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Cross-border comparison of land cover and landscape pattern in Eastern Europe using a hybrid classification technique

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Abstract

Eastern Europe has experienced drastic changes in political and economic conditions following the breakdown of the Soviet Union. Furthermore, these changes often differ among neighboring countries. This offers unique possibilities to assess the relative importance of broad-scale political and socioeconomic factors on land cover and landscape pattern. Our question was how much land cover differed in the Polish, the Slovak, and the Ukrainian Carpathian Mountains and to what extent these differences can be related to dissimilarities in societal, economic, and political conditions. We used a hybrid classification technique, combining advantages from supervised and unsupervised methods, to derive a land cover map from three Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) images from 2000. Results showed marked differences in land cover between the three countries. Forest cover and composition was different for the three countries, for example Slovakia and Poland had about 20% more forest cover at higher elevations than Ukraine. Broadleaved forest dominated in Slovakia while high percentages of conifers were found in Poland and Ukraine. Agriculture was most abundant in Slovakia where the lowest level of agricultural fragmentation was found (22% core area compared to less than 5% in Poland and Ukraine). Post-socialist land change was greatest in Ukraine, were we found high agricultural fragmentation and widespread early-successional shrublands indicating extensive land abandonment. Concerning forests, differences can largely be explained by socialist forest management. The abundance and pattern of arable land and grassland can be explained by two factors: land tenure in socialist times and economic transition since 1990. These results suggest that broad-scale socioeconomic and political factors are of major significance for land cover patterns in Eastern Europe, and possibly elsewhere.

Keywords: Central and Eastern Europe; CEEC; Carpathians; Post-socialist transformation; Transition; Land cover; Hybrid classification; Land abandonment; Fragmentation; Landscape pattern; Landsat; TM; ETM+

1. Introduction

Humans are the main force behind global conversions of land cover and remote sensing has been a key technology for monitoring this change (Vitousek et al., 1997). To better understand the human dimension of land change it is crucial to link observed changes to their underlying socioeconomic and political causes (Geist & Lambin, 2002). Land use decisions are made at a range of nested scales. At the finest scales, individuals make decisions about the use of their land. However, individuals are constrained by broad scale determinants such as land management policies, economic conditions, and societal structures. Land change science has focused on fine scale factors and a number of studies have shown their importance (Geist & Lambin, 2002; Linderman et al., 2005). For example, local land use history, individual decision making by landowners, local attitudes, household numbers, and land ownership patterns are all factors affecting land cover change (Dale et al., 1993; Geoghegan et al., 2001; Liu et al., 2003; Pfaff, 1999).

Less is known about the effect of broad-scale political and socioeconomic factors on land cover, despite suggestions that they may increasingly override local factors (Lambin et al., 2001). Investigating the relative importance of broad-scale factors is challenging because they cannot be altered experimentally. An

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alternative approach is to study areas where sudden changes in political and socioeconomic structures occurred, thereby creating "natural experiments" (sensu Diamond, 2001). Eastern Europe has undergone such a natural experiment following the collapse of the Soviet Union in 1990. The shift from a socialistic planning system to a market oriented economy has resulted in fundamental changes to the political and social institutions as well as economic conditions (Bicik et al., 2001; Csaki, 2000). This affected how land use decisions were made, with an increased emphasis on economic rather than political influences (Bicik et al., 2001). In the agricultural sector, the main changes after 1990 have been extensive changes in land ownership and fragmentation of farm fields due to land reforms (Csaki, 2000; Sabates-Wheeler, 2002). In terms of land cover change, land abandonment is occurring at unprecedented rates, and large areas are converting to grassland and forest (Augustyn, 2004; Ioffe et al., 2004; Turnock, 1998). In many Eastern European countries, Estonia (Palang et al., 1998); Czech Republic (Bicik et al., 2001); and Poland (Kozak, 2003), to name a few, forest cover increased slightly throughout the 20th century (Augustyn, 2004). Secondary succession and afforestation on marginal arable land have amplified this trend in the post-socialist period (Augustyn, 2004; Turnock, 1998).

While general land cover change trends in Eastern Europe are recognized, detailed spatial data on these trends are lacking. In Eastern Europe, conventional data such as maps, agricultural censuses, and statistical data differ in scale and accuracy, making comparisons among countries difficult. Remote sensing can provide land cover information in an efficient, unbiased, and representative way for large areas.

Land cover changes in the post-socialist period have been targeted by few remote sensing studies. In Estonia for example, 30% of agricultural lands used in Soviet times had been abandoned by 1993 (Peterson and Aunap, 1998). Changes in village structure were found for an area in southeast Poland and two processes, land abandonment and agricultural intensification, were identified based on a visual assessment of a Landsat image and historic maps (Angelstam et al., 2003). In sub-catchments of the Tisza River in Ukraine, comparison of the Global Land Cover Characterization (GLCC) and the Moderate Resolution Imaging Spectroradiometer (MODIS) land cover product showed a 20% increase in forest cover (Dezso et al., 2005). Landsat TM and Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) data in conjunction with historic maps revealed that forest cover increased up to 40% in the 20th century for a study area in the Western Polish Carpathians (Kozak, 2003).

For the socialist period, the intensification of agriculture in mountain valleys and loss in forest cover of up to 9% occurred in Slovakia during the period 1976 to 1992. These trends were derived from the analysis of Coordination of Information on the Environment of the European Union (CORINE) land cover data at a scale of 1:100,000 (Feranec et al., 2003). Similarly, a small study area in Ukraine showed patterns of abandonment of arable land and agricultural intensification for the period from 1966 to 1990 (Poudevigne & Alard, 1997).

Thus, although some studies have used remote sensing data to assess land cover change in Eastern Europe, the few existing studies all assess land cover within single countries, often for very small study sites. Comparative meta-analysis of existing studies is impossible due to differences in time periods and methods. No study to date utilizes the natural experiment that occurred in Eastern Europe by comparing land cover or landscape pattern among neighboring countries.

We decided to study the Carpathian Mountains because they are ecologically relatively homogeneous, yet heavily dissected by political borders. Already in socialist times, the Carpathian countries displayed distinct differences in broad-scale socioeconomic factors, for instance in land ownership patterns and land management policies (Turnock, 2002). These differences have been magnified since the fall of the Iron Curtain (Mathijs & Swinnen, 1998) and make the area ideal for cross-border comparisons. The challenge is to select a classification method that is appropriate in this mountainous region for which relatively little ancillary information is available.

The validity of any comparison of land cover among countries depends on the classification accuracy of the land cover map. For Landsat data, phenology information inherent in multitemporal images improves classification accuracy (Dymond et al., 2002; Schriever & Congalton, 1995; Wolter et al., 1995). Using multitemporal imagery however, requires precise georeferencing, because misregistration strongly affects classification accuracy (Townshend et al., 1992). In mountainous terrain, geometric rectification is also necessary to account for relief displacement (Hill & Mehl, 2003; Itten & Meyer, 1993). Publicly available topographic maps from Eastern Europe and the former Soviet Union do not provide the degree of accuracy needed for accurate geometric correction. On the other hand, the manual collection of a well distributed set of ground control points (GCPs) is not feasible for large areas, rugged terrain, or where natural ecosystems dominate and identifiable objects are scarce. An alternative is the use of automated methods based on correlation windows that allow for fast collection of large numbers of GCPs (Hill & Mehl, 2003; Shlien, 1979).

Supervised classification methods are more effective in identifying complex land cover classes compared to unsupervised approaches, if detailed a-priori knowledge of the study area and good training data exist (Cihlar et al., 1998). The latter is particularly important for studies in Eastern Europe, where traditional and reliable data sources for ground truth such as aerial photographs are often lacking. Similarly, obtaining a good training data set for complex study sites (e.g. with a gradient in elevation) in the field is often challenging (Cihlar et al., 1998). In such situations, unsupervised approaches might be preferable (Bauer et al., 1994; Lark, 1995) and they have been rated more robust and repeatable (Cihlar et al., 1998; Wulder et al., 2004).

Ultimately it may be best to combine unsupervised and supervised classification techniques. Three uses of hybrid approaches can be distinguished: first, unsupervised clustering is useful to stratify input images prior to subsequent supervised classifications (Lo & Choi, 2004; Tommervik et al., 2003); second, unsupervised methods can reveal spectrally homogeneous areas for optimized training and ground truth collection (McCaffrey & Franklin, 1993; Rees & Williams, 1997); and third, manually collected training data can be clustered into spectrally homogeneous subclasses for use in a subsequent supervised classification ('guided clustering'; Bauer et al., 1994; Stuckens et al., 2000). Thus, hybrid approaches bear significant potential to overcome difficulties in delineating appropriate training samples for complex mountainous study areas. However, no standard procedure exists to date and hybrid approaches have to be adjusted to data availability and study region properties. In our study, the challenge was to develop a hybrid approach that yields a consistent land cover map for cross-border comparisons in the Carpathians.

Comparisons of land cover among countries are interesting but can potentially miss differences in landscape pattern. This is important because some processes only become apparent in the configuration of land cover units and not in the abundance of land cover types (e.g. the physical fragmentation of agricultural plots does not necessarily lead to changes in the quantity of arable land). Landscape ecology has focused on developing methods to quantify landscape pattern and fragmentation (Forman & Godron, 1986; Turner, 1989). However, landscape metrics (e.g. O'Neill et al., 1988) often do not measure the location of fragmentation and calculate only one aggregate index. This is problematic where fragmentation levels vary. The solution is to use spatially explicit fragmentation measures (Riitters et al., 2002). These methods estimate the local degree of fragmentation, within predefined neighborhoods. Thus, averaging is avoided and patterns of fragmentation may be revealed.

In summary, the Carpathians are an interesting region to study land cover across borders, but land cover classifications that allow the assessment of land cover abundances and landscape pattern may not be trivial. The overarching objective of our project was to investigate whether there are distinct differences in land cover and landscape patterns between portions of three neighboring countries in the Carpathian Mountains (Poland, Slovakia and Ukraine) for the year 2000. Our specific aims were:

1. To derive a consistent land cover map from the multitemporal Landsat Thematic Mapper (TM) and the Enhanced Thematic Mapper Plus (ETM+) data for cross-border comparisons and to develop and test a hybrid classification method to overcome difficulties in delineating appropriate training samples for complex mountainous study areas.
2. To compare landscapes across borders based on land cover abundances, landscape metrics, and spatially explicit fragmentation measures adopted from Riitters et al. (2002).

2. Study region

We studied the border triangle of Poland, Slovakia, and Ukraine. The area was part of the Austro-Hungarian Empire for about 150 years until 1918 and during this period, political institutions and land management policies were homogeneous. Since World War II, the region has been subject to fundamental changes in political and socioeconomic systems, which in turn affected population density and land use practices (Augustyn, 2004; Turnock, 2002). These changes differ among countries. For example, population density in Ukraine and Slovakia has increased while some areas in the Polish region of the study area were depopulated after 1947 following border changes between the Soviet Union and Poland (Turnock, 2002). As a result, large areas in Poland were converted to forests (Augustyn, 2004). Agricultural land in Slovakia and Ukraine was almost completely collectivized, while in the Polish region a large fraction of farmland remained in private ownership. Since 1990, the speed and intensity of the economic transition has differed among the three countries. This is mainly due to dissimilar starting points as well as the integration of Poland and Slovakia into the European Union (Csaki, 2000; Turnock, 2002).

The study area (Fig. 1) is centered on the border triangle. Boundaries were based on the extent of the Landsat TM scene, landscape features such as rivers and valleys as well as administrative borders. The study area encompasses 17,800 km^2 and is characterized by mountainous topography with altitudes ranging from 200 to over 1300 m above sea level. The climate is moderately cool and humid with marked continental influence and an annual mean temperature of 5.9 °C (at 300 m). The average annual precipitation is between 1100 and 1200 mm (Augustyn, 2004). Although a variation in the amount of precipitation along the altitudinal gradient may exist, it has not been reported. The uniform bedrock is composed of Carpathian flysh, consisting of sandstone and shale (Augustyn, 2004; Denisiuk & Stoyko, 2000). Climate, topography, and anthropogenic factors produce complex vegetation patterns including broadleaved forests dominated by beech (*Fagus sylvatica*) and sycamore (*Acer pseudoplatanus),* mixed forests with beech and fir (*Abies alba*), coniferous forests composed of fir, Norway spruce (*Picea abies*), and Scots Pine (*Pinus sylvestris*), mountain meadows, grasslands, and arable land (Denisiuk & Stoyko, 2000). Specific for the Eastern Carpathians are mountain meadows, so-called *poloniny,* which are found at higher altitudes and on hilltops (Denisiuk & Stoyko, 2000). Although the area is environmentally relatively homogeneous (UNESCO, 2003), climate variations between the northern and the southern rim affect forest composition (Denisiuk & Stoyko, 2000). For instance beech/fir forests are a natural vegetation formation on north-facing slopes, while beech forests would dominate south-facing slopes without anthropogenic influence.

3. Data and methods

3.1. Satellite and field data

Three images from path 186, row 26 were acquired for the year 2000 (ETM+ for 2000-06-10, TM for 2000-08-21, and ETM+ for 2000-09-30). The thermal bands were not retained for the analysis because of their lower spatial resolution and the weaker signal to noise ratio. The 3 arc second Space Shuttle Radar Topography Mission (SRTM) digital elevation model (DEM) was acquired from Aeronautics and Space Administration (NASA) and resampled using bilinear interpolation to match the spatial resolution of the Landsat data.

Ground truth data to be used in the assessment of classification accuracy was gathered in the field in the summer of 2004 and spring of 2005. Plots were mapped for all 10 land cover classes (compare Table 1) in areas with good accessibility (i.e. close to roads and trails) using non-differential Global Positioning System (GPS) receivers. Inaccessible areas were photo-documented, the area covered by the pictures was located in the imagery and ground

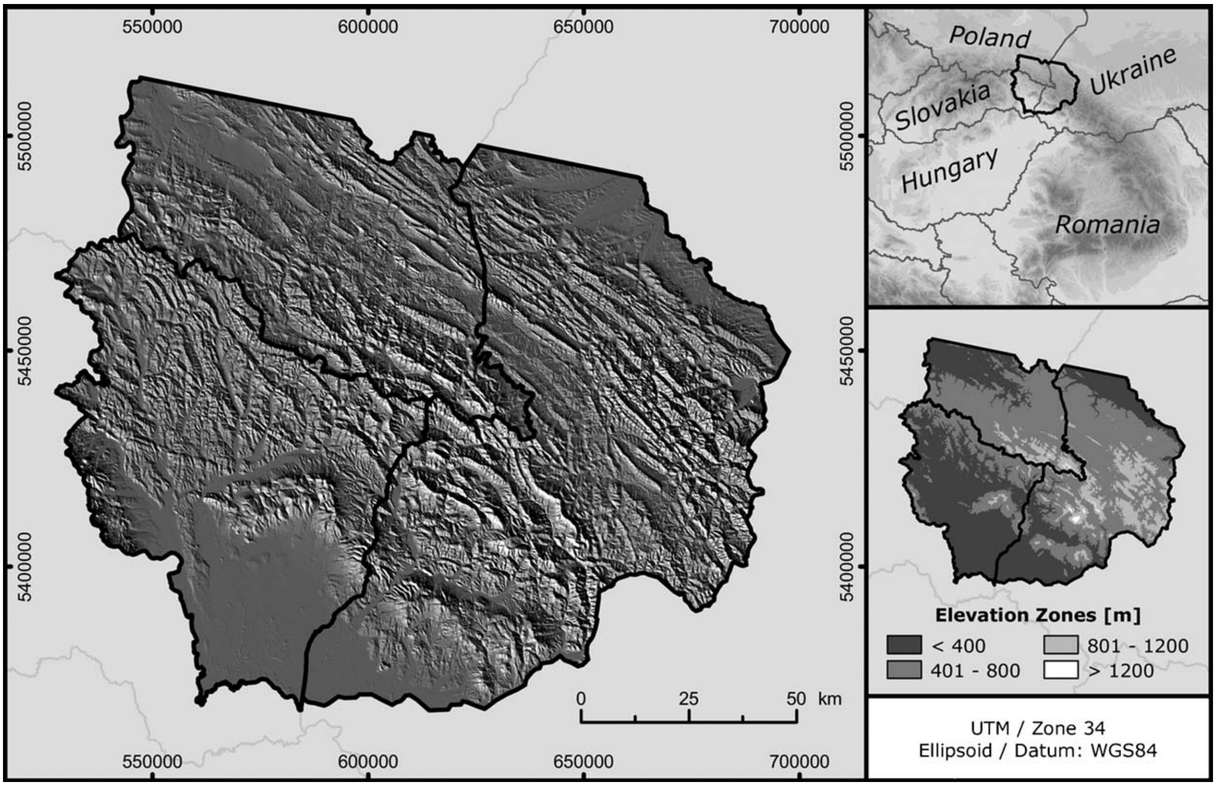


Fig. 1. The border triangle of Poland, Slovakia and Ukraine, located in the north-eastern part of the Carpathian ridge (shaded SRTM relief).

truth points were digitized on screen. Additional ground truth plots were collected from ancillary dataset sources. Three Quickbird images (2003-05-07) were available for the Ukrainian region of the study area. For a portion of the study area in Poland, forest inventory maps and stand statistics were made available by the Polish Forest Administration. These maps were produced between 1995 and 1999 and provide a wide variety of information including stand age and composition. Care was taken to gather ground truth data only for locally homogenous sites (i.e. 90 × 90 m or 3 × 3 Landsat TM pixels) to rule out erroneous assignments due to positional uncertainty.

Categorization of ground truth plots for mixed forest classes (e.g. to distinguish broad-leaved, mixed, and coniferous forest) was guided by the forestry inventory information. Mixed forest was defined as not having a dominating fraction (i.e. more than 70%) of broadleaved or coniferous species. Shrubs and secondary succession stands were categorized visually into two classes (sparse shrub cover and medium to dense shrub cover) using a threshold of about 15% shrub cover. Only plots with medium to dense shrub cover were classified as shrublands. Areas with sparse shrub cover (i.e. early stages of secondary succession) were labeled as grasslands. Due to the time span between image acquisition (2000) and field campaigns (2004–05), sparse shrub cover likely evolved after the recording of the Landsat images. In total, 1477 control points (905 based on ground visits and 572 from additional datasets) were used in the accuracy assessment.

To facilitate class labeling and training data collection in the classification process, 3 sites in Poland and 2 sites in Slovakia were mapped extensively, in addition to the ground truth data mentioned above. The sites covered a total of 124 km^2 and were chosen to represent characteristic landscapes of the study area. Mapping was carried out using non-differential GPS units and handheld computers. For the Ukrainian region of the study area, training

Table 1
Class scheme, class descriptions, classification method and training data for the hybrid classification (*H = hybrid classification; C = ISODATA clustering; KB = knowledge-based; **number of clusters)

Classes	Acronym	Description	Classification approach*	# training signatures
Water	W	Open water, rivers and lakes	H	1
Dense settlements	DS	Dense built up areas, cities, construction areas	H	9
Open settlements	OS	Suburbs, villages, small gardens and orchards	H	6
Broadleaved forest	BF	Minimum fraction of broadleaved trees of 70%	C	24**
Mixed forest	MF	Neither broadleaved nor coniferous species dominate	C	8**
Coniferous forest	CF	Minimum fraction of coniferous trees of 70%	C	7**
Shrubland	SH	Secondary succession on fallow land, early reforestation and heath lands	H	19
Grassland	GR	Pastures, meadows and unmanaged grasslands	H	32
Poloniny	PO	High mountain grasslands	KB	–
Arable land	AL	Agricultural areas	H	58

sites mapped in summer 2000 were available from a previous project (BMBF, 2005).

3.2. Preprocessing of Landsat data

Precise georeferencing and correction of geometric distortions, requires a set of high quality ground control points (GCPs). To ensure high positional accuracy, we used an automated search algorithm to delineate large numbers of GCPs (Hill & Mehl, 2003). This method requires a rough manual co-registration of the base map and raw image with a limited number (<10) of control points. Locations of potential GCPs are derived using a systematic sampling technique (e.g. a grid with a mesh size of 100 pixels). The quality of each potential GCP in this grid is evaluated based on correlation windows. A correlation coefficient is calculated between the spectral values of corresponding subsets in the base map and the uncorrected image. First, a small window (e.g. 10 × 10 pixels) is centered on a potential GCP in the base map. This window is correlated with all equally sized windows within a user-specified neighborhood around the approximate location of the corresponding point in the unregistered image. A correlation coefficient is calculated for each pixel in the neighborhood of a potential GCP, resulting in a plane of correlation coefficients. The peak in that plane indicates good agreement between the potential GCP location in the base map and the location of the peaking pixel in the unregistered image (Hill & Mehl, 2003) (Fig. 2).

We georectified the June ETM+ image using the referenced SRTM DEM as the base map due to the lack of freely available detailed topographic maps for the area. A shaded topographic image was derived from the DEM using sun azimuth and elevation from the June ETM+ image. To ensure the best possible agreement of the topographic model and the Landsat imagery, we also added the parallax error (i.e. off-nadir relief displacement due to local terrain elevation) to the DEM. Correlating the resulting topography model with the near infrared band (band 4) yielded the best results, presumably because it displays strong topographically induced illumination differences while having a high signal to noise ratio. The resulting large number of potential GCPs (>500) was screened based on individual error contribution as well as spatial and altitudinal distribution and suboptimal points were dismissed. The June image was rectified to the Universal Transverse Mercator (UTM) coordinate system and the World Geodetic System 1984 (WGS84) datum and ellipsoid using collinearity equations and considering elevation information to accommodate for relief displacement. The August and September images were registered to the June image based on a correlation of the near infrared bands using the same procedure. Overall root mean square errors (RMSE) of all GCPs were 0.16, 0.24, and 0.24 pixels for the June, August and September images, respectively. Comparison with field data (control points and road tracks mapped via GPS) confirmed high positional accuracy.

Atmospheric correction and topographic normalization can improve classification results (Hale & Rock, 2003; Song et al., 2001). The latter is particularly important for mountainous areas and multitemporal data, because spatial variations in illumination and radiance can cause identical surfaces to reflect differently (Itten & Meyer, 1993). Correcting topographic and atmospheric influence concurrently can avoid overcorrection common to simple topographic normalizations such as the cosine-correction (Hill et al., 1995; Richter, 1998). Also, the global flux for non-planar pixels can be precisely calculated, because topographic-induced differences in surface reflectance are taken into account (Hill et al., 1995). We applied a two-stage absolute atmospheric correction. First, at-satellite radiance was calculated using TM calibration gains (Chander et al., 2004) and biases (Markham & Barker, 1986). The ETM+ data was processed using reported calibration constants (USGS, 2005). Second, at-sensor radiance was converted to target reflectance using radiative transfer modeling (Tanre et al., 1990). We used a modified 5S-Code that incorporates a terrain dependent illumination correction (Hill & Mehl, 2003; Hill & Sturm, 1991; Radeloff et al., 1997). To prevent overcorrection in areas of low illumination (because Lambertian reflectance is assumed for non-Lambertian surfaces such as vegetation), the Minnaert constant (e.g. Ekstrand, 1996; Itten & Meyerm, 1993) was set to 0.75 for the late summer and autumn image. Comparison of neighboring spectra from shaded and unshaded hillsides and a visual assessment showed that

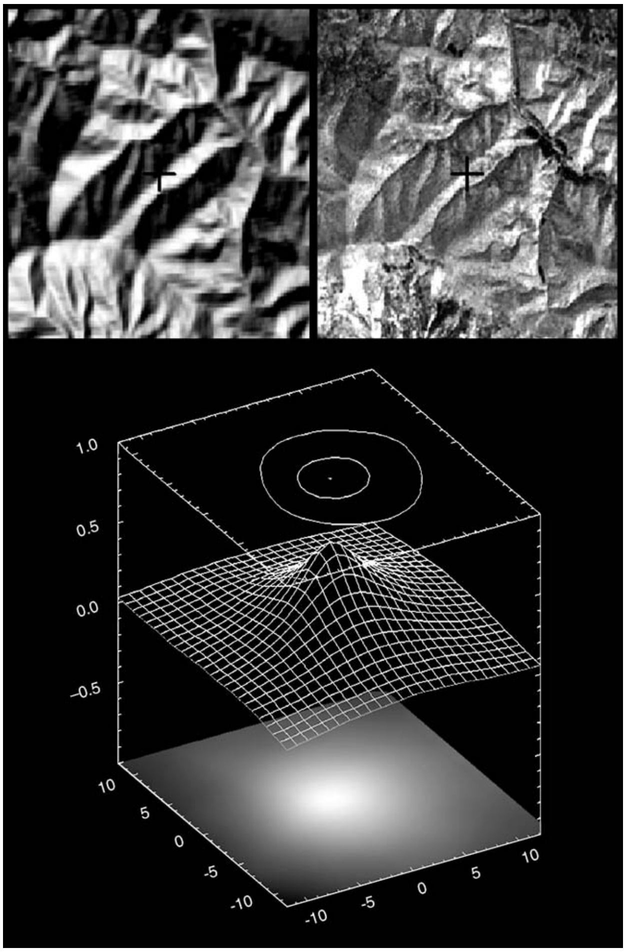


Fig. 2. Top: Corresponding windows of the base map (shaded SRTM DEM) and raw image (ETM + band 4) centered on a potential GCP. Bottom: Visualization of a plane of correlation coefficients calculated by correlating a 10 × 10 pixel-wide window centered on a potential GCP in the base map with all 10 × 10 sized windows within the subset of the raw image. A good GCP is represented by a high peak in the plane of correlation coefficients (*x*,*y*-axes: pixel position, *z*-axis: R).

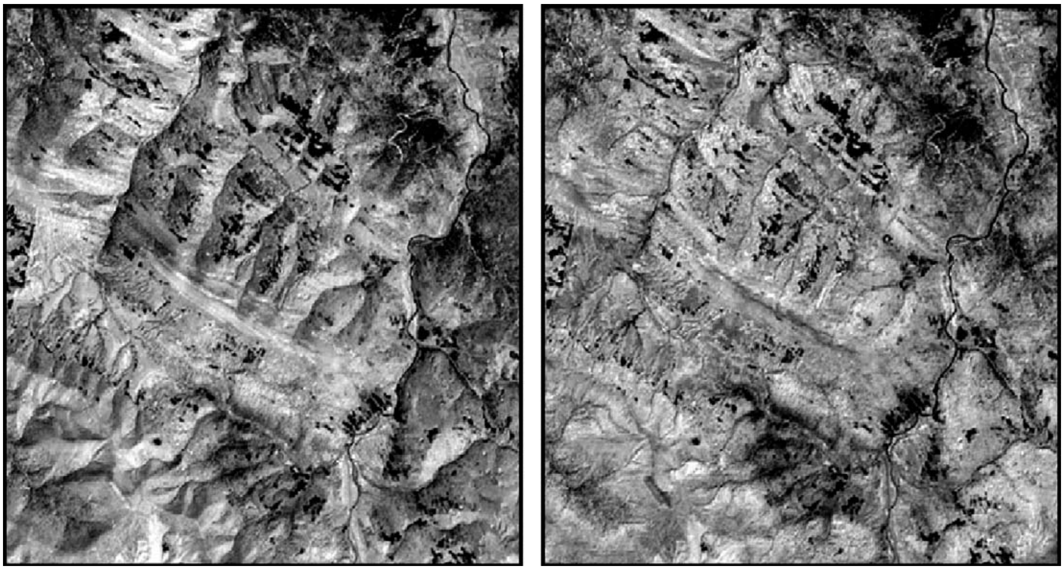


Fig. 3. First principal component from 2000-06-10 before (left) and after (right) radiometric rectification and topographic correction.

topographic distortions were effectively removed without causing overcorrection (Fig. 3).

The stack of all three images was transformed into principal components (PCs) to enhance signal to noise ratio and to reduce data volume. Typically, the first three principal components account for most of the variation in the data. In our case, PC 4 to 8 proved to be valuable because phenological differences between the three images fell into these components and phenology differences between arable land and grassland were important to separate theses classes. PCs 4 to 8 also contained significant amounts of variance based on eigenvalue analysis. Together, PCs 1 to 8 accounted for 98% of the variance in the stack of all three images. In addition, we computed Tasseled Cap images for each phenological period (Crist & Cicone, 1984) because brightness, greenness, and wetness (BGW) bands capture phenological differences and can enhance classification results (Dymond et al., 2002; Oetter et al., 2001).

3.3. Classification

To combine the benefits of supervised and unsupervised approaches, we used a hybrid classification (Fig. 4) to derive 10 land cover classes (Table 1). PC bands 1 to 8 and the BGW bands of the individual images were used as input. Initially, we conducted an unsupervised Iterative Self-Organizing Data Analysis (ISODATA) clustering into 40 clusters to separate forest and non-forest. Hyperclustering, i.e., using a much higher number of clusters than classes (Bauer et al., 1994) was chosen because the exact number of spectral classes in the data set was unknown (Cihlar, 2000). The potential difficulty with hyperclustering lies in small spectral classes that may be hard to label (Cihlar, 2000). Initial tests showed that 40 classes could adequately distinguish forest from non-forest while still being interpretable. Subsequently, forested areas were clustered again into 40 classes and labeled as broadleaf, mixed, and coniferous forest based on field data and forestry maps. For the non-forested pixels, clustering techniques alone proved to be inadequate. Instead, a two stage combination of unsupervised and supervised methods was used. First, we conducted unsupervised hyperclustering to minimize bias in the selection of training areas and seed signatures. Eighty classes proved to be a good compromise between spectral pureness and interpretability. Class signatures were examined using feature space images and dendrograms depicting hierarchical relations between classes. On-the-fly parallelepiped classification was used to evaluate spectral pureness of classes. Unambiguous signatures were retained, small classes were deleted, and spectrally similar classes of identical land cover type were merged. Ambivalent classes were masked out and further sub-clustered (using 10–25 sub-classes) to obtain unambiguous signatures for all land cover types. The comprehensive set of spectral class signatures was used in the second stage as training data for a maximum likelihood (MLH) classification. In an iterative procedure, the signature set was refined and additional signatures were gathered manually for areas where misclassifications occurred and Mahalanobis distances to existing cluster means were high.

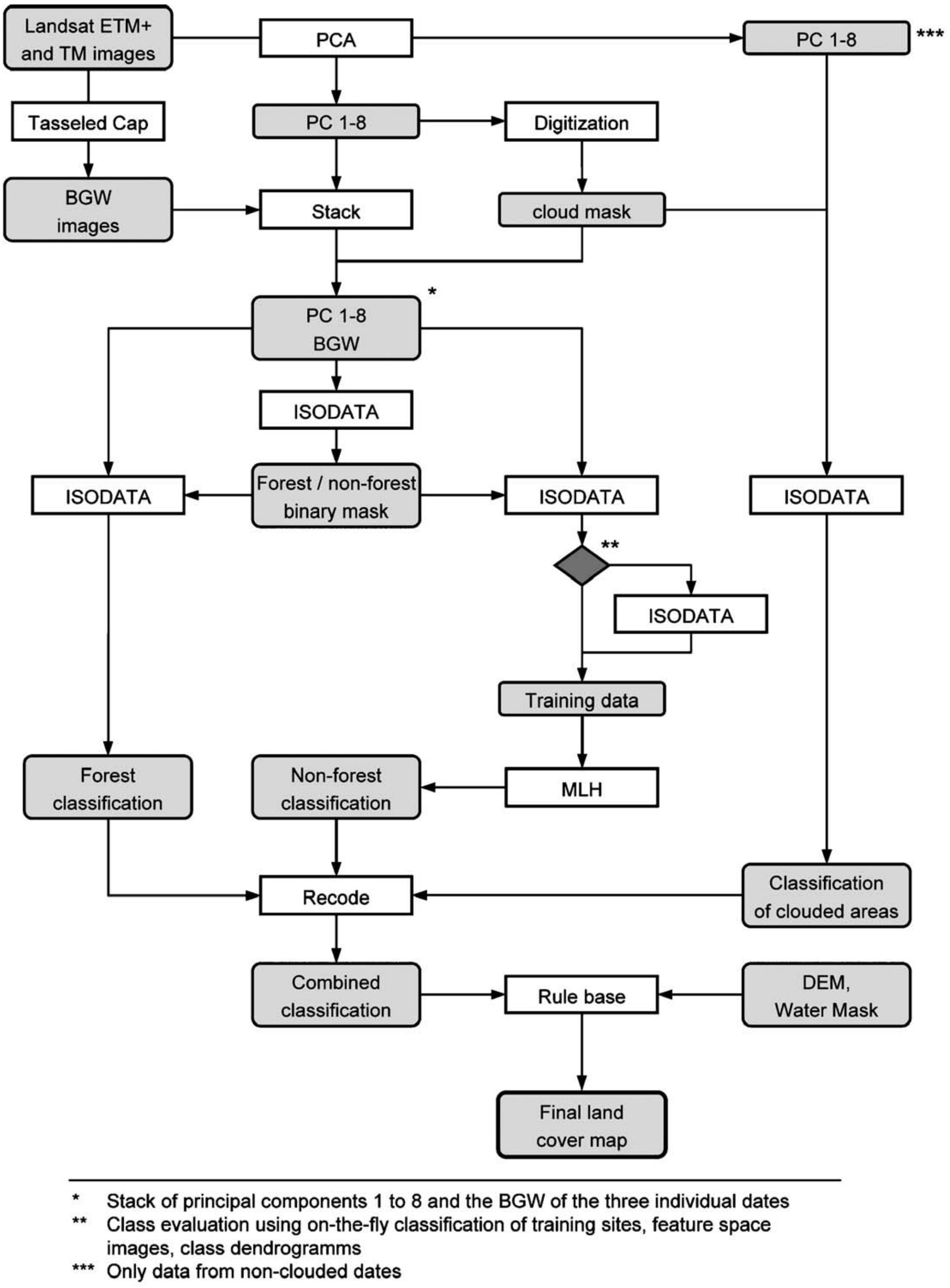
The autumn image (2000-09-30) included 3 clouds (~3% of the study area). Clouded areas and their corresponding cloud shadows were digitized manually. These areas were classified separately using only data from the remaining, cloud-free images. Because the affected area was small and contained dominantly forest classes, unsupervised ISODATA clustering with 40 classes proved to be adequate. A 300 m buffer around the clouds was established and class labeling was carried out in comparison with the classification product of cloud free areas to ensure consistency.

A post-classification step allowed separation of the mountain meadows (*poloniny*) class and improved the classification of water. The *poloniny* class was spectrally not separable and classified using an elevation threshold of 1030 m. The shallow creeks and rivers of the study site lead to confusion with the coniferous forest class. The class was improved by deriving water pixels based on thresholds for PCs 1 and 2.

The land cover map was stratified into elevation zones to enable the assessment of land cover across borders. Comparisons of land cover were based on relative proportions within single elevation zones, to avoid potential biases introduced by the selection of study region boundaries (Fig. 1).

3.4. Landscape structure

Post-socialist land reforms and land abandonment were expected to have an effect on landscape pattern and landscape fragmentation. These processes were not assumed to occur uniformly along an altitudinal gradient. For example, land abandonment was expected to occur on marginal land that is more frequently found at higher altitudes. We calculated the average size of each land cover patch and its mean elevation. To assess the relationship of these two variables, we derived two-dimensional density distributions using an axis-aligned bivariate normal kernel (Venables & Ripley, 2002). This was done for the land cover types arable land, grassland, and shrubland, because land reforms were



* Stack of principal components 1 to 8 and the BGW of the three individual dates
** Class evaluation using on-the-fly classification of training sites, feature space images, class dendrogramms
*** Only data from non-clouded dates

Fig. 4. Classification scheme (for details compare to text; MLH = maximum likelihood classification, PCA = principal component analysis).

assumed to exert influence on the patch sizes of these cover types. Density distribution did not prove useful to assess forest cover, because forest patches are very large in the region resulting in a relatively small number of patches. To exclude micro-patches from the analysis, the land cover map was majority filtered using a 3 × 3 operator prior to the calculations of patch metrics.

Fragmentation of the land cover classes arable land, grassland, and total forest were further assessed in a spatially explicit way using fragmentation indices proposed by (Riitters et al., 2002). These indices are based on two measures, land cover proportion (P_{LC}) and land cover connectivity (C_{LC}), and were calculated around each pixel. P_{LC} is the percentage of the target land cover class in the neighborhood. To calculate C_{LC}, we first determined the number of true edges (edges between pixels of the target land cover type and other land cover types, e.g. forest–non-forest edges) and the number of interior edges (edges between pixels of the target land cover type, e.g. forest–forest edges) of a neighborhood based on the grey level co-occurrence matrix. C_{LC} is the sum of interior edges divided by the sum of true edges and interior edges. Thus, C_{LC} is an approximation of the probability that a land cover pixel is located next to a pixel of the same land cover and high values of C_{LC} indicate a higher degree of land cover connectivity (Riitters et al., 2002). Two differently sized neighborhoods, 2.25 ha (5 × 5 pixels) and 7.29 ha (9 × 9 pixels) were applied for the land cover classes arable land and grassland. For forest cover, an additional scale of 65.61 ha (27 × 27 pixels) was included to accommodate for bigger patch sizes of this land cover type.

P_{LC} was categorized into four classes for each scale to enable comparison between countries: core ($P_{LC}=1$), interior ($1>$

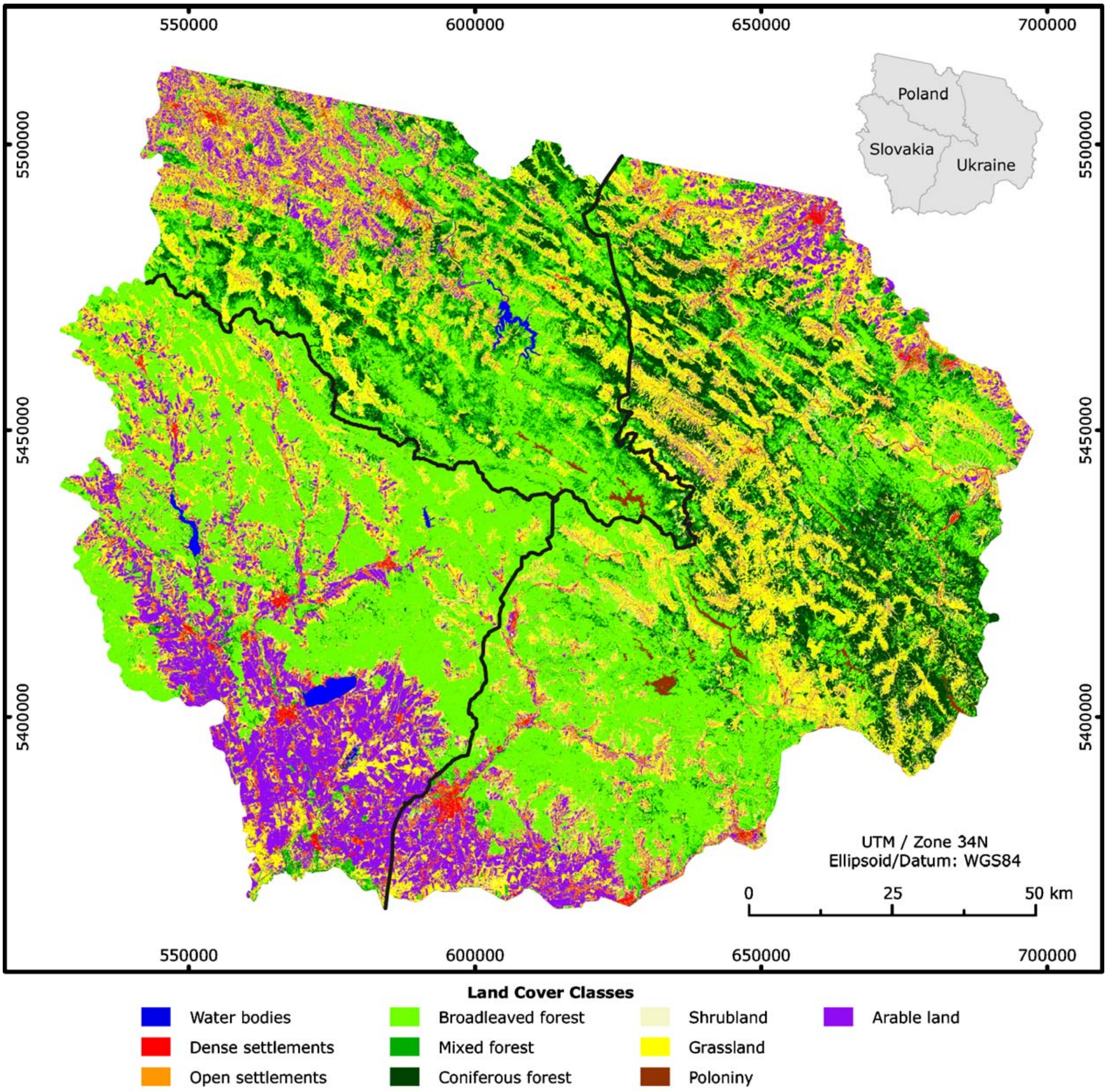


Fig. 5. Land cover map for the border triangle Poland, Slovakia, and Ukraine.

$P_{LC}>0.9$), dominant ($0.9 \geq P_{LC}>0.6$), and intermediate ($0.6 \geq P_{LC}>0.4$). To analyze the location of fragmentation, a rule-base was adapted to assign each pixel to one of four components of fragmentation (Riitters et al., 2002). "Core" is equivalent to the core component of P_{LC} and "patch" represents the dominant and intermediate classes of P_{LC}. Where P_{LC} was between 0.6 and 1, a pixel was labeled "perforated" for $P_{LC}>C_{LC}$ and labeled "edge" for $P_{LC} \leq C_{LC}$. This implies that the configuration of land cover units is compact for the perforated class while the edge class is characterized by a disconnected pattern (Riitters et al., 2002).

4. Results and discussion

4.1. Land cover classification

The land cover classification showed that the majority of the slopes of the Carpathian ridge were forested (Fig. 5). In the mountain valleys, a patchwork of grassland and agriculture was observed at intermediate altitudes while at higher altitudes grasslands prevailed. The lower areas in the southern, northwestern and northeastern regions of the study area were dominated by arable land.

The hybrid classification approach performed well and resulted in a reliable land cover map for cross-border comparisons with an overall classification accuracy of 84% and an adjusted kappa of 0.80. Broadleaved forest, coniferous forest, and *poloniny*, had users and producers accuracy of more than 90% (Table 2). Multitemporal imagery and Tasseled Cap transformations separated arable land and grassland well considering the degree of spectral collinearity of some spectral sub-classes. The unsupervised clustering prior to the maximum likelihood classification was helpful in identifying spectral classes and reducing bias in the collection of training data.

The land cover classes open settlements, mixed forest, and shrublands show accuracies of less than 80% (Table 2). Generally, the classification of mixed classes may be problematic, because class borders are drawn artificially (Foody, 2002; Schriever & Congalton, 1995), and often there is an underlying conflict regarding the desired thematic classes and their spectral separability. Shrublands proved particularly difficult to classify because of their overlap with grassland and the high degree of spectral heterogeneity. For instance, the composition of shrublands ranges from encroaching alder (*Alnus spec.*), hawthorn (*Crataegus spec.*), or pine (*Pinus spec.*) shrubs on meadows in Poland, to juniper (*Juniperus communis*) heath communities in Ukraine.

Accuracy assessment is most reliable when using a random sample of ground truth points (Congalton, 1991) but obtaining such a data set is not always feasible (Foody, 2002). In our case, inaccessibility of some areas, rugged terrain and other practical restrictions inhibited the manual collection of a randomly distributed set of points. The set of ground control points used in this study was carefully selected to be independent from the training data, to cover a wide area, different altitudinal zones and to represent the spectral sub-classes of the land cover types, but we cannot completely rule out a bias. However, we suggest that any potential bias is distributed evenly throughout the study area, and would not have affected our country comparisons.

4.2. Cross-border comparison of land cover and landscape pattern

The border area of Poland, Slovakia, and Ukraine is environmentally fairly homogeneous yet the comparison of land cover revealed marked differences in land cover proportions and landscape pattern among these countries. We suggest that these differences at least partially reflect differences in the socioeconomic conditions, both currently and in the past. From 1772 until 1918 the area belonged to one country (the Austro-Hungarian Empire) (Augustyn, 2004). This suggests that differences in land cover are largely a result of changes during socialist and post-socialist times.

4.2.1. Forests

Forest cover and forest composition differed most strongly among the three countries. In mountainous areas, forest cover was much lower in Ukraine compared to Poland and Slovakia. For instance at elevations of 400–800 m, forest cover was 84% in Slovakia, but only 61% in Ukraine (Fig. 6). Concerning forest composition, the main difference was the dominance of

Table 2

Confusion matrix for the hybrid classification (UAC = user's accuracy, PAC = producer's accuracy, CKA = conditional kappa; acronyms are explained in Table 1)

		Reference data											
		W	DS	OS	BF	MF	CF	SH	GR	PO	AL	∑	UAC
Classified data	W	**23**	0	0	0	0	0	0	0	0	0	23	1.00
	DS	1	**45**	5	0	0	0	0	0	0	1	52	0.87
	OS	1	7	**55**	0	1	0	2	1	0	3	70	0.79
	BF	0	0	0	**233**	12	1	7	8	1	2	264	0.88
	MF	1	0	0	9	**45**	15	1	0	0	0	71	0.63
	CF	4	0	0	0	10	**142**	1	0	0	0	157	0.90
	SH	1	0	1	0	1	0	**51**	23	0	3	80	0.64
	GR	0	0	6	3	0	0	33	**378**	0	43	463	0.82
	PO	0	0	0	0	0	0	0	0	**19**	0	19	1.00
	AL	0	1	7	0	0	0	2	21	0	**247**	278	0.89
	∑	31	53	74	245	69	158	97	431	20	299	1477	
	PAC	0.74	0.85	0.74	0.95	0.65	0.90	0.53	0.88	0.95	0.83		
	CKA	1.00	0.86	0.77	0.86	0.62	0.89	0.61	0.74	1.00	0.86		

broadleaved forest in Slovakia while coniferous and mixed forests were more abundant in Poland and Ukraine (Fig. 6). Differences were again most prominent at higher elevations, where Slovakia had up to 48% more broadleaved forest than the other countries, and Ukraine displayed striking percentages of conifers (Figs. 6 and 7).

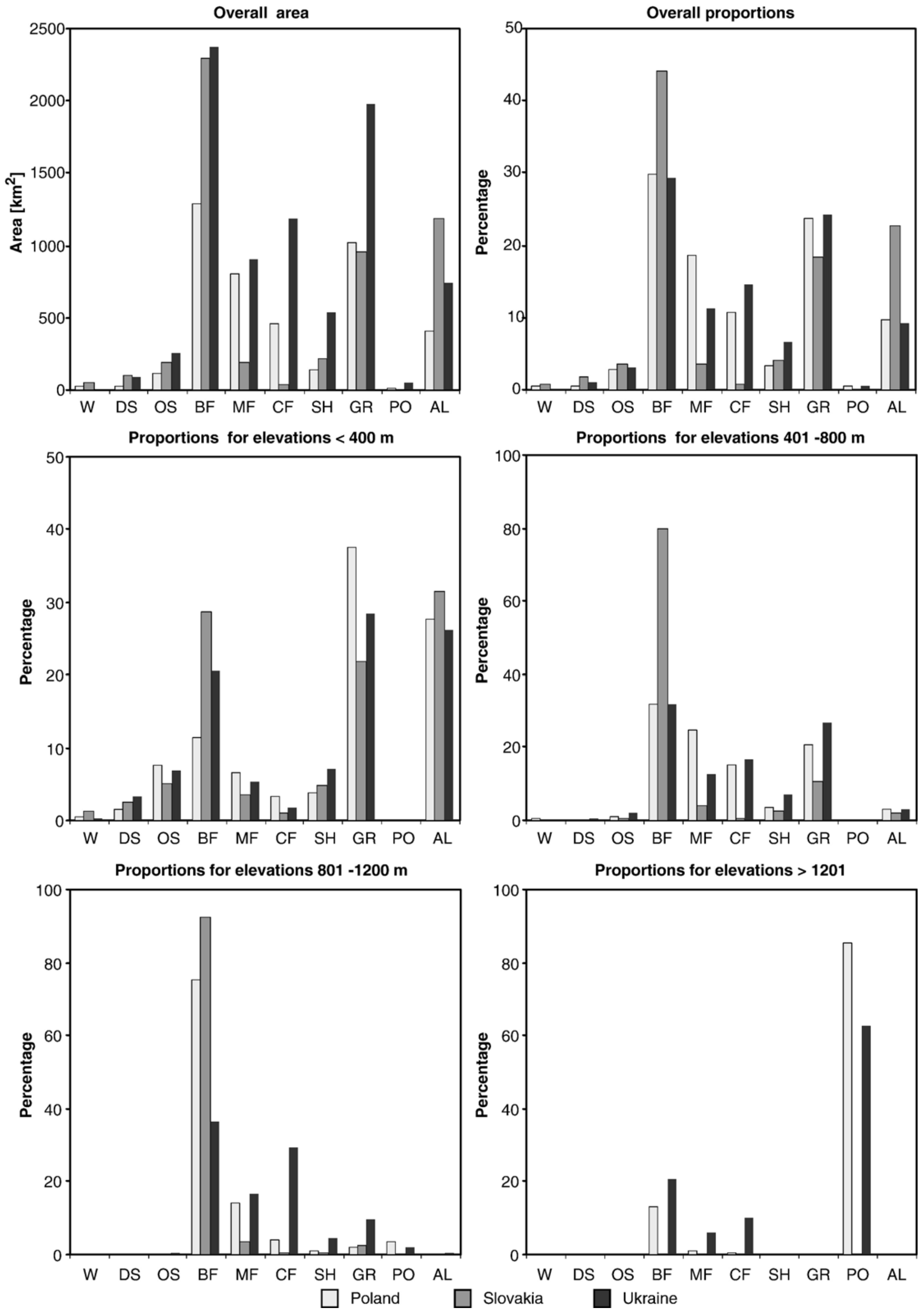


Fig. 6. Comparison of land cover between the three countries. Top left: absolute area; top right: proportion of land cover normalized by the total area of each country. Middle and bottom: proportions of land cover classes per altitudinal zone (acronyms are explained in Table 1).

Natural vegetation in the study area is beech (*F. sylvatica*) forest on the southern slopes and mixed beech and fir (*A. alba*)

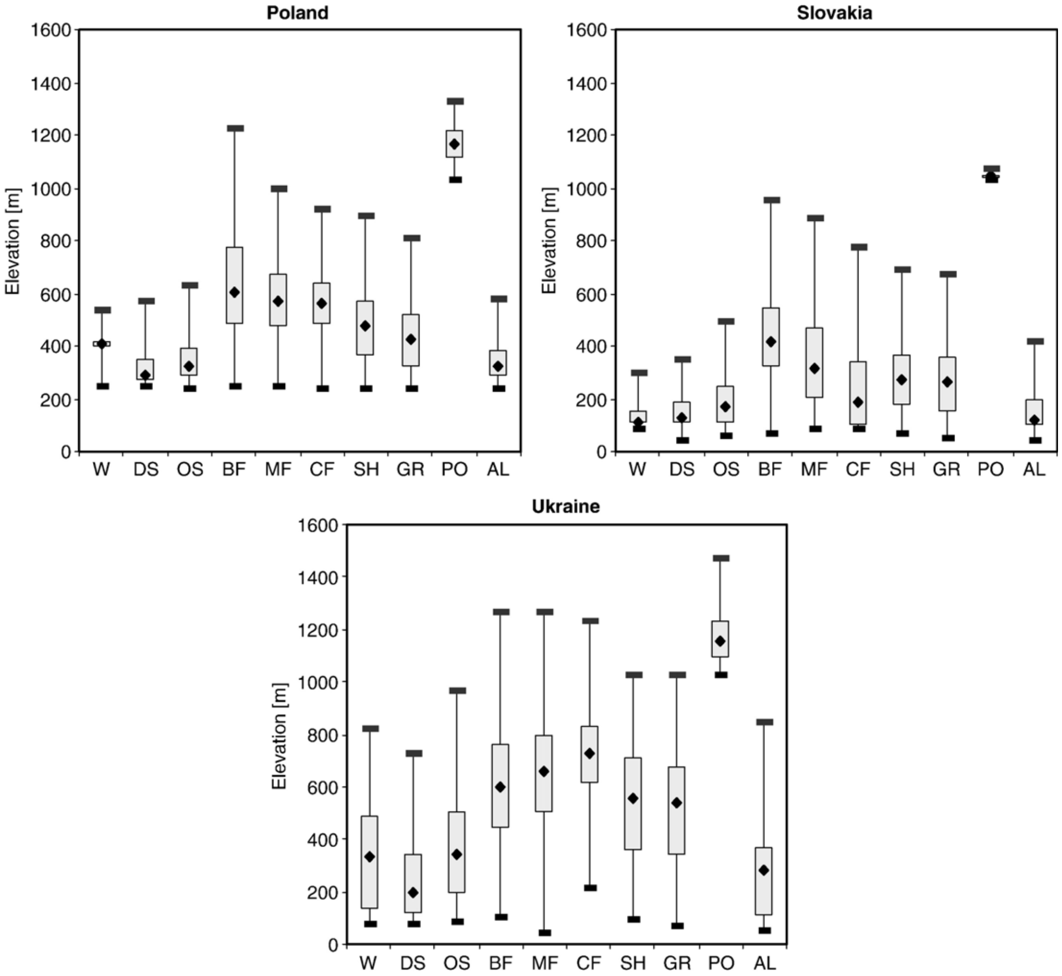


Fig. 7. Boxplot graphs of the distribution of elevation for each class and country (◆ represents the class medians; box determines the first and third quartile; whiskers represent the upper and lower range, max/min values exceeding the range of ±3 standard deviations (STD) were treated as outliers and the 3STD limit was taken instead; acronyms are explained in Table 1).

forest on the northern rim (Denisiuk & Stoyko, 2000). Although there are differences in forest composition between north and south slopes, we suggest that the observed differences in forest composition are largely anthropogenic in origin. Particularly, pure coniferous forests that we found in Poland and Ukraine (Fig. 5) do not occur naturally in the area. These differences are most likely a legacy of socialist forest management practices and policies, because almost all forests were harvested at least once in the 20th century and the vast majority of forests were mature in 1990 (Turnock, 2002).

In Poland, forest cover was significantly lower before World War II than it is today (Turnock, 2002). Following border changes between Poland and the Soviet Union, large areas of the Eastern Polish Carpathians were depopulated between 1945 and 1947 causing widespread afforestation with conifers (mainly spruce) and natural succession (Augustyn, 2004; Turnock, 2002). This resulted in considerable amounts of coniferous and mixed forests at lower altitudes (Fig. 6), especially on sites close to the lower tree line in the valleys (Fig. 5). Afforestation following the forced resettlement is also a likely explanation of the unique altitudinal distribution of forest types found in Poland, where coniferous forests were on average found in lower elevations compared to other forest types (Fig. 7). Since the 1970s, Poland changed its forest policy for the Eastern Carpathian area from clear cutting to selective harvesting and broadleaved forest was no longer replaced by coniferous forest (Turnock, 2002). The reported increase in forest cover after 1947 in conjunction with the low population density explains the lowest level of forest fragmentation (Fig. 8) and the higher amount of core forest areas we found in Poland (Table 3).

Slovakia's forest composition is dominated by deciduous forests, particularly at altitudes above 400 m, and thus is closer to natural vegetation than forests in Poland and Ukraine (Fig. 6). Yet, forests in Slovakia are highly managed and clear cutting was widespread in socialist times and continues today (Feranec et al., 2003). As a result, we found forest fragmentation to be highest in Slovakia. Slovakian forest harvesting is often conducted in very narrow strips. Although small clear cuts were common, the narrowest strips may not exceed the width of a Landsat TM or ETM+ pixel (30 m), and thus may be difficult to detect. Therefore the level of forest fragmentation in Slovakia may be even higher than indicated in our findings.

In Ukraine, lower forest cover, the high proportion of coniferous (Fig. 6) forest, and the high forest fragmentation (Fig. 8) can be explained by three processes. First, Ukrainian forests were overexploited in Soviet times (Turnock, 2002) and natural forests were replaced with fast-growing conifers, particularly at higher elevations (Fig. 7). While this was most extensive on northern slopes, former clear cuts are also found on southern slopes, and these clear cuts are now occupied by successional shrublands or mixed forest. Second, population density is relatively high in Ukrainian mountain valleys (UNESCO, 2003) thus forests are generally only found on sites unsuitable for agriculture and generally at higher altitudes than in the other countries. Third, Ukrainian forest practices are based on clear cuts. Extensive logging supported by foreign capital as well as presumably illegal forest harvesting have occurred in Ukraine in post-socialist times

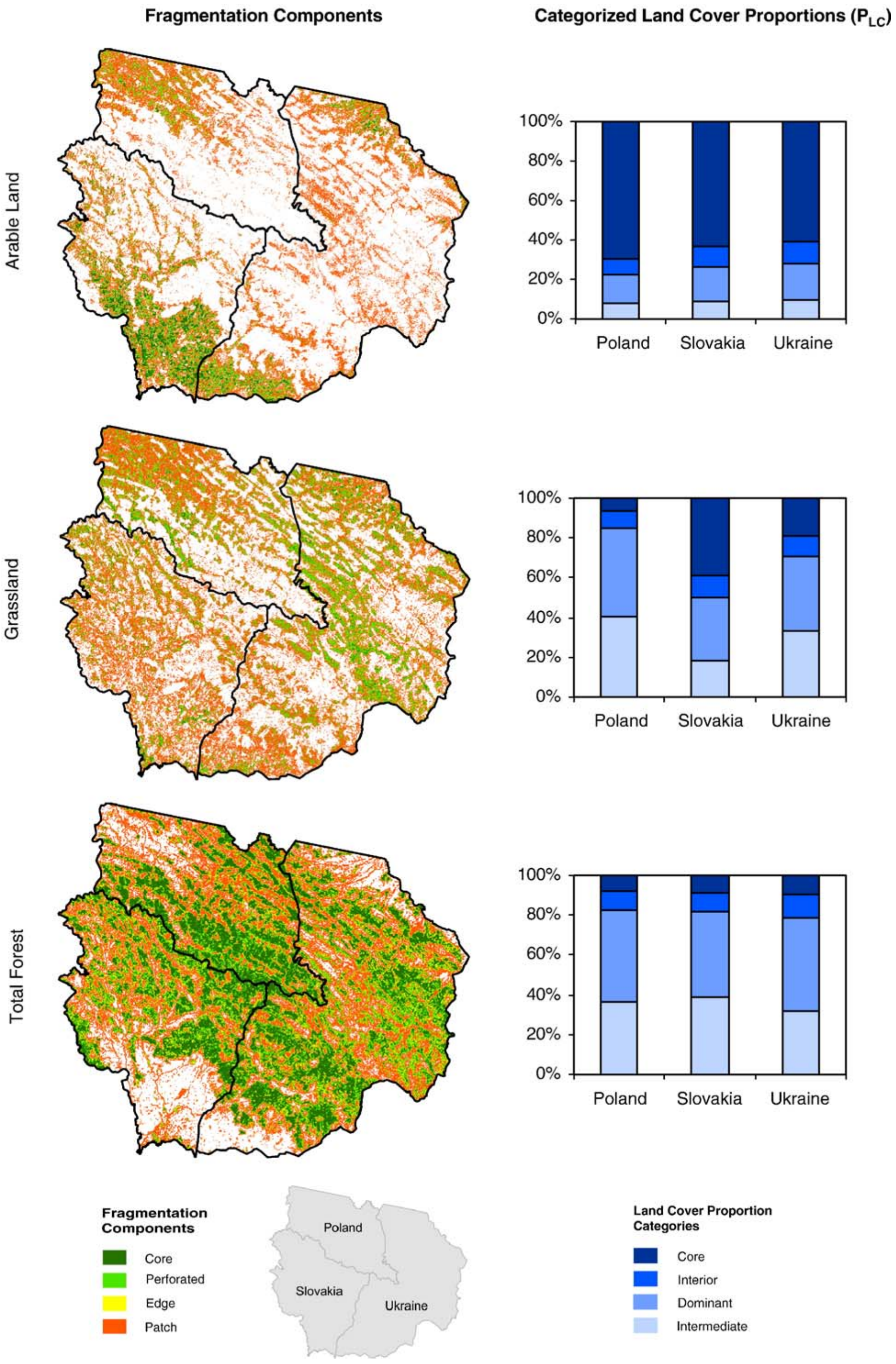


Fig. 8. Maps of fragmentation components (left) and categorized proportions of P_{LC} with the classes core, interior, dominant, and intermediate (normalized over the sum of these components; right). Results are based on a neighborhood size of 2.25 ha for arable land and grassland and on a neighborhood size of 7.29 ha for the forest class.

Table 3
Distribution of four fragmentation components per country for the land cover types forest, arable land and grassland

Land cover type (neighborhood size)	Country	Fragmentation component			
		Core	Perforated	Edge	Patch
Forest (2.25 ha)	Poland	55.4%	9.5%	8.4%	26.7%
	Slovakia	49.9%	11.4%	10.3%	28.3%
	Ukraine	48.1%	13.8%	9.5%	28.7%
Forest (7.29 ha)	Poland	37.7%	11.6%	14.5%	36.2%
	Slovakia	30.0%	13.7%	17.2%	39.1%
	Ukraine	29.1%	15.6%	17.4%	37.9%
Forest (65.61 ha)	Poland	8.0%	16.4%	31.5%	44.1%
	Slovakia	3.6%	13.3%	31.5%	51.7%
	Ukraine	4.2%	12.5%	37.4%	46.0%
Arable Land (2.25 ha)	Poland	2.0%	12.9%	6.9%	78.2%
	Slovakia	21.9%	15.1%	9.4%	53.6%
	Ukraine	5.1%	9.3%	4.5%	81.1%
Arable Land (7.29 ha)	Poland	0.3%	5.8%	6.4%	87.6%
	Slovakia	8.9%	11.9%	15.5%	63.7%
	Ukraine	1.4%	5.4%	5.0%	88.2%
Grassland (2.25 ha)	Poland	4.3%	22.3%	9.0%	64.4%
	Slovakia	3.5%	13.5%	6.8%	76.2%
	Ukraine	5.0%	23.0%	8.3%	63.7%
Grassland (7.29 ha)	Poland	0.4%	13.3%	10.0%	76.3%
	Slovakia	0.3%	6.2%	6.8%	86.8%
	Ukraine	0.4%	14.8%	9.5%	75.3%

Fragmentation components were calculated for three differently sized neighborhoods for the forest class (2.25 ha = 5 pixels; 7.29 ha = 9 pixels; 65.61 ha = 27 pixels) and for two differently sized neighborhoods (2.25 ha and 7.29 ha) for the land cover types arable land and grassland (rows may not sum to 100% due to rounding).

(Turnock, 2002). Comparing valleys dissected by the Polish–Ukrainian border, we speculate that today's forest cover in Ukraine may be comparable to the extent of forest found on the Polish side before the depopulation (Fig. 5).

4.2.2. Arable land, grassland, and shrubland

The land cover map revealed considerable differences in the abundance and configuration of arable land, grassland, and shrubland between Poland, Slovakia, and Ukraine. Arable land was most dominant in Slovakia, particularly below 400 m (22%) with substantial amounts between 400 m and 800 m (Fig. 6). Agricultural fragmentation proved to be lowest in Slovakia at all scales (e.g. core area 21.9% compared to 2% in Poland and 5% in Ukraine for the 2.25 ha neighborhood) (Table 3). The density distributions of patch size versus patch elevation (Fig. 9) revealed largest patches of arable land in Slovakia (mean patch sizes Poland 4.7 ha, Slovakia 18.9 ha, Ukraine 4.4 ha). Poland and Ukraine had lower percentages of arable land but higher proportions of grassland (Fig. 6) and higher levels of agricultural fragmentation (Fig. 8).

Shrubland occurred almost exclusively in very small patches (Fig. 9) and highest abundances were found in Ukraine, especially above 400 m (Fig. 6). The occurrence of shrubland may be interpreted as an indicator of land abandonment in all three countries, because shrubland is not expected to occur naturally below treeline apart from disturbed areas (e.g. flood plains). In total, 548 km^2 were covered by shrubland in Ukraine compared to 140 km^2 and 214 km^2 in Poland and Slovakia, respectively.

Differences in the abundance of arable land, grassland, and shrubland among countries are likely due to political and socio-economic factors, especially land tenure. In Poland, the majority of non-forested land in the northern part of the study area was in private ownership throughout socialist times, but land in the south that had been depopulated after 1947 was taken by the state (Augustyn, 2004). A high proportion of very small subsistence farms persisted where private ownership dominated, those areas did not change significantly during the last 60 years (Gorz & Kurek, 1998; Sabates-Wheeler, 2002). This is reflected in our findings through the high degree of agricultural fragmentation and a lower mean patch size of arable land (Figs. 8 and 9). Also, the distribution of patch sizes suggested highest levels of landscape fragmentation in Poland, where high densities of small patches of arable land and grassland co-occur.

In Poland, grassland and shrubland dominated formerly state owned land, particularly in the mountain valleys on the border with Slovakia (Fig. 5). Large areas of former state farms have been set aside or abandoned since 1990, often because they were only marginally suited for agriculture (Gorz & Kurek, 1998). The Polish Forest Service claimed land that is now either reforested or undergoing secondary succession (Augustyn, 2004).

In Slovakia, all land was collectivized and managed in large scale farming cooperatives (Csaki et al., 2003; Drgona et al., 1998). However, the members of the collectives continued to own their land and Slovakia restituted land to owners after 1990 (Csaki et al., 2003). Yet, our results suggested that the socialist large scale farming structure has changed little. Slovakia had larger patches (Fig. 9) and the highest share of arable land (Fig. 6) as well as significantly lower agricultural fragmentation compared to Poland and Ukraine (Fig. 8). A likely explanation is the restitution process. The vast majority of landowners left their land within the successor organizations (often co-operatives) of former collectives, for example because shares were too small to sustain economically profitable private farming. Thus, restitution in Slovakia has slowed down decollectivization and preserved Slovakia's socialist farmland patterns (Csaki, 2000; Drgona et al., 1998; Mathijs & Swinnen, 1998). Most shrubland in Slovakia occurred in former clear cuts, but some shrubland was also found in mountain valleys where land abandonment occurred after 1990. Many of these sites are not well suited for agriculture and were converted to arable land during the period of agricultural industrialization between 1970 and 1990 (Feranec et al., 2003).

Landscapes in Ukraine were most strongly affected by post-socialistic changes. Arable land was completely state owned in the former Soviet Union and managed by large agricultural enterprises (Ash, 1998). Ukraine privatized land, but land reform is slow, a functioning land market is lacking, and only few private farms existed by the end of the 1990s (Ash, 1998; Lerman, 1999). Some formerly state owned farms continue to operate as collectives (Ash, 1998) and consequently we found many large patches of arable land, particularly at lower elevations (Fig. 9). On the other hand, much arable land was subdivided for subsistence farming, leading to a high level of agricultural fragmentation in some areas (Fig. 8). Compared to Poland or Slovakia, subsistence farming is more important in Ukraine, where settlements were found at high elevations and the mountain valleys are more

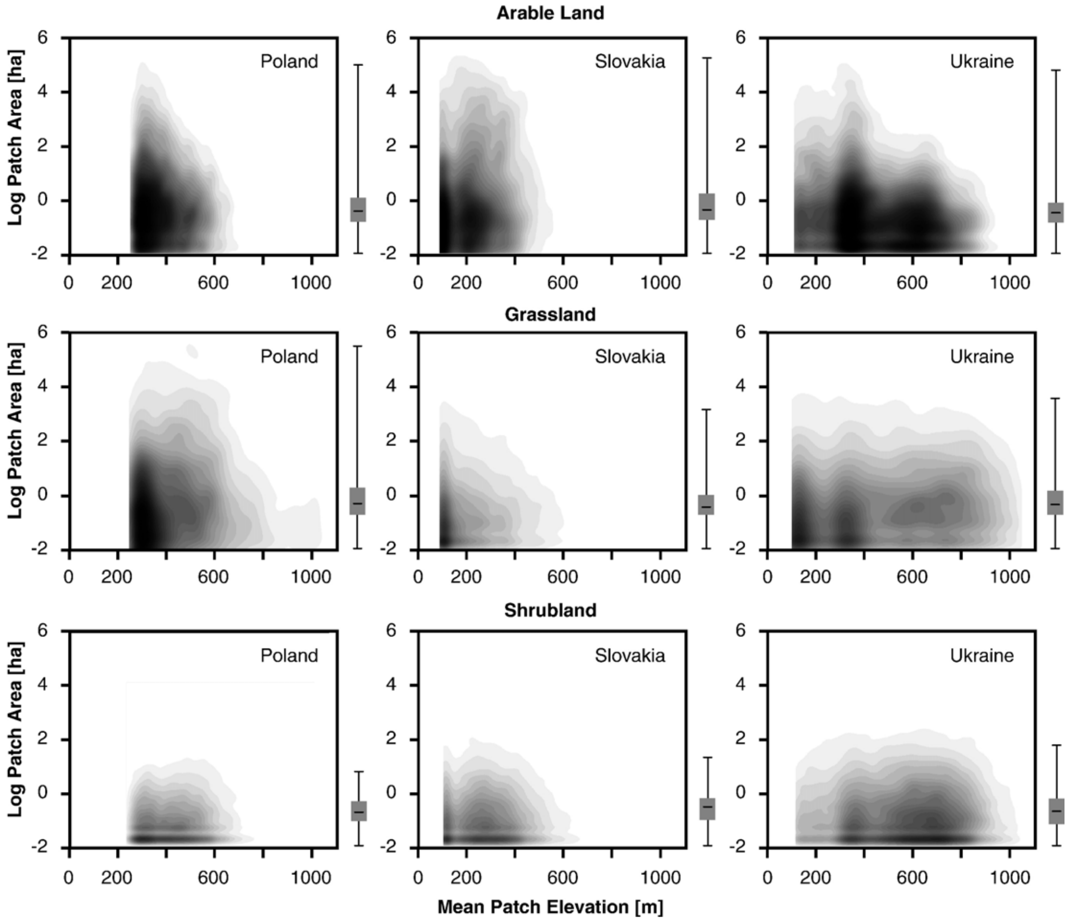


Fig. 9. Two-dimensional density distributions of logarithmized patch size [ha] and mean patch elevation [m] per country and for the land cover classes arable land, grassland and shrubland.

populated than in the other countries. The abundances of grasslands at higher altitudes were mainly due to lower forest cover (Fig. 6), because grasslands are important as meadows for animal husbandry.

Also, arable land covered a much wider altitudinal range in Ukraine than in Poland or Slovakia (Fig. 7), and significant amounts of highly fragmented small scale agriculture existed at elevations up to 800 m. It is also notable that today's agricultural fragmentation in Ukraine is comparable to Poland (Fig. 8, Table 3), where private land ownership was common even in socialist times, although Ukraine and Slovakia had similar farming structures before 1990.

Many state owned agricultural enterprises in Ukraine went bankrupt after the system change (Ash, 1998), particularly in the Carpathians, where they often operated on marginal land (Augustyn, 2004). Also, access to machinery is limited and farmers can only cultivate a small portion of the potentially available land. As a consequence, large areas have been converted to grassland or simply have been abandoned, and are undergoing secondary succession. Consequently, high abundances of grassland existed in Ukraine, especially above 400 m (Fig. 6). Land abandonment is also indicated by the high amounts of shrubland in Ukraine, substantially more than in the other countries (Fig. 6), particularly at elevations above 600 m where land is only marginally suited for agriculture (Fig. 9).

The co-occurring patterns of three post-socialist developments in Ukraine, land abandonment, agricultural fragmentation for subsistence farming, and a preservation of parts of the large scale farming structure, are also an explanation for the high degree of landscape fragmentation for the arable land and grassland classes in Ukraine (Fig. 8).

5. Conclusions

This study compared landscapes across borders for a relatively environmentally homogeneous region in the Carpathian Mountains. To avoid potential biases arising from external factors such as study region boundaries, comparisons were based on relative proportions and land cover was stratified for elevation zones. Distinct differences in land cover and landscape pattern were found between portions of Poland, Slovakia, and Ukraine. We suggest that these differences can be attributed largely to differences in broad-scale socioeconomic and political factors.

Forest cover and composition varied considerably between the Polish, Slovakian, and Ukrainian regions of the study area. For example, forest cover is higher in Poland, likely due to afforestation and natural succession following the forced depopulation in 1947. In Ukraine, Soviet forest management resulted in widespread replacement of natural forest communities with coniferous forest. Concerning agriculture, we suggest that land tenure in socialist times and the land reform chosen by the respective countries are important to explain land cover and to understand post-socialist land cover change. On formerly state owned land (virtually all land in Ukraine and some areas in Poland), land abandonment is common, often accompanied by shrub encroachment. The occurrence of shrublands is a good indicator for this process, because shrublands are not a natural vegetation formation in the area. Restitution of arable land to former owners in Slovakia led to a preservation of the large scale farming structure. However, agricultural fragmentation is highest where private land ownership was allowed in socialist times (Poland) and where state farms were dissolved and the land was made available to the people (Ukraine). For example, Ukraine showed a similar farming structure to Slovakia in socialist times, while today's agricultural fragmentation has reached a level comparable to Poland.

No study to date has conducted comparative analysis of land cover and landscape pattern between different countries in Eastern Europe. The cross-border comparison of landscapes carried out in this research may thus be an important step towards a better understanding of the consequences of the political and economic transition on land cover. For the area studied, broad-scale socioeconomic factors and policies were important to understand differences in land cover and post-socialist land change, and we suggest that they may be equally important in other areas as well.

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