

## Mapping and monitoring of land use changes in post-Soviet western Ukraine using remote sensing data

Jan Stefanski <sup>a,\*</sup>, Oleh Chaskovsky <sup>b</sup>, Björn Waske <sup>a</sup>

<sup>a</sup> Institute of Geographical Sciences, Freie Universität Berlin, Malteserstrasse 74-100, 12249 Berlin, Germany

<sup>b</sup> Institute of Forest Management, Ukrainian National Forestry University, vul. Gen. Chuprynyk, 103, 79031 Lviv, Ukraine



### ARTICLE INFO

#### Article history:

Available online 29 September 2014

#### Keywords:

Land management  
Change detection  
Object-based  
Multisensor  
Landsat  
ERS SAR

### ABSTRACT

While agriculture is expanded and intensified in many parts of the world, decreases in land use intensity and farmland abandonment take place in other parts. Eastern Europe experienced widespread changes of agricultural land use after the collapse of the Soviet Union in 1991, however, rates and patterns of these changes are still not well understood. Our objective was to map and analyze changes of land management regimes, including large-scale cropland, small-scale cropland, and abandoned farmland. Monitoring land management regimes is a promising avenue to better understand the temporal and spatial patterns of land use intensity changes. For mapping and change detection, we used an object-based approach with Superpixel segmentation for delineating objects and a Random Forest classifier. We applied this approach to Landsat and ERS SAR data for the years 1986, 1993, 1999, 2006, and 2010 to estimate change trajectories for this time period in western Ukraine. The first period during the 1990s was characterized by post-socialist transition processes including farmland abandonment and substantial subsistence agriculture. Later on, recultivation processes and the recurrence of industrial, large-scale farming were triggered by global food prices that have led to a growing interest in this region.

© 2014 Elsevier Ltd. All rights reserved.

### Introduction

Substantial increase in land-based production (e.g., food, fiber, bioenergy) is needed as long as the global demand for agricultural products steadily increases and no changes in consumption occur (Godfray et al., 2010; Lotze-Campen et al., 2010; Tilman, Balzer, Hill, & Befort, 2011). To increase land-based production, either agriculture can be expanded into (other) ecosystems, existing farmland can be intensified, or abandoned farmland can be recultivated. While the transformation of forest to agricultural systems is widely studied and relatively well understood, particularly in the tropics, (Geist & Lambin, 2002; Hansen et al., 2008), patterns of agricultural intensification and abandonment remain unclear for most parts of the world (Fritz et al., 2013; Kuemmerle et al., 2013). However, monitoring status and trends of agricultural landscapes can provide important information to reduce the environmental impact of agricultural production (Zaks & Kucharik, 2011) and to identify potential regions for sustainable intensification or recultivation.

During the last decades remote sensing became a valuable tool for environmental monitoring and land cover mapping. In context

of agriculture, existing studies mainly focused on mapping different crop types (McNairn, Champagne, Shang, Holmstrom, & Reichert, 2009; Wardlow, Egbert, & Kastens, 2007; Waske & Braun, 2009) as well as on monitoring changes in cropland extent and the proximate drivers so far (Shalaby & Tateishi, 2007; Wagner, Kumar, & Schneider, 2013; Zhang et al., 2013). However, there are lacks of approaches sensitive to land use intensity because remote sensing can only rarely measure the complex terms of land use intensity (Kuemmerle et al., 2013).

One way for a more nuanced representation of agricultural landscapes is to map land management regimes as proxies of land use intensity (Kuemmerle et al., 2013; Stefanski et al., 2014; Verburg, Neumann, & Nol, 2011). Only a few studies have used such approaches at global (Ellis & Ramankutty, 2008; Václavík, Lautenbach, Kuemmerle, & Seppelt, 2013) or regional scales (Stefanski et al., 2014). Stefanski et al. (2014), for example, used the representation of management regimes that differed in field sizes, i.e., (1) large-scale, mechanized agriculture, (2) small-scale, subsistence agriculture, and (3) fallow or abandoned farmland. While large-scale, mechanized agriculture implied high management intensity, small-scale, subsistence agriculture had basically a low management intensity. To monitor land management regimes, however, requires adequate data sets and methods.

\* Corresponding author.

E-mail address: [j.stefanski@fu-berlin.de](mailto:j.stefanski@fu-berlin.de) (J. Stefanski).

Although optical remote sensing data are generally a powerful tool for mapping land use/cover changes (El-Kawy, Rød, Ismail, & Suliman, 2011; Loveland, Cochrane, & Henebry, 2008), the problem of cloud cover is a potentially limiting factor (Moran, Hymer, Qi, & Kerr, 2002). This seems particularly critical in context of agricultural landscapes. Managed cropland and grassland show typical temporal patterns due to the phenology of planted crops and management activities, while abandoned farmland is not affected by these activities. Nevertheless, a differentiation between grassland and cropland or grassland and abandoned farmland can be challenging due to spectral ambiguity of the multispectral remote sensing data. Accordingly, the use of multitemporal data seems promising. Prishchepov, Radeloff, Dubinin, and Alcantara (2012) recommends the use of three Landsat scenes – from spring, summer, and fall – for a reliable mapping of agricultural abandonment in Eastern Europe.

Moreover, besides the requirement of an adequate data set for one time period, the monitoring of land management changes requires multitemporal data sets from different years for the same study site. However, regarding the repetition rate of typical systems like Landsat and the problem of cloud cover, the generation of adequate multitemporal data sets can be challenging, while data with higher temporal coverage and wide swath (e.g., MODIS and MERIS) are inadequate in capturing land use/cover changes at fine scales.

Synthetic Aperture Radar (SAR) data on the other hand might overcome spectral ambiguities of multispectral data and are (almost) weather independent and thus useful to fill gaps in optical time series. Furthermore, multispectral and SAR systems operate in different wavelengths, ranging from visible to microwave and consequently provide different, but often complementary information (Pohl & Van Genderen, 1998). Thus, a combination of multispectral imagery with SAR data is worthwhile and it has been demonstrated in several studies that multisensor analysis significantly improves the accuracy of land use/cover classifications (Kuplich, Freitas, & Soares, 2000; McNairn, Champagne, et al., 2009; Waske & Benediktsson, 2007).

Besides the availability of adequate image data for all relevant time periods, the use of adequate classifier algorithms and change detection approaches is critical. Standard classifiers are often not adequate for classifying multisensor and multitemporal data sets, because in most cases the class distributions cannot be modeled by adequate multivariate statistical models. However, machine learning algorithms such as support vector machines and classifier ensembles have emerged over the past years in the remote sensing community and are well suited for handling diverse remote sensing data sets (Gislason, Benediktsson, & Sveinsson, 2006; Mountrakis, Im, & Ogole, 2011; Waske, Chi, Benediktsson, van der Linden, & Koetz, 2009). Particularly the classifier ensemble Random Forests (Breiman, 2001) is well suited for handling multitemporal SAR and multisensor data and has proved to be simple and accurate (Rodríguez-Galiano, Ghimire, Rogan, Chica-Olmo, & Rigol-Sánchez, 2012; Waske & Braun, 2009; Waske & van der Linden, 2008).

Remote sensing based change detection includes basically bi-temporal and trajectory-based change detection methods (McRoberts, 2013). While bi-temporal change detection assesses only the type and extent of change between two defined points in time, trajectory analyses use three or more dates to additionally assess trends and temporal patterns of change over time (Carmona & Nahuelhual, 2012; Kennedy, Cohen, & Schroeder, 2007; Mertens & Lambin, 2000). However, using trajectory analyses for detailed characterization of land change dynamics typically requires extensive time series (Kennedy et al., 2007; Sieber et al., 2013). Since the backscatter intensity of SAR data is almost independent

from weather conditions, time-series can be produced most reliably using SAR imagery.

