Remote Sensing of Environment 213 (2018) 49–60

Contents lists available at ScienceDirect

Remote Sensing of Environment

journal homepage: www.elsevier.com/locate/rse

Mapping the timing of cropland abandonment and recultivation in northern Kazakhstan using annual Landsat time series

Andrey Dara[a,b,*], Matthias Baumann[a], Tobias Kuemmerle[a,c], Dirk Pflugmacher[a], Andreas Rabe[a], Patrick Griffiths[a], Norbert Hölzel[d], Johannes Kamp[d], Martin Freitag[d], Patrick Hostert[a,c]

[a] *Geography Department, Humboldt-Universität zu Berlin, Unter den Linden 6, 10099 Berlin, Germany*
[b] *Leibniz Institute for Agricultural Development in Transition Economies (IAMO), Theodor-Lieser-Str. 2, 06120 Halle (Saale), Germany*
[c] *Integrative Research Institute on Transformations of Human-Environment Systems (IRI THESys), Humboldt-Universität zu Berlin, Unter den Linden 6, 10099 Berlin, Germany*
[d] *Institute of Landscape Ecology, University Münster, Heisenbergstr. 2, 48149 Münster, Germany*

ARTICLE INFO

Keywords:
Agricultural abandonment
Change detection
Data scarcity
Farmland
Temporal resolution
Post-soviet land-use change
LandTrendr
Class probability

ABSTRACT

Much of the world's temperate grasslands have been converted to croplands, yet these trends can reverse in some regions. This is the case for the steppes of northern Kazakhstan, where the breakdown of the Soviet Union led to widespread cropland abandonment, creating restoration opportunities. Understanding when abandonment happened and whether it persists is important for making use of these opportunities. We developed a trajectory-based change detection approach to identify cropland abandonment between 1988 and 2013 and recultivation between 1991 and 2013. Our approach is based on annual time series of cropland probabilities derived from Landsat imagery and resulted in reliable maps (89% overall accuracy), with abandonment being detected more accurately (user's accuracy of 93%) than recultivation (73%). Most of the remaining uncertainty in our maps was due to low image availability during the mid-1990s, leading to abandonment in the 1990s sometimes only being detected in the 2000s. Our results suggest that of the ~4.7 million ha of cropland in our study area in 1985, roughly 40% had been abandoned by 2013. Knowing the timing of abandonment allowed for deeper insights into what drives these dynamics: recultivation after 2007 happened preferentially on those lands that had been abandoned most recently, suggesting that the most productive croplands were abandoned last and recultivated first. Likewise, knowing the timing of abandonment allowed for more precise estimates of the environmental impacts of abandonment (e.g., soil organic carbon sequestration estimated at 16.3 Mt. C compared to 24.0 Mt. C when assuming all abandonment happened right after the breakdown of the Soviet Union, with the uncertainty around emission estimates decreasing by 63%). Overall, our study emphasizes the value of the Landsat archive for understanding agricultural land-use dynamics, and the opportunities of trajectory-based approaches for mapping these dynamics.

1. Introduction

Grasslands cover about one fifth of the Earth's surface (Lieth, 1978), are rich in biodiversity (Suttie et al., 2005), and play an important role in global carbon storage (Scurlock and Hall, 1998; Anderson, 1991). At the same time, grasslands are often found on soils that are well-suited for agriculture (Millennium Ecosystem Assessment, 2005) and can be plowed at comparably low costs (Briggs et al., 2008). However, in some grassland regions croplands are abandoned, potentially leading to a restoration of native biodiversity (Benayas et al., 2007; Brinkert et al., 2016; Kamp et al., 2011) and carbon stocks (Kurganova et al., 2014; Sala et al., 1996). The degree of restoration, however, depends on the time since abandonment, and recovery often follows a non-linear trajectory. For example, carbon sequestration rates were estimated to be significantly lower for croplands abandoned at an earlier date than for more recently abandoned fields in Russia (the first 20 years vs. the next 30 years in Kurganova et al., 2014; the first 10 years vs. the next 20 years in Wertebach et al., 2017). Similarly, success in restoration of native grass species and a restitution of soil properties were highly dependent on the time since abandonment in China (Zhao et al., 2005). Given recent trends to recultivate some abandoned croplands (Meyfroidt et al., 2016; Schierhorn et al., 2014; Smaliychuk et al., 2016), better information on when croplands were abandoned is important.

* Corresponding author at: Geography Department, Humboldt-Universität zu Berlin, Unter den Linden 6, 10099 Berlin, Germany.
E-mail address: andrey.dara@geo.hu-berlin.de (A. Dara).

https://doi.org/10.1016/j.rse.2018.05.005
Received 2 September 2017; Received in revised form 27 April 2018; Accepted 3 May 2018

The Eurasian steppe belt is an example of a grassland region that has experienced widespread cropland abandonment, starting in the 1980s. Much of the Eurasian steppe belt is located in the former Soviet Union, and a major share of this region was plowed and converted into croplands during the Soviet Virgin Land Campaign (McCauley, 1976). While the region continues to be one of the world's major bread baskets (Swinnen et al., 2017), it experienced substantial cropland abandonment after the breakdown of the Soviet Union (Baydildina et al., 2000; Schierhorn et al., 2013). This may create an opportunity for mitigating environmental impacts of pre-abandonment land uses and restoring steppe ecosystems (Gerla et al., 2012), as biodiversity and soil carbon stocks can recover with adequate grazing levels and fire regimes (Benayas et al., 2007; Brinkert et al., 2016; Kamp et al., 2011; Kurganova et al., 2014; Sala et al., 1996). Yet, it takes time for soil and vegetation to fully recover, and while both depend on many factors, previous land use is a key factor (Wright et al., 2012). Identifying those areas that have recovered most, and that might be most valuable from a conservation perspective, depends on understanding land abandonment trajectories. However, reliable data of the exact timing of cropland abandonment in this vast region does not exist.

Remote sensing can play a key role in mapping the extent of cropland abandonment, for example in Eastern Europe (Alcantara et al., 2013; de Beurs and Ioffe, 2014; Estel et al., 2015; Prishchepov et al., 2012a), the African Sahel (Tong et al., 2017; Leroux et al., 2017), and in Central Asia (de Beurs et al., 2015; de Beurs and Henebry, 2004). Most studies that have focused on large areas have relied on coarser resolution data, mainly from the Moderate Resolution Imaging Spectroradiometer (MODIS, Alcantara et al., 2013; Estel et al., 2015; Yin et al., 2014). While MODIS data provide the high temporal resolution needed to monitor gradual processes such as post-abandonment recovery, MODIS and similar sensors (e.g., VIIRS) lack the temporal depth to assess agricultural abandonment trends in the post-Soviet era of the 1990s. Landsat Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM+), and Operational Land Imager (OLI) data has a higher spatial resolution and the long temporal record, reaching back into the 1980s, allowing to characterize land use since late Soviet times. However, existing Landsat-based work in the Eurasian steppe belt has relied on snapshots in time and generally lacked the temporal density to detect the exact timing of abandonment and recultivation (Kraemer et al., 2015; Baumann et al., 2011; Prishchepov et al., 2013). For example, cropland systems in Eurasia's steppes are often characterized by a few years of cultivation followed by one fallow year. Thus, studies relying on a few snapshots in time, as in Kraemer et al. (2015), may therefore confuse fallow periods with abandonment, or miss abandonment phases altogether if areas are put back into production after a few years. With the global availability of Landsat time series data (Wulder et al., 2016), there are now opportunities to overcome these issues by mapping cropland abandonment and recultivation at annual intervals.

Mapping cropland dynamics is challenging because of the high inter- and intra-annual spectral variabilities of cropland (Prishchepov et al., 2012b; Yin et al., 2014). Landsat-based time series approaches can help to overcome these challenges and several such approaches have recently been developed, albeit not with a focus on cropland dynamics. These approaches can be broadly categorized into two groups. The first involves time-series-based classifications of annual land cover (e.g. Vogelmann et al., 2009; Zhu, 2017) that captures transitions between land cover classes. The second category of time series approaches fits temporal trajectories to spectral indices for detecting vegetation changes (e.g. Forkel and Wutzler, 2015; Kennedy et al., 2010; Verbesselt et al., 2010), which can detect abrupt breakpoints and continuous trends, but cannot be used if the target class is spectrally highly variable, as is the case with croplands. A useful approach for overcoming these limitations, and making use of the advantages of both groups of time series approaches, is to first predict land-cover probabilities and then use time series of these probabilities as spectral metrics in trajectory-based change algorithms. Such an approach has so far only been applied to MODIS imagery (Yin et al., 2014, 2018) and it remains to be tested whether this approach can be transferred to Landsat time series to map cropland dynamics.

Another challenge for mapping gradual land-use trends with Landsat time series is variable data availability. While some areas, such as the conterminous Unites States or Australia, have a very high availability of Landsat imagery back to the 1980s (Wulder et al., 2016), imagery is scarce for many areas on the globe for at least some periods, often the 1990s (Kovalskyy and Roy, 2013). This is also one of the main challenges in utilizing Landsat imagery for mapping cropland abandonment and recultivation in post-Soviet countries, as data acquisition in the 1990s was often lower, while a majority of abandonment happened in this period. It is thus unclear whether it is possible to detect cropland abandonment and recultivation given such constraints in image availability (Kovalskyy and Roy, 2013; Loveland and Dwyer, 2012).

Our overarching goal therefore was to develop and test a trajectory-based mapping of cropland abandonment and recultivation in Eurasia‘s steppes. Focusing on northern Kazakhstan, we use all available Landsat imagery between 1984 and 2016 to create annual maps of cropland abandonment and recultivation, and to assess the impact of data sparseness on the reliability of our maps. Specifically, we addressed the following research questions:

1. How well do trajectory-based analyses of Landsat time series capture land abandonment and recultivation?
2. How do data-scarce periods affect the accuracy of time series analysis?
3. What is the potential value of more detailed information on abandonment for understanding agricultural dynamics and their environmental impacts?

2. Methods

2.1. Study area

Our study region covers ~79,000 km^2 in the Kostanay Oblast in northern Kazakhstan and considerably smaller border areas of Russia (Fig. 1). The area is interesting from the perspective of methods development for a number of reasons. First, Landsat data availability was scarce in the area during the 1990s. Such a situation is representative for post-Soviet countries and testing the robustness of methods towards data scarcity is therefore important. Secondly, the region is characterized by dynamic and regionally variable patterns of abandonment and recultivation, while at the same time allowing for comparisons with cropland areas that were farmed continuously. Third, the area experienced land-use change patterns typical for the whole region, i.e., cropland abandonment starting in the 1990s and recultivation after 2000 (Meyfroidt et al., 2016). Moreover, we have substantial knowledge of land-use processes in the region, including extensive land-use data useful for ground-truthing from several extensive field trips to the area.

The terrain in the study region is mostly flat, with elevation ranging between 150 and 300 m above sea level. Climate is continental, with cold and windy winters, followed by hot and dry summers. Annual precipitation varies depending on latitude from 250 to 400 mm. Average monthly temperatures range between −18 °C in February and +22 °C in July (Ilyakova et al., 2016). These climatic conditions result in a rather short growing season of about 150–180 days (Afonin et al., 2008), and snow cover for approximately 150 days per year (Kauazov et al., 2016). The most common soils are *Chernozems* in the more humid north and *Kastanozems* in the drier southern part of the study area (Beznosov and Uspanov, 1960). Both soil types are generally well-suited for agriculture.

The region has a long land-use history, characterized by nomadic pastoralism for millennia. Cropland cultivation started in the 19th

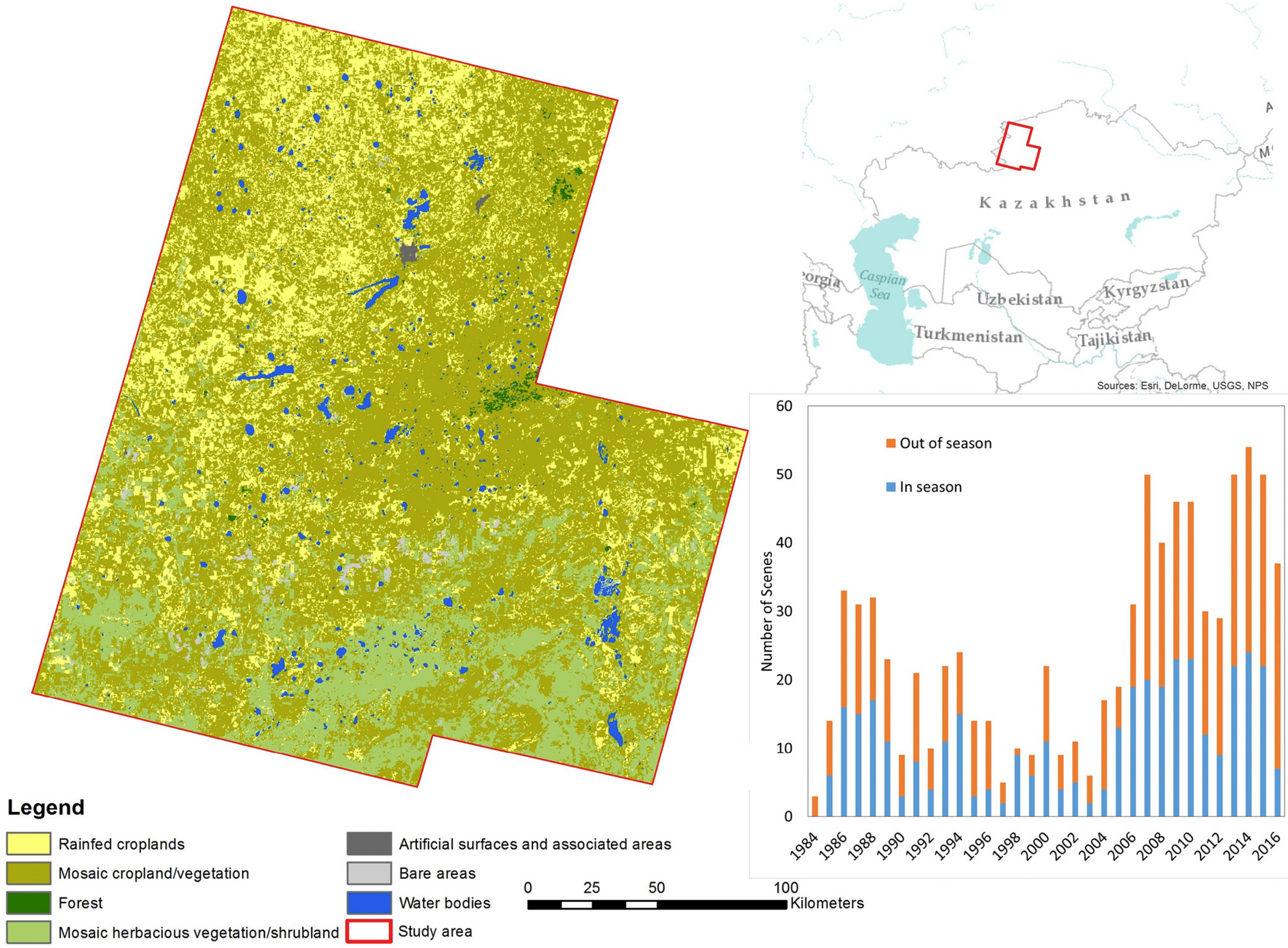

Fig. 1. Study area and data availability. Left: Land cover from GlobCover 2009 (ESA 2010 and UCLouvain). Upper right: Study region in Central Asia. Lower right: Chart of data availability with number of scenes suitable for separating cropland from grassland (in orange: DOY 132 to167 for plowing, and 231 to 294 for harvesting). Landsat data from other DOY in blue. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

century when Russian settlers started growing wheat crops. Yet substantial cropland expansion happened in the 1950s during Khrushchev's Virgin Lands campaign, when most of the region was plowed, reaching the largest cropland extent in 1963. Neither effects on the environment (Grote, 1997; Josephson et al., 2013), nor severe climatic conditions (Lioubimtseva and Henebry, 2012) were taken into account when converting grasslands to croplands, leading to the abandonment of some areas already during Soviet times. Following the breakdown of the Soviet Union, large wheat cultivation areas were abandoned (Baydildina et al., 2000; Schierhorn et al., 2013). This process was driven by the change from state-controlled to market-oriented economies (de Beurs and Henebry, 2004; Meyfroidt et al., 2016; Prishchepov et al., 2012a), the subsequent decline in agricultural subsidies (Lioubimtseva and Henebry, 2009), and strong rural outmigration (Danzer et al., 2013; Prishchepov et al., 2013). In parallel, livestock numbers dropped dramatically (Robinson and Milner-Gulland, 2003), resulting in a decreasing demand for fodder crops and an associated further contraction of cropland after 1990. Recently, recultivation of abandoned cropland has occurred (Meyfroidt et al., 2016) and governmental programs ("Kazakhstan 2020", Nazarbayev, 2010) seek to revive the livestock sector including through using some of abandoned fields as managed grasslands.

Today, croplands are primarily found in the northern part of the region with its more fertile *Chernozem* soils, whereas livestock grazing is the dominating land use in the drier southern part of our study region. Spring wheat is the historically predominant crop in the region, and only smaller areas are planted with flax, rape, sunflower, and potatoes, however, there has been a tendency to diversify crops in recent years (Ministry of Agriculture of the Republic of Kazakhstan, 2014). The agricultural cycle in the region usually starts with plowing and sowing between mid-May to mid-June. The peak of vegetation growth is in June, and harvesting takes place from late August to late October, depending on weather conditions. Agricultural fields are left fallow for one year once in five to ten years as part of the crop rotation cycle to restore soil water potential. During this fallow year the fields are either being plowed but not sown (so-called "black *par*"), or receive a large amount of herbicides, glyphosate in particular ("chemical *par*"). In recent years, farmers also increasingly use no- or low-till practices. No-till was used on over > 1 million ha of cropland in Kazakhstan in 2008 and has increased substantially since 2004 (Kienzler et al., 2012; Derpsch et al., 2010). We describe cropping practices that are most common in the study area. However, the area is considered risky for wheat cropping because of frequent droughts, moreover, not all farmers follow good cropping practices, such as crop rotation.

2.2. Generating annual Landsat time series of spectral variability metrics

We acquired surface reflectance data for three Landsat footprints

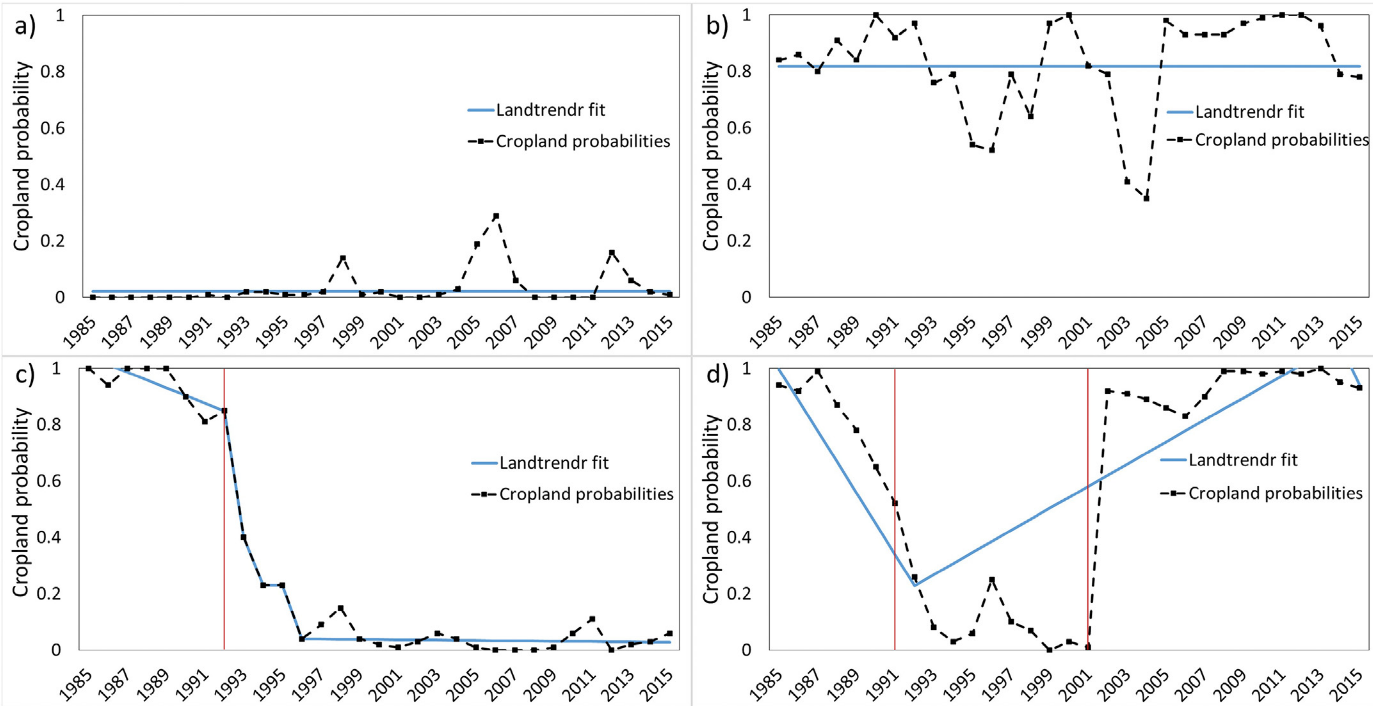

Fig. 2. Cropland probability time series and LandTrendr fit. Black: cropland probability for the respective year. Blue: LandTrend segments. Examples for (a) stable non-cropland, (b) stable cropland with crop rotation and intermittent fallow years, (c) abandonment, and (d) abandonment and recultivation. Red vertical line: the breakpoints detected by our algorithm. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

(WRS-2 paths/rows 161/23, 161/23, and 160/24) for all years between 1984 and 2016 from Landsat TM/ETM+/OLI both from the United States Geological Survey (USGS, 783 scenes) and from the European Space Agency (ESA, 38 scenes) archives (Fig. 1), as the Landsat archive consolidation is still ongoing, and not all ESA scenes are available at the USGS. From the USGS archives, we acquired orthorectified and terrain-corrected (L1T) imagery including cloud and cloud shadow masks based on CFMask (USGS, 2015). Imagery from the ESA archive had to undergo additional geometric correction, as well as cloud and cloud shadow masking. We applied the automated precise registration and orthorectification package (AROP) that resamples all images to a common base image to align the ESA data to the USGS data (Gao et al., 2009). After orthocorrection, we masked clouds and cloud shadows with the Function of Mask (FMask) algorithm (Zhu and Woodcock, 2012), applied the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) for atmospheric correction of Landsat TM and ETM+ imagery (Masek et al., 2006), and followed Vermote et al. (2016) to correct the OLI images.

We considered images between day of year (DOY) 80 and 319, as this approximately corresponds to the period without snow cover. Applying a cloud cover threshold of $< 80\%$ resulted in 821 images across the three footprints in our study area (Fig. 1). The images were not equally distributed over the years, but featured a period of particularly low data availability during the late-1980s and mid-1990s. While wheat can be separated from grassland in intensively managed systems, cropping in Kazakhstan often does not reach highest productivity (e.g. due to low fertilizer inputs), leading to confusion with grasslands. To allow differentiating croplands from grasslands, we therefore used multi-season imagery. For some years (e.g., 1984, 1997, 2003) no imagery was available from spring (plowing season, DOY 132 to 167) or fall (harvesting season, DOY 231 to 294), although these seasons are critical for separating croplands from grasslands (Prishchepov et al., 2012b; Baumann et al., 2015) as recently plowed or harvested fields allow most reliable distinction from the other land covers. To compensate, we used a temporal moving window of three years to generate spectral variability metrics (Griffiths et al., 2013b) as a first step to overcome data scarcity. These metrics statistically describe the time series of spectral values, are relatively robust to noise and seasonal fluctuations, and can serve as an input for classification algorithms (Zhu, 2017). Within each moving window, we derived the per-pixel minimum, median, maximum, mean, standard deviation, and percentiles (5, 25, 75, and 95) for the red, green, blue, NIR, SWIR1, and SWIR2 bands. In addition, we calculated the Normalized Difference Vegetation Index (NDVI), the Normalized Burn Ratio (NBR) and the Modified Soil-Adjusted Vegetation Index (MSAVI2) from which we derived the same metrics as for the six Landsat bands. In total, this yielded a set of 81 input features for each year.

2.3. Trajectory analyses to map the timing of abandonment and recultivation

Abandoned areas spectrally align along a gradient between cropped and uncropped areas. This is represented well in class probabilities of cropland vs. non-cropland classes (Yin et al., 2014, 2018). We thus derived cropland probabilities between 1985 and 2015 which then served as input for a trajectory-based approach to detect abandonment and recultivation events over time. This allowed omitting the high inter-annual spectral changes of cropland at the pixel level. Another advantage of using probabilities is their robustness against mixed pixels in the land cover class of interest (Colditz et al., 2011; Yin et al., 2014).

We used random forest classification (Breiman, 2001; Pedregosa et al., 2011) to map cropland probabilities for each year using the annual Landsat spectral variability metrics as predictor variables. We chose random forests because of the model's strength in dealing with classification problems that contain non-normal class distributions and heterogeneous input data (Abdel-Rahman et al., 2014; Breiman, 2001). Class membership probability in random forests is the proportion of tree votes for that class in relation to the total number of trees. We trained the random forest model with reference data collected over stable croplands (i.e., areas that were permanently cropped between

1985 and 2015) and stable non-croplands (i.e., areas that were never cropped) based on visual interpretation of the Landsat time series (Cohen et al., 2010). We collected 900 sample pixels for each of the stable classes (i.e., cropland and non-cropland), as this enabled us to use a single training dataset for subsequently estimating cropland probabilities for each year. We identified agricultural fields considering their respective spectra, shape information and texture. The latter two were only used for visual interpretation. The non-cropland class included both managed and semi-natural grasslands, as well as water, urban land, forests, sand, wetlands, and salt marshes ("*solonchak*"). This resulted in annual maps of cropland probabilities for our study area.

We then used the temporal segmentation and change detection algorithm LandTrendr (Kennedy et al., 2010) on the annual time series of cropland probabilities to map the timing of cropland abandonment (Fig. 2). By fitting a series of linear segments using LandTrendr, we further reduced remaining inter-annual noise while capturing abrupt change events and gradual change. LandTrendr was originally designed to analyze forest disturbances, but recent applications suggest its suitability in identifying cropland dynamics as well (Yin et al., 2018, 2014).

To initiate LandTrendr, four main parameters need to be set. First, a *maximum segments* parameter limits the number of trend segments allowed during the fitting process. Second, *the de-spiking* parameter limits the influence of single outliers with higher values resulting in less smoothing, but also less consequent spike elimination. Third, a *recovery threshold* determines the maximum length of segments representing a positive trend. All three parameters are useful for separating short-term cropland-grassland cycles from long-term abandonment signals, as one or two fallow years may be falsely identified as abandonment. Lastly, LandTrendr requires setting the so-called *p-of-F value* that determines the goodness-of-fit. We tested different values of these parameters and selected the best combination by visually evaluating both the pixel-wise trajectory fit (using ca. 50 samples) and the parcel-wise homogeneity. We considered a parcel homogeneous when pixels of the same value (e.g., the same year of abandonment) were grouped in a shape typical for agricultural fields. We then fit two LandTrendr models: one to detect cropland abandonment, and a second one for detecting recultivation. We were then able to set the *maximum number of segments*, *de-spiking* and *recovery* parameters individually for both land-use change processes, which allowed handling the different spectral-temporal nature of abandonment as opposed to recultivation. We define an area as being abandoned when three consecutive years with cultivation were followed by three consecutive years without cultivation. We deliberately omitted areas that are not in line with our definition of abandonment (i.e., we accounted for up to two fallow years, or drought years).

We applied a rule-based filter to the LandTrendr-segmented probability time series to determine whether and when cropland was abandoned or whether it was fallow in a given year. We did this by analyzing the time series based on a temporal moving window of six years (Fig. 3). We considered a cropland pixel as representing abandonment in a particular year if the average cropland probability for three years was above a pre-defined threshold, followed by three years in which the average cropland probability was below the threshold. The exact year of abandonment was defined as the first year in which the cropland probability fell under the threshold. To empirically define a probability threshold, we tested values of 0.45, 0.5, 0.55, and 0.6, produced an abandonment map based on each of the thresholds, and visually selected the most appropriate one i.e., the threshold that led to homogeneous parcels and plausible spatial patterns according to expert knowledge of the area.

We also identified recultivated croplands that were previously abandoned for at least three consecutive years. Similar to the detection of abandonment, we categorized a pixel as representing recultivation if the mean cropland probability value for the first three years of recultivation was below a pre-defined threshold and the mean cropland probability before recultivation was above the threshold. We then defined the year of recultivation as the first year when the cropland probability was above the threshold (Fig. 3). Analogous to the abandonment detection, we tested a range of thresholds.

2.4. Map validation

To validate the abandonment and recultivation maps, we followed the good practices for accuracy assessments (Olofsson et al., 2014) based on a stratified-random sample of validation points derived from visually interpreting the Landsat time series and high-resolution imagery in Google Earth, if available (Cohen et al., 2010). We did two types of accuracy assessments for which we collected independent validation data. First, we validated the classification of stable croplands, stable non-croplands, abandoned croplands and recultivated croplands. Then, we assessed the accuracy of the annual abandonment and the annual recultivation maps. We randomly selected 50 pixels from each stable class and 30 pixels per year from the abandoned cropland classes (30×25 years = 750 samples). To adequately assess recultivation, we selected 20 pixels per class (i.e., per year) during the last 22 years, as there were not enough points representing recultivation from the first dataset. Thus, we selected 1290 independent reference samples in total.

Considering the gradual spectral change on abandoned land and, consequently, the complicated nature of visually identifying abandoned croplands, we applied a fuzzy validation approach allowing a confidence interval of ± 1 year. We then generated a confusion matrix, and estimated the overall accuracy and user's (UA) and producer's accuracies (PA) including the corresponding standard errors by adjusting for the unequal probability sampling (Olofsson et al., 2014). We also calculated area estimates and associated confidence intervals (Olofsson et al., 2014).

As a final confidence check, we compared our results to field-based estimates of the timing of cropland abandonment. We used 115 quadrats of $10 \times 10\,m^2$ from a vegetation survey carried out in Kostanay province in 2015 and 2016 and followed the methods described in Brinkert et al. (2016). All plots were categorized into seven land-use classes, namely (1) croplands under cultivation, (2) recently abandoned croplands (after ca. 2011), (3) medium-long abandoned croplands (between ca. 2000 and ca. 2011), (4) longer-term abandoned croplands (before ca. 2000), (5) fodder grass fields (cut for hay, sown with crested

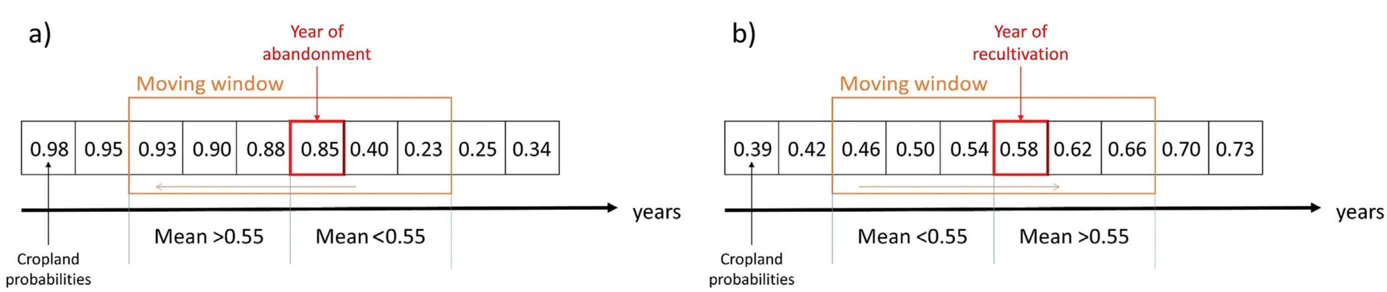

Fig. 3. Ruleset for detecting timing of (a) abandonment and (b) recultivation within a moving temporal window of six years. Cropland probabilities in the figure represent fitted LandTrendr outputs of typical abandonment and recultivation cases.

wheatgrass *Agropyron cristatum*), (6) heavily grazed steppe, and (7) ungrazed ("pristine" steppe). The distinction between the different time periods of land abandonment was based on the dominance of plant species that are characteristic for certain age stages of abandoned fields in Kazakhstan (Marinych et al., 2002; Brinkert et al., 2016). Recently abandoned croplands are characterized by high cover of annual plants, medium-old ones by the dominance of certain *Artemisia* (wormwood and sagebrush) species, and the oldest ones by a higher cover of native steppe grasses of the genera *Stipa* and *Festuca*. For our study, we lumped classes 5–7 into one "non-cropland" category. We categorized the map classes from the remote sensing analysis accordingly and compared the time since abandonment estimated in the field to our abandonment map. Finally, we summarized the results in a confusion matrix.

2.5. Assessing the influence of image availability

We extracted the number of available clear-sky observations for each pixel and year for the time periods used to compute the spectral variability metrics to study how image availability affected the accuracy. First, we analyzed the difference between the year of abandonment detected by our algorithm and the year according to the reference from the validation dataset. We then assessed how this difference related to the number of images available in the year of abandonment according to our map, and the year of abandonment according to the reference. Finally, we investigated the difference in the number of scenes in temporal windows around the actual abandonment year (reference data) and the year of detection based on the Landsat time series.

2.6. Assessing the impact of the timing of abandonment

Using our time series of cropland abandonment, we carried out two comparisons to demonstrate the value of knowing the exact timing of abandonment. First, we calculated the overall area of abandonment and recultivation for each year, as well as corresponding change rates between the years. We also calculated the number of years since abandonment and marked a year of abandonment for each pixel that we identified as "recultivated" to understand if recultivation primarily occurred on recently abandoned croplands or on those abandoned earlier.

Second, we compared soil organic carbon (SOC) sequestration rates on abandoned croplands between our temporal exact information of abandonment, and for two scenarios assuming (a) that all abandonment occurred in 1990, and (b) assuming that all abandonment occurred in 2010. This represented scenarios one could assume for situations where cropland abandonment was mapped for broad time-intervals only, corresponding to prior existing research for the region. To estimate the difference in post-abandonment SOC sequestration, we combined SOC sequestration rates from an extensive field study for the region, based on 470 field plots (SOC stock in 0–5 cm ~0.066 kg/m^2/year, Wertebach et al., 2017) with the area estimates from our classification. We calculated annual SOC sequestration as well as SOC sequestration for the entire period 1990–2010, considering the confidence intervals in area estimations from our classification to calculate upper and lower confidence levels around our SOC sequestration estimates.

3. Results

The overall accuracy of the aggregated map (i.e., one abandonment and recultivation class) was 88.8%. UA was highest for the abandonment class (93.3%) and lowest for the recultivation class (73.0%). PA was highest for the recultivation class (95.1%) and lowest for the abandonment class (65.2%, Table 1). For the annual abandonment map and annual recultivation map (Fig. 4), classification accuracies for the individual years were lower and varied strongly between individual years. The overall accuracy of the maps with yearly abandonment classes and yearly recultivation classes was 80.0% and 88.0%, respectively. For the year 2013, we achieved the highest UA (97.4%). On the contrary, for 2004 our UA was only 14.9%. The highest PA were achieved in 2006 (100.0%) and lowest PA were achieved in 2004 (25.3%; Table 2). Similarly, UAs for the recultivation map varied between 100.0% (2008 and 2010) and 14.5% (1995), as did PAs (100.0% for 1992–1994, 1996–1999, 2012; 54.8% for 2003).

Table 1
Accuracy assessment of the aggregated map of abandonment and recultivation (disregarding the year of abandonment/recultivation).

Class	User's accuracy (standard error)	Producer's accuracy (standard error)	Area proportion estimate (standard error)
Stable cropland	0.84 (0.02)	0.93 (0.01)	0.321 (0.014)
Stable non-cropland	0.93 (0.01)	0.94 (0.01)	0.455 (0.012)
Abandonment	0.93 (0.02)	0.65 (0.02)	0.180 (0.014)
Recultivation after abandonment	0.73 (0.05)	0.95 (0.03)	0.044 (0.006)

When assessing the reliability of our maps using a fuzzy accuracy assessment classification, accuracies increased moderately. For the abandonment map, the overall classification accuracy increased by 3.8% and for the recultivation map by 1.6%. We found stronger increases in classification accuracies for individual years. On average, per-year UAs and PAs increased by 20.3% and 24.2%, respectively, in our yearly abandonment maps and by 24.0% and 34.0% for UAs and PAs, respectively, in our yearly recultivation maps.

Comparing our mapping results to the field-based timing of abandonment generally showed high agreement. Overall, 76% of the classes in our map showed an agreement with the categories from the field inventories based on vegetation composition (Table 3). In 57.4% of all cases the mapped year of abandonment differed by ± 1 year compared to the validation data and 70.8% matched within ± 3 years (Fig. 6). Our algorithm tended to identify the year of cropland abandonment later than in the validation dataset (Fig. 6 and Fig. 7). This trend correlated with the number of images available for the yearly cropland classification (Fig. 7 and Fig. 8). For example, the difference between the number of scenes in a temporal window of 6 years rarely exceed 50 when the difference in abandonment year detected visually vs. by our algorithm was < 5 years, but much higher (up to 200 images) if the difference in abandonment year was high.

According to our area estimation, ~4.7 million ha of the study area were cultivated as cropland in 1985, equaling 59.8% of the region. By 2013, 1.8 million (~40.5%) ± 54,000 ha of the previously cultivated land was abandoned. More cropland was abandoned between 1988 and 2000 compared to 2000–2013. The maximum annual abandonment of ~250,000 ± 73,000 ha we found for the year 1995, equaling 13.0% of all cropland abandonment for the entire period (Fig. 5). Contrarily, we found the smallest area of abandonment in 2012 (~7000 ± 10,000 ha, 0.3%).

A substantial proportion of the abandoned cropland had been recultivated by the end of our study period in 2013, with ~350,000 ± 54,000 ha recultivated by that time (20.0%). Recultivation peaked in 2005, when ~32,000 ± 20,000 ha were recultivated (8.0% of all recultivation), while lowest recultivation rates occurred in 1995 (2.2% of all recultivation). Fields were more likely to be recultivated when abandonment had occurred < 5 years ago (9.6%). Moreover, once an area was abandoned for > 13 years, it was much less likely to become recultivated (of all areas abandoned longer than 13 years, only 34.0% were recultivated; Fig. 5).

Estimated SOC sequestration on abandoned cropland showed marked differences when based on our annual map (16.3 ± 3.5 Mt. C) compared to scenarios that assumed all cropland abandonment had happened in 1990 (24.0 ± 5.8 Mt. C) or in 2010 (3.3 ± 0.8 Mt. C). Interestingly, the highest annual sequestration rate was fairly similar when comparing our map (1.07 Mt. C for the year 2013) to the other

Remote Sensing of Environment 213 (2018) 49–60

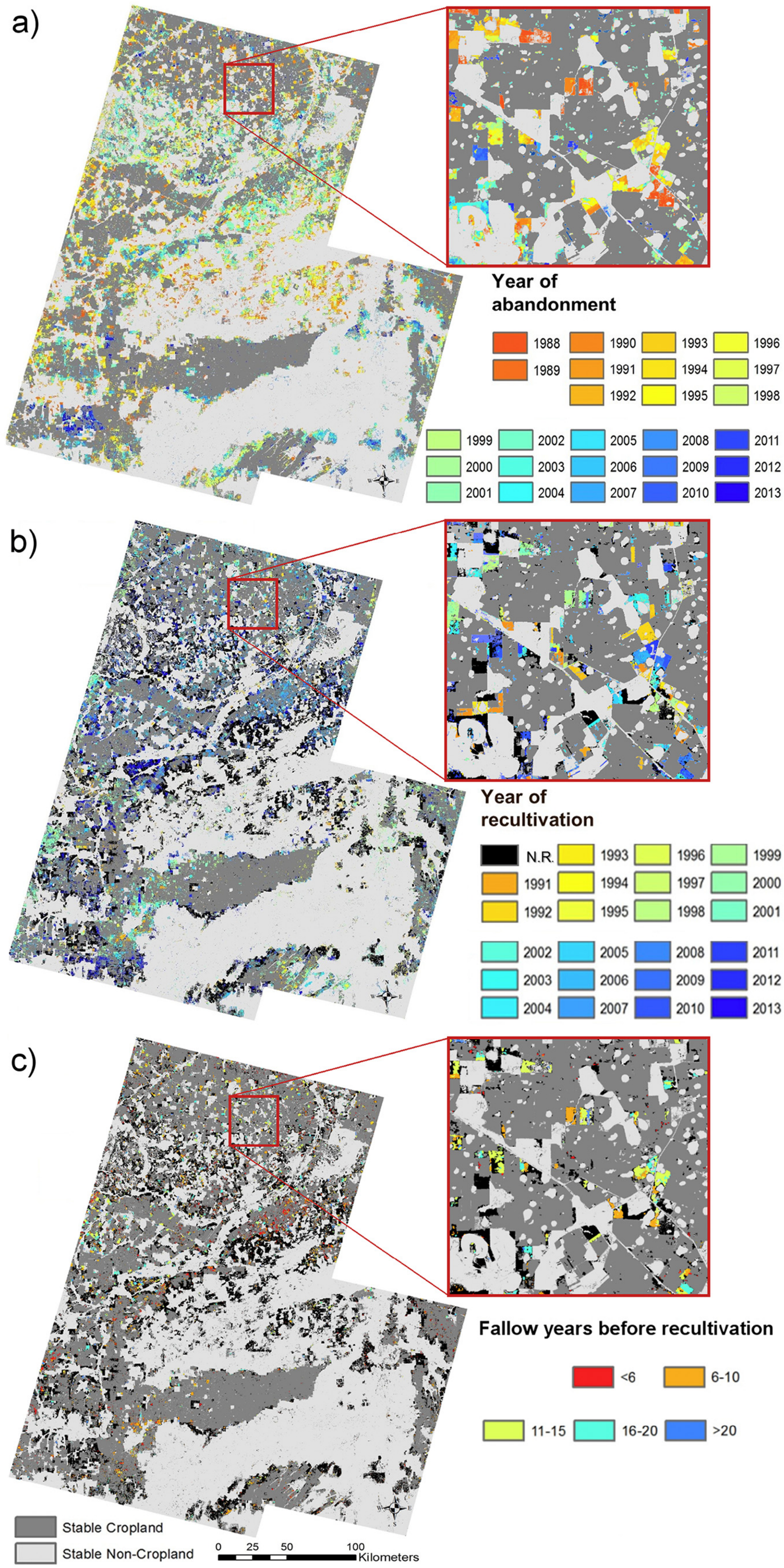

Fig. 4. Maps of abandonment timing in northern Kazakhstan from 1988 to 2013 (a), recultivation timing in northern Kazakhstan from 1991 to 2013 (b), and years between the abandonment and recultivation (c). N.R. means not recultivated as for 2013.

Table 2
Fuzzy accuracy assessment per year.

