Phenology-based cropland retirement remote sensing model: a case study in Yan’an, Loess Plateau, China

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ABSTRACT
Cropland retirement is a widespread phenomenon across the world. The conversion of inefficient cropland to forest or grassland is a policy aimed at restoring ecology, improving the environment, and promoting economic development. However, in most developing countries, the results of cropland retirement and land restoration are characterized by spatial fragmentation, and there are significant temporal differences as a result of poor agricultural intensification, human interference, and regional environmental differences. This substantially increases the difficulty of information extraction and reduces the extraction accuracy of remote sensing methods. In this paper, we developed a new phenology-based cropland retirement remote sensing (PCRRS) model to detect the extent and timing of cropland retirement. Considering the characteristic growth of crops, the normalized difference vegetation index (NDVI), at the start, middle, and end of the growth cycle, is the phenological metric to distinguish cropland from other vegetation types. In addition, the interannual variation of phenological metrics is significant after cropland retirement, which is the key to effectively identify retired cropland. High-resolution Google Earth images were used to verify the accuracy of the algorithm. The results suggested that the overall accuracy of our algorithm exceeded 85%, and was more suitable for sloping cropland. In comparison with other cropland retirement extraction methods, the PCRRS model had high sensitivity and stability. We found it was common for sloping cropland to be retired earlier, and we also identified the existing inter-planting phenomena between crops and shrubs in areas with gentle slopes. Overall, this study provided a basis for understanding the drivers of cropland retirement and evaluating their environmental effects.

1. Introduction
Cropland retirement is a major form of agricultural land-use change and affect water resources, carbon storage and biodiversity (Isbell et al. 2019). In the last century, large-scale cropland retirement has occurred in North America (Brown et al. 2005; Klooster 2003), Europe (Estel et al. 2015; Griffiths et al. 2013; Prischepov et al. 2012b), and Central Asia (Dara et al. 2018; Kraemer et al. 2015). However, much less is known about the spatial and temporal distribution results of cropland retirement.

In recent decades, cropland retirement and reforestation have become widespread in developing countries (Diaz et al. 2011; Li et al. 2017), especially China (Wang et al. 2015). The ecological restoration “Grain for Green” (GFG) program enacted in 1999 covers vast tracts of China. Several benefits in the project implementation region have been reported, including increased vegetation coverage, control of water and soil erosion, and reduced sediment loads in water bodies (Cao et al. 2017; Chansheng, He, and He 2016; Lü et al. 2017). In the conversion area, environmental consequences (Xu et al. 2019) such as ecological restoration, carbon storage (Deng, Liu, and Shangguan 2015; Scott et al. 2015), and water resources (Benayas 2007) depend on the time that has elapsed since cropland retirement. Few studies have focused on the spatiotemporal patterns of cropland retirement. The lack of spatially explicit data complicates evaluations of the drivers and environmental effects of cropland retirement.

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Analysis of satellite imagery is the most convenient and efficient way to monitor changes in agricultural fields, such as cropland retirement (Duveiller and Defourny 2010; Zheng et al. 2015). Because agricultural land abandonment is defined as cropland going unused for a minimum of 2–5 years (Yin et al. 2020), previous studies that relied on satellite imagery at specific times (Bergen et al. 2012; Falcucci, Maiorano, and Boitani 2007) resulted in retired cropland being easily confused with fallow areas (Prischepov et al. 2013). Land use datasets are as source of data about cropland–forest conversions (Buchner et al. 2020; Yin et al. 2018b); however, the process of dataset interpretation is time-consuming and labor-intensive, and mapping error has transitivity (Cao, Chen, and Yu 2009; Liu, Liu, and Kuang 2020). Recently, several time-series methods that map the temporal trajectories of spectral indices to land-cover variation (Dara et al. 2018; Nguyen et al. 2018; Yin et al. 2018a), such as the normalized difference vegetation index (NDVI), have been used to monitor changes within specific land cover categories (Devries et al. 2015; Tong et al. 2017; Yan and Roy 2015). However, it is difficult for these methods to identify agricultural land conversions accurately due to insufficient spectral reflectance, which also varies greatly after changes in crop types and planting patterns on cultivated land (Pazúr et al. 2020; Yin et al. 2020). Clouds and haze present a challenge for data availability in optical time-series algorithms, and high-quality training data for identifying cropland retirement maps are also difficult to obtain (Gomez, White, and Wulder 2016; Xu et al. 2018).

Differences in phenology are key to separating retired cropland from cropland still in use (Alcantara et al. 2012). Multiple images covering different periods of the growing season, especially in the early and late stages, are typically used to obtain the highest classification accuracy in any land cover category (Homer et al. 2004; Pax-Lenney and Woodcock 1997). Because of the large particles investigated and low complexity of land use types, these studies have not been affected by the mixed pixel problem (Yang et al. 2019). Cultivated land and retired cropland are spatially dispersed and easily disturbed by mixed pixels due to the low agricultural productivity and scarce per capita cultivated land area in most developing countries. Therefore, coarse resolution remote sensing images may not be able to achieve the extraction accuracy required to identify retired cropland (Yin et al. 2018b). In addition, studies based on phenological changes have significant limitations, because phenology changes with the climate (Beurs and Henebry 2004).

Considering the complexity of cropland retirement recognition and inapplicability of existing mainstream methods, this study developed an efficient method to identify and extract the spatiotemporal distribution of cropland retirement, by combining the phenological metrics of the start, middle, and end of the crop growth cycle. With the rapid growth of crops during the growing period and rapid decline of the NDVI value in the harvesting period (Xiao et al. 2016), a reasonable threshold of the temporal change rate of the NDVI value can effectively eliminate the interference of the mixed-pixel problem on model accuracy. More importantly, differences in phenological metrics caused by climate change are slight due to the low vegetation coverage post-abandonment (Ma, Churkina, and Trusilova 2012). We simulated the distribution of cropland retirement using the relationship between the interannual variation of crop phenological metrics and the proportion of cropland conversion area. Our method can effectively avoid interference by the phenological changes caused by climate change. With an increase in the time density of mapping, our model can effectively prevent any impact of fallow fields on the mapping accuracy of cropland retirement.

We selected a typical semi-arid region in China as the study area. The area has experienced large-scale cropland retirement in the past 20 years. The low agricultural intensification, single economic source, and human disturbance has led to irregularities in the size and shape of retired cropland areas. The study area of Yan’an is located on the Loess Plateau of China and is a focal region for the implementation of the GFG program. Specifically, we developed a high-precision remote-sensing extraction model for cropland retirement in areas with severely mixed pixels and revealed the temporal and spatial patterns of cropland retirement on the Loess Plateau of China.

2. Study area and data

2.1 Study area

The Yan’an region is located in the center of the Loess Plateau in China, and a total land area of 37,000 km² (Figure 1). The terrain is largely hills and gullies. The
semi-arