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Comparing the determinants of cropland abandonment in Albania and Romania using boosted regression trees

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ABSTRACT

The collapse of socialist governance structures in Central and Eastern Europe led to the widespread abandonment of agricultural land. We estimated and compared the determinants of cropland abandonment in Albania and Romania during the postsocialist transitional period from 1990 to 2005. The data set included cropland abandonment derived from satellite image analysis, spatially continuous biogeophysical indicators, and socioeconomic surveys. Data were analyzed using boosted regression trees. Boosted regression trees can account for nonlinearities and interactions between variables and combine high predictive accuracy with appealing options to interpret the results. The results revealed important similarities between cropland abandonment in the countries and showed a strong correlation of abandonment with elevation and slope. Differences between cropland abandonment in Albania and Romania were apparent when the influence of topography was excluded. While physical accessibility tended to be more important in Albania, the density of cropland and input intensity were more decisive in Romania. The immediate time period following the collapse of socialism was dominated by extensive cropland abandonment in areas where agricultural production was no longer profitable. Gradual changes were observed in later stages of the transition period.

1. Introduction

Cropland abandonment was a major land-use change in countries in the Northern hemisphere during the last century (Ramankutty and Foley, 1999). The decrease in agricultural areas has important implications on the services derived from agro-ecosystems (Stoate et al., 2009). It influences agricultural output (Verburg et al., 2008), alters ecosystem services (Bondeau et al., 2007; Knops and Tilman, 2000), and affects biodiversity (Cramer et al., 2008; MacDonald et al., 2000). Robust spatial insights into the determinants of cropland abandonment will provide a better understanding of the dynamics and consequences of agricultural land-use change.

Particularly high rates of cropland abandonment were observed in the former Soviet Union and the former socialist countries in Central and Eastern Europe following the collapse of socialism (Bakker et al., 2011; Ioffe and Nefedova, 2004; Kuemmerle et al., 2008). This "most widespread and abrupt episode of land change in the twentieth century" (Henebry, 2009) poses numerous threats and opportunities for ecosystems and the services they provide. For example, cropland abandonment may result in the loss of traditional farming landscapes with high conservation values (Cremene et al., 2005; Fischer et al., 2012) and significant modifications of the carbon cycle (Kuemmerle et al., 2011; Vuichard et al., 2008). The decrease in cultivated areas in former socialist countries is particularly interesting to study due to the rapid rate of abandonment, the size of the areas relinquished, and the relative paucity of studies that have been conducted in the region.

Studying postsocialist landscapes allows to examine the impacts from a specific set of broad-scale changes on human–environment interactions in the land system. The transition from command-driven to market-based systems has been accompanied by market and price liberalization. Market forces resulted in drastic declines in the ratio between output and input prices, which led to widespread decreases in input usage, lay-offs of farm workers, and a plummeting consumption of fertilizer and pesticide (Rozelle and Swinnen, 2004). Land reforms privatized land ownership and individualized land use, which resulted in changes in farm structure and size, and considerably affected land-use outcomes (Lerman, 2001; Sikor and Müller, 2009). These factors translated into rapid, widespread cropland abandonment across Eastern Europe and the former Soviet Union (Nikodemus et al., 2005; Palang et al., 2006).

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Variations in the effects of socialist legacies, reform policies, and postsocialist developments were crucial in shaping local land-use outcomes. The resulting changes in land use and land cover are markedly different between countries (Rozelle and Swinnen, 2004; Taff et al., 2010). Transboundary studies demonstrated that the diverging pathways of postsocialist cropland abandonment in similar natural settings can be attributed to differences in political and institutional characteristics (Alix-Garcia et al., 2012; Hostert et al., 2011; Kuemmerle et al., 2008; Prishchepov et al., 2012). We contribute a novel and rigorous statistical comparison of various influences on cropland abandonment in individual countries since the collapse of socialism.

The evaluation of rapid transformations in political and economic frameworks assists in understanding the impact of other major global ecosystem shifts. The progression of the postsocialist transition resembles recent developments in other countries related to economic globalization that have also resulted in an increased flow of goods, services, and information (Gallagher, 2009; Hecht, 2010). In a certain sense, the postsocialist transition can be regarded as a particular, expedited form of globalization, providing lessons that extend beyond the geographic extent of Central and Eastern Europe. An understanding of the postsocialist transition may provide valuable insights into the processes of global political, economic, and institutional changes and their impacts on local and regional environments through land-use changes. Above all, our insights from two postsocialist countries may indicate how liberalization policies affect land use in different countries through shared, 'global' dynamics or by way of distinct, country-specific dynamics.

A significant body of literature has relied on regression analysis to assess the determinants of land-use change using spatially explicit data. Regression analysis typically relies on a predefined theory to formulate a parametric model, collect data for the hypothesized influential predictors, and estimate the parameters of the model. Most of the applications of regression analysis in land-change science have investigated land-use changes at the pixel level using parametric approaches, such as binomial (Crk et al., 2009; Müller et al., 2011) or multinomial logistic regressions (Müller and Zeller, 2002). Other authors have estimated area-based regressions to examine the quantity of land change (Baumann et al., 2011; Meyfroidt and Lambin, 2008; Müller and Sikor, 2006; Vanwambeke et al., 2012). These "traditional" regression models have scientific merit because they are easy to understand and interpret and provide numerous options to estimate the parameters that relate the input data to the output data. Spatially explicit regression analysis continues to be an influential tool to examine theoretical assumptions, rank relative factors, and test predefined hypotheses (Munroe and Müller, 2007). However, problems with unknown and possibly nonlinear relationships between input and output variables are difficult to consider in these regression frameworks. These limitations often prevent accurate and robust results from being attained, particularly for out-of-sample predictions, which can compromise the model generality.

There is a growing recognition of the complexities in relationships between land-use change and a set of determinants, with ample evidence of nonlinearity, interactions, and feedback effects (Turner et al., 2007; Verburg, 2006). Analytical approaches in data mining are emerging that take advantage of the increasing availability of data, software, and computing power. The absence of parametric assumptions contributes to higher predictive accuracies than in parametric regression analyses. Because there are few assumptions underpinning the selection of input data, assessing the results of the model becomes a central aspect of data mining and the predictive accuracy determines the model's ability to generalize the data (Hastie et al., 2009). However, the methods involve complex statistical approaches that often come at the cost of reduced interpretability of the results (Breiman, 2001b). Recent research has placed an increased emphasis on improving the interpretation of model results, including describing functional relationships between individual predictors and outcomes.

We used boosted regression trees (BRTs) to analyze the determinants of cropland abandonment following the collapse of socialism in two eastern European countries, Albania and Romania. Our key objective was to reveal the salient differences and the commonalities in determinants of cropland abandonment between the two countries and for two periods. The principal question was whether cropland abandonment in the two countries follows the same causal dynamics (which would only lead to different outcomes due to different local conditions) or actually takes place through distinct sets of causal forces. We relied on two rich datasets that are very similar in structure and depth. The data combined environmental and accessibility indicators, and primary socioeconomic information. The model results allowed the identification of similarities and key differences in postsocialist cropland abandonment patterns in these two countries. To obtain comparative insights, we rigorously employed the same conceptual and analytical approaches to both country cases. Country comparisons allowed the extraction of the paramount factors that are salient to the dynamics of cropland abandonment over time and space in each country. We had the unique opportunity to substantiate the quantitative evidence with valuable insights from the political ecology in both countries derived from in-depth case study research.

2. Material and methods

2.1. Study areas

Albania and Romania transitioned to market-based economies around 1991. In many respects, the two countries followed similar reform trajectories. Both were under socialist governments, experienced massive changes in land ownership structures in response to comprehensive land privatization programs that were enacted in 1991, and underwent radical liberalization of domestic and international trade (Swinnen, 1997; Swinnen et al., 1997). Both countries also experienced large waves of internal and international migration (Bonifazi et al., 2006). They both continued to suffer from high poverty rates into the new millennium, and large numbers of their workforces remained in the agricultural sector (Hutton and Redmond, 2000).

There were significant differences between the two countries with regard to their agricultural sectors that were partly inherited from socialism, but also resulted from the different policies enacted by postsocialist governments. First, the agriculture sector in Romania achieved a much higher level of mechanization in 1990 than Albania (Rozelle and Swinnen, 2004). Second, Albanian land reform mandated the distribution of all agricultural land among the contemporary agricultural workforce, while the land laws in Romania called for the restitution of agricultural land (up to a maximum of 10 ha) to historical owners and their heirs (Swinnen, 1997). Third, the liberalization of domestic and international trade took place in Albania at a rapid pace in the early 1990s, while Romania's government sought to protect domestic producers until the late 1990s (Csaki and Kray, 2005).

The empirical case studies involve one distinct study area in each country (Fig. 1). In Albania, the study area included four districts in Southeastern Albania and covered 3800 km^2. The study area in Romania is the county of Argeş, with a size of 6800 km^2. The data combined land use, biophysical, geophysical, and socioeconomic variables that were compiled using comparable data collection strategies including remote sensing analysis, geographical

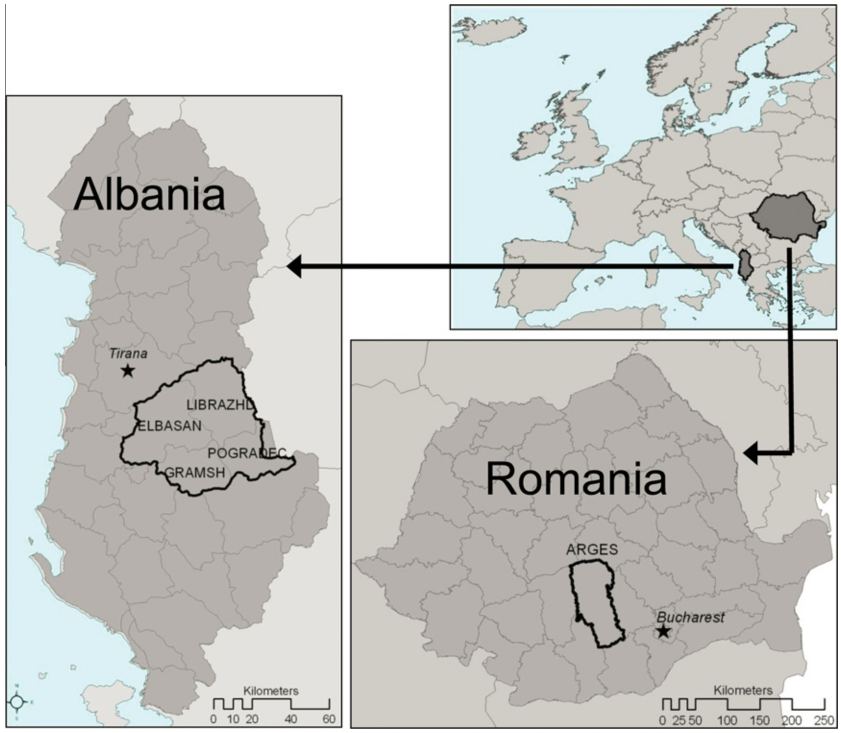

Fig. 1. Study areas.

information systems (GIS) techniques, and collection of survey data. The common data structures permitted a rigorous case comparison of the two countries. This allowed identical analytical methods to be applied that enabled the systematic extraction of characteristic similarities and differences in cropland abandonment trajectories.

2.2. Mapping cropland abandonment

High resolution satellite images were used in both country case studies. In Romania, automated image classification was employed to derive land-cover maps from Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) satellite images for 1990, 1995, and 2005 (for details of the satellite data and classification procedure, see Kuemmerle et al., 2009). In Albania, on-screen digitization of Landsat TM and Terra Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) images were used to derive land-cover maps for 1988, 1996, and 2003 (see Müller and Munroe, 2008, for specifics of the image data and analysis). All final land-cover maps were resampled to a spatial resolution of 30 m and extensively compared to ground truth points. In the Albania case study, the results were regularly verified before and during image interpretation using over 300 reference points (Müller and Munroe, 2008). In the Romania case study, the resulting land-cover map was validated using over independent 700 reference points that yielded an overall accuracy of over 90% (Kuemmerle et al., 2009).

The years 1988 (Albania) and 1990 (Romania) were used as starting dates and were labeled as "1990" in both cases for simplicity. These dates represent a time when communism was still formally in existence in both countries. Intermediate time steps were 1996 (Albania) and 1995 (Romania), hereafter referred to as "1995". We use the most recent year (2003 in the Albania case study and 2005 in the Romania case study) as the end points of our analysis, which were labeled "2005". In both case studies, we specified a category for cropland that contained arable land under annual or permanent cultivation from the land-cover data. Abandoned pixels were defined as pixels that were covered by cropland in the first time step, but not in the subsequent time step. Two periods of change were calculated from the cropland data: the first time period was from 1990 to 1995, which represented immediate responses to the collapse of socialism, and the second time period was from 1995 to 2005, when more gradual adjustments to market-based conditions prevailed.

2.3. Explanatory variables

Physical accessibility is a critical factor that affects land rents and land use (von Thünen, 1826). We approximated accessibility using the Euclidean distance to district capitals in Albania and municipalities in Romania (*distance to municipalities*), populated places and settlements of any size (*distance to build-up*), village and commune centers, and three different road quality categories (*distance to major*, *secondary*, and *tertiary roads*). Accessibility was considered time-invariant. In addition, we captured topography with the missing-value corrected Shuttle Radar Topography Mission (SRTM) in Romania (Slater et al., 2006). The SRTM was used to calculate *elevation* and *slope*. In Albania, we received a digital elevation model (DEM) from the Albanian National Forest Inventory (ANFI). The DEM was based on the interpolation of contour lines from topographic maps at a scale of 1:10,000 and had a spatial resolution of 15 m that was resampled to 30 by 30 m. Rainfall data were only available from a small number of meteorological stations. The resulting rainfall surfaces were highly collinear with elevation in both case studies and were therefore excluded from subsequent analyses.

Collection of primary socioeconomic data was performed to identify the pertinent variables that were hypothesized to influence land use and land-use change in both countries. Group interviews were organized and administered by trained enumerators. We used recall techniques to collect information on past events (Groves, 1989). In Romania, we conducted a census of all 93 rural communes in Argeş county (Müller et al., 2009), and in Albania, a survey was conducted in 100 out of a total of 425 rural villages (Müller and Sikor, 2006). We calculated the *farm fragmentation* variable based on the number of parcels that were restituted or distributed to the households in land reforms. Because land transactions were limited in both countries, the number of parcels was constant in the majority of cases between 1991 and 2005 and represented a potentially important legacy of the land reform. *Population density* was described as the number of households per hectare in each village (in Albania) or commune (in Romania). A proxy for demographic and economic change was the percentage of households that relied on *cash remittances* from internal or international migration as their main source of cash income. The number of cattle, sheep, and goats per commune or village was converted into livestock units based on Chilonda and Otte (2006) and analyzed as the *livestock density* (per square kilometer). Agricultural inputs captured the intensity of agricultural production. We included the mean share of *irrigated area* of the total agricultural area per commune or village and the number of tractors per square kilometer of cropland (*tractor density*). We calculated the *density of cropland* from the cropland maps as the number of cells covered by cropland at the onset of each period of change in a three-by-three window. All of the time-variant data were included in the models as the value at the beginning of the respective periods of change. For example, the status of a particular variable in 1990 served as the determinant for cropland abandonment between 1990 and 1995. This reduces potential simultaneity between cause and effect, which improves interpretability.

2.4. Sampling strategy and dataset compilation

Several sampling steps assisted in reducing the number of observations and computing time, introduced randomness to improve generality, and reduced potential spatial autocorrelations in the data. All of the observations within 500 m of the border of each study area were deleted from the sample to diminish the potential influences from neighboring sites. We imposed a systematic grid of points (at grid cell centers) spaced 200 m apart. From this grid, we only selected the observations that were cropland at the beginning of each period of change (because abandonment cannot occur on non-cropland observations) for each country. The sample points were intersected with all of the predictor variables, resulting in point shapes that included all of the data in the respective attribute table. Finally, we randomly sampled 4000 observations per country and per period of change. Table 1 presents the descriptions of the final sample data that were used for subsequent calculations (for detailed descriptive statistics of the final sample data, see Table A1 in the Appendix).

Table 1
Variable description.

Variable	Unit	Scale
Cropland abandonment	0/1	Pixel
Slope	Degrees	Pixel
Elevation	Meter	Pixel
Distance to major roads	Kilometer	Pixel
Distance to secondary roads	Kilometer	Pixel
Distance to tertiary roads	Kilometer	Pixel
Distance to village/commune center	Kilometer	Pixel
Distance to build-up	Kilometer	Pixel
Distance to municipalities	Kilometer	Pixel
Cropland density	Number in 3 × 3 window	Pixel
Irrigated area	Hectare	Village/commune
Tractor density	Number per km^2 cropland	Village/commune
Credit use	Percent of households	Village/commune
Livestock density	Units per km^2	Village/commune
Household density	Households per km^2	Village/commune
Parcels per household	Number	Village/commune
Cash remittances	Percent of households	Village/commune

2.5. Boosted regression trees

BRTs are statistical models that combine the strengths of decision trees and boosting. Decision trees analyze the variation of a response variable for a set of predictor variables. The predictor variables are subject to a binary split that fits a simple model to each resulting section, such as use of a constant for the most probable outcome in binary classification trees or the mean response for continuous outcomes (Elith et al., 2008; Hastie et al., 2009). The data are further split so that the split-point achieves the best model fit. This is repeated many times until a stopping criterion is reached, such as the minimization of prediction error (Hastie et al., 2009). Decision trees are becoming increasingly popular because they are easy to implement, interpret, and visualize (Elith et al., 2008; Hastie et al., 2009), and they tend to be robust with regard to missing data and irrelevant input variables (Friedman, 2001). Decision trees are currently being used in many fields, including ecology (De'ath and Fabricius, 2000; Thuiller et al., 2003), remote sensing (Hansen et al., 2000), and land-use change (Etter et al., 2006; Gellrich et al., 2008).

The central idea behind boosting is the combination of many weak models into a powerful ensemble with a greatly improved performance (Hastie et al., 2009). Boosting entered the field of statistics after the discovery that it allows for the sequential optimization of an additive model on the logistic scale (Friedman et al., 2000). Boosted regression trees rely on stochastic gradient boosting, which allows for more accurate and faster computations through numerical optimization and regularization (Friedman, 2001). Boosting can dramatically increase the performance of a classifier and is likely one of the best classifiers in terms of low error rates (Bauer and Kohavi, 1999; Hastie et al., 2009). The sequential process of training classifiers is the key difference between BRTs and other ensemble methods, such as bootstrap aggregation (bagging, see Breiman, 1996) as implemented in Random Forests (Breiman, 2001a). Compared to Random Forests, BRTs tend to be more robust against overfitting, because of the use of randomly selected subsamples to fit the data at each iteration (Dormann et al., in press; Friedman, 2002; Hastie et al., 2009). Another particular advantage of BRTs compared to other data mining approaches is the combination of a high predictive accuracy and good interpretability of resulting input–output relationships (Friedman, 2001).

2.6. Model parameterization

We applied BRTs as developed by Friedman et al. (2000) and implemented in R (R Development Core Team, 2011) using the code from the 'gbm' package (Elith et al., 2008; Ridgeway, 2007). Stochastic gradient boosting incorporates a random component to build the tree structure by selecting subsequent subsets of the training data. This randomization is similar to bagging (Breiman, 1996) and reduces computation time, potential biases, and avoids overfitting (De'ath, 2007; Hastie et al., 2009). We used a bagging factor of 0.5 as suggested by Friedman (2001), which has the additional advantage of reducing the computation time by approximately 50% (De'ath, 2007).

The BRT calibration is done through three main parameters: the maximum number of splits (tree complexity) for fitting each regression tree; the number of iterations (number of trees); and the model regularization (or shrinkage) parameter (Hastie et al., 2009). The number of splits defines the depth of the tree and the maximum level of interaction between the predictor variables. For example, a model with a tree complexity of one (single "decision stump") corresponds to an additive model with only main effects (no interactions), and a model with a tree complexity of two (two splits) allows for two-variable interaction effects, and so on. The appropriate number of splits depends on the particular application, but Hastie et al. (2009) suggested that four to eight splits are sufficient in most cases. Because information regarding the actual level of interaction in the data was lacking, we tested the interaction levels from one to six.

The number of iterations defines the model complexity. Too many iterations tend to overfit the model to the training data and compromise the ability for generalization. Very simple models tend to have a large bias in predictions, whereas highly complex models tend to have a large predictive variance, which is a phenomenon known as "bias-variance tradeoff" (De'ath, 2007). We calculated the actual number of iterations by maximizing the model log likelihood with a 10-fold cross-validation (Elith et al., 2008).

The shrinkage parameter (or learning rate) scales the contribution of each additional tree (Hastie et al., 2009). Smaller shrinkage values result in slower learning rates and require a larger number of iterations at the expense of more computation time. We set the shrinkage so that a trade-off between computation time and predictive performance was achieved and ultimately used a shrinkage of 0.0025.

Tuning of the two latter parameters was repeated for each maximum interaction level (one to six). The performance measure used to determine the ideal interaction level was the area under the receiver operating characteristics curve (AUC), which was calculated from a 10-fold cross-validation procedure. When marginal model improvement fell below 0.01 for an additional interaction level, we concluded that there was no benefit in further increasing the model complexity and chose the previous interaction level as ideal for the specific case.

2.7. Model fitting

Variable selection is not necessary in constructing BRTs because they generally ignore non-informative predictors (Elith et al., 2008). We included 16 predictor variables to model cropland abandonment (Table 1). All predictor variables and measurement scales were identical in both country case studies. Nine of the predictors were spatially explicit measurements at the pixel level that capture topography, physical accessibility, and cropland density at a spatial resolution of 30 m (Table 1). The remaining variables shown in Table 1 were derived from the collection of census and survey data and relate to village and commune areas. These variables represent agricultural input intensity, the density of livestock units, household density, and the fragmentation of agricultural land.

We tested a range of different variable setups using BRTs. We calculated models that pooled the data from both countries into one model and estimated the pooled model with and without a binary variable that captured country effects. The results from the pooled model (not shown) were in between the two country models in terms of fit and variable influence. The variable capturing country effects had a negligible influence on the model outcomes in terms of improvement of model fit and variable contribution. We concluded that the BRTs successfully detected virtually all of the differences between the countries. We then estimated two separate models for each country to elucidate the differences between the countries in terms of model fit, variable contribution, and partial variable influences.

We initially estimated the models by including topography (elevation and slope). In Albania, elevation contributed 20% of relative importance to the BRT results in the first time period, but elevation in the second time period and slope in both of the periods had little bearing on the final outcomes with very small variable contributions. The strong elevation gradient in Romania, with plains in the South, hilly areas in the center, and mountainous terrain in the North, shaped the spatial patterns of cropland occurrence and cropland change (Müller et al., 2009). This is demonstrated in the results from the BRTs where elevation and slope together contributed to 73% and 67% of the relative importance in the first and second time periods of analysis, respectively. Although topographic variation dominated the results of the model in Romania, it provided little interpretative value for policy or management purposes. Therefore, we also calculated the BRT models without topography. Remarkably, the models without topography had a similar predictive performance. The important, but trivial (and, from a management perspective, non-informative) effects of topography were represented by other variables. In Romania, the density of tractors and livestock emerged as important contributors in both periods, and in Albania, most of the variation related to topography was represented by the accessibility measures despite low statistical correlation between access and elevation. Pearson's correlation coefficients between elevation and the density of tractors and livestock were significant at the 1% level, but fairly low (correlation coefficients of −0.21 and 0.12, respectively). These results suggest that the variance explained by topography in the BRTs was captured by the socioeconomic variables, which provided more informative insights. We hence excluded elevation and slope from our final models and interpreted the BRTs using 14 predictor variables.

2.8. Model inference

BRTs allow the visual exploration of the relationships between predictors and responses, which can be observed through the relative importance of the predictor variables in the models (Friedman, 2001; Friedman and Meulman, 2003). The relative importance is derived based on the number of times a variable is selected for splitting, weighted by the squared improvements, and averaged over all of the trees (Friedman and Meulman, 2003). The relative influences are then standardized such that the sum adds up to 100, and the individual contributions are expressed as percentages. We calculated the relative importance of all of the variables for both countries and both periods, including the change in importance that resulted from the exclusion of topography. Variables with a model importance smaller than expected due to chance (100 divided by the number of variables) were not considered relevant for interpretation. With 14 predictor variables in this evaluation, the threshold was set at 7.14%, or 1/14.

For visualizing of the results, we calculated the partial dependencies that depict the relationships between the response and one predictor variable while controlling for the average effects of all other predictors (Friedman, 2001; Friedman and Meulman, 2003). This allows to derive partial dependence plots (PDP) that depict the influence of a variable when other variables are kept constant, which provides a useful basis for interpretation. We plotted the partial dependencies to compare the influences of all of the variables across time and countries. For improved interpretation, the actual response plots were smoothed using a smoothing spline, with the exception of cropland density, which was maintained as a discrete step-like graph because the data are discrete (from zero to nine). The responses were log transformed and shown as a probability scale. Higher median probability values correspond to a higher likelihood of cropland abandonment. Rug plots were added to the PDP showing the percentile distribution of the response variable (cropland abandonment) along the data range of the predictor variable.

From the predictor variables that were considered relevant for interpretation (variables with a model importance greater than expected due to chance, i.e., greater than 7.14%), we selected the two most important variables per model and the variables with relevant importance for both periods or both countries. This resulted in the following six variables: distance to build-up areas, distance to capitals, distance to major roads, cropland density, livestock density, and the density of tractors. Partial dependencies were plotted and interpreted for these six variables.

3. Results

The calculation of yearly rates of abandonment per period and country showed that abandonment rates were consistently higher in the first time period in both countries, with 2.9% per year in Albania between 1988 and 1996 and 3.6% per year in Romania between 1990 and 1995 (Fig. 2). In the second time period, yearly abandonment rates dropped to 1.1% in Albania (1996–2003) and 0.5% in Romania (1995–2005). Overall, 34% of all cropland was abandoned in Albania from 1998 to 2003 compared to 28% in Romania from 1990 to 2005.

The BRT models performed better in the Albania case study than the Romania case study in both time periods. There was an improvement in performance in the Albania models for a greater number of interactions in both periods (Fig. 3). In the Romania models, the AUC increased very modestly from 0.85 and 0.84 in the first and second time periods, respectively, to 0.86 in the second period (much better than the AUC for a logistic regression with the same data and very similar to the AUC achieved with neural networks; see Lakes et al., 2009). Our stopping criterion for the "best model" was reached at interaction levels of two in the first period and three in the second period with 7950 and 7500 trees, respectively. In Albania, the model improved rapidly in both periods with increasing model complexity. The stopping criterion revealed three interaction levels as the best model from 1990 to 1995 and four interactions from 1995 to 2005, each with an AUC of 0.96 (Fig. 3). The Albanian model required more than 25,000 trees in both periods (25,150 and 25,250 in the first and second time periods, respectively) to reach the stopping criterion, which suggests a much more complex data structure in the Albania model. For example, a model with only main effects (no variable interactions) would fit considerably poorer in the Albania study in the first time period, with an AUC of 0.89. Conversely, the low effect of tree complexity on the performance of the Romania model suggests that complex variable interactions did not affect cropland abandonment.

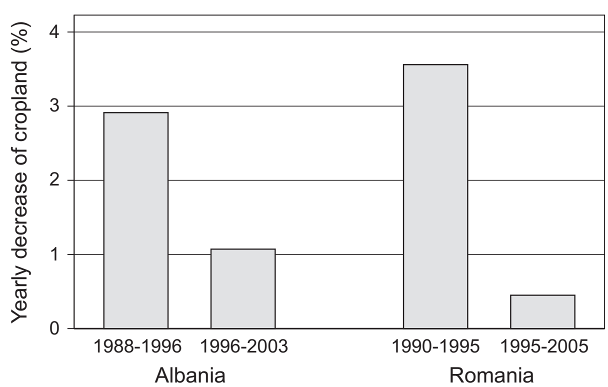

Fig. 2. Rates of cropland abandonment. Note: The yearly changes are calculated for different time spans in the two countries (see explanations in the text).

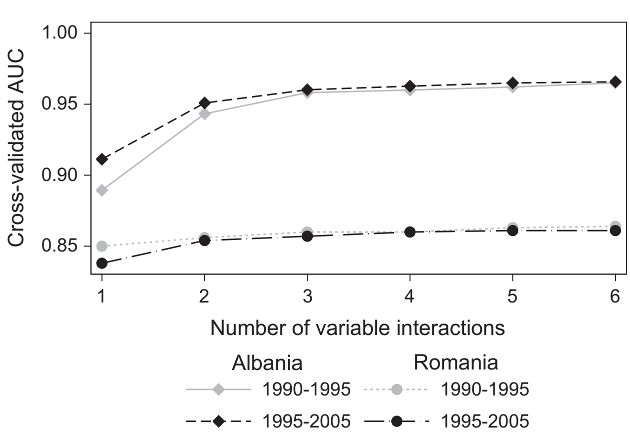

Fig. 3. Change in model performance with increasing number of variable interactions. Note: AUC = Area under the curve of the receiver operating characteristics (see explanations in the text).

The importance of the predictor variables are shown in Fig. 4. We observed that livestock density substantially contributed to the models in both time periods and in both countries and household density was important in Albania. The exclusion of topography resulted in a slight increase in most of the variables in the Albanian case study. In Romania, the results were radically different. Patterns of cropland abandonment after the exclusion of topography were dominated by cropland and tractor densities in both periods, although these variables were more important in the first time period. Compared to the models with topography, tractor density increased from a relative contribution of 2% to 28% in the first time period and from 2% to 14% in the second time period. The importance of cropland density also increased in the two time periods by 22% and 15%, respectively. Fig. 4 shows the larger importance of most accessibility-based predictors in Albania in the second period and, with the contribution of accessibility considerably increased over time for all distance measures in Romania.

The PDP of the selected (relevant) variables show the effects of each predictor on the response for its entire range of values (Fig. 5). The rug plot along the top of the *x*-axis (in black) shows the distribution of the response variables during the first time period, while the rug plot along the bottom of the axis (in light grey) represents the distribution of the variables in the second time period.

4. Discussion

The yearly rates of cropland abandonment were slightly higher in Romania than in Albania in the first period and higher in Albania in the second period. The difference in abandonment rates may in part relate to the different time periods in the satellite analysis that includes the last years of socialism in Albania (from 1988 to 1996) when most land continued to be ploughed under socialist agriculture. In Romania, however, the land cover data commences in 1990 and last only until 1995; therefore the Romanian data capture the most dynamic period of postsocialist cropland abandonment.

The dominant influence of transitioning from a planned to a market economy on agricultural land use was confirmed by the high incidence of abandonment in the first time period and the relatively lower rates observed in the second time period (see Fig. 2). This mirrors the rapid adjustments to the market economy in the earlier years of transition, while land-use adaptations became more gradual in later years. But little recultivation of former agri-

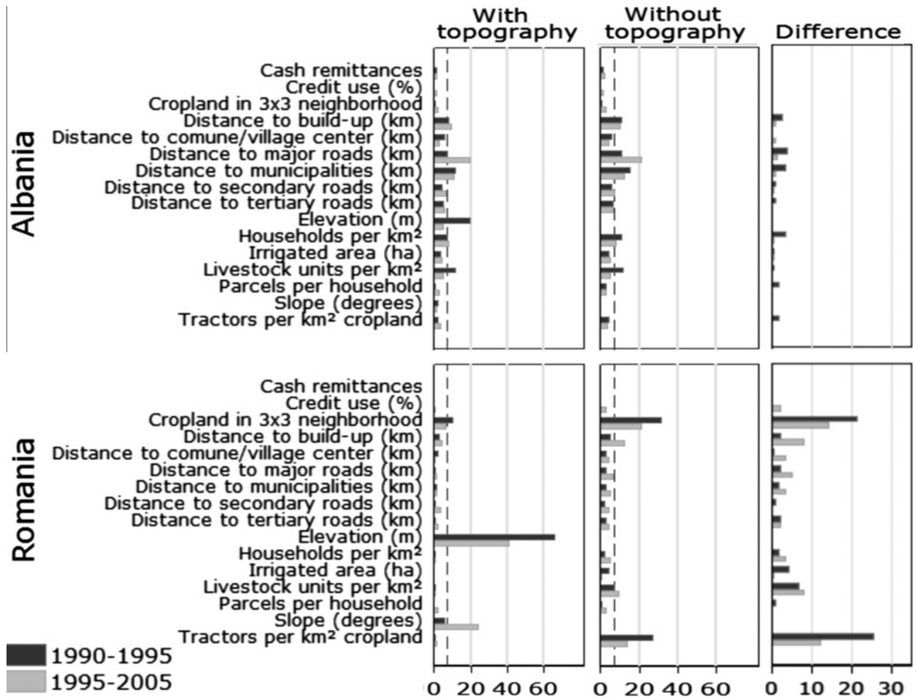

Fig. 4. Relative importance of explanatory variables. Note: Relative importance of variables in percentage; the axis scale differs in the right panel that denotes the difference in variable importance, i.e., the subtraction of "without topography" (center panel) from "with topography" (left panel).

cultural land took place in our study areas, contrary to evidence from Latvia (Vanwambeke et al., 2012). The advanced stage of vegetation regrowth in older abandoned fields suggests a considerable carbon sink in postsocialist landscapes (Kuemmerle et al., 2011). Recultivation costs of these lands will rise with increasing vegetation succession (Larsson and Nilsson, 2005; Verburg and Overmars, 2009).

Cropland abandonment was largely determined by topography in Romania and, to a lesser extent, in Albania (Fig. 4; Müller and Kuemmerle, 2009; Müller and Munroe, 2008). The inclusion of topography in the BRT models accounted for most of the variation in the outcomes and left only a small window for insightful explanations regarding the other predictors that were hypothesized to influence cropland abandonment. The similar statistical performance between the final models and the models that included topography suggests that topographic differences also translated into differences in time- and country-specific socio-economic features, which were depicted in the models. The changes in the variable contributions between the models constructed with and without topography (Fig. 4) provided additional insights into the geographic characteristics of features. The influence of topography also suggests similar dynamics in land-use change between the two countries. Topography was a less important criterion in the allocation of inputs in agricultural production before 1990 due to the inefficiencies of socialist agriculture and the priority given to maximizing output, including the cultivation on lands with low natural suitability for cropping. Market-based production made producers fully accountable for the profitability of production and became a dominant influence on the geographic distribution of agriculture (Müller et al., 2009; Müller and Munroe, 2008).

The spatial patterns of cropland cover and the mechanization variables show the largest influence on cropland abandonment in Romania (Fig. 4). The density of cropland was a key aspect in both of the time periods. It was more important and had a larger effect in the first time period when more isolated cropland pixels were at a considerably increased risk of becoming abandoned, while abandonment was less likely in areas with dense cropland cover (Figs. 4 and 5). If all of the other variables were maintained at their mean values, a low cropland density (1–3) would result in a probability of approximately 80% land abandonment in Romania (Fig. 5). Consequently, the separation between land-use classes diminished and agricultural land use consolidated in suitable areas, similar to processes observed in Latvia (Vanwambeke et al., 2012). In Albania, the effect of cropland density had little impact on the likelihood of abandonment in both time periods (Fig. 4).

The effects of mechanization in Romania reflect the influence of political economic factors on land use. Although the machine operators did not fully adjust their services to meet the demand, they were able to monopolize markets for machinery services to some degree. Some regions did not have access to any machinery services with direct implications on abandonment (Fig. 5). This information matches other local-level insights from Central and Eastern Europe which indicated that the market for agricultural input and output did not function perfectly because they were controlled by powerful entities, such as observed in Bulgaria (Giordano and Kostova, 2002).

When comparing the influence of mechanization and cropland density on land abandonment between the two countries, the greater importance in Romania reflects the higher degree of mechanization in the Romanian agricultural sector in 1990 (Fig. 5). After the shift to a market economy, farmers in less densely cultivated areas faced problems acquiring the required machinery services in Romania because tractor owners concentrated their services in the more profitable plains regions. In Albania, this factor did not come into play because most farmers worked the land without any machinery. Most of these effects only became evident when topography was excluded from the models.

Distance variables had very different effects in both countries. In Albania, the distance measurements were more important in shaping cropland abandonment than in Romania. The overall importance of distances variables was higher in the second time period than in the first in both countries, though in most cases be-

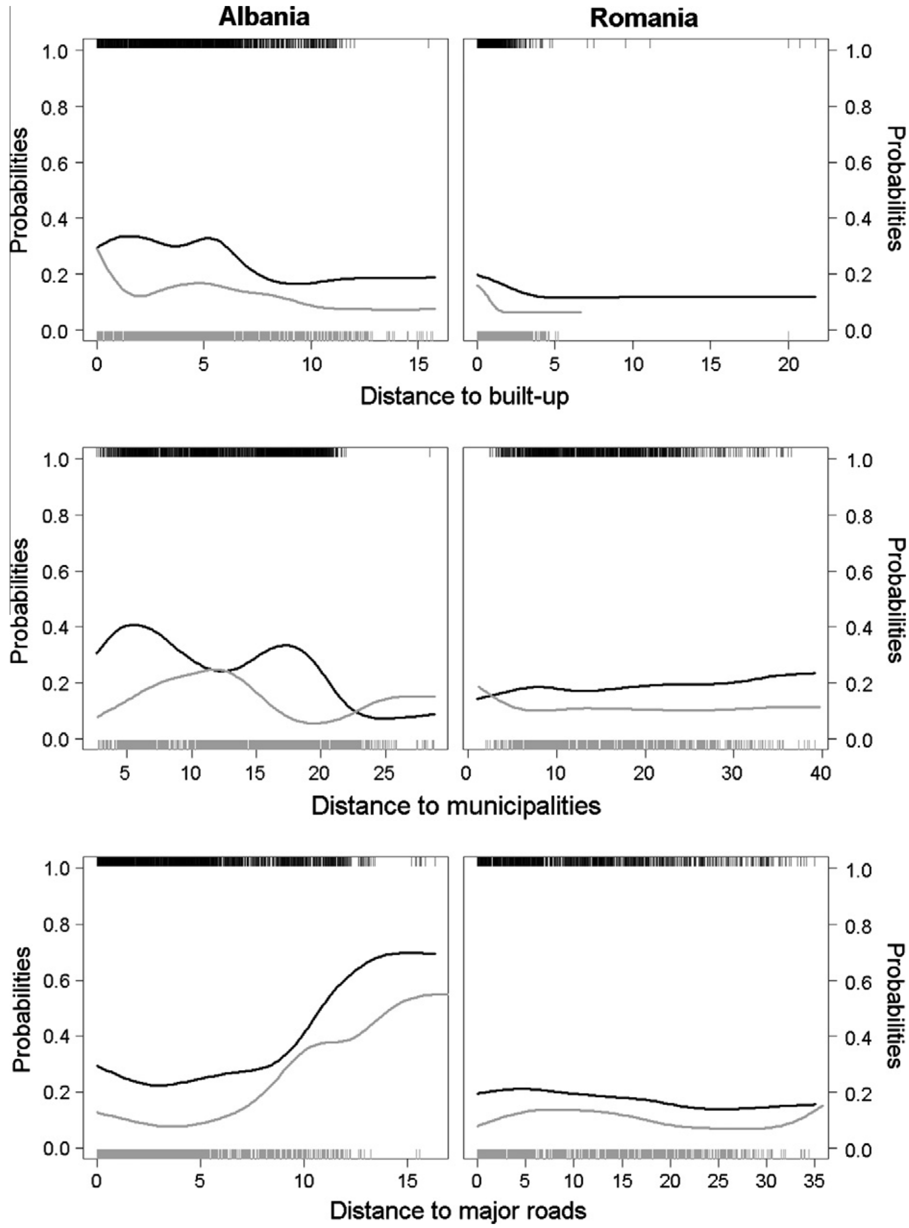

Fig. 5. Influence of explanatory variables on the probability of cropland abandonment. Note: These partial dependence plots illustrate the change in predictions (probabilities on the *y*-axis) along an explanatory variable range (*x*-axis), while keeping all other variables fixed at their mean value. On the top and bottom of each plot, along the *x*-axis, the rug plots represent the density of data points. The first time period is represented in black and light grey represents the second time period for all response curves and rug plots.

low our threshold for relevant variable contributions in Romania (Fig. 4). In areas that were at least 5 km away from major roads in Albania, the influence of distance on abandonment gradually increased in both periods and became the dominating factor for observations that were located farther than 10 km away (Fig. 5). The large influence and importance of accessibility indicates, particular in Albania, the rise of economic principles in postsocialist land-use patterns as farmers increasingly adapted land use to market conditions (cf. Ioffe and Nefedova, 2004; Müller et al., 2009; Müller and Sikor, 2006; Prishchepov et al., 2013). Agricultural producers abandoned the cultivation of land located far away from roads, as it was no longer profitable under the emerging market economy. Unfavorable access to markets, population centers, and roads was not only a decisive determinant for abandonment, but also contributed to the dismal livelihood opportunities in the remote Albanian countryside (Stahl, 2010; Stahl and Sikor, 2009). In particular, young economically active people left in large numbers in search of better livelihoods, which transformed Albania into a ‘‘country on the move’’ (Carletto et al., 2006) through large waves of domestic and international migration (Agorastakis and Sidiropoulos, 2007; King, 2005).

The continuing importance of household and livestock density for cropland abandonment in both countries substantiates this interpretation. Whereas livestock herding increased in Albania, it decreased in Romania (Table A1). The increase in livestock density in Albania was mainly due to increases in the number of sheep and goats that are predominantly raised for subsistence purposes. Given the near absence of commercial livestock production, this phenomenon suggests that subsistence or semi-subsistence production continued to play an important role in rural Albania, similar to many other villages in Southeastern Europe (Baumann et al., 2011; Kostov and Lingard, 2002; Mathijs and Noev, 2004;

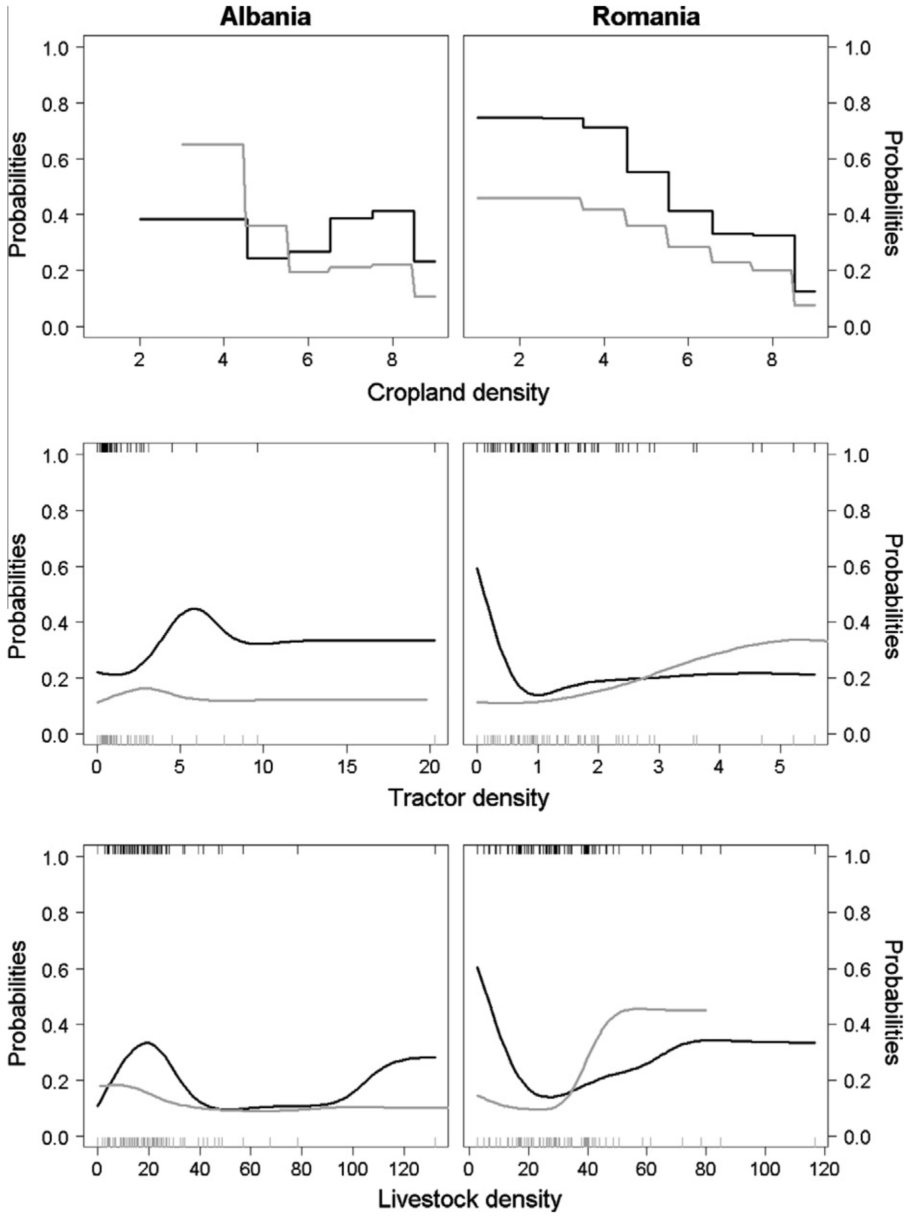

Fig. 5. (*continued*)

Meurs, 2002; Seeth et al., 1998). Overall, this indicates how the status of human welfare conditions the determinants of land-use change. In Albania, with its lower income levels and higher poverty rates, cropland abandonment was importantly related to factors that affect the livelihood strategies of individuals in a semi-subsistence environment. Subsistence-oriented livestock production, land scarcity induced by higher household density, and market accessibility therefore play important roles for agricultural development. Comparatively small changes that impose additional economic pressure on rural populations tended to cause significant shifts in livelihoods, with the most prominent choice being domestic or international emigration.

The difference in model performance between the two countries is likely due in part to differences in the quality of the input data, particularly the variables derived from remote sensing. The automated classification-based results in the Romania case study are based on a smaller minimum mapping unit than the visual interpretations conducted in Albania. The visual interpretations resulted in more clustered patterns of land-use patches compared to the high spatial heterogeneity of the classification results in Romania. Increased accuracy in the Albania model may be related to the finer resolution of the village-level socioeconomic data. We had to rely on communal averages for the data in Romania, which resulted in a greater degree of mismatch between the response and predictor variables.

The explanatory data at the village and commune level yields an "average" picture for the administrative units with less spatial variation than the pixel-level bio- and geophysical and accessibility data. From a statistical point of view, this is not a problem for BRTs, but from a thematic perspective, socioeconomic data with higher spatial resolution are preferable. Comparisons with area-based regression results for cropland abandonment at larger administrative units are useful, but were omitted here for the sake of brevity. Yet, Müller and Sikor (2006) arrived at similar conclusions with data aggregated to the village level in seemingly unrelated regressions of land-use determinants in Albania. We believe the use of aggregated socioeconomic data did not cause the modifiable areal unit problem (MAUP) in Albania, because villages are old and homogenous entities that are typically surrounded by the agricultural land used by villagers. While village boundaries are fuzzy and not officially recognized in Albania, this is unlikely a problem for our analysis, because most agricultural land is situated closer to the village location. The lands further from the village (closer to the village boundaries) are typically occupied by pastures, shrubland, and forests.

The communes in Romania are considerably larger than the villages in Albania (the largest village in Albania covers about 50 km^2 while two Romanian communes are larger than 400 km^2). For this reason, the mismatch between spatially explicit and socioeconomic data is larger in Romania. But the majority of the larger Romanian communes are located in the Carpathian foothill zone and are mainly covered by forest with little cropland and minor amounts of cropland abandonment, and will therefore have negligible effects on the model results. Moreover, commune boundaries in Romania often follow watershed boundaries and are official administrative units with assigned budgets from the county governments. Hence, it is unlikely that MAUP is a big concern for the Romanian results.

5. Conclusions

Cropland abandonment was the dominant land-use change in the transitional economies of Central and Eastern Europe and the former Soviet Union and has profound implications on ecosystem characteristics. In Albania and Romania, croplands decreased by approximately 34% and 28% between 1990 and 2005, respectively. Although both countries enacted comprehensive land reforms in 1991 and subsequently liberalized agricultural markets, they experienced considerably divergent postsocialist developments, such as different land reform laws and varying economic growth patterns. Unfortunately, there is little empirical evidence regarding the factors that contributed to the deviations in postsocialist abandonment pathways.

We applied boosted regression trees (BRTs) to study the determinants of cropland abandonment in Albania and Romania and to understand the differences and commonalities of predictors of abandonment between and within the two countries. Data mining approaches are particularly appropriate for analyzing cropland abandonment due to the complexities inherent in the patterns and processes that shape abandonment trajectories. Our analysis relied on two datasets describing cropland abandonment (both derived from remote sensing) as the response variable with an equivalent set of biophysical and socioeconomic features as predictor variables. We conducted the BRT analyses using identical meta–parameters to compare predictive performance of the BRTs and the influences of the predictors on the response variable.

We found that cropland abandonment was largely determined by topography, particularly in Romania. The inclusion of topography captured most of the variation in the outcome and left only a small window for insightful explanation of the other predictors that were hypothesized to influence cropland abandonment. The exclusion of topography revealed the impact of accessibility, cropland structures, and input intensity on postsocialist agricultural landscapes. This was particularly evident in Romania where cropland and tractor density emerged as main predictors in the first period and where accessibility gained in importance in later stages of the postsocialist transition.

Variables that influence land rents, such as market access, became increasingly critical in determining cropland-change trajectories, which indicates the growing importance of market principles in shaping agricultural landscapes. However, we also suggest that the underlying causes of land-use change differed substantially between the two countries once one looks beyond the dominant influence of topography. In Albania, variables that adversely affected subsistence agricultural production often resulted in fundamental changes in livelihood strategies, frequently away from agriculture and toward migration. In Romania, the factors that impaired the profitability of agriculture were the crucial determinants of cropland abandonment. We come to this conclusion on the basis of our special methodological approach and unique dataset as this study is to our knowledge the first to rigorously compare land-change processes in two countries not only of the postsocialist world but more generally in a situation characterized by drastic socioeconomic and institutional changes.

Data mining offers a variety of opportunities that are particularly promising for the analysis of land-use and ecosystem changes, because data mining provides compelling options that account for nonlinearities and interactions. Improvements in technology, software, and data will likely lead to a wider adoption of data mining algorithms for regression and classification approaches in the field of land-system science. The usefulness of data mining has often been compromised by a limited ability to interpret model outcomes. BRTs are particularly promising alternatives because they combine high predictive accuracy with appealing options for the interpretation of model outcomes. In a time of continuous and dramatic land-use and ecosystem changes, it is extremely important to describe and understand the driving forces and resulting spatial patterns of change. Novel methods will continue to provide us with the tools necessary for improved insights into these challenging tasks.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.agsy.2012.12.010.

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