In our study, we explored the potential of multispectral Landsat and ERS SAR data to monitor land management regimes in western Ukraine. After the collapse of the Soviet Union, Eastern Europe experienced drastic political and socio-economic changes. This led to farmland abandonment as well as the conversion of (collectivized) large-scale agriculture to small fields, used for subsistence agriculture (Alcantara, Kuemmerle, Prishchepov, & Radeloff, 2012; Kuemmerle, Radeloff, Perzanowski, & Hostert, 2006; Müller & Sikor, 2006). While widespread farmland abandonment often results in land fragmentation and simplification of landscapes (Peringer et al., 2013; Sikor, Müller, & Stahl, 2009), small-scale agriculture or basically subsistence agriculture in rural areas can preserve natural resources (Ioja, Nita, & Stupariu, 2014). Analyzing traditional agricultural land use with its positive aspects for natural and cultural biodiversity in a case study in Eastern Europe seems therefore particularly interesting (Angelstam et al., 2013; Munteanu et al., 2014). More recently, recultivation of abandoned farmland emerges, triggered by the global trend of food prices. Overall, this region is particularly interesting to monitor land management regimes over the past decades.

Farmland abandonment in Eastern Europe was successfully mapped in different studies, using optical remote sensing data at different scales (Alcantara et al., 2012; Griffiths, Müller, Kuemmerle, & Hostert, 2013; Kuemmerle et al., 2006, 2011). In contrast to this, the recultivation of abandoned farmland and extend of subsistence agriculture were rarely discussed. Stefanski et al. (2014) mapped current land management regimes in western Ukraine, including large-scale agriculture and small fields, using optical and SAR data. However, this study is based on a data set from one time period and consequently, temporal changes in land use management were not analyzed. Therefore, we explore the spatio-temporal patterns of land management regimes between 1986 and 2010 in this study.

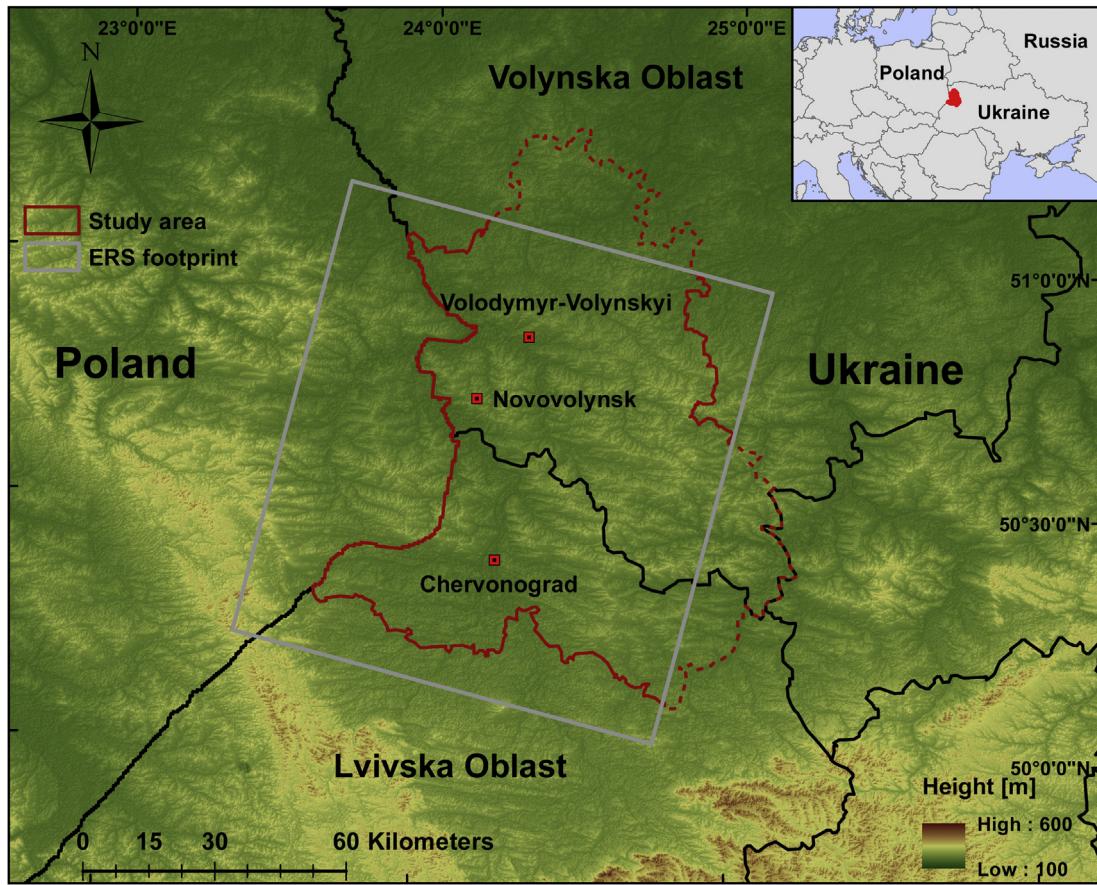
We used an object-based approach based on Landsat and ERS SAR data to map land use/cover in the years: 1986, 1993, 1999, 2006, and 2010. Then, we used change trajectories to derive changes of cropland (including large-scale and small-scale cropland), grassland, and fallow or abandoned land. Overall, we focused on the following objectives: (1) assessing the potential of SAR data to complement optical data for monitoring land management regimes, (2) analyzing the changes of land management intensities, i.e., the transformation of industrial, large-scale farming to subsistence agriculture, and (3) analyzing the spatio-temporal patterns of farmland abandonment and recultivation.

## Material

### Study area

Our study area is located in Volynska and Lvivska Oblasts in western Ukraine and covers about 7,500 km<sup>2</sup> (Fig. 1). The study region is dominated by agriculture and forests. Agricultural land use types vary from large-scale, intensively managed farmland to small-scale, subsistence and low intensively managed farmland to fallow or abandoned farmland.

The study area is particularly interesting to monitor land management regimes because this region is characterized by a large variability of socio-economic and environmental conditions, which caused marked spatial heterogeneity in management intensity. During the Soviet time, land management was characterized by collectivized, large-scale farmland (Mathijss & Swinnen, 1998). With the breakdown of the Soviet Union in 1991, drastic shifts in political and socio-economic conditions triggered widespread land changes such as land fragmentation, substantial abandonment of



**Fig. 1.** Map showing the study area in western Ukraine and a footprint of the used ERS data.

agricultural fields, and the emergence of subsistence agriculture (Baumann et al., 2011; Kuemmerle et al., 2006; Sabates-Wheeler, 2002). Yet, with the recent integration of this region into world markets, recultivation of abandoned land takes place.

#### Data set and preprocessing

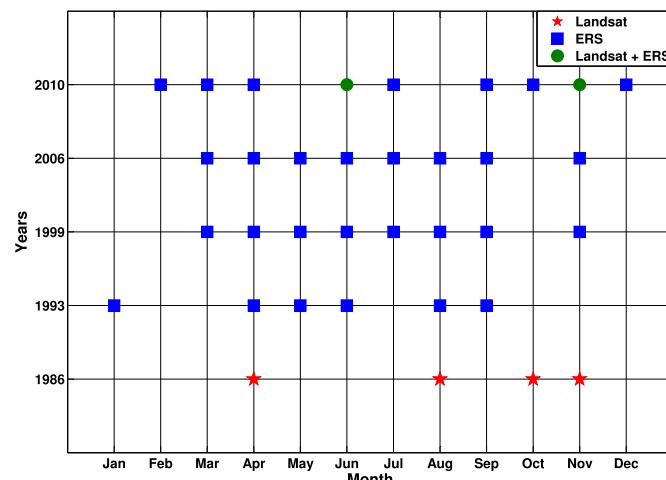
To monitor land management regimes between 1986 and 2010, we used optical (Landsat) and SAR (ERS) data for different dates

(Fig. 2). As the ERS-1 satellite was launched in 1991, we used four Landsat scenes (path/row 185/25) recorded at 4 April, 8 August, 11 October, and 12 November 1986 to map land use and land cover during the Soviet period. To map the land use changes in the following years, we used six (1993) and eight (1999, 2006) ERS SAR images. For the mapping of land management regimes in 2010, we combined two Landsat (7 June 2010 and 14 November 2010) and nine ERS images (Fig. 2).