Class	Abandonment		Recultivation	
	User's accuracy (standard error)	Producer's accuracy (standard error)	User's accuracy (standard error)	Producer's accuracy (standard error)
1988	0.46 (0.13)	0.38 (0.10)	–	–
1989	0.71 (0.21)	0.38 (0.12)	–	–
1990	0.86 (0.16)	0.48 (0.12)	–	–
1991	0.76 (0.19)	0.48 (0.13)	0.78 (0.17)	0.80 (0.15)
1992	0.71 (0.21)	0.64 (0.18)	0.63 (0.41)	1.00 (0.00)
1993	0.74 (0.15)	0.47 (0.10)	0.39 (0.48)	1.00 (0.00)
1994	0.74 (0.13)	0.48 (0.09)	0.76 (0.36)	1.00 (0.00)
1995	0.73 (0.13)	0.25 (0.05)	0.14 (0.37)	0.76 (0.99)
1996	0.79 (0.12)	0.36 (0.07)	0.32 (0.49)	1.00 (0.00)
1997	0.52 (0.17)	0.41 (0.12)	0.51 (0.46)	1.00 (0.00)
1998	0.79 (0.13)	0.31 (0.06)	0.34 (0.42)	1.00 (0.00)
1999	0.38 (0.12)	0.33 (0.09)	0.19 (0.16)	1.00 (0.00)
2000	0.36 (0.18)	0.49 (0.20)	0.25 (0.20)	0.90 (0.25)
2001	0.19 (0.10)	0.59 (0.20)	0.52 (0.26)	0.64 (0.23)
2002	0.20 (0.10)	0.81 (0.19)	0.87 (0.19)	0.68 (0.19)
2003	0.23 (0.11)	0.72 (0.20)	0.63 (0.29)	0.55 (0.23)
2004	0.15 (0.15)	0.25 (0.22)	0.69 (0.32)	0.67 (0.28)
2005	0.19 (0.16)	0.50 (0.31)	0.70 (0.21)	0.59 (0.17)
2006	0.23 (0.21)	1.00 (0.00)	0.59 (0.22)	0.83 (0.18)
2007	0.38 (0.22)	0.81 (0.25)	0.59 (0.20)	0.82 (0.17)
2008	0.21 (0.22)	0.05 (0.05)	1.00 (0.00)	0.83 (0.15)
2009	0.34 (0.31)	0.73 (0.40)	0.86 (0.22)	0.60 (0.21)
2010	0.29 (0.36)	0.40 (0.41)	1.00 (0.00)	0.84 (0.18)
2011	0.36 (0.38)	0.66 (0.47)	0.79 (0.21)	0.79 (0.19)
2012	0.60 (0.46)	0.83 (0.39)	0.84 (0.19)	1.00 (0.00)
2013	0.97 (0.10)	0.76 (0.20)	0.30 (0.15)	0.77 (0.21)
Cropland	0.88 (0.59)	0.93 (0.41)	0.84 (0.02)	0.93 (0.01)
Non-cropland	0.93 (0.35)	0.94 (0.31)	0.94 (0.01)	0.95 (0.01)
Abandonment	–	–	0.93 (0.02)	0.65 (0.02)

two scenarios (1.09 Mt. C). Likewise, the confidence intervals around the SOC sequestration estimates, both for the annual and overall calculation, became narrower when using our annual map (Fig. 9).

4. Discussion

Understanding spatial patterns and dynamics of agricultural abandonment is important to assess the potential of abandoned land for conservation, carbon sequestration, or agricultural production. However, existing cropland abandonment maps are either snapshots in time or lack the spatial detail needed to inform land managers at regional and national levels. To address this knowledge gap, we developed a trajectory-based method to map cropland abandonment and recultivation from annual Landsat time series. Our test area in northern Kazakhstan experienced widespread abandonment and recultivation as well as marked periods of image scarcity since the 1980s, all of which is representative for post-Soviet countries. Our study provides a number of key insights on how to utilize and optimize Landsat time series for monitoring agricultural dynamics such as land abandonment and recultivation at high temporal resolution.

First, our study demonstrates that it is possible to estimate the trends of cropland abandonment and recultivation timing in grassland regions. Using cropland probabilities classified from spectral metrics allowed us to account for inter-annual variability, and feeding these probabilities to the segmentation module of LandTrendr allowed mapping abandonment trajectories reliably in most years. Using all available Landsat data, we were able to detect the annual timing of cropland abandonment within ± one year with an accuracy of 80%, and the reliability of our maps was further confirmed by the comparison to in-situ vegetation plot data. Spectrally, cropland abandonment is a gradual, not a sudden change (Estel et al., 2015; Prishchepov et al., 2012b), which was likely better captured by our approach of using continuous cropland probabilities as input for our trajectory analyses (Yin et al., 2014) than when mapping abandonment based on image snapshots. Indeed, in the first years after abandonment former crop fields still had high cropland probabilities, and only after several years of abandonment these probabilities dropped.

A second major insight relates to the spatio-temporal patterns of abandonment that we found to have occurred in northern Kazakhstan after 1990. Our time series of abandonment revealed distinct episodes of cropland abandonment in our study area. The first of these episodes occurred right after the breakdown of the Soviet Union (1993–1999), when the vast majority of this abandonment occurred because of rural outmigration, loss of guaranteed market, and reduced funding of the agricultural sector as well as reduced profits in agriculture (Henebry, 2009; Ioffe and Nefedova, 2004). These areas that have been abandoned for a long time are likely those that are least profitable to cultivate, that is, where agroecological conditions are worst (Prishchepov et al., 2013), and socio-economic constraints strongest (Meyfroidt et al., 2016). With the breakdown of the Soviet Union and the associated declining subsidies, such areas became permanently unattractive to farmers (Prishchepov et al., 2013). Interestingly though, a second, significantly smaller wave of abandonment appeared to occur in 2007–2009, explained rather by poor infrastructure (Meyfroidt et al., 2016). Indeed, in marginal regions of our study area, cropland abandonment even continued after recultivation started elsewhere. Our approach based on annual time steps allowed the discovery of these complex land-use change patterns, because this second wave of abandonment was superposed by an increasing recultivation trend due to an increase of subsidies from the government (Meyfroidt et al., 2016). The recultivation wave started in 2001 and reached the rates of abandonment by 2003, dropped slightly afterwards, and stabilized by 2008.

We compared our abandonment map to the only other existing Landsat-based map we know of for Kazakhstan (Kraemer et al., 2015). Our map shows smaller rates of abandonment (26% between 1990 and 2010), compared to 45% in Kraemer et al. (2015). We suggest our estimate is more reliable and this difference can mainly be explained by crop rotations. Studies based on two time periods (Kraemer et al., 2015; Baumann et al., 2011; Prishchepov et al., 2013) only overestimate abandonment area due to fallowing, which is widespread in the study region. An alternative explanation could be that our approach underestimated abandonment in the 1990s due to a tendency for time-

Table 3
Confusion matrix according to vegetation plots based on field observations.

		Reference					Sum
		Non-cropland	Abandoned after 2010	Abandoned between 2000 and 2009	Abandoned before 2000	Cropland	
Classification	Non-cropland	59		2	6	1	68
	Abandoned after 2010		2				2
	Abandoned between 2000 and 2010			4			4
	Abandoned before 2000	6	1	1	2	2	12
	Cropland	3	3	1		22	29
	Sum	68	6	8	8	25	115

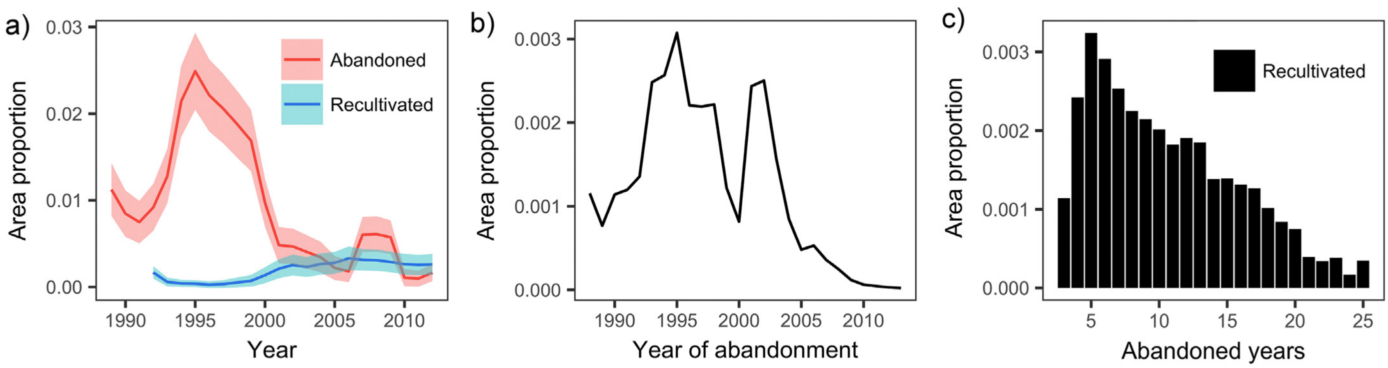

Fig. 5. Analysis of dynamics of cropland abandonment and recultivation in 1988–2015. (a): red - area proportion of abandoned land, blue - recultivated land, both with respective standard error, (b): year of abandonment event on recultivated parcels. (c) duration of fallow period before recultivation. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

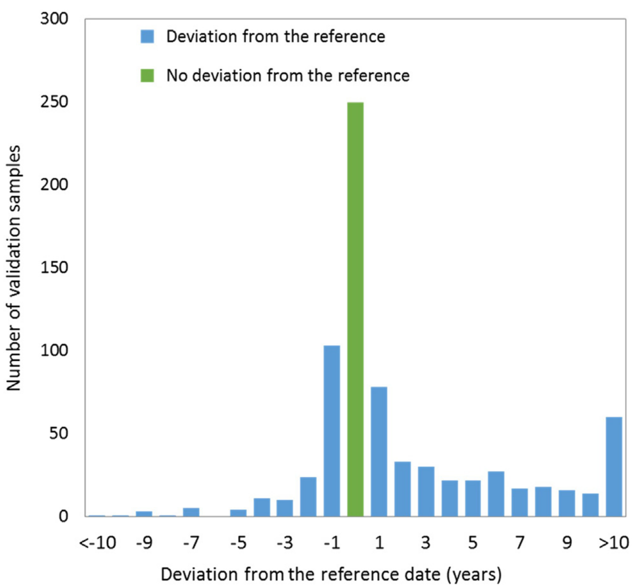

Fig. 6. Deviation of abandonment dates relative to the reference dataset.

delayed abandonment detection, but the substantially higher overall accuracy in our study (88% compared to 78% in Kraemer et al. (2015)) suggests this plays a lesser role in explaining the different abandoned area estimates of the two studies.

A third major insight from our study was that about one fifth of all abandoned croplands had been recultivated by 2013. Most of these areas were located in more fertile and productive areas with Chernozem soils (based on a qualitative comparison to soil samples taken at the vegetation plots we used), again indicating that recultivation primarily occurred in areas where farming conditions are best. This is in line with existing research on the post-Soviet region (Prishchepov et al., 2012a; Meyfroidt et al., 2016; Kraemer et al., 2015; Griffiths et al., 2013a). This indicates a spatial reorganization of agricultural production in northern Kazakhstan towards the most profitable areas.

