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Forest disturbances, forest recovery, and changes in forest types across the Carpathian ecoregion from 1985 to 2010 based on Landsat image composites

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In this paper, a long time series of Landsat image composites at five year intervals is used to study the dynamics of forest disturbance, recovery and changes in forest types across the Carpathian ecoregion. Please make sure to read the paper thoroughly and focus on the following broad questions:

What is the motivation for this article?
What is the key method used in the study?
What are the uncertainties related to the findings?

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ABSTRACT

Detailed knowledge of forest cover dynamics is crucial for many applications from resource management to ecosystem service assessments. Landsat data provides the necessary spatial, temporal and spectral detail to map and analyze forest cover and forest change processes. With the opening of the Landsat archive, new opportunities arise to monitor forest dynamics on regional to continental scales. In this study we analyzed changes in forest types, forest disturbances, and forest recovery for the Carpathian ecoregion in Eastern Europe. We generated a series of image composites at five year intervals between 1985 and 2010 and utilized a hybrid analysis strategy consisting of radiometric change classification, post-classification comparison and continuous index- and segment-based post-disturbance recovery assessment. For validation of the disturbance map we used a point-based accuracy assessment, and assessed the accuracy of our forest type maps using forest inventory data and statistically sampled ground truth data for 2010. Our Carpathian-wide disturbance map achieved an overall accuracy of 86% and the forest type maps up to 73% accuracy. While our results suggested a small net forest increase in the Carpathians, almost 20% of the forests experienced stand-replacing disturbances over the past 25 years. Forest recovery seemed to only partly counterbalance the widespread natural disturbances and clear-cutting activities. Disturbances were most widespread during the late 1980s and early 1990s, but some areas also exhibited extensive forest disturbances after 2000, especially in the Polish, Czech and Romanian Carpathians. Considerable shifts in forest composition occurred in the Carpathians, with disturbances increasingly affecting coniferous forests, and a relative decrease in coniferous and mixed forests. Both aspects are likely connected to an increased vulnerability of spruce plantations to pests and pathogens in the Carpathians. Overall, our results exemplify the highly dynamic nature of forest cover during times of socio-economic and institutional change, and highlight the value of the Landsat archive for monitoring these dynamics.

1. Introduction

Globally, forests provide important resources and ecosystem services that are essential for human well-being, including timber and non-timber forest product provision, watershed protection, habitat for biodiversity, and recreational amenities (GLP, 2005; Millennium Ecosystem Assessment, M.A, 2005). Similarly, the role of forests for climate regulation, carbon sequestration, and surface radiation modulation is of global importance (IPCC, 2000). However, forest resources and related ecosystem services depend on forest type and composition as well as on forest condition and management (e.g. rotation interval, mechanization, fertilizer use, plantation schemes), making it paramount to monitor forests repeatedly and consistently across larger areas and with high spatial detail.

Remote sensing has long been instrumental for mapping and monitoring forest cover changes and it was satellite imagery that highlighted widespread deforestation in the world's tropical regions (Pfaff, 1999; Skole & Tucker, 1993). In contrast though, forest area is increasing in many developed nations due to combined effects of advances in agricultural productivity and increasing awareness regarding the environmental importance of forests (Lambin & Meyfroidt, 2010; Meyfroidt & Lambin, 2011). However, information on forests and forest cover changes are not always publicly accessible and we still lack comprehensive knowledge of spatio-temporally explicit forest cover dynamics,

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especially across large areas and with sufficient spatial detail to resolve the full range of forest change processes.

Knowing forest area alone does not suffice. In many regions, natural primary forest is or has been converted to plantations and secondary forests. While the total forest area may remain stable or even increase, such forest types often do not provide the ecological services provided by natural forests (FAO, 2005). Last but not least, the disturbance regime is crucial for ecological functioning, with related spatial disturbance patterns and frequencies being equally important to understand if natural disturbance regimes persist or have been replaced by forest harvesting.

Remote sensing has established itself as the key technology for forest mapping and monitoring at different spatial and temporal scales. Sensor systems such as the Moderate Resolution Imaging Spectrometer (MODIS) enable global forest monitoring and can be used to map broad-scale changes in temperate forests (Potapov, Hansen, Stehman, Pittman, & Turubanova, 2009), but are limited in their ability to provide detailed information on forest composition changes or fine-scale forest change processes. Data from the Landsat sensors, on the other hand, provide spatial and spectral detail that allows capturing forest attributes at adequate scales, while featuring archived data back to the early 1970s. When working over larger geographical extents (i.e., ecoregions, biomes or continents) at 30 m spatial resolution, however, Landsat data analysis poses numerous challenges. The sensor-specific field-of-view and the resulting scene coverage, coupled with frequent cloud cover and phenological effects due to the timing of image acquisitions, require specific conceptual frameworks to allow for adequate mapping and monitoring over larger areas. The opening of the USGS Landsat archive in 2008 sparked many new algorithms in this respect. Continental or even global Landsat data analyses are now feasible as advanced and automated preprocessing methods as well as improved processing and data storage capabilities allow for mass processing of imagery (Townshend et al., 2012; Wulder, Masek, Cohen, Loveland, & Woodcock, 2012).

One approach to better exploit the wealth of Landsat images with partial cloud cover is pixel-based compositing methods, which combine several images into one cloud-free composite (Potapov, Turubanova, & Hansen, 2011; Roy et al., 2010). Compositing algorithms were initially developed for wide-swath sensor data, where observations are very frequent, but no image is ever completely cloud-free, and reducing cloud contamination and other atmospheric effects is therefore essential (Cihlar, Manak, & Diorio, 1994; Holben, 1986). For Landsat data, compositing offers comparable advantages, though. By selecting the best observation on a per-pixel basis, cloudy imagery (typically discarded within scene-based approaches) can be exploited for high quality observations and the 16-day repeat cycle can be overcome through utilization of the across track overlap between adjacent image acquisition paths, which is considerable at higher latitudes. A single, “global” classification/regression model can be trained and applied if composites have sufficient seasonal and radiometric consistency, making large area mapping and monitoring approaches with Landsat more practicable.

Initial attempts to composite Landsat data were made during the generation of the Global Land Survey 2005 dataset (Gutman et al., 2008). Compositing was then used to fill data gaps in ETM+ imagery due to the failure of the scan line corrector since May 2003 (Arvidson, Goward, Gasch, & Williams, 2006). Compositing has also been implemented to allow broad-scale deforestation mapping. Hansen et al. (2008), for example, produced two regional Landsat composites for change detection in the Congo basin and incorporated the MODIS Vegetation Continuous Field product (Hansen et al., 2003) for training of the classifiers. Potapov et al. (2011) studied boreal forest changes between 2000 and 2005 in European Russia using composited Landsat data and achieved high agreement with independently derived samples of forest change. Both studies demonstrated the ability of Landsat imagery for wall-to-wall mapping and regional monitoring of forest cover changes. Thus, Landsat image compositing has so far greatly advanced regional forest mapping and monitoring with a focus on reporting changes in forest extents. It is therefore desirable to advance remote sensing based methods towards analyzing spatio-temporal patterns of forest types, disturbance and recovery regimes across large areas. Also, more applications in diverse forested regions of the world are necessary to advance compositing and related algorithms, and to better assess their potential and limitations.

In this study, we utilize a series of large-area composites to map forest disturbances, forest recovery, and changes in forest types in a temperate forest region, the Carpathian ecoregion in Eastern Europe. The forests in the Carpathian Mountains represent Europe's largest temperate forest ecosystem and are of exceptional ecological value, providing resources and ecological services to a region much larger than the Carpathians themselves. Carpathian forests have been exploited and managed for centuries, leading to the widespread conversion of natural forests (i.e., beech-dominated, deciduous and mixed forests) to monoculture plantations of Norway spruce (Keeton & Crow, 2009; UNEP, 2007). These spruce plantations are highly susceptible to pest outbreaks and storm damages, and during the last decades forest managers are increasingly converting them to more natural forest types (Keeton & Crow, 2009). The remaining semi-natural and old-growth forests, on the other hand, are threatened by the major socio-economic restructuring processes that occurred with the transition from state-led to market-oriented economy after the collapse of Eastern European socialism (Hostert et al., 2011; Knorn, Kuemmerle, Radeloff, Szabo, et al., 2012; Kuemmerle, Chaskovskyy, et al., 2009; Kuemmerle, Kozak, Radeloff, & Hostert, 2009). This highlights the importance to analyze forest dynamics across the entire Carpathians.

Accordingly, our goal here was to map forest disturbances and change in forest types across the Carpathian region from 1985 to 2010 using Landsat satellite images, applying automated image preprocessing and compositing as well as a hybrid change detection approach. Our specific research questions were:

- How were broad forest types distributed in the Carpathians at the end of the socialist period and how did this distribution change over time?
- What were the rates and spatial and temporal patterns of forest disturbances since 1985?
- What were the spatio-temporal patterns of post-disturbance forest recovery?

The results of this study are publicly available (see http://www.hu-geomatics.de).

2. Methods

2.1. Study area

We studied the Carpathian mountain range in Central Eastern Europe. The study region boundaries were based on the Carpathian Ecoregion Initiative (CERI) boundaries (CERI, 2001) and were extended to include adjacent administrative units in their entirety (Nomenclature of Territorial Units for Statistics (NUTS) level three, and oblasts in the case of Ukraine). The study region covered 390,000 km^2 including parts of the Czech Republic, Austria, Poland, Hungary, Ukraine, Romania and all of Slovakia (Fig. 1). The total population of the Carpathian ecoregion is around 17 million (CERI, 2001). The Carpathians extend in a curve shaped arc over a length of about 1500 km at a maximal width of 350 km. Elevations reach 2600 m in the Tatra Mountains in Poland and Slovakia, and 2500 m in the FăgăraŞ Mountains in Romania. The region is characterized by a temperate continental climate. Precipitation ranges from 400 mm in the southeastern parts to over 2000 mm at the highest elevations (Ptacek, Letal, Ruffini, & Renner, 2009). Annual average temperatures vary with elevation and are about 2 °C around mid-elevations (UNEP, 2007).

Forests cover between 50% and 60% of the Carpathian ecoregion and approximately 30% of the region is used for agriculture (Ruffini, Hoffmann, Streifeneder, & Renner, 2008). The most common tree species are European beech (Fagus sylvatica), Norway spruce (*Picea abies*) and silver fir (*Abies alba*). Natural forest types follow a vertical

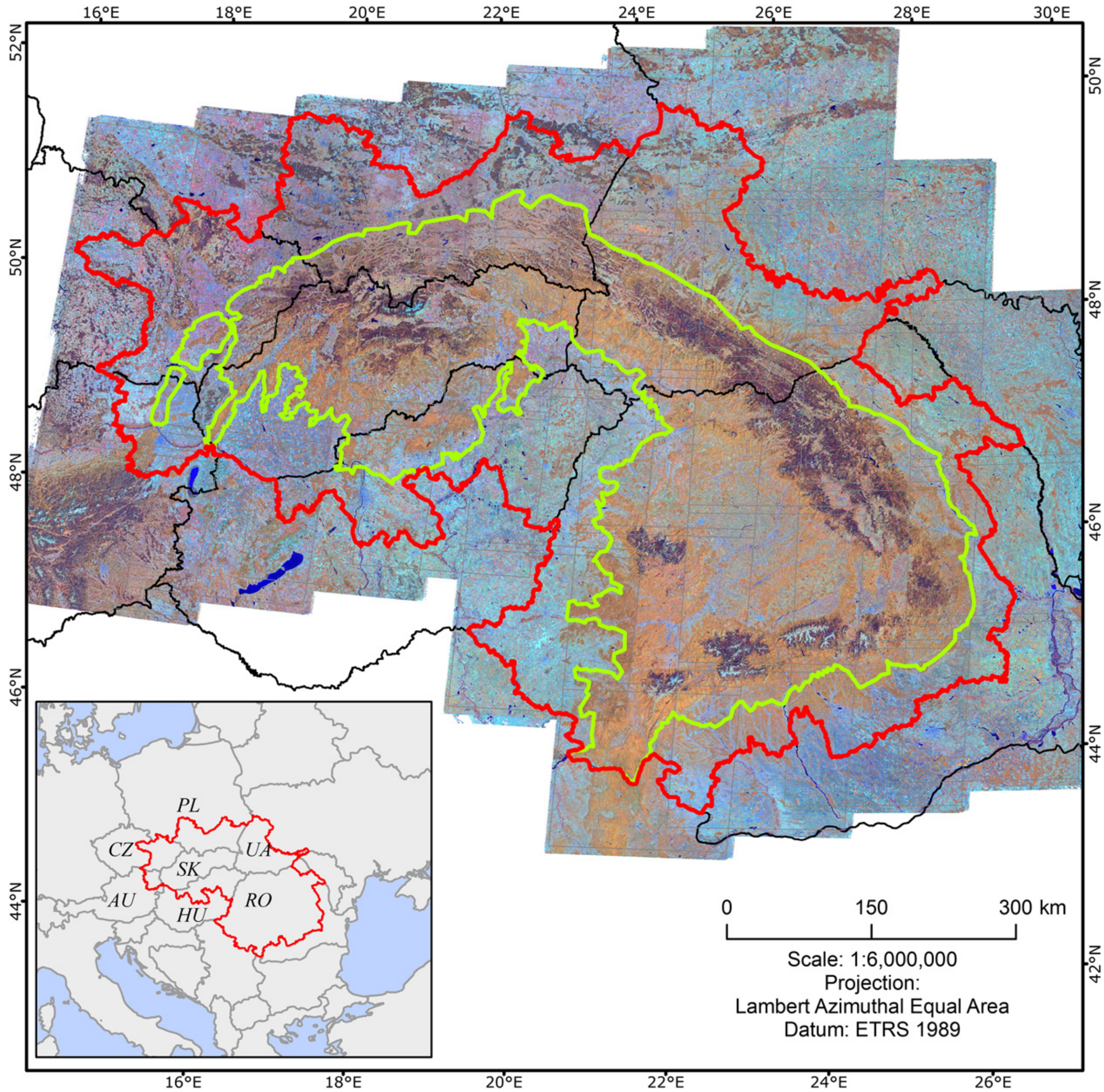

Fig. 1. The study region boundaries (red), the Carpathian ecoregion (green), the national borders (black) overlaid on the best observation image composite for the target year 2005 (RGB = 4, 5, 3). A total of 1407 scenes were provided to the compositing algorithm, which was parameterized to produce a cloud free, leaf-on seasonal state composite, considering imagery from 2003 to 2007. A series of six similar composites was made at five year intervals between 1985 and 2010. Coverage of Landsat footprints is superimposed in gray rectangles. The small inset shows the regional setting (AU = Austria, CZ = Czech Republic, HU = Hungary, PL = Poland, SK = Slovakia, RO = Romania, UA = Ukraine).

stratification. Broadleaved forests (mostly beech mixed with pedunculate oak (*Quercus robur*), sycamore maple (*Acer pseudoplantanus*) and ash (*Fraxinus excelsior*)) and mixed forests (beech mixed with silver fir and Norway spruce) dominate the lowlands and the lower mountain forest zone, while spruce-fir forests dominate at higher elevations. The treeline is located at around 1500 m in the Tatra Mountains (Svajda, Solar, Janiga, & Buliak, 2011). Despite centuries of human use, the Carpathians harbor the largest remains of semi-natural and virgin forests in Europe (Veen et al., 2010), provide habitat for Europe's largest populations of wolves, lynx, brown bear (Salvatori et al., 2002) as well as European Bison, and feature about one third of all plant species in Europe, including many endemics (UNEP, 2007).

The Carpathian region underwent several major political and socioeconomic changes in the 19th and 20th centuries. Since the 19th century, clear-cuts in former broadleaved or mixed forests were commonly replanted with non-native spruce species altering regional forest composition (Keeton & Crow, 2009). Widespread forest decline occurred during the mid-1980s partly because of severe industrial pollution and acid rain, commonly followed by fungi and other pest outbreaks (Csóka, 2005; Oszlanyi, 1997) and coniferous stands generally declined more severely than deciduous stands (Badea et al., 2004). Natural disturbance regimes are dominated by wind falls and to lesser degrees by snow damages and insect infestations, and forest fires are rare (Schelhaas, Nabuurs, & Schuck, 2003). High intensity wind throws recently increased, especially in spruce plantations (Popa, 2008).

After 1989, collectively owned state forests were returned to the pre-1948 owners through restitution, distribution or auctioning in most of the Carpathians countries. Ukraine and Poland made exceptions, where most forests remained state property (Kozak, 2010; Nijnik, 2004). In Slovakia and Romania between 50% and 60% of the forests are now under some form of non-state ownership (Abrudan et al., 2009; Weiss, Guduric, & Wolfslehner, 2012). Carpathian forests were heavily exploited during the socialist period (e.g. payments of war debts, developing industrial capabilities) and constituted a major source of state revenues (Cioroianu, 2007; Nijnik & van Kooten, 2000). Harvesting rates after the regime collapse, however, are not well known. Official statistics indicate declining harvesting activities (UNEP, 2007), but in the Ukrainian Carpathians satellite data revealed increased forest disturbances before and after the system collapse (Kuemmerle, Chaskovskyy, et al., 2009; Kuemmerle, Kozak, et al., 2009). In Romania, higher forest harvesting due to uncertainty in tenure rights after restitution emerged only after 2000 (Griffiths et al., 2012; Knorn, Kuemmerle, Radeloff, Szabo, et al., 2012). Today, all countries with the exception of Ukraine are in the European Union and the national forest legislations follow EU guidelines (Weiss et al., 2012). Altogether, this highlights the need to monitor forest changes in the region repeatedly and over longer time periods.

2.2. Satellite data, pre-processing and compositing

We utilize a compositing algorithm that combines tools to mask clouds and convert images to surface reflectance with a methodology to produce seasonally and radiometrically consistent image composites from the Landsat archive (Griffiths, Van der Linden, Kuemmerle, & Hostert, 2013). Here, we compiled regional composites of Landsat data for six five-year time steps from 1985 to 2010, and employed a hybrid analysis strategy consisting of radiometric change classification and post-classification map comparison to derive changes in forest area, forest disturbances, and forest types. In addition, we developed a method to quantify post-disturbance forest recovery from the composited data using the disturbance index (Healey, Cohen, Yang, & Krankina, 2005) and image segmentation.

For the 32 footprints covering the study region (Fig. 1), we obtained all precision terrain corrected Landsat imagery (L1T) from the USGS archive that were acquired between mid-February and mid-November and that had metadata based cloud cover estimates of less than or equal to 70% (Table 1). To ensure radiometric consistency, we employed the Landsat Ecosystem Adaptive Processing System (LEDAPS, Masek et al., 2006), which converts raw Landsat data to surface reflectance. Subsequently, we generated cloud/shadow masks for each image using the Fmask algorithm (Zhu & Woodcock, 2012). All masks were produced using conservative thresholds on cloud/shadow probabilities and the dilation parameter to capture as much clouds/shadows as possible. All imagery and masks were reprojected from the original UTM coordinate system to the Lambert Azimuthal Equal Area projection as our study region extended over three UTM zones. The total number of images available for compositing ranged between 323 for the 1990 and 1407 for the 2005 composite (Table 1).

The objective during image compositing was to produce six regional image datasets at five-year intervals from 1985 to 2010 (hereafter: target years). For each composite we considered imagery from ± two years around the target year (in the following referred to as "ca.1990 composite" for the composite with the target year 1990, etc.). The compositing algorithm was parameterized to produce cloud-free, best-observation composites of leaf-on phenology, while prioritizing acquisitions closest to the respective target year. The best observation was selected from all cloud-free acquisitions for a given pixel via a parametric decision function. The parameters were (1) the acquisition year, (2) the acquisition day-of-year (which control annual and seasonal consistency, respectively), and (3) a pixel's distance to the next cloud/shadow (greater distances are prioritized). For each unique acquisition, scores across the parameters were summed up and for a given pixel all spectral band values of the acquisition with the highest total score were written into the final best observation composite.

Table 1
Total number of images used to create the series of six image composites over the 32 footprints. Moreover, the distribution of acquisition dates is provided.

Composite	# images	Number of images with offset to target year					
		−2	−1	0	+1	+2	Median DOY
1985	547	0	65	24	251	207	210
1990	323	94	43	29	92	65	204
1995	397	112	257	16	4	8	205
2000	647	0	75	192	169	211	185
2005	1407	254	183	216	372	382	204
2010	1370	249	420	392	305	4	198

The parameterization of the day-of-year (DOY) score was based on the analysis of data from areas with high data availability over a 10-year period. We assessed how well selected unchanged areas with a natural, climate driven phenology (i.e. natural grasslands and forests) spectrally corresponded to selected reference images, which were cloud-free and acquired as close as possible to the central day of a given year (July 2nd or DOY 183). We used DOY 183 to approximate leaf-on peak photosynthetic activity and assessed correlations of all available imagery to the selected reference images using coefficients of determination of band five values. This allows to parameterize a Gaussian DOY score function (the resulting target DOY was 193 or July 12th with a standard deviation of 33 days). We then calculated the DOY score offset values for ±30 and ±45 days and used these offsets to construct a piecewise linear year score function. This results, for example, in favoring acquisitions acquired within 30 days of the target DOY but with a one year offset to the target year, over images acquired within 45 days of the target DOY within the actual target year. Overall, developing the two temporal score functions interdependently, ensured that seasonal consistency was generally favored over annual consistency (Griffiths et al., 2013).

In addition to the best observation composites, we calculated temporal–spectral variability measures and datasets providing meta-information on a per-pixel basis (hereafter: flag images) for each composite. The former utilize all available cloud free acquisitions for a given pixel to calculate the band-wise spectral mean bands and variability (standard deviation & range) bands. The flag images provide information on, for example, the year and day of year of the image acquisition, and the sun zenith angle during the acquisition. Both types of additional outputs provide valuable features for subsequent analyses. Further details on the compositing methodology are provided in Griffiths et al. (2013).

2.3. Forest type, disturbance and recovery mapping

In order to gain better understanding of the distribution of forest types across the Carpathians, as well as of how disturbances were distributed across forest types, we produced two forest type maps, one for 1985 and one for 2010, and classified deciduous, coniferous and mixed forests. The latter was defined as having neither a dominance (i.e. more than 70%) of deciduous nor coniferous trees (Herold, Hubald, & Di Gregorio, 2009). For each classification, we stacked the best-observation composite (6 bands), the spectral variability layers (19 bands) and selected flag images (year, DOY, decision score, and acquisition sun zenith angle), yielding 29 bands.

Training data were selected independently for both classifications based on the interpretation of the original Landsat input data. We used spring and autumn acquisitions together with the summer leaf-on imagery to improve the delineation of our training data for conifer, deciduous and mixed forests. Areas where the forest type was clearly discernible were digitized on screen for both time steps simultaneously to ensure comparability of both training datasets. Additional ancillary data for image interpretation and training data generation included high-resolution imagery in GoogleEarth, CORINE land-cover data and data from several field trips conducted in the Carpathians between 2006 and 2011. The digitized training areas were spatially relatively evenly distributed over the study region and the total number of polygons was between 60 and 80 for the three forest classes combined, for both 1985 and 2010. We drew a stratified random sample of pixels from all training polygons to select the final training dataset, yielding approximately 4500 pixels for the non-forest class and between 2000 and 3000 samples for each of the forest types.

We used a Random Forests classifier for all classifications (Breiman, 2001). Random Forests belong to the realm of machine learning classifiers and represent an ensemble of simple decision trees, each trained on a randomly selected feature subset. The final decision is made using a majority vote across all trees. Key advantages of Random Forests are that they can deal with all types of differently scaled data and that they can analyze large datasets very efficiently. Random Forests classifiers achieve comparable or better results than other classifiers, including other machine learning algorithms, with relatively small training data sets (Waske, van der Linden, Benediktsson, Rabe, & Hostert, 2010). We trained the Random Forests models based on 300 individual decision trees using the square root of the number of input bands as the number of random features considered at each decision tree split (Held et al., 2012).

For the forest disturbance mapping, we assembled an image stack consisting of the six composites for the years 1985 through 2010 plus the spectral variability bands and selected flag images, yielding a total of 174 bands. We then digitized training data for the disturbance classes on screen based on composite datasets in conjunction with few original (i.e. not composited) Landsat scenes. We here defined forest disturbances as full canopy removal due to natural and/or anthropogenic processes. We also derived training data for stable forest areas, where the forest class (i.e., deciduous, mixed or coniferous forest) was clearly discernible and did not appear to change over time. The training dataset also featured a generic non-forest class, which included, for example, urban and agricultural land. We then performed a stratified-random sampling within the digitized areas, yielding approximately 2000 pixels for each of the five disturbance classes, ~3000 pixels for each of the forest classes and ~4500 pixels for the non-forest class. The stable forest type training areas identified here were also used for the forest type classifications. The radiometric change classification for the disturbance map was carried out with the Random Forests classifier in a similar fashion as for the forest type mapping.

We developed a continuous proxy for vegetation recovery for disturbance patches utilizing the disturbance index (DI, Healey et al., 2005) to evaluate post-disturbance recovery dynamics. As our recovery proxy approach quantifies spectral recovery only, it is not a direct measure of recovery in an ecological sense. Field visits and the substantial regional knowledge of the author team suggest that our recovery indicator is plausible. Still, as a validation of the recovery assessment would require extensive reference data or systematic field surveys on biomass recovery (both of which are not available), we caution that these results are experimental. We base our approach on the DI, which is a linear combination of the components of the Tasseled Cap transformation (Crist & Cicone, 1984), which are normalized over the reflectance properties of the forest population in a Landsat image. We used those pixels identified as forest in both forest type maps as a "global" study area wide norming population to re-scale the Tasseled Cap components derived from the composites. While scene-specific normalizing might be desirable, our approach prevents the use of unrepresentative normalization statistics caused by, for example, scene statistics from very cloudy images, which ultimately may cause unnecessary "patchiness" in the output layers. For each of the six target years, the DI was subsequently derived according to:

$$DI = Bn - (Gn + Wn) \qquad (1)$$

where Bn, Gn and Wn were the normalized brightness, greenness and wetness components, respectively. We delineated disturbance patches based on an eight-pixel neighborhood and the disturbance map, and assessed the mean DI values for each disturbance patch.

We derived six features that we used to assess post-disturbance recovery dynamics: patch-level mean pre-disturbance DI value, the DI disturbance magnitude, and the post-disturbance recovery status (Fig. 2). The mean pre-disturbance DI value was obtained by simply averaging the patch DI values of the years preceding a disturbance event. The spectral disturbance magnitude was derived according to:

$$\mathrm{Mag}_{\mathrm{Dist}} = \left|\mathrm{mean}\left(\mathrm{DI}_{\mathrm{preDistYears}}\right) - \mathrm{DI}_{\mathrm{DistYear}}\right| \qquad (2)$$

where $\mathrm{DI}_{\mathrm{preDistYears}}$ is the patch-based DI value in the years preceding the disturbance event, and $\mathrm{DI}_{\mathrm{DistYear}}$ is the patch-mean DI value in the year of disturbance detection. The post-disturbance recovery status was derived as the percentage of recovery in a year following a disturbance relative to the disturbance magnitude (Fig. 2):

$$\mathrm{Recovery}_{\mathrm{postDistYear}} = \left(\frac{\mathrm{DI}_{\mathrm{postDistYear}} - \mathrm{mean}\left(\mathrm{DI}_{\mathrm{preDistYears}}\right)}{\mathrm{Mag}_{\mathrm{Dist}}}\right). \qquad (3)$$

For disturbance patches where the pre-disturbance DI value was higher than the post disturbance DI value, the spectral magnitude was set to zero. This allowed for eliminating such patches during post-processing, as these cases likely represent false positive detections. We applied a minimum mapping unit of 03 pixels (i.e., 0.27 ha) using an 8-pixel neighborhood to the resulting forest type and the disturbance maps, recoding patches smaller than this threshold to the surrounding class.

The initial disturbance classification yielded high levels of false positives for the 1985/1990 and the 1995/2000 disturbance classes, due to falsely detected disturbance events on non-forest land which might relate to erroneous training pixels and likely the generally poorer data coverage for the first three target year composites (Table 1). To correct for this, a patch mapped as disturbance 1985/1990 or 1995/2000 was recoded to non-forest if the disturbance magnitude was zero. To further reduce false positives, patches classified as disturbed between 1985/1990 were recoded to non-forest if less than 50% of its pixels were mapped as non-forest in the 1985 forest type map. Second, for the 1985/1990 class, if the patch-mean 1985 DI value was high and the disturbance magnitude was low, this patch was recoded to the non-forest class. After carefully investigating such cases we used 3 and 0.7 as the respective thresholds. Finally, if the pre-disturbance DI value was higher than all subsequent patch-based DI values, the patch was recoded to a new class: "recovery from pre 1985 disturbance", as these cases mostly related to forest stands recovering from disturbances that occurred before 1985.

2.4. Forest inventory data, validation strategy, and result summaries

For the validation of the forest disturbance map, we gathered a stratified random sample of 700 points for all stable forests, 600 for the non-forest class, and a total of 650 points for the five disturbance classes. All samples were visually interpreted by independent analysts using original Landsat images and the composite imagery, as well as high resolution imagery in Google Earth (Cohen, Yang, & Kennedy, 2010) and labeled each sample according to the interpreted class membership. As some samples could not be labeled due to data gaps, the final number of interpreted samples was 1873. We accounted for the stratified sampling design by correcting the resulting confusion matrix by the area proportions of each class (Foody, 2002). We corrected our accuracy estimates for potential sampling bias, calculated true area estimates for all disturbance classes and assessed the 95% confidence intervals around these estimates (Card, 1982; Olofsson, Foody, Stehman, & Woodcock, 2013). Finally, we used those samples that were either interpreted as permanent forest or non-forest to validate the forest area delineation in the forest type maps for 1985 and 2010. This yielded error adjusted area estimates and the 95% confidence interval around them.

The validation of the forest type maps was more demanding, because determining the true composition of a forest on the ground reliably based on the Landsat data alone is not feasible. First, we compared

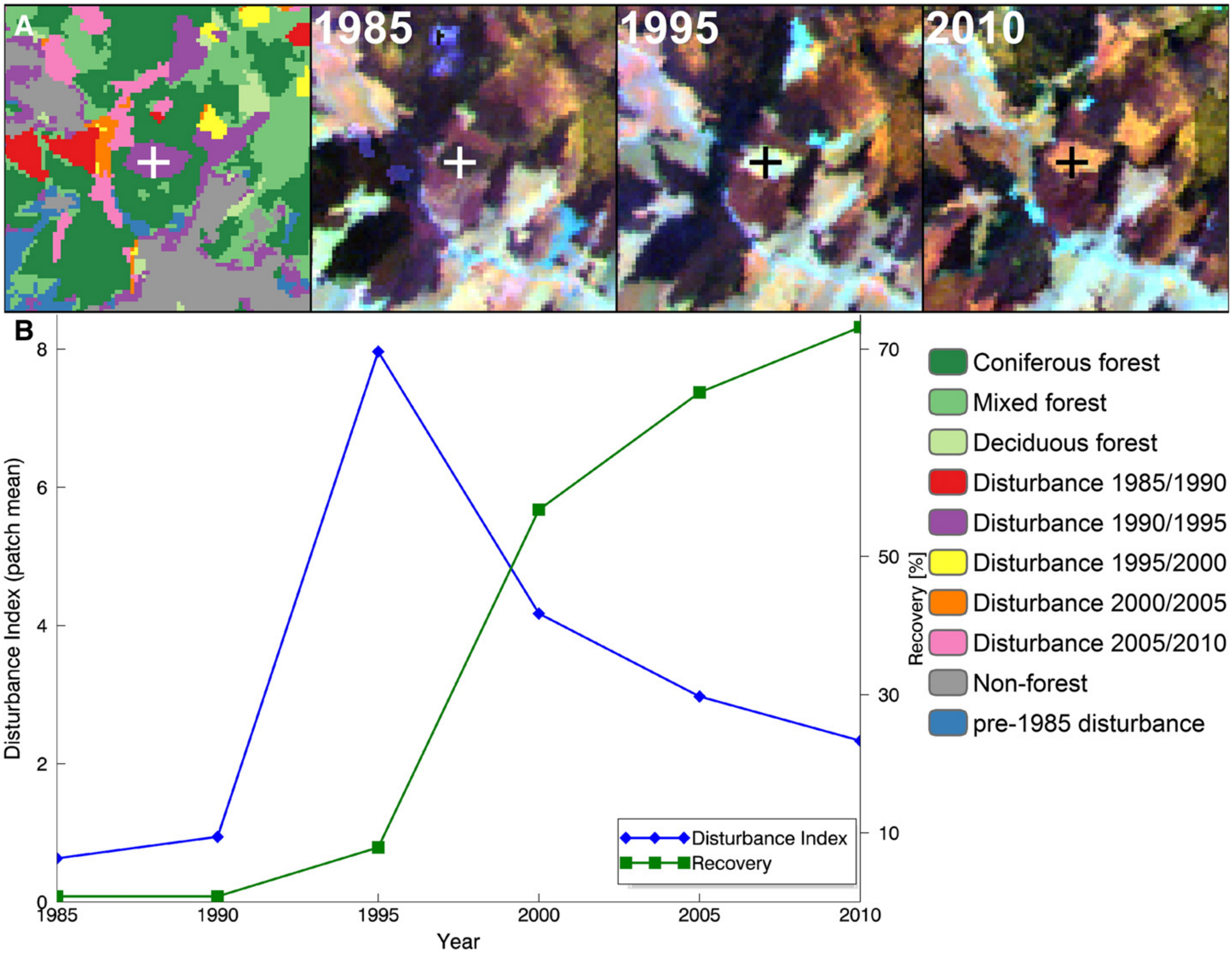

Fig. 2. An illustration of the recovery assessment methodology: the example shows (A) the disturbance map (the legend is provided on the lower right), and corresponding image chips for the years 1985, 1995 and 2010. For the central disturbance patch (indicated by the cross hair) the mean DI trajectory is shown (B, blue plot) as well as the resulting patch recovery metric (B, green plot). The patch mean pre-disturbance DI value is written into the first two recovery bands (1985, 1990), the disturbance magnitude is written into band three (1995) and the post-disturbance recovery status is written into bands four to six.

our map with forest inventory data for Slovakia, Romania and Poland. All forest inventory data was generated after the year 2000 and provided varying levels of detail and spatial extent. For example, the Slovakian forest inventory data covered the entire country at the individual stand level and provided estimates of the proportion of five dominant species at 1% intervals. For Poland and Romania, the species composition was provided in 10% intervals. We categorized individual forest management stands into deciduous, mixed or coniferous forest based on these species compositions by aggregating our remote sensing based forest type classification to the same stand polygon boundaries and applying the 70% species composition threshold. We selected all units of 1 ha (11 pixels) and above to validate the 2010 forest type map. We thereby reduced uncertainties from geometric inconsistencies between field and satellite data. Units where our disturbance map indicated disturbances between 2005/2010 were excluded. Using a total of over 300,000 units, we created confusion matrices and assessed commission and omission errors for Slovakia, Poland and Romania. We used the Land use/Cover Area frame statistical Survey (LUCAS, Palmieri, Dominici, Kasanko, & Martino, 2011) from 2009 as an additional data source for validating the 2010 forest type map. The LUCAS data are based on a systematic sampling design and field visits and provide information on land cover and land use across Europe, but do not include Romania and Ukraine. The forest classes in the LUCAS legend use a 75% composition threshold which is close to our 70% value. After discarding forest samples with unsuited land use categories (e.g. fisheries), we extracted a total sample of 2965 points for the three forest classes.

In order to validate the 1985 forest type map, we created subselections of the inventory data, including all units that had an estimated stand age of at least 30 years and that were at least 1 ha in size. The former step ensured that the forest composition in these units had not changed between 1985 and 2010 while the latter reduced uncertainties due to geometric alignment of inventory and composite data. For the Romanian inventory data we only selected units with at least 60% estimated stand closure in 2010 in order to further reduce units that had changed since 1985. For Poland, only about 40 out of 11,000 forest management units remained for the validation of the deciduous forest class and we therefore did not use the Polish inventory data to validate the 1985 forest type map. The total sample size for the validation of the 1985 forest type map was 216,000 units.

To summarize our classifications, we calculated the total forest area and the distribution of the three forest types for 1985 and 2010 for the 7 countries in our study region. We assumed that changes in forest types in the Carpathians can only happen if a pixel experienced disturbance.

We calculated forest disturbances for the different points in time and the individual countries. We also calculated pre-disturbance forest cover for each disturbance patch for the different countries and the post-disturbance recovery dynamics for the five disturbance classes. For the former, we segmented all disturbance patches and categorized each patch as coniferous, mixed or deciduous if the percentage of pixels from the respective class was >70%. In order to be able to categorize inventory units where none of the forest types had a sufficient forest type share, the percentage of mixed forest pixels was evenly distributed between deciduous and coniferous forests. If then neither deciduous nor coniferous achieved more than 70%, the patch was categorized as mixed forest. Disturbance patches with less than 50% of forest pixels were categorized as non-forest.

We also derived the net change rate and summarized annual disturbance rates (Kuemmerle, Chaskovskyy, et al., 2009) on the basis of administrative units (NUTS3 for Romania, Hungary and Austria, district-level for Czech Republic, Poland, Slovakia and Ukraine) according to:

$$NCR = \left(\frac{FC_{2010}}{(FC_{1985}) - 1}\right) * 100 \quad (4)$$

$$DR_j = \left(\frac{D_j}{FC_j}\right) * \frac{100}{a} \quad (5)$$

where NCR is the net change rate with FC_{1985} denoting forest cover in the 1985 map, DR is the annual disturbance rate for the administrative unit at time period j, D represents the disturbances at time period j, FC is the forest cover at time period j and a is the number of years between image acquisitions. Here we used the 1985 forest cover, but subtracted the disturbed forest area since 1985 and added formerly disturbed pixels if they had recovered, i.e. the post disturbance recovery rate was at least 70%. As the composites contained pixels from different years, we assessed the average time difference between two points in time (term a in Eq. (5)). Finally, we derived a relative disturbance recovery rate RR_j for the years 1995 (i.e. the first year that recovery from disturbance could have occurred in our analysis) through 2010 as:

$$RR_j = \left(\frac{cumRec_{1995:j}}{cumD1985:j}\right) * 100 \quad (6)$$

where $cumRec$ is the cumulated recovery from disturbances through the years 1995 to j (using the 70% recovery threshold), and $cumD$ is the cumulated disturbances for the years 1985 to j.

3. Results

3.1. Image compositing

Using the 4691 preprocessed Landsat images, we generated six cloud-free, best-observation composites that provided observations

Table 2
Annual and seasonal compositions of pixels in the six generated composite datasets. Annual composition refers to the offset in years to the respective target year, and seasonal composition refers to the percentage of pixels with a relative acquisition date within 30 and 45 days from the target DOY (193 or July 12th).

Year	Annual composition [%]					Seasonal composition [%]		
	−2	−1	0	+1	+2	No data	±30 days	±45 days
1985	–	5.42	38.07	41.71	14.81	0.01	82.81	98.74
1990	6.04	21.86	29.44	25.02	17.08	0.56	95.88	98.36
1995	4.25	82.05	13.60	0.02	0.01	0.08	97.65	99.51
2000	–	4.57	68.08	25.98	1.36	0.00	85.01	99.71
2005	0.08	2.48	61.64	34.03	1.78	0.00	98.76	99.96
2010	0.04	7.64	90.75	1.58	0.00	0.00	97.70	99.98

Table 3
Summary of forest cover changes between 1985 and 2010 for the country areas in the study region. Provided is the total forest area for 1985 and 2010 as well as the proportion of the three forest types of the total forest area and the changes in forest area and forest type proportions (CF = coniferous forest, MF = mixed forest, DF = deciduous forest).

	1985 [km²]			1985 [%]				2010 [km²]			2010 [%]				Changes 2010 − 1985				
	CF	MF	DF	Forest	CF	MF	DF	CF	MF	DF	Forest	CF	MF	DF	Forest [km²]	Forest [%]	CF [%]	MF [%]	DF [%]
Austria	212.99	211.42	1204.79	22.35	13.07	12.98	73.95	191.51	195.45	1317.09	23.37	11.24	11.47	77.29	74.84	1.03	−1.83	−1.51	3.34
Czech Rep.	4156.89	2362.36	2967.42	36.11	43.82	24.90	31.28	3819.16	2147.85	3744.07	36.97	39.33	22.12	38.55	224.40	0.85	−4.49	−2.78	7.27
Hungary	410.31	601.84	5069.58	17.50	6.75	9.90	83.36	443.95	565.30	6943.12	22.89	5.58	7.11	87.31	1870.63	5.38	−1.16	−2.79	3.95
Poland	7306.76	5462.06	3918.11	36.68	43.79	32.73	23.48	7466.37	5440.56	5558.24	40.59	40.43	29.46	30.10	1778.24	3.91	−3.35	−3.27	6.62
Romania	16354.30	20472.60	23446.80	35.51	27.13	33.97	38.90	14381.60	22805.50	34397.10	42.17	20.09	31.86	48.05	11310.60	6.66	−7.04	−2.11	9.15
Slovakia	4924.72	5820.02	11812.00	46.02	21.83	25.80	52.37	4082.34	5701.47	13370.10	47.24	17.63	24.62	57.74	597.11	1.22	−4.20	−1.18	5.38
Ukraine	7493.09	6480.89	7747.11	38.38	34.50	29.84	35.67	6490.65	6620.24	11725.70	43.89	26.13	26.66	47.21	3115.52	5.51	−8.36	−3.18	11.55

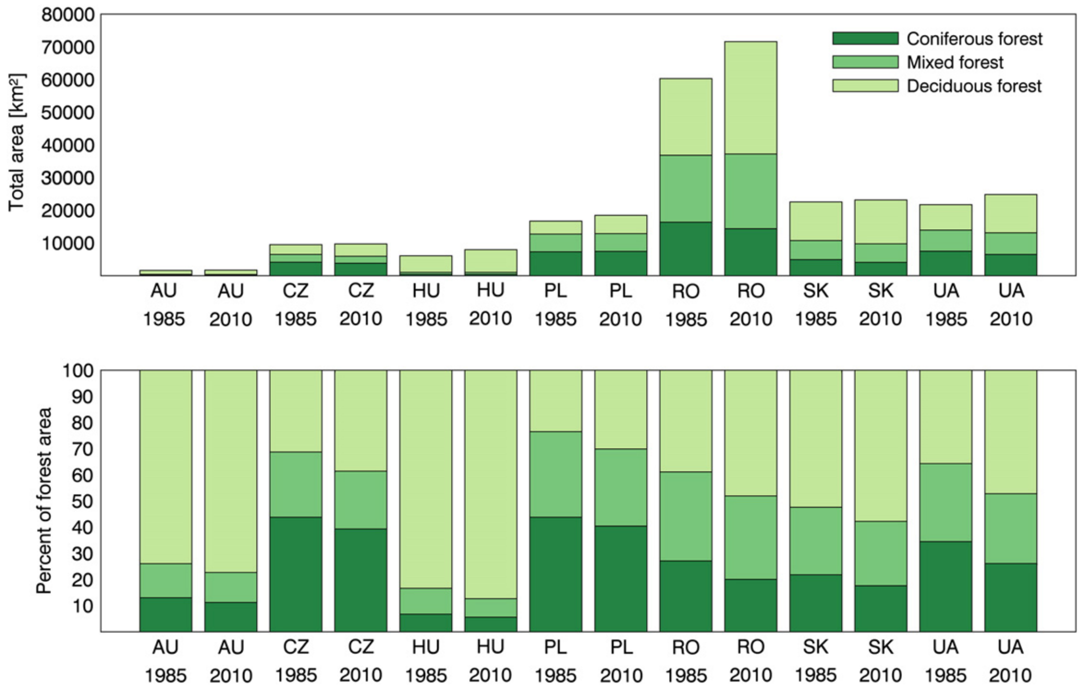

Fig. 3. Total forest area and forest type by country for the years 1985 and 2010 in square kilometers (top), changes in the proportion of forest types between 1985 and 2010 for the seven countries, expressed as the percentage of the total country forest area in the study region (bottom).

for almost all pixels in the study region (the ca.1990 composite lacked observations for 0.6% of pixels). The overall annual consistency (i.e. offset to target year) was high: more than 98% of pixels had been acquired within one year of the respective target year for the ca.2000, 2005 and 2010 composites (Table 2). Similarly, high overall seasonal consistency (i.e. relative offset to the target DOY) was achieved, with four out of six composites containing 95% of observations from within 30 days of the target DOY.

