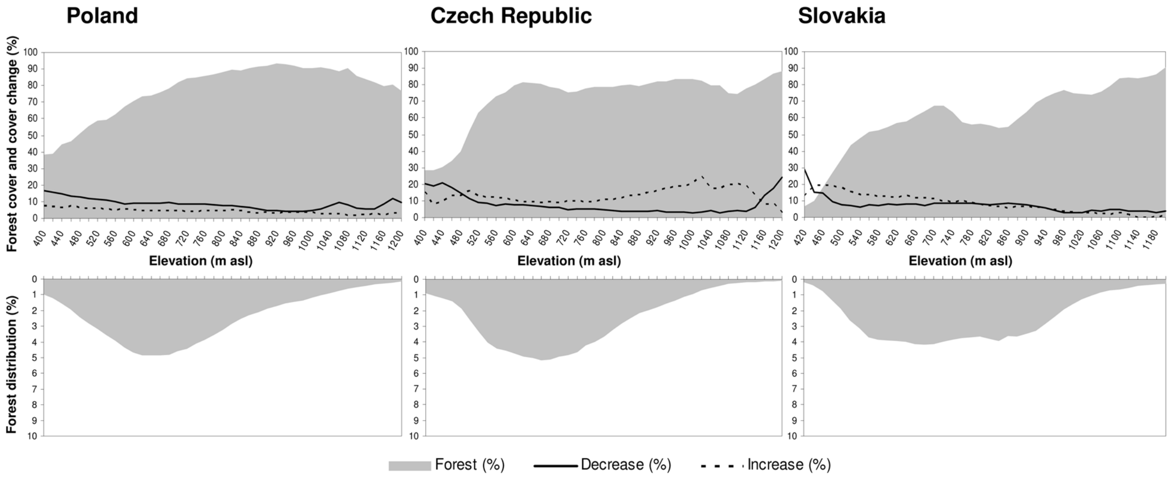

Figure II-5: Forest change, forest distribution (2005) and elevation.

Forest cover decrease in Poland amounted to 17% at 400 m and dropped to 4% at 1000 m. Secondary maxima of over a 10% decrease occurred between 1060 and 1200 m. Areas of forest cover increase were almost evenly distributed along the whole elevation range. Areas of forest cover decrease exhibited a very similar pattern between 400 and 1000 m in the Czech Republic, as well as in Poland. However, the disturbance peak of over 20% at 1200 m was more pronounced. Reforestation and regeneration rates were generally high – usually between 10 and 20% of any elevation range in the Czech Republic – and increase to over 20% between 1000 and 1120 m. In Slovakia, patterns of forest cover decrease differed markedly with altitude: in the lower montane zone, forest cover dropped from over 30% at 400 m to below 10% at 500 m and did not change substantially up to 900 m. Decrease rates dropped further in higher elevations and leveled at around 5% between 1000 and 1200 m, with no secondary peak in forest cover decrease in high elevations. By and large, areas of afforestation and reforestation continuously dropped from between 10 and 20% above 400 m, to almost no forest increase around 1060 m and above.

Comparing the overall forest distribution with aspect, forest cover increase was more pronounced on northeast-facing slopes (Figure II-6). Specifically, south and southeastern aspects were disproportionally decreasing in forest cover. It was difficult to compare aspect and forest cover change across countries. Landsat data availability limited our analysis to a non-representative area for the Czech Republic and Slovakia in terms of aspect distribution. We therefore decided on aggregating results across countries to find overall patterns of change in relation to aspect.

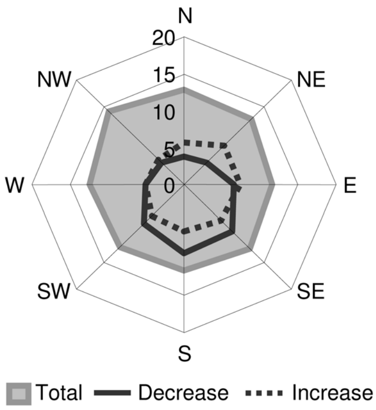

Figure II-6: Forest change and aspect.

4.3 Accuracy assessment

Accuracies of forest type classifications are detailed in Tables II-3 and II-4. Producer’s and user's accuracies were high for landscape scale multitemporal analyses. Forest type separation accuracy resulted in homogeneous values around 90% in 2005, regardless of forest type. Deciduous forests were depicted less accurately in 1987, when misclassifications with mixed stands or grasslands occurred. However, the rather small area of deciduous forests in the study area did prevent strong effects on overall accuracies and kappa coefficient.

The overall accuracy of the class-aggregated change map was 96.2%, with a kappa coefficient of 0.89. Producer’s and user’s accuracies for forest cover decrease are 90.0% and 88.2%, respectively. Forest cover increase was estimated with a producer’s accuracy of 86.0% and a user’s accuracy of 97.7%. Unchanged areas were classified with 97.0% of user’s and 98.2% of producer’s accuracy.

Table II-3: Forest type classification accuracy assessment 1987.

reference	classification				
	Coniferous	Deciduous	Mixed	Non-forest	Total
Coniferous	132	0	13	3	148
Deciduous	0	49	7	4	60
Mixed	3	5	146	1	155
Non-forest	0	0	1	136	137
Total	135	54	167	144	500
Producer‘s accuracy (%)	97.8	90.7	87.4	94.4	
User‘s accuracy (%)	91.0	81.7	94.2	99.2	
Overall accuracy (%)					92.6
Overall Kappa					0.90

Table II-4: Forest type classification accuracy assessment 2005.

reference	classification				
	Coniferous	Deciduous	Mixed	Non-forest	Total
Coniferous	84	0	9	4	97
Deciduous	0	52	5	2	59
Mixed	11	3	162	3	179
Non-forest	0	1	6	158	165
Total	95	56	182	167	500
Producer‘s accuracy (%)	88.4	92.9	89.0	94.6	
User‘s accuracy (%)	89.4	88.1	90.5	95.8	
Overall accuracy (%)					91.2
Overall Kappa					0.88

5 Discussion

Areas of forest cover increase in our analysis relate to forest openings in the early to mid-1980s and largely reflect new plantations. Historic forest management from Austro-Hungarian times led to widespread spruce monocultures. The subsequent forest management practices in the region (mostly the first half of the 20th century) inherited much of that tradition and continued in spruce plantation to ensure short harvesting cycles and quick revenues (RDLP-Katowice 1997; Kozak et al. 1999; Szozda 2006), which is confirmed through Polish forest inventory statistics. It is therefore reasonable to assume that most areas of forest increase reflect the forest dynamics of previous spruce plantations.

Our regional analysis depicts a net increase of forested areas in the Czech Republic and Slovakia of 4.6% and 2%, respectively, between 1987 and 2005, while we found an overall decrease of 4.2% in forest cover for the Polish part of the study site. These results prove that there are large regional differences in forest cover changes in and between the three countries which are not depicted in national forest statistics (Feranec et al. 2000; Bielecka and Ciolkosz 2004; FAO 2005; Feranec et al. 2007). Moreover, statistics focusing on net forest cover neglect the spatio-temporal correspondence of forest disturbances and reforestation. FAO statistics, for example, generally exclude logging and subsequent regeneration from forest cover change statistics, rather considering those processes as system-intrinsic dynamics.

For our study region, similar net forest cover increases in the Czech Republic and Slovakia can be explained by the history of both countries, which were united until 1992 (Czechoslovakia) and therefore were based on the same forest management system. Moreover, our forest change statistics and map (Figure II-7) confirmed that extensive forest damage in the Czech Republic and Slovakia occurred substantially earlier than in Poland, leaving a longer period for forest regeneration. As forest degradation accelerated in this region in Poland since the 1990s (Kozak et al. 1995), regeneration measures to sustainably stabilize Polish forests in this area are still ongoing.

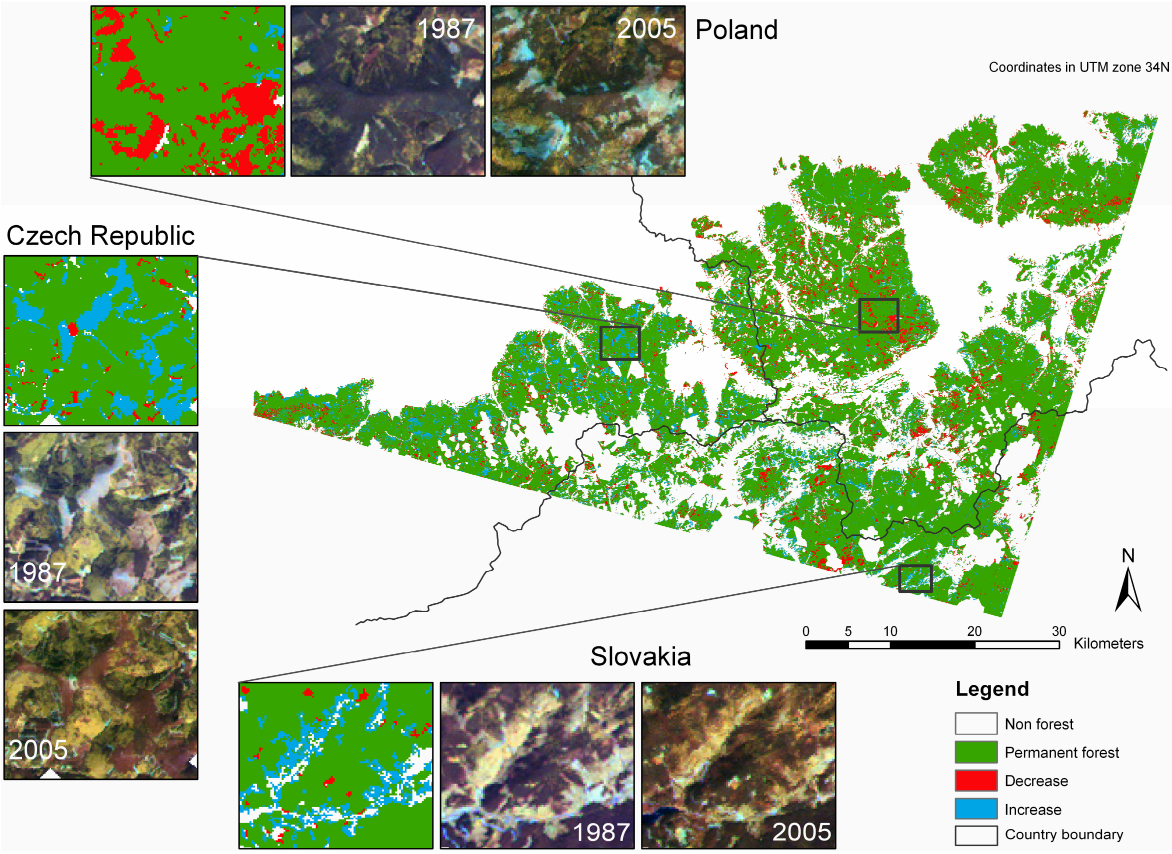

Figure II-7: Forest change map with close-ups on Landsat TM images from 1987 and 2005.

5.1 Forest cover change and forest type

From the mid-19th century, forest management during the Austro-Hungarian Empire introduced Norway spruce (*Picea abies*) across its territory, which replaced natural fir and beech stands. Spruce plantations were mostly planted from seeds of foreign origin, thereby also introducing inappropriate genetic traits that ultimately resulted in lower resistance against infestations and diseases (Mijal and Kulis 2004). At present, spruce stands still occupy major areas of the Western Carpathians. However, Bielecka and Ciołkosz (2004) observed decreasing coniferous forest cover in Poland. Our study confirms this not only for Poland, but for the entire study area (Figure II-4). Nevertheless, we also observe a decline in mixed forests with high shares of coniferous trees that are similarly susceptible to forest health decline and, for example, related windfall events.

Forest type changes and prevailing forest types prove the significant conversion from spruce monocultures to mixed stands in post-communist times (Table II-2). This replacement is related to forest degradation, observed first in the Czech Republic at the end of the 1980s (Kubikova 1991; Štefančík and Cicák 1994) and later in Poland (Kozak 1996; Widacki 1999), followed by forest regeneration measures based on a new forest code in 1992 (The Act Concerning Forest of 28th of September, 1991). Moreover, afforestation is strongly dominated by the mixed forest. This means that already before 2003 and the onset of the *Programme for the Beskid Mountains* (RDLP-Katowice 2003) in Poland, forest management activities and natural succession transformed forest types from prevailing spruce monocultures to mixed forests that better resemble the potential natural vegetation of the region. The observed transition from mixed forest to coniferous forests occurs mostly in young stands with lower stand densities, rather suggesting misclassifications of young coniferous stands in 1987 as mixed forests.

5.2 Forest cover and topography

In the study area, forest cover increase and decrease equal out at elevations between 500 and 880 m. The slight dominance of forest cover decrease in the foothill and mountain top zones is partly equalized through the dominance of forest cover increase between 900 and 1020 m. Those findings are confirmed in the cover change statistics, with a slight net decrease of forest cover of 0.5% between 1987 and 2005 for the whole study area.

Forest cover increase in all three countries exhibits significant differences between elevations, as reforestation management differs in Poland compared to the Czech Republic and Slovakia. Reforestation on damaged stands dispersed along elevation gradient is an important management component in Poland, while compacted plantations on clear-cuts are typical in the Czech Republic and Slovakia. Reforestation on large and compact patches dominates elevation ranges between 800 and 1120 m in the Czech Republic (Figure II-7), while reforestation in Slovakia mostly occurs on smaller strip clear-cuts that mostly prevail between 400 and 660 m.

Our analysis shows that in all countries, forest cover decrease generally dominates in the foothill zone (up to 500 m). Nevertheless, in the Czech Republic and Poland, decline at the mountain tops (above 1100 m), manifested by broad openings, is also observed. Various reasons are likely to correspond with forest cover decrease in different elevation zones: on the one hand, conditions in the foothill zone are inadequate for spruce. On the other hand, the expansion of a winter tourism infrastructure is abundant, especially in the foothill and mountain top zones (Figure II-5). While elevations above 1000 m provide ideal environmental conditions for coniferous species, these are also most exposed to the immission of air pollutants from long-range transport. Deteriorating forest health and resistance to windfalls are the consequences.

This is largely in line with the findings of other authors: Kozak et al. (1995), Kozak (1996) and Widacki (1999) noted that Western Beskid forests started to degrade at the highest elevations in the north and northwest aspects, where airborne pollution from the Upper Silesia and Ostrava industrial districts were immitted. During communism, rapid industrial development in Poland and Czechoslovakia largely disregarded environmental standards, with significant consequences concerning air pollution. Kubikova (1991) reports that the annual deposition of SO_2 in Czechoslovakia was on average about 23 t km^{-2} $year^{-1}$ in 1982, much higher than in any neighboring countries. In Poland, the deposition of SO_2 was estimated to reach about 10 t km^{-2} $year^{-1}$. After the fall of the Iron Curtain, pollution levels decreased, as confirmed by almost continuous measurements of SO_2 on the Lysa Hora mountain top (1324 m) in the Beskid Mountains (Figure II-8). At the same time, Hunova (2001, 2003) reports ongoing high wet deposition levels between 1996 and 1999 in the Ostrava industrial region, located close to the Western Beskid Mountains in the Czech Republic. Heavy metal and nitrogen deposition (Fiala et al. 2008; Novotný et al. 2008), the acidification of soils and unfavorable nutrition conditions for spruce forest also still prevail (Ditmarová et al. 2007; Małek and Barszcz 2008).

Further comparison between forest type and elevation proves that the fraction of coniferous stands decreases between 1987 and 2005 for elevations below 1000 m (Figure II-9), while the mixed forest fraction increases. This suggests that damaged coniferous monocultures are replaced with mixed forests across the entire elevation range. Coniferous stands only prevail in the highest elevations. Forest type changes with elevation and hence clearly reflects post-communism management efforts that aim to return to more sustainable forest structures that closely resemble the potential natural forests in the region.

Wind measurements on the Lysa Hora summit exhibit a strong dominance of western and southern wind directions (Figure II-8). We can therefore assume a western to southern dominance of windfall damages. These would manifest themselves in increasing forest cover on affected slopes from reforestation measures after 1987 and in apparent storm damages in recent imagery. However, this is not necessarily the case. Rather, we find forest cover increase since 1987 mostly on eastern slopes, while recent damages show a strong southern maximum.

While it is obvious that prevailing wind direction and aspect must play an important role in wind damage distribution, other factors seem to influence windfall patterns as well. Apparently, insect pest outbreaks along the damaged northern slopes of the Western Beskids occurred in the 1980s, triggering rehabilitation measures and re-planting early on. Insect populations then traversed towards favorable southern aspects (Sauvard 2004), culminating in recent forest damage. Meteorological observations also reveal an increasing number of days with wind speeds above 20 m/s per year since 1997, leading to an increased risk of windbreak (Lorenc 2003). Maximum wind speeds have reached hurricane level (above 32.7 m/s) in every year since 1997. A maximum wind speed of 42.6 m/s was measured on January 1st 2002, which caused widespread damage and destruction (Figure II-8). For example, the timber volume affected by windbreak during a storm in November 2004 exceeded 40,000 m^3 in the Slovakian Beskid region of Cadca (Lesoprojekt Zvolen, 2004); in the Polish part of the region, the storm resulted in a significant increase in sanitary cuttings in 2005 (Grodzki 2007).

The synergetic effect of land use legacies (spruce monocultures) and pollution legacies (heavy air pollution and high immissions and deposition rates) led to weakened forest stands that were less resistant to stress factors such as insect pests, diseases and consequently failed to withstand extreme weather events (Kozak 1996; Widacki 1999; Grodzki et al. 2004).

6 Conclusions

Already 200 years ago, during the Austro-Hungarian Empire, unsustainable forest management led to massive changes in forest cover and composition in the Western Carpathians. The replacement of natural forests by Norway spruce monocultures made stands less resistant to diverse stressors (Spiecker 2000). Since communist times, spruce forests in the Western Carpathians have been excessively exposed to a number of environmental stressors of varying duration and intensity (Grodzińska and Szarek-Łukaszewska 1997; Zwoliński et al. 2001). Disease symptoms in spruce stands emerged in the 1970s and intensified in the 1990s. In weakened spruce stands, fungal diseases developed (e.g., *Armillaria* spp.) and insect pests are widespread (e.g., *Ips typographus*)

(Grodzki 2006; Szozda 2006). As a consequence, severe tree damage was caused by windfall and snowbreak in 1992, 1997, and 2004.

Since the fall of the Iron Curtain, each country has approached forest monitoring, protection and the improvement of forest conditions in its own way. In 2003 for example, "*The Programme for the Beskid Mountains*" was created in Poland as an integrated effort to sustain forest resources and mitigate pressure on Western Carpathian forest ecosystems. One of this program's major goals is to slow down the progressive damage of spruce stands by changing their composition through adding beech, fir, larch, sycamore, ash and elm (RDLP-Katowice 2003).

Our study shows that although forest cover in the Western Carpathians is quite stable (net forest cover change reaches about 0.5%), it is a net result of extensive forest degradation and subsequent regeneration or reforestation. In addition the differences between countries are relevant. In Slovakia, forest increase and decrease occurred at similar rates. In Poland, however, areas of forest cover decrease are almost twice as large as forest cover increase, while in the Czech Republic, reforestation and regeneration significantly exceed forest decline. We found that those changes are related to varying occurrence times of forest disturbance and various forest management activities. In fact, forest decline first appeared in the Czech Republic in the early 1980s, followed by Poland in the mid-1990s. Further, we suggest that most reforested or regenerated areas occurred on previously-disturbed spruce plantations. The significant conversion from spruce monocultures to mixed stands in post-communist times, predominantly undertaken in Poland and the Czech Republic, confirms successful forest management efforts, i.e., changing forest composition within previously disturbed areas.

So far, there is no clear evidence that reduced emissions of sulfur, nitrogen and heavy metals in post-communist times have resulted in significant improvements of forest stand conditions in our study site. Moreover, pollution legacies weakened forest stands and led to lower resistance to stress factors such as insect pests, diseases and, consequently, extreme weather events. We therefore conclude that the synergetic effect of unsustainable forest management in the past, supported by high levels of air pollution and wet deposition during communist times, caused significant damage to coniferous forests in the Western Carpathians. Related effects still prevail and it is likely that increased forest damage from insect pests and windfall will extend in the future, especially since even moderate climate change scenarios will modify the climate in Europe towards sub-optimum conditions for spruce forests in most mountain ecosystems in the Carpathians (IPCC 2000). At the same time, conditions will also deteriorate due to an increased threat by insect pests triggered by, among other reasons, rising temperatures. Considering our findings for the border triangle of Poland, Slovakia, and the Czech Republic, it seems sensible to extend related evidence to the whole Carpathian Ecoregion (UNEP 2007), especially in areas where spruce plantations were widely introduced.

Acknowledgements

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Chapter III:
Evaluating the remote sensing and inventory-based estimation of biomass in the Western Carpathians

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Abstract

Understanding the potential of forest ecosystems as global carbon sinks requires a thorough knowledge of forest carbon dynamics, including both sequestration and fluxes among multiple pools. The accurate quantification of biomass is important to better understand forest productivity and carbon cycling dynamics. Stand-based inventories (SBIs) are widely used for quantifying forest characteristics and for estimating biomass, but information may quickly become outdated in dynamic forest environments. Satellite remote sensing may provide a supplement or substitute, though. In a Picea abies forest in the Western Carpathian Mountains, we tested the accuracy of aboveground biomass estimates modeled from a combination of Landsat Thematic Mapper (TM) imagery and topographic data, as well as SBI-derived variables. We employed Random Forests for non-parametric, regression tree-based modeling. Results indicated a difference in the importance of SBI-based and remote sensing-based predictors when estimating aboveground biomass. The most accurate models for biomass prediction ranged from a correlation coefficient of 0.52 for the TM- and topography-based model, to 0.98 for the inventory-based model. While, Landsat-based biomass estimates were measurably less accurate than those derived from SBI, adding tree height or stand-volume as a field-based predictor to TM and topography based models increased performance to 0.36 and 0.86, respectively. Our results illustrate the potential of spectral data to reveal spatial details in stand structure and ecological complexity.

1 Introduction

Monitoring long-term forest productivity will be critical for determining the strength of forest ecosystems as carbon sinks to counter the anthropogenically-induced disruption of regional and global climate systems (Bonan 2008; Eggers et al. 2008; Schulp et al. 2008). Rising levels of atmospheric carbon dioxide and potentially complex interactions with other anthropogenic stressors (Aber et al. 2001; Ollinger et al. 2002) require rigorous analytical approaches for quantifying forest carbon sequestration and fluxes among multiple pools at scales ranging from individual stands to entire landscapes and bioregions (Kuemmerle et al. 2011). As a consequence, research on forest carbon modeling has advanced considerably over recent decades (Running and Gower 1991; Cienciala et al. 1998; Song and Woodcock 2003; Eggers et al. 2008; Beer et al. 2010). Models focusing on forest carbon fixation require information on forest structural characteristics as essential input parameters, a constraint which often limits carbon budget modeling across large areas. Accurate estimate of forest biomass is sometimes viewed as one of the most important parameter for carbon modeling (Hall et al. 1995). Forest biomass is highly recognized for its large carbon sequestration potential (Schulp et al. 2008). Applications range from individual trees, to whole regions to support the estimation of fixed carbon in forests (Asner et al. 2003; Kutsch et al. 2005).

For applications of limited spatial extent, aboveground biomass is often derived from plot-based forest inventory data. However, regional to global carbon budget models require parameters such as tree biomass that are typically modeled from remote sensing data. Here, we evaluate the utility of an integrated approach by combining inventory data, remotely-sensed information and derivatives from topography data to predict aboveground tree biomass (AGB) at landscape to regional scales.

1.1 Estimating forest biomass

Direct AGB measurements in the field are not always reliable, and are also labour intensive and time consuming (Lu 2006). Typically, AGB is estimated using allometric equations and tree measurements such as diameter at breast height (dbh) and height (Wulder et al. 2008c). For example, Jenkins et al. (2003) compiled available dbh-based regression equations for tree species in the United States, while Lakida et al. (1996) and Zianis et al. (2005) identified and summarized relationships for estimating forest biomass for European tree species. As Lakida et al. (1996) focused on European mountain tree species, our study utilizes their findings.

Remote sensing data from Landsat sensors has been regularly used to predict forest biomass, as Landsat data offer a long-term data record and a good compromise between spatial resolution, aerial coverage, and spectral sensitivity. Landsat Thematic Mapper (TM) imagery has been widely used to predict biomass in boreal and mountain forest studies; Luther et al. (2006), for example, predicted biomass for dominating tree species in Newfoundland, Canada, using Landsat TM and forest inventory data. These authors determined that deriving forest type and structure from Landsat TM imagery was effective for mapping biomass when the availability of plot data is limited, but photo inventory information is not. Wulder et al. (2008c) investigated AGB estimates using forest inventory and land cover data, together with vegetation density information derived from TM imagery. These authors concluded that the integrated approach provided the most accurate and spatially explicit estimates of AGB over large areas.

1.2 Objectives and approach

While evidence from previous studies proves that great potential exists for both SBI-based and remote sensing-based approaches for estimating aboveground biomass, not much research has been dedicated towards integrating these approaches. We suggest adequate input variables, either from remote sensing, SBI, or both combined for biomass estimates, depending on available input information. Our approach focuses on a dynamic region with high forest disturbance rates, i.e. on a region where stand-based forest inventories quickly become outdated and remote sensing may offer opportunities for substituting SBI-based input variables for biomass models.

Numerous algorithms have been tested for modeling forest structure, many of them employing simple or multiple linear regression models (Nilson et al. 1999; Chen et al. 2002; Shvidenko et al. 2007), or vegetation canopy models (Wu and Strahler 1994; Hall et al. 1995; Peddle et al. 1999; Eklundh et al. 2001). The latter describe canopy architecture in both vertical and horizontal dimensions, but depend on a priori knowledge of canopy complexity, atmospheric conditions, illumination and viewing geometry, and topography (Lu 2006). De Veaux (1995) and Moisen and Frescino (2002) compared five modeling techniques, including linear models, generalized additive models, classification and regression trees (CART), multivariate adaptive regression splines and artificial neural networks. These authors found that the most parsimonious linear models were more efficient for forest structure prediction, but sometimes excluded variables that also had predictive strength. This implies that more flexible modeling methods, for instance incorporating correlated variables or both categorical and continuous variables, might have greater utility. Investigating a full set of variables from TM spectral bands, topography and SBI despite some high correlations, was also a goal of this study.

An analytical method that captures the modeling flexibility described above is the Random Forests (RF) approach (Breiman 2001). RF is a non-parametric ensemble method of the CART algorithm (Morgan and Sonquist 1963; Breiman et al. 1984) that introduces some modifications to the latter. RF changes the strategy of constructing the regression trees from choosing the best split among all variables (as standard trees do) to randomly sampling variables at each node and choosing the best split from among them (Liaw and Wiener 2002). RF has received considerable attention in the ecological and remote sensing literature because of its utility for ranking the relative predictive strength of multiple independent variables and its robustness to over-fitting (Breiman 2001; Cutler et al. 2007). This multivariate technique requires no assumption of normality, simultaneously incorporates both categorical and continuous data, and produces easily interpretable results (Prasad et al. 2006; Francke et al. 2008). We employed RF in our study for the above reasons, and because they have proven effective in previous research on forest succession (Falkowski et al. 2009) and mapping nationwide forest aboveground biomass in the U.S. (Powell et al. 2010).

To our knowledge, no previous study has compared the potential of solely Landsat-based and combined Landsat- and inventory-based predictors for biomass modeling at local to regional scales. The overarching goal of our study is, therefore, to predict aboveground tree biomass from satellite data (Landsat TM) alone, as well as from combined inventory and satellite data.