A fourth major insight was that image availability substantially influenced the ability to accurately determine the timing of abandonment and recultivation. For some years, accuracy was much lower, especially during the early 2000s. A similar effect was found in earlier pan-European work (Estel et al., 2015), and we suggest at least two factors may explain these lower accuracies. First, despite ongoing Landsat archive consolidation (Wulder et al., 2016), wide areas of Central Asia continue to be relatively data scarce for the 1990s. As a consequence, our spectral metrics during these years may not have been as robust as compared to the 1980s, or 2000s, when more imagery are available (Wulder et al., 2008). For example, fewer images can be expected to lead to higher variability in spectral metrics of abandoned areas (e.g., due to a higher influence of outliers or phenology), and this might obscure abandonment signals, resulting in a delayed detection of abandonment (Fig. 7). Moreover, it is difficult to detect croplands when the spectral breakpoints related to plowing and harvesting are missing

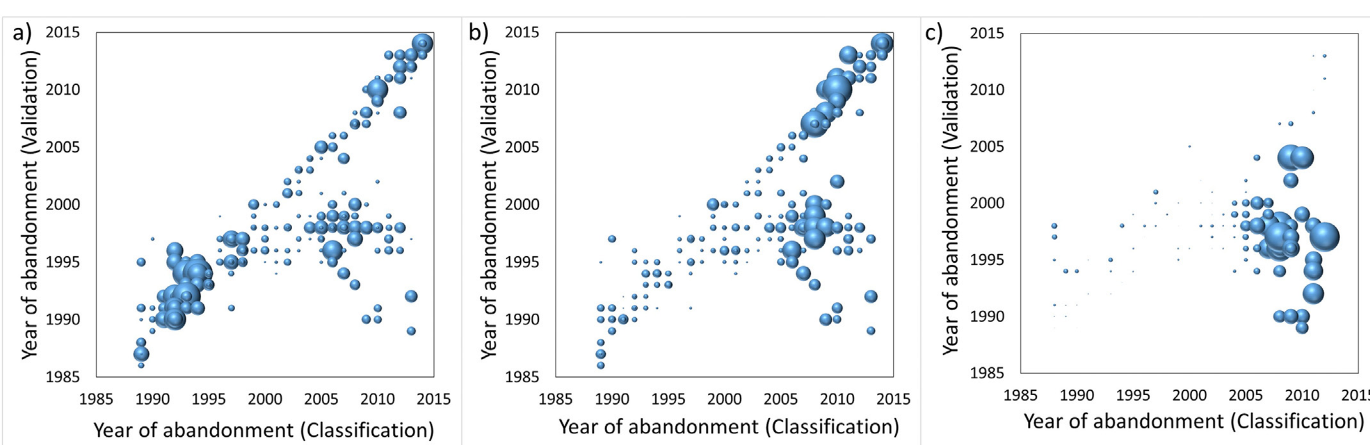

Fig. 7. Scatter plots of the abandonment date detected by our algorithm versus dates detected by visual interpretation. The size of the points represent: a) the number of scenes used in spectral variability metrics in a year of abandonment according to visual interpretation; b) the number of scenes used in spectral variability metrics in a year of abandonment according to automatic detection; c) a difference between the number of scenes used in spectral variability metrics in a year of abandonment according to visual interpretation and the number of scenes used in spectral variability metrics of a year of abandonment according to automatic detection.

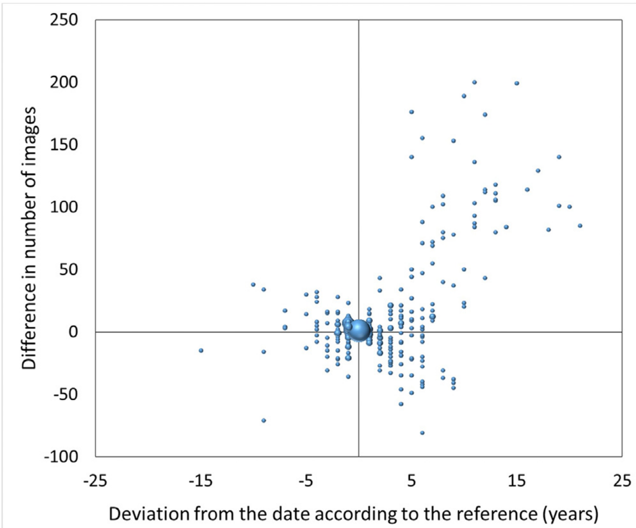

Fig. 8. Dependence of deviation of identified abandonment year on data availability. On horizontal axis is deviation of abandonment dates estimated by our algorithm from the dates according to the reference dataset. Vertical axis represents the difference between the number of scenes used for detecting abandonment using visual interpretation and the number of scenes used for detecting abandonment using automatic interpretation. The point size is proportional to the number of points with the same Cartesian coordinates of the plot (the size of the central bubble is reduced to 30 from 103 for visibility purposes).

in the time series, or no-till technology is applied, as it is increasingly the case in recent years in our study region. No-till farming leads to less abrupt changes in the abandonment (or recultivation) signal and generally decreases the signal-to-noise ratio of the time series (i.e. time series variability compared to the signal-change related to non-cropping). Second, even after cultivation ceased, the spectral characteristics of abandoned fields can remain similar to managed cropland for a while (Estel et al., 2015; Prishchepov et al., 2012b), such as when crops from previous years dominate successive vegetation (Carson and Barrett, 1988), or crop residue retention (i.e., when farmers keep stubble longer than usual in order to detain snow on the field) is practiced (Kienzler et al., 2012). Field observations and conversations with local farmers suggest both can occur in our study area for up to 3 years, explaining smaller timing errors. Another reason for lower user accuracies in years 1999–2013 is the small area proportion of the abandonment class during these years. Our maps thus might underestimate land-use change for these years. However, it is important to note that our area estimates are not retrieved from the maps, but instead calculated using a post-stratified estimator and the probability sample of visually interpreted plots, thus accounting for classification uncertainty (see Olofsson et al., 2014). Despite related uncertainties, we emphasize that our approach resulted in a map that allowed identifying the timing of abandonment within ± one year in the majority of cases, highlighting the value of long time series of Landsat data.

A final key insight from our study was the value of knowing the timing of abandonment for a better understanding of agricultural land-use change and its environmental impacts. Our results showed that abandoned croplands were less likely to become recultivated the longer they stayed abandoned, especially if they were abandoned for five or more years. As explained above, the least profitable areas with poorer soils were abandoned first. Similarly, accurate information on the timing of abandonment can help to better estimate the environmental outcomes of abandonment, as in our assessment of SOC sequestration on abandoned croplands. Without precise abandonment maps, estimations of SOC sequestration could be either under- or overestimated (the first by 80%, and the latter by up to 47%), and the uncertainty around these estimates is much lower than without annual time series. Much research effort has gone into quantifying the terrestrial carbon sink that has emerged due to cropland abandonment in the post-Soviet sphere (Kurganova et al., 2014; Schierhorn et al., 2013; Vuichard et al., 2008), and our study highlights the need for incorporating time series of abandoned and managed cropland for making these estimates more accurate. Similarly, the biodiversity value of abandoned cropland largely depends on the time since abandonment, with older sites being closer to natural steppes in terms of species composition and structural and functional characteristics (Brinkert et al., 2016; Kamp et al., 2011; Kämpf et al., 2016). Knowing the timing of abandonment is thus important from a conservation perspective as well, as it would allow researchers to target those areas with the highest carbon accumulation and the lowest chance of being recultivated (Gerla et al., 2012), thus minimizing conflicts due to competing land-use interests.

Our analyses yielded robust and plausible abandonment maps, but a few uncertainties remain. First, LandTrendr may confuse shorter fallow periods with abandonment, but visual comparison of more restrictive threshold suggests this effect is minor in our case. Furthermore, we consider only one abandonment event per pixel, while in theory more complex land-use change patterns are possible. Third, our method

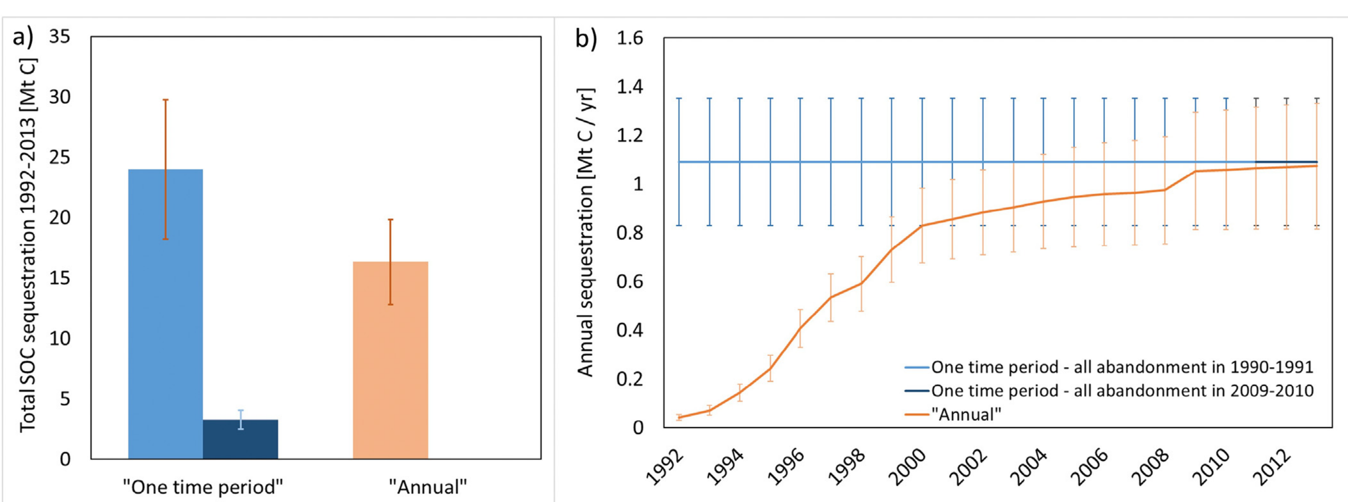

Fig. 9. Difference in estimates of a) total SOC sequestration and b) annual SOC sequestration rates when using annual estimates of abandonment area (in orange) versus assuming abandonment in 1990 (light blue) or in 2010 (dark blue). Confidence intervals are based on abandonment area estimates. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

reduces the time series length. Although we used imagery from 1984 to 2016 (32 years), our temporal moving window approach reduced this to 30 years, and our trajectory ruleset allowed for abandonment mapping only between 1988 and 2013 (25 years) and recultivation mapping from 1991 to 2013 (22 years). Finally, following our definition of recultivation we only mapped cropland expansion on previously abandoned areas. However, to our knowledge there was no significant cropland expansion in previously unplowed areas. Despite these limitations, we suggest that our method has great potential to be used in similar areas, provided adequate training data for croplands and non-croplands exists. Our method can be flexibly scaled and thus should be applicable to larger areas as well.