3.2. Forest composition and changes within forest types

Our error adjusted area estimates suggest that the total forest area in the study region increased slightly from 39.4% in 1985 (153,000 km^2 ± 6764 km^2) to 40.3% in 2010 (157,000 km^2 ± 6086 km^2). The overall composition of forest types in the study region changed markedly: coniferous forests made up 30% of the forest area in 1985 but only 23% in 2010. The share of mixed forests decreased by 2.3% between 1985 and 2010 while the percentage of deciduous forests increased by 9%.

On the per country level, forests covered between 47% in the Slovakian and 23% in the Hungarian parts of the study region in 2010. An increase in the countries forest area was found in all countries, but was most pronounced in Romania, Ukraine and Hungary (Table 3, Fig. 3). The composition of the countries forest area in the Carpathians differed considerably. For example, the 2010 forest area in Hungary featured 87% of deciduous forests while these only accounted for 30% of the forest area in Poland. Forests in the Polish and the Czech parts of the study region were clearly dominated by coniferous forests (both 44% in 1985). The largest changes in forest composition occurred in Romania and Ukraine: coniferous forests decreased by 8.4% and 7%, while deciduous forests increased 12% and 9%, respectively, between 1985 and 2010. Several countries featured decreasing proportions of mixed forest, most notably Poland, Hungary and Czech Republic (Table 3, Fig. 3).

3.3. Forest disturbances

Forest disturbances were infrequent and spatially dispersed in the Austrian part of the study region but were very abundant and occurred highly clustered in the Ukrainian and Romanian parts of the study region (Fig. 4). We also observed strong differences within countries, for example disturbances were rather scarce in the eastern parts of the Polish Carpathians but were highly abundant and formed distinct hotspots in the western and southwestern Polish Carpathians.

According to our error adjusted area estimates, the total area of forest disturbances detected between 1985 and 2010 amounted to 30,800 km^2 (±6629 km^2), which related to 19.4% of the 2010 forest area (Fig. 5). Overall, most disturbances occurred between 1985/1990 (~30%) while the least disturbances took place between 2005/2010 (13%).

On the per-country basis, the greatest total forest area mapped as disturbed occurred in Romania between 1995/2000 with more than 2500 km^2 (3.5% of the 2010 forest area in Romania, Fig. 5). In most countries, disturbances were mainly detected between 1985/1990, with the exception of Romania and Ukraine. The Romanian Carpathians exhibited continuously increasing levels of disturbance until 2000/2005 when disturbances decreased substantially. Disturbances in the Ukrainian Carpathians peaked during 1990/1995 and then decreased continuously thereafter. Comparable temporal patterns, albeit of differing magnitude, were observed for the Czech, Polish and Slovakian Carpathians: sharp drops in disturbance levels after 1985/1990, and increasing levels of disturbance in the more recent years of the analysis.

With regard to the disturbances aggregated to the level of administrative units, the mean annual disturbance rates decreased from 0.9% to 1% between 1985/1990 and 1990/1995, to no higher than 0.5% during subsequent years. The highest disturbance rates during the early periods (i.e. between 1985 and 1995) concentrated on the Czech and Polish Carpathians as well as on the Ukrainian and Romanian boarder region (Fig. 6A). This overall pattern changed considerably starting from 1995/2000: annual disturbance rates decreased markedly in all formerly mentioned regions and the highest disturbance rates were now detected within Romania (especially Covasna and Harghita regions). During 2005/2010 the Polish, Slovak and Czech boarder region emerged as a distinct disturbance hotspot.

The examination of the pre-disturbance forest types clearly suggests that disturbance increasingly occurred within coniferous forests (Fig. 7). This was especially true for the Polish, Czech, and Slovakian parts of the

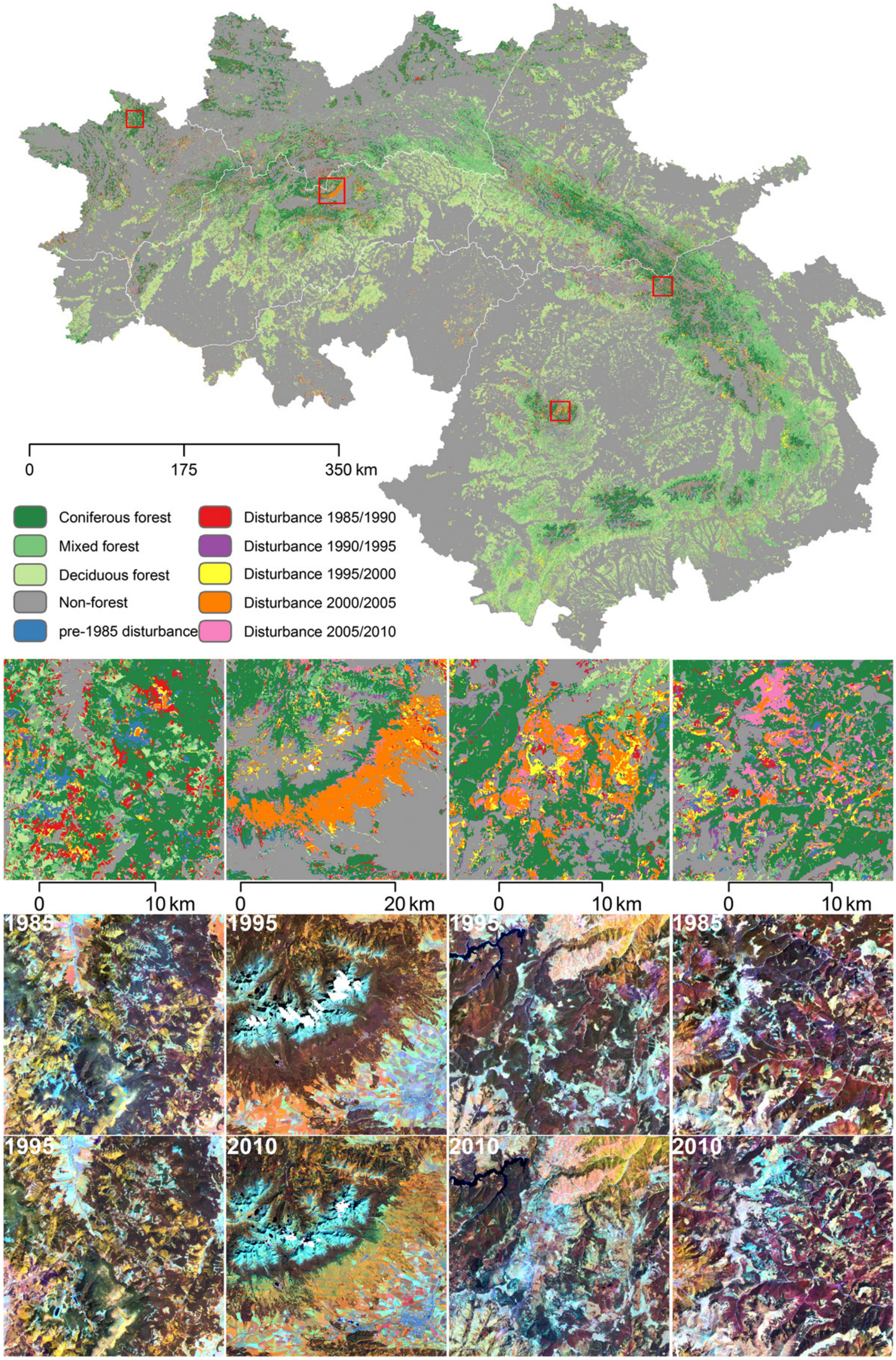

Fig. 4. The disturbance map showing the stable forest areas as well as the five disturbance classes, the national boundaries are overlaid in white. The extent of four details in the disturbance map is indicated by the red frames. Below we provide for each detail the disturbance map subset along with the respective composite imagery subsets for two points in time.

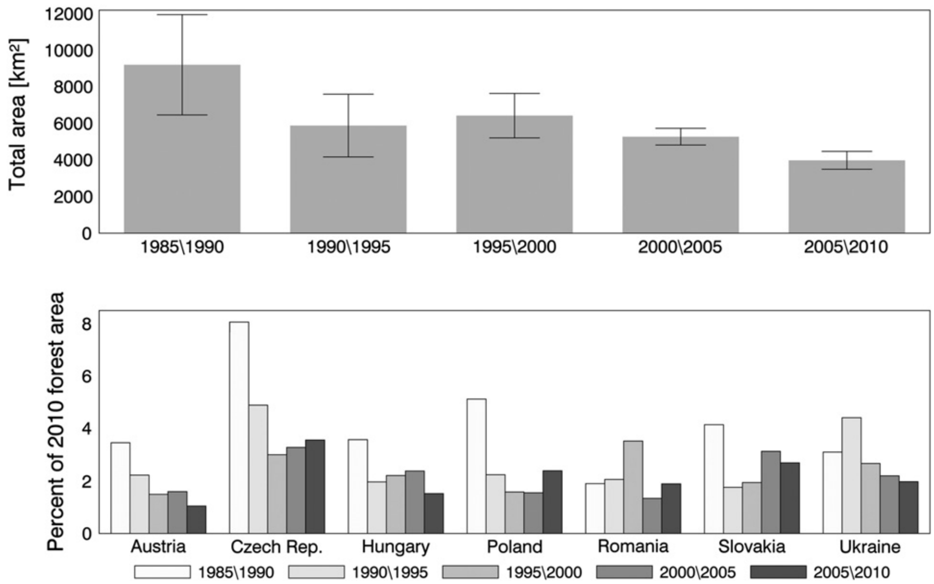

Fig. 5. Error adjusted area estimates of disturbed forest area for the five disturbance classes in square kilometers, with error bars indicating the 95% confidence interval around these estimates (top). Disturbed forest area for the five disturbance classes and the seven countries in the study area, expressed as the percentage of the 2010 country's forest cover in the study region (bottom).

study region: the percentage of disturbances in coniferous forests more than doubled in Poland and Czech Republic between 1985 and 2010 and more than quadrupled in the Slovakian Carpathians between the same years. A similar increase was also observed in Romania and Ukraine, however to a slightly lesser degree. In Hungary, the percentage of disturbances occurring in coniferous and mixed forests remained relatively stable, and most disturbances were detected in deciduous forests.