2 Study area

The study area covers 250,000 ha within the Carpathian Mountains in Poland, the Czech Republic, and Slovakia (Figure III-1). Forest covers the lower montane zone between 500-1200 m above sea level (asl) and mainly consists of Norway spruce (*Picea abies* Karst.) monocultures or mixed stands, dominated by European beech (*Fagus sylvatica*), spruce, and European silver fir (*Abies alba*). Forests in this area are characterized by highly variable tree vigor and mortality rates due to severe airborne pollution during communist

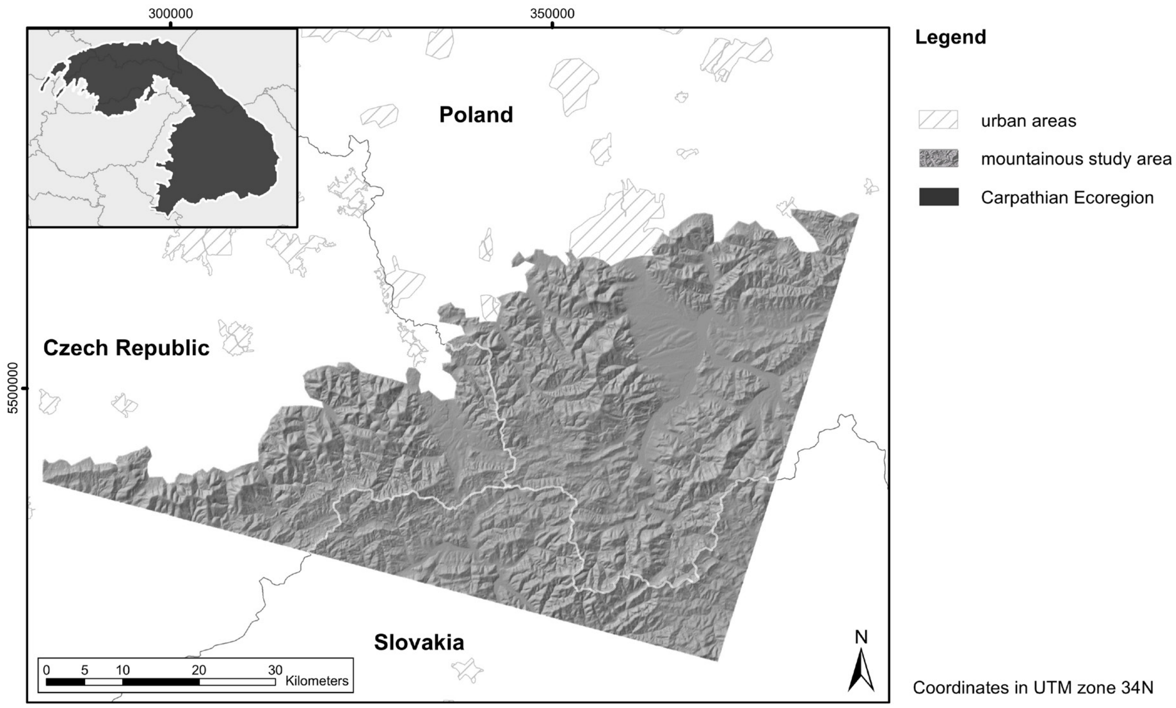

Figure III-1: Study area within the Carpathian Mountains in the border region of Poland, the Czech Republic and Slovakia.

times, as well as unsustainable forest management (Kozak 1996; Bytnerowicz et al. 2003; Grodzki 2006; Main-Knorn et al. 2009). The conversion of uneven-aged, mixed species stands to spruce plantations in the 19th and 20th century (Fabijanowski and Jaworski 1995) homogenized species composition and stand structure at the stand and landscape scales. This in turn led to lower tree resistance to stress factors such as air pollution, insect pests, diseases, and extreme weather events, ultimately resulting in the heavy spruce dieback now being experienced throughout the region (Ditmarová et al. 2007; Grodzki 2007; Šrámek et al. 2008). We found spruce monocultures to be easily identifiable in satellite imagery due to the homogenous spectral response. The application of our approach to this region was also facilitated by the availability of stand-specific field data, ground-truthing and expert knowledge from earlier studies (Main-Knorn et al. 2009).

3 Data and field sampling design

Stand-specific inventory data from 2003-2004 and 2007 were provided by the Polish State Forest Holding and covered about 14% of the study area. These data included dominant species, mean stand diameter (1.30 m ht, dbh), tree height and age, tree form factor, stand area, growing stock and stand volume, stem density and relative density indices, soil structure and type, presence of insects or fungi, ecological forest type and management history.

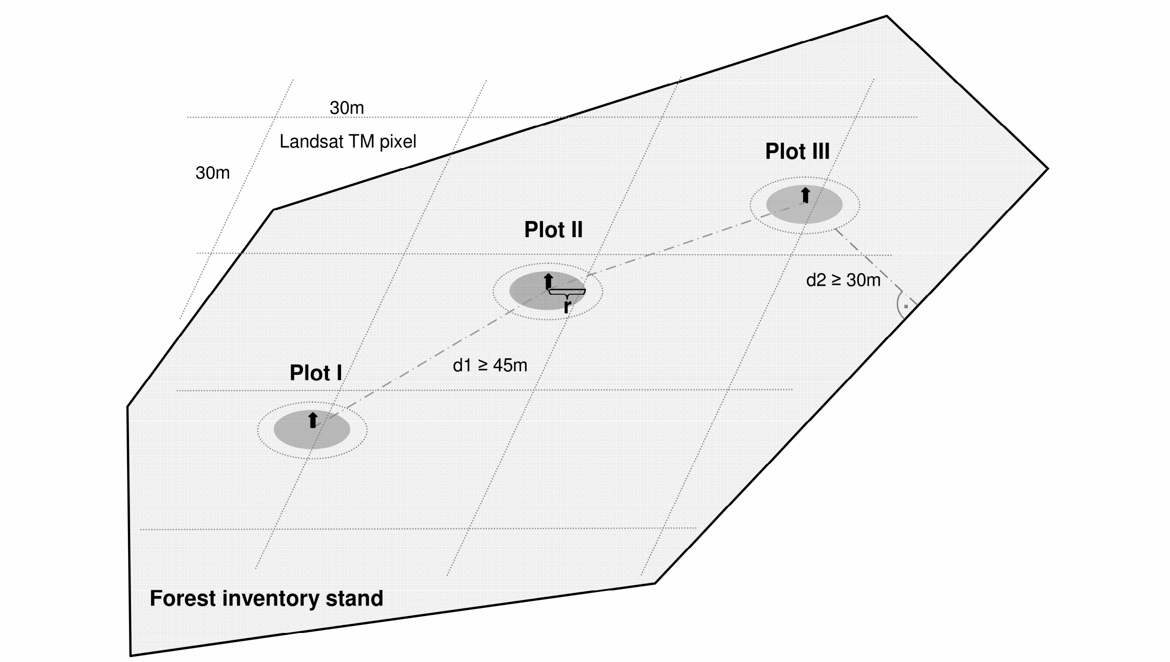

Figure III-2: Sample design and field data collection. 105 even-aged spruce plantation stands were randomly selected from SBI districts and re-sampled based on a simplified procedure of the Polish Forestry Service. Sample design for every selected stand based on three plots. First plot - as representation for general stand homogeneity/ heterogeneity - was localized in the core part of the stand. Two further representative plots were then localized along a transect, a min. 45 m distance (d1) from one another, which brought us deeper into the stand. Additionally, every plot was located a min. 30 m distance (d2) from the stand's border.

Poland initiated the development of a digital forest database in the 1990s, but work is still ongoing. Therefore, the availability of digital inventory data varies by forest district. It is necessary to verify the accuracy and comparability of the given parameters across different districts, as related field inventories may substantially vary in acquisition time. Therefore, 105 spruce forest inventory stands were randomly selected and sampled during field campaigns in 2006 and 2007. All of the randomly selected stands were pure, even-aged spruce plantations with dominant cohort ages ranging between 40 and 150 years. Our sampling scheme was adopted from the Polish Forest Inventory to be compatible with stand-based estimates from official data sources. We selected three representative plots per stand, each covering approximately 100 m^2 for detailed sampling, following a simplified version of the standard procedure of the Polish Forestry Service (Figure III-2). Accordingly, when the number of trees per 100 m^2 with a dbh above 7 cm was less than 7, we doubled the plot size to capture a more representative sample of larger trees. We counted the number of trees per plot to estimate stem density and measured dbh and tree height. Mean values of these parameters were calculated per forest stand and compared with the Polish Forest Inventory data. These verification procedures enabled us to find and correct for incompatible stand-specific inventory data.

We used a Landsat TM image (path/row 189/025) from 9th September 2005 and excluded the thermal band from the analysis. A 90 m DEM from the Space Shuttle Radar Topography Mission (SRTM) (Slater et al. 2006) was resampled to 30 m using bilinear interpolation to match the spatial resolution of Landsat TM data. The image was ortho-corrected to Universal Transverse Mercator (UTM) coordinates (World Geodetic System [WGS] 1984) based on a semi-automatic image registration software using ground reference points gathered in the field (Hill and Mehl 2003). We calibrated the image using a modified 5S radiative transfer model to radiometrically correct the TM images (Tanre et al. 1990; Hill and Mehl 2003). Clouds and cloud shadows were digitized and masked.

4 Methods

4.1 Response variable

Biomass is defined as organic material both aboveground and belowground and both living and dead (IPCC 2003). We limited our biomass prediction to aboveground living and dead organic material.

We applied biomass equations for Carpathian spruce forests based on Lakida et al. (1996), who analyzed and modeled forest biomass in European countries that were part of the former Soviet Union. Estimates of AGB were based on parameters extracted from Ukrainian spruce forests in the Carpathian Mountains, the ecologically most similar forests to those in our study area for which parameters are available in the literature. AGB was calculated with:

$$M_{fr} = V_{st} R_{v(ab)} \tag{1}$$

where M_{fr} is the weight of tree biomass fraction in Mg, V_{st} is the growing stock of stemwood in $m^3\ ha^{-1}$, and $R_{v(ab)}$ is the ratio between aboveground standing tree biomass and the volume of the growing stock over bark, calculated as:

$$R_{v(ab)} = a_0 A^{a_1} \tag{2}$$

where A is the average age of the respective stand in years and a_0 and a_1 are species dependent regression coefficients. Regression coefficients were adopted with a_0 = 2.058

and a_1 = -0.383 after Lakida et al. (1996). Values of V_{st} and A were available from the verified SBI. Biomass in our study area ranged from 75.5 to 307.0 Mg ha^{-1}.

4.2 Preparation of predictor datasets

Three groups of predictors were defined: stand-based, pixel-based, and combined predictors. Stand-based predictors (INVE) derived from forest inventory data were composed of volume of trees per hectare, canopy cover, stem density and relative density (as a dimensionless index), tree age, tree height, tree form factor, growing stock per tree and stump surface at 1.37 m ht. Pixel-based predictors from Landsat TM and topography data (TMTO) included reflectance from the visible, NIR and short-wave infrared (SWIR) wavelength regions, Tasseled Cap (TC) brightness, greenness and wetness, Disturbance Index (DI) after Healey et al. (2005), and NDVI. We also added elevation, slope and direct solar radiation extracted from the DEM to the dataset. A third setup (ALL) combined all pixel- and stand-based information.

4.3 Modeling technique

Random Forests (RFs) (Breiman 2001) is a robust, non-parametric and ensemble modeling technique that provides well-supported predictions (Cutler et al. 2007). RF models consist of many independent regression trees, where for each regression tree, a bootstrap sample of the training data is chosen. At the root node, a small random sample of explanatory variables is selected and the best split made using that limited set of variables. At each subsequent node, another small random sample of the explanatory variables is chosen, and the best split made. The regression tree continues to grow until it reaches the largest possible size, and is left un-pruned. The whole process is often repeated based on new bootstrap samples. The final prediction is a weighted plurality vote or the average from predicting all regression trees. RF has the ability to deal with non-linearity between predictors as well as with missing values, which are handled effectively and with minimal loss of information (Prasad et al. 2006; Rehfeldt et al. 2006; Falkowski et al. 2009; Marmion et al. 2009).

4.4 Evaluation criteria / Accuracy assessment

We estimated the prediction error based on a 10-fold cross-validation. Pearson's and Spearman's correlations were calculated between observed and predicted values for every model, as well as the degree of determination for R-squared and root mean squared errors (RMSE).

RF provides a relative measure of importance for each predictor variable. This ranking is based on the percentage of mean squared error increase (%IncMSE) calculated from the out-of-bag sample (samples not included in the bootstrap sample used to build that particular tree) through the RF decision trees, while randomly noising the values of one predictor variable at a time (random permutation). This metric shows how much accuracy is lost after each variable "drops out" of the model (Breiman 2001). We also explored the RF-generated biomass model's prediction potential by plotting and comparing changes in density functions (distribution of observed and modeled biomass values) from models based on stand-wise predictors, pixel-wise predictors, and both combined.

Since forest inventories are missing in most regions of the world, we additionally tested which field-derived predictors should be added to improve our TMTO-based models. In this approach we included single SBI variables to the pixel-based predictor's set and assessed the change in model performance. Finally, we evaluated our spatially explicit results by comparing the mapped structures of biomass with and without remote sensing data.

5 Results

We first compared the different model performances for calculating biomass with and without remote sensing-based data. We also evaluated the respective importance of individual predicting variables in each model. We then applied the INVE and TMTO models to produce biomass maps. Our final comparison of model results was exemplified by a difference map between INVE-based and TMTO-based biomass estimates.

5.1 Model performance

Models incorporating SBI metrics were the most predictive of AGB (Figure III-3, Table III-1). Cross-validated biomass estimates (Table III-1) were statistically significant ($P < 0.05$), with R^2 values ranging from 0.94 to 0.96 for the ALL and INVE models, respectively. TMTO model-based estimates only reached R^2 values of 0.27. Our model fits (Table III-2) reached R^2 values of 0.30 for TMTO, 0.94 for ALL, and 0.96 for INVE models.

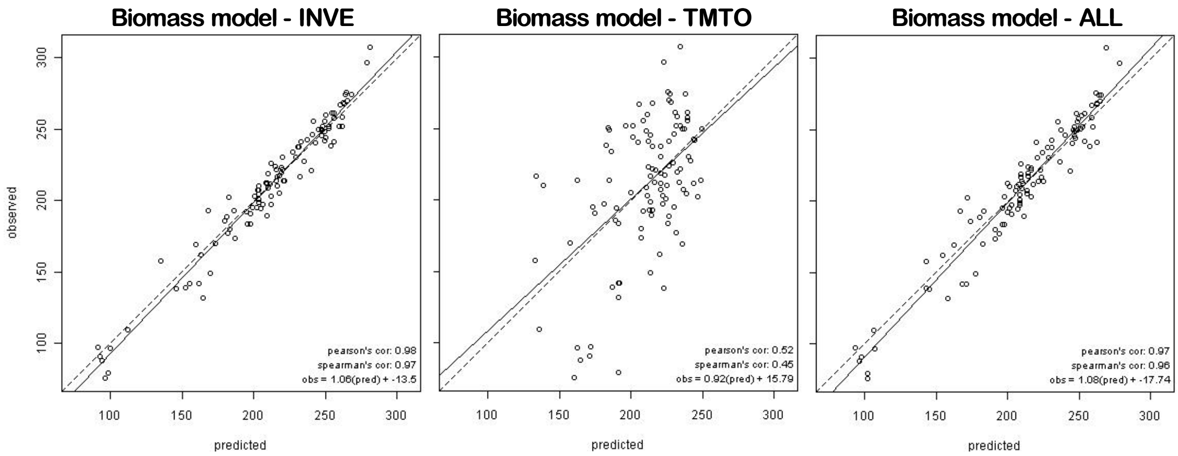

Figure III-3: Correlation coefficients for biomass prediction, based on the INVE, TMTO and ALL models.

Table III-1: Cross-validated results for biomass modeling.

	Biomass model		
	ALL	TMTO	INVE
Pearson's correlation	0.97	0.52	0.98
Spearman's correlation	0.96	0.45	0.97
R-squared	0.94	0.27	0.96
p	2.20E-16	1.45E-08	2.20E-16
MSE	159.84	1651.79	104.49
RMSE	12.64	40.64	10.22

Table III-2: Model fit.

	Biomass model		
	ALL	TMTO	INVE
Pearson's correlation	0.97	0.55	0.98
Spearman's correlation	0.97	0.45	0.97
R-squared	0.94	0.30	0.96
p	2.20E-16	1.55E-09	2.20E-16

As illustrated in Figure III-3, the forest aboveground biomass was estimated with correlation coefficients ranging from 0.52 under the TMTO scenario to 0.97 for ALL and 0.98 for INVE. Spearman's correlation for biomass prediction ranged from 0.45 for TMTO to 0.96 for ALL and 0.97 for INVE. Biomass was generally over-predicted for low (below 100 Mg ha^{-1}) and under-predicted for high Mg ha^{-1} biomass values (above 300 Mg ha^{-1}). The INVE model showed the lowest RMSE with 10.22 Mg ha^{-1}, increasing to 12.64 Mg ha^{-1} for ALL and to 40.64 Mg ha^{-1} for TMTO.

For all models we examined the density functions (Figure III-4) of predicted biomass values. Comparing the observed (field-based) biomass values with the modeled estimates, the best fit in regression relationships were found for values ranging between 150 and

180 Mg ha^{-1}, and 250 to 300 Mg ha^{-1}. This held true for all three model types. Generally, the INVE and ALL models performed similarly well, while the TMTO model allowed biomass estimates in the range of 100 and 275 Mg ha^{-1} only.

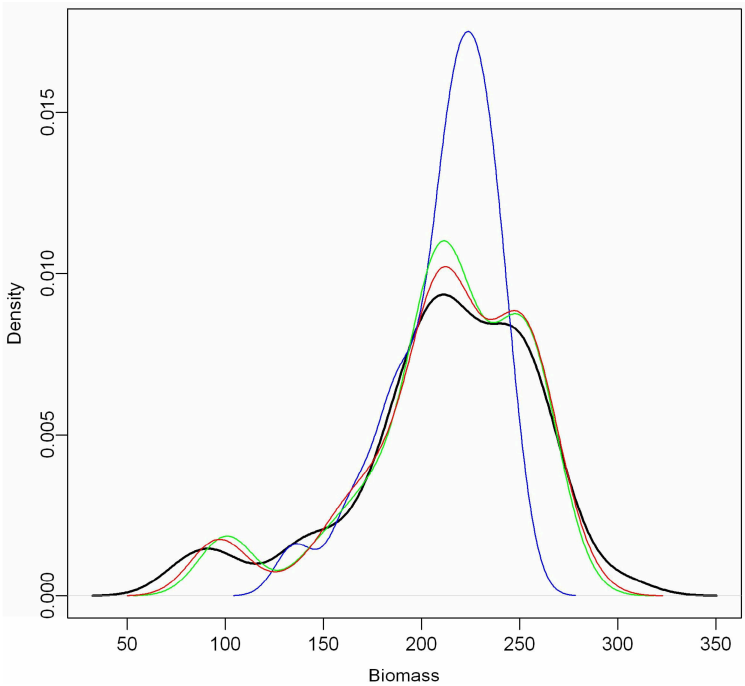

Figure III-4: Density functions of observed (black line) and predicted values of biomass for different models: INVE (red line), TMTO (blue line), and ALL (green line) models.

5.2 Variable importance

The RF results presented in Figure III-5 and Table III-3 hierarchically rank the relative importance of predictors for all three models. The most important predictors were volume of trees per ha, relative density, tree age and stem density. This held true for both the INVE and the ALL models. It is interesting to note that the four most important variables in the ALL model were also the four highest ranked in the INVE model. The random permutation of volume values, for example, caused an %IncMSE of almost 70% in both models. Random permutation of relative density, tree age or stem density decreased predictive accuracy by 15-30%.

The relative importance of predictors for the TMTO model identified elevation as the most crucial variable for biomass estimate. When random noise was introduced, %IncMSE reached 25%. Other strong predictors of aboveground biomass for the TMTO model included (in order of decreasing predictive strength) the visible green, visible red, SWIR II and SWIR I bands of Landsat TM, respectively (Table III-3). The random permutation procedure reduced the predictive accuracy by 5-10% for all of these variables.

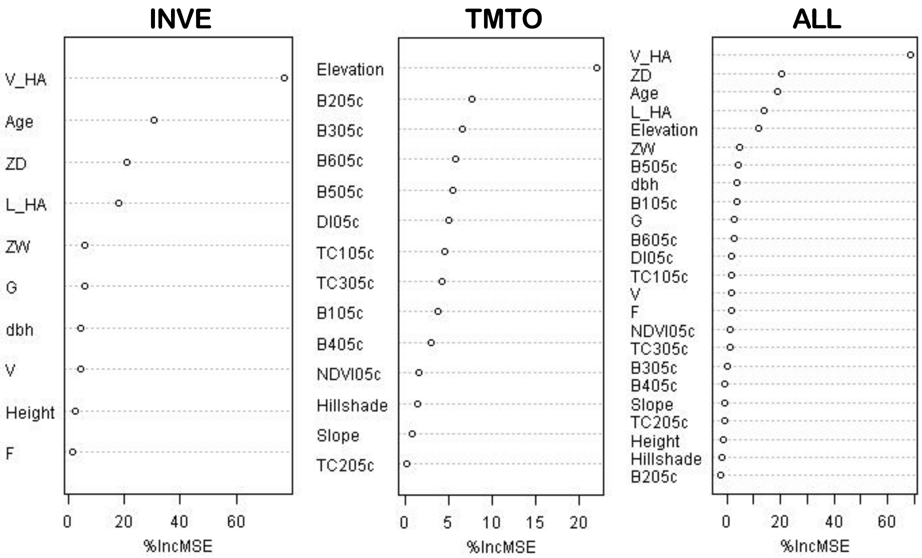

Figure III-5: Predictor's importance ranking for biomass prediction, based on INVE, TMTO and ALL models. Description of predictors: Landsat TM bands (B105c, B205c, B305c, B405c B505c, B605c), TC brightness (TC105c), TC greenness (TC205c), TC wetness (TC305c), Disturbance Index (DI05c), NDVI (NDVI05c), volume of trees per ha (V_HA), relative density (ZD), canopy cover (ZW), tree age (Age), tree height (Height), tree stem density (L_HA), tree form factor (F), growing stock for single tree (V) and stump surface at dbh (G).

Table III-3: Relative importance of predictors measured in increase of mean squared error [in %].

	Biomass model		
Predictor	ALL	TMTO	INVE
B105c	3.51	3.73	
B205c	-2.49	7.56	
B305c	0.09	6.54	
B405c	-0.67	2.89	
B505c	4.05	5.37	
B605c	2.55	5.79	
TC105c	1.84	4.54	
TC205c	-0.99	0.07	
TC305c	1.29	4.25	
DI05c	1.93	4.99	
Elevation	11.88	21.90	
NDVI05c	1.46	1.48	
Hillshade	-1.60	1.44	
Slope	-0.70	0.71	
Age	19.15		30.54
Height	-1.07		2.85
dbh	3.78		4.77
ZW	4.69		5.96
V_HA	68.32		76.84
L_HA	13.68		17.91
F	1.55		1.82
G	2.71		5.88
V	1.66		4.62
ZD	20.42		20.74

We also tested which individual field-derived predictors would generally improve biomass estimates from satellite data for cases where SBIs are not available (Table III-4, Table III-5). We found that the correlation between observed and predicted biomass increased significantly when models included tree height (r=0.60), relative density (r=0.85) or stand volume (r=0.93).

Table III-4: Cross-validated results for biomass based on TMTO model and single forest parameter.

	Biomass model			
	TMTO	TMTO	TMTO	TMTO
Pearson's correlation	0.57	0.60	0.85	0.93
Spearman's correlation	0.54	0.51	0.82	0.89
R-squared	0.32	0.36	0.72	0.86

Table III-5: Relative importance of predictors by TMTO model including single forest parameter measured in increase of mean squared error [in %].

	Biomass model			
Predictor	TMTO + age	TMTO + height	TMTO + relative density	TMTO + volume
B105c	2.44	2.05	-0.66	0.39
B205c	6.83	6.64	2.46	0.77
B305c	4.66	4.02	0.04	0.77
B405c	3.92	4.57	-0.72	1.19
B505c	6.15	6.93	3.32	8.23
B605c	7.03	3.90	3.67	6.07
TC105c	4.77	5.23	1.86	4.33
TC205c	0.02	-0.79	-0.29	-0.35
TC305c	4.68	4.23	1.66	2.43
DI05c	6.45	6.63	1.68	4.48
Elevation	17.67	16.14	26.58	16.46
NDVI05c	-0.07	1.48	4.53	-1.00
Hillshade	1.00	3.37	-3.66	-0.41
Slope	-0.08	-1.77	-0.60	-1.38
Age	6.91			
Height		11.33		
Relative density			45.59	
Volume_ha				70.39

5.3 Biomass and difference maps

Both similarities and differences are obvious in the comparison of inventory- and remote sensing-based biomass estimates (Figure III-6). Overall patterns of biomass distribution throughout the study area were similar, with biomass decreasing with increasing elevation. Overall, tolerable differences occurred for approximately half of our test site. TMTO-based biomass values were overestimated for stands with very open canopies, as well as stands with an average tree age below 50 years (red colours in the difference map). Vice versa underestimates of TMTO-based biomass (blue colours in the difference map) occurred in dense and old forest stands (>100 years).

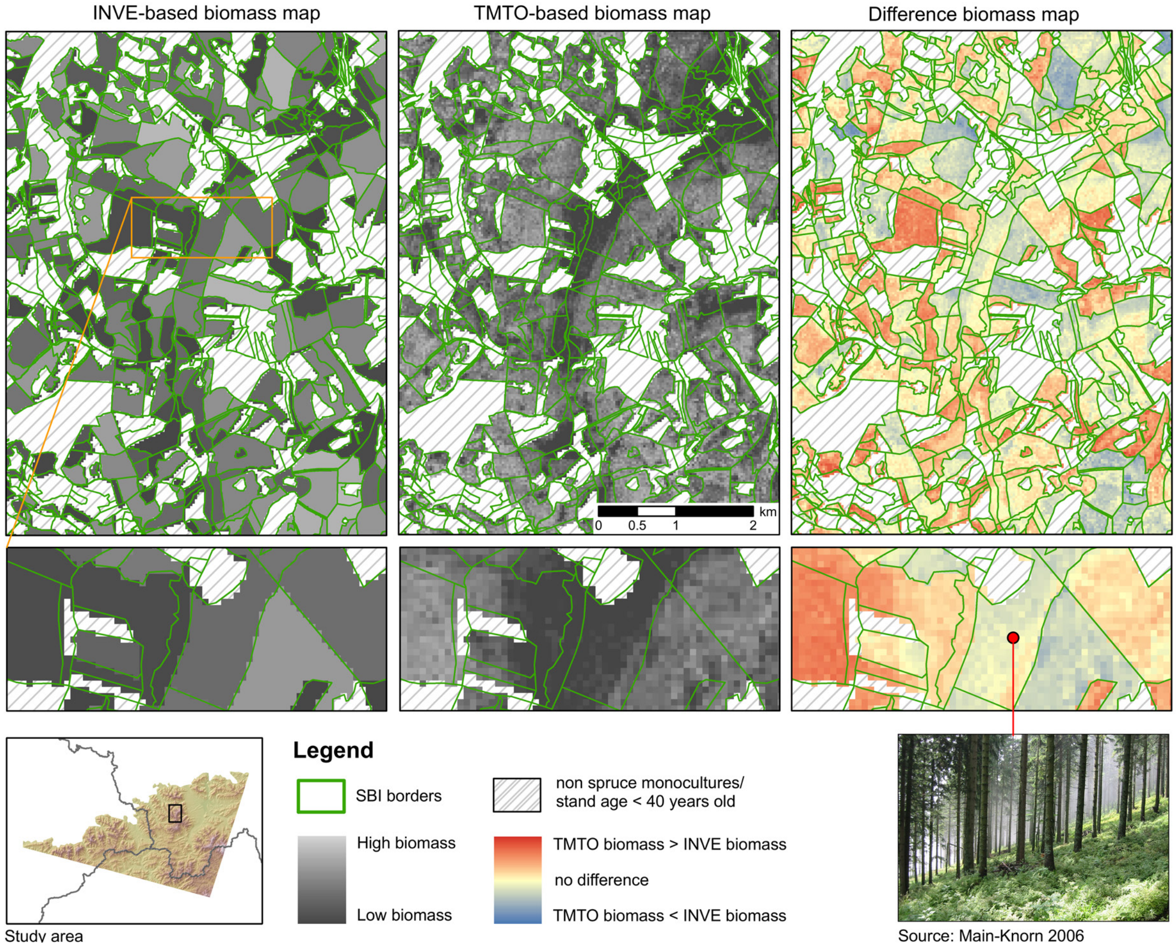

Figure III-6: Single model-based biomass maps and the difference biomass map.

6 Discussion

6.1 Biomass models

Spatially explicit and timely biomass estimates for forests are of prime importance for biogeochemical models of forest productivity, but are also vital for the newly-developing carbon markets. Field-based estimates from inventories therefore need to be complemented by remote sensing-based measures in order to fulfill the spatio-temporal needs of many users from scientific and applied domains alike.

Our results showed a very strong relationship between inventory-based predictors and estimated biomass (Table III-1). The INVE model was the most predictive for biomass, and captured the complete observed biomass range from approximately 100 to 300 Mg ha^{-1} (Figure III-3). These values are consistent with the typical range for boreal and temperate coniferous forests (Fehrmann and Kleinn 2006; Wulder et al. 2008c; Keeton et al. 2010). Using our modeling techniques for areas with up-to-date SBI, we found stand volume, relative density, and dominant tree age (Table III-3) to be the strongest predictors for biomass estimation. This is consistent with allometric equations that often also incorporate these variables (Lakida et al. 1996; Wulder et al. 2008c). Generally, the predictive power of inventory-derived stand structure metrics is very high, especially for stand volume (Table III-3).

Biomass estimates for areas lacking forest inventory data (TMTO) led to considerably less precise results. None of the pixel-based variables, aside from elevation, significantly contributed to biomass prediction. Powell et al. (2010) also reported similar results based on Landsat data and in areas with strong elevational gradients. In our case, elevation is often correlated with the forest dieback experienced during the past decade, which may explain its relationship to biomass distribution (Main-Knorn et al. 2009).

Tests on individual field-derived predictors which have improved TMTO-based biomass estimates (Table III-4, Table III-5) provide promising results. We found that stand volume or even tree height - parameters easily taken in the field - increased significantly the correlation between observed and predicted biomass. Moreover, as tree height is easily measured in the field or can be measured from airborne Lidar data, we strongly recommend its inclusion to improve prediction results. To summarize, as might be expected, models based on SBI predicted biomass better than models based on satellite data. However, by integrating TM data and stand volume or tree height information, our biomass estimate accuracy increased significantly. Our method therefore provides increased spatial detail within inventory polygons and fills the “knowledge gaps” in areas lacking SBI.

Beyond absolute model quality, we focused on the usefulness of remote sensing-based results in dealing with spatial variability within forest inventory stands. Our difference map highlights the potential of spectral data compared to polygon-based inventory layers that average stand-wise heterogeneity (Figure III-6). Even in homogenous areas such as those selected for this study, it is obvious that remote sensing-based mapping results support decision-making at a sub-stand level and reveal spatial detail that are averaged out otherwise. Adding to this increased timeliness of remote sensing-based estimates of forest stand parameters, it rather depends on the research or management question at hand if accuracy trade-offs between field-based and remote sensing-based results may be more important than spatial or temporal detail.

TMTO-based estimates better represent short-term dynamics that often do not show up in biomass estimates from INVE-models. Long intervals between field-based inventories lead to mismatches between TMTO- and INVE-based biomass estimates. Differences are particularly obvious along forest stand borders, where, e.g., windbreak frequently caused great dynamics. Furthermore, the INVE-based biomass estimates for the whole southern part of the study area were overestimated compared to the satellite-based estimates. This is mainly related to temporal inconsistencies in the reference data (see section 6.2).

Further differences between INVE- and TMTO-based biomass estimates relate to the spatial heterogeneity within forest stands. SBI-based estimates provide averaged biomass values for each stand, ignoring the spatial distribution of biomass and ecological complexity on the sub-stand level (Figure III-6). Thus, stand-based inventory details may be sufficient for accomplishing forest management tasks, while the same information may not be sufficient to describe temporal and spatial dynamics in forest ecosystems, e.g., related to carbon sequestration potential.

6.2 Innovation and limitations

The availability of ground truthed data and a homogeneous forest structure in our study site facilitated the evaluation of different models' predictive power. Nevertheless, few uncertainties remained. First, different explanatory variables might not perfectly match each other due to temporal differences in our reference data. SBI data from different forest districts are collected independently of each other and consequently also in different years. The latest SBI data updates were available for 2003, 2004 and 2007 in the different districts, respectively. Thus, the extent of windbreak after the destructive storms in November 2004 and following sanitary cutting in 2005 might be missed in some of our district's SBI. Similarly, Landsat data from early September 2005 might not reflect the total extent of sanitary clear-cut measures. Thus, inevitable time shifts between SBI, Landsat data and field measurements (2006, 2007) do not reflect exactly the same forest situation.

Second, the model estimates tend to bias for low and high target values. We found slight over- and underestimates for lower and higher biomass values, respectively. The tendency to over-predict low biomass and under-predict high biomass conditions (Figure III-3) has also been identified in previous studies, for instance where regression tree techniques (Blackard et al. 2008) or k-Nearest Neighbor (kNN) algorithms (Reese et al. 2002) were applied. This tendency may most likely be related to two factors: optical sensors have a limited sensitivity for reproducing the canopy structure in dense forests, where biomass can lead to saturated measurements. There is also the confounding effect of understory vegetation in sparse and/or young forests, where forest biomass is generally low. We illustrated these effects in the example of AGB by comparing relative stand density with observed and predicted biomass values (Figure III-7). AGB is highly positively correlated with relative density, as shown for observed biomass (reference) and INVE-based estimates. TMTO-based estimates revealed only a moderate relationship to stand density. Regarding dense forests, we observed considerable underestimates of TMTO-based biomass for relative forest densities above 0.9. Additionally, overestimated TMTO-based biomass values, as found in the case of low relative stand density and in the presence of understory as well as underwood, confirms their confounding effect in spectral data. Moreover, overestimation of biomass for spruce stands with tree age below 50 years may also be related to a low sample representation (about 3%) of young forest stands in the modeling process.

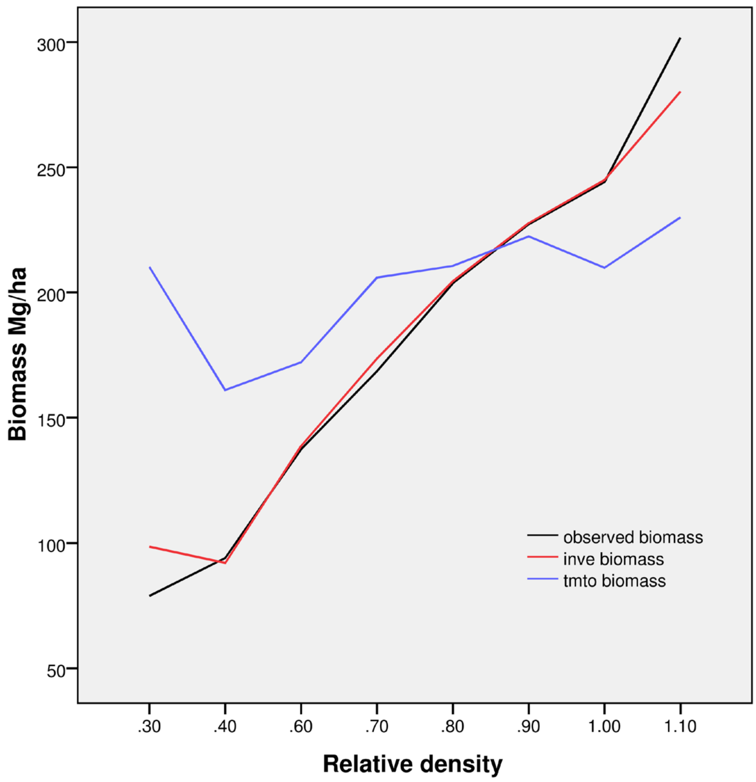

Figure III-7: Relative stand density, observed biomass (black line) and predicted values of biomass for models INVE (red line) and TMTO (blue line) for all of 105 stands we sampled in summer 2006 and 2007.

Third, while spruce stands in our study area and Ukraine are very similar, differences due to regional climate variability and genetic origin exist. Minor inaccuracies in model parameterization and hence biomass estimates can therefore not be completely ruled out.

An integrated modeling approach combining SBI and satellite data has obvious advantages for determining spatial variability in forest biomass and structure. Our findings demonstrated that the integrated use of satellite data compliments stand level inventories, though the latter had the greater predictive strength for aboveground biomass if SBI information is updated regularly. Nevertheless, field-based information alone will, due to time- and work-intensive updating procedures, not timely deliver all the necessary information in such a dynamic region.

Combining SBI and satellite data (ALL) did not improve the accuracy of biomass estimates. However, an integrated approach facilitates better detection of horizontal structural heterogeneity in forest systems (Franklin et al. 2002), thereby guiding ground-based sampling intensity and distribution. It would also not just reveal important information about mean carbon stocks, but also about the spatial distribution in stand structure and ecological complexity with which biomass is correlated (Figure III-6). The capacity to map spatial co-variation among multiple ecosystem attributes has important implications for sustainable forest management and planning where the objective is to optimize the provision of multiple ecosystem services, including carbon storage, timber harvest, and biodiversity (Keeton 2007; Wolfslehner and Seidl 2010).

7 Conclusions

We modeled forest AGB estimates for spruce monocultures in the Western Carpathians using additional data sources, as suggested, for example, by Lu (2006). Where inventory data is available, it is an excellent source of spatial information regarding biomass in the Western Carpathians. However, in the case of missing, outdated or incomplete inventories, alternative approaches are needed. We elaborate on how to use spectral data to model biomass, thereby substituting or minimizing the need for inventory data. Our approach has been tested for vertically simple canopies as found, for example, in even-aged monocultures. Further research is needed to infer transferability to more complex or boreal conditions.

Based on Landsat and topography data alone, the AGB prediction model captured 27% of the biomass variability in the study area. However, including inventory-based stand volume, our modeling accuracies increased to 86%. Results suggest that spectral and topography data combined with selected inventory information provide highly accurate AGB estimates.

Our results encourage applications of biomass estimates to spruce forest stands across the entire Carpathian Mountain range. The next step, therefore, is to investigate the applicability of our findings to homogeneous spruce stands across this mountain range and beyond. This will require additional sensitivity analyses, e.g., concerning the influence of forest health status on modeling accuracy. There are several promising directions for further research. These include: (1) exploration of the influence of canopy structure and condition (e.g., tree vigor, defoliation, etc.) on biomass prediction; (2) assessment of how relationships between forest dieback, elevational gradients and understory reflectance might influence biomass modeling; and (3) research on the integration of TM data, and at least one selected inventory-based forest parameter for improving AGB modeling.

Acknowledgements

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Chapter IV:
Monitoring coniferous forest biomass change using a Landsat trajectory-based approach

in preparation

Magdalena Main-Knorn, Warren B. Cohen, Robert E. Kennedy, Wojciech Grodzki, Dirk Pflugmacher, Patrick Griffiths, and Patrick Hostert

Abstract

Forest biomass is a major store of carbon and thus plays an important role in the regional and global carbon cycle. Accurate forest carbon sequestration assessment requires estimation of both forest biomass and forest biomass dynamics over time. Forest dynamics are characterized by disturbances and recovery, key processes affecting site productivity and the forest carbon cycle. Thus, spatially and temporally explicit knowledge of these processes and their drivers are critical for understanding regional carbon cycles. Here, we present a new and efficient method of using satellite data to assess aboveground coniferous forest biomass changes in the Western Carpathian Mountains between 1985 and 2010. This study area was affected by long-term anthropogenic pressure, followed by recent coniferous forest decline. We used a regression trees modeling approach and a near-annual time series of satellite images to estimate yearly aboveground biomass. Further, using a trajectory-based change detection approach, the history of disturbances and recovery was reconstructed. We found a dramatic decrease in forest biomass over time that intensified after 2005. Moderate to strong disturbances occurred on about 30% of the area, which equals almost 17,000 ha of the area's total coniferous cover, causing either degradation or complete removal of forest biomass. At the same time, 11.2% of the area (~6300 ha) was reforested or regenerated on previously damaged forest stands, whereas only 4.1% of the total forest was undisturbed over the entire period. Disturbance hotspots indicate high insect infestation levels in many areas and reveal strong interactions between biomass and climate conditions. Our study demonstrates how spatial and temporal estimates of biomass help to understand regional forest dynamics and derive degradation trends in regard to regional climate change.

1 Introduction

Forests store large amounts of carbon and play an important role in the regional and global carbon cycle. Accurate estimates of forest biomass require accounting for the spatial effects of disturbances and recovery, both affecting site productivity and forest carbon dynamics. The spatial extent and the rate of disturbance and regrowth determine the net carbon flux of a forest and the magnitude of carbon loss during and after disturbance (Frolking et al. 2009; Luyssaert et al. 2010). Disturbances can convert forests from a net carbon sink to a net carbon source (during and after the disturbance occurred) (Kurz et al. 2008a; Kurz et al. 2008b). Because productivity varies considerably by ecoregion and forest type, accurately estimating the mass of living forest material and its changes is critical especially for regional scale carbon models (Kimball et al. 2000; Schroeder et al. 2008). Remote sensing data and their derivatives provide unique and appropriate input information to assess changes in forest biomass across spatial and temporal scales (Mickler et al. 2002; Powell et al. 2010). Here we present a method to estimate and monitor aboveground forest biomass changes with near-annual time-series data.

Forest disturbance and recovery are key processes in forest ecosystem dynamics. Recovery is reestablishment of a new forest stand following a previous disturbance or damage, which occurred due to management regime (e.g., harvest), or to abiotic (e.g., windstorm) or biotic (insect pests, diseases) factors. From a management perspective, natural forest disturbance is defined as an event that causes unforeseen loss of forest biomass or an event that decreases the actual or potential value of the wood or forest stand (Schelhaas et al. 2003). However, from an ecological perspective, natural disturbance is merely a cyclical stage of forest *destruction-creation* dynamic (Moran and Ostrom 2005; Rull 2011). Furthermore, Schelhass et al. (2003) showed that the most significant causes of natural forest disturbances in European forests are storm events (53% of total damage), fires (16%) and biotic factors (e.g., pest) (16%).

The Carpathian Mountains sustain Europe's largest continuous forest ecosystem, and are a bridge between Europe's southern and northern forests, serving as an important refuge and corridor for flora and fauna. Carpathian forests provide high biodiversity and productivity, and are a key element of the European carbon cycle (Schulp et al. 2008). However, these forests have been influenced by human actions for many centuries. During the Austro-Hungarian Empire and expansion of the industrial revolution in the mid-19th century, the demand for energy and thus fuel increased. In consequence, exponentially increasing demand for softwood and its products triggered the beginning of regular forest management. Tree species ensuring high productivity, short harvesting cycle and quick revenues were propagated. Thus, most of natural mountain hardwood and mixed forest stands have been replaced by conifer tree species, particularly productive and "cost-effective" Norway spruce (*Picea abies* (L.) Karst.).

Apart from forest management practices, rapid industrialization in the second half of the 20^{th} century, along with inadequate environmental standards, led to increased environmental pollution in Central Europe. Long-term critical atmospheric deposition of sulphur and nitrogen caused an acidification and eutrophication of ecosystems and hindered their functions, causing widespread deterioration of forest health and decreasing resistance to diverse stressors (Materna 1989; Schulze 1989; Kubikova 1991). With the fall of communism in 1989, a phase of institutional and socio-economic changes begun, having direct and indirect impact on Carpathian forests. On the one side, logging rates triggered by forest privatization and restitution increased (Griffiths et al. 2012; Knorn et al. 2012). On the other side, widespread forest decline due to the synergistic effect of previous forest management regime and pollution legacies occurred (Kubikova 1991; Muzika et al. 2004; Main-Knorn et al. 2009). Since the late 1990s increasing degradation and mortality of spruce stands in the Western Carpathians have been reported (Kozak 1996; Badea et al. 2004; Grodzki et al. 2004), followed by the forest decline at present (Ditmarová et al. 2007; Grodzki 2007; Šrámek et al. 2008; Durło 2010). Nowadays, most disturbances result predominantly from the synergistic effect of fungal pathogen activity (*Armillaria* spp.), unfavourable weather conditions, extreme storm events and subsequent bark beetle [e.g., *Ips typographus* (L.)] outbreaks. Moreover, the observed degradation of spruce stands in the Western Carpathians due to storm events and biotic factors (e.g., insect outbreaks) is expected to increase with climate change in the future (Hlásny et al. 2010a). Thus, assessing the spatial and temporal dimension of disturbances enables identification of the agents behind them and determination of potential degradation trends. It could also improve regional-scale carbon models, provide an important input to model possible impacts of climate change on spruce-dominated forests and underpin new paradigms for management strategy/activities by local and regional policy makers.

As forest biomass dynamic is characterized by disturbances and subsequent recovery processes, the quantification of biomass variability over space and time is critical for accurate carbon accounting (Houghton 2005). If available, forest inventories based on plot measurements provide high precision biomass estimates, but these inventory-based approaches are spatially and temporally sparse. Providing the averaged measurements at administrative units for 10-year time intervals, they miss internal changes in the biomass distribution over space and time (Houghton 2005). Since the net carbon flux of a forest and the magnitude of carbon loss and uptake are determined by the rate of biomass change (reduction or accumulation) at fine spatial and temporal scale, only satellite data can adequately capture its dynamics (Wulder et al. 2008b; Huang et al. 2010; Powell et al. 2010). Moreover, using remote sensing data both continuous and subtle (associated with forest degradation or recovery) as well as discontinuous and sudden (e.g., clear-cuts, wind-throws) forest change phenomena can be assessed, quantified and monitored (Kennedy et al. 2007). Thus, remote sensing imagery became a universal tool and is likely to evolve into a standard instrument in the professional forest management (Smith et al. 2003).

Landsat instruments provide a unique, continuous record of earth observation at sufficient spatial and spectral resolution since 1972 and hence, are well-suited for long-term forest change analysis (Cohen and Goward 2004; Kennedy et al. 2010). Moreover, since the recent opening of the Landsat archive by the United States Geological Survey (USGS), the development of new methodological approaches making use of the Landsat temporal depth has been accelerated. Two trajectory-based approaches have recently been developed, the Landsat-based detection of Trends in Disturbance and Recovery (LandTrendr) and the Vegetation Change Tracker (VCT) (Huang et al. 2010; Kennedy et al. 2010). Both approaches provide an opportunity for reconstructing the disturbance history with annual resolution and mapping of long-term trends. Therefore, can these methods be applied to directly track the spatial and temporal variation in the forest biomass during and after the disturbance or to track gradual changes? So far, Powell et al. (2010) used LandTrendr for quantifying live aboveground forest biomass dynamic in the United States, using Landsat time-series and field inventory data. They compared three statistical approaches (Random Forests, Reduced Major Axis regression, and Gradient Nearest Neighbor imputation) to empirically model biomass over time and then derived biomass trajectories to track forest biomass change. To assess the temporal trends of changes and reduce inter-annual noise in the biomass estimates, the LandTrendr fitting approach was applied. The main outcome from this study was that the consistency of Landsat data through time and space makes it possible to accurately monitor and quantify trends in biomass. Secondly, the Random Forests (RF)-based models (Breiman 2001) were identified as an attractive and robust approach to estimate biomass, due to their non-parametric nature, low prediction error, ease of implementation and the ability to deal with correlated variables.

In a previous study, Main-Knorn et al. (2011) used RF-based models to estimate forest biomass with satellite and inventory data. Therein it was found that Landsat- and topography-based biomass estimates were less accurate than those inventory-derived, while the potential of spectral data to reveal spatial variability of biomass could not be overlooked. Moreover, if inventory data is missing, incomplete or outdated, a satellite-based approach is a promising alternative to ground-based estimates. Here, we build on those findings to improve our biomass modeling and mapping approach by adding a temporal depth and extending the range of potential biomass estimates. We use RF and a near-annual time-series consisting of Landsat imagery, Satellite Pour l'Observation de la Terre (SPOT) and Indian Remote Sensing Satellite with the Linear Imaging Self-Scanning Sensor (IRS LISS) data, as well as LandTrendr algorithms to prepare and evaluate coniferous biomass trajectories between 1985 and 2010.

The overarching goal of our study was to map forest biomass and biomass change for a spruce-dominated forest region in the Western Carpathian Mountains. The specific objectives were:

1. to distinguish and compare abrupt and gradual forest changes, and
2. to derive *quasi* Landsat trajectories of biomass change and quantify net change between 1985 and 2010.

2 Study area

Our study area comprised in total ~115,700 ha of forest area located in the Beskid Mountains of the northwestern Carpathian Mountain Range (Figure IV-1). Here, we focused on coniferous forests which encompass ~56,100 ha of the total forested area. Elevations in the study region extend up to 1550 m above sea level (asl) in the Beskid Żywiecki Massif. The climate is typical for moderate continental mountain zones with an annual precipitation of 1200 mm (Durło 2010). The yearly mean temperature is about 7°C below 700 m asl and about 4°C at 1100 m. The dominant wind directions are western, south- and northwestern, with the highest speed between November and March causing great damage to forest stands (Barszcz and Małek 2008). Warm foehn winds from the south and south-west as well as temperature inversion in valleys are important aspects of the regional climate.

Forest mainly consists of Norway spruce monocultures and mixed spruce stands (total amount of about 80% of forested area) (Barszcz and Małek 2008) with the admixture of European beech (*Fagus sylvatica*) and European silver fir (*Abies alba*). As a result of ongoing stands conversion, some lower elevations feature mixed beech forests along with Scots pine (*Pinus sylvestris* L.), spruce, and fir.

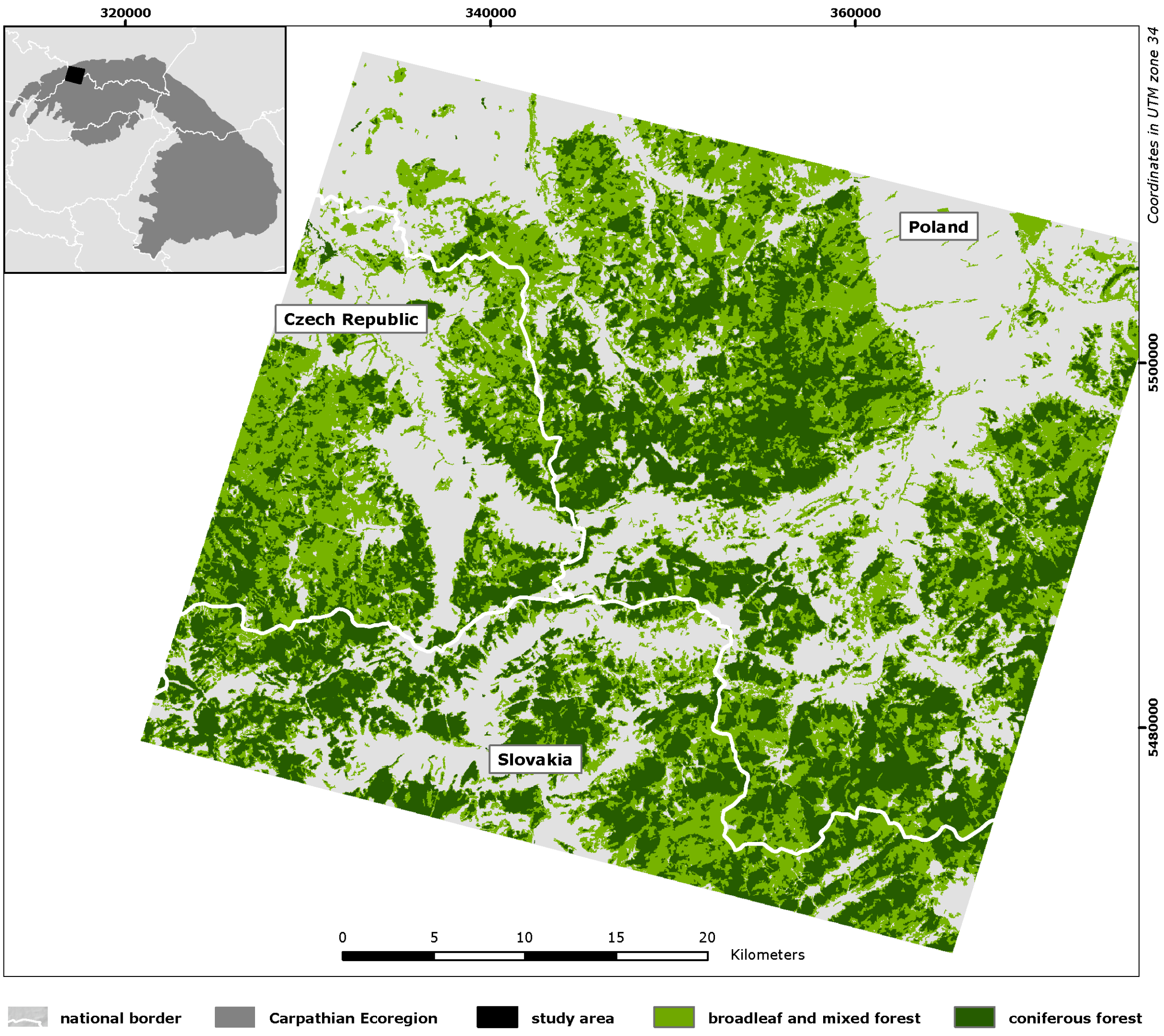

Figure IV-1: Study area within the Beskid Mountains in the border region of Poland, the Czech Republic and Slovakia.

Since the late 1990s increasing degradation of spruce stands in the Beskid Mountains have been observed (Kozak 1996; Badea et al. 2004; Grodzki 2004), caused by synergistic effects of forest management history, pollution legacies and an increasing fungal pathogen activity. The present spruce forest decline is triggered predominantly by unfavorable weather conditions, extreme storm events and subsequent bark beetle (e.g., *Ips* *typographus*) outbreaks (Ditmarová et al. 2007; Grodzki 2007; Šrámek et al. 2008; Durło 2010).

3 Data and methods

Our study region encompasses the overlap area of two Landsat footprints (path/row: 189/25 and 188/26). We acquired a near-annual time series of Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) images for the period 1985 – 2010 (Figure IV-2). For 2009 only ETM+ images with data gaps caused by a failure of the sensor's scan-line-corrector (SLC) were available. To fill these data gaps, we used three adjacent images acquired in the same year (path/row: 189/25, 188/25, 188/26). Further, due to the limited availability of Landsat data between 1996 and 1999, we also included imagery from SPOT and IRS LISS satellites. These sensors have spatial and spectral properties similar to Landsat, and have been used in other Landsat-based time-series studies (Hill and Aifadopoulou 1990; Wilson and Sader 2002; Powell et al. 2007; Huang et al. 2010). We acquired a SPOT 1 image (path/row 73/249) and an IRS-C1 LISS III image (path/row 33/33) for the years 1997 and 1998, respectively. The SPOT 1 image consists of three spectral bands registered in the green (0.50-0.59µm), red (0.61-0.68µm), and near-infrared (0.78-0.89µm) wavelength of the electromagnetic spectrum, with a pixel resolution of 20 m. The IRS-C1 LISS image features two visible bands (0.52-0.59µm and 0.62-0.68µm) and one near-infrared band (0.77-0.86µm) of 23.5m spatial resolution each, as well as one short-wave infrared band (1.55-1.70µm) with a 70.5 m pixel resolution.

3.1 Satellite data preparation

Geometric and radiometric normalization of time series images are crucial for any form of change detection over time (Lu et al. 2004). We used geometric and radiometric processing techniques described in detail by Schroeder et al. (2006). Briefly, geometric correction was based on an automated detection of image tie points (Kennedy and Cohen 2003) between the reference (here the orthorectified [L1T] 2001 image) and the input image. After more than 300 tie points were identified, a polynomial transformation was used to spatially align the images. Note, that the SPOT and IRS LISS images were resampled to a 30 m spatial resolution to match the spatial resolution of Landsat images. Co-registration between images resulted in an overall positional error <0.5 pixels.

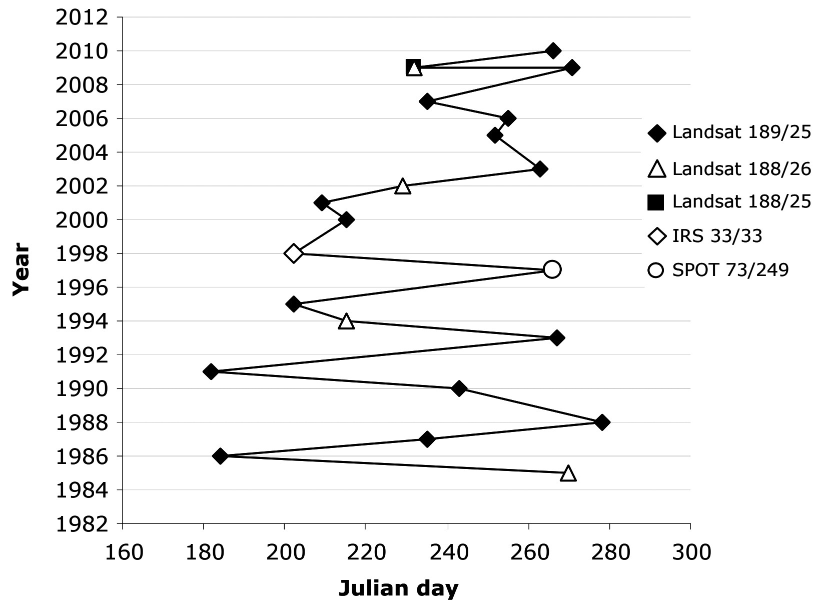

Figure IV-2: Scene acquisition dates by year, path and row and the sensor type. Julian days were calculated relative to January 1st.

The cloud-free 2003 image was atmospherically corrected using the COST method (Chavez 1996). All other images (Landsat, SPOT and IRS LISS) were radiometrically normalized to the corrected 2003 image using the MADCAL (Multivariate Alteration Detection and Calibration) algorithm of Canty et al. (2004). Since our study focused on the coniferous forest, we applied a Support Vector Machine (SVM) classifier (Pal and Mather 2005) and streamlined procedure from previous study (Main-Knorn et al. 2009) to establish the coniferous forest mask for the study area. Finally, clouds and cloud shadows were digitized and masked.

SPOT-1 data consists of three spectral bands (two visible bands and one near-infrared band), with similar characteristics to the Landsat TM system. However, unlike Landsat, SPOT-1 does not include a short-wave infrared (SWIR) band, which is useful for detecting vegetation changes, particularly in forests. Moreover, in a previous study, SWIR was found as one of the most important explanatory variable for biomass estimates (Main-Knorn et al. 2011). We hence considered alternative options to cope with the lack of the SWIR by modeling the artificial SWIR band for SPOT image and then including such modified SPOT image into the Landsat time series. Using 1000 training samples from Landsat 1995 image, a linear regression model of Landsat TM SWIR channel (band 5) based on two visible bands and one near-infrared band (Landsat bands: 2, 3, and 4, respectively) was established. Once the model was tested and validated on the 1995 and 1992 images (the latter was chosen because of the cloud-free cover and close acquisition dates), the artificial SPOT 1997 SWIR band was created, based on the established SWIR model and three existing SPOT-1 bands (Figure IV-3). Finally, the created SWIR band and remaining SPOT bands were stacked and included in the Landsat time-series.

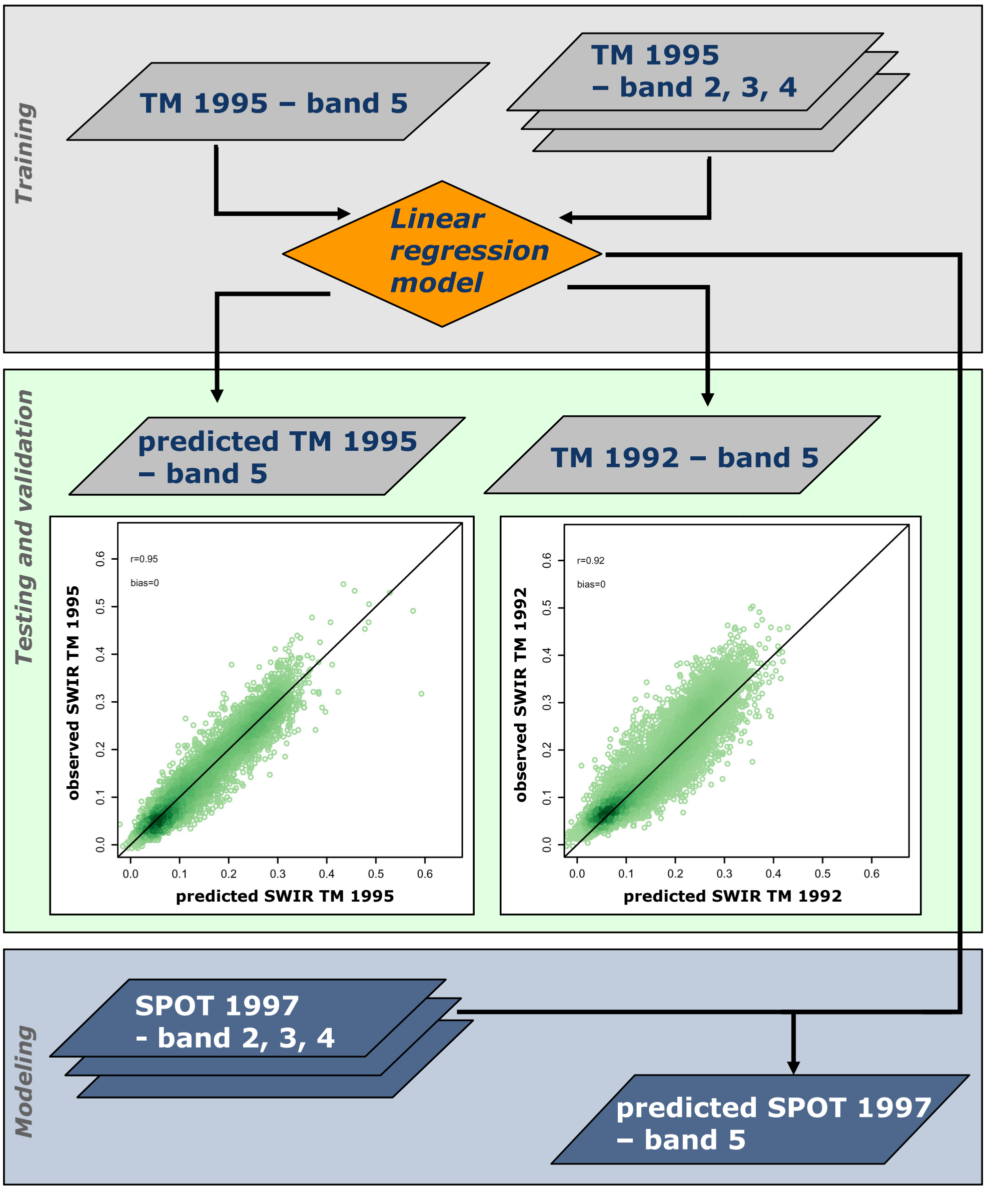

Figure IV-3: Workflow of the SPOT SWIR modeling.

3.2 Biomass estimation and model validation

After a near-annual image time series was constructed, the biomass modeling technique based on Random Forests (RF) was applied. A detailed description of RF can be found in Breiman (2001), Prasad et al. (2006) and Cutler at al. (2007). The application for remote-sensing based biomass modeling is introduced by Main-Knorn et al. (2011). Therefore, in the following we provide only a brief description of the modeling and modification details.

Biomass consists of living and dead organic material both above- and below-ground (IPCC 2003). We limited our prediction to aboveground living and dead forest biomass (AGB), and applied the biomass equation for Carpathian Norway spruce forests provided by Lakida et al. (1996). AGB as the weight of tree biomass fraction [Mg] was calculated with:

$$AGB = V_{st} R_{v(ab)} \tag{1}$$

where V_{st} in the growing stock of stemwood [m^3 ha^{-1}], and $R_{v(ab)}$ is the ratio between aboveground standing biomass and the volume of the growing stock over bark. The ratio was calculated as:

$$R_{v(ab)} = a_0 A^{a_1} \tag{2}$$

where A is the average age of the respective stand [years], and a_0 and a_1 are spruce-dependent regression coefficients, equaling 2.058 and -0.383 respectively (Lakida et al. 1996). Values of the averaged growing stock and tree age were available from stand-based inventory (Main-Knorn et al. 2011).

Our previous Landsat- and topography-based model (TMTO) was designed to capture the observed static biomass range (for year 2005) from approximately 100 to 300 Mg ha^{-1} (Main-Knorn et al. 2011). Since we here considered the temporal dimension, the hypothesis that forest biomass could be strongly reduced or removed over time due to different disturbances has to be taken into account. Thus, we modified the previous TMTO biomass model in terms of its ability to predict very low to zero forest biomass values. For doing so, 200 training biomass samples were complemented by 11 zero forest biomass training samples, localized on, e.g., meadows or clear-cuts. Additionally, we adapted the previous TMTO model algorithm for the spectral resolution of IRS LISS and the modified SPOT data by creating two explanatory variable sets:

A. 6 original TM bands (1-5, 7), slope and direct solar radiation (dsr)
B. 1-4 original (IRS LISS) or 1-3 original plus 1 modified (here SPOT SWIR) bands, slope, and dsr.

We applied the RF modeling technique by setting 1500 regression trees for the 1st variable set (A) and 1000 regression trees for the 2nd variable set (B). The number of explanatory variables selected at each node was fixed at five for (A) and three for (B), respectively. Consequently, two biomass models were created and evaluated.

The evaluation of the models was based on a 10-fold cross-validation. A Pearson's correlation was calculated between observed and predicted values for every model, as well as the coefficient of determination (R^2) and the root mean squared error (RMSE). Additionally, based on the no-change pixels and the density function (Main-Knorn et al. 2011), stability of biomass estimates across different Landsat footprints as well as across different sensors (Landsat, SPOT, IRS LISS) was evaluated. For this purpose, we extracted 50 no-change pixels (stable forest) from the normalized Landsat, SPOT and IRS LISS data between 1993 and 2005. Then, the standard deviation of biomass estimates was calculated and its distribution was plotted. Finally, the respective biomass model was then applied to the corresponding image, resulting in the establishment of near-yearly biomass maps over 25 years.

3.3 Trajectory analysis

Developed by Kennedy et al. (2010), LandTrendr has been successfully used in different forest studies (Powell et al. 2010; Meigs et al. 2011; Griffiths et al. 2012; Kennedy et al. 2012; Pflugmacher et al. 2012) and proved to be a powerful tool for reconstructing the disturbance history of forest landscaped. Meigs et al. (2011) applied the LandTrendr algorithms to characterize insect activity dynamic and its impact on tree mortality. In other studies annual disturbance maps were derived to predict forest structure (Pflugmacher et al. 2012), and to explore the effects of institutional changes to forests (Griffiths et al. 2012). To-date, the only application of LandTrendr to track forest biomass change was done by Powell et al. (2010).

Once our biomass maps were created, the image stack was composed and the LandTrendr temporal segmentation and fitting algorithms were applied. Briefly, the temporal segmentation procedure delineated sequences of segments (periods) for a given pixel, capturing the broad features of the biomass trajectory over time, while minimizing year-to-year noise caused by illumination or phenology. The fitting procedure derived simplified trajectory sequences of segments, using regression-based and point-to-point fitting algorithms (Kennedy et al. 2010). The resulting stack of near-annual fitted/synthetic biomass values enabled capturing main forest dynamic processes.

LandTrendr labels segments and sequences of segments per pixel over time based on four parameters: onset year of a change event, relative magnitude of change (%), duration (number of years), and biomass value prior to the change event. The relative magnitude of change was defined as:

$$Magnitude_{rel} = \frac{100\left(PercentBiomass_{pre} - PercentBiomass_{post}\right)}{PercentBiomass_{pre}} \quad (3)$$

where $\text{PercentBiomass}_{\text{pre}}$ and $\text{PercentBiomass}_{\text{post}}$ related to biomass before and after change event, respectively. Percent biomass was calculated as:

$$PercentBiomass = \left(\frac{Biomass - lowVal}{highVal - lowVal}\right)100 \quad (4)$$

where 'highVal – lowVal' was the range of biomass estimates for the entire coniferous area. Since LandTrendr was designed to set thresholds and reduce false detection in relation to vegetation cover, the conversion of absolute biomass values from Mg ha^{-1} to percent biomass provides such a forest cover approximation.

Mapping forest biomass loss and accumulation

We were interested in four main forest processes: abrupt biomass loss, gradual biomass decrease, gradual biomass increase, and biomass stability (no change). Each of these processes can be represented by a single segment in the biomass trajectory. However, often more than one process occurred within the 25-year period. To describe dynamic processes through trajectories we defined the following classes: disturbance, gradual decrease, disturbance then recovery, gradual decrease then recovery, and gradual increase. We narrowed Schelhaas et al.'s (2003) 'disturbance' definition to be an abrupt event that caused the loss of living forest biomass over a period no longer than three years in duration. Conversely, 'gradual decrease' was defined as a persistent, long-term process (more than 3 years) resulting in a decrease of living forest biomass. The differentiation between abrupt disturbance and gradual biomass decrease enabled us to assess different processes. Those were first, clear-cuts and wind-throws (which occur abruptly), and second, forest degradation (e.g., defoliation, yellowing) and selective logging (which cause longer-duration biomass loss). Moreover, since the aggregated loss of carbon resulting from forest degradation could be higher than from deforestation (Houghton 2005), quantifying the extent, rates and duration of biomass loss could improve the state-of-the-art of carbon stock assessments.

To assess gradual biomass accumulation, we defined a recovery class and a gradual increase class. 'Recovery' was defined as an increase in forest biomass following a disturbance or gradual decrease. When an increase in biomass occurred but was not associated with a disturbance during the last 25 years, it was classified as 'gradual increase'.

Finally, we mapped abrupt loss of biomass (disturbance) as well as gradual biomass changes over time.

Validation

To validate the disturbance map, we selected a reference dataset based on a stratified random sample. We collected 290 reference points for the "abrupt disturbances" class, and allocated them proportionally in a class-wise stratified manner (19 years = 19 classes), after eliminating patches of 2 pixels or less. We assigned a maximum number of 20 samples to the largest class (2009) and a minimum of 5 samples to those classes that had an areal coverage below 1%. The number of samples for classes in-between was linearly scaled. In addition, a sum of 397 points was randomly sampled and proportionally allocated for long-term gradual biomass changes (decrease, recovery, and increase) and the no-change class. In a total, 687 samples were selected for validation purpose. We recorded the onset year of abrupt disturbances based on the satellite time series using TimeSync (Cohen et al. 2010), a visualization and interpretation tool for chronological satellite image sequences. Additionally, gradual biomass changes were interpreted by simultaneously assessing satellite images and temporal profiles of biomass. When the normalized time-series reflectance values showed a continuously decreasing trend over a period of more than three years, the pixel was interpreted as gradual biomass decrease. In contrast, constantly increasing reflectance values over 25 years were associated with the "gradual biomass increase" class. When a marked decrease in the reflectance was followed by a reestablishment in reflectance, a pixel was validated as "biomass recovery". We compared the LandTrendr change results against the TimeSync reference database and calculated an error matrix. We derived overall accuracy as well as omission and commission errors, taking into account sampling bias and the true class distribution (Card 1982). Finally, we calculated true area-estimates for all classes as well as the 95% confidence intervals (Cochran 1977).

3.4 Temporal and spatial patterns

We derived overall patterns of biomass change distribution throughout the study area by establishing four pixel-based maps: the disturbance onset map, a total gradual decrease and increase map, a recovery onset map, and a net biomass change map. To summarize disturbance rates and patterns, we calculated the total disturbed area per year and for 5-year periods, splitting disturbance rates equally for missing years among adjacent years. Similarly, we summarized the total disturbed area per year for gradual biomass changes. Note, that year here indicates the first year of gradual biomass decrease or increase, as gradual change is a continuous process.

Further, magnitudes of abrupt and gradual changes over time were assessed on pixel level. We classified biomass loss to be “severe”, “moderate” and “low” when the relative magnitude of biomass change was above 75%, 50-75%, and below 50%, respectively.

We calculated net biomass increase per pixel associated with forest recovery after abrupt and gradual disturbances, based on the magnitude of a singe recovery trajectory. Then, we selected only pixels that underwent a stand-replacing disturbance (post-disturbance biomass levels below 10 Mg ha^{-1}) and calculated the annual mean recovery rate and mean recovery trajectories over a 15-year period. Similarly, we summarized the annual gradual increase rates and coniferous growth profile over 25 years.

4 Results

The regression model to predict the artificial 1997 SPOT SWIR from VIS and NIR bands was strong and statistically significant ($P < 0.001$, R^2 of 0.9). Separately, the estimation of forest aboveground biomass was robust, having an RMSE of 40 Mg ha^{-1} and a correlation coefficient of 0.8 based on the Landsat bands (set A). Estimates based on SPOT and IRS LISS data (set B) were almost equally accurate, showing an r of 0.79 and RMSE of 41.3 Mg ha^{-1} (Table IV-1). The density function for the no-change pixels extracted between 1993 and 2005 (Figure IV-4), showed a generally low standard deviation between annual biomass estimates (the density peak culminates with 17 Mg ha^{-1}) and is clearly below the higher mean biomass estimation error.

Table IV-1: Cross-validated results for the biomass modeling.

	Variables								Accuracy assessment		
									r	R^2	RMSE
TMTO Model	B1	B2	B3	B4	B5	B7	dsr	Slope			
Landsat	x	x	x	x	x	x	x	x	0.8	0.64	40.1
Spot-IRS		x	x	x	x		x	x	0.79	0.62	41.3

Concerning the performance of disturbance mapping, LandTrendr yielded highly reliable biomass change maps with an overall accuracy of 83.33% (Table IV-2). The stable forest (no change class - NC) and gradual decrease class (GD) both showed omission and commission errors below 20%. The recovery class (REC) achieved almost 20% higher producer and user accuracies than the gradual increase class (GI). Commission errors for the individual biomass disturbance classes were generally low (mean=16.9%, standard deviation=0.16) with lowest errors for 1987, 1988, 1990 and 2001, and highest errors for 2002 and 2003. In comparison, omission errors were higher (mean=20.6%, standard deviation=0.25) with greatest errors in 1987 and 2005 (Tables IV-2 and IV-3).

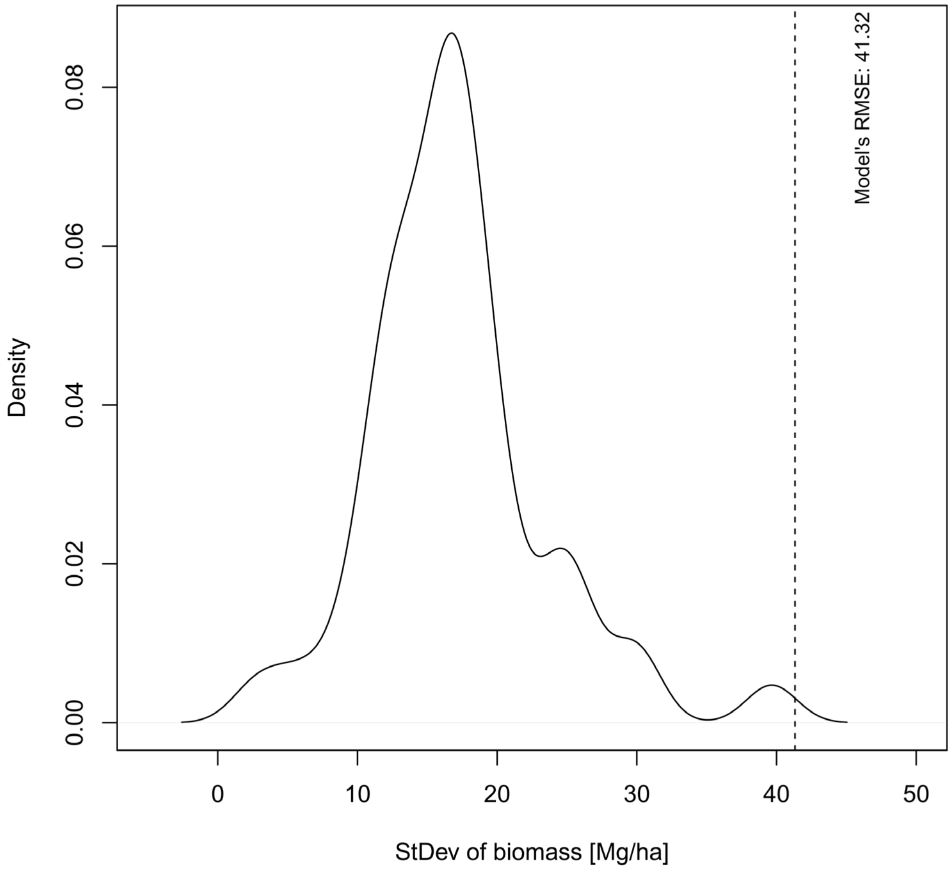

Figure IV-4: Density function – distribution of the standard deviation of no-change biomass pixel extracted from the normalized Landsat, SPOT and IRS LISS data between 1993 and 2005.

Overall, ~23,000 ha (41%) of total coniferous area were stable (no change) throughout the last 25 years, whereas 33,100 ha (59%) showed either an increase or decrease in forest biomass. We found widespread biomass decrease across the study area, in terms of both abrupt loss and gradual decrease. Generally, ~10,060 ha (18%) of coniferous forest area were affected by biotic, abiotic or both factors, causing abrupt biomass loss between 1985 and 2010, while ~15,800 ha (28%) experienced gradual biomass decrease. Note, that

~3400 ha of gradual biomass decrease (6% of total coniferous area) were followed by abrupt biomass loss (disturbance). In contrary, recovery processes were observed on ~4900 ha of previously disturbed coniferous area and on ~1400 ha heretofore affected by gradual biomass decrease (8.7% and 2.5% of total coniferous area, respectively). Additionally, gradual increase over at least 20 years was assessed for ~4200 ha (7.5%) of total coniferous area.

Table IV-2: Summary of results of the accuracy assessment for the biomass change classes: stable forest (no change - NC), biomass disturbance onset year, and the gradual biomass change classes gradual decrease (GD), recovery (REC), and gradual increase (GI). Producer's accuracy (PA), user's accuracy (UA), error of omission (O), error of commission (C), and overall accuracy (OAC).

Class	PA	UA	O	C
1986	100.00%	63.64%	0.00%	36.36%
1987	3.28%	100.00%	96.72%	0.00%
1988	100.00%	100.00%	0.00%	0.00%
1990	79.97%	100.00%	20.03%	0.00%
1991	88.06%	90.91%	11.94%	9.09%
1993	100.00%	83.33%	0.00%	16.67%
1994	57.43%	75.00%	42.57%	25.00%
1995	68.24%	83.33%	31.76%	16.67%
1997	100.00%	75.00%	0.00%	25.00%
1998	96.88%	80.00%	3.12%	20.00%
2000	80.72%	84.62%	19.28%	15.38%
2001	60.85%	100.00%	39.15%	0.00%
2002	86.62%	46.67%	13.38%	53.33%
2003	81.28%	50.00%	18.72%	50.00%
2005	43.10%	91.67%	56.90%	8.33%
2006	100.00%	90.48%	0.00%	9.52%
2007	76.17%	90.48%	23.83%	9.52%
2009	85.13%	86.96%	14.87%	13.04%
2010	100.00%	87.50%	0.00%	12.50%
GD	80.79%	92.11%	19.21%	7.89%
REC	86.43%	75.68%	13.57%	24.32%
GI	69.18%	54.29%	30.82%	45.71%
NC	85.30%	84.74%	14.70%	15.26%
OAC =	83.33%			

Table IV-3. Confusion matrix resulting from the validation of the stable forest class (no change - NC), biomass disturbance onset year, and the gradual biomass change classes: gradual decrease (GD), recovery (REC), and gradual increase (GI).

	Reference year																						
Disturbance Map	86	87	88	90	91	93	94	95	97	98	00	01	02	03	05	06	07	09	10	GD	REC	GI	NC	Total
1986	7	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	11
1987	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5
1988	0	0	12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	12
1990	0	0	0	12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	12
1991	0	0	0	1	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	11
1993	0	0	0	0	0	10	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	12
1994	0	0	0	0	0	0	9	1	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	12
1995	0	0	0	0	0	0	1	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	12
1997	0	0	0	0	1	0	0	0	9	0	0	1	0	0	0	0	0	0	0	1	0	0	0	12
1998	0	1	0	0	0	0	0	1	0	12	0	0	0	0	0	0	0	0	0	0	0	0	1	15
2000	0	0	0	0	0	0	0	0	0	0	11	0	0	0	0	0	0	1	0	0	0	0	1	13
2001	0	0	0	0	0	0	0	0	0	0	0	12	0	0	0	0	0	0	0	0	0	0	0	12
2002	0	0	0	0	0	0	0	0	0	0	0	2	7	1	0	0	2	1	0	0	0	0	2	15
2003	0	0	0	0	0	0	0	0	0	0	2	1	1	6	1	0	0	0	0	0	0	0	1	12
2005	0	0	0	0	0	0	0	0	0	0	0	0	1	0	11	0	0	0	0	0	0	0	0	12
2006	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	19	0	0	0	0	0	0	0	21
2007	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	19	0	0	0	0	0	1	21
2009	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	40	0	0	0	1	2	46
2010	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	21	0	0	0	1	24
GD	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	70	0	0	4	76
REC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	28	1	6	37
GI	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	5	0	19	10	35
NC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	22	8	8	211	249
Total	7	8	12	13	11	10	11	12	9	13	14	16	9	7	14	19	24	47	21	100	37	32	241	687

Biomass loss

Abrupt biomass loss was detected across the entire study area, with clusters in the central part along a north-south gradient (Figure IV-5). Disturbances occurred throughout our studied time period following an exponentially increasing trend (Figure IV-6a). Most disturbances (82% of total) were observed between 2005 and 2010. For the same time period the fraction of severely disturbed area (relative magnitude of biomass loss above 75%) strongly increased compared to previous time periods, and comprised approximately 55% of all disturbances detected between 2005 and 2010 (Figure IV-6b). Moderate disturbances (relative magnitude 50-75%) were observed for about 20% of the total disturbed area between 1985 and 1999, and decreased slightly from 20% to 15% during the last 10 years, while low to moderate disturbances (relative magnitude below 50%) were predominant especially for the time period between 2000 and 2004.

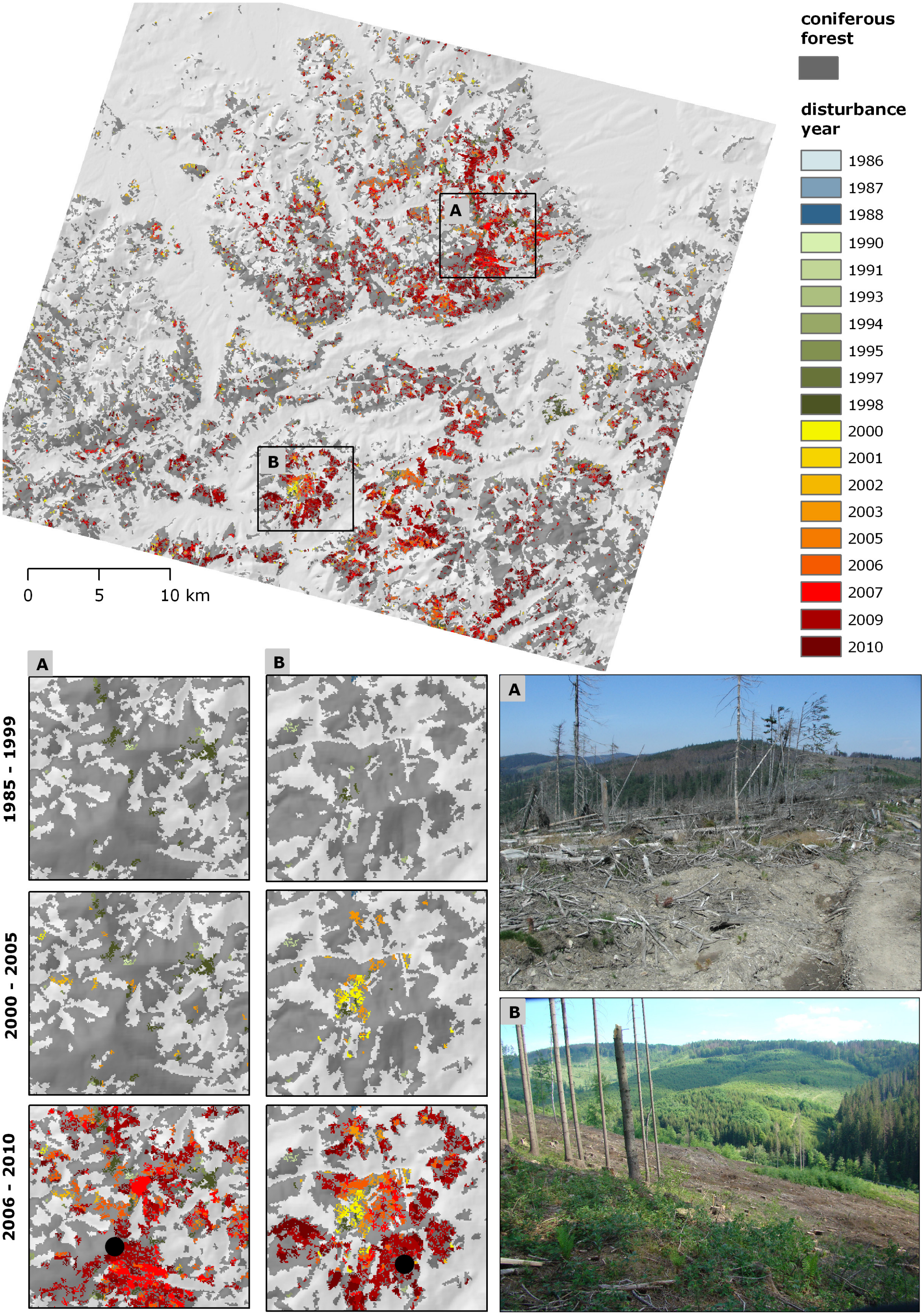

Figure IV-5: Disturbance map with squares highlighting the Barania Góra massif in Poland (A) and the Javorské massif in Slovakia (B), as well as corresponding photographs taken in 2007 (source: J. Kozak) and in 2009 (source: L. Kulla), respectively (black dots).

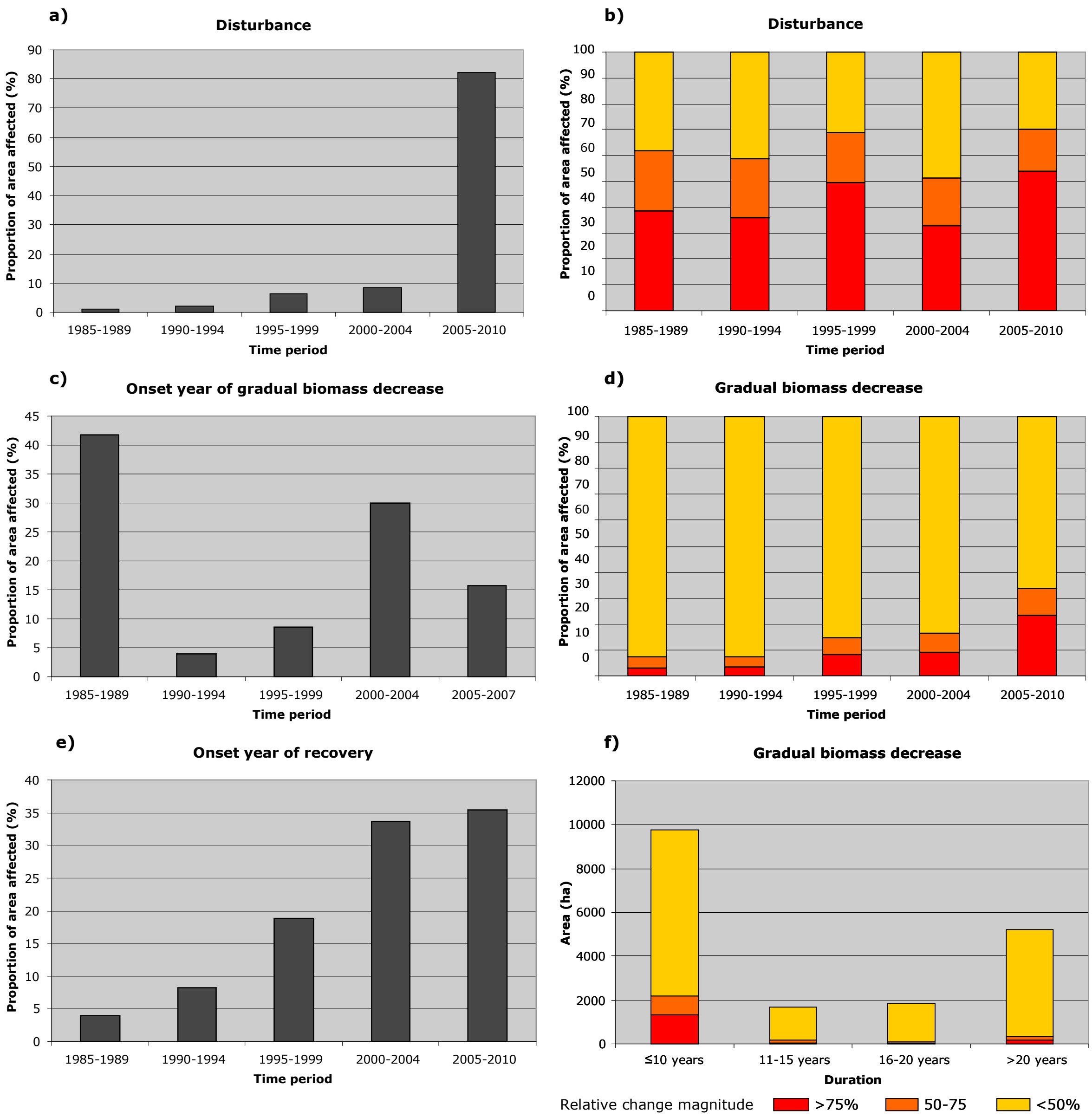

Figure IV-6: Distribution of disturbances along time periods (a) and corresponding relative magnitude of severe, moderate and low biomass loss (b); onset year of gradual biomass decrease (c) and corresponding distribution of the relative magnitude classes (d); recovery onset year distribution (e); proportion of the relative magnitude classes along with duration of gradual biomass decrease (f).

Gradual biomass decrease affected 10% more coniferous area than abrupt biomass loss, while 21.5% of the latter was influenced by prior gradual biomass decrease. In general, long-term biomass decrease was more evenly distributed across the entire study area. However, areas with moderate to severe biomass decrease (above 50% of relative magnitude) were concentrated in the central part of the study area and thus covered spatial patterns of abrupt biomass loss (Figure IV-7-I). In most cases, the onset year of gradual decrease appeared in the very beginning of our time series; however, we also observed a second culmination between 2000 and 2004 (Figure IV-6c).

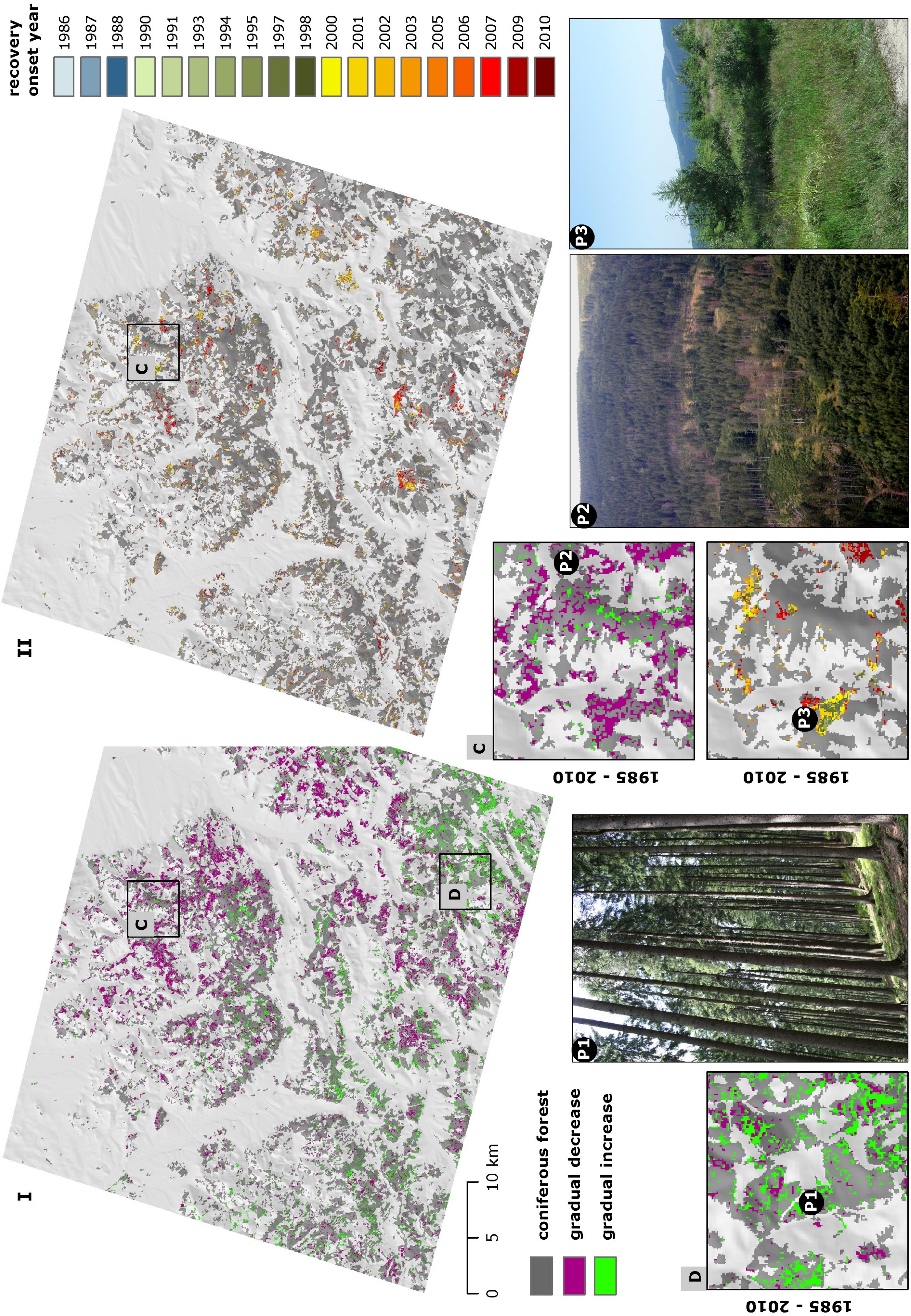

Figure IV-7: Gradual biomass change maps. Gradual decrease and increase (I); recovery onset year (II). Highlighted two example areas: between the Malinowska Skała and the Skrzyczne massif in Poland (C), and the Wielka Rycerzowa massif along the Polish-Slovak border (D). Corresponding photographs: P1 and P2 (source: M. Main-Knorn 2006), P3 (source: J. Kozak 2006).

The fractions of severe and moderate biomass decrease increased from 8% to 35% over time, whereas the proportion of low to moderate change intensity declined (Figure IV-6d). Overall, low to moderate intensity of biomass decrease dominated across all years. Regarding the duration of gradual biomass decrease, most changes occurred over no more than ten years, while a considerable area (~5200 ha) exhibited a biomass decrease over the entire study period (Figure IV-6f).

Biomass accumulation

Generally, 11.2% of the total coniferous area showed evidence of a regrowth process. Recovery was observed on almost 49% of all previously disturbed pixels, while only 10.3% of the area affected by gradual biomass decrease showed recovery trends. For more than 70% of all recovery pixels, the recovery started between 2000 and 2010 (Figures IV-6e and IV-7-II). We compared biomass recovery trajectories following abrupt or gradual biomass loss, as well as their magnitude. We found no considerable differences between these trajectories in relation to previous change and intensity. Hence, we established a generalized recovery profile for the entire coniferous study area (Figure IV-8-I). The average recovery trajectory and the annual growth rates signaled intensive biomass increase, particularly within the first five recovery years. However, note that primary recovery here applies to general vegetation reestablishment (not necessarily conifer growth) as an early succession stage. Biomass recovered from up to 10 Mg ha^{-1} for the post-disturbance stage to 155 Mg ha^{-1} of aboveground biomass after the 15^{th} recovery year. Finally, an averaged gradual increase profile for the 25-year period was established (Figure IV-8-II). Here, a linear increase of biomass from 156 Mg ha^{-1} in 1985 to 217 Mg ha^{-1} in 2010 was quantified. The annual growth rates were constant and reach 2.5 Mg ha^{-1} yr^{-1} (+/- 0.04 Mg ha^{-1}) of biomass increase.

Net biomass change

The net biomass change map (Figure IV-9) shows an overall net negative impact on 38% of the coniferous area, while a positive net change was accounted for only 8.4%. The remaining 53.6% of the coniferous stands present a stable condition (note that stability threshold was set on zero +/- 20 Mg ha^{-1}). We observed slight or highly negative net biomass change on 22.5% (~12,616 ha) and almost 9% (~3860 ha) of the coniferous stands, respectively. In contrast, no highly positive net change could be found, while slight positive net biomass change occurred on 7.8% (4356 ha) of the coniferous area. The maximum negative net change reached -302 Mg ha^{-1}, while the highest positive net change equaled 304 Mg ha^{-1}. The weighted mean net biomass change for the study area was -36.2 Mg ha^{-1}. The frequency of negative biomass change values reached two culminations by -38 Mg ha^{-1} (694 ha of total coniferous area) and -215 Mg ha^{-1} (~293 ha). Finally, we found similar spatial patterns between highly negative net biomass change and abrupt biomass loss (disturbances) across the entire study area.

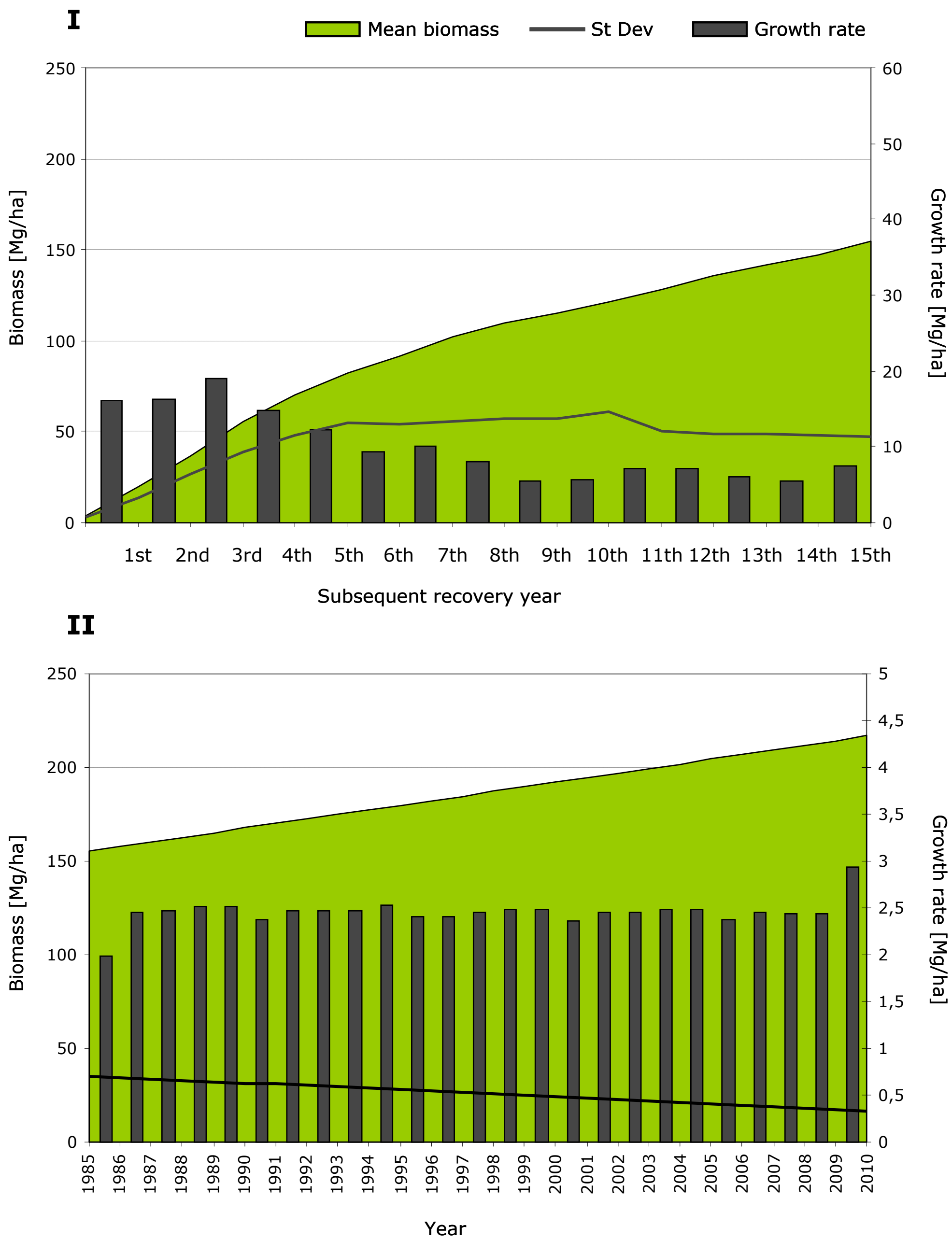

Figure IV-8: Averaged recovery (I) and gradual growth (II) trajectories.

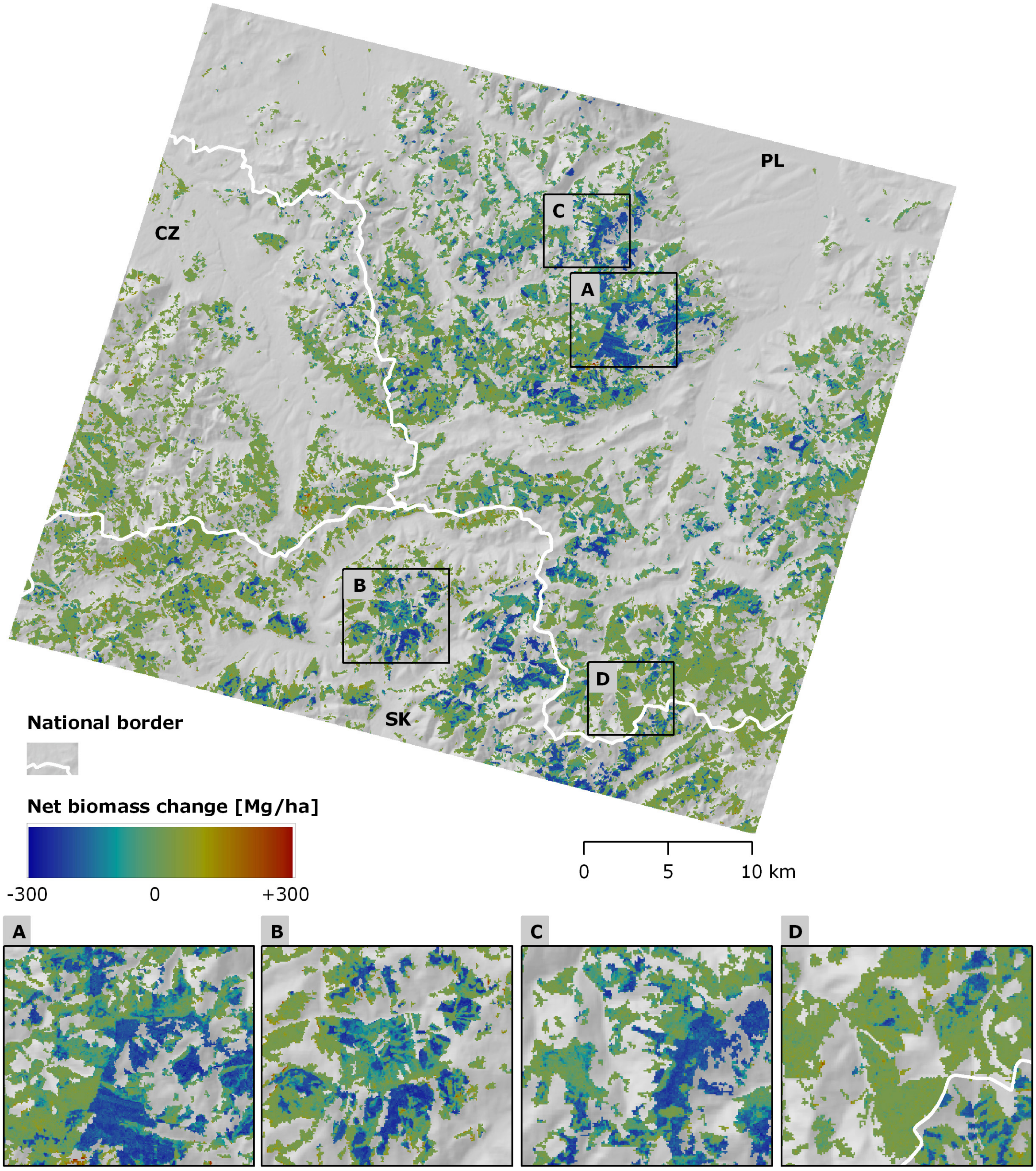

Figure IV-9: Net biomass change map with four example areas: the Barania Góra massif (A), the Javorské massif (B), around the Skrzyczne massif (C), and around the Wielka Rycerzowa massif (D).

5 Discussion

Modeling biomass trajectories using the LandTrendr algorithms revealed a dramatic decline in aboveground forest biomass between 1985 and 2010, affecting almost 60% of the total coniferous forest in the Western Carpathians. Moreover, the area affected by both stand-replacing disturbances and long-term degradation seems to enlarge exponentially and this process has peaked during the last five years. This corroborates reported increases in salvage cuttings for the Slovak, Polish and Czech part of the Beskids, particularly since 2005 (Hlásny et al. 2010b), as well as decreasing forest cover (Main-Knorn et al. 2009). Additionally, massive biomass loss since 2005, as well as considerable surplus of salvage cuttings (personal communication Grodzki, W. 2012), amplified the negative balance of net forest biomass change. Consequently, we assume that the coniferous forest in our study area transitioned from a net carbon sink to a net carbon source during our observation period.

There are few biotic and abiotic drivers responsible for the above mentioned trend, though their real impact can only be assessed and understood in the context of their synergistic interactions. First, low resistance of spruce occurred due to unfavorable forest composition and foreign species ecotype. During the Austro-Hungarian time and the expansion of the industrial revolution in mid-19th century, the demand for energy and thus fuel increased extremely. This was reflected in exponentially increasing demand for softwood and its products, favoring propagation of tree species with high productivity, short harvesting cycle and quick revenues. Norway spruce was the most promoted tree species across the Carpathian Mountains, covering the demand for wood products and ensuring profits. Hence, particularly in the Western Carpathians, natural fir and beech forests were largely replaced by spruce monocultures of foreign origin. The subsequent forest practices in the 20th century followed that tradition and took extensive benefit from spruce monocultures (Capecki 1994).

Second, weakened spruce was then affected by long-term air pollution leading to a loss of tree vigor and retardation of growth. In the second half of the 20th century, atmospheric deposition of sulphur and nitrogen in Central Europe reached critical concentrations and caused direct damage of trees, as well as degradation of soil chemistry and extinction of soil microorganisms. In consequence, the natural symbiotic forest ecosystem was damaged and could no longer provide protective functions for the trees (Matiakowska and Szabla 2007; Hlásny and Sitková 2010). Effects on trees could be observed either immediately (through discoloration and defoliation), or delayed causing long-term loss of vigor and elevated activity of fungal pathogens (*Armillaria* spp.) (Longauerová et al. 2010). Our results show a long-term gradual biomass decrease since 1985, quantified on 13,600 ha of coniferous area (corresponding to 41% of the total biomass change area).

Third, we show that moderate to severe biomass loss is constantly increasing (Figures IV-6a and IV-6b), which could be explained by: 1) markedly delayed response of the soil environment to long-term atmospheric toxic loads, and 2) a negative development of spruce stands since the early 1990s resulting in a lower resistance against biotic and abiotic factors (Mijal and Kulis 2004). On the one hand, less resistant spruce was susceptible for fungal diseases and bark beetle infestation, on the other hand adverse climate conditions with subsequent extreme weather events occurred. The latter has intensified particularly between 2002-2004 and 2006-2009 (Figure IV-10), causing physiological drought (2003) and summer drought (2003, 2006, 2007, and 2008), as well as direct wind-driven forest destruction (November 2004, January 2007). Additionally, temperature and precipitation regimes changed significantly. The years 2000-2005 experienced high levels of averaged precipitation and lower mean winter temperatures, while the years 2006-2009 experienced higher mean winter and summer air temperatures. These extreme events and favorable thermal conditions increased bark beetle survival and generation return frequency, leading to extensive insect outbreaks since 2003 (Grodzki 2010; Hlásny et al. 2010c).

Presumably, if these biotic and abiotic drivers would not have worked coincidentally, the current situation in the Beskids would differ markedly. In fact, their synergistic effect caused severe and widespread loss of biomass. This can be shown in two sub-regions: the Barania Góra massif in Poland (A) and the Javorské massif in Slovakia (B) (Figure IV-5). The first example delineates two time peaks of biomass loss, first in the late 90s and second, about ten years later (Figure IV-5A). Both peaks were biotically-induced (fungal pathogens and bark beetle), while the second event (still ongoing) has been additionally accelerated by unfavorable weather conditions and a windstorm in 2004. Between 1995 and 2005 abrupt biomass change occurred on relatively small patches, scattered at lower altitudes. In contrast, disturbances between 2006 and 2010 affected a continuous forest area and caused a tremendous biomass loss along the entire elevation gradient. A second example, the area of the Javorské massif (B), reflects ongoing forest disturbances which begun in 2000. Here, the initiating driver in 2000 was the activity of the pathogenic fungus (*Armillaria* spp.) followed by bark beetle infestation since 2005 (Hlásny and Sitková 2010). Similarly to biomass loss on the Barania Góra massif, extreme weather conditions in 2003 and 2004 accelerated extensive bark beetle outbreaks (Grodzki 2010). In this case, the biomass loss is likely to be a continuously and gradually developing process, starting as distinct patches on the mountain peaks and then spreading downhill.

Although both examples differ in terms of temporal and spatial disturbance onset, the final stage of biomass loss seems to be very similar. Though, due to the fungal activity and the windstorm in November 2004, intensive salvage logging was conducted, leaving a large amount of broken and fallen trees suitable for bark beetle breeding and reproduction. Simultaneously, a mild winter and dry growing season in 2003 and following years facilitated the insect survival and reproduction, and boosted outbreaks. Finally, once the bark beetle population has reached a critical size, it affects whole stands and damages trees independently of their health status (Hlásny et al. 2010c).

Generally, the recovery map (Figure IV-7-II) shows only a small regeneration area compared to an area of previously damaged forest stands. Nevertheless, to demonstrate recovery processes after long-term gradual biomass decrease until the mid-90s followed by abrupt biomass loss (disturbances), we choose an example area localized between the Malinowska Skała and the Skrzyczne massif (Figure IV-7-II C). Slow reestablishment of new forest cover is organized in compact patches, suggesting intensive silvicultural measures. For this pattern, there are two explanations. First, although natural regeneration of spruce has been proven in several locations of the study area, its quality, vitality and survival chances are not sufficient to guarantee continuous spruce forest expansion above 800 m (Barszcz and Małek 2008). Moreover, adverse site- and weather conditions limit the intensity of spruce fructification and thus natural regeneration (Longauer et al. 2010). Therefore, recovery has to rely on artificial regeneration of spruce using seeds of local origin (provenance) (Barszcz and Małek 2008; Slodičák et al. 2010). Second, critical biomass loss in the study area forces forest managers to develop a stable and close-to-nature forest, consisting of European beech, silver fir, sycamore maple (*Acer pseudoplatanus*), and admixture of Norway spruce (Slodičák et al. 2010). These species are promoted and artificially introduced on previously damaged stands, but also as conversion of existing spruce monocultures. However, as silvicultural measures are time- and work consuming, and are hampered by adverse site and weather conditions in our study area, low recovery rates seem to be comprehensible.

Our averaged recovery profile shows biomass increase from up to 10 Mg ha^{-1} for post-disturbance stage to 155 Mg ha^{-1} of aboveground biomass after 15 recovery years. The recovery curve and the growth rates indicate intensive biomass increase, particularly within the first five recovery years, and slight slowdown of growth for the subsequent years. These findings are in line with the general knowledge of forest reestablishment, arising shortly after disturbance and expanding quickly before leveling off (McMahon et al. 2010). Although we were not able to observe the above mentioned leveling off due to our short observation time, we were able to assess the variability of growth rates in the early succession stage, indicating a high complexity of the recovery process due to external factors. However, better understanding temporal patterns of forest regeneration and their drivers requires detailed knowledge of the site- and micro-climate conditions, as well as silvicultural measures at the stand level. Finally, because spatial patterns of recovery are in line with the disturbance history and known silvicultural approaches, and because the averaged growth trend confirms our expectation, we propose that trajectory-based analysis provides comprehensive spatio-temporal information on the reestablishment of new forest.

Our last example is located around the Wielka Rycerzowa massif (Figure IV-7-I D). This site reflects coniferous stands gradually increasing in biomass and remaining in a sufficiently healthy condition. This area belongs to the southern part of the study region, which is known to be in the orographical "air pollution shadow" of the surrounding Polish and Czech Beskids (Šrámek et al. 2010), where no significant emission sources were present. Additionally, applying far beyond this particular example site, it has been proven that natural Norway spruce populations under stress are genetically adaptable to the local site conditions (Krajmerová and Longauer 2000). Evidently, several local provenances, particularly the Istebna spruce, perform high growth and survival adaptations, while tolerating seasonal water shortcomings (Boratyński and Bugała 1998; Longauer et al. 2010). Fortunately, we could prove these acquired traits of spruce by the averaged gradual growth profile, established for the stable coniferous forest condition. This profile shows a linear increase of biomass from 156 Mg ha^{-1} in 1985 to 217 Mg ha^{-1} in 2010. The annual growth rates are constant throughout all considered years and reach 2.5 Mg ha^{-1} yr^{-1} (+/- 0.04 Mg ha^{-1}) of biomass increase, beyond the first and the last considered year with ~2 Mg ha^{-1} and ~3 Mg ha^{-1}, respectively. These values are in line with the typical ranges reported for boreal and temperate coniferous forests dominated by spruce species (Boratyński and Bugała 1998; McMahon et al. 2010). Although growth rates are stable across time, slight periodical fluctuations occurred. We found that these sudden periodical interruptions correlate significantly with the spring precipitation (r=0.62). Additionally, the winter averaged air temperature (especially for February) seems to be significantly related to the gradual growth rates (r=0.37). Our findings are in accordance with general knowledge regarding spruce growth responses to climate variables (Boratyński and Bugała 1998; Longauer et al. 2010). Nonetheless, the comprehensive interpretation of forest regeneration and gradual increase processes in relation to climate and climate changes is highly challenging, thus requiring further research.

Besides these general outcomes across the entire study area, the net biomass change map (Figure IV-9) exhibits significant differences in silvicultural measures between the Polish and Slovakian part of the Beskids. Comparing the previously introduced example areas A and C (both localized in Poland) with the areas B and D (the first solely placed in Slovakia, the second located along the border), different spatial patterns of biomass decrease and recovery (if present) occurred (Figure IV-9). In Poland, biomass loss corresponds to broad openings with either linear or fuzzy patch borders (A and C), while compact patches of small strip clear-cuts dominate in the Slovakian part (B and D). These findings confirm outcomes from a previous study (Main-Knorn et al. 2009) and underline different forest management practices leading to more sustainable and stable forest structure.

While our analyses yielded reliable biomass change maps with high temporal resolution, some sources of uncertainty remain. First, optical remote sensing has a limited sensitivity for reproducing biomass in dense forests, and is susceptible to the confounding effect of understory vegetation in sparse forests. Thus, as stated by Main-Knorn et al. (2011), a slight bias in biomass estimates may occur with tendency to over-predict lower and to under-predict higher biomass values. Additionally, due to data limitations, biomass references were calculated as a living aboveground biomass, disregarding potential dead aboveground biomass allocated in snags as well as in form of coarse woody debris. In contrast, our satellite-based modeling approach estimated the combined pool of living and dead aboveground biomass. Hence, reference data and biomass estimates might slightly differ, especially in areas where coarse woody debris was present. However, how significant the uncertainties are, again depends on the forest/canopy density. Second, biomass reference data varied temporally across forest districts and featured measurements conducted over 10-year management periods, limiting long-term change accuracy assessment across the study area. Therefore, satellite imagery was used to interpret and validate spatial and temporal biomass changes. However, limitations in labeling became apparent where a year was missing in the time series (1989, 1992, 1996, 1999, 2004, and 2008). Third, although the LandTrendr fitting approach interpolates missing/masked pixel values and generally reduces phenology effects and inter-annual noise, misclassifications cannot be ruled out. For 1987 this can be explained by a higher vulnerability of the fitting algorithm to outliers at the beginning of the time series. For 1994 and 2002, misclassifications are likely caused by high cloud coverage (17% and 13% of the total study area, respectively). Fourth, the gradual increase class performs moderately in terms of omission and commission errors, and favors the no change class in case of misclassifications. This can be explained by low annual growth rates, particularly in old-growth forest stands, leading to the labeling as stable forest. Last but not least, in accordance with the guidance for silvicultural measures, bark beetle infested trees or stands should be removed within the same year through salvage logging, while wind-throw treatment depends on the timing, affected range, and potential insect pest risk (CILP 2004). Hence, annual silvicultural statistics might not perfectly match our annual biomass loss estimates. Moreover, official statistics on volume of removed trees comprise a certain degree of uncertainty, which might be related to *in situ* estimation errors and registration errors of harvested wood. In consequence, no accuracy assessment of change magnitude was possible.

Summarizing, in respect to the methodological core of this study, we showed the effectiveness of Landsat trajectory-based approach, supplemented by SPOT and IRS LISS data, in terms of mapping both abrupt and gradual biomass changes in the Western Carpathians. A near-annual time-series provided detailed information on stand-replacing disturbances as well as long-term degradation and regeneration, altogether processes affecting biomass stock. The LandTrendr approach enabled us to quantify how much biomass was allocated in forests before, during and after specific disturbance event, and to evaluate biomass accumulation rates. The capability to distinguish between single disturbances occurring within one or more years is a meaningful advantage of the time-series approach over bi-temporal change detection, where all disturbances are clustered in large patches.

Moreover, a time-series approach provides spatially and temporally continuous quantification of biomass and covers its variability within forest inventory stands. This is a fundamental distinction to forest inventory, where spatial details might be averaged out and short-term dynamics might be overlooked (Main-Knorn et al. 2011).

The Landsat imagery provided sufficient temporal, spectral and spatial detail, and formed “the backbone” of our study. However, due to the Landsat data gaps between 1996 and 2000, the SPOT and IRS LISS data had to be introduced into the time-series. In terms of spatial, spectral (besides the visible blue and SWIR bands), and temporal resolution, SPOT and IRS feature similar characteristics as Landsat sensors. They are therefore considered “Landsat-like” sensors and can complement or replace Landsat data (Powell et al. 2007). Since the SPOT image did not provide spectral coverage in the SWIR (~1.55-1.75µm), we modeled an artificial SWIR band and used it as a proxy. The validation of the SWIR model showed highly significant results, making the incorporation of such a modified SPOT image into the Landsat time series feasible. Finally, we found no evidence that multi-sensor trajectory of Landsat, SPOT and IRS LISS data affected the standard deviation and the mean biomass estimation errors (Figure IV-4). Similarly, the validation of the disturbance map revealed no discrepancies in accuracies when incorporating “Landsat-like” sensors (Tables IV-2 and IV-3). However, a comprehensive analysis on these data limitations and their potential impacts on trajectory-based biomass quantification was beyond the scope of this study.

Contextualizing our findings in a regional context, it is evident that between 1985 and 2010 massive biomass loss, triggered by the synergistic effect of biotic and abiotic drivers, dominated in the Western Carpathians. This loss spatially and temporally exceeded previous forecasts (Hlásny et al. 2010a; Hlásny et al. 2010b). Our net biomass change map highlights this negative ratio (balance), showing a widespread and severe biomass loss along a north-south gradient. In contrast, some scattered plots featured a positive biomass balance although these were overall scarce. Summing up, we assume that coniferous forests in our study area converted from a net carbon sink to a net carbon source between 1985 and 2010.

Outlook

Obviously not the individual drivers, but the interdependencies between those are responsible for the current critical status of the coniferous forests in the Western Carpathians. Yet, future forest status mainly depends on sustainable forest management and changing climate conditions, while the latter will largely trigger spruce forest distribution. For both meteorological stations, Lysa Hora (1324 m) and Jaworzynka (675 m), increasing mean annual and summer temperatures within the last 25 years have been documented (Figure IV-10-I and IV-10-II).

Similarly to Hlásny et al. (2010a), we found an increasing trend in total annual and spring precipitation at higher altitudes, and an decreasing annual trend in precipitation at lower elevations. Therefore, we presume that mainly spruce forests at lower altitudes will suffer from persisting drought stress. However, not the decreasing amount of precipitation but its timing and frequency will hamper spruce productivity in the Western Carpathians (Durło 2010).

Current climate conditions clearly foster bark beetle outbreaks and therefore also insect related disturbances. In the future, above all, bark beetle infestations will benefit from increasing temperatures and prolonged growing season, as well as from the forecasted increase in windstorm frequency (Giorgi and Coppola 2007).

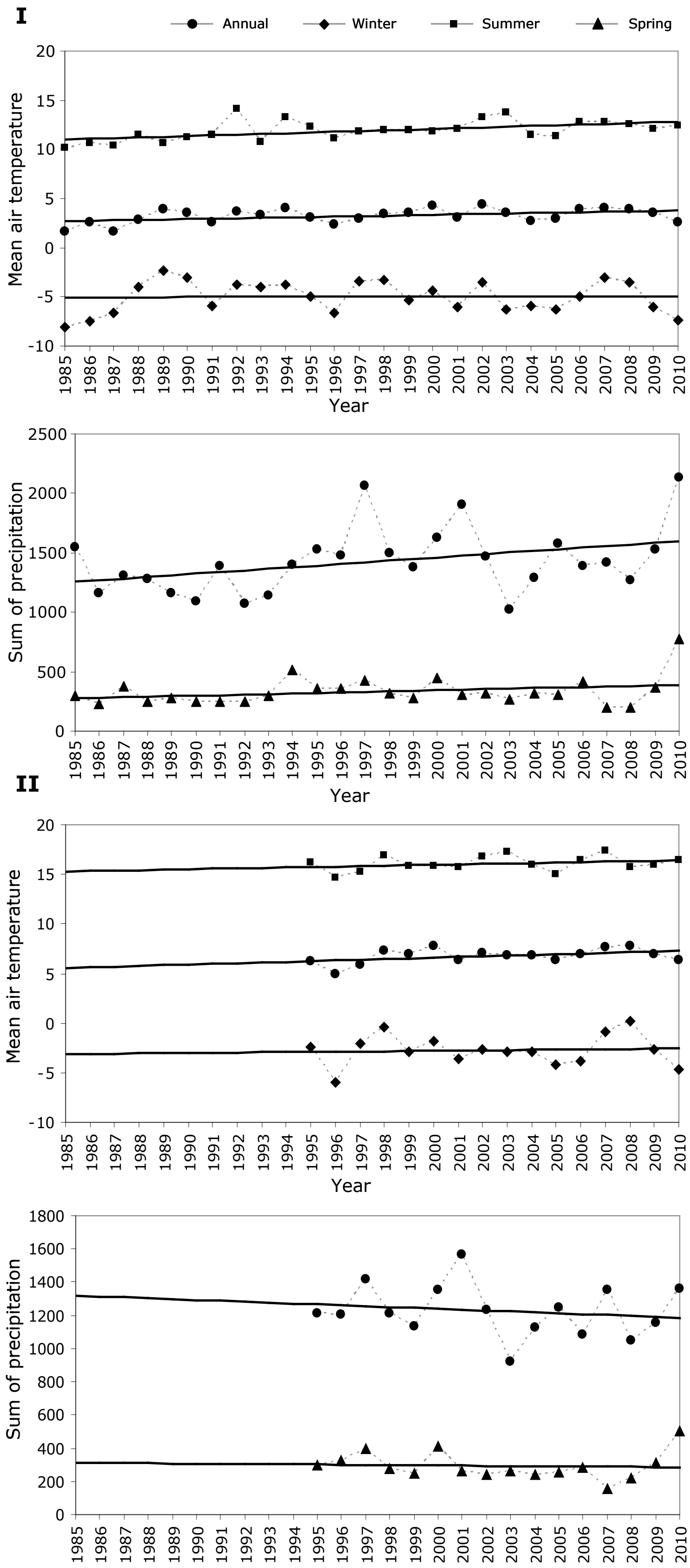

Figure IV-10: Mean air temperature and sum of precipitation from meteorological stations on (I) Lysa Hora (1324m) and (II) Jaworzynka (675m).

Presumably, climate change will foster increasing numbers of bark beetle generations per growing season, trigging long-term insect-related disturbances. Moreover, the expected widespread impact of insect pest as well as reduced production of spruce due to the altitudinal shift (Jump et al. 2009; Hlásny et al. 2010a) will definitively diminish its importance in forest composition and regeneration. Finally, since climate change and pest scenarios forecasted by Hlásny et al. (2010a) for the period 2021 and 2050 are already happening, we strongly believe that by the end of the century, spruce forests in the Beskids will occur only marginally.

Concluding, despite the known limitations regarding the empirical modeling of biomass with optical remote sensing data, this study provides a first approximation of biomass loss and accumulation rates in the spruce-dominated Western Carpathian forests. Advanced remote sensing approaches, such as the modeling of biomass and the application of trajectory-based change detection algorithms, provide spatially and temporally explicit quantifications of biomass variability within inventory stands. This study underlines that monitoring of spatio-temporal patterns of forest ecosystem dynamics is only feasible when applying enhanced remote sensing methods.

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Chapter V:
Synthesis

1 Summary

The ability to monitor and quantify forest change is a prerequisite for better understanding human-induced environmental changes and their impact on forest ecosystems. Moreover, the questions relating to the spatial (where) and temporal (when) dimensions, and its magnitude (how much) remain fundamental to forest services concerns (Hall et al. 2007). Since inventory data, if existent, is temporally and spatially constrained, remote sensing is playing a crucial role in providing more extensive answers to these questions. The overarching goal of this thesis was to monitor and quantify forest change in the Western Carpathians using, primarily, remote sensing techniques. Firstly, forest cover and composition were used as proxies to investigate politic and socio-economic patterns triggering land-use management and pollution legacies across national borders. Secondly, forest biomass and LAI modeling approaches were developed to quantify forest productivity and assess its spatial variability. Finally, remote sensing based modeling was applied to study forest biomass dynamics and their impact on the local carbon storage potential.

The Western Carpathians were of particular interest due to their complex land-use legacies and histories, pollution loads, as well as ongoing severe forest declines.

The three research questions stated in Chapter I and covered in Chapters II-IV, are now reviewed individually:

<u>Research question I:</u> *How do pollution legacies from communist times, in the context of historic and contemporary forest management, affect forest ecosystems across the Polish, Czech and Slovak border?*

In Chapter II, an SVM algorithm was applied to classify forest types in 1987 and 2005, followed by a bi-temporal change analysis. This was a premise to assess general forest cover change between 1987 and 2005, and quantify 12 transition classes between different forest types together with a no-change class. In order to investigate reasons for forest cover changes in post-communist times, forest changes were additionally analyzed with respect to forest type, topographic factors, and the prevailing wind direction for the whole study area and for each country separately.

This chapter reveals that unsustainable forest management during the Austro-Hungarian Empire and high levels of air pollution and wet deposition during communist times were the predisposing factors for forest cover change and coniferous forest degradation in the Western Carpathians. Although general forest cover was quite stable during the study period (net forest cover change of only 0.5%), it reflects the result of a net forest decline followed by reforestation or regeneration. Concerning forest cover and composition changes, relevant differences across borders were observed. In the Slovakian part of the study area, forest cover decrease and increase were counterbalanced. In the Czech Republic, forest reforestation and regeneration significantly exceeded forest decline. In contrast, forest cover *decrease* was almost twice as large as cover increase in Poland. These changes can be explained by varying occurrence and timing of forest decline (early 1980s in the Czech Republic, the mid-1990s in Poland), different exposition to air pollution, and diverse forest management activities undertaken by these three countries. The latter differs particularly concerning harvesting and reforestation practices during post-communist times, resulting in various rates and patterns of forest composition conversion towards mixed stands. For example, reforestation on previously damaged forest stands dispersed along entire elevation gradients was undertaken in Poland, while compacted plantations on clear-cuts were typical in the Czech Republic and Slovakia. In summary, the findings in Chapter II revealed the importance of historic and current forest management, as well as the influence of pollution legacies from communist times in explaining today's forest change patterns.

<u>Research question II:</u> *What are the spatial patterns of coniferous forest productivity in the Western Carpathians and which methodological approach enables their comprehensive investigation?*

The methodological core of Chapter III and Appendix A was to investigate the potential of either forest stand-based inventory, remote sensing imagery, or both data types, for the spatially continuous quantification of coniferous forest productivity in the Western Carpathians. Therefore, a regression tree-based modeling approach was developed to estimate forest biomass and leaf area index (LAI), both recognized as key parameters for assessing forest productivity.

The outcomes of this chapter clearly show that the inventory-based approach was the most suitable for predicting aboveground biomass. It captured the complete observed biomass range (100-300 Mg ha^{-1}). In contrast, biomass estimates for areas lacking forest inventory led to considerably less accurate results (r=0.52). However, integrating both satellite data and forest parameters (the latter, such as tree height, easily taken in the field) significantly increased prediction accuracy. Generally, stand volume, relative stem density and dominant tree age (inventory-based approach), as well as elevation (remote sensing-based approach) were identified as the strongest predictors. These inventory-derived variables are widely recognized for their predictive power and are often incorporated in allometric biomass calculations. In contrast, the predictive strength of elevation data was somewhat of a surprise. It seems to be related to the forest decline in the study area, allocated along an altitudinal gradient.

Regarding the ability of the before-mentioned approaches to identify the spatial patterns of coniferous forest biomass, the satellite-based approach was clearly the best performing one. This approach enabled to cover spatial variability within forest inventory stands, and revealed spatial details that otherwise would have been averaged out. Moreover, since forest inventory only provides averaged data for 10-year intervals, short-term dynamics might be overlooked. Thus, a remote sensing-based approach is very suitable for determining spatial and temporal variability in forest biomass and structure.

Additionally, further contributing to this research question, Appendix A investigated the case of comprehensive LAI estimates by comparing the predictive power of the same data types as it was done for biomass estimates. Also, a narrow range of LAI values (0.5-3.0) compared to other spruce-oriented studies was registered in the study area. This can be explained by (1) an even-aged stand type, typically found in spruce plantations, and (2) poor spruce health conditions reflected in a low live crown ratio.

Evidently, the satellite-based approach was the most predictive one for LAI estimates ($r=0.57$). However, only a limited range of observed LAI values was covered by the algorithm (1.0–2.3). Additionally, neither the inventory-based nor the combined approach improved the accuracy of LAI estimates. It was thus assumed that stand-based inventories were not representative for local forest structure measurements. Although the remote sensing based algorithm performed better, consideration of the influence of understory in sparse spruce stands and the saturation effect in dense forest appears to be necessary to improve LAI estimates.

<u>Research question III:</u> *How do forest dynamics affect coniferous productivity in the Western Carpathians and what are the main driving forces?*

In Chapter IV, a RF-based modeling approach was applied to monitor forest biomass and quantify its variability across space and time. The methodological core built upon the results from Chapter III in order to improve biomass modeling and mapping, in particular by adding a temporal depth and extending the range of potential biomass estimates. Using the trajectory-based approach (LandTrend), abrupt (disturbance) and gradual (degradation, selective logging, or recovery) forest biomass changes were distinguished, and their spatial and temporal variation was described. Finally, the net biomass change was quantified and coniferous forest in the study area was investigated in terms of its carbon sequestration potential.

This Chapter revealed a dramatic decline in aboveground forest biomass between 1985 and 2010, affecting almost 60% of total coniferous forest in the Western Carpathians. The underlying synergistic effect of the main driving forces affecting forest decline was contextualized and assessed in detail.

First, unfavorable forest composition (spruce plantations), introduced during the Austro-Hungarian Empire and continuing into the 20th century, as well as long-term air pollution during communist times caused widespread loss of tree conditions and retarded its growth. Both factors led to lower spruce resistance against fungal pathogens and extreme weather events. It was further shown that forest decline has enlarged exponentially, reaching a climax during the last five years. The initiating factors here were (1) adverse climate conditions with subsequent extreme weather events (e.g., windstorms, physiological drought), and (2) increasing activity of bark beetle. Once the bark beetle population has reached a critical size, it affects whole stands, regardless of forest health status.

Although area-wide biomass loss dominated in the study region, slow and scarce reestablishment of new forest cover could be observed as well. The regeneration was organized in the form of compact patches on previously disturbed area, suggesting intensive silvicultural measures. On the one hand, various tree species (e.g., beech, fir, maple, and spruce) have been promoted and planted on damaged stands, on the other, conversion of existing spruce monocultures has occurred. Both of these silvicultural activities underline the sustained effort in establishing a stable and close-to-natural forest. Additionally, the regeneration patches revealed significant differences in silvicultural measures between the Polish and Slovak part of the Western Carpathians, confirming the outcomes from Chapter II. Only a small area showed a constant growth of coniferous forest stands (approx. 7.5% of the total coniferous forest area). Spruce health conditions sufficient for accumulating biomass were found either in the orographical “air pollution shadow” where no significant emission source was present, or in locations with the Istebna spruce as the dominating local provenance. This underlines the capacity of natural Norway spruce to adapt genetically to the local site conditions, when exposed to stress factors.

Finally, the net biomass change map highlighted the negative change ratio, suggesting a conversion of coniferous forests in our study area from a net carbon sink to a net carbon source.

Appendix B extended the knowledge of biomass distribution and its loss in relation to topographic factors and dominant stand age. Generally, abrupt biomass changes followed similar distribution patterns as gradual biomass loss, while the latter affected more area at every altitude and slope zone than abrupt changes. The distribution of the relative magnitude of biomass loss (low, moderate, and severe loss) by elevation and slope zones underlined further dissimilarities. In contrast, similar patterns of disturbances and gradual changes occurred on south, southwestern, and southeastern facing slopes, where severe abrupt and long-term biomass losses were dominating. Concerning the duration and magnitude of gradual biomass losses, the most severe changes lasted up to ten years. Moreover, the proportion of long-term changes increased with altitude and decreased with slope. Finally, disturbances were clearly predominant within older coniferous stands, particularly those having an averaged stand age between 90 and 120 years.

Both Chapter IV and the supplementing material presented in the Appendix B highlight how different patterns of biomass distribution and its dynamics can be distinguished. It complements present knowledge concerning the extent and relationship between forest biomass loss and site-specific characteristics.

2 Main conclusions

Forest change concerns different scales and dimensions. It is determined by a wide variety of factors and can be assessed using various methods. This thesis highlights the operational use of remote sensing approaches for (1) monitoring forest cover and its change with respect to land-use and pollution legacies, and (2) modeling forest productivity and tracking its dynamics concerning local carbon sequestration potential.

Generally speaking, the synergistic effect of unsustainable forest management in the past, catalyzed by high levels of pollution loads during communist times caused a significant damage to the coniferous forests in the Western Carpathians. Since the early 1990s spruce-dominated stands have shown low resistance against biotic and abiotic factors. They have thus been susceptible to fungal diseases and insects outbreaks on the one hand, and adverse climate condition with subsequent extreme weather events on the other. Since 2005, widespread and severe biomass loss has taken place, exceeding previous forecasts both spatially and temporally. Nowadays, a transition of local coniferous forests from a net carbon sink to a net carbon source evolved in the study area, reflecting the great diversity and dynamics of forest capacity to serve as a carbon pool.

The cross-border analysis emphasized the role of site characteristics such as forest type, predominant species, topographic conditions, pollution hotspots, microclimate, and the interactions between them in forest decline. This analysis also provided evidence that forest management decisions play a key prevention role, especially when sustainability measures are considered. Once the unfavorable nexus of climatic and biotic conditions appeared, critical disintegration of whole stands began which lasts until today.

What are the main messages assessed from the research presented in this thesis?

First, the bias of political regimes towards productivity and profits is the main human-driven factor predisposing forest change. While in other parts of the Carpathians this is directly related to legal and illegal logging rates (Knorn et al. 2012), in the Western Carpathians ongoing forest change was triggered by politics and is today boosted predominantly by climate factors.

Second, human-induced forest change in the past, resulting from conversion of natural forests to plantations, modification of forest structure, introduction of invasive species, overexploitation or contamination of soil, has far-reaching consequences for present forest ecosystem dynamics. Beyond that, even if natural disturbances (e.g., infestation or wind-throw) are factored in as cyclical stages of forest dynamics, their range and magnitude is at least partly human-induced.

Third, changing forest dynamics and the disturbance and regeneration patterns affect forests in their function as a carbon stock and, ultimately, their future carbon sequestration potential. At present, this leads to high local to regional fluctuations in carbon uptake, triggered by a loss and accumulation of forest biomass. In the near future, owing to climate change, the rate of both local losses and accumulations in the Carpathians is expected to increase, according to a changing composition of tree species. However, expected accumulations will probably not compensate biomass losses due to the "bottleneck effect" causing an altitudinal shift and migration of species (Vos et al. 2008), a long-term adaptation manner of trees, as well as a slow implementation of new forest management strategies.

Finally, sustainable forest management is a very challenging task. Defining sustainability as "a matter of justice at three levels: between humans of the same generation, between humans of different generations, and between humans and nature" (Baumgaertner and Quaas 2010), sustainable forest management should consider both the present and the future. Therefore, management priorities should focus on monitoring forest changes, protecting and supporting forest needs and services at the present stage, as well as taking forecasted future changes into consideration and adapting to them. The only sufficient and comprehensive way of monitoring forest changes consists of the integration of traditional forest inventory and remote sensing data / methods. Their incorporation hence provides a unique solution to tackle the persistent shortage of human resources when annual forest inventory is intended (Mickler et al. 2002). Furthermore, the ability to assess forest productivity and its dynamic across space and time allows to better evaluate the role of forests in the local to regional carbon balance, and to estimate its future development.

3 Innovations and limitations

Using advanced methods of remote sensing, this thesis conveys a very interesting but complex socio-ecological story. While many scientific disciplines have focused on assessing the degradation of forest ecosystems, little research has been dedicated towards a more interdisciplinary and holistic method design. In the present work, techniques of traditional inventory as well as advanced remote sensing and modeling approaches were combined to determine and quantify forest change across space and time. In doing so, an assessment of not only important information about forest productivity, but also the spatial distribution in stand structure and ecological complexity was carried out. The capacity to map spatial co-variation among multiple ecosystem attributes has important implications for a sustainable forest management, in particular in optimizing the provision of multiple ecosystem services (e.g., carbon storage, timber harvest, and biodiversity) (Wulder 2006; Keeton 2007; Wolfslehner and Seidl 2010).

Nevertheless, the integration of different data types and methods, as well as the data characteristic itself also entails certain challenges. Since the biomass modeling presented in Chapter III builds upon traditional forest inventory and remote sensing imagery, advantages and limitations of both must be taken into account. Accordingly, the accuracy and the level of up-to-dateness of official inventories vary even between neighboring forest districts, leading to potential discrepancies and limiting the applicability of this data as a reference. Moreover, optical remote sensing has a limited sensitivity for reproducing biomass in dense forests, and it is susceptible to the confounding effect of understory vegetation in sparse forests. Thus, a slight bias in the estimates occurred, with the tendency to over-predicting lower and under-predicting higher target values. While the observed biomass bias may provide an estimation error at one particular point in time, the application of the biomass model for the temporal analysis would result in consistent inaccuracies throughout time. Consequently, a reliable determination of relative changes can be ensured.

Finally, the application of biomass modeling and trajectory-based change detection enabled the assessment of first approximations of biomass loss and accumulation rates in the spruce-dominated Carpathian forests. Despite the limitation mentioned earlier (with respect to the empirical biomass modeling with optical remote sensing) such approximation would not be possible without the spatial continuity and temporal depth of satellite data. Landsat provides an invaluable data source for change detection studies, thanks to its convenient spectral, spatial and temporal resolution, together with an extensive archive that is openly accessible and free of charge (Woodcock et al. 2001; Cohen and Goward 2004). Indeed, a recent study demonstrated how the opening of the Landsat archive in 2008 resulted in an incredible increase in Landsat's application in scientific investigations (Wulder et al. 2012). However, extensive spatio-temporal Landsat coverage predominantly encloses the United States (Goward et al. 2006). Beyond that the failure of the Scan Line Corrector onboard Landsat 7 and the suspension of imaging from the Landsat-5 Thematic Mapper (TM) instrument in 2011 due to degradation of the X-band transmitter (Wulder et al. 2012), lead to a reduced quality of the data and limits its applications. For the Western Carpathian case study, for instance, a significant gap in the Landsat data exists between 1996 and 2000. In this thesis, one possible solution to cope with this lack of Landsat imagery was introduced by including other "Landsat-like" data types (SPOT and IRS) into the time-series and thus filling these gaps. In doing so, complete and consistent biomass trajectories could be established and biomass dynamics quantified.

4 Future research

Over the course of this thesis, several interesting additional research questions and issues for future research arose.

Assessing cross-border forest cover change led to important conclusions about how different management practices and pollution legacies in Poland, The Czech Republic and Slovakia affect ecosystem changes. As the Carpathian Ecoregion is stretching across seven countries and is thus characterized by various political and socio-economic histories and situations (leading to diverse silvicultural management and environmental policies), there is a great potential and evident need to gain a better understanding of cross-border processes and their driving forces. This unique natural "experiment" is of special interest because the Carpathian Ecoregion is marked by a large diversity of silvicultural practices and environmental policies that shape forest ecosystems. Although only a handful of studies compared land cover (Kuemmerle et al. 2006) and land-use change (Kuemmerle et al. 2008) across some of the Carpathian borders, little if any research has been carried out to compare forest change with respect to forest management, ownership patterns, and environmental policies.

This thesis provided a first approximation of biomass loss and accumulation rates in the spruce-dominated Western Carpathian forests. Building upon this work, a number of subsequent research issues may become of interest. First, as spruce plantations were established across the whole Carpathians (Anfodillo et al. 2008), it would be valuable to compare their biomass dynamics and distinguish their main driving factors across the Ecoregion. A comprehensive description of the entire area of the Carpathian spruce forests would improve the knowledge of spruce adaptation potential and provide the necessary information for area-wide carbon stock assessments and models. Hence, when using the modeling approach presented in this study, an investigation of the applicability of the biomass models to various spruce stands across the Carpathians and beyond would be required. One promising direction for such additional sensitivity analysis could be the exploration of the influence of forest health status (defoliation, discoloration, and tree vigor), altitudinal gradients and understory reflectance on the modeling accuracy.

Second, it could be of great interest to evaluate the combined and separated pools of both living and dead aboveground biomass, and to explore the feasibility of separation of their fractions in the modeling algorithm. Present LiDAR sensors (light detection and ranging) provide the most accurate estimates of forest biomass, and enable to distinguish between its live and dead fractions (Kim et al. 2009). However, LiDAR's applicability is limited by its spatial and temporal coverage (Pflugmacher et al. 2012). Hence, as soon as broad-scale continuous analysis and monitoring is required, optical remote sensing is likely to be the only feasible solution. The normalized difference moisture index (NDMI) has been shown to be sensitive to the foliage water content and fraction of dead leaf material (Hunt et al. 1987; Coops et al. 2011). Moreover, a recent study on predicting dead aboveground biomass and tracking its changes using Landsat time-series yielded some promising results (Pflugmacher et al. 2012). Thus, further exploration of the Landsat data capacity to distinguish between living and dead biomass could improve the state-of-the-art knowledge in biomass modeling.

Third, this thesis considered a multi-sensor time-series of Landsat, SPOT and IRS LISS data to cope with the Landsat temporal discontinuity for the Western Carpathian study area between 1996 and 2000. Since information gathered at the sensor is influenced by many factors (e.g., solar zenith angle, sun-object-sensor orientation), even multi-temporal analysis based on data from the same sensor, but acquired under different atmospheric conditions or seasonal phenology, requires accurate image normalization (Coops et al. 2006). When analyzing multi-temporal imagery from different sensors, additional differences in the spectral and spatial resolutions, as well as calibration coefficients must be considered (Wulder et al. 2008a). Here, applying a multi-temporal approach requires careful cross-sensor normalization. Several studies explored robust cross-calibrations between Landsat sensors (Hostert et al. 2003; Chen et al. 2005; Schroeder et al. 2006), while little if any research has been dedicated at cross-sensor normalization. In Chapter III, the multivariate alteration detection and calibration algorithm (MADCAL) of Canty et al. (2004) was used for cross-sensor normalization of Landsat, SPOT and IRS LISS imagery. However, MADCAL was originally developed and validated on Landsat TM, ETM+ and SPOT HRV (high resolution visible) imagery. Based on the results presented in Chapter III, no evidence indicated that multi-sensor trajectories of Landsat, SPOT and IRS LISS data affected the biomass estimation accuracy. However, since the analysis on limitations of this data and their potential impact on trajectory-based biomass quantification were beyond the scope of this study, a comprehensive sensitivity analysis could improve the knowledge and provide useful insights for future cross-sensor studies.

Fourth, since this study focused on estimating biomass and its dynamics for spruce-dominated stands, extending biomass model capacity to other common Carpathian species (e.g., beech, fir, sycamore maple) would also be of interest. Clearly, when using optical remote sensing data such as Landsat imagery, it would be rather challenging and time consuming to establish highly accurate biomass modeling algorithms for all species across the Carpathians. However, in focussing the modeling algorithm on the most dominant and meaningful species one might forthwith be able to establish a first approximation of biomass losses and accumulations across Carpathian forests. Doing so could become a milestone both in assessing Carpathian forest productivity dynamics and in estimating Carpathians carbon sequestration potential.

Finally, both the current global economic course and climate change exert extreme pressure on forests worldwide (Meyfroidt and Lambin 2011). The immediate effects of economics can contribute to either an increase or decrease of forest cover. An increase is reflected in expanding industrial forestry and plantations establishment. However, it is controversial how valuable these forests really are (beside the rough timber value), and how much they contribute to ecosystem services. In contrast, a decrease in forest cover due to economic issues results from increased logging (both legal and illegal) (Bouriaud 2005; Kuemmerle et al. 2009; Knorn et al. 2012), and the conversion of forests to agricultural land (Foley et al. 2007b; Meyfroidt et al. 2010). Climate change, in contrast to economic drivers, is expected to be a long and constantly acting force when it comes to forest change. It can affect forest ecosystems either directly (such as tree mortality through extreme weather events), indirectly (such as by inducing synergies between driving forces and amplifying their effects), or both. Increasing temperatures are expected to have various effects on the Carpathian ecosystems. They will cause altitudinal shifts of species in mountainous areas (Jump et al. 2009), change the frequency of forest pests (Wolf et al. 2008; Hlásny et al. 2010a), and trigger migration of insects along altitude and latitude (Dale et al. 2001). The Carpathian forests are thus likely to be threatened by a loss of biodiversity and impairment of ecosystem services. There is hence a great potential and need for further investigations on how economic- and climate-driven factors may shape the Carpathians in the future. At last, comprehensive research to clarify how forests and forest management worldwide can adapt to these forces and how these forces can be mitigated by forests and forest management becomes fundamental.

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Appendix A:
Remote sensing and inventory-based estimation of coniferous leaf area index in the Beskid Mountains, Poland

in preparation

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William S. Keeton, Elizabeth Freeman, and Patrick Hostert

Abstract

Leaf area index (LAI) is an important biophysical parameter for environmental applications such as water and carbon cycle modeling. LAI characterizes the canopy-atmosphere interface, and is often used in process-based models of vegetation canopy response to global environmental change. Therefore, accurate and rapid determination of LAI is of great interest. Numerous methods and various datasets have been applied to quantify LAI, but so far little comparative research has been carried out. In this study, we explore the capacity of remote sensing imagery and stand-based inventory data to determine LAI in coniferous stands. Results show that the inventory-based approach failed in terms of accurate prediction of LAI. In contrast, a solely satellite-based approach performed better, and has obvious advantage for determining LAI spatial variability. Our findings demonstrate that stand level inventories are not representative for very local canopy measurements and cannot compliment remote sensing LAI models.

1 Introduction

Leaf area index (LAI) is a well-established proxy that captures aspects of canopy structure and microclimate as well as water and gas exchange. It is thus a useful parameter for modeling the biogeochemical cycle of tree canopies (Running and Gower 1991; Breda 2003; Parker et al. 2004). Direct LAI measurements require harvesting, litter collection, and allometry, and are therefore time-consuming. Indirect methods estimate LAI by measuring canopy transmittance, canopy gap fractions and leaf-angle distribution (Breda 2003). This is done for example with optical devices such as the LAI-2000 Plant Canopy Analyzer or hemispherical photography (Miller 1967; Lang 1987; Norman and Campbell 1989; Keeton et al. 2007). Although both direct and indirect methods are highly accurate, their applicability is spatially and temporally constrained. In consequence, remote sensing-based approaches have been developed to cope with these limitations.

For over two decades, direct and indirect LAI measurements have been used as a reference for modeling and validating forest LAI from remotely sensed data. Most empirical, regression-based LAI modeling approaches use spectral vegetation indices, such as the normalized difference vegetation index (NDVI), or the simple ration (SR) (Cohen et al. 2003). However, there is still little agreement in the literature about which spectral vegetation index is best suited for estimating LAI (Gray and Song 2012) and how to overcome saturation problems at moderate to high LAI values (due to limited sensitivity of optical remote sensing). Chen and Cihlar (1996), estimated the canopy LAI over boreal forests from NDVI, derived from Landsat Tematic Mapper (TM) images. They reported a moderate correlation between modeled and field-measured LAI (R^2 <0.5), probably due to the confounding effects of understory vegetation. Turner et al. (1999) compared the relation between NDVI, SR, and the soil adjusted vegetation index (SAVI) to LAI and found SR and SAVI more sensitive to higher LAI range than NDVI. Nilson et al. (1999) explored single spectral bands of Landsat TM and Satellite Pour d'Observation de la Terre (SPOT) images towards coniferous LAI estimation. They found the short-wave infrared (SWIR), visible red, and near infrared (NIR) spectral bands more sensitive to the stand LAI than NDVI when using logarithmic regression. While a more recent study proposed a new vegetation index to cope with saturation problems, the so called Normalized Hotspot-signature Vegetation Index (NHVI), a robust validation is still required (Hasegawa et al. 2010).

Other approaches apply physically based models to describe the propagation of light in canopy and develop reflectance-based inversion models (Kuusk and Nilson 2000). Rautiainen et al. (2003) tested the Kuusk-Nilson (Kuusk and Nilson 2000) forest reflectance model for estimating the LAI of Scots pine (*Pinus silvestris*) stands. Their findings indicate that Landsat spectral bands most commonly used for LAI estimation, namely visible red and NIR, might overemphasize or suppress the role of ground vegetation reflectance in LAI estimates.

Besides the Landsat-based approaches, for several years other sensors have provided multi-decadal and consistent LAI maps at global to regional scale. LAI estimates from the Advanced Very High Resolution Radiometer (AVHRR), the Moderate Resolution Imaging Spectroradiometer (MODIS), and the SPOT-VGT (SPOT – VEGETATION) are available at resolutions of 1 km to 1° (Chen et al. 2002; Myneni et al. 2002). However, this coarse spatial resolution diminishes their application for regional to local studies as well as for heterogeneous forest conditions. One recently discussed promising approach for improving these spatial limitations is the so called cross-sensor fusion of information (Gray and Song 2012). Nevertheless, further improvements in this methodology are inevitable. Therefore, to-date accurate high-resolution LAI estimates from Landsat data at the local and regional level are still of highest interest for forest managers and policy makers.

Study area

This case study examines the border triangle of Poland, the Czech Republic, and Slovakia, encompassing the Beskid Mountains within the Carpathian Ecoregion. Here, forests dominate in the lower montane zone (500 m-1200 m), and consist of Norway spruce (*Picea abies* Karst.), European beech (*Fagus sylvatica*), and European silver fir (*Abies alba*). However, since the 19th century, forest composition has been shaped mainly by spruce monocultures or mixed stands dominated by spruce (Fabijanowski and Jaworski 1995). Nowadays, spruce monocultures in this region are subject to a variety of forest health problems, including regionally pronounced spruce decline. The availability of stand-specific field data, ground-truthing, and expert knowledge from earlier studies (Main-Knorn et al. 2009; Main-Knorn et al. 2011) facilitated the interpretation and validation of our work.

Objectives

While previous studies explored the potential and limitations of remote sensing spectral vegetation indices for estimating LAI, little research evaluated the predictive strength of single Landsat spectral bands specifically. Additionally, although Franklin et al. (1997) reported higher accuracies of LAI estimates when applying Landsat and forest inventory data, the integration of both data types for LAI prediction has been widely disregarded. The overarching goal of this study was hence, to compare the potential of Landsat data alone, forest inventories, and both combined to model LAI at local to regional scales.

2 Data

We used stand-based inventory (SBI) data from 2003-2004 and 2007 provided by the 'Polish State Forest Holding'. Since the inventory update level varies from district to district and is collected separately by each forest district (within a 10-year interval), a sound verification of the accuracy and comparability of the given parameters across different districts was required. For doing so, 105 spruce inventory stands were randomly selected and sampled in 2006 and 2007. All selected stands were even-aged spruce plantations with dominant cohort ages ranging between 40 and 150 years. We measured diameter at the breast height and tree height, and counted the number of trees per plot to estimate stem density. Then, we averaged these parameters, recalculated them to the stand level, and therewith verified the Polish Forest Inventory data. Finally, three hemispherical photos were taken in the center of each plot for LAI estimates (see methods section). A detailed description of the field sampling design can be found in Main-Knorn et al. (2011).

Besides the forest inventory, we used satellite data, specifically a Landsat TM image and a digital elevation model (DEM – resampled to 30 m) from the Space Shuttle Radar Topography Mission (SRTM) (Slater et al. 2006). The Landsat TM image was acquired on the 9th September 2005 (path 189 and row 025), and the thermal band was excluded from the analysis. The image was ortho-corrected to Universal Transverse Mercator (UTM) coordinates (World Geodetic System (WGS) 1984) based on a semi-automatic image registration software using ground reference points gathered in the field (Hill and Mehl 2003). For radiometric correction, the TM image was calibrated using a modified 5S radiative transfer model (Tanré et al. 1990; Hill and Mehl 2003). Clouds and cloud shadows were digitized and masked.

3 Methods

LAI is defined as the one-sided green leaf area per unit ground area in deciduous canopies, or as the projected needleleaf area per unit ground area in conifer canopies (Watson 1947; Chen and Black 1992). We assessed the LAI values in each of the 105 stands. The LAI value per stand was derived by averaging 3 single measurements (digital hemispheric photographs), taken in the center of the plots (Figure A-1).

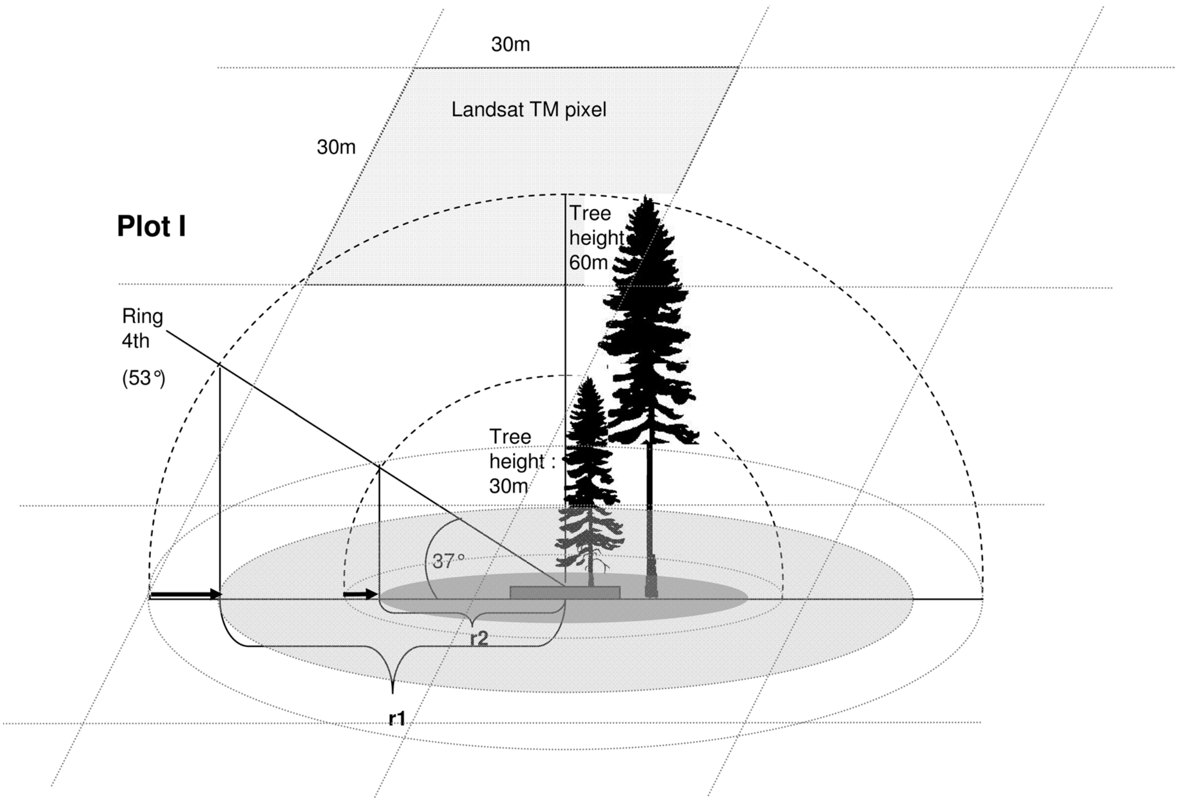

Figure A-1: Field data collection. 105 even-aged spruce plantation stands were randomly selected from SBI districts and re-sampled based on a simplified procedure of the Polish Forestry Service. Sample design for every selected stand was based on three plots. For every plot the following parameters were collected: diameter at the breast height, tree height, the number of trees per plot, as well as three hemispherical photos were taken. On the figure, the dependency of pixel-wise extracted LAI values with tree height were illustrated.

Single measurements varied between 0.51 and 3.96 LAI units and averaged LAI per polygon ranged from 0.66 to 2.69 LAI units. We used an Olympus C-8080 Wide Zoom camera with a Raynox DCR-CF 185PRO convertor to take photographs at 1 m above ground. The photographs were processed in the Hemisfer software package developed by The Swiss Federal Institute for Forest, Snow and Landscape Research (Schleppi et al. 2011) (Figure A-2). Thresholds for a binary mask separating sky and canopy pixels were calculated based on the method suggested by Nobis and Hunziker (2005). LAI was estimated from transmitted radiation after Miller (1967), resulting in LAI for hemisperical sky views of 7°, 23°, 38°, 53° and 68°. Finally, as suggested by Leblanc and Chen (2001), all but the widest angle for LAI modeling and prediction was applied, for different solar zenith angles and LAI values.

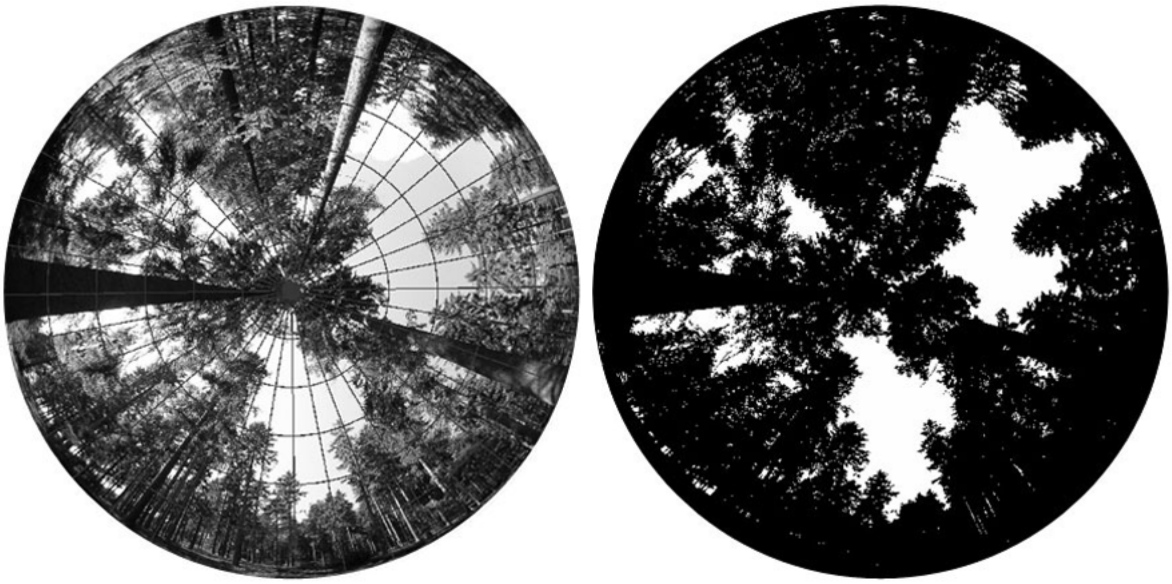

Figure A-2: Fish-eye photography (left) and binary sky-canopy mask (right).

Predictor datasets

We defined three groups of predictors: stand-based (inventory), pixel-based (satellite), and combined predictors. The inventory predictor set (INVE) consisted of volume of trees per hectare, canopy cover, stem density and relative density (as a dimensionless index), tree age, tree height, tree form factor, growing stock per tree and stump surface at 1.37 m height. The satellite predictor set (TMTO) was based on 6 Landsat TM bands (the visible, NIR and short-wave infrared (SWIR) wavelength regions), its derivates (Tasseled Cap [TC] brightness, greenness and wetness, Disturbance Index [DI] after Healey et al. (2005), and NDVI), as well as three topographic factors (elevation, slope and direct solar radiation extracted from the DEM). A third setup (ALL) combined all pixel- and stand-based information.

As the proportion of hemispherical sky-view depends on canopy height in the respective plots, LAI values measured in the field varied with different fields of view (Figure A-1). However, since LAI calculations yield a dimensionless index of leaf area in m^2 per m^2 of ground surface, the base area from which it is calculated does not influence LAI values. Nevertheless, because our goal was to predict LAI per pixel, we had to extract reflectance from the number of pixels that corresponds with the area covered by LAI measurements in the field. Reflectance values were therefore weighted depending on the respective pixel fraction. We applied this procedure to all pixel-based data derived for every plot and finally averaged results for each stand.

Modeling technique

Ensemble non-parametric algorithms have currently received considerable attention in ecological modeling applications (Prasad et al. 2006; Araújo and New 2007). One well established ensemble algorithms is Random Forests (RFs) (Breiman 2001). RF is a robust, non-parametric modeling technique employing the Classification and Regression Tree (CART) algorithm (Morgan and Sonquist 1963; Breiman et al. 1984) providing well-supported and readily interpreted output and predictions (Cutler et al. 2007). Ensemble models such as RF models consist of many independently trained regression trees, where for each tree, a bootstrap sample of the training data is chosen. The algorithm randomly samples a small set of explanatory variables at each node and chooses the best split from among them (Liaw and Wiener 2002). The regression tree grows until it reaches the largest possible size and is left un-pruned. The whole process is frequently repeated based on new bootstrap samples and the final prediction is a weighted plurality vote or the average from predicting all regression trees. Additionally, RF provides a hierarchical list of the relative predictive strength of multiple independent variables. RF requires no assumption of normality, simultaneously incorporates both categorical and continuous data, and produces easily interpretable results (Prasad et al. 2006; Francke et al. 2008; Casalegno et al. 2010).

Accuracy assessment

The prediction error was estimated based on a 10-fold cross-validation. Then, Pearson's correlations, the degree of determination for R-squared, and root mean squared errors (RMSE) between observed and predicted values were calculated. Further, model's prediction potentials were explored by plotting and comparing changes in density functions (distribution of observed and modeled LAI values) from models based on the three predictor sets (INVE, TMTO, and ALL).

4 Results

We compared the different model performances for calculating LAI with and without satellite-based data. We also evaluated the respective importance of individual predicting variables in each model.

Model performance

Our results suggest that TMTO models were the most predictive for LAI (Figure A-3, Table A-1). R^2 values for cross-validated LAI estimates ranged from 0.30 to 0.33 for the ALL and TMTO models, respectively (Table A-1), and were statistically significant ($P < 0.05$). The INVE model was the least predictive, with an R^2 of about 0.03, and was not significant ($P = 0.063$). Our model fits (Table A-2) had R^2 values as low as 0.04 for the INVE, but reached 0.31 for the ALL, and 0.34 for the TMTO models.

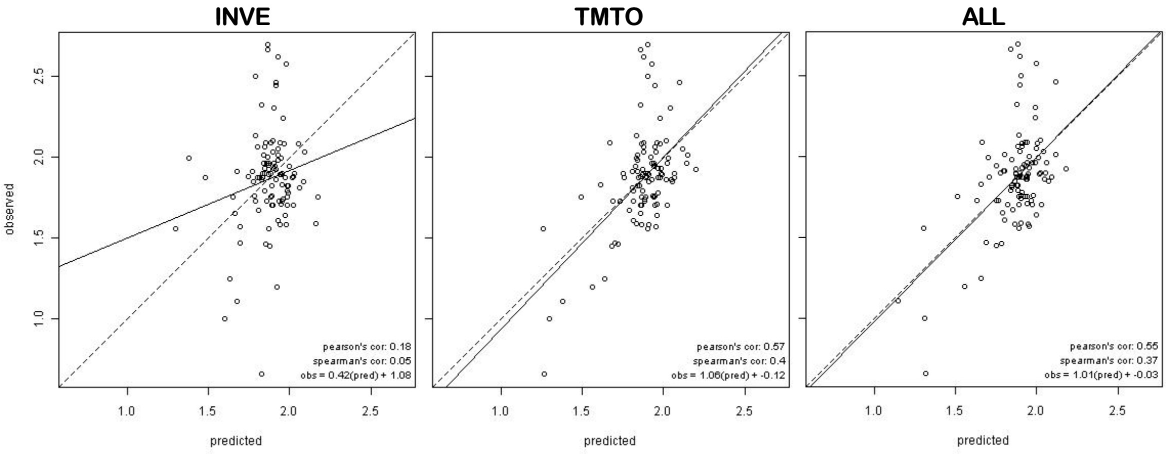

Figure A-3: Correlation coefficients for LAI prediction based on the INVE, TMTO, and ALL models.

Pearson’s correlation coefficients for LAI prediction ranged from 0.18 for the INVE model to 0.57 for the TMTO model (Figure A-3, Table A-1). Moreover, we observed the effect of model saturation with LAI, which effectively limited the predictive range for high LAI values. Comparing RMSE statistics, we obtained the lowest RMSE for the TMTO model with 0.25, followed by the ALL model with an error of 0.26, and the INVE model with an error of 0.31.

Table A-1: Cross-validated results for LAI models.

	Model		
	ALL	TMTO	INVE
Pearson's correlation	0.55	0.57	0.18
R-squared	0.30	0.33	0.03
p	1.04E-09	2.73E-10	0.06307
MSE	0.07	0.06	0.10
RMSE	0.26	0.25	0.31

Table A-2: Model fit for LAI estimates.

	Model		
	ALL	TMTO	INVE
Pearson's correlation	0.56	0.58	0.20
R-squared	0.31	0.34	0.04
p	7.54E-10	1.31E-10	0.04328

The model's density functions (Figure A-4) revealed partial over- and underestimates by all of the models, with the TMTO model having a better overall agreement between observed and predicted LAI values compared to the INVE and ALL models.

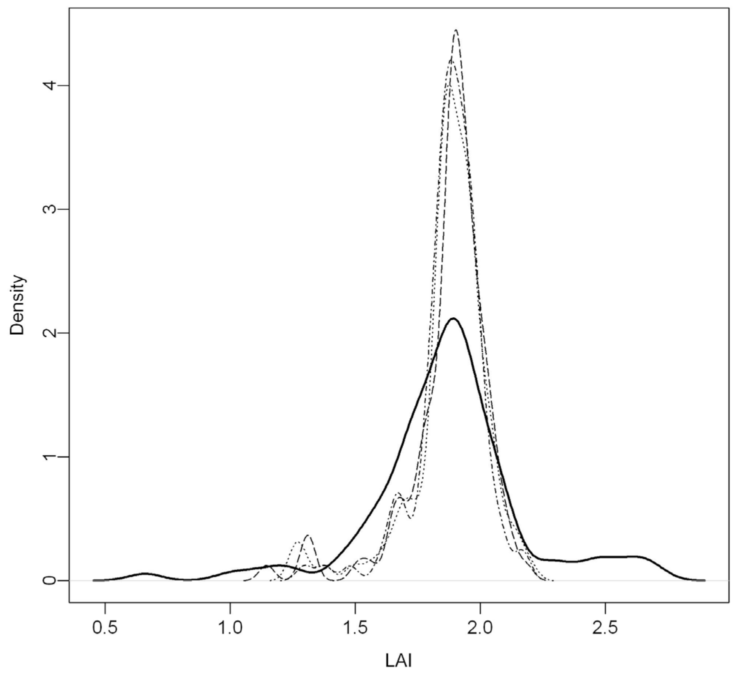

Figure A-4: Density functions of observed (solid line) and predicted values of LAI for different models: INVE (dot-dashed line), TMTO (dotted line), and ALL (long-dashed line).

Variable importance

Comparing the predictor's importance (Figure A-5, Table A-3), we observed that spectrally-based variables from Landsat data were dominant in the ALL model. Moreover, the two most important predictors – the visible red and green Landsat bands, respectively – were identically ranked in the TMTO model, with DI being identified as the third most important predictor. Random permutation of TM band 3 (visible red) increased the relative error by 12% for the ALL model and by 14% for the TMTO model. Permutation of remaining predictor variables resulted in %IncMSE by 8 to 10%. The strongest predictors of LAI in the INVE model (Figure A-5, Table A-3) were stem density and canopy cover. Permutation of those parameters decreased the model's predictive accuracy by 7-9%.

Table A-3: Relative importance of the predictors measured in increase of mean squared error [in %].

	Model		
Predictor	ALL	TMTO	INVE
B105c	7.43	6.78	
B205c	10.19	10.74	
B305c	11.85	13.17	
B405c	5.49	6.92	
B505c	5.12	6.03	
B605c	8.03	7.34	
TC105c	6.07	6.04	
TC205c	7.16	8.33	
TC305c	3.99	5.81	
DI05c	6.41	9.16	
Elevation	2.04	-0.33	
NDVI05c	6.91	8.85	
Hillshade	1.48	0.72	
Slope	0.47	2.73	
Age	6.56		5.39
Height	-0.12		5.55
dbh	2.76		3.22
ZW	1.12		7.68
V_HA	1.38		4.64
L_HA	2.55		8.75
F	0.03		2.80
G	2.01		4.04
V	1.74		3.60
ZD	3.69		6.84

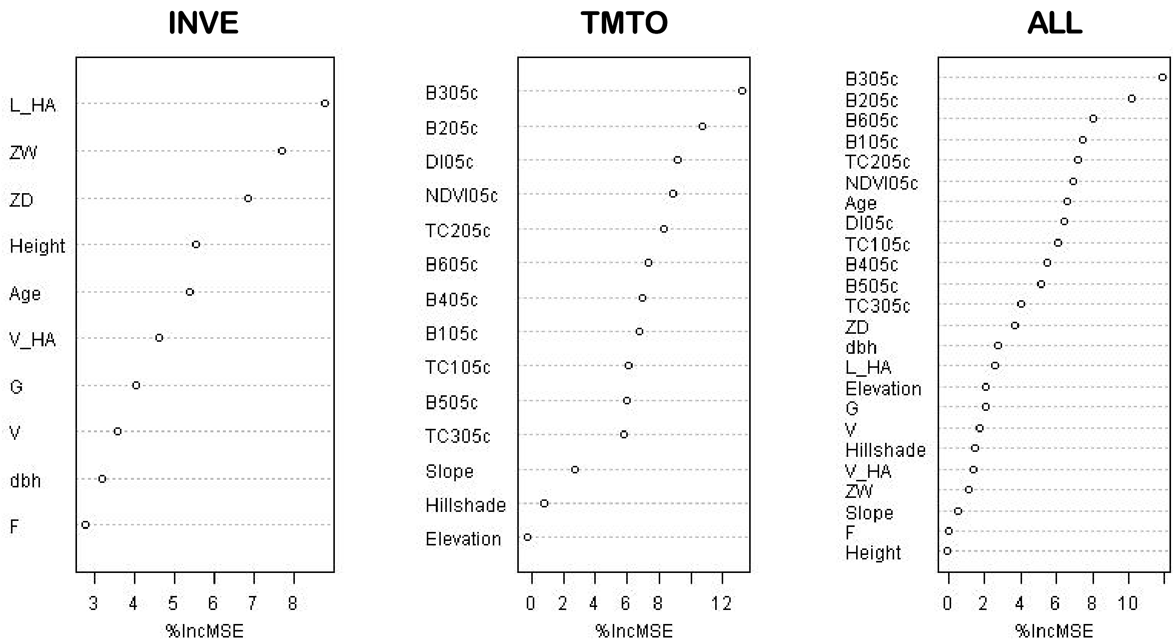

Figure A-1: Predictor's importance ranking for LAI prediction based on INVE, TMTO, and ALL models.

5 Discussion

The ability to assess forest productivity and its spatial dynamic using LAI as a proxy could enable more accurate evaluations of the role of forests in the local to regional carbon balance. Although field inventories yield high quality and accuracy, they are spatially and temporally constrained, and thus do not fulfill the requirements of continuous forest monitoring. Therefore, remote sensing approaches could provide an alternative solution.

