



## Forest cover change and illegal logging in the Ukrainian Carpathians in the transition period from 1988 to 2007

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### ABSTRACT

Illegal logging is a major environmental and economic problem, and exceeds in some countries the amounts of legally harvested timber. In Eastern Europe and the former Soviet Union, illegal logging increased and reforestation on abandoned farmland was widespread after the breakdown of socialism, and the region's forest cover trends remain overall largely unclear. Our goal here was to map forest cover change and to assess the extent of illegal logging and reforestation in the Ukrainian Carpathians. We used Landsat TM/ETM+ images and Support Vector Machines (SVM) to derive forest change trajectories between 1988 and 2007 for the entire Ukrainian Carpathians. We calculated logging and reforestation rates, and compared Landsat-based forest trends to official statistics and inventory maps. Our classification resulted in reliable forest/non-forest maps (overall accuracies between 97.1%–98.01%) and high clear cut detection rates (on average 89.4%). Forest cover change was widespread in the Ukrainian Carpathians between 1988 and 2007. We found forest cover increase in peripheral areas, forest loss in the interior Carpathians, and increased logging in remote areas. Overall, our results suggest that unsustainable forest use from socialist times likely persisted in the post-socialist period, resulting in a continued loss of older forests and forest fragmentation. Landsat-based forest trends differed substantially from official forest resource statistics. Illegal logging appears to have been at least as extensive as documented logging during the early 1990s and so-called sanitary clear-cuts represent a major loophole for overharvesting and logging in restricted areas. Reforestation and illegal logging are frequently not accounted for in forest resource statistics, highlighting limitations of these data. Combating illegal logging and transitioning towards sustainable forestry requires better monitoring and up-to-date accounting of forest resources, in the Carpathians and elsewhere in Eastern Europe, and remote sensing can be a key technology to achieve these goals.

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### 1. Introduction

Changes in forest cover have widespread effects on the provision of ecosystem services, affect biodiversity, and provide important feedbacks to climate change and human welfare (Bonan, 2008; MA, 2005). As human pressure on the planet rises, monitoring forest cover trends from global to regional scales is therefore of growing international concern (Hansen et al., 2008; Lepers et al., 2005). Official forest resource statistics such as national inventories or the periodic Forest Resource Assessments (FRA) of the Food and Agriculture Organization

of the United Nations (FAO, 2005) are the most frequently used datasets to monitor forest trends.

The problem is that forest resource statistics often have uneven quality in time and space, inconsistent survey methods, and utilize varying definitions across nations (Grainger, 2008; Rudel et al., 2005). Furthermore, official forest resource statistics frequently fail to capture illegal logging, particularly in developing nations, where illegal logging can exceed legal harvesting (e.g., >80% in Indonesia, >50% in Central Africa, or >60% in the Brazilian Amazon, Greenpeace, 2008; WWF, 2002, 2004). Assessing the reliability of official forestry statistics and the nature of forest cover trends therefore continues to be a major challenge in many parts of the world and remote sensing plays an important role by providing better estimates.

Illegal logging (i.e., timber harvesting in violation of national laws) can take many different forms and there is no internationally accepted definition of what is illegal (FERN, 2002). Two broad categories of

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illegal logging are usually distinguished (Bouriaud, 2005). Timber thefts mostly satisfy local people's demands (e.g., for fuel wood) and are often driven by poverty. On the other hand, unauthorized logging represents timber harvests that deliberately exceed harvesting limits, using corrupt means to gain access to forests, disobeying protected areas and forest laws, or capitalizing on gaps in legislation (Bouriaud & Niskanen, 2003; Brack, 2007). Thus, unauthorized logging is often connected to failures in forest governance, weak institutions, or a lack of law enforcement (Contreras-Hermosilla, 2002; Irland, 2008; Morozov, 2000). In this article, we consider logging illegal if it is not consistent with harvesting policies and forest laws for any of the above reasons, and therefore not accounted for in official forest resource statistics and inventory data.

Eastern Europe and the former Soviet Union experienced fundamental changes in their political, economic, and institutional structures after the breakdown of socialism. This raised considerable concerns about forest governance and illegal logging, because the transition period was characterized by economic hardships, and weakened institutions (Elbakidze & Angelstam, 2007; Kissling-Naf & Bisang, 2001; Lerman et al., 2004). Shadow businesses and corruption in the forestry sector have thrived in some countries, and illegal logging has been reported for the Russian Far East (WWF, 2002), Siberia (Vandergert & Newell, 2003), northern Russian Karelia (Piipponen, 1999), Estonia (Hain & Aha, 2004), the Caucasus (Greenpeace, 2000), and the Carpathian Mountains (Turnock, 2002). Substantial proportions of timber exports from Eastern Europe and European Russia are illegal (Bouriaud & Niskanen, 2003; WWF, 2004). However, the extent of illegal logging remains unclear, and available estimates vary among different sources (Bouriaud, 2005).

The transition from planned to market-oriented economies in Eastern Europe also resulted in widespread farmland abandonment particularly on marginal sites (DLG, 2005; Ioffe et al., 2004; Kuemmerle et al., 2008). Much of the abandoned land is now reverting back to forests, but just like illegal logging, reforestation (i.e., forest expansion via natural succession or planting) is frequently not included in official forest statistics. This impedes assessing net forest cover changes in Eastern Europe and the former Soviet Union, hampers subsequent analyses such as carbon budgeting, and poses serious challenges for policy makers aiming to implement sustainable forest management plans.

Eastern Europe is also still rich in vast and relatively undisturbed forest landscapes (Wesolowski, 2005). For example, the Carpathian Mountains constitute Europe's largest temperate forest ecosystems and are a biodiversity hotspot (UNEP, 2007). The Ukrainian region of the Carpathians is particularly important, because it bridges the northern and southern Carpathians, and includes some of Europe's last and largest old-growth beech forests (Herenchuk, 1968; Holubets et al., 1988; Wesolowski, 2005). Forest use has changed substantially in the Ukrainian Carpathians after the country became independent in 1991. Forest harvesting increased in some areas (Kuemmerle et al., 2007) and illegal logging occurred (Buksha et al., 2003; Nijnik & Van Kooten, 2000). On the other hand, forest expansion on abandoned farmland was widespread (Elbakidze & Angelstam, 2007; Kuemmerle et al., 2008) and Ukraine issued a national forest planting program in 2002. These opposite processes raise questions about net forest cover trends in the Ukrainian Carpathians in the post-socialist period. Unfortunately, available statistical forest resource data provide vastly differing numbers. For example, harvesting rates between 1991–1995 reported by Nilsson and Shvidenko (1999) are up to 60% higher than Zibtsev's (1998) rates. Even the direction of post-socialist harvesting trends is unclear with most studies reporting decreased harvesting (Buksha et al., 2003; FAO, 2005; Nilsson & Shvidenko, 1999), whereas others suggest increased logging during the early 1990s (Nijnik & Van Kooten, 2000). Overall, net forest cover changes in the Ukrainian Carpathians since the breakdown of socialism have only been examined for small study areas (Kozak et al., 2007b; Kuemmerle

et al., 2007; Sitko & Troll, 2008) and no study has so far compared actual forest cover change with official forest resource data.

The lack of an area-wide forest change map is partly explained by the challenges that large-area mapping of forest cover change in mountain regions face. Phenology, illumination effects, and variability in vegetation communities along altitudinal gradients frequently result in spectrally complex thematic classes (i.e., multi-modal, non-normal, Itten & Meyer, 1993; Seto & Liu, 2003). Non-parametric classifiers are powerful tools in such situations, because they do not assume specific *a-priori* density distributions per class (Friedl & Brodley, 1997; Seto & Liu, 2003). Support Vector Machines (SVM) perform equally well or better than other non-parametric approaches, while requiring fewer training samples (Foody & Mathur, 2004b; Pal & Mather, 2005). SVM discriminate classes by fitting a separating hyperplane in the feature space based on training samples (Huang et al., 2002) and have been successfully applied to map forest cover changes over large areas (Huang et al., 2008; Kuemmerle et al., 2008).

The increasing availability of long image time series, such as the Landsat data archive, now allows for moving from simplistic from-to assessments towards detailed change trajectory analyses (Hostert et al., 2003; Kennedy et al., 2007; Röder et al., 2008). Many change detection methods exist to analyze image pairs (Coppin et al., 2004), but tools for investigating dense time series of Landsat imagery are largely lacking (Kennedy et al., 2007). The challenge is that the complexity of a composite classification (Coppin & Bauer, 1996) increases exponentially with every additional image (e.g., 256 change classes for four land cover classes and four time periods). This often inhibits the collection of a representative training sample. In such situations, classifying images individually and assessing change *a-posteriori* may be the better option, if accurate individual classifications can be achieved.

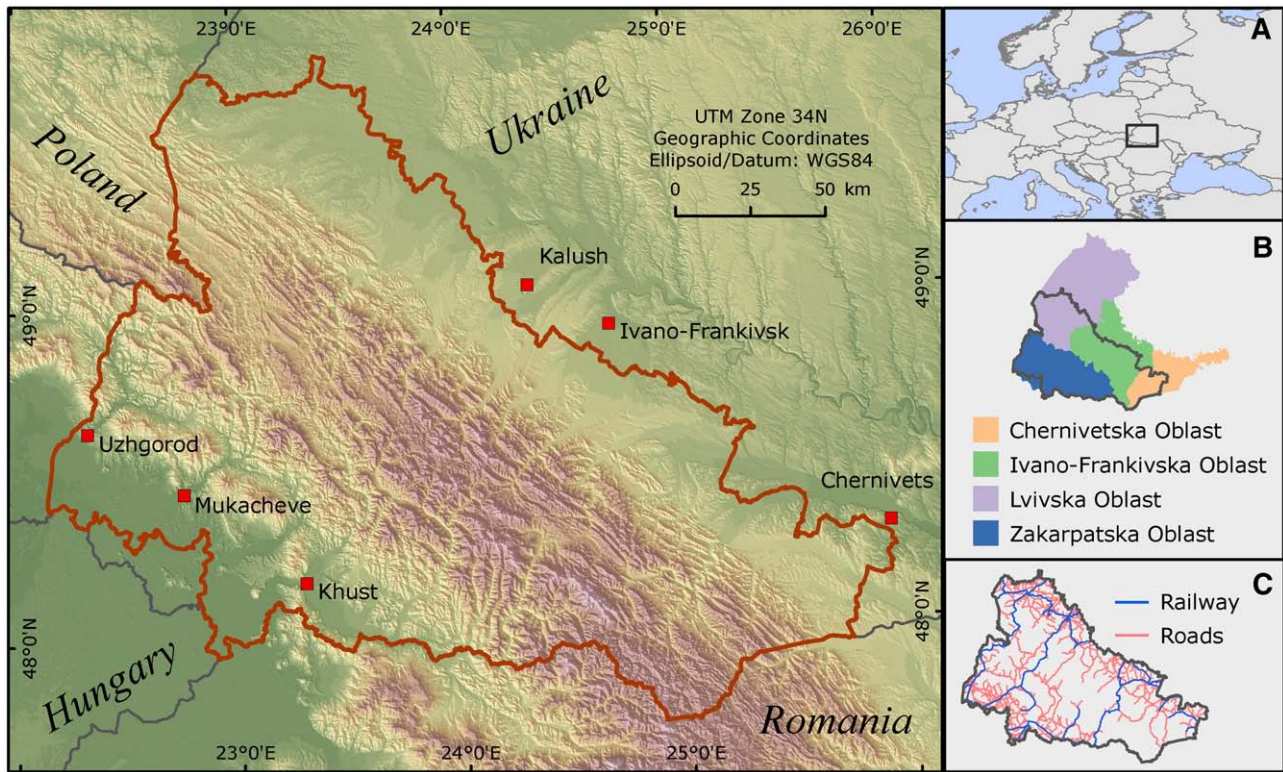
Our goal here was to assess the extent of illegal logging and reforestation in the Ukrainian Carpathians by exploring whether post-socialist forest cover trends mapped from satellite images differed from those reported in official forest resource data and forest inventories. This required us to derive the first area-wide forest cover change map for the Ukrainian Carpathians using Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) images. Our specific objectives were to:

- (1) map forest cover change in the Ukrainian Carpathians before and after the system change (1988–2007) from Landsat TM/ETM+ images using SVM,
- (2) compare satellite-based forest trends with official forest statistics,
- (3) compare satellite-based logging maps with forest inventory maps, and
- (4) assess the spatial pattern of logging in relation to topography and the visibility of logging sites.