The opening of the Landsat archive provides unprecedented opportunities to reconstruct land-use and land-cover change histories back to the 1980s based on dense image time series of high-resolution imagery since the 1980s. So far, these opportunities have mainly been leveraged for mapping dynamics in forest cover, but our study highlights the value of the Landsat archives for an improved agricultural monitoring as well. Our approach to combine class probability time series with trajectory approaches overcame two challenges common to agricultural monitoring, with the high spectral within-class variability on the one hand and data sparseness common for many world regions on the other. Finally, our study highlights the possibility of Landsat to provide more accurate land-use/cover change maps in steppe regions, which have been understudied, and thus providing baseline information for conservation planning and land-use planning.

Acknowledgements

We thank D. Mueller and A. Prishchepov for valuable comments and B. Jakimow for help with the coding. We are grateful for the financial support by the Volkswagen Foundation through the project BALTRAK (#A112025). This research contributes to the USGS Landsat Science Team (http://landsat.usgs.gov/) and the Global Land Program (GLP, www.glp.earth). We thank three anonymous reviewers for their very useful and constructive comments.

References

Abdel-Rahman, E.M., Mutanga, O., Adam, E., Ismail, R., 2014. Detecting *Sirex noctilio* grey-attacked and lightning-struck pine trees using airborne hyperspectral data, random forest and support vector machines classifiers. ISPRS J. Photogramm. Remote Sens. 88, 48–59. http://dx.doi.org/10.1016/j.isprsjprs.2013.11.013.

Afonin, A.N., Greene, S.L., Dzyubenko, A.N., Frolov, A.N., 2008. Interactive agricultural ecological atlas of Russia and neighboring countries. In: Economic Plants and their Diseases, Pests and Weeds, (Online).

Alcantara, C., Kuemmerle, T., Baumann, M., Bragina, E.V., Griffiths, P., Hostert, P., Knorn, J., Müller, D., Prishchepov, A.V., Schierhorn, F., Sieber, A., Radeloff, V.C., 2013. Mapping the extent of abandoned farmland in central and Eastern Europe using MODIS time series satellite data. Environ. Res. Lett. 8, 035035. http://dx.doi.org/10.1088/1748-9326/8/3/035035.

Anderson, J., 1991. The effects of climate change on decomposition processes in grassland and coniferous forests. Ecol. Appl. 326–347.

Baumann, M., Kuemmerle, T., Elbakidze, M., Ozdogan, M., Radeloff, V.C., Keuler, N.S., Prishchepov, A.V., Kruhlov, I., Hostert, P., 2011. Patterns and drivers of post-socialist farmland abandonment in western Ukraine. Land Use Policy 28, 552–562. http://dx.doi.org/10.1016/j.landusepol.2010.11.003.

Baumann, M., Radeloff, V.C., Avedian, V., Kuemmerle, T., 2015. Land-use change in the Caucasus during and after the Nagorno-Karabakh conflict. Reg. Environ. Chang. 15, 1703–1716. http://dx.doi.org/10.1007/s10113-014-0728-3.

Baydildina, A., Alishbay, A., Bayetova, M., 2000. Policy reforms in Kazakhstan and their implications for policy research needs. In: Tashmatov, A., Babu, S.C. (Eds.), Food Policy Reforms in Central Asia: Setting the Research Priorities. International Food Policy Research Institute, Washington, D.C., pp. 177–192.

Benayas, R.J., Martins, A., Nicolau, J.M., Schulz, J.J., 2007. Abandonment of agricultural land: an overview of drivers and consequences. CAB Rev. Perspect. Agric. Vet. Sci. Nutr. Nat. Resour. 2. http://dx.doi.org/10.1079/PAVSNNR20072057.

Beznosov, A.I., Uspanov, U.U., 1960. Soils of KazSSR. Soils of Kazakh SSR in 16 Vol Academy of Science KazUSSR.

Breiman, L., 2001. Random forests. Mach. Learn. 45, 5–32.

Briggs, J.M., Knapp, A.K., Collins, S.L., 2008. Steppes and praires. In: Encyclopedia of Ecology. Elsevier, Oxford, UK, pp. 3373–3382.

Brinkert, A., Hölzel, N., Sidorova, T.V., Kamp, J., 2016. Spontaneous steppe restoration on abandoned cropland in Kazakhstan: grazing affects successional pathways. Biodivers. Conserv. 25, 2543–2561. http://dx.doi.org/10.1007/s10531-015-1020-7.

Carson, W.P., Barrett, G.W., 1988. Succession in old-field plant communities: effects of contrasting types of nutrient enrichment. Ecology 69, 984–994. http://dx.doi.org/10.2307/1941253.

Cohen, W.B., Yang, Z., Kennedy, R., 2010. Detecting trends in forest disturbance and recovery using yearly Landsat time series: 2. TimeSync — tools for calibration and validation. Remote Sens. Environ. 114, 2911–2924. http://dx.doi.org/10.1016/j.rse.2010.07.010.

Colditz, R.R., Schmidt, M., Conrad, C., Hansen, M.C., Dech, S., 2011. Land cover classification with coarse spatial resolution data to derive continuous and discrete maps for complex regions. Remote Sens. Environ. 115, 3264–3275. http://dx.doi.org/10.1016/j.rse.2011.07.010.

Danzer, A.M., Dietz, B., Gatskova, K., 2013. Kazakhstan Migration and Remittances Survey: Migration, Welfare and the Labor Market in an Emerging Economy (Survey Report). Institute for East and Southeast European Studies, Regensburg.

de Beurs, K.M., Henebry, G.M., 2004. Land surface phenology, climatic variation, and institutional change: analyzing agricultural land cover change in Kazakhstan. Remote Sens. Environ. 89, 497–509. http://dx.doi.org/10.1016/j.rse.2003.11.006.

de Beurs, K.M., Ioffe, G., 2014. Use of Landsat and MODIS data to remotely estimate Russia's sown area. J. Land Use Sci. 9, 377–401. http://dx.doi.org/10.1080/1747423X.2013.798038.

de Beurs, K.M., Henebry, G.M., Owsley, B.C., Sokolik, I., 2015. Using multiple remote sensing perspectives to identify and attribute land surface dynamics in Central Asia 2001–2013. Remote Sens. Environ. 170, 48–61. http://dx.doi.org/10.1016/j.rse.2015.08.018.

Derpsch, R., Friedrich, T., Kassam, A., Li, H., 2010. Current status of adoption of no-till farming in the world and some of its main benefits. Int. J. Agric. Biol. Eng. 1–25.

Estel, S., Kuemmerle, T., Alcántara, C., Levers, C., Prishchepov, A., Hostert, P., 2015. Mapping farmland abandonment and recultivation across Europe using MODIS NDVI time series. Remote Sens. Environ. 163, 312–325. http://dx.doi.org/10.1016/j.rse.2015.03.028.

Forkel, M., Wutzler, T., 2015. Greenbrown - land surface phenology and trend analysis. In: A Package for the R Software. Version 2.2, [WWW Document]. URL. http://greenbrown.r-forge.r-project.org/ (accessed 8.29.16).

Gao, F., Wolfe, R., Masek, J., 2009. Automated registration and orthorectification package for Landsat and Landsat-like data processing. J. Appl. Remote. Sens. 3 (033515). http://dx.doi.org/10.1117/1.3104620.

Gerla, P., Cornett, M., Ekstein, J., Ahlering, M., 2012. Talking big: lessons learned from a 9000 hectare restoration in the northern tallgrass prairie. Sustainability 4, 3066–3087. http://dx.doi.org/10.3390/su4113066.

Griffiths, P., Müller, D., Kuemmerle, T., Hostert, P., 2013a. Agricultural land change in the Carpathian ecoregion after the breakdown of socialism and expansion of the European Union. Environ. Res. Lett. 8, 045024. http://dx.doi.org/10.1088/1748-9326/8/4/045024.

Griffiths, P., van der Linden, S., Kuemmerle, T., Hostert, P., 2013b. A pixel-based Landsat compositing algorithm for large area land cover mapping. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 6, 2088–2101. http://dx.doi.org/10.1109/JSTARS.2012.2228167.

Grote, U., 1997. Central Asian Environments in Transition. Environment Division, Asian Development Bank, Manila, Philippines.

Henebry, G.M., 2009. Global change: carbon in idle croplands. Nature 457, 1089–1090. http://dx.doi.org/10.1038/4571089a.

Ilyakova, R.M., Monkayeva, G.E., Dolgikh, S.A., Smirnova, E.Y., 2016. Annual Bulletin of Monitoring Climate Condition and Climate Change in Kazakhstan: Year 2015. National Hydrometeorological Service of Kazakhstan, Astana.

Ioffe, G., Nefedova, T., 2004. Marginal farmland in European Russia. Eurasian Geogr. Econ. 45, 45–59.

Josephson, P., Dronin, N., Mnatsakanian, R., Cherp, A., Efremenko, D., Larin, V., 2013. An Environmental History of Russia. Cambridge University Press, Cambridge.

Kamp, J., Urazaliev, R., Donald, P.F., Hölzel, N., 2011. Post-Soviet agricultural change predicts future declines after recent recovery in Eurasian steppe bird populations. Biol. Conserv. 144, 2607–2614. http://dx.doi.org/10.1016/j.biocon.2011.07.010.

Kämpf, I., Mathar, W., Kuzmin, I., Hölzel, N., Kiehl, K., 2016. Post-Soviet recovery of grassland vegetation on abandoned fields in the forest steppe zone of western Siberia. Biodivers. Conserv. 25, 2563–2580. http://dx.doi.org/10.1007/s10531-016-1078-x.

Kauazov, A.M., Dara, A.S., Batyrbayeva, M.Z., Vitkovskaya, I.S., Muratova, N.R., Salnikov, V.G., Turulina, G.K., Polyakova, S.E., Spivak, L.F., Turebayeva, S.I., 2016. Investigation of timing dynamics of snow cover loss in Northern Kazakhstan. Curr. Probl. Remote Sens. Earth Space 13, 161–168. http://dx.doi.org/10.21046/2070-7401-2016-13-1-161-168.

Kennedy, R.E., Yang, Z., Cohen, W.B., 2010. Detecting trends in forest disturbance and recovery using yearly Landsat time series: 1. LandTrendr — temporal segmentation algorithms. Remote Sens. Environ. 114, 2897–2910. http://dx.doi.org/10.1016/j.rse.2010.07.008.

Kienzler, K.M., Lamers, J.P.A., McDonald, A., Mirzabaev, A., Ibragimov, N., Egamberdiev, O., Ruzibaev, E., Akramkhanov, A., 2012. Conservation agriculture in Central Asia—what do we know and where do we go from here? Field Crops Res. 132, 95–105. http://dx.doi.org/10.1016/j.fcr.2011.12.008.

Kovalskyy, V., Roy, D.P., 2013. The global availability of Landsat 5 TM and Landsat 7 ETM+ land surface observations and implications for global 30 m Landsat data product generation. Remote Sens. Environ. 130, 280–293. http://dx.doi.org/10.1016/j.rse.2012.12.003.