We acquired the Landsat scenes already preprocessed on level L1T, which ensured a sufficient geometric and radiometric accuracy for our analysis (USGS, 2013). All ERS scenes were acquired in a single look complex (SLC) image format. We applied a standard SAR preprocessing using NEST-4C separate for each year, including radiometric and geometric corrections as well as Gamma speckle-filtering. Finally, we resampled all ERS images to 30 m pixel size to match the resolution of Landsat data.

Reference data were acquired during an extensive field campaign in 2012 (Stefanski et al., 2014). By using a random clustered sampling technique, we allocated 357 points to be used for validation. Three surveying teams assessed the points in the field by using a survey protocol based on the Land Use and Cover Area frame Survey (LUCAS) guidelines (EUROSTAT, 2009). Additionally, high-resolution RapidEye images supported the field mission and generation of the reference set. To adjust the 357 points for validation to the years 1986, 1993, and 2006, we visually interpreted Landsat data for each year.

To acquire training data for 2010, we used information collected during the field campaign that was independent from validation data and, additionally, visually interpreted RapidEye data. During the generation of the training data, we ensured that training and



**Fig. 2.** Acquisition dates of remote sensing data used in this study.

test data were spatially disjoint. The adjustment of the training set to the years 1986, 1993, and 2006 was analogous to the validation set.

## Methods

The monitoring of land management regimes was based on object-based approaches with the following steps: (1) generating a base map for 1986, including the land use classes cropland, grassland, forest, and urban, (2) mapping cropland and grassland for the years 1993, 1999, and 2006, (3) mapping land management regimes for 2010, including *large-scale cropland*, *small-scale cropland*, and *grassland*, and finally (4) a trajectory analysis to determine changes of land management regimes. Based on our field campaign and visual interpretation of remote sensing data, we made three general assumptions in our study. First, the class *cropland* incorporated solely *large-scale cropland* in 1986. An explanation for this is the general collectivization of agricultural fields to large fields in the Soviet system. Second, as we did not find changes of forest and urban areas over the time, we summarized both classes in "*Forest and Urban*" and masked them. Third, we analyzed the abandonment of cropland (i.e., the transition of *cropland* to *grassland*) and did not differentiate managed/unmanaged grassland, which is not resolvable with Landsat and ERS SAR data.

For the classifications of step (1)–(3), we used an object-based approach by using the Superpixel Contour algorithm (Mester, Conrad, & Guevara, 2011) for image segmentation and the Random Forest classifier (Breiman, 2001) for classification. The Superpixel Contour segmentation, the freely available Random Forest code (Jaaintilal, 2009), and the trajectory analysis were implemented in MATLAB.

### Object-based classification

The Superpixel Contour (SPc) algorithm is an iterative, region-based segmentation approach introduced by Mester et al. (2011). The SPc proved well in context of remote sensing and provides very similar results in comparison to the widely-used segmentation algorithm in eCognition (Stefanski, Mack, & Waske, 2013). The general principle of a segmentation algorithm is to separate an image into homogenous regions such as segments or superpixels, which ideally represent real world objects. To do so, the SPc optimizes a non-specified initial segmentation along its boundaries based on the statistical distribution of each segment. An iteratively running maximum-a-posteriori (MAP) segmentation is used to assign the boundary pixels to the region that maximizes the posterior distribution. Because only the boundary pixels of each segment have to be optimized, the SPc algorithm is computationally efficient. To find adequate segmentation parameters, we used a semi-automatic parameter selection (Stefanski et al., 2013) that is based on the out-of-bag error provided by Random Forests.

The Random Forest (RF) classifier was introduced by Breiman (2001) and demonstrated excellent performance in classifying remote sensing data (Gislason et al., 2006; Ghosh, Sharma, & Joshi, 2014; Waske & Braun, 2009). The RF has several advantages for its application in remote sensing. For example, the RF can efficiently handle large data sets and input variables, is robust to outliers and overfitting, and its parameter selection is user-friendly (Breiman, 2001). The principle of the RF is to build an ensemble of  $k$  randomly generated decision trees and using a majority voting over all trees to receive the final result. Each tree is built by choosing randomly  $m$  features at each split node of the tree, whereby  $m$  is a subset of all features. Furthermore, for each tree only a randomly selected subset of the training data is used for classifier training. Remaining training samples, the so called "out-of-bag" (OOB)

samples, allow an estimation of the classification error. To estimate this OOB error, the out-of-bag samples are classified by the particular decision tree and the final OOB error is derived by the classification error of all OOB samples. Since the RF is relatively insensitive to the parameters  $k$  and  $m$  when using a certain amount of trees, standard values for the parameters can be used. We used 500 trees for  $k$  and the square root of the number of input features for  $m$ .

The features of our object-based classification contained for each pixel both the spectral values and object features (mean values). For training the classifier, we used 1000 training samples per class. The training samples were selected by an equalized random sampling out of the training set. We validated the classification results by calculating confusion matrices, producer's, user's, and overall accuracies (Foody, 2002; Olofsson, Foody, Stehman, & Woodcock, 2013), which were based on the randomly clustered field-based validation set.

### Trajectory analysis

The change trajectories were defined by the successive transitions between the land use/cover categories between the years. To monitor land management regimes, we used every cropland and grassland pixel in 1986 to determine changes, while urban and forest areas have been masked. We defined the following eight major change trajectories with regard to 2010: (1) *permanent large-scale cropland*, (2) *permanent grassland*, (3) *permanently abandoned* (i.e., conversion of cropland to grassland with no subsequent use), (4) *LSC* → *abandoned* → *LSC* (i.e., large-scale cropland to abandonment to large-scale cropland), (5) *LSC* → *abandoned* → *SSC* (i.e., large-scale cropland to abandonment to small-scale cropland), (6) *LSC* → *SSC* (cropland parcellation, i.e., transformation of large-scale cropland to small-scale cropland), (7) *grassland* → *large-scale cropland*, and (8) *grassland* → *small-scale cropland*. We summarized the remaining land use changes under the class "*Others*", including, for example, multiple changes of cropland to grassland (e.g., cropland 1986 → grassland 1993 → cropland 1999 → grassland 2006). The eight major change trajectories enabled the analysis of the pattern of land management regimes and potential changes of land use intensity: *large-scale cropland* to *small-scale cropland* as potentially decreasing land use intensity and cropland abandonment, which implied no active land use intensity. However, the time period of farmland abandonment and recultivation were not assessed with this approach.

Thus, for a more detailed analysis of the spatio-temporal patterns of abandonment and recultivation, we analyzed the following change trajectories: (1) *permanent cropland* (2) *permanent grassland*, (3) *permanently abandoned* 1993 (i.e., conversion of cropland to grassland until 1993 with no subsequent conversion), (4) *permanently abandoned* 1999, (5) *permanently abandoned* 2006, (6) *permanently abandoned* 2010, (7) *recultivated* 1999 (i.e., fields that became abandoned till 1993 and recultivated again until 1999), (8) *recultivated* 2006, (9) *recultivated* 2010, and (10) *grassland to cropland*. We summarized the remaining land use changes under the class "*Others*".

As the previous trajectory analysis investigated the permanent abandonment and the recultivation, a third trajectory analysis assessed the total abandonment rate for each year of investigation. Therefore, we used the trajectories of *cropland to grassland* between 1986 and 2010 without considering whether the field is permanently abandoned or recultivated afterwards. With other words, we detected the total rate of farmland abandonment for each year. Differences between permanent abandonment and total abandonment may result from the fact that total abandonment can also include multiple changes of cropland/grassland conversion, which

is not included in the permanent abandonment, but in the class "Others".