## 2. Study region

As a study region, we selected the entire Ukrainian Carpathians (Fig. 1). Study region boundaries were based on administrative borders at the county (*raion*) level and we selected all raions that were at least partly within the ecoregion (using the Carpathian Ecoregion Initiative's boundary, [www.carpat.es.org](http://www.carpat.es.org), Kruhlov, 2008). The study region intersects with four provinces (*oblasts*): Chernivetska Oblast, Ivano-Frankivska Oblast, Lvivska Oblast, and Zakarpatska Oblast. It covers an area of 30,890 km<sup>2</sup>, and its total population is about 2 million (UNEP, 2007).

The region is characterized by a northwest-southeast running mountain range, predominately consisting of flysch and some volcanic and metamorphic rocks in the southwest. Altitude varies from > 100 m to 2061 m. The climate is temperate with a moderate continental influence and varies significantly depending on topography (temperature range



**Fig. 1.** Study region in the Ukrainian Carpathians. Main frame: study region boundaries (red), topography (elevation range >100–2,060 m), and major population centers. Inset A: location of the study region in Europe. Inset B: the four provinces (oblasts) comprising the Ukrainian Carpathians. Inset C: Major roads and railway tracks. Source: SRTM DEM (elevation data); ESRI World Data and Maps Kit 2005 (national boundaries and population centers); *Geodezkartinformatyka* (1997) (oblast boundaries, roads, railways).

between 20 °C to 6 °C in summer and –3 °C to –10 °C in winter; annual precipitation is 900–1200 mm, *Buchinskyi et al., 1971; Herenchuk, 1968*). Four altitudinal zones of natural vegetation occur in the study region. The foothills and adjacent plains (<300 m) are covered by broadleaved forests with pedunculate and sessile oak (*Quercus robur*, *Q. petraea*), often mixed with European beech (*Fagus sylvatica*), linden (*Tilia cordata*), hornbeam (*Carpinus betulus*), and ash (*Fraxinus excelsior*). The lower montane zone (300–1100 m) consists of beech forests with silver fir (*Abies alba*), Norway spruce (*Picea abies*), and sycamore maple (*Acer pseudoplatanus*). The upper montane zone extends up to the timberline (1500 m) and is dominated by coniferous species, mainly spruce and Arolla pine (*Pinus cembra*). Above timberline, mountain pine (*Pinus mugo*), green alder (*Alnus viridis*), and juniper (*Juniperus communis subsp. alpina*) shrubs and alpine grasslands prevail (*Herenchuk, 1968; Kruhlov et al., 2008*).

Land use has substantially affected the Ukrainian Carpathians. Much of the region's forestland was converted to farmland during the Austro-Hungarian Empire (1772–1918) and the foothill zone remains dominated by agriculture. Since the early 20th century, forest cover has been increasing slowly (*Kozak et al., 2007a*). However, forests have also been excessively exploited since the 19th century, especially under Soviet rule, resulting in an age distribution dominated by young age classes, increased forest fragmentation, and widespread spruce plantations (*Ireland & Kremenetska, 2008; Strochinskii et al., 2001; Turnock, 2002*). Mountain tops have traditionally been used for grazing, resulting in lowered timberlines in some regions (*Sitko & Troll, 2008*).

### 3. Datasets used and methodology

#### 3.1. Satellite images and ancillary data

We acquired 19 mid-summer and early fall Landsat TM and ETM+ images for ~1988, 1994, ~2000, and ~2007. Five Landsat footprints covered the full extent of the study region (path/row 184/26, 184/27,

185/26, 185/27, and 186/26). Full cloud-free coverage of the study region for a single year was only possible for 1994. For the late 1980s and the most recent time period (2007) we used images acquired  $\pm 1$  year, and two 2002 images complemented the 2000 imagery (acquisition dates are listed in *Table 2* in the results section).

Five of the images from the GeoCover dataset were already orthorectified (*Tucker et al., 2004*). The remaining 14 images were co-registered to the GeoCover dataset. To account for relief displacement, we included the Space Shuttle Topography Mission (SRTM) digital elevation model, resampled to 30 m. Tie points between GeoCover and uncorrected images were gathered automatically based on image correlation (*Kuemmerle et al., 2006*). All co-registered images had a positional accuracy of <0.5 pixel (*Tucker et al., 2004*). Clouds and cloud shadows were digitized and masked.

Ground truth data were gathered based on approximately 120 Quickbird images from 2002 to 2007 available in Google Earth™ (*earth.google.com*), covering 43.3% of our study area. Overlaying topographic maps and GPS tracks gathered in the field between 2004 and 2006 suggested that the positional accuracy of the Quickbird images was comparable to that of the Landsat images. For each Landsat footprint, we selected a random sample of ground truth points within the Quickbird image footprints, overlaid points on the Quickbird images in Google Earth™, and labeled each point as either 'forest' or 'non-forest' based on visual interpretation. A point was considered forested if tree cover exceeded 60% (i.e., 'closed tree cover' in the Land Cover Classification System, *Di Gregorio, 2005*) and if tree-dominated patches covered at least one Landsat pixel (30×30 m). Thus, our forest definition included orchards, but not single trees, treelines, and open shrubland. We only considered points where class membership was stable between 1988–2007 (i.e. either permanent forest or permanent non-forest), based on visual interpretation of the Landsat images. Ground truth points with unclear class membership, points in cloud areas, and points closer to forest/non-forest borders than the remaining positional uncertainty (less than 15 m) were

discarded (3% of a random sample at most). Training samples of 300 to 500 ground truth points per class resulted in stable classification accuracies and 1,400 random points per image provided this minimum amount of points per class (Knorn et al., in press). For three footprints (path/row 185/26, 185/27, and 186/26), we also used ground truth points mapped in the field between 2004 and 2006 (Kuemmerle et al., 2007, 2008). Points in overlap areas between Landsat paths were used for both footprints. In total, we used a sample of 5211 points (2373 forest, and 2838 non-forest) of which 4481 (1976, 2505) were mapped from Quickbird data and 730 (397, 333) were mapped in the field (see Section 4, Table 2).

Administrative boundaries at the province (*oblast*) and district (*raion*) level were digitized from topographic maps at a scale of 1:100,000 while road and railway networks were extracted from the digital topographic maps at a scale of 1:200,000 (Geodezkartinformatyka, 1997). Roads were classified as highways, paved roads, or dirt roads, and railway tracks as major tracks or narrow-gauge tracks. Country boundaries and major population centers were obtained from the Environmental Systems Research Institute's (ESRI) World Data & Maps Kit 2005.

Forest resource statistics at the oblast level were obtained from the Statistical Yearbook of Ukraine for the years 1985–1987, 1990, 1995, 2000, and 2002–2007 (The State Statistics Committee of Ukraine, 2006, 2007). We extracted two indicators: (1) areas designated for post-clear-cut forest regeneration (i.e., where forest regeneration *should* have been carried out), and (2) areas dedicated for new forest planting. We also acquired a digital forest inventory map at a scale of 1:10,000 covering all state-managed forests in Zakarpatska Oblast. This map contains more than 89,000 polygons and provided detailed stand-level information on forest management practices carried out between 1999–2007. Polygons in this map represent the finest scale of forest management units in the Ukrainian Carpathians. We categorized all forest management practices into practices where forest cover is retained, partly removed (e.g. single or group selection harvesting), or fully removed (e.g., clear-cuts). Planned forest management practices that had not yet been implemented were excluded. Where several forest management practices had been carried out (e.g., clear-cutting followed by forest regeneration practices), we considered only the oldest practice where forest cover was fully removed (or partially removed where forest cover was never fully removed). To assess the accuracy of the forest inventory maps, we randomly selected 100 polygons designated as clear-cuts and checked them visually by overlaying them with the Landsat images. Each polygon was assigned to one of the three classes 'No forest cover removal', 'Partial forest cover removal', or 'Complete forest cover removal'.

### 3.2. Forest cover change mapping using support vector machines

Image classification with SVM is based on fitting a separating linear hyperplane between two classes in the multidimensional feature space (Foody & Mathur, 2004a; Huang et al., 2002). The optimal hyperplane is constructed by maximizing the margin between training samples of opposite classes. Thus, instead of using all available training data to describe classes, SVM use only those training samples that describe class boundaries, the so-called *support vectors* (Foody & Mathur, 2004b, 2006). To separate classes with non-linear boundaries, kernel functions are used to transform training data into a higher-dimensional space, where linear class separation is possible (Huang et al., 2002). This allows SVM to effectively handle complex class distributions (i.e., non-linear, multi-modal) while requiring relatively few training samples (Foody & Mathur, 2004b; Pal & Mather, 2005). A detailed mathematical description of SVM concepts is found in Burges (1998). Detailed introductions in a remote sensing context are provided by Huang et al. (2002) and Foody and Mathur (2004a).

We used SVMs to delineate forest/non-forest maps for each of the four time periods and assessed forest cover change via post-classification map comparison. This reduced the complexity of our classification

approach to a binary problem for which SVM were originally developed (Huang et al., 2002). As a kernel function, we decided to use a Gaussian radial basis function (Huang et al., 2002), that requires setting the kernel width ( $\gamma$ ). Parameterizing the SVM also requires setting a regularization parameter  $C$ , that penalizes misclassified training data to control the trade-off between maximizing the margin and training error (Pal & Mather, 2005). Small  $C$ -values tend to emphasize the margin while ignoring outliers, whereas large  $C$ -values may result in over-fitting. Thus, the best-performing combination of  $\gamma$  and  $C$  depends on the training data and is not known *a-priori*. We systematically tested a wide range of parameter combinations ( $\gamma$  from 0.00001 to 100,000 and  $C$  from 0.1 to 1000) by fitting individual SVM to each parameter pair and comparing models based on cross-validation errors (Janz et al., 2007; Kuemmerle et al., 2008). This allowed us to identify optimal parameter combinations for each image individually.

Once optimal  $\gamma$  and  $C$  were found, we classified each of the 19 Landsat TM/ETM+ images based on the six multi-spectral bands. We split all available ground truth points into training (90%) and validation (10%) samples. Based on the validation sample, we then calculated an error matrix, overall accuracy, user's and producer's accuracy, and the kappa statistics (Congalton, 1991; Foody, 2002). We also derived the  $F$ -measure, an indicator of overall classification accuracy based on the weighted harmonic mean of producer's and user's accuracy (Baeza-Yates & Ribeiro-Neto, 1999). To derive robust error estimations, we classified each image 10 times for all 10 possible splits, derived the accuracy measures, and then calculated mean error estimates (Friedl & Brodley, 1997; Steele, 2005). The final classification was calculated using 100% of the ground truth data, and the mean error estimate is thus a conservative estimator of the true accuracy (Burman, 1989). The SVM parameter search, image classification, and accuracy assessment were carried out with the software imageSVM ([www.hu-geomatics.de](http://www.hu-geomatics.de)).

We mosaicked the forest/non-forest maps for each time period. Maps with higher accuracy were given priority in overlap areas and we filled clouded areas with data from overlapping paths wherever possible. Remaining clouds were masked from all mosaics (<1.0% of the study region). Once mosaics for all four time periods were available, we established a rule-set to derive a forest cover change map (Table 1). Depending on the time of disturbance and the post-disturbance regeneration, we defined eight disturbance classes. The term disturbance here refers to the complete or near-complete removal of forest cover by anthropogenic processes (e.g., logging) or natural events (e.g., storms).

We assumed reforestation on abandoned farmland to take longer than six years, because forest planting virtually stopped after the system change and natural succession is slow in the Carpathians

**Table 1**

Rule set for delineating the forest cover change map based on the forest/non-forest classifications for each time period (F = forest; NF = non-forest).

ID	Class label	Time period			
		1988	1994	2000	2007
1	Permanent forest	F	F	F	F
2	Permanent non-forest	NF	NF	NF	NF
3	Forest disturbance before 1988	NF	F	F	F
4	Forest disturbance in 1988–1994 (a)	F	NF	F	F
5	Forest disturbance in 1988–1994 (b)	F	NF	NF	F
6	Permanent clearing in 1988–1994	F	NF	NF	NF
7	Forest disturbance in 1994–2000 (a)	F	F	NF	F
8	Forest disturbance in 1994–2000 (b)	F	F	NF	NF
9	Forest disturbance in 2000–2007	F	F	F	NF
10	Forest disturbance before 1988 and in 2000–2007	NF	F	F	NF
11	Reforestation 1988–2000 or Forest disturbance before 1988	NF	NF	F	F
12	Reforestation 1988–2000–2007	NF	NF	NF	F
13	Misclassification (a)	NF	F	NF	F
14	Misclassification (b)	F	NF	F	NF
15	Misclassification (c)	NF	NF	F	NF
16	Misclassification (d)	NF	F	NF	NF

**Table 2**  
Landsat TM/ETM+ images used and classification accuracies [%] of the forest (F)/non-forest (NF) maps for each image.

Time period	Path/row	Acquisition date	Sensor	Overall accuracy	Kappa	User's accuracy		Producer's accuracy		F-measure		Number of points		
						F	NF	F	NF	F	NF	Total	F	NF
1988	184/26	1989/07/08	TM5	98.72	0.97	97.87	99.08	97.50	99.18	97.69	99.13	1343	369	974
	184/27	1989/07/08	TM5	95.43	0.90	96.59	93.26	96.59	93.10	96.59	93.18	1279	851	428
	185/26	1988/08/21	TM4	97.94	0.96	97.64	98.20	97.41	98.31	97.52	98.26	1316	543	773
	185/27	1988/08/13	TM5	97.59	0.94	94.56	98.83	97.00	97.82	95.76	98.32	1096	307	789
	186/26	1988/07/27	TM4	98.05	0.96	97.85	98.22	97.00	98.67	97.42	98.45	1342	503	839
1994	184/26	1994/09/08	TM5	98.65	0.97	97.32	99.18	97.78	98.97	97.55	99.07	1343	369	974
	184/27	1994/09/08	TM5	97.34	0.94	98.07	96.01	97.93	96.19	98.00	96.10	1255	826	429
	185/26	1994/07/29	TM5	98.14	0.96	97.49	98.66	98.18	98.11	97.83	98.38	1297	552	745
2000	186/26	1994/07/04	TM5	97.15	0.94	94.91	98.62	97.76	96.79	96.31	97.70	1309	490	819
	184/26	2002/08/21	ETM+	99.40	0.98	98.65	99.69	99.17	99.48	98.91	99.59	1343	369	974
	184/27	2002/07/04	ETM+	96.61	0.92	96.34	97.30	98.61	92.86	97.46	95.03	1220	797	423
	185/26	2000/06/03	ETM+	96.34	0.93	95.89	96.90	96.82	95.86	96.35	96.38	1738	859	879
	185/27	2000/08/22	ETM+	96.55	0.92	93.47	97.98	95.23	97.12	94.34	97.55	1493	448	1045
2007	186/26	2000/06/10	ETM+	97.04	0.94	95.40	98.17	97.18	96.94	96.28	97.55	2003	785	1218
	184/26	2006/09/25	TM5	98.80	0.97	97.07	99.49	98.61	98.87	97.84	99.18	1343	369	974
	184/27	2006/10/11	TM5	94.68	0.88	94.70	94.87	97.70	88.29	96.18	91.46	1103	746	357
	185/26	2007/07/17	TM5	96.59	0.93	93.43	99.17	98.87	95.00	96.07	97.04	1296	531	765
	185/27	2007/07/17	TM5	97.94	0.95	96.30	98.65	96.75	98.44	96.52	98.54	1364	403	961
	186/26	2007/07/24	TM5	95.57	0.91	92.87	97.41	95.71	95.49	94.27	96.44	1311	491	820

(Buksa et al., 2003; Kuemmerle et al., 2008). Farmland abandonment was not widespread before 1988, and this means that forest regeneration in 1988–1994 largely reflected pre-1988 disturbances, and reforestation could not have occurred before 1994–2000. Initial tests suggested that the reforestation classes contained some disturbances where forest regeneration was slow. We therefore selected all reforestation patches within forests (>80% relative border to permanent forest or disturbances) and assigned such patches to the pre-1988 disturbance class. Four of the possible 16 change classes suggested two disturbance events within a 12-year period (Table 1). Comparing these classes to high-resolution imagery revealed that they almost exclusively represented misclassifications due to phenology differences among images and all such patches were assigned to 'Permanent non-forest'. These four classes together covered about 1.2% of the study region.

To eliminate small disturbance patches representing mostly misclassifications, small forest patches that were functionally not forest (e.g., hedgerows, trees along roads and creeks, groups of trees between fields, etc), and the salt-and-pepper effect common to pixel-based classifications, we assigned patches with <7 pixels to the dominating surrounding class. This threshold was selected because the smallest forest management unit in Ukraine is 0.5 ha. We also selected all disturbance patches fully surrounded by non-forest, disturbance patches (but not reforestation patches) above the timberline (i.e., mean elevation of >1350 m and relative border to permanent non-forest >0.8), and narrow disturbances along rivers (disturbance patches with length/width ratios >4.5) and assigned them to permanent non-forest, because field visits and high-resolution images suggested these patches represented mostly misclassifications.

**Table 3**  
Validation of disturbance detectability before 1988, in 1988–1994, in 1994–2000, and in 2000–2007.

Classified data		Reference data			
		Disturbances before 1988	Disturbances in 1988–1994	Disturbances in 1994–2000	Disturbances in 2000–2007
	Permanent forest	3.02	7.93	8.20	2.29
	Permanent non-forest	8.98	0.82	0.00	0.14
	Forest disturbance before 1988	83.49	0.29	0.00	0.00
	Forest disturbance 1988–1994	2.35	87.67	0.85	0.14
	Forest disturbance 1994–2000	0.14	2.73	89.70	0.70
	Forest disturbance 2000–2007	0.32	0.57	1.25	96.73
	Reforestation 1988–2000	0.14	0.00	0.00	0.00
	Reforestation 1988–2000–2007	1.58	0.00	0.00	0.00

Numbers indicate relative abundance (in percent) of different classes mapped from the Landsat TM/ETM+ images in each of the four disturbance categories of the reference data.

In addition to the accuracy assessment of the individual classifications, we conducted a validation of the detectability of disturbances. We randomly selected 25 points and digitized the closest disturbance for each of the four time periods based on the Landsat TM/ETM+ images. This resulted in a total of 100 disturbance polygons, together covering an area of 877 ha, and we cross-tabulated these areas with the forest cover change map.

### 3.3. Analyzing forest cover change

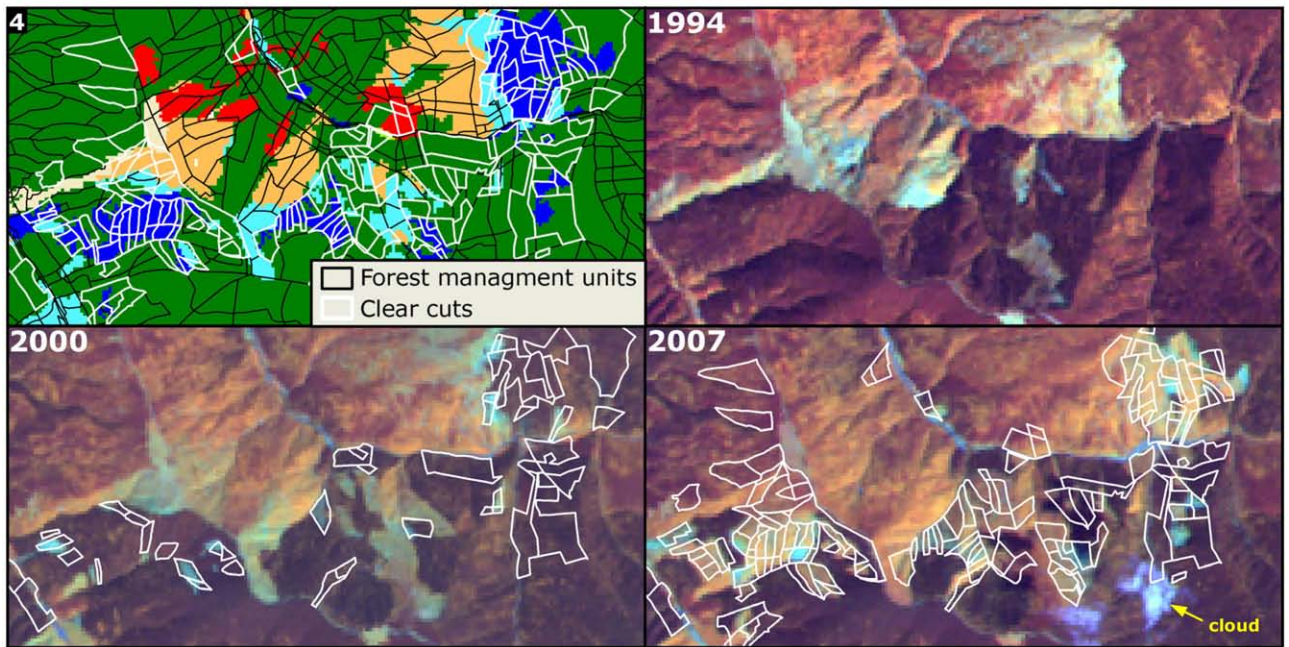
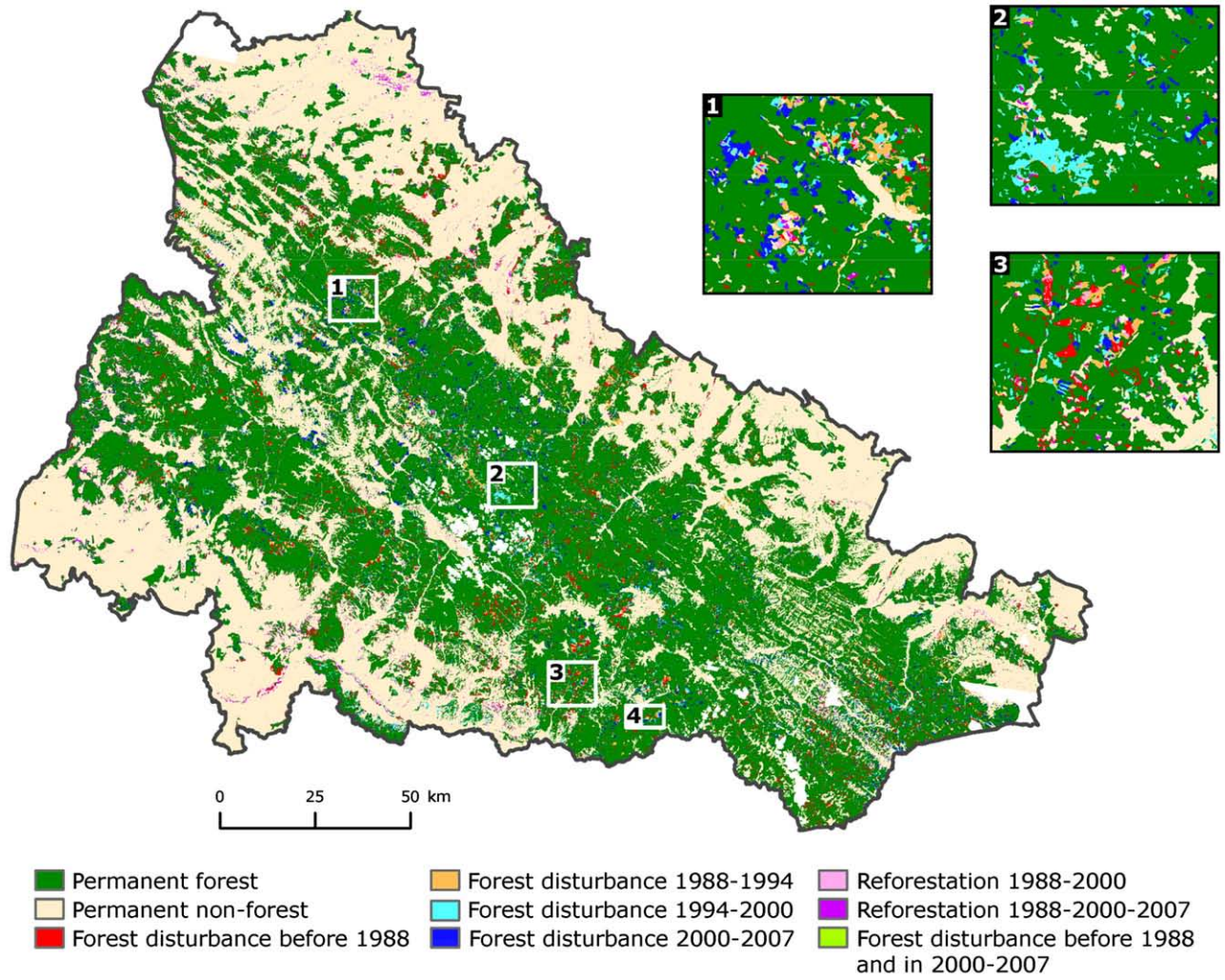
To compare forest change among different regions and time periods, we calculated absolute and relative net forest cover changes as well as annual disturbance and reforestation rates for the full study region, for each oblast, and for each raion. Net change was calculated as the difference in forest cover (in km<sup>2</sup>) between 1988 and 2007, whereas relative net change (RNC) was calculated as:

$$RNC = (FC_{2007} / FC_{1988} - 1) * 100 \quad (1)$$

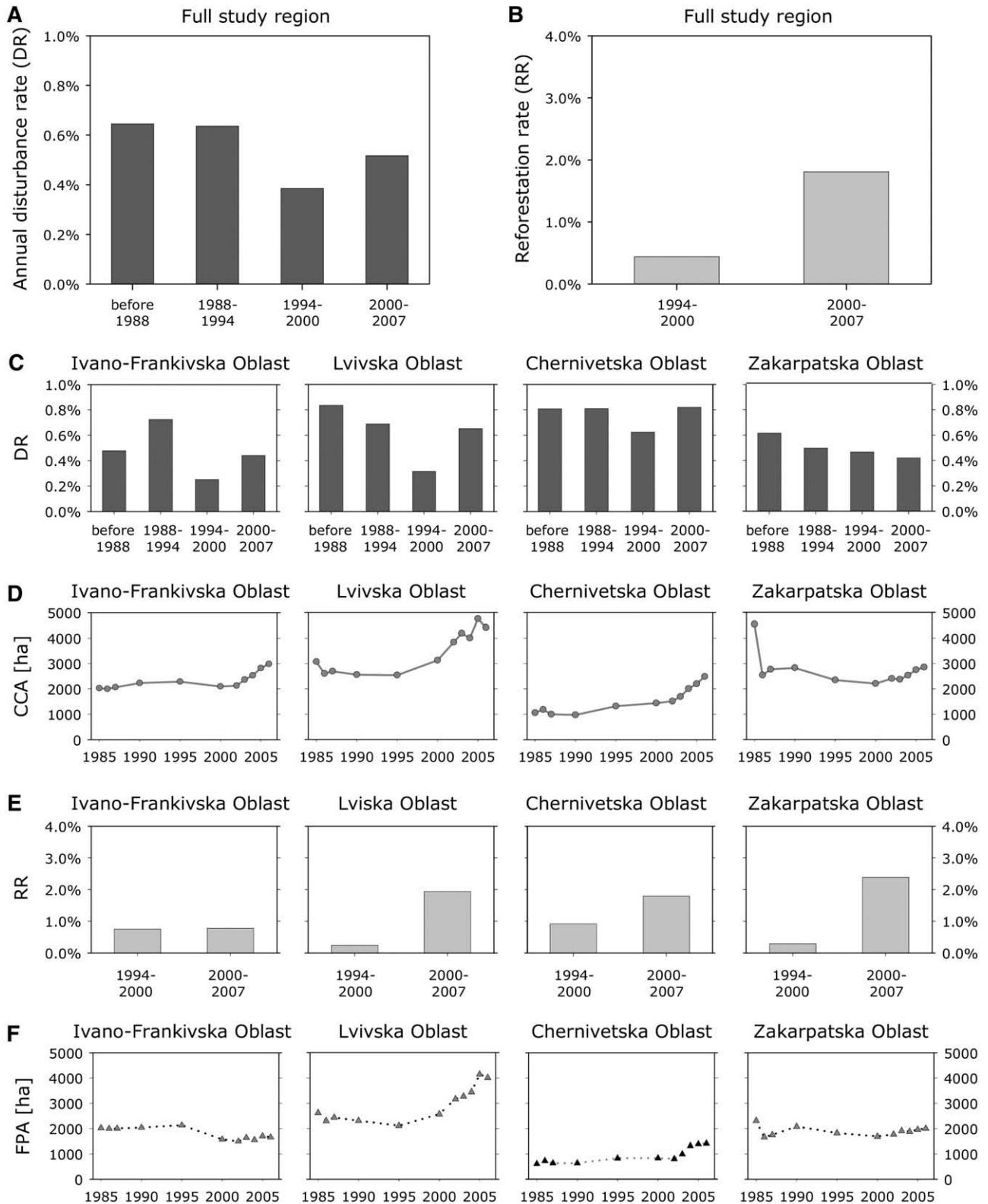
where FC denotes forest cover (in km<sup>2</sup>). Annual disturbance rates (DR) were calculated for each time period  $j$  as:

$$DR_j = (D_j / FCB_j) * 100 / a \quad (2)$$

where  $D$  is the sum of disturbances in time period  $j$ , FCB denotes forest cover at the beginning of time period  $j$ , and  $a$  is the number of years between image acquisition. Because images from one time period were not always from a single year, we intersected the Landsat footprints from the beginning and end of a time period (considering



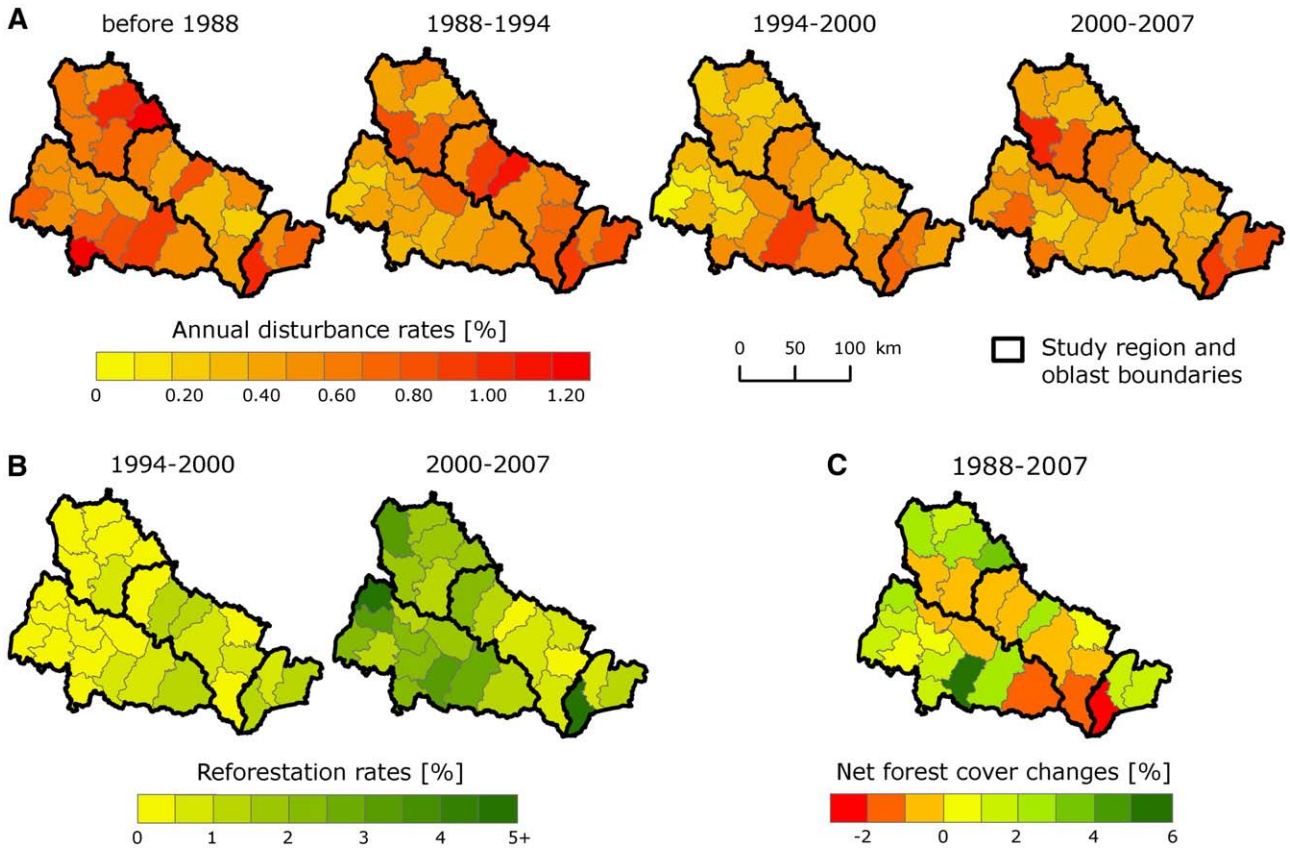
**Fig. 2.** Top: Forest cover changes between 1988 and 2007. Bottom: Comparison of the satellite-based forest cover change map, stand-level forest management maps, and Landsat TM/ETM+ images from 1994, 2000, 2007 for an area close to Rakhiv, Zakarpatska Oblast. Source: Ukrainian National Forestry University (inventory maps).



**Fig. 3.** Remote-sensing-based disturbance and reforestation rates at the study region and oblast level and forest resource statistics at the oblast level from the Statistical Yearbook of Ukraine (2006 and 2007). A: Annual disturbance rates for the full study region. B: Reforestation in the study region (relative to 1988-non-forest land). C: Annual disturbance rates (DR) per oblast. D: Official trends in forest regeneration (i.e., clear-cut) area (CCA) per oblast. E: Reforestation rates (RR, relative to 1988-non-forest land) per oblast. F: Official trends in forest planting area (FPA) per oblast. Source: [The State Statistics Committee of Ukraine \(2006, 2007\)](#) (forest resource statistics).

how images had been mosaicked in overlap areas to adjacent footprints). We then assigned the number of years between image acquisition (*a*) for each segment, and calculated disturbance rates per segment. To summarize disturbance rates at the study region, oblast,

and raion level, we calculated the area-weighted mean of disturbance rates. Detection of older disturbances in temperate forest ecosystems can be challenging because of forest regeneration (Healey et al., 2005; Kennedy et al., 2007). We thus decided to use a maximum *a* of 6 years



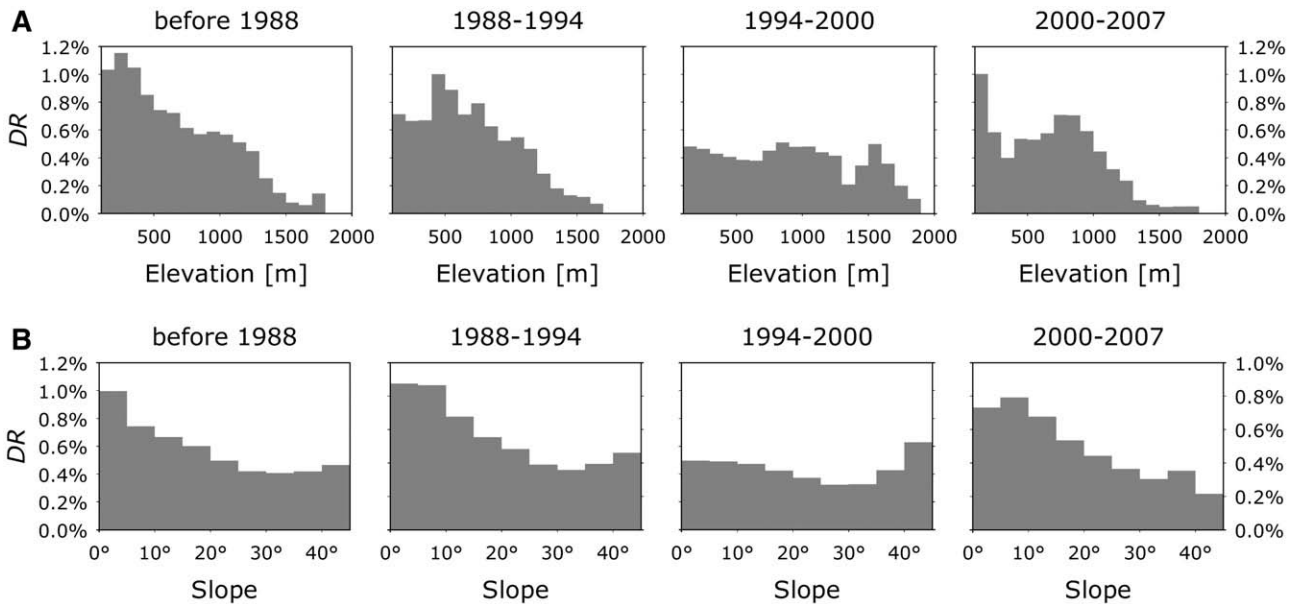
**Fig. 4.** Disturbance rates (DR), reforestation rates (RR), and relative net change (RNC) rates at the raion level. A: Annual disturbance rates. B: Reforestation in the study region (relative to 1988-non-forest land). C: Net forest cover change (relative to raion area). Source: *Geodezkartinformatyka* (1997) (oblast and raion boundaries).

based on prior experience (Kuemmerle et al., 2007). Reforestation rates (RR) were calculated as:

$$RR_j = \left( R_j / NF_{1988} \right) * 100 \quad (3)$$

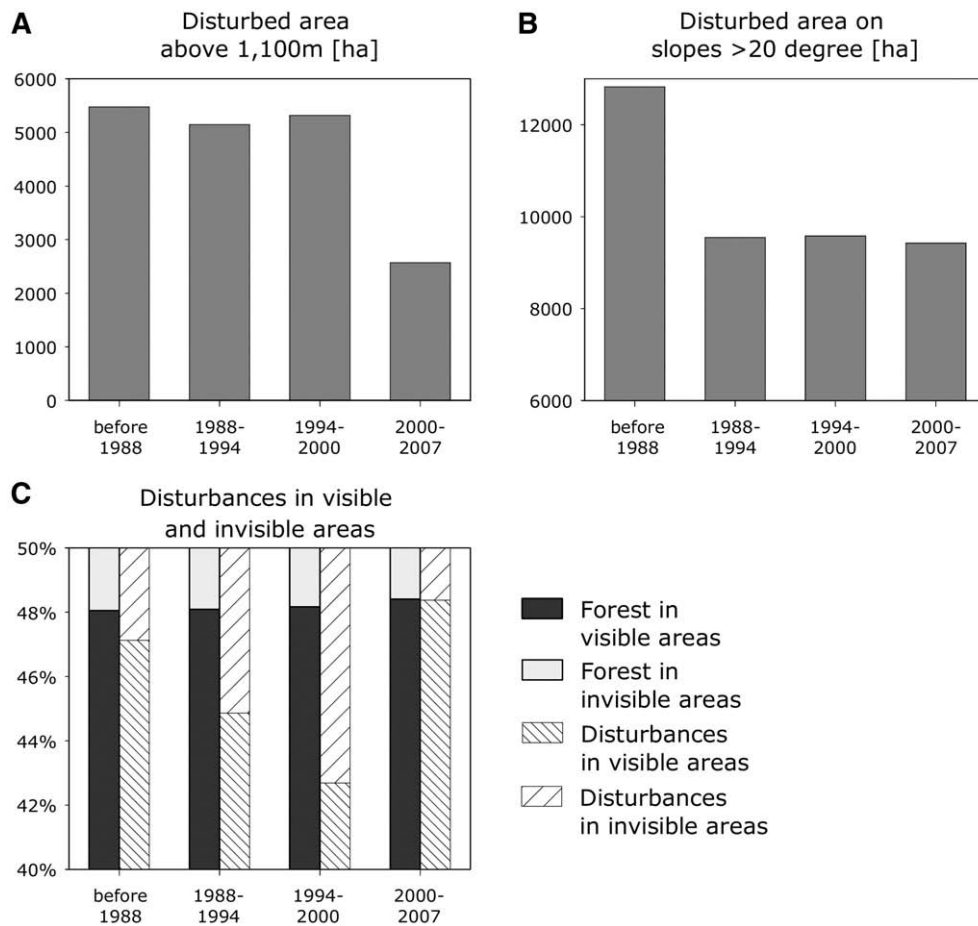
where  $R$  is the reforestation area per time period, and  $NF_{1988}$  denotes all non-forest land (excluding disturbances) in 1988.

To assess whether forest cover change varied with altitude, we stratified the DEM into 100 m strata and calculated mean annual disturbance rates for each stratum and time period. Likewise, we summarized disturbance rates for 9 slope classes using 5-degree breaks. To compare the forest inventory map and the Landsat forest cover change map, we summarized unchanged, disturbed, and reforested areas from the change map for each forest management



**Fig. 5.** Changes in disturbance rates by elevation (A) and slope (B).





**Fig. 6.** Disturbed area above and below 1,100 m elevation (A), and on slopes  $>20^\circ$  and  $<20^\circ$  (B). Proportions of forest and disturbances in areas visible or invisible from major roads and railway tracks (C).

practice and for each of the three aggregated forest management categories (full, partial, or no forest cover removal).

New forest legislation prohibiting clear-cuts in beech-fir forest above 1100 m and on steep slopes  $>20^\circ$  was put in place in Ukraine in 2000 (Verkhovna Rada, 2000a,b). To assess how these policies affected disturbance rates, we summarized the disturbance area above 1100 m and on slopes steeper than  $20^\circ$  for each time period. Because illegal logging is often hidden, we also assessed the proportion of disturbances visible from highways, paved roads and railway tracks using a viewshed analysis. We categorized our study region into areas that were either visible or invisible from these features and summarized disturbances for both categories and each time period.

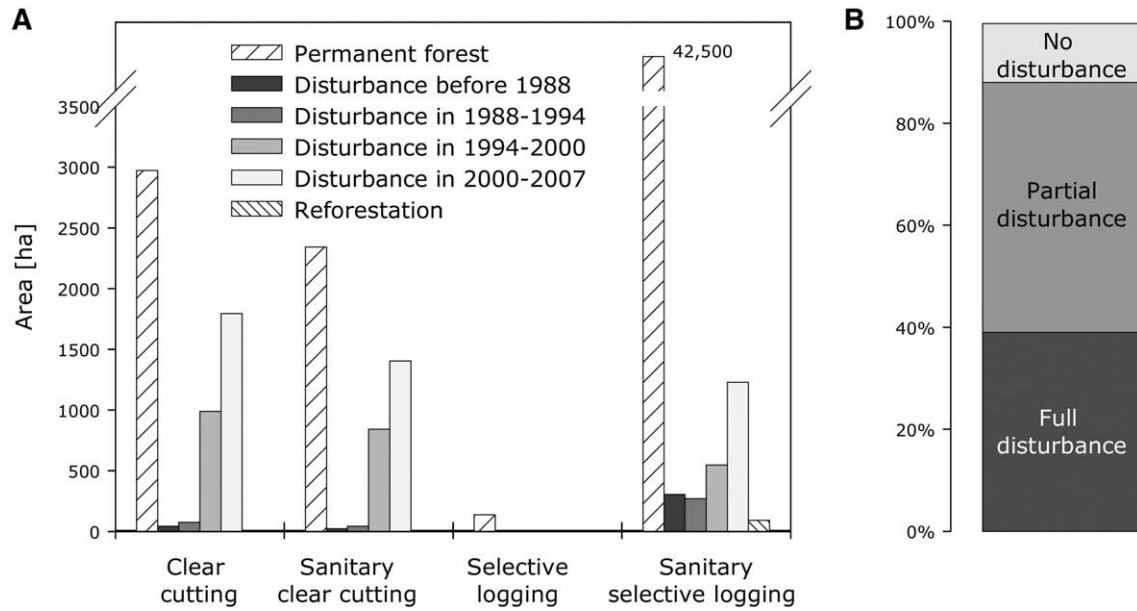
#### 4. Results

Our SVM-based classification approach resulted in reliable forest/non-forest maps for all Landsat TM/ETM+ footprints and time periods. Overall accuracies of the individual classifications ranged from 94.68 to 99.40% (kappa 0.88 to 0.98, Table 2).

Disturbances in 1988–1994, 1994–2000, and 2000–2007 were captured with high accuracies ( $>87\%$ , Table 3). Disturbances before 1988 were detected with a slightly lower accuracy (83%), due to confusion with permanent non-forest areas. The overall accuracy of our change map, estimated as the product of the individual map accuracies (Coppin et al., 2004), was 95.81% for the 1988–1994 period, 95.29% for the 1994–2000 period, and 94.61% for the 2000–2007 period.

**Table 4**  
Distribution of permanent forest, disturbances, and reforestation mapped from Landsat TM/ETM+ imagery within different categories of forest management practices as indicated by the inventory map of Zakarpatska Oblast (in ha).

		Forest inventory map				Sum
		No forest management practices	Forest management without forest cover removal	Partial forest cover removal	Complete forest cover removal	
Satellite-based forest change map	Permanent forest	314,388.36	9,592.11	63,023.22	5698.26	392,701.95
	Disturbance before 1988	10,307.16	373.23	4392.9	74.43	15,147.72
	Disturbance in 1988–1994	4608.99	2491.56	3258.72	124.29	10,483.56
	Disturbance in 1994–2000	3885.93	3516.84	1555.47	1877.4	10,835.64
	Disturbance in 2000–2007	3696.39	605.61	2317.86	3369.6	9989.46
	Reforestation	929.07	50.67	216	2.79	1198.53
	Sum	337,815.9	16,630.02	74,764.17	11,146.77	



**Fig. 7.** A: Distribution of permanent forest, disturbances, and reforestation mapped from the Landsat images for four forest management practices documented in the inventory map (clear cutting, sanitary clear-cutting, selective logging, and sanitary selective logging) (A). Visual assessment of 100 forest management polygons designated as clear-cuts in the inventory data. All polygons were checked against the Landsat images, whether forest cover was intact, partially removed, or fully removed (B).

Forest cover changed substantially in the Ukrainian Carpathians between 1988 and 2007 (Fig. 2, top) mainly due to disturbances, which affected 6.83% of the study region (2072 km<sup>2</sup>). Forests had regenerated on the majority (1365 km<sup>2</sup>) of these areas in 2007. Disturbances occurred highly clustered. Before 1994 disturbance clusters were mainly found in the northern and southwestern foothills, and close to the Romanian border. After 1994, disturbance clusters mainly occurred in the interior Carpathians. Reforestation occurred on 2.25% of all non-forest land in 1988 (equaling 306 km<sup>2</sup>), mainly in the plains in the Southwest and Northeast of the study region (Fig. 2, top). Overall, forest cover increase slightly in the Ukrainian Carpathians between 1988–2007 (0.82% of the study region, equaling 250 km<sup>2</sup>).

Our Landsat-based forest cover change map differed markedly from the forest inventory map (Fig. 2, bottom). Between 2000 and 2007, most disturbances mapped in the satellite images were documented as clear-cuts in the forest inventory maps, although clear-cuts were sometimes larger than documented. Conversely, there were also clear cuts in the inventory data that appeared only partially or not at all harvested in the satellite images. Before 2000, only a relatively small proportion of the disturbances appeared in the forest inventory maps, and disturbances were often substantially larger than reported (Fig. 2, bottom).

Annual disturbance across the study region remained nearly constant until 1994, but dropped markedly (by 39%) in 1994–2000 and increased again after 2000 (by 34%, Fig. 3A). Reforestation rates were four times higher in 2000–2007 compared to 1994–2000 (Fig. 3B). Forest trends differed markedly among the four oblasts (provinces). Disturbance rates in Ivano-Frankivska Oblast increased in 1988–1994 (by 52%), remained stable in Chernivetska Oblast, and decreased in Lvivska and Zakarpatska Oblasts (Fig. 3C). In contrast to the other three provinces, disturbance rates in Zakarpatska Oblast decreased gradually in 1988–2007 (by 32%). Reforestation trends also differed among oblasts. Reforestation rates in Lvivska Oblast and Zakarpatska Oblast were about eight times higher in 2000–2007 compared to 1994–2000, but increased only moderately in Chernivetska Oblast and Ivano-Frankivska Oblast (Fig. 3E). Overall, forest cover increased by 1.29% of the oblast area (equaling 88 km<sup>2</sup>) in Lvivska Oblast, by 0.83% (23 km<sup>2</sup>) in Chernivetska Oblast, and by 1.26% (151 km<sup>2</sup>) in Zakarpatska Oblast, whereas there was a net forest cover decrease of 0.14% (12 km<sup>2</sup>) in Ivano-Frankivska Oblast.

Disturbance rates also displayed marked heterogeneity at the raion (district) level (Fig. 4). Raions in the interior Carpathians generally exhibited increasing disturbance rates (e.g., Turka and Skole in Lvivska Oblast, Rozhnativ and Bohorodchany in Ivano-Frankivska Oblast, or Putyla in Chernivetska Oblast), but more peripheral raions generally showed decreasing rates (e.g., Drohobych and Stryi in Lvivska Oblast or Tiachiv and Vynohradiv Zakarpatska Oblast). Disturbance rates generally dropped in 1994–2000, but some raions displayed increasing disturbances (e.g. in the East of Zakarpatska Oblast). And the 2000–2007 increase in disturbance rates was most pronounced in the western interior Carpathians (Fig. 4A). High reforestation rates were generally associated with peripheral raions (Fig. 4B), and as a result, peripheral raions dominantly increased forest cover, whereas almost all raions in the interior Carpathians lost forest cover from 1988 to 2007 (Fig. 4C).

Disturbance rates also varied substantially with altitude. Before 1988, the highest disturbance rates occurred at lower elevations (<500 m, Fig. 5A). After 1988 higher disturbance rates occurred at higher elevations, and in 1994–2000, the highest rates were found above 1000 m. The extent of disturbances above 1100 m did not vary substantially until 2000, but dropped by about 50% after new forest legislation became effective (Fig. 6A). Disturbance rates increased on all slopes in 1988–1994, but there was a clear tendency towards steeper slopes (>30°) in 1994–2000 (Fig. 5B). However, the extent of disturbances on slopes steeper than 20° was similar before and after 2000 (Fig. 6B). Last but not least, the proportion of disturbances visible from major roads and railway tracks changed markedly through time. Already before 1988, the majority of disturbances (53%) occurred in invisible areas. After 1988, the proportion of visible forest area increased slightly, yet disturbances increasingly tended to occur in invisible areas. This trend reversed in the time period from 2000–2007 when the proportions of forest and disturbances in visible and invisible areas were approximately equal (Fig. 6C).

Forest cover trends mapped from Landsat images differed markedly from official forest resource data at the oblast level. According to official statistics documented in the Statistical Yearbook of Ukraine, the area of clear-cuts was relatively low until 2000, and increased in most oblasts after 2000. While the post-2000 increase in the statistics was paralleled in our forest disturbance rates in all but Zakarpatska Oblast, the relatively high disturbance rates we found before 1994 in Lvivska and Chernivetska Oblasts and the marked

increase in disturbance rates in Ivano-Frankivska Oblast after 1988 were not depicted in the forest resource data (Fig. 3D). Likewise, forest planting trends in forest resource data differed markedly from satellite-based reforestation trends (Fig. 3F).

Similarly, the vast majority of forest disturbances before 2000 mapped from the Landsat images were not documented in the inventory map of Zakarpatska Oblast (Table 4). After 2000, about 34% of all disturbances were detected in areas designated as clear cuts. However, 23% (2,318 ha) of all disturbances in 2000–2007 were found in areas where the inventory maps indicated only partial harvesting, and 43% (4302 ha) occurred where officially no forest management had taken place. Also, more than 5698 ha of clear cuts in the inventory maps remained unchanged forest based on the classified Landsat images (Table 4).

In the inventory map, regular clear cuts and sanitary clear-cuts were almost equally common (Fig. 7A). Sanitary clear-cuts are harvests in response to tree mortality, mainly due to insect disturbance. Selective logging was not very widespread and very few disturbances occurred in such areas. However, sanitary selective logging covered large areas and we found substantial forest disturbances in sanitary selective logging sites. The majority of the areas designated as clear cuts or selective logging sites in the inventory maps were found to represent permanent forest based on the satellite images (Fig. 7A). Visual comparison of clear-cut polygons and Landsat images revealed that forest cover had been completely removed in only 39% of these polygons. Forest cover had only partially been removed in 49% of all polygons, and no disturbance could be visually identified in 12% of all cases (Fig. 7B).

## 5. Discussion

### 5.1. Post-socialist forest cover trends and illegal logging in the Ukrainian Carpathians

Forest disturbance and reforestation resulted in widespread forest cover change in the Ukrainian Carpathians in 1988–2007. The vast majority of disturbances in the study region were due to logging, and forest harvesting trends mapped from satellite images thus differed substantially from forest resource statistics and inventory maps in the Ukrainian Carpathians. What are the reasons for this disagreement? While our accuracy assessments confirmed the high reliability of the Landsat-based change map (see Section 5.2 for a detailed discussion of the mapping approach), the inventory data, from which higher-level forest resource statistics are aggregated, exhibited considerable uncertainty. We suggest this uncertainty is the main reason for diverging patterns of satellite-based trends and forest resource statistics.

Updating problems (e.g., where management units were subdivided or merged) and deliberate misreporting cause errors and ambiguity in inventory data (Gerasimov & Karjalainen, 2006; Houghton et al., 2007). Even when analyzing only the 2000–2007 period, our results showed that almost 60% of the polygons designated as clear cuts in the inventory map from Zakarpatska Oblast were only partially harvested or not yet harvested (Fig. 7B), possibly because forest management practices were only applied to a portion of the area of the forest management unit.

Conversely, undocumented logging was widespread in the Ukrainian Carpathians. We found frequent harvesting in areas not designated for harvests as well as over-harvesting beyond the boundaries of designated areas (Fig. 2, Table 4). While a lack of funding to update inventories may have contributed to these patterns, we suggest illegal logging is the main reason explaining the disagreement between remote sensing and forest inventory maps. After 1991, Ukraine's economy collapsed, state control diminished, and law enforcement, a prime factor in guarding forests from overuse (Chhatre & Agrawal, 2008), was weak. Overall, this resulted in emerging shadow business in the Ukrainian forest sector (Buksha et al., 2003; Nijnik & Van Kooten, 2000, 2006). Our results indicate that

illegal logging may have been especially widespread during the first half of the 1990s, when the discrepancy between satellite-based trends and forest resource statistics was greatest (Fig. 3), and at a time when funds, machines, and fuel were still available to keep forest enterprises running.

Ukraine has since then taken important steps to combat unsustainable forest use. Several protected areas were designated in the Carpathians during the second half of the 1990s, the quality of forest resource statistics improved after 2000, and a new forest code that aims for multi-functional, sustainable forestry, forest certification, and accounting of forest resources, was implemented in 1994 (with important amendments in 2000 and 2006, Nordberg, 2007; Soloviy & Cubbage, 2007). This clearly affected forest management practices, such as the drop in harvesting above 1100 m and a decrease in disturbances in invisible areas after 2000 (Fig. 6). Moreover, convictions of corrupt forestry staff have recently become public, including the imprisonment of a former head of a forest management enterprise.

Despite these positive trends, corruption continues to be a major problem in Ukraine (Corruption Perceptions Index 2.5/10 in 2007, www.transparency.org). Most importantly, the misuse of the sanitary clear-cut system has emerged as the principal means of illegal logging since the late 1990s (e.g., harvesting of healthy stands, over-harvesting, harvesting in protected areas and at high altitudes, full canopy harvesting in areas designated for selective logging, etc.). Commercial and sanitary logging were almost equally widespread in 2000–2007 in Zakarpatska Oblast. And whereas commercial selective logging frequently did not show up as disturbance in our forest cover change map, disturbances were widespread in sanitary selective logging sites, likely because forest cover was fully removed in many of these sites. Thus, the sanitary logging system represents a substantial loophole in forest legislation (Contreras-Hermosilla, 2002) that is very difficult to monitor. This is exacerbated by the fact that the Ukrainian forest code allows sanitary clear-cuts to be larger than the maximum regular clear-cut size (4 ha). While sanitary logging appears to have been heavily misused, it is important to emphasize that there are also many excellent examples of forest restoration via adequate sanitary logging in the Ukrainian Carpathians.

So what was the extent of illegal logging in the Ukrainian Carpathians after the breakdown of socialism? Uncertainties in the forest inventory data, differences in satellite-based and statistical indicators, and difficulties in separating legal and illegal sanitary logging do not allow answering this question with a hard number. However, four factors suggest that illegal logging may have been at least as extensive as legal logging in the Ukrainian Carpathians. First, forest statistics and satellite-based harvesting rates both showed increased logging after 2000 (when reporting likely improved), but our change map suggests up to 2.8 times higher logging rates before 1994 than documented in the forest resource data (Fig. 3). Second, logging outside areas designated for clear-cuts in the inventory maps was at least as high as in areas declared as clear-cuts. Third, there was still substantial logging above 1100 m, and high-resolution images and field visits suggest that logging in beech-fir forests has not ceased after it was banned. And fourth, substantially higher disturbance rates were observed in areas that were hidden from roads and railways.

Large-scale natural disturbances could offer an alternative explanation for the discrepancy between satellite-based forest trends and forest resource statistics and inventory maps. Wind throw, root fungi, and insect infestation occur in the Ukrainian Carpathians, but two major factors suggest these processes cannot account for the extent of undocumented disturbances we mapped in the Landsat images. First, most natural disturbances in the Ukrainian Carpathians result only in fine-scale forest cover changes, affecting only single trees or small groups of trees, and our analyses does not map such subtle disturbances (see Section 5.2). Large-scale natural disturbances are overall rare (Ireland & Kremenetska, 2008; Lavnyy & Lässig, 2007). For instance, storms represent the region's most frequent natural disturbance, but affected mostly small areas during the last decades and only two

extensive windthrow events (1989 and 1992) were documented (Lavnyy & Lässig, 2007). Moreover, most large-scale natural disturbances are associated with spruce plantations that were established during socialism and in Austro-Hungarian times, often on unfavorable sites (Badea et al., 2004; Irland & Kremenetska, 2008; Nilsson & Shvidenko, 1999). Higher disturbance rates in such areas are thus at least partly self-inflicted and not a result of natural disturbance regimes (Irland & Kremenetska, 2008). Second, where large-scale natural disturbances occur, forest management enterprises almost always carry out salvage logging or sanitary clear-cutting (Irland & Kremenetska, 2008; Lavnyy & Lässig, 2007), and such disturbances should therefore be documented in the inventory data. Thus, the vast majority of forest disturbance events we mapped from the satellite images were due to forest harvesting, but we cannot exclude the possibility that some of these harvests were prompted by natural disturbance events.

Forests were already severely overexploited during socialism, resulting in increasingly younger forests in many areas (Nijnik & Van Kooten, 2000, 2006; Turnock, 2002). Our results showed a clear tendency towards logging in more remote areas and a net forest cover decrease in the interior Carpathians, likely reflecting an increasing scarcity of high-value timber elsewhere. This raises significant concerns about the fate of Ukraine's Carpathian forest, and especially of ecologically valuable older stands, during the transition. Our results suggest that some regions experienced a net forest cover decrease due to undocumented, illegal logging. This drastically contrasts the popular claim of increasing forest cover in the Ukrainian Carpathians, which recently sparked calls for increased forest harvesting (Polyakov & Sydor, 2006).

Reforestation compensated to some extent for high logging rates in the post-socialist period, but mostly in peripheral regions of the Ukrainian Carpathians where much land was managed by state farms prior to 1991. The decreasing profitability of farming frequently resulted in the bankruptcy of these farms, followed by widespread farmland abandonment (DLG, 2005). Moreover, Ukraine established a forest planting program in 2002, which may partly explain higher reforestation rates we found between 2000–2007. By and large, however, our results support earlier claims of a slow reforestation in the Carpathians (Kozak et al., 2007a; Kuemmerle et al., 2008; Müller et al., 2009), and only a minor proportion of the region's abandoned farmland has so far reverted back to forests. Reason for this may be that subsistence farming became increasingly important as a livelihood strategy after 1991, particularly in the mountain valleys of the interior Carpathians, and the inconsistent implementation of the national reforestation program.

## 5.2. Change detection approach

Our change detection approach based on post-classification map comparison of individual forest cover maps yielded a reliable forest change map, which was confirmed by two independent validations ( $n$ -fold cross-validation and our disturbance detectability assessment). The  $n$ -fold cross-validation we used, widely accepted in other communities (Burman, 1989; Burnham & Anderson, 1998; Guisan & Zimmermann, 2000), has rarely been applied in remote sensing. However, if ground truth is collected via random sampling,  $n$ -fold cross-validation results in more robust and conservative error estimates than simply splitting ground truth into a training and validation set (Steele, 2005). It is important to note that training and validation data are treated as fully independent datasets each time an error is estimated (i.e., ground truth points used to fit an SVM model are never used to estimate model robustness).

Disturbance detectability was highest in 2000–2007, possibly due to increased logging in spruce plantations after the new forest code was implemented in 2000. Clear cuts in such stands result in higher spectral contrast than in beech/fir forests and are thus easier to map. Although wall-to-wall data did not exist prior to 1988, detection accuracy was similar to 1988–1994 and 1994–2000, suggesting that three post-

disturbance images allowed for robust forest regeneration detection. Due to uncertainty in the inventory maps, we digitized disturbance polygons for our validation directly from the Landsat images. While we cannot completely rule out a positive bias, image-based approach typically provide nearly identical results for stand replacement disturbances compared to independent ground truth data (Cohen et al., 1998), and may often be the only option if historic land cover maps are unavailable. Moreover, traditional ground truth sources (e.g., forest inventory maps, cadastre maps, aerial photos, etc) may be connected to substantial uncertainty, thus introducing a negative bias when assessing the accuracy remote sensing analyses (Foody, 2008).

Our results suggest that post-classification map comparisons yield a useful change map if individual classifications are highly accurate and the SVM resulted in very reliable classifications. The non-parametric nature of the SVM allowed us to directly extract thematic classes without having to characterize the substantial spectral variability that existed within these classes due to phenology, illumination, and different land use systems. Long records of satellite images are becoming increasingly available and our approach may help to move from bi-temporal change detection towards the mapping of trajectories of change. We suggest post-classification map comparisons may be especially useful in cases where individual classifications are simple (i.e., forest/non-forest), where gathering a representative training set for an integrated multitemporal analyses is not feasible, and where limited data availability precludes full time-series analyses (Kennedy et al., 2007; Röder et al., 2008).

Although our change map was overall highly reliable, a few factors may have contributed uncertainty. Some farmland abandonment may have occurred during socialism (Turnock, 2002), which would have inflated pre-1988 logging rates. Likewise, pre-1988 logging rates would be overestimated if forest regeneration took longer than 6 years. However, field visits and prior work (Healey et al., 2005; Kuemmerle et al., 2007) suggest this was not the case, particularly when considering that post-clear-cut planting was carried out prior to the breakdown of the Soviet Union (Buksha et al., 2003). Conversely, we would have underestimated logging rates if regeneration was substantially faster. Field visits render this also unlikely, but we cannot rule out such underestimation completely. It is important to note that underestimation would have affected all time periods similarly and would thus suggest even higher illegal logging rates. Our sampling scheme avoided ground truth points on forest/non-forest boundaries, because positional uncertainty in the Landsat and Quickbird images, and in the non-differential GPS points (<15 m) inhibited us from labeling these points. This could have resulted in overestimated map accuracy, if mixed pixels were widespread in the study region. Yet, the number of discarded points was very low (<3% at most), forest/non-forest boundaries are frequently sharp (even at the timberline) and logging patches are large in the Ukrainian Carpathians, and our validation based on disturbance polygons (which included boundary pixels) confirmed the high accuracy of our maps. Last, our minimum mapping unit of 0.5 ha could have masked fine-scale logging patterns (e.g., fuel wood collection), but was important to remove salt-and-pepper distortions common in pixel-based classifications. While analyzing forest use of local people can give interesting insights (Elbakidze & Angelstam, 2007), our focus here was on assessing large-scale forest cover trends (both legal and illegal) which are almost entirely connected to forestry enterprises operating at management units >0.5 ha. Moreover, our minimum mapping unit helped to excluded almost all natural disturbances from our analyses, thus allowing us to separate legal and illegal harvesting.

## 6. Conclusions

Logging and reforestation on abandoned farmland resulted in widespread forest cover changes in the Ukrainian Carpathians after the breakdown of the Soviet Union. We observed a slight forest cover

increase for the entire Ukrainian Carpathians, and the two converse forest change processes led to substantial variability in fine-scale forest cover trends. Peripheral areas, characterized by a high share of pre-1991 farmland, experienced forest cover increase, whereas forest cover decreased in many regions in the interior Carpathians. We also found a clear tendency towards logging in more remote areas and at higher altitudes in the post-socialist period.

Forest trends mapped from Landsat images differed substantially from forest resource statistics and inventory maps. Logging rates did not drop, as suggested by official statistics, during the first years after the breakdown of socialism. To the contrary some regions experienced increased logging. Agreement between satellite-based and statistical indicators was better after 2000, when both sources indicated increasing logging trends. Our analyses also showed that the reliability of inventory maps was mixed.

We suggest that reporting and updating problems as well as illegal logging are the main reasons explaining the mismatch between satellite-based and statistical forest trends. Illegal logging appears to have been especially widespread in the early years after the Ukrainian independence and was likely at least as extensive as legal logging. Ukraine has taken important steps towards sustainable forestry in recent years, and reporting and forest monitoring have improved significantly. Yet, the sanitary clear-cut system remains a major loophole in forest legislation that is almost impossible to control and likely misused for illegal logging (e.g., more timber was logged on sanitary clear-cuts than on commercial clear-cuts in 2000–2007). Overall, our results suggest that unsustainable forest use from socialist times has persisted in the post-socialist period, resulting in continued loss of older forests and their services, and the ongoing fragmentation of some of Europe's last large mountain forests. Transitioning towards sustainable use of these forests and combating illegal logging requires better and up-to-date accounting of forest resources. Remote-sensing-based monitoring can be key to achieving these goals in the Carpathians and elsewhere in Eastern Europe and the former Soviet Union.

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## References

- Badea, O., Tanase, M., Georgeta, J., Anisoara, L., Peiov, A., Uhlir, H., et al. (2004). Forest health status in the Carpathian Mountains over the period 1997–2001. *Environmental Pollution*, 130, 93–98.
- Baeza-Yates, R., & Ribeiro-Neto, B. (1999). *Modern Information Retrieval*. Harlow Addison-Wesley-Longman.
- Bonan, G. B. (2008). Forests and climate change: forcings, feedbacks, and the climate benefits of forests. *Science*, 320, 1444–1449.
- Bouriaud, L. (2005). Causes of illegal logging in Central and Eastern Europe. *Small-scale Forest Economics, Management and Policy*, 4, 269–292.
- Bouriaud, L., & Niskanen, A. (2003). *Illegal logging in the context of the sound use of wood [online]*. Available from: <http://www.unece.org/trade/timber/docs/sem-1/papers/r30Niskanen.pdf> [accessed 25th March 2008].
- Brack, D. (2007). *Illegal logging* (pp. 4). London The Royal Institute of International Affairs.
- Buchinsky, I., Volevaka, M., & Korzhov, V. (1971). *Klimat Ukrainskikh Karpat [Climate of the Ukrainian Carpathians]*. Kyiv Naukova dumka (in Ukrainian).
- Buksha, I., Pasternak, V., & Romanovsky, V. (2003). *Forest and Forest Products Country Profile Ukraine, UN-ECE/FAO Timber and Forest Discussion Papers*. Geneva UN-ECE/FAO.
- Burges, C. J. C. (1998). A tutorial on support vector machines for pattern recognition. *Data Mining and Knowledge Discovery*, 2, 121–167.
- Burman, P. (1989). A comparative-study of ordinary cross-validation, v-fold cross-validation and the repeated learning-testing methods. *Biometrika*, 76, 503–514.
- Burnham, K. P., & Anderson, D. R. (1998). *Model selection and Inference: A Practical Information-Theoretic Approach*. New York Springer.
- Chhatre, A., & Agrawal, A. (2008). Forest commons and local enforcement. *Proceedings of the National Academy of Sciences of the United States of America*, 105, 13286–13291.
- Cohen, W. B., Fiorella, M., Gray, J., Helmer, E., & Anderson, K. (1998). An efficient and accurate method for mapping forest clearcuts in the Pacific Northwest using Landsat imagery. *Photogrammetric Engineering and Remote Sensing*, 64, 293–300.
- Congalton, R. G. (1991). A review of assessing the accuracy of classifications of remotely sensed data. *Remote Sensing of Environment*, 37, 35–46.
- Contreras-Hermosilla, A. (2002). *Illegal forest production and trade. An overview [online]*. Available from: <http://www.iucn.org/places/brao/toolkiteng/Background%20Papers/Contreras%20Overview%20of%20Illegal%20Forest%20Production%20and%20Trade.pdf> [accessed 26 August 2008].
- Coppin, P., & Bauer, M. E. (1996). Digital change detection in forest ecosystems with remote sensing imagery. *Remote Sensing Reviews*, 13, 207–234.
- Coppin, P., Jonckheere, I., Nackaerts, K., Muys, B., & Lambin, E. (2004). Digital change detection methods in ecosystem monitoring: a review. *International Journal of Remote Sensing*, 25, 1565–1596.
- Di Gregorio, A. (2005). *Land Cover Classification System Classification (LCCS)*. Concepts and User Manual Software Version 2 Rome Food and Agriculture Organisation of the United Nations.
- DLG [Government Service for Land and Water Management of the Netherlands] (2005). Land abandonment, biodiversity, and the CAP. *Land abandonment and biodiversity in relation to the 1st and 2nd pillars of the EU's Common Agricultural Policy; Outcome of an international seminar in Sigulda, Latvia, 7–8 October, 2004* (pp. 62). Utrecht, The Netherlands Government Service for Land and Water Management of the Netherlands (DLG).
- Elbakidze, M., & Angelstam, P. (2007). Implementing sustainable forest management in Ukraine's Carpathian Mountains: the role of traditional village systems. *Forest Ecology and Management*, 249, 28–38.
- FAO [Food and Agriculture Organization of the United Nations] (2005). *Global Forest Resources Assessment 2005. Progress towards sustainable forest management*. In FAO (Ed.), *Forestry Papers* Rome, Italy Food and Agriculture Organization of the United Nations.
- FERN [The Forests and the European Union Resource Network] (2002). *Illegal logging, and the global trade in illegally sourced timber: a crime against forests and people [online]*. Available from: [www.fern.org/pubs/ngostats/logging.pdf](http://www.fern.org/pubs/ngostats/logging.pdf) [accessed 26 August 2008].
- Foody, G. M. (2002). Status of land cover classification accuracy assessment. *Remote Sensing of Environment*, 80, 185–201.
- Foody, G. M. (2008). Harshness in image classification accuracy assessment. *International Journal of Remote Sensing*, 29, 3137–3158.
- Foody, G. M., & Mathur, A. (2004). A relative evaluation of multiclass image classification by support vector machines. *IEEE Transactions on Geoscience and Remote Sensing*, 42, 1335–1343.
- Foody, G. M., & Mathur, A. (2004). Toward intelligent training of supervised image classifications: directing training data acquisition for SVM classification. *Remote Sensing of Environment*, 93, 107–117.
- Foody, G. M., & Mathur, A. (2006). The use of small training sets containing mixed pixels for accurate hard image classification: training on mixed spectral responses for classification by a SVM. *Remote Sensing of Environment*, 103, 179–189.
- Friedl, M. A., & Brodley, C. E. (1997). Decision tree classification of land cover from remotely sensed data. *Remote Sensing of Environment*, 61, 399–409.
- Geodezkartinformatyka (1997). *Tsyfrova topographichna karta mashtabu 1:200 000 Lvivskoyi, Ivano-Frankivskoyi, Ternopilskoyi, Zakarpatskoyi Oblastey [Digital topographic map]*. Kyiv Geodezkartinformatyka (in Ukrainian).
- Gerasimov, Y., & Karjalainen, T. (2006). Development of wood procurement in Northwest Russia: round wood balance and unreported flows. *European Journal of Forest Research*, 125, 189–199.
- Grainger, A. (2008). Difficulties in tracking the long-term global trend in tropical forest area. *Proceedings of the National Academy of Sciences*, 105, 818–823.
- Greenpeace (2000). *Illegal forest felling activities in Russia [online]*. Available from: <http://www.greenpeace.org/international/campaigns/forests/threats/illegal-logging> [accessed 26 August 2008].
- Greenpeace (2008). *Illegal logging - destroying the last Ancient Forests [online]*. Available from: <http://www.greenpeace.org/international/campaigns/forests/threats/illegal-logging> [accessed 21 August 2008].
- Guisan, A., & Zimmermann, N. E. (2000). Predictive habitat distribution models in ecology. *Ecological Modelling*, 135, 147–186.
- Hain, H., & Aha, R. (2004). *Illegal forestry and Estonian timber exports*. Tartu Estonian Green Movement.
- Hansen, M. C., Stehman, S. V., Potapov, P. V., Loveland, T. R., Townshend, J. R. G., DeFries, R. S., et al. (2008). Humid tropical forest clearing from 2000 to 2005 quantified by using multitemporal and multiresolution remotely sensed data. *Proceedings of the National Academy of Sciences*, 105, 9439–9444.
- Healey, S. P., Cohen, W. B., Yang, Z. Q., & Frankina, O. N. (2005). Comparison of Tasseled Cap-based Landsat data structures for use in forest disturbance detection. *Remote Sensing of Environment*, 97, 301–310.
- Herenchuk, K. I. (Ed.). (1968). *Pryroda Ukrainyyskikh Karpat [Nature of the Ukrainian Carpathians]* Lviv Vydavnytstvo Lvivskoho Universytetu (in Ukrainian).
- Holubets, M. A., Honchar, M. T., Komendar, V. I., Kucheryavyi, V. A., & Odynek, Y. P. (Eds.). (1988). *Ukrainskiye Karpaty. Priroda [The Nature of the Ukrainian Carpathians]* Kyiv Naukova Dumka (in Russian).
- Hostert, P., Roder, A., & Hill, J. (2003). Coupling spectral unmixing and trend analysis for monitoring of long-term vegetation dynamics in Mediterranean rangelands. *Remote Sensing of Environment*, 87, 183–197.

- Houghton, R. A., Butman, D., Bunn, A. G., Krankina, O. N., Schlesinger, P., & Stone, T. A. (2007). Mapping Russian forest biomass with data from satellites and forest inventories. *Environmental Research Letters*, 2, 045032.
- Huang, C., Davis, L. S., & Townshend, J. R. G. (2002). An assessment of support vector machines for land cover classification. *International Journal of Remote Sensing*, 23, 725–749.
- Huang, C., Song, K., Kim, S., Townshend, J. R. G., Davis, P., Masek, J. G., et al. (2008). Use of a dark object concept and support vector machines to automate forest cover change analysis. *Remote Sensing of Environment*, 112, 970–985.
- Ioffe, G., Nefedova, T., & Zaslavsky, I. (2004). From spatial continuity to fragmentation: the case of Russian farming. *Annals of the Association of American Geographers*, 94, 913–943.
- Irland, L. (2008). State failure, corruption, and warfare: challenges for forest policy. *Journal of Sustainable Forestry*, 27, 189–223.
- Irland, L., & Kremenetska, E. (2008). Practical economics of forest ecosystems management: the case of the Ukrainian Carpathians. *Journal of Sustainable Forestry*, in review.
- Itten, K. I., & Meyer, P. (1993). Geometric and radiometric correction of TM data of mountainous forested areas. *IEEE Transactions on Geoscience and Remote Sensing*, 31, 764–770.
- Janz, A., van der Linden, S., Waske, B., & Hostert, P. (2007). imageSVM—a user-oriented tool for advanced classification of hyperspectral data using support vector machines. In I. Reusen & J. Cools (Eds.), *EARSeL SIG Imaging Spectroscopy* Bruges, Belgium.
- Kennedy, R. E., Cohen, W. B., & Schroeder, T. A. (2007). Trajectory-based change detection for automated characterization of forest disturbance dynamics. *Remote Sensing of Environment*, 110, 370–386.
- Kissling-Naf, I., & Bisang, K. (2001). Rethinking recent changes of forest regimes in Europe through property-rights theory and policy analysis. *Forest Policy and Economics*, 3, 99–111.
- Knorn, J., Janz, A., Radeloff, V. C., Kuemmerle, T., Kozak, J., & Hostert, P. (in press). Land cover mapping of large areas using chain classification of neighboring satellite images. *Remote Sensing of Environment*.
- Kozak, J., Estreguil, C., & Troll, M. (2007). Forest cover changes in the northern Carpathians in the 20th century: a slow transition. *Journal of Land Use Science*, 2, 127–149.
- Kozak, J., Estreguil, C., & Vogt, P. (2007). Forest cover and pattern changes in the Carpathians over the last decades. *European Journal of Forest Research*, 126, 77–90.
- Kruhlov, I. (2008). Delimitatsiya, metryzatsiya ta klasyfikatsiya morfogenykh ekoregioniv Ukrayinskukh Karpat [Delimitation, metrisation and classification of morphogenic ecoregions of the Ukrainian Carpathians]. *Ukrainskyi Geografichnyi Zhurnal*, 3 (in Ukrainian).
- Kruhlov, I., Mukha, B., & Senchyna, B. (2008). Natural geoecosystems. In M. Roth R. Nobis I. S.V. & Kruhlov (Eds.), *Transformation processes in the Western Ukraine. Concepts for a sustainable land use* (pp. 81–98). Berlin Wiessensee Verlag.
- Kuemmerle, T., Hostert, P., Perzanowski, K., & Radeloff, V. C. (2006). Cross-border comparison of land cover and landscape pattern in Eastern Europe using a hybrid classification technique. *Remote Sensing of Environment*, 103, 449–464.
- Kuemmerle, T., Hostert, P., Radeloff, V. C., Perzanowski, K., & Kruhlov, I. (2007). Post-socialist forest disturbance in the Carpathian border region of Poland, Slovakia, and Ukraine. *Ecological Applications*, 17, 1279–1295.
- Kuemmerle, T., Hostert, P., Radeloff, V. C., van der Linden, S., Perzanowski, K., & Kruhlov, I. (2008). Cross-border comparison of post-socialist farmland abandonment in the Carpathians. *Ecosystems*, 11, 614–628.
- Lavnyy, V., & Lässig, R. (2007). Häufigkeit und Ausmass von Windwürfen in den ukrainischen Karpaten [Frequency and extent of wind throw events in the Ukrainian Carpathians]. *Tagungsband Deutscher Verband Forstlicher Forschungsanstalten, Sektion Waldbau. Beiträge zur Jahrestagung vom 18.-19. September 2006 in Tharandt* (pp. 75–86). Dresden Technische Universität Dresden (in German).
- Lepers, E., Lambin, E. F., Janetos, A. C., DeFries, R., Achard, F., Ramankutty, N., et al. (2005). A synthesis of information on rapid land-cover change for the period 1981–2000. *Bioscience*, 55, 115–124.
- Lerman, Z., Csaki, C., & Feder, G. (2004). Evolving farm structures and land-use patterns in former socialist countries. *Quarterly Journal of International Agriculture*, 43, 309–335.
- MA [Millennium Ecosystem Assessment] (2005). *Ecosystems and Human Well-being: Current State and Trends* (pp. 137). Washington D.C. Island Press.
- Morozov, A. (2000). *Survey of Illegal Forest Felling Activities in Russia (forms and methods of illegal cuttings)* [online]. Available from: <http://www.forest.ru/eng/publications/illegal/> [accessed 26 August 2008].
- Müller, M., Kuemmerle, T., Rusu, M., & Griffiths, P. (2000). Lost in transition. Determinants of cropland abandonment in postsocialist Romania. *Journal of Land Use Science*, 4, 109–129.
- Nijnik, M., & Van Kooten, G. C. (2000). Forestry in the Ukraine: the road ahead? *Forest Policy and Economics*, 1, 139–151.
- Nijnik, M., & Van Kooten, G. C. (2006). Forestry in the Ukraine: the road ahead? Reply. *Forest Policy and Economics*, 8, 6–9.
- Nilsson, S., & Shvidenko, A. (1999). *The Ukrainian Forest Sector in a Global Perspective*. Laxenburg International Institute for Applied Systems Analysis.
- Nordberg, M. (2007). Ukraine reforms in forestry 1990–2000. *Forest Policy and Economics*, 9, 713–729.
- Pal, M., & Mather, P. M. (2005). Support vector machines for classification in remote sensing. *International Journal of Remote Sensing*, 26, 1007–1011.
- Piipponen, M. (1999). Transition in the forest sector of the Republic of Karelia. *Fennia*, 177, 185–233.
- Polyakov, M., & Sydor, T. (2006). Forestry in Ukraine: the road ahead? Comment. *Forest Policy and Economics*, 8, 1–5.
- Röder, A., Hill, J., Duguay, B., Alloza, J. A., & Vallejo, R. (2008). Using long time series of Landsat data to monitor fire events and post-fire dynamics and identify driving factors. A case study in the Ayora region (eastern Spain). *Remote Sensing of Environment*, 112, 259–273.
- Rudel, T. K., Coomes, O. T., Moran, E., Achard, F., Angelsen, A., Xu, J. C., et al. (2005). Forest transitions: towards a global understanding of land use change. *Global Environmental Change-Human and Policy Dimensions*, 15, 23–31.
- Seto, K. C., & Liu, W. G. (2003). Comparing ARTMAP neural network with the maximum-likelihood classifier for detecting urban change. *Photogrammetric Engineering and Remote Sensing*, 69, 981–990.
- Sitko, I., & Troll, M. (2008). Timberline changes in relation to summer farming in the Western Chornohora (Ukrainian Carpathians). *Mountain Research and Development*, 28, 263–271.
- Soloviy, I. P., & Cabbage, F. W. (2007). Forest policy in aroused society: Ukrainian post-Orange Revolution challenges. *Forest Policy and Economics*, 10, 60–69.
- Steele, B. M. (2005). Maximum posterior probability estimators of map accuracy. *Remote Sensing of Environment*, 99, 254–270.
- Strochinskii, A. A., Pozvyvailo, Y. M., & Jungst, S. E. (2001). Forests and forestry in Ukraine: standing on the brink of a market economy. *Journal of Forestry*, 99, 34–38.
- The State Statistics Committee of Ukraine (2006). *Statistical Yearbook of Ukraine 2006 - Environment of Ukraine*. Kyiv The State Statistics Committee of Ukraine (in Ukrainian).
- The State Statistics Committee of Ukraine (2007). *Statistical Yearbook of Ukraine 2007 - Environment of Ukraine*. Kyiv The State Statistics Committee of Ukraine (in Ukrainian).
- Tucker, C. J., Grant, D. M., & Dykstra, J. D. (2004). NASA's global orthorectified Landsat data set. *Photogrammetric Engineering and Remote Sensing*, 70, 313–322.
- Turnock, D. (2002). Ecoregion-based conservation in the Carpathians and the land-use implications. *Land Use Policy*, 19, 47–63.
- UNEP [United Nations Environment Programme] (2007). *Carpathians Environment Outlook* (pp. 232). Geneva United Nations Environment Programme.
- Vandergert, P., & Newell, J. (2003). Illegal logging in the Russian Far East and Siberia. *International Forestry Review*, 5, 303–306.
- Verkhovna Rada (2000). Zakon Ukrayiny pro Moratori na provedennya sutsilnykh rubok na hirsykykh skhylakh v yalytsevo-bukovykh lisakh Karpatskoho Rehionu [Ukrainian law on the moratorium of clear cutting in fir-beech mountain forest in the Carpathian region]. *Vidomosti Verkhovnoyi Rad*, 13, 99 (in Ukrainian).
- Verkhovna Rada (2000). Zakon Ukrayiny pro Zahalnoderzhavnu prohramu formuvannya natsionalnoyi ekolohichnoyi merezhi Ukrayiny na 2000–2015 roky [Ukrainian law on the state program for the formation of a national ecological network in Ukraine for the years 2000–2015]. *Vidomosti Verkhovnoyi Rad*, 47, 405 (in Ukrainian).
- Wesolowski, T. (2005). Virtual conservation: how the European Union is turning a blind eye to its vanishing primeval forests. *Conservation Biology*, 19, 1349–1358.
- WWF [World Wildlife Fund] (2002). *Illegal logging in the southern part of the Russian Far East* (pp. 18). Moscow World Wildlife Fund.
- WWF [World Wildlife Fund] (2004). Failing the forests. *Europe's Illegal Timber Trade* (pp. 97). Surrey World Wildlife Fund.
- Zibtsev, S., Kaletnik, M. V., & Savuschik, M. P. (1998). *Forest and Forestry of Ukraine in the Transition Period, FAO/Austria Expert Meeting on Environmentally Sound Forest Operations for Countries in Transition to Market Economies*. Gmunden.