Kraemer, R., Prishchepov, A.V., Müller, D., Kuemmerle, T., Radeloff, V.C., Dara, A., Terekhov, A., Frühauf, M., 2015. Long-term agricultural land-cover change and potential for cropland expansion in the former Virgin Lands area of Kazakhstan. Environ. Res. Lett. 10 (054012). http://dx.doi.org/10.1088/1748-9326/10/5/

054012.
Kurganova, I., Lopes de Gerenyu, V., Six, J., Kuzyakov, Y., 2014. Carbon cost of collective farming collapse in Russia. Glob. Change Biol. 20, 938–947. http://dx.doi.org/10.1111/gcb.12379.
Leroux, L., Bégué, A., Lo Seen, D., Jolivot, A., Kayitakire, F., 2017. Driving forces of recent vegetation changes in the Sahel: lessons learned from regional and local level analyses. Remote Sens. Environ. 191, 38–54. http://dx.doi.org/10.1016/j.rse.2017.01.014.
Lieth, H. (Ed.), 1978. Patterns of Primary Production in the Biosphere, Benchmark Papers in Ecology. Vol. 8 Dowden, Hutchinson & Ross; distributed by Academic Press, Stroudsburg, PA., New York.
Lioubimtseva, E., Henebry, G.M., 2009. Climate and environmental change in arid Central Asia: impacts, vulnerability, and adaptations. J. Arid Environ. 73, 963–977. http://dx.doi.org/10.1016/j.jaridenv.2009.04.022.
Lioubimtseva, E., Henebry, G.M., 2012. Grain production trends in Russia, Ukraine and Kazakhstan: new opportunities in an increasingly unstable world? Front. Earth Sci. 6, 157–166. http://dx.doi.org/10.1007/s11707-012-0318-y.
Loveland, T.R., Dwyer, J.L., 2012. Landsat: building a strong future. Remote Sens. Environ. 122, 22–29. http://dx.doi.org/10.1016/j.rse.2011.09.022.
Marinych, O.V., Rachkovskaya, E.I., Sadvokasov, P.E., Temirbekov, S.S., 2002. Perspectives of steppe regeneration on abandoned arable land in Northern Kazakhstan. In: Stepnoi Byulleten, pp. 54–59.
Masek, J.G., Vermote, E.F., Saleous, N.E., Wolfe, R., Hall, F.G., Huemmrich, K.F., Gao, F., Kutler, J., Lim, T.-K., 2006. A Landsat surface reflectance dataset for North America, 1990–2000. IEEE Geosci. Remote Sens. Lett. 3, 68–72. http://dx.doi.org/10.1109/LGRS.2005.857030.
McCauley, M., 1976. Khrushchev and the Development of Soviet Agriculture. Palgrave Macmillan UK, London. http://dx.doi.org/10.1007/978-1-349-03059-0.
Meyfroidt, P., Schierhorn, F., Prishchepov, A.V., Müller, D., Kuemmerle, T., 2016. Drivers, constraints and trade-offs associated with recultivating abandoned cropland in Russia, Ukraine and Kazakhstan. Glob. Environ. Change 37, 1–15. http://dx.doi.org/10.1016/j.gloenvcha.2016.01.003.
Millennium Ecosystem Assessment, 2005. Ecosystems and Human Well-Being: Biodiversity Synthesis. World Resources Institute, Washington, DC.
Ministry of Agriculture of the Republic of Kazakhstan, 2014. The Strategic Plan of the Ministry of Agriculture of the Republic of Kazakhstan for 2014–2018.
Nazarbayev, N.A., 2010. The Strategic Plan for Development of the Republic of Kazakhstan Until the Year 2020.
Olofsson, P., Foody, G.M., Herold, M., Stehman, S.V., Woodcock, C.E., Wulder, M.A., 2014. Good Practices for Estimating Area and Assessing Accuracy of Land Change. Remote Sens. Environ. 148, 42–57. http://dx.doi.org/10.1016/j.rse.2014.02.015.
Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., Duchesnay, É., 2011. Scikit-learn: machine learning in python. J. Mach. Learn. Res. 12, 2825–2830.
Prishchepov, A.V., Radeloff, V.C., Baumann, M., Kuemmerle, T., Müller, D., 2012a. Effects of institutional changes on land use: agricultural land abandonment during the transition from state-command to market-driven economies in post-Soviet Eastern Europe. Environ. Res. Lett. 7 (024021). http://dx.doi.org/10.1088/1748-9326/7/2/024021.
Prishchepov, A.V., Radeloff, V.C., Dubinin, M., Alcantara, C., 2012b. The effect of Landsat ETM/ETM + image acquisition dates on the detection of agricultural land abandonment in Eastern Europe. Remote Sens. Environ. 126, 195–209. http://dx.doi.org/10.1016/j.rse.2012.08.017.
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. http://dx.doi.org/10.1016/j.landusepol.2012.06.011.
Robinson, S., Milner-Gulland, E.J., 2003. Political change and factors limiting numbers of wild and domestic ungulates in Kazakhstan. Hum. Ecol. 31, 87–110.
Sala, O.E., Lauenroth, W.K., Burke, I.C., 1996. Carbon budgets of temperate grasslands and the effects of global change. In: Breymeyer, A.I., International Council of Scientific Unions (Eds.), Global Change: Effects on Coniferous Forests and Grasslands, SCOPE. Wiley, Chichester; New York, pp. 101–119.
Schierhorn, F., Müller, D., Beringer, T., Prishchepov, A.V., Kuemmerle, T., Balmann, A., 2013. Post-Soviet cropland abandonment and carbon sequestration in European Russia, Ukraine, and Belarus: abandonment and carbon sequestration. Glob. Biogeochem. Cycles 27, 1175–1185. http://dx.doi.org/10.1002/2013GB004654.
Schierhorn, F., Müller, D., Prishchepov, A.V., Faramarzi, M., Balmann, A., 2014. The potential of Russia to increase its wheat production through cropland expansion and intensification. Glob. Food Secur. 3, 133–141. http://dx.doi.org/10.1016/j.gfs.2014.10.007.
Scurlock, J.M.O., Hall, D.O., 1998. The global carbon sink: a grassland perspective. Glob. Change Biol. 4, 229–233.
Smaliychuk, A., Müller, D., Prishchepov, A.V., Levers, C., Kruhlov, I., Kuemmerle, T., 2016. Recultivation of abandoned agricultural lands in Ukraine: patterns and drivers. Glob. Environ. Change 38, 70–81. http://dx.doi.org/10.1016/j.gloenvcha.2016.02.009.
Suttie, J.M., Reynolds, S.G., Batello, C., Food and Agriculture Organization of the United Nations (Eds.), 2005. Grasslands of the World, Plant Production and Protection Series. Food and Agricultural Organization of the United Nations, Rome.
Swinnen, J., Burkitbayeva, S., Schierhorn, F., Prishchepov, A.V., Müller, D., 2017. Production potential in the “bread baskets” of Eastern Europe and Central Asia. Glob. Food Secur. http://dx.doi.org/10.1016/j.gfs.2017.03.005.
Tong, X., Brandt, M., Hiernaux, P., Herrmann, S.M., Tian, F., Prishchepov, A.V., Fensholt, R., 2017. Revisiting the coupling between NDVI trends and cropland changes in the Sahel drylands: a case study in western Niger. Remote Sens. Environ. 191, 286–296. http://dx.doi.org/10.1016/j.rse.2017.01.030.
USGS, 2015. LEDAPS Release Notes.
Verbesselt, J., Hyndman, R., Zeileis, A., Culvenor, D., 2010. Phenological change detection while accounting for abrupt and gradual trends in satellite image time series. Remote Sens. Environ. 114, 2970–2980. http://dx.doi.org/10.1016/j.rse.2010.08.003.
Vermote, E., Justice, C., Claverie, M., Franch, B., 2016. Preliminary analysis of the performance of the Landsat 8/OLI land surface reflectance product. Remote Sens. Environ. 185, 46–56. http://dx.doi.org/10.1016/j.rse.2016.04.008.
Vogelmann, J.E., Tolk, B., Zhu, Z., 2009. Monitoring forest changes in the southwestern United States using multitemporal Landsat data. Remote Sens. Environ. 113, 1739–1748. http://dx.doi.org/10.1016/j.rse.2009.04.014.
Vuichard, N., Ciais, P., Belelli, L., Smith, P., Valentini, R., 2008. Carbon sequestration due to the abandonment of agriculture in the former USSR since 1990: C sequestration over abandoned croplands. Glob. Biogeochem. http://dx.doi.org/10.1029/2008GB003212. (Cycles 22, n/a-n/a).
Wertebach, T.-M., Hölzel, N., Kämpf, I., Yurtaev, A., Tupitsin, S., Kiehl, K., Kamp, J., Kleinebecker, T., 2017. Soil carbon sequestration due to post-Soviet cropland abandonment: estimates from a large-scale soil organic carbon field inventory. Glob. Change Biol. http://dx.doi.org/10.1111/gcb.13650.
Wright, C.K., de Beurs, K.M., Henebry, G.M., 2012. Combined analysis of land cover change and NDVI trends in the northern Eurasian grain belt. Front. Earth Sci. 6, 177–187. http://dx.doi.org/10.1007/s11707-012-0327-x.
Wulder, M.A., White, J.C., Goward, S.N., Masek, J.G., Irons, J.R., Herold, M., Cohen, W.B., Loveland, T.R., Woodcock, C.E., 2008. Landsat continuity: issues and opportunities for land cover monitoring. Remote Sens. Environ. 112, 955–969. http://dx.doi.org/10.1016/j.rse.2007.07.004.
Wulder, M.A., White, J.C., Loveland, T.R., Woodcock, C.E., Belward, A.S., Cohen, W.B., Fosnight, E.A., Shaw, J., Masek, J.G., Roy, D.P., 2016. The global Landsat archive: status, consolidation, and direction. Remote Sens. Environ. 185, 271–283. http://dx.doi.org/10.1016/j.rse.2015.11.032.
Yin, H., Pflugmacher, D., Kennedy, R.E., Sulla-Menashe, D., Hostert, P., 2014. Mapping annual land use and land cover changes using MODIS time series. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 7, 3421–3427. http://dx.doi.org/10.1109/JSTARS.2014.2348411.
Yin, H., Pflugmacher, D., Li, A., Li, Z., Hostert, P., 2018. Land use and land cover change in Inner Mongolia - understanding the effects of China's re-vegetation programs. Remote Sens. Environ. 204, 918–930.
Zhao, W.Z., Xiao, H.L., Liu, Z.M., Li, J., 2005. Soil degradation and restoration as affected by land use change in the semiarid Bashang area, northern China. Catena 59, 173–186. http://dx.doi.org/10.1016/j.catena.2004.06.004.
Zhu, Z., 2017. Change detection using landsat time series: a review of frequencies, preprocessing, algorithms, and applications. ISPRS J. Photogramm. Remote Sens. 130, 370–384. http://dx.doi.org/10.1016/j.isprsjprs.2017.06.013.
Zhu, Z., Woodcock, C.E., 2012. Object-based cloud and cloud shadow detection in Landsat imagery. Remote Sens. Environ. 118, 83–94. http://dx.doi.org/10.1016/j.rse.2011.10.028.