## Results

### Object-based classification

We generated five different land use/cover maps: 1986 (Landsat), 1993, 1999, 2006 (ERS SAR), and 2010 (Landsat + ERS SAR), using an object-based approach. Our accuracy assessment was based on confusion matrices to calculate the overall, producer's, and user's accuracies.

The base map of 1986 showed an overall accuracy of 97.2% (**Table 1**). In addition, the classification resulted in high producer's and user's accuracies for the individual classes (*cropland*, *grassland*, *forest*, and *urban*).

In the next step, we classified the ERS data of the years 1993, 1999, and 2006 into *cropland* and *grassland* and achieved high class-specific as well as overall accuracies with 97.4%, 93.2%, and 92.1%, respectively (**Table 2**). Although the overall accuracy was lowest for 2006, the accuracy was still on a very high level (92.1%).

The classification 2010 achieved a good separation of the different land management regimes and showed an overall accuracy of 87.2% (**Table 3**). The producer's and user's accuracies of *large-scale cropland* and *grassland* reached accuracies between 85.1% and 90.0%. The producer's and user's accuracies of *small-scale cropland* was 91.8% and 71.4%, respectively.

Overall, these five land use/cover maps showed very high overall accuracies, which is essential for an accurate change trajectory analysis.

### Trajectory analysis

We used a change trajectory analysis to assess land management regimes changes between 1986 and 2010. Generally, our change detection showed substantial potential for monitoring land management regimes due to high accuracies of our classification of each year.

The final land management regimes change map showed that large parts of the study area were permanently used for *large-scale cropland*, mainly in the center of the study area (**Fig. 3**). In the central eastern part of the study area, the farmland parcellation, i.e., the transformation from *large-scale cropland* to *small-scale cropland* (dark yellow) (in web version), frequently occurred. In contrast, in the south east of the study area, *large-scale cropland*, which was temporarily abandoned, was recultivated as *large-scale cropland* until 2010 (orange) (in web version). Land use conversion from *grassland* to either *large-scale cropland* or *small-scale cropland* was spread over the study area, however, it was very rare in its extent.

The non-forest and non-urban area (from now on referred to as area) covered about 453,000 ha. About 24.5% of this area was permanently cultivated with *large-scale cropland* between 1986 and

**Table 2**

Accuracy assessment: classification results for 1993, 1999, and 2006 (PA = producer's accuracy, UA = user's accuracy, OA = overall accuracy).

Classes	1993		1999		2006	
	PA [%]	UA [%]	PA [%]	UA [%]	PA [%]	UA [%]
Cropland	99.1	97.7	93.2	97.3	89.7	96.5
Grassland	89.6	95.6	93.4	84.5	95.5	86.9
OA	97.4		93.2		92.1	

**Table 3**

Accuracy assessment: classification results for 2010 (PA = producer's accuracy, UA = user's accuracy, OA = overall accuracy, LSC = large-scale cropland, SSC = small-scale cropland).

Classes	2010	
	PA [%]	UA [%]
LSC	85.1	89.7
SSC	91.8	71.4
Grassland	90.0	88.3
OA	87.2	

2010 while 18.5% was transformed from large-scale cropland to small-scale cropland (**Table 4**). At the same time, 10.8% of the area was recultivated as *large-scale cropland* after becoming abandoned and 6.9% was recultivated as *small-scale cropland*. While about 17.7% (10.8% + 6.9%) of the area was only temporally abandoned and recultivated later on, 17.7% became permanently abandoned and was not recultivated during the observation period.

Analyzing the spatio-temporal patterns of farmland abandonment revealed that parts of the northern study area were the first that became permanently abandoned in the 1990s (yellow and orange) (in web version). Thus, permanent grassland and abandonment were dominant in the northern part of the study area (**Fig. 4**). Conversely, in the south and west of the study site farmland abandonment occurred at a later time, particularly between 2000 and 2006 as well as between 2007 and 2010 (dark red and light red) (in web version). Moreover, selected areas were recultivated until 2010 (dark green) (in web version).

The analysis of the temporal stages of farmland abandonment revealed that only about 3.4% of the non-forest/non-urban area was permanently abandoned since 1993 (**Table 5**). In 1999, 7.9% (sum of 1993 and 1999) of the area was already permanently abandoned. The cumulative permanent farmland abandonment increased to 13.9% in 2006. Until 2010, we observed the highest permanent abandonment with 17.7% of the area, while about 3.8% became permanently abandoned between 2006 and 2010. Moreover, 17.7% of former abandonment was recultivated, particularly at the end of the 2000s (i.e., 13.5% recultivated 2010).

The quantitative analysis of the total abandonment revealed that about 11.1% (47,897 ha) of the non-forest/non-urban area that was cropland in the 1980s was abandoned in 1993 (**Table 6**). In 1999, the total abandonment increased to 13.7% of the area. The highest total abandonment was in 2006 with 30.6% (132,406 ha) of the study area. In 2010, the total abandonment decreased in comparison to 2006 to 19.7%.

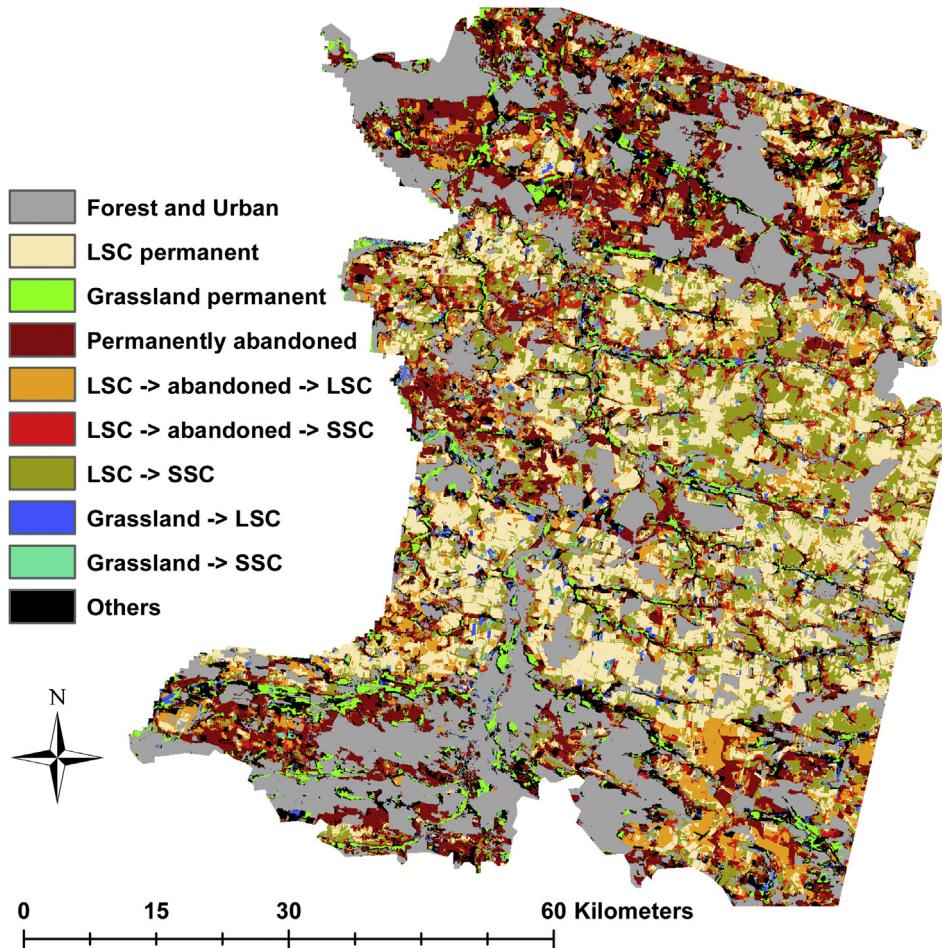
## Discussion

In the presented study, we monitored and analyzed changes in land use and management, including farmland abandonment, recultivation, and the transformation from common large-scale agriculture to small-scale agriculture. Due to spectral ambiguities, phenological variability, and limited data availability, a detailed and

**Table 1**

Accuracy assessment: classification results for 1986 (PA = producer's accuracy, UA = user's accuracy, OA = overall accuracy).