Our results show that LAI values measured for multiple spruce plantations in the Western Carpathians covered only a narrow range compared to LAI values for spruce stands reported by other authors (Nilson et al. 1999; Lucas et al. 2000; Asner et al. 2003). This phenomenon can be explained by: (1) even-aged stand types (typically simple one-story condition), and (2) poor health conditions of spruce plantations in the Western Carpathians. The latter is evidenced by reduced tree vigor, decline and mortality, and thus low live crown ratio and foliar area. Similarly narrow LAI ranges are reported by Chen et al. (2002) for fire-devastated conifer forests in Radisson, Canada. Hence, we assume that the applicability of our approach would be limited to forest stands with relatively low forest vigor, as well as simple forest structure, such as even-aged forests.

Our measurements within "homogenous" inventory plots varied by up to 3.96 LAI units in extreme cases. This is a result most likely due to highly variable tree vigor/crown density. Sample densities in standard forest inventory procedures of the Polish Forest Service – which we adopted for reasons of comparability – may therefore not be sufficient to describe such variable stand conditions, and reported mean values are not necessarily representative.

TMTO-based estimates cover only about one-third of the observed LAI values in our study area. There are three possible explanations for this phenomenon. First, we might not have had enough reference samples in the higher LAI range. Second, the algorithm might introduce a tendency to predict towards the mean of the reference data, which would be in line with results by Blackard et al. (2008) and Reese et al. (2002). Third, the reference LAI measurements were conducted under varying weather conditions. While we carefully screened our field data and eliminated the potentially compromising measurements of which we were aware, we cannot completely rule out that our dataset included inaccurate LAI measurements. The importance of a large reference sample for capturing the whole LAI range as well as the role of data proofing cannot be disregarded. The latter is particularly important for filtering inaccurate readings related to variable weather conditions.

Spectral ranges between 0.63µm and 0.69µm (visible red), as well as 0.52µm and 0.60µm (visible green), were best related to LAI. This is similar to findings by Nilson et al. (1999) and Eklundh et al. (2001). In contrast to other authors (Fang and Liang 2003; Stenberg et al. 2004), the inclusion of the SWIR band (1.55-1.75µm) – known to be sensitive to understory effect – did not substantially improved our LAI estimates. However, SWIR predictive strength could have been stronger if more reference samples by open canopy condition and understory vegetation would have been gathered. Neither the INVE, nor the ALL models improved the accuracy of LAI estimates. We therefore believe that polygon-wise average SBI data is not representative for very local canopy measurements such as LAI.

While the evaluation of different models' predictive power was facilitated by the availability of reference data and a homogeneous forest structure, few uncertainties remain. First, explanatory variables from SBI and Landsat data, as well as reference LAI data might not perfectly match each other due to temporal differences. Generally, SBI data are collected in 10-year intervals independently for every forest district. For three districts in our study area, the latest SBI data updates were available for 2003, 2004 and 2007, respectively. Thus, some discrepancies might have occurred. One acute example concerns the extent of wind-throw after the high intensity storms in November 2004 and following sanitary cutting in 2005 and 2006. Landsat imagery from early September 2005 might also not reflect the total extent of these sanitary measures. Finally, time discrepancies between SBI, Landsat and field-based LAI estimates (2006, 2007) might not reflect exactly the same forest condition.

Second, the model tends to slightly overestimate lower and underestimate higher LAI values. Similar tendency has also been observed in other studies, for instance where regression tree techniques (Blackard et al., 2008) or k-Nearest Neighbor (kNN) algorithms (Reese et al., 2002) were applied. The bias of high LAI values is likely due to the limited sensitivity of Landsat data (as a passive sensor) to reproduce the canopy structure in dense forests. Here LAI can lead to saturated measurements. Few studies reported the tendency of spectral-based models to saturate already by moderately high LAI of ~3 (Turner et al. 1999). One potential method to overcome the saturation effect could consider including texture measures as additional model variable (Wulder et al. 1998), as these measures include information about structural attributes of forest stands.

Further, we presume that the tendency of our model to bias lower LAI estimates is related to the confounding effect of understory in sparse forests. The more open the canopy, the stronger the influence of understory vegetation on remotely-based LAI predictions (Rautiainen 2005; Eriksson et al. 2006). Consequently, we recommend including information that describes local canopy closure and defoliation (here texture measure could provide important insights), as well as information on understory structure to aid further modeling development.

Summarizing, the inventory-based approach failed in terms of highly accurate prediction of coniferous LAI. In contrast, the solely satellite-based approach performed the most accurate LAI estimates and has obvious advantages for determining their spatial variability. Moreover, results suggest that spectral and topography data combined with stand-inventory did not improved LAI estimates. Our findings demonstrated that stand level inventories are not representative for very local canopy measurements and average the variability within stands. They therefore cannot compliment remote sensing LAI models. We believe that texture measures could improve the predictive strength of our satellite-based model towards high-resolution LAI mapping at the local to regional scale, suggesting further investigations with additional texture variables.

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Appendix B:
Analyzing the relationship between forest biomass loss in respect to topographic factors and forest stand age

1 Introduction

This supplementary material provides additional information to Chapter IV and describes the relationship among biomass loss (abrupt and gradual) identified for the Western Carpathians and site characteristics (topographic factors and averaged forest stand age).

2 Data and methods

This analysis is based on the coniferous forest map (spruce-dominated stands) and the maps of abrupt and gradual biomass decrease, from Chapter IV of this thesis. Both biomass loss maps are characterized by onset year, magnitude and duration of the change, which were used for the further analysis. The averaged tree age map at the inventory stand level was provided by the Polish State Forest Holding. The topographical factors were calculated from the resampled 30 m digital elevation model (Chapter IV).

The magnitude of biomass loss was defined as “severe”, “moderate” and “low” when the relative magnitude of biomass change was above 75%, 50-75%, and below 50%, respectively. Duration of gradual biomass loss was divided into four classes: ≤10 years, 11-15 years, 16-20 years, and above 20 years. The area and the magnitude of abrupt and gradual biomass decrease were summarized for six elevation zones (≤400 m, 401-600 m, 601-800 m, 801- 1000 m, 1001-1200 m, and >1200 m), seven slope zones (≤5°, 6-10°, 11-15°, 16-20°, 21-25°, 26-30°, and >30°), as well as eight 45° facing slope zones (N, NE, E, SE, S, SW, W, and NW). Finally, the area of abrupt changes and forest inventory stand age were compared.

3 Results

Generally, coniferous forest in the study region mostly covers the lower montane zone (~400 m to 1200 m), with the highest forested fraction between 601 m and 800 m. This elevation zone experienced remarkable abrupt and gradual biomass losses (Figure B-1a). However, when comparing the area of abrupt and gradual biomass loss at the altitude between 401-600 m, 601-800 m and 801-1200 m, gradual decrease entailed ~72%, ~65%, and 50% more area than abrupt changes, respectively.

Regarding the magnitude of biomass loss, areas of abrupt changes experienced higher relative magnitudes along entire elevation gradients than areas of gradual changes (Figure B-1b). While the fraction of low gradual biomass decrease was clearly predominant over all elevation zones, the fraction of severe gradual loss increased from 22% (≤400 m) to 57% (up to 1200 m) (Figure B-1b).

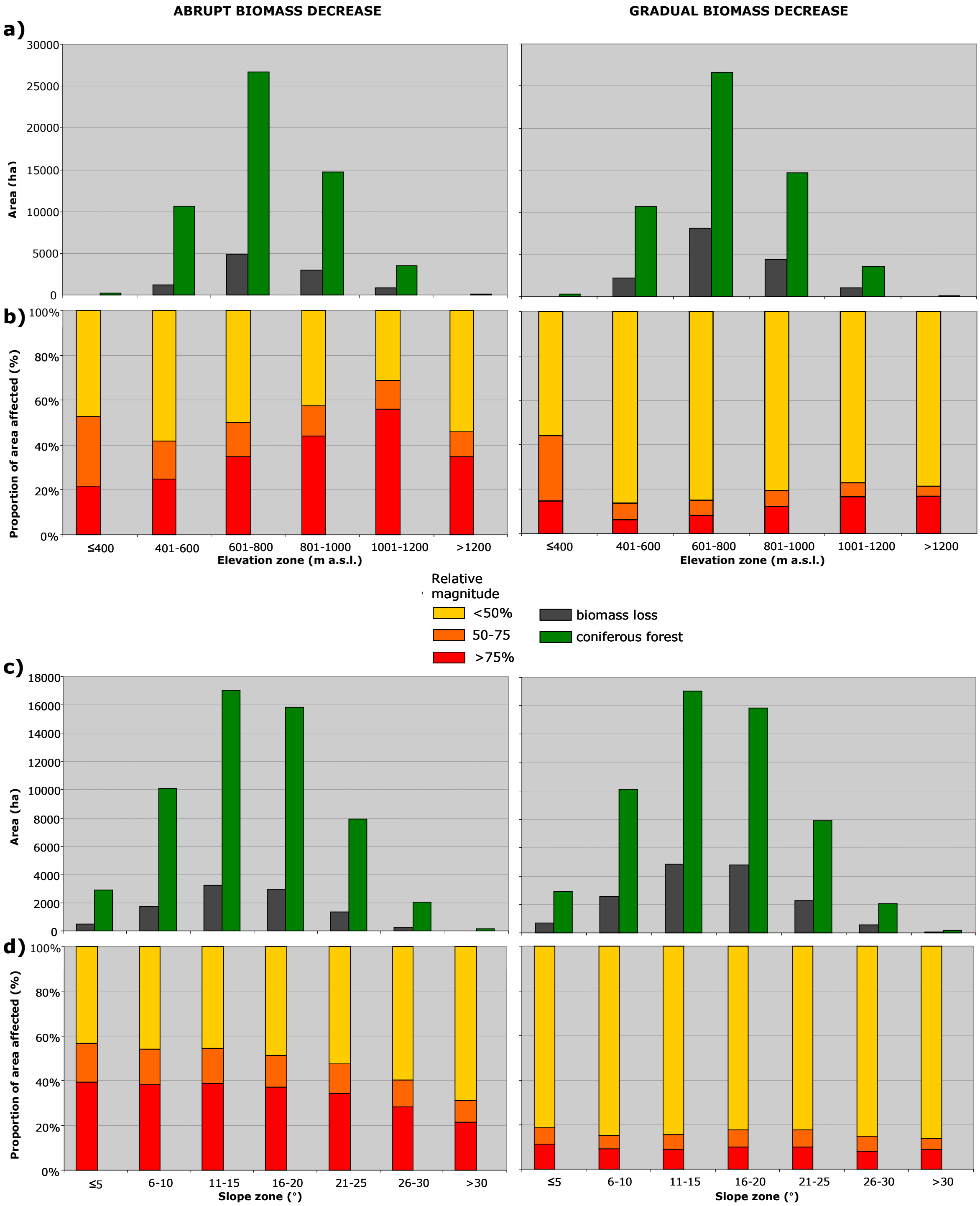

Figure B-1: Distribution of coniferous forest fraction, abrupt and gradual biomass decrease (a) and corresponding relative magnitude of severe, moderate and low biomass loss by elevation zones (b); coniferous forest fractions, abrupt and gradual biomass decrease (c) and corresponding relative magnitude of severe, moderate and low biomass loss by slope zones (d).

Slope zones between 11° and 20° comprise most of the coniferous forests in the study site and have been predominantly affected by biomass loss (Figure B-1c). Similarly, biomass losses due to gradual change affected more forested area than due to abrupt changes. This difference in biomass loss increased from 38% for up to 5° slope to ~200% of biomass loss in the 26°-30° slope zone. While the area affected by severe and moderate abrupt changes decreased from ~57% to 30% with increasing slope zone, gradual changes maintained a stable rate for all magnitude classes and slope zones (Figure B-1d).

Overall, areas with south, southwestern, and southeastern facing slopes showed higher fraction of abrupt biomass loss than gradual loss (Figure B-2a). However, independent of the pace of change, similar southern facing slopes (S, SW and SE) were disproportionally more affected by severe biomass loss than by changes of moderate or low magnitude (Figure B-2b). Regarding the averaged tree age, more than half of the forested area consists of stands between 71 and 110 years (Figure B-3). Disturbances were clearly predominant in the spruce averaged stand age between 91 and 120 years.

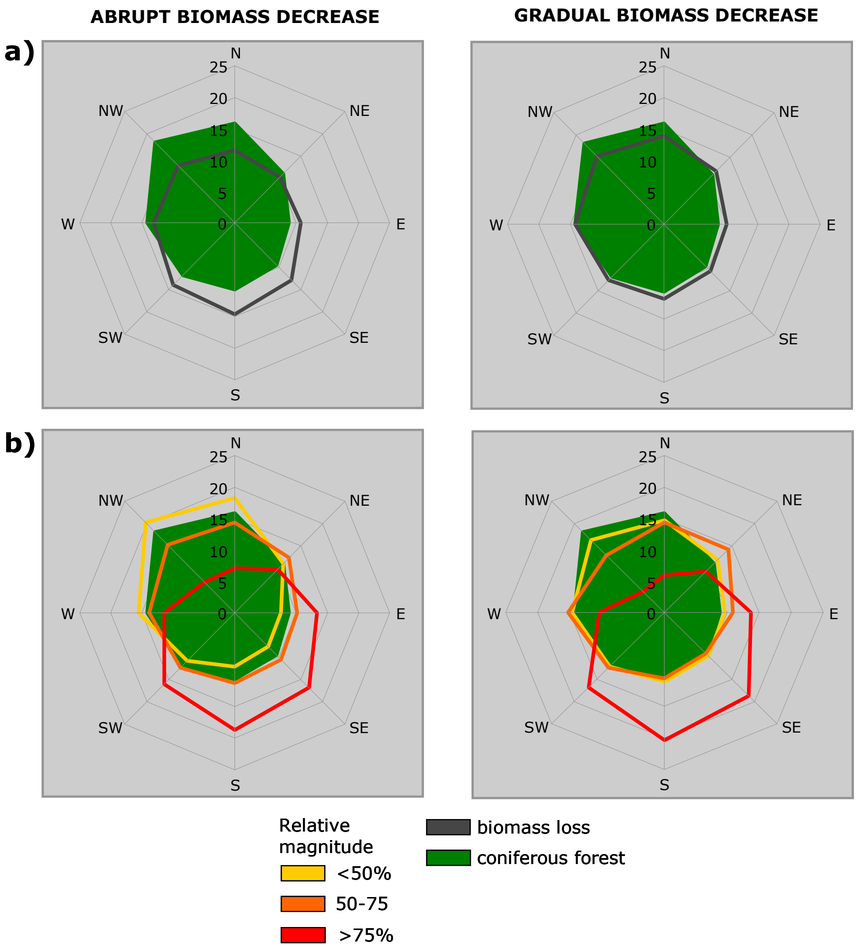

Figure B-2: Distribution of coniferous forest fraction, abrupt and gradual biomass decrease (a) and corresponding relative magnitude of severe, moderate and low biomass loss by facing slope (b).

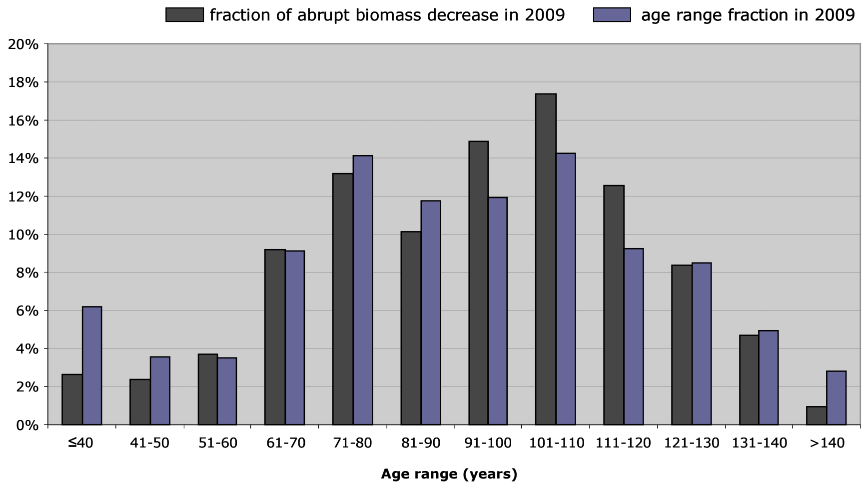

Figure B-3: Fractions of abrupt biomass loss versus averaged stand age (status 2009).

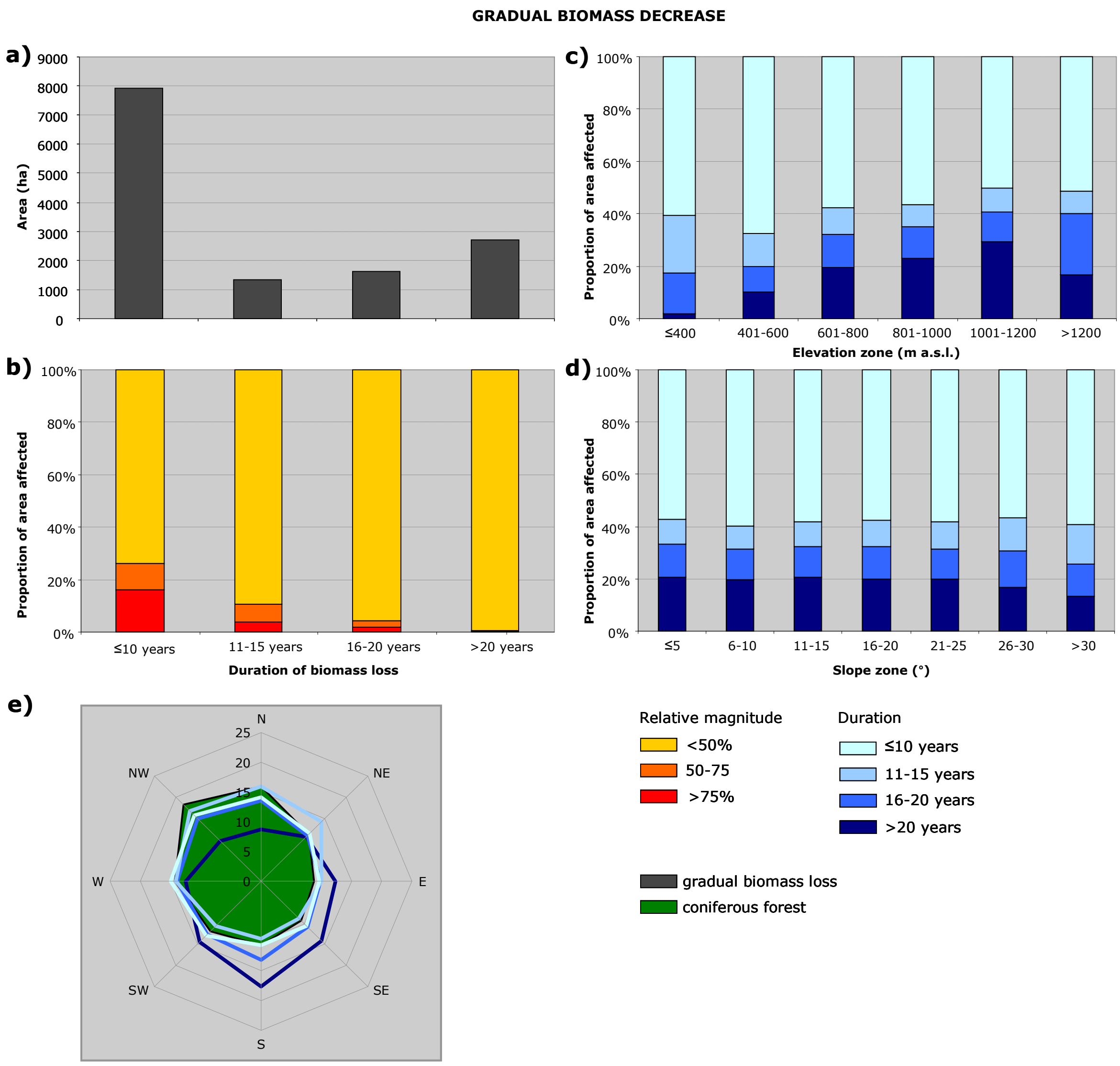

Figure B-4: Area of gradual biomass decrease (a) and corresponding relative magnitude of severe, moderate and low biomass loss in relation to duration of change (b); duration of gradual biomass decrease by elevation zone (c) and by slope zone (d); coniferous forest fractions, and duration of gradual biomass decrease by facing slope (e).

In majority, gradual biomass decrease lasted up to 10 years, and such a process affected almost 8000 ha of coniferous forests (Figure B-4a). However, the long-term biomass loss (above 20 years) was the second most important, occurring on ~2800 ha. Moreover, the longer the duration of biomass loss, the lower the fraction of moderate and severe changes, decreasing from 27% to 1% of the affected area (Figure B-4b). Results also show that forest at altitudinal gradients between 801 m and 1200 m was exposed to long-term changes in greater extent than stands at other elevations (Figure B-4c).

In terms of the duration of change, proportions of areas experiencing gradual biomass decrease up to 20 years stayed constant for all slopes, except for the highest slope zones (>30°) (Figure B-4d). In contrast, the area affected by long-term changes showed decreasing tendency with increasing slope gradient, from 20% in flat areas (≤5°) to 12% for a steep gradient (>30%) (Figure B-4d). Also, similarly to the distribution of severe biomass loss, areas with south, southwestern, and southeastern facing slopes were particularly exposed to long-term changes (Figure B-4e).

4 Discussion

This supplementary analysis investigated biomass distribution and its loss in relation to topographic factors and dominant stand age. Generally, results indicate more chronic and long-term than acute biomass losses in the study area, which is in line with other studies (Hlásny et al. 2010). Abrupt and severe biomass loss has most likely been caused by either windstorm or intensive harvesting. The rates of biomass loss were the lowest for slope gradients higher than 30° and increased with decreasing slope steepness. Also the elevation gradients above 1200 m were less affected by severe changes than lower altitudes. This can partly be explained by the harvest regulations of the State Forests Holding, prescribing no timber harvesting in the upper forest zone (above 900 m) and on the steepest slopes (Koziol 2007). The highest fraction of moderate to severe abrupt changes occurred between 1001 and 1200 m, and was apparently caused by windstorm events and salvage logging related to pests.

Long-term biomass gradual changes could be associated with selective logging, degradation of spruce stands caused by bark beetle outbreaks, and fungal pathogens activity. Concerning the duration and magnitude of gradual biomass losses, the most severe changes lasted up to ten years. This temporal aspect of gradual biomass loss was precisely described in Chapter IV. The share of long-term changes increased with altitude (except elevation zone ≤400 m), and decreased with slope. The highest rate of long-term severe biomass loss has been observed for spruce stands located either below 400 m or above 1001 m. Downhill elevations were predominantly affected by bark beetle and fungal activity, and hence led to increasing sanitary cuttings since 2003 (Grodzki 2007). In contrast, the areas at the highest altitudes were strongly exposed to long-term depositions of sulphur during communist times, causing direct forest mortality or degradation of stand vitality (Hadaš 2008).

Comparing abrupt and gradual biomass loss, significant similarities and differences were revealed. Generally, abrupt changes followed similar distribution patterns for gradual biomass loss, while the latter affected more area at every altitude and slope zone than abrupt changes. The distribution of relative magnitude of biomass losses (low, moderate, and severe loss) by elevation and slope zones underlined further spatial dissimilarities. In contrast, similar patterns of disturbances and gradual changes occurred on south, southwestern, and southeastern facing slopes, where severe abrupt and long-term biomass losses were dominant. On the one hand, forests on SW and S slopes were particularly affected by air pollution from the Orava industrial region, what caused lower resistance of spruce to pest and diseases (Šrámek et al. 2010). On the other hand, sun-exposed slopes and sites have been proven to be especially susceptible to bark beetle outbreaks (Jakuš 1995; Grodzki et al. 2006). The synergistic effect of low spruce resistance and optimal topographic conditions for bark beetle was amplified by wind damage, forest edge effects, and human management (salvage logging). Prevailing western and southern winds caused wind-throw or snowbreak (Barszcz and Małek 2008), resulting in damaged trees and open forest edges. Both wind-throw and windbreak, as well as originated forest edges were predisposed to elevated bark beetle activity (Jakuš et al. 2011).

Finally, results show that particularly older spruce stands were affected by abrupt changes. Partially, this can be explained by a preference of bark beetle to infest older trees with larger diameter (Akkuzu et al. 2009; Jakuš et al. 2011). Additionally, these results are in line with the official rotation time, which is fixed between 90 years and 120 years, depending on the forest district (Koziol 2007). Summarizing, the topographical and age-related characteristics of biomass loss provide important insights into the general knowledge about forest decline in the Western Carpathians. These findings could support the local decision making towards a more sustainable forest management in terms of counteracting and preventing forests from pests.

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Publikationen

PEER-REVIEWED ARTICLES

Main-Knorn, M., Moisen, G., Healey, S., Keeton, W. S., Freeman, E., & Hostert, P. (2011). Evaluating the remote sensing and inventory-based estimation of biomass in the Western Carpathians. *Remote Sensing, 3*, 1427-1446.

Keeton, W.S., Chernyavskyy, M., Gratzer, G., Main-Knorn, M., Shpylchak, M., & Bihun, Y., (2010). Structural characteristics and aboveground biomass of old-growth spruce-fir stands in the eastern Carpathian Mountains, Ukraine. *Plant Biosystems 144*, 148-159.

Main-Knorn, M., Hostert, P., Kozak, J., & Kuemmerle, T. (2009). How pollution legacies and land use histories shape post-communist forest cover trends in the Western Carpathians. *Forest Ecology and Management, 258*, 60-70.

CONFERENCE PROCEEDINGS

Main, M., & Hostert, P. (2006). Forest decline in the Western Carpathians. *In: Braun, M. (ed): Proceedings of the Second EARSeL SIG Land-Use & Land-Cover Workshop,* Bonn, Germany.

CONFERENCE PRESENTATIONS

Main-Knorn, M., Cohen, W. B., Kennedy, R. E., Grodzki, W., Pflugmacher, D., Griffiths, P., & Hostert, P. (2012). Estimation of coniferous forest biomass change using a Landsat trajectory-based approach. *Forum Carpaticum 2012*, Stará Lesná, Slovakia. Oral presentation.

Main-Knorn, M., Moisen, G., Healey, S., & Hostert, P. (2010). Modelling aboveground forest biomass in the Western Carpathians. *Forum Carpaticum 2010,* Kraków, Poland. Oral presentation.

Main-Knorn, M., & Hostert, P. (2009). Forest cover trends and their legacies in the Western Carpathians. *Third EARSeL SIG Land-Use & Land-Cover Workshop*, Bonn, Germany. Poster presentation.

Main-Knorn, M., & Hostert, P. (2009). Analiza zmian w obrębie powierzchni leśnych Karpat Zachodnich w latach 1987-2005 [Analysis of forest cover change between 1987 and 2005 in the Western Carpathians]. *Ogólnopolskie Sympozjum Geoinformacyjne*. Kraków, Poland. Oral presentation.

van der Linden, S., Kuemmerle, T., Knorn, J., Main, M., Müller, D., & Hostert, P. (2008). Post-socialist land use change in the Carpathians - a remote sensing perspective. *Science for the Carpathians: S4C - Strategy Development and Networking Workshop*. Kraków, Poland. Oral presentation.

Kuemmerle, T., Knorn, J., Main, M., Müller, M., van der Linden, S., & Hostert, P. (2008). Mapping post-socialist farmland abandonment and forest cover change in the Carpathian ecoregion. *Second EURAC Workshop on Applied Remote Sensing in Mountain Regions*. Bolzano, Italy. Oral presentation.

Main, M., Hostert, P., & Kuemmerle, T. (2007). Multi-temporal analysis of forest cover change in the Western Carpathians. *MultiTemp2007*. Leuven, Belgium. Poster presentation.

Hostert, P., Kuemmerle, T., & Main, M. (2007). Post-socialist forest disturbance in the Polish Carpathians. *FORESTSAT 2007 Conference*. Montpellier, France. Oral presentation.

Gawor, Ł., & Main, M. (2007). Ausgewählte Umweltprobleme in Ruhrgebiet und Oberschlesischen Kohlenbezirk (GZW) auf dem Beispiel von Bergehalden [Chosen environmental problems in Ruhr District and Upper Silesian Coal Basin exemplified on mining waste heaps]. *16. Tagung für Ingenieurgeologie und Forum „Junge Ingenieurgeologen“*. Bochum, Germany. Oral presentation.

Eidesstattliche Erklärung

Hiermit erkläre ich, die vorliegende Dissertation selbstständig und ohne Verwendung unerlaubter Hilfe angefertigt zu haben. Die aus fremden Quellen direkt oder indirekt übernommenen Inhalte sind als solche kenntlich gemacht. Die Dissertation wird erstmalig und nur an der Humboldt-Universität zu Berlin eingereicht. Weiterhin erkläre ich, nicht bereits einen Doktortitel im Fach Geographie zu besitzen. Die dem Verfahren zu Grunde liegende Promotionsordnung ist mir bekannt.

Magdalena Main- Knorn

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