3.4. Forest recovery from disturbance

Post-disturbance recovery assessed in 2010 was most pronounced in the Hungarian, Romanian and Ukrainian Carpathians and much weaker in the Czech, Polish and Slovakian parts of the study region (Fig. 8). Recovery from disturbance in Slovakia was strong during 1985/1990 and 1990/1995, but much weaker during the later periods. On the contrary, recovering patches disturbed between 1985/1990 in the Hungarian Carpathians did not show exceptional recovery tendencies when compared to other regions, but Hungary showed the strongest recovery dynamics among the Carpathian countries for all subsequent disturbance classes. In all countries (except Romania and Czech Republic) more disturbance patches had recovered from 1990/1995 disturbance events compared to those detected between 1985/1990.

The recovery rate (RR_j) at the level of administrative units revealed lower recovery dynamics during 2000 in the eastern and southern Carpathians of Romania, but higher recovery rates in western Romania (Fig. 6B). The northeastern Romanian Carpathians continued to exhibit lower recovery dynamics through 2005 and 2010 compared to other regions in the Romanian Carpathians. The relative recovery rate in the Slovakian, Polish and Czech boarder region decreased noticeably in 2010, which is related to the increasing prevalence of large-scale disturbances that occurred between 2000 and 2010 and counterbalanced the recovery.

When we assessed the relative net change in forest cover aggregated to administrative units, the overall pattern revealed a cluster of districts with strong negative balance in the Western Carpathians (Czech, Polish and Slovakian border region, Fig. 6C). The strongest net increase in forest cover was observed not only in the foothills and forelands of the Polish and Ukrainian Carpathians, but also several areas in north eastern Hungary and western Romania showed overall positive balances.

3.5. Mapping accuracy

After accounting for the potential bias due to the stratified sampling design (Olofsson et al., 2013), our disturbance map achieved an overall accuracy of 85.8%. The stable deciduous and coniferous forest classes achieved relatively high user's and producer's accuracies, while the mixed forest class resulted in lower accuracies predominantly related to confusion with the other forest classes (Tables 4 & 5).

All disturbance classes contained higher omission than commission errors, with the highest commission errors assessed for the 1985/1990 disturbance class, partly owed to falsely detected disturbances on non-forest areas. Omission errors were considerably higher for the earlier disturbance classes, and commission errors were lower for the more recent disturbance classes (no more than 23%, Table 4). Errors within the disturbance classes were predominantly related to the timing, with the exception of the 2005/2010 disturbance class (Table 5).

Using the interpreted sample of permanent forest and non-forest validation points, the forest area delineation achieved overall accuracies of 95% for the 1985 and 98% for the 2010 forest type maps. The comparison of our forest type maps with the forest inventory data resulted in overall accuracies ranging from 73% in Slovakia for 1985 to 57% in Poland for the 2010 map (Table 6). The overall agreement with the inventory data across countries was 68% for 2010 and 71% for 1985. Mixed forests had the highest omission and commission errors, while deciduous and coniferous forest errors were lower. The coniferous forest class had the lowest errors of commission in Romania and Slovakia (all below 10%), but omission errors were higher (up to 41%). The deciduous forest class was validated with omission and commission errors of no more than 15% in Slovakia in 1985, but errors were considerably higher in the Polish Carpathians. The validation of the 2010 forest type map based on LUCAS data resulted in an overall accuracy of 63%. The deciduous forest classes had omission and commission errors of no more than 25% and the coniferous class had only slightly higher uncertainty. The mixed forest class also had high uncertainties using the LUCAS data for validation (Table 6).

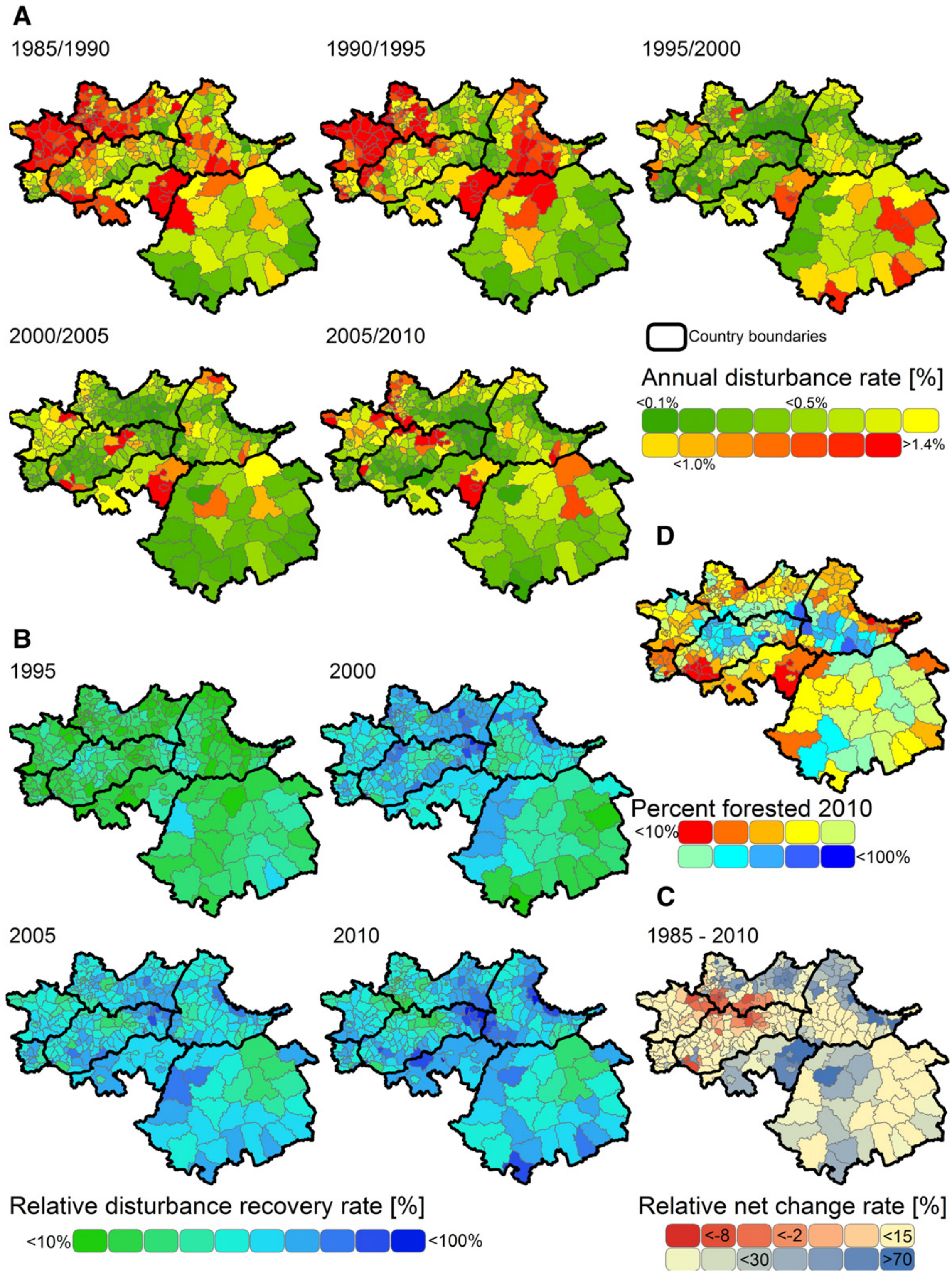

Fig. 6. (A) Annual disturbance rates provided for the five disturbance periods and the administrative units in the study region (NUTS3 level for Austria, Hungary and Romania, district level for Czech Republic, Poland, Ukraine and Slovakia), (B) relative disturbance recovery rate, (C) relative net Change rate, (D) percent 2010 forest cover per region.

4. Discussion

Understanding changes in forest cover is crucial in order to address many environmental and resource related questions and results are most valuable, when major forest types and their changes are captured. Wall-to-wall analyses for large regions help avoiding extrapolations from case studies to larger regions, thereby potentially reducing uncertainties. We utilized the full Landsat archive as well as the automated image pre-processing and compositing algorithms to analyze changes in forest composition, forest disturbances and recovery from disturbance for the Carpathian ecoregion since the mid-1980s. Forests in the Carpathians have changed considerably over the past 25 years. Our results suggest a slight net increase in forest cover. Forest composition in the Carpathians changed markedly over the past 25 years. The share of mixed and

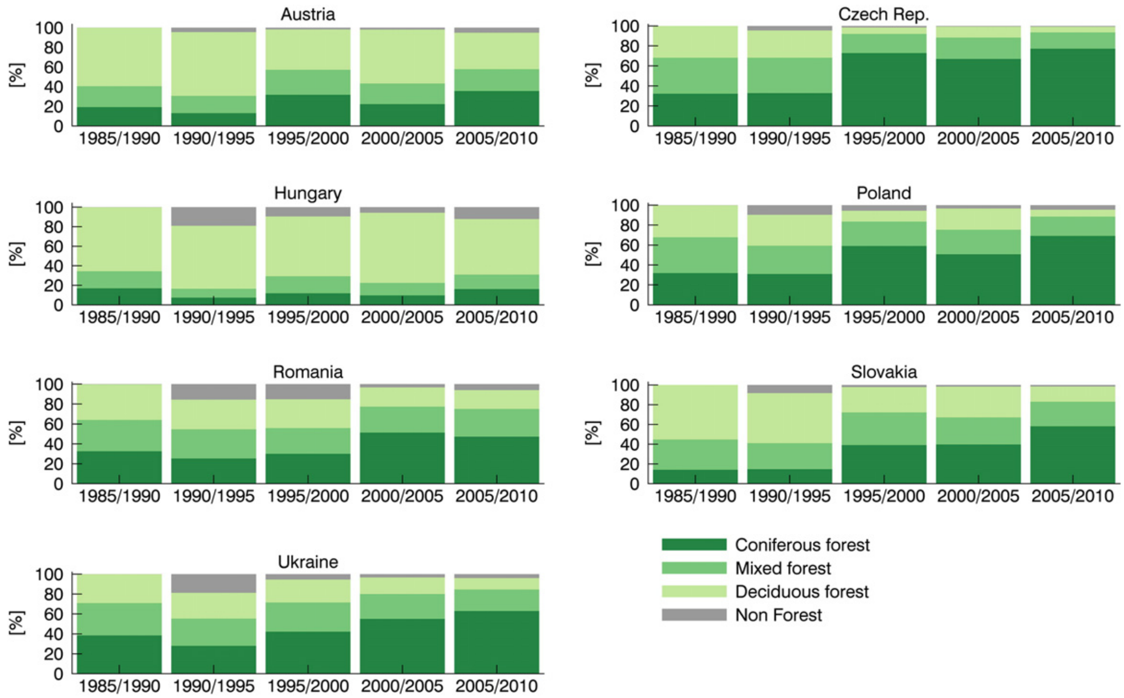

Fig. 7. Disturbance patch-based pre-disturbance forest type, provided for the five disturbance classes and the seven countries in the study region, expressed as the percentage of all disturbance patches of a given class in a given country.

especially coniferous forest decreased, while deciduous forest increased. While forest cover has likely increased locally due to abandoned agriculture or afforestation policies (Baumann et al., 2011; Kozak, 2010; Mueller, Kuemmerle, Rusu, & Griffiths, 2009), our results indicate that almost 20% of the forests in the study area experienced disturbances, which can take a long time to regrow to forests again without targeted reforestation measures. Changes in forest composition, on the other hand, may reflect a shift towards sustainable forest management principles and a deemphasizing of timber production, but could also be the result of insect and pollution damages that mainly affect coniferous forests and especially plantations. Forest disturbances have overall decreased since the mid-1980s, most likely due to diminishing activities in the forestry sectors since the system change and a decreasing emphasis on economic returns. Forest recovery from disturbance showed regional variation and was overall most pronounced in Romania and Hungary and much weaker in Czech Republic and Poland.