Classes	1986	
	PA [%]	UA [%]
Cropland	97.3	98.6
Grassland	93.3	95.5
Forest	98.7	100.0
Urban	100.0	73.7
OA	97.2	



**Fig. 3.** Land management regimes change map, based on Landsat and ERS data between 1986 and 2010 (LSC = large-scale cropland, SSC = small-scale cropland).

accurate mapping of these processes is challenging. Therefore, an adequate strategy to monitor land management regimes is proposed, using an object-based approach with multitemporal SAR and multispectral remote sensing data.

By using Landsat and ERS SAR data, we received high overall classification accuracies between 87.2% and 97.4%. The good temporal coverage of at least one observation per season (Fig. 2) has possibly favored the detection of land management. For example, grassland has a relatively constant signal signature during a year while, for example, plowing and harvesting can cause sharp changes in the signal of arable land. As expected, the use of spatial information due to object-based features in addition to the spectral information of each pixel ensured the precise mapping of classes that are hard to differentiate solely at pixel level, such as large-scale

cropland and small-scale cropland (Hussain, Chen, Cheng, Wei, & Stanley, 2013; Stefanski et al., 2014). This is in accordance with other studies that have shown the benefit of object-based classification of remote sensing data (Blaschke et al., 2014; Stefanski et al., 2013; Whiteside, Boggs, & Maier, 2011).

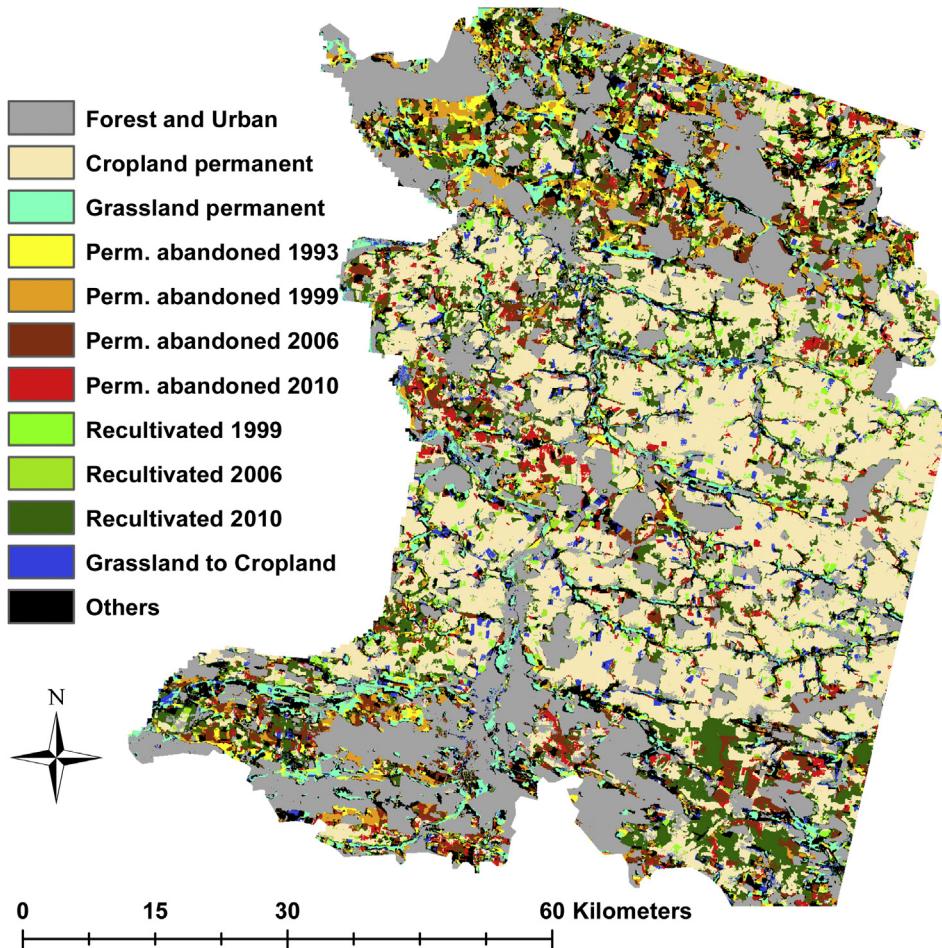
The analysis of change trajectories demand accurate classifications at every time step, which we achieved in general with relative high producer's and user's accuracies. Furthermore, the class "Others" summarized all remaining, not particularly investigated change classes, including implausible classes such as multiple changes of cropland to grassland. Therefore, inaccurate change classes were more likely assigned to this residue class, while the mapping of the relevant change classes were more reliably.

The first objective was the assessment of the value of SAR data for complementing optical data for monitoring land management regimes. Estimating land use and land cover changes by change trajectory analysis demand accurate land cover maps at each step. Our accuracy assessment clearly showed that SAR data are very well suited for mapping cropland and grassland with high classification accuracies (Table 2). The high accuracies for mapping agricultural classes, which are hard to separate by mono-temporal analyses, underline the value of multitemporal analyses. This is in accordance with the results in other studies (Blaes, Vanhalle, & Defourny, 2005; McNairn, Shang, Jiao, & Champagne, 2009; Waske & Braun, 2009), where multitemporal C-Band data was used for crop type mapping. In general, these findings indicate that multitemporal SAR data are a promising alternative to complement optical data. SAR-based classifications can be used to fill temporal

**Table 4**

Quantification of the land management regimes change (LSC = large-scale cropland, SSC = small-scale cropland).

Change estimation	[ha]	[%]
LSC permanent	105,867	24.5
Grassland permanent	22,340	5.2
Permanently abandoned	76,591	17.7
LSC → abandoned → LSC	46,593	10.8
LSC → abandoned → SSC	29,738	6.9
LSC → SSC	79,735	18.5
Grassland → LSC	8,402	1.9
Grassland → SSC	4,379	1.0
Others	58,412	13.5



**Fig. 4.** Change map showing farmland abandonment and recultivation, based on Landsat and ERS data between 1986 and 2010.

data gaps where no optical data is available for a particular year of interest and thus, enable a more detailed change analysis within time. Although most applications are based on C-band data, land cover information can be mapped by other frequencies such as X- and L-band data (McNairn, Shang, et al., 2009; Sonobe, Tani, Wang, Kobayashi, & Shimamura, 2014), for example, provided by TerraSAR-X and ALOS PALSAR. Nevertheless, for long-term monitoring the use of C-band is particularly interesting, because ERS-2, Envisat and Radarsat have provided SAR data for several years. Moreover, data continuity is secured due to ongoing missions such as Radarsat-2 and the recently launched Sentinel-1.

As discussed in other studies, the classification accuracy can be further increased by combining optical and SAR data (McNairn, Shang, et al., 2009; Stefanski et al., 2014; Waske & van der

Linden, 2008). The main reason for this is assumed to be the different nature of the used data types. SAR and optical systems operate in different wavelengths, ranging from visible to microwave domain. Consequently, the two systems provide different information. Moreover, optical data are characterized by a high spectral resolution, when compared to SAR data, while multi-temporal data sets within one growing season can be produced most reliably using SAR systems. The latter fact seems particularly relevant when the application demands specific acquisition periods. In context of mapping farmland abandonment, a spring observation is highly relevant to differentiate arable land and abandoned arable land. Moreover, a higher number of observations further increases the mapping accuracy (Prishchepov et al., 2012). The combination of SAR data with (a limited number of) optical images seems particularly relevant over larger areas, where the availability of adequate optical data sets is likely to decrease. Moreover, SAR-based maps can be used to fill-in spatial gaps in optical-based classifications, where clouds and haze result in missing values (McNairn, Shang, et al., 2009).

**Table 5**  
Quantification of farmland abandonment and recultivation.

Change estimation	[ha]	[%]
Cropland permanent	185,602	43.0
Grassland permanent	22,340	5.2
Permanently abandoned 1993	14,734	3.4
Permanently abandoned 1999	19,500	4.5
Permanently abandoned 2006	26,134	6.0
Permanently abandoned 2010	16,223	3.8
Recultivated 1999	10,238	2.4
Recultivated 2006	7,670	1.8
Recultivated 2010	58,423	13.5
Grassland → Cropland	12,781	2.9
Others	58,412	13.5

**Table 6**  
Quantification of the total abandonment for each time step.

Change estimation	[ha]	[%]
Total abandonment 1993	47,897	11.1
Total abandonment 1999	59,120	13.7
Total abandonment 2006	132,406	30.6
Total abandonment 2010	85,171	19.7

Our second objective was to analyze the changes of land management intensities between 1986 and 2010. The mapped changes such as the substantial permanent farmland abandonment (17.7% – **Table 4**) and the emerge of subsistence agriculture (26.4% – **Table 4**) can be traced back to the collapse of the Soviet Union and its planned-economy, which led to the end of guaranteed prices, the breakaway of former markets, and a rising foreign competition (Baumann et al., 2011; Kuemmerle et al., 2006; Sabates-Wheeler, 2002; ). The limits in infrastructure and migration from rural areas were additional issues that lead to increases in farmland abandonment (Ioffe, Nefedova, & Zaslavsky, 2004; Müller & Munroe, 2008).

Economic transition in Eastern Europe led to the emergence of a large subsistence sector (Kostov & Lingard, 2004). Subsistence agriculture is often seen as a reaction of rural households to deal with hardships of transition (Mathijs & Noev, 2004), which is emphasized by the fact that the majority of subsistence agriculture (small-scale cropland) in our study area was directly converted from large-scale cropland. This process of land use intensity change was likely favored by the substantial political changes that led to the abandonment of the kolkhoz (i.e., collective farms in the Soviet Union) and thus, the ownership of the fields passed to the private property of the rural population.

However, about one quarter of the non-forest/non-urban area was permanently cultivated as large-scale cropland. The high rate of recultivation as large-scale cropland (i.e., potentially high intensive farming) led to a rate of 24.5% large-scale farming in 2010. The main reason for this may lie in the dominant soil types in this region. Stefanski et al. (2014) found that 54% of the large-scale cropland and even 60% of the small-scale cropland was cultivated on fertile Phaeozems and Chernozems, which are attractive for agriculture.

Our third objective was the analysis of spatio-temporal patterns of farmland abandonment and recultivation between 1986 and 2010. While about 11.1% of the area became abandoned until 1993, most fields were recultivated later on and only 3.4% in 1993 became permanently abandoned. That most fields became abandoned between 1999 and 2006 up to a rate of 30.6% was unexpected, as we expected the highest rates of abandonment in the 1990s (**Table 6**). However, we mentioned above that the kolkhoz collapsed in the 1990s and during these times a high amount of fields had to be used for subsistence farming. In the year 1999, an important page was turned in agricultural policy in Ukraine, including land reforms and a more stable trade policy (Aslund, 2002; OECD, 2004). This led to a period of improved efficiency-driven growth in the agricultural sector. Consequently, less farmland for self-sufficiency was needed and a continued decline in formal farm employment took place (OECD, 2004). This may explain the high rate of abandonment in 2006. With the recent integration in world markets and the emergence of agri-business, large areas were recultivated in 2010 while the abandonment rate decreased (**Table 5**).

Our agricultural land change rates are in accordance to previous case studies in Eastern Europe. For example, Kuemmerle et al. (2011) detected about 13% of farmland abandonment in western Ukraine in 2007. Likely reasons for the moderate differences to our results (17.7% permanent abandonment) are that their abandonment rate was based on the entire study area, and not just accounting the non-forest and non-urban area, as it was in our case. Alcantara et al. (2012) detected 15.1% abandoned cropland in Eastern Europe for 2005 by using MODIS data at a large scale (parts of the Baltic States, Belarus, Poland, and Ukraine). In contrast to this, other studies showed abandonment rates of 21% in Southern Romania (Kuemmerle, Hostert, St-Louis, & Radloff, 2009) and 29% in the Carpathians Mountains (Griffiths et al., 2013). However, mountainous regions are marginal for agriculture and thus,

farmland abandonment is more likely in such less suitable regions (Griffiths et al., 2013; Ioffe, Nefedova, & De Beurs, 2012; Prishchepov, Müller, Dubinin, Baumann, & Radloff, 2013).

## Conclusions

We monitored land use changes, including large-scale cropland, small-scale cropland, farmland abandonment, and recultivation in western Ukraine by using an object-based approach with Landsat and ERS SAR data. With the utilization of a change trajectory analysis, we successfully estimated long term changes of land use intensity. We showed that SAR data is worthwhile to fill gaps of optical data. The good results that we received for separating different land use/cover classes at several time periods enabled a detailed trajectory analysis. This is especially beneficial as the availability of optical data can be limited due to cloud cover. This fact is particularly critical when mapping large areas and the accurate separation of individual land cover classes demands specific acquisitions. While the availability of adequate optical data sets can be limited in this context, data sets with high temporal coverage within a year can best be produced by using synthetic aperture radar. In our study region, we found substantial farmland abandonment both in the 1990s, basically characterized by the post-socialist transition processes, and in the 2000s. Some reasons for farmland abandonment in the 2000s might be land reforms and a more stable trade policy that led to a period of improved efficiency-driven growth in the agricultural sector. Furthermore, we found a noticeable conversion of large-scale cropland to small-scale cropland in western Ukraine, showing the emerge of subsistence agriculture due to the demand of self-sufficiency. Especially between 2006 and 2010, we detected an increasing recultivation rate of abandoned cropland in western Ukraine, traced back to the recent integration in world markets and the emergence of agri-business. Overall, our approach constitutes a feasible and accurate approach for monitoring land management regimes over a long time period.

## Acknowledgments

This work was supported by the German Research Foundation (DFG-WA 2728/2-1; WA 2728/2-2) and the State Fund of Fundamental Research of Ukraine (N 0113U002752). ERS data was provided by ESA (C1P.10962). RapidEye data was provided from the RapidEye Science Archive (RESA) by DLR under the proposal id490.

## References

- Alcantara, C., Kuemmerle, T., Prishchepov, A. V., & Radloff, V. C. (2012). Mapping abandoned agriculture with multi-temporal MODIS satellite data. *Remote Sensing of Environment*, 124, 334–347.
- Angelstam, P., Elbakidze, M., Axelsson, R., Čupa, P., Halada, L., Molnar, Z., et al. (2013). Maintaining cultural and natural biodiversity in the Carpathian mountain ecoregion: need for an integrated landscape approach. In J. Kozak, K. Ostapowicz, A. Bytnarowicz, & B. Wyzga (Eds.), *The Carpathians: Integrating Nature and Society Towards Sustainability Environmental Science and Engineering* (pp. 393–424). Berlin Heidelberg: Springer.
- Aslund, A. (2002). *Why has Ukraine returned to economic growth?*. Technical Report Kiev, Ukraine: Institute for Economic Research and Policy Consulting. Working Paper No. 15.
- Baumann, M., Kuemmerle, T., Elbakidze, M., Ozdogan, M., Radloff, V. C., Keuler, N. S., et al. (2011). Patterns and drivers of post-socialist farmland abandonment in western Ukraine. *Land Use Policy*, 28, 552–562.
- Blaes, X., Vanhalte, L., & Defourny, P. (2005). Efficiency of crop identification based on optical and SAR image time series. *Remote Sensing of Environment*, 96, 352–365.
- Blaschke, T., Hay, G. J., Kelly, M., Lang, S., Hofmann, P., Addink, E., et al. (2014). Geographic object-based image analysis - towards a new paradigm. *ISPRS Journal of Photogrammetry and Remote Sensing : Official Publication of the International Society for Photogrammetry and Remote Sensing (ISPRS)*, 87, 180–191.
- Breiman, L. (2001). Random forests. *Machine Learning*, 45, 5–32.

- Carmona, A., & Nahuelhual, L. (2012). Combining land transitions and trajectories in assessing forest cover change. *Applied Geography*, 32, 904–915.
- El-Kawy, O. A., Rød, J., Ismail, H., & Suliman, A. (2011). Land use and land cover change detection in the western Nile delta of Egypt using remote sensing data. *Applied Geography*, 31, 483–494.
- Ellis, E. C., & Ramankutty, N. (2008). Putting people in the map: anthropogenic biomes of the world. *Frontiers in Ecology and the Environment*, 6, 439–447.
- EUROSTAT. (2009). *LUCAS 2009 (Land Use/Cover area frame survey) - Instructions for surveyors*. [http://epp.eurostat.ec.europa.eu/portal/page/portal/lucas/documents/LUCAS2009\\_C1-Instructions\\_Revised20130925.pdf](http://epp.eurostat.ec.europa.eu/portal/page/portal/lucas/documents/LUCAS2009_C1-Instructions_Revised20130925.pdf) Accessed on 11.06.14.
- Foody, G. M. (2002). Status of land cover classification accuracy assessment. *Remote Sensing of Environment*, 80, 185–201.
- Fritz, S., See, L., You, L., Justice, C., Becker-Reshef, I., Bydekerke, L., et al. (2013). The need for improved maps of global cropland. *Eos, Transactions American Geophysical Union*, 94, 31–32.
- Geist, H. J., & Lambin, E. F. (2002). Proximate causes and underlying driving forces of tropical deforestation. *BioScience*, 52, 143.
- Ghosh, A., Sharma, R., & Joshi, P. (2014). Random forest classification of urban landscape using Landsat archive and ancillary data: combining seasonal maps with decision level fusion. *Applied Geography*, 48, 31–41.
- Gislason, P. O., Benediktsson, J. A., & Sveinsson, J. R. (2006). Random Forests for land cover classification. *Pattern Recognition Letters*, 27, 294–300.
- Godfray, H. C. J., Beddington, J. R., Crute, I. R., Haddad, L., Lawrence, D., Muir, J. F., et al. (2010). Food security: the challenge of feeding 9 billion people. *Science*, 327, 812–818.
- Griffiths, P., Müller, D., Kuemmerle, T., & Hostert, P. (2013). Agricultural land change in the Carpathian ecoregion after the breakdown of socialism and expansion of the European Union. *Environmental Research Letters*, 8, 045024.
- Hansen, M. C., Stehman, S. V., Potapov, P. V., Loveland, T. R., Townshend, J. R. G., DeFries, R. S., et al. (2008). Humid tropical forest clearing from 2000 to 2005 quantified by using multitemporal and multisource remotely sensed data. *Proceedings of the National Academy of Sciences*, 105, 9439–9444.
- Hussain, M., Chen, D., Cheng, A., Wei, H., & Stanley, D. (2013). Change detection from remotely sensed images: from pixel-based to object-based approaches. *ISPRS Journal of Photogrammetry and Remote Sensing*, 80, 91–106.
- Ioffe, G., Nefedova, T., & De Beurs, K. (2012). Land abandonment in Russia. *Eurasian Geography and Economics*, 53, 527–549.
- Ioffe, G., Nefedova, T., & Zaslavsky, I. (2004). From spatial continuity to fragmentation: the case of Russian farming. *Annals of the Association of American Geographers*, 94, 913–943.
- Ioja, C., Nita, M. R., & Stupariu, I. G. (2014). Resource conservation: key elements in sustainable rural development. In Z. Andreopoulou, V. Samathrakis, S. Louca, & M. Vlachopoulou (Eds.), *E-Innovation for sustainable development of rural resources during global economic crisis* (pp. 80–97). Hershey, PA: Business Science Reference.
- Jaintialal, A. (2009). *Classification and regression by randomforest-matlab*. Available at <http://code.google.com/p/randomforest-matlab> Accessed on 11.06.14.
- Kennedy, R. E., Cohen, W. B., & Schroeder, T. A. (2007). Trajectory-based change detection for automated characterization of forest disturbance dynamics. *Remote Sensing of Environment*, 110, 370–386.
- Kostov, P., & Lingard, J. (2004). Subsistence agriculture in transition economies: Its roles and determinants. *Journal of Agricultural Economics*, 55, 565–579.
- Kuemmerle, T., Erb, K., Meyfroidt, P., Müller, D., Verburg, P. H., Estel, S., et al. (2013). Challenges and opportunities in mapping land use intensity globally. *Current Opinion in Environmental Sustainability*, 5, 484–493.
- Kuemmerle, T., Hostert, P., St-Louis, V., & Radeloff, V. C. (2009). Using image texture to map farmland field size: a case study in Eastern Europe. *Journal of Land Use Science*, 4, 85–107.
- Kuemmerle, T., Olofsson, P., Chaskovskyy, O., Baumann, M., Ostapowicz, K., Woodcock, C. E., et al. (2011). Post-Soviet farmland abandonment, forest recovery, and carbon sequestration in western Ukraine. *Global Change Biology*, 17, 1335–1349.
- Kuemmerle, T., Radeloff, V. C., Perzanowski, K., & Hostert, P. (2006). Cross-border comparison of land cover and landscape pattern in Eastern Europe using a hybrid classification technique. *Remote Sensing of Environment*, 103, 449–464.
- Kuplich, T., Freitas, C. d. C., & Soares, J. (2000). The study of ERS-1 SAR and Landsat TM synergism for land use classification. *International Journal of Remote Sensing*, 21, 2101–2111.
- Lotze-Campen, H., Popp, A., Beringer, T., Müller, C., Bondeau, A., Rost, S., et al. (2010). Scenarios of global bioenergy production: the trade-offs between agricultural expansion, intensification and trade. *Ecological Modelling*, 221, 2188–2196.
- Loveland, T. R., Cochrane, M. A., & Henebry, G. M. (2008). Landsat still contributing to environmental research. *Trends in Ecology & Evolution*, 23, 182–183.
- Mathijs, E., & Noev, N. (2004). Subsistence farming in Central and Eastern Europe: empirical evidence from Albania, Bulgaria, Hungary, and Romania. *Eastern European Economics*, 42, 72–89.
- Mathijs, E., & Swinnen, J. F. M. (1998). The economics of agricultural decollectivization in East Central Europe and the former Soviet Union. *Economic Development and Cultural Change*, 47, 1–26.
- McNairn, H., Champagne, C., Shang, J., Holmstrom, D., & Reichert, G. (2009). Integration of optical and Synthetic Aperture Radar (SAR) imagery for delivering operational annual crop inventories. *ISPRS Journal of Photogrammetry and Remote Sensing*, 64, 434–449.
- McNairn, H., Shang, J., Jiao, X., & Champagne, C. (2009). The contribution of ALOS PALSAR multipolarization and polarimetric data to crop classification. *Geoscience and Remote Sensing, IEEE Transactions on*, 47, 3981–3992.
- McRoberts, R. E. (2013). Post-classification approaches to estimating change in forest area using remotely sensed auxiliary data. *Remote Sensing of Environment*.
- Mertens, B., & Lambin, E. F. (2000). Land-cover-change trajectories in southern Cameroon. *Annals of the Association of American Geographers*, 90, 467–494.
- Mester, R., Conrad, C., & Guevara, A. (2011). Multichannel segmentation using contour relaxation: fast super-pixels and temporal propagation. In *Proceedings of the 17th Scandinavian conference on Image analysis SCIA'11* (pp. 250–261). Berlin, Heidelberg: Springer-Verlag.
- Moran, M., Hymer, D. C., Qi, J., & Kerr, Y. (2002). Comparison of ERS-2 SAR and Landsat TM imagery for monitoring agricultural crop and soil conditions. *Remote Sensing of Environment*, 79, 243–252.
- Mountrakis, G., Im, J., & Ogole, C. (2011). Support vector machines in remote sensing: a review. *ISPRS Journal of Photogrammetry and Remote Sensing*, 66, 247–259.
- Müller, D., & Munroe, D. K. (2008). Changing rural landscapes in Albania: cropland abandonment and forest clearing in the postsocialist transition. *Annals of the Association of American Geographers*, 98, 855–876.
- Müller, D., & Sikor, T. (2006). Effects of postsocialist reforms on land cover and land use in South-Eastern Albania. *Applied Geography*, 26, 175–191.
- Munteanu, C., Kuemmerle, T., Boltzian, M., Butsic, V., Gimmi, U., Halada, L., et al. (2014). Forest and agricultural land change in the Carpathian region – a meta-analysis of long-term patterns and drivers of change. *Land Use Policy*, 38, 685–697.
- OECD. (2004). *Achieving Ukraine's agricultural potential*. Organization for Economic Co-operation and Development & the Environmentally and Socially Sustainable Development Unit, Europe and Central Asia Region. Washington: The World Bank.
- Olofsson, P., Foody, G. M., Stehman, S. V., & Woodcock, C. (2013). Making better use of accuracy data in land change studies: estimating accuracy and area and quantifying uncertainty using stratified estimation. *Remote Sensing of Environment*, 129, 122–131.
- Peringer, A., Siehoff, S., Chételat, J., Spiegelberger, T., Buttler, A., & Gillet, F. (2013). Past and future landscape dynamics in pasture-woodlands of the Swiss Jura Mountains under climate change. *Ecology and Society*, 18.
- Pohl, C., & Van Genderen, J. L. (1998). Review article multisensor image fusion in remote sensing: concepts, methods and applications. *International Journal of Remote Sensing*, 19, 823–854.
- Prishchepov, A. V., Müller, D., Dubinin, M., Baumann, M., & Radeloff, V. C. (2013). Determinants of agricultural land abandonment in post-Soviet European Russia. *Land Use Policy*, 30, 873–884.
- Prishchepov, A. V., Radeloff, V. C., Dubinin, M., & Alcantara, C. (2012). The effect of Landsat ETM/ETM<sup>+</sup> image acquisition dates on the detection of agricultural land abandonment in Eastern Europe. *Remote Sensing of Environment*, 126, 195–209.
- Rodriguez-Galiano, V., Ghimire, B., Rogan, J., Chica-Olmo, M., & Rigol-Sánchez, J. (2012). An assessment of the effectiveness of a random forest classifier for land-cover classification. *ISPRS Journal of Photogrammetry and Remote Sensing*, 67, 93–104.
- Sabates-Wheeler, R. (2002). Consolidation initiatives after land reform: responses to multiple dimensions of land fragmentation in Eastern European agriculture. *Journal of International Development*, 14, 1005–1018.
- Shalaby, A., & Tateishi, R. (2007). Remote sensing and GIS for mapping and monitoring land cover and land-use changes in the northwestern coastal zone of Egypt. *Applied Geography*, 27, 28–41.
- Sieber, A., Kuemmerle, T., Prishchepov, A. V., Wendland, K. J., Baumann, M., Radeloff, V. C., et al. (2013). Landsat-based mapping of post-Soviet land-use change to assess the effectiveness of the Oksky and Mordovsky protected areas in European Russia. *Remote Sensing of Environment*, 133, 38–51.
- Sikor, T., Müller, D., & Stahl, J. (2009). Land fragmentation and cropland abandonment in Albania: implications for the roles of state and community in post-socialist land consolidation. *World Development*, 37, 1411–1423.
- Sonobe, R., Tani, H., Wang, X., Kobayashi, N., & Shimamura, H. (2014). Random forest classification of crop type using multi-temporal TerraSAR-X dual-polarimetric data. *Remote Sensing Letters*, 5, 157–164.
- Stefanski, J., Kuemmerle, T., Chaskovskyy, O., Griffiths, P., Havryluk, V., Knorn, J., et al. (2014). Integrating optical and radar images for mapping land management regimes in western Ukraine. *Remote Sensing*, 6, 5279–5305.
- Stefanski, J., Mack, B., & Waske, B. (2013). Optimization of object-based image analysis with Random Forests for land cover mapping. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 6, 2492–2504.
- Tilman, D., Balzer, C., Hill, J., & Befort, B. L. (2011). From the cover: global food demand and the sustainable intensification of agriculture. *Proceedings of the National Academy of Sciences*, 108, 20260–20264.
- USGS. (2013). *Landsat processing Details*. United States Geological Survey (USGS). [http://landsat.usgs.gov/Landsat\\_Processing\\_Details.php](http://landsat.usgs.gov/Landsat_Processing_Details.php) Accessed on 11.06.14.
- Václavík, T., Lautenbach, S., Kuemmerle, T., & Seppelt, R. (2013). Mapping global land system archetypes. *Global Environmental Change*, 23, 1637–1647.
- Verburg, P. H., Neumann, K., & Nol, L. (2011). Challenges in using land use and land cover data for global change studies. *Global Change Biology*, 17, 974–989.
- Wagner, P. D., Kumar, S., & Schneider, K. (2013). An assessment of land use change impacts on the water resources of the Mula and Mutha rivers catchment upstream of Pune, India. *Hydrology and Earth System Sciences*, 17, 2233–2246.

- Wardlow, B. D., Egbert, S. L., & Kastens, J. H. (2007). Analysis of time-series MODIS 250m vegetation index data for crop classification in the U.S. Central Great Plains. *Remote Sensing of Environment*, 108, 290–310.
- Waske, B., & Benediktsson, J. (2007). Fusion of support vector machines for classification of multisensor data. *IEEE Transactions on Geoscience and Remote Sensing*, 45, 3858–3866.
- Waske, B., & Braun, M. (2009). Classifier ensembles for land cover mapping using multitemporal SAR imagery. *ISPRS Journal of Photogrammetry and Remote Sensing*, 64, 450–457.
- Waske, B., Chi, M., Benediktsson, J., van der Linden, S., & Koetz, B. (2009). Algorithms and applications for land cover classification - a review. In D. Li, J. Gong, & Shan (Eds.), *Geospatial Technology for Earth Observation*. Springer.
- Waske, B., & van der Linden, S. (2008). Classifying multilevel imagery from SAR and optical sensors by decision fusion. *IEEE Transactions on Geoscience and Remote Sensing*, 46, 1457–1466.
- Whiteside, T. G., Boggs, G. S., & Maier, S. W. (2011). Comparing object-based and pixel-based classifications for mapping savannas. *International Journal of Applied Earth Observation and Geoinformation*, 13, 884–893.
- Zaks, D. P. M., & Kucharik, C. J. (2011). Data and monitoring needs for a more ecological agriculture. *Environmental Research Letters*, 6, 014017.
- Zhang, H., Qi, Z., Ye, X., Cai, Y., Ma, W., & Chen, M. (2013). Analysis of land use/land cover change, population shift, and their effects on spatiotemporal patterns of urban heat islands in metropolitan Shanghai, China. *Applied Geography*, 44, 121–133.