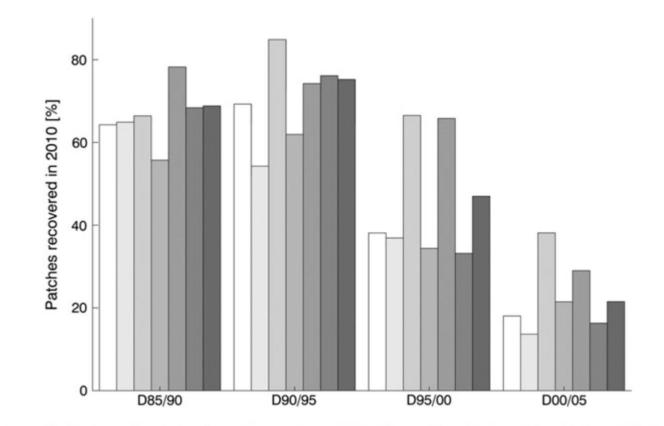

Fig. 8. The percentage of disturbance patches that had recovered by at least 70% spectral recovery magnitude in 2010, provided for the seven countries in the study region and the five disturbance classes.

A net forest cover increase has been reported for individual regions in the Carpathians (e.g. Kozak, Estreguil, & Troll, 2007 for the Northern Carpathians) and on the national level in official forest statistics (FAO, 2010; Feranec, Jaffrain, Soukup, & Hazeu, 2010). In accordance with those findings, our results also show a slight increase in net forest cover, which is however related to some uncertainty as the net forest cover increase was well within the confidence interval of the forest area estimates for 1985 and 2010. Agricultural land abandonment on former collectively managed land and decreasing grazing pressure at the timber line (Mihai, Savulescu, Sandric, & Oprea, 2006) have resulted in increased forest cover locally, partly due to natural forest expansion and partly due to forest planting (Fig. 9A, Abrudan et al., 2003; Kozak, 2010; Nijnik & van Kooten, 2000; Oszlanyi, 1997). Land abandonment was widespread in Ukraine (Baumann et al., 2011; Kuemmerle et al., 2011) and in Romania (Kuemmerle, Muller, Griffiths, & Rusu, 2009; Mueller et al., 2009) but also occurred in Poland (Kozak, Ostapowicz, Szablowska-Midor, & Widacki, 2004). In 2010, i.e. about 20 years after the collapse of socialism, these areas have often matured from shrubland and early successional forests to young forest stands that can potentially be detected in Landsat data. Nevertheless, with almost 20% of Carpathian forests experiencing stand-replacing disturbances over the same time period, the net effect of these processes is overall small and is counterbalanced by the relatively slow recovery of forests, as forest planting is often not carried out and natural regeneration takes longer.

The overall composition of forests in the Carpathians underwent profound changes, and we found increasing dominance of broadleaved forests. Coniferous monocultures were originally economically motivated, but forest managers increasingly recognize and value ecological and social forest functions (Keeton & Crow, 2009; UNEP, 2007). The decrease in coniferous forests was largest in Romania and Ukraine. We observed large-scale disturbance patterns in both countries for the periods 1995/2000 and 2000/2005 which are untypical for harvesting activities (e.g. Fig. 9D). Field evidence suggests that most of those disturbances can be attributed to large-scale wind throw or snow break events. This is not surprising, however, as both countries' forestry sectors focused on widespread establishment of spruce plantations in earlier decades. These spruce plantations are vulnerable to storm

Table 4
Summary of the disturbance map validation (omission and commission errors provided).

Disturbance map class	Omission	Commission
Coniferous forest	38.03%	12.58%
Mixed forest	36.03%	47.12%
Deciduous forest	21.63%	23.87%
Disturbance 1985/1990	61.51%	31.37%
Disturbance 1990/1995	54.15%	33.56%
Disturbance 1995/2000	43.52%	17.86%
Disturbance 2000/2005	55.56%	23.20%
Disturbance 2005/2010	31.27%	19.35%
Non-forest	1.31%	6.19%

or snow damages and also often suffer from pest outbreaks (Badea et al., 2004; Csóka, 2005; Oszlanyi, 1997). In accordance with a change in management practices towards multifunctional forestry, those plantations are today often converted into stands dominated by deciduous species after harvesting (Keeton & Crow, 2009).

Similarly, spruce forests experienced widespread pest outbreaks, dieback and large scale wind damages in the Czech and Polish Carpathians (Main-Knorn, Hostert, Kozak, & Kuemmerle, 2009). In most Carpathian countries, disturbances were increasingly encountered in former coniferous forests (Fig. 7). Maturing coniferous stands and especially spruce plantations are increasingly vulnerable to wind damages and pest outbreaks (Csóka, 2005; Keeton & Crow, 2009; Nijnik, 2004). Infested or degraded stands are subsequently subject to sanitary logging activities. Thus, forest managers are likely to harvest maturing spruce stands before the actual rotation age is reached to avoid suffering economic losses.

Forest disturbances were overall most abundant during the early periods of our analysis, especially 1985/1990 (Fig. 5). Disturbances generally decreased thereafter, but several areas also exhibited extensive disturbances in later years. For example the Czech, Slovakian and Polish border region featured high disturbance rates between 2005/2010 (Figs. 6A & 9B), while during the same period high disturbance rates occurred in northeastern Romania (Fig. 6A). Natural disturbances in the Carpathians are mostly caused by wind and snow but often affect forests weakened by pests, insects or industrial pollution (Oszlanyi, 1997). Forest fires are rare, especially large fires occur infrequently (Anfodillo et al., 2008). While wind damages are often below our minimum mapping unit (Popa, 2008), large scale disturbances in recent decades increased in frequency and have occurred, for example in the Romanian Eastern Carpathians (Fig. 9D) in 1994 (Mihalciuc, Simionescu, & Mircioiu, 1999) and in Slovakian Tatra Mountains (Fig. 4) in 2004 (Soltes, Skolek, Homolova, & Kyselova, 2010). All natural disturbances are typically followed by salvage logging which commonly accounts for a considerable proportion of the total annual cut, for example between 40% and 60% in the case of Slovakia since

Table 6
Summary of the comparison of the 1985 and 2010 forest type maps with forest inventory data (omission and commission errors provided), for 2010 comparison with statistically sampled ground truth data is additionally provided (OAC = overall accuracy).

	Omission	Commission
2010 Combined	OAC = 68.24%	
Coniferous	44.31%	9.32%
Mixed	55.77%	73.34%
Deciduous	15.82%	21.25%
2010 Romania	OAC = 59.65%	
Coniferous	41.00%	2.29%
Mixed	33.81%	80.15%
Deciduous	41.59%	30.92%
2010 Poland	OAC = 57.35%	
Coniferous	22.70%	29.58%
Mixed	62.44%	58.41%
Deciduous	61.45%	57.54%
2010 Slovakia	OAC = 69.12%	
Coniferous	46.02%	7.31%
Mixed	55.90%	73.65%
Deciduous	14.39%	20.55%
2010 LUCAS	OAC = 63.43%	
Coniferous	33.08%	44.32%
Mixed	62.00%	58.19%
Deciduous	24.46%	21.08%
1985 Combined	OAC = 71.19%	
Coniferous	40.95%	7.52%
Mixed	45.89%	74.07%
Deciduous	16.13%	15.44%
1985 Romania	OAC = 65.86%	
Coniferous	22.25%	7.10%
Mixed	38.84%	79.51%
Deciduous	51.14%	23.78%
1985 Slovakia	OAC = 72.81%	
Coniferous	40.70%	4.97%
Mixed	48.43%	74.90%
Deciduous	13.77%	15.30%

1985 (Oszlanyi, 1997). Following the 2004 wind throw in the Tatra Mountains which blew down 12,000 ha of forests (Fig. 4, example 2), the regional timber market was saturated for years as a result of extensive salvage logging which again led to decreased timber harvesting (Suchomel, Gejdos, Tucek, & Jurica, 2011).

However, the majority of detected disturbances are likely related to logging that occurred independent of prior natural disturbance events. Reasons for the elevated disturbance levels in 1985/1990 and 1990/1995 most likely relate to the fact that the timber industry was a major source of revenues and ensured large guaranteed outlet markets during socialist time. Especially in Ukraine, foresters continued to manage forest logging based on large scale clear cuts and timber remained a central source of economic revenues long after the collapse of socialism (Turnock, 2002; UNEP, 2007). Our results show that disturbance levels dropped after 1995 in many regions (Fig. 6A). With the collapse of

Table 5
Confusion matrix obtained from the validation of the disturbance map (CF = coniferous forest, MF = mixed forest, DF = deciduous forest, NF = non forest, DYY/YY refers to the disturbance class detected between the respective years).

	Reference									
Class	CF	MF	DF	D85/90	D90/95	D95/00	D00/05	D05/10	NF	Sum
CF	139	10	1	–	2	1	2	2	2	159
MF	48	110	32	3	2	4	7	1	1	208
DF	8	30	185	1	2	3	4	3	7	243
D85/90	4	9	6	70	4	–	–	–	9	102
D90/95	11	11	6	4	97	8	–	1	8	146
D95/00	5	3	5	4	3	138	5	–	5	168
D00/05	8	5	–	2	4	5	96	1	4	125
D05/10	5	2	3	1	–	1	10	100	2	124
NF	3	4	13	11	4	2	–	–	561	598
Sum	231	184	251	96	118	162	124	108	599	1873

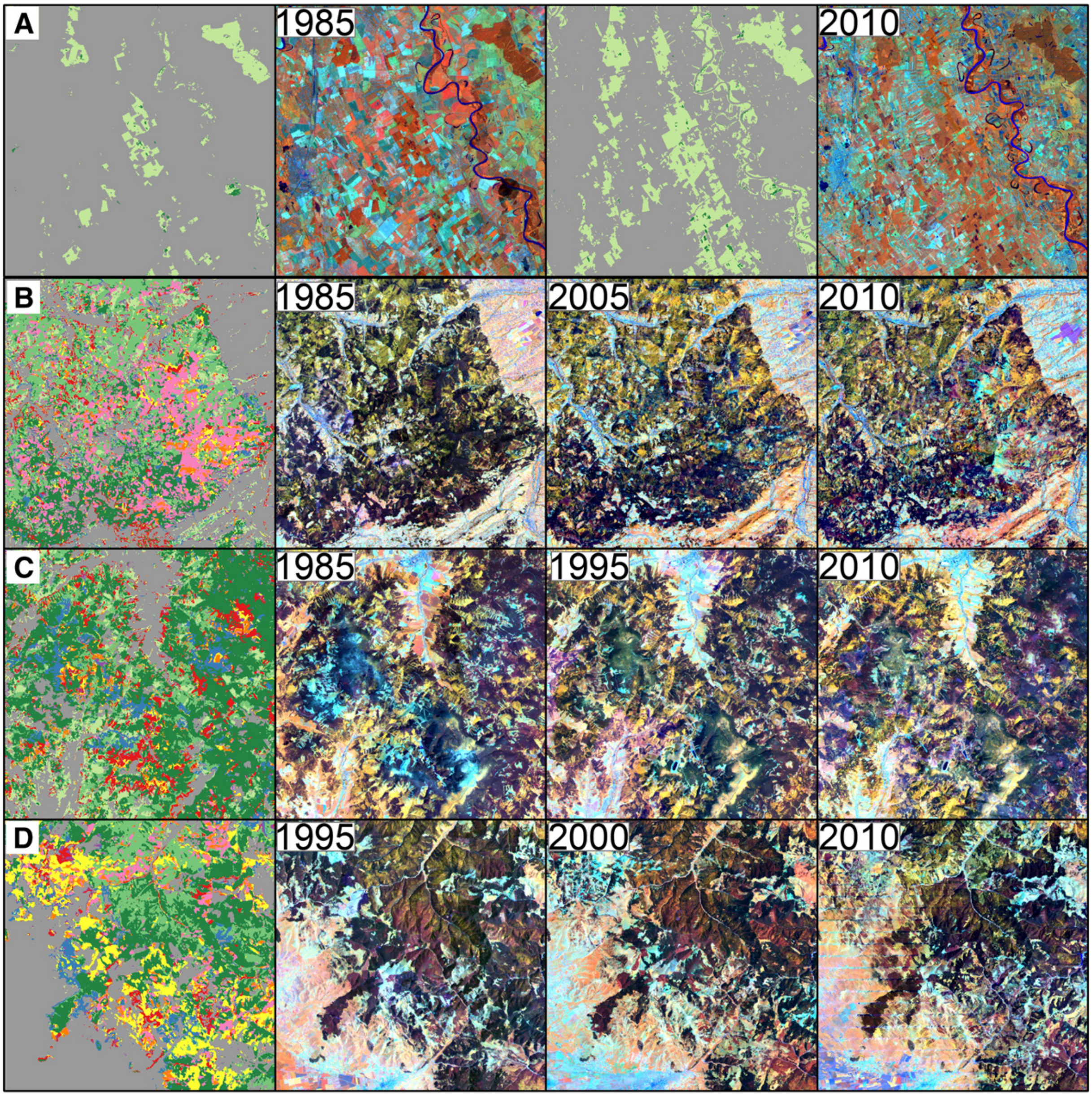

Fig. 9. Four process examples (all provided at 1:475,000 scale): (A) areas with pronounced forest cover increase between 1985 and 2010 on former agricultural land in Hungary (forest type maps and composite subsets provided for 1985 and 2010), (B) large-scale disturbances in the Polish-Slovakian-Czech border region, (C) disturbance patterns in Czech Republic, (D) large-scale disturbances in the Romanian Eastern Carpathians (The legend for the forest type and disturbance map is provided in Fig. 4).

socialism in Eastern Europe, the timber product industry collapsed as well and subsequently had to be restructured, resulting in less logging (Csóka, 2005). Moreover, as a result of excessive timber exploitation in the Ukrainian Carpathians under communism, most mature stands have been harvested, age structure of remaining stands has shifted to younger ages and consequently timber harvesting decreased, which is also reflected in our results (Nijnik & van Kooten, 2000). Official round wood extraction statistics support our findings for Slovakia and Hungary, but differ for Ukraine and Czech Republic where national statistics show increasing levels of timber extraction since 1990 (FAO, 2010). Partly, this might relate to increased commercial thinning rather than clear-cutting that has been reported in Ukraine for recent years, due to a lack of mature stands (Nijnik, 2004; Nijnik & van Kooten, 2000). As thinning activities are mostly not captured in our mapping approach, this aspect might have influenced decreasing disturbance levels in our results. In Poland and the Czech Republic, disturbances decreased considerably after 1995, but increased again in 2005/2010 likely due to widespread spruce decline and subsequent salvage logging in the Polish–Czech–Slovakian border region (Main-Knorn et al., 2009).

In addition to changes in forest management objectives and natural forest disturbances, forest ownership changes also most likely affected the observed disturbance rates. While in Ukraine and Poland most forests remained property of the federal state, in other countries forest ownership has changed substantially. For example in the case of Romania, forests were largely restituted based on three forest restitution laws since 1991 (Abrudan et al., 2009). With poor management regulations for privately owned forest in the first years of the restitution process as well as uncertainties regarding the permanence of obtained tenure rights, many new forest owners opted for immediate economic benefits rather than sustainable forestry leading to increased logging, especially after 2000 (Irimie & Essmann, 2009; Vasile & Mantescu, 2009). As a consequence, increased foreign investment in the Romanian forestry sector has been documented since 2000 (Ioras & Abrudan, 2006) and could represent a potential driver of increasing disturbance levels observed between 2005/2010. In Slovakia, restitution of forests continues and more than 50% of forests are non-state owned (Weiss et al., 2012). However, many restituted forest areas are now within protected areas or under other forms of conservation which represents a major source of conflicts in both, Romania (Knorn, Kuemmerle, Radeloff, Keeton, et al., 2012) and Slovakia (Kovalčík et al., 2012; Sarvasova, Salka, & Dobsinska, 2013).

Our results show that post-disturbance forest recovery differed considerably among the countries in the Carpathians (Fig. 8). Especially in recent years, forest disturbances in Hungary, Romania and Ukraine showed markedly stronger recovery than in the Czech, Polish or Slovakian Carpathians. Natural recovery after harvests is favored over replanting throughout the Carpathians, the latter being predominantly utilized for stand conversion and restoration forestry (Keeton & Crow, 2009; UNEP, 2007). However, natural recovery is generally slow and can take several decades depending on the forest type, topography, soil quality, and forest management history. Overall natural regeneration has likely not counterbalanced the widespread disturbances that amounted to 20% of the Carpathian forests over the study period.

Our approach highlighted that detailed mapping of forest types, forest disturbances and forest recovery is possible using large-area composites of Landsat data. The overall spatial and temporal patterns of detected disturbances in the Ukrainian Carpathians agree well with results of previous studies, e.g., by Kuemmerle, Chaskovskyy, et al. (2009). Even though the temporal intervals of the incorporated imagery are not directly comparable, we identified approximately 2.6% more disturbances in western Ukraine than Kuemmerle, Chaskovskyy, et al. (2009). With respect to the extent of the study area and the complexity of the target classes the achieved accuracies indicated overall reliable results, but few sources of uncertainty deserve particular mention. While composited surface reflectance data allow for extrapolating training data across large areas, the generation of representative training data over large areas with high spatial detail is not a trivial task. It is challenging to account for the total spectral variability of target classes across space and time and thus approaches for automated training data generation hold great potential and should be further pursued (Huang et al., 2008). We detected fewer disturbances during the later years and these also related to much smaller levels of uncertainty. Overall, the individual disturbance class accuracies showed higher levels of omission than commission errors (Table 4), which suggest that the total extent of disturbances in our results is rather conservative. The forest type maps achieved high accuracies for the deciduous and coniferous forest classes while the mixed forest class related to considerable uncertainties. Due to its mixed nature, the mixed forest class is intrinsically challenging to map and the comparison of rather subjectively gathered training data with objectively measured inventory data is problematic. Moreover, while absolute and relative geometric accuracy of L1T imagery is unprecedented, some images especially for the years between 1985 and 1995, exhibited some spatial inaccuracies and automated geometric quality assessments should be incorporated into future compositing approaches (Gao, Masek, & Wolfe, 2009).

Overall, temporal compositing of Landsat imagery holds great potential for land cover mapping and change detection on regional to continental scales. Data availability for the 1980s and 1990s was generally lower (Table 1), but compositing still allowed for assembling of regional, cloud-free datasets. Consistent surface reflectance measurements for historic acquisitions are a great asset, and allow for radiometric change classification in multi-temporal stacks of large-area datasets. Alternative large-area approaches using scene-based classifications are limited with respect to the number and complexity of the classes of interest (Knorn et al., 2009; Olthof, Butson, & Fraser, 2005). Scene-based change detection approaches that focus on variations of spectral indices and annual time-series trajectory approaches generally depend on the availability of cloud-free anniversary acquisitions which might not be available for many areas around the globe (Huang et al., 2010; Kennedy, Yang, & Cohen, 2010; Masek et al., 2008). Compositing of Landsat data therefore is a valuable alternative for large-area change detection.

In this study, we successfully analyzed a series of large-area composites yielding forest type maps as well as forest disturbances and recovery dynamics. To our best knowledge, this is the first study to utilize a series of six large-area image composites in an integrated approach to analyze forest disturbances and recovery in relation to three broad forest types. Our results provided valuable insights into spatial and temporal patterns of forest changes in the Carpathians and may serve as a framework for similar studies to be conducted elsewhere. The resulting maps are foreseen to provide indispensable inputs to ecological, social and economic studies of land-change in the Carpathian ecoregion. Increased geometric and radiometric standard image quality, improved preprocessing algorithms and free-of-cost data have enabled Landsat data analyses to advance considerably in recent years. Moreover, this study again highlights the value of the open Landsat archive for retrospective land change analysis and the need for data continuity. With the upcoming Landsat-8 (Irons, Dwyer, & Barsi, 2012) as well as the European Sentinel-2 missions (Drusch et al., 2012), new opportunities arise for land change monitoring through combined use of both data sources featuring enhanced spectral and temporal data characteristics. Compositing will be one powerful aspect for monitoring approaches combining these new sensor systems and thus greatly enhance capabilities for global mapping and monitoring at landscape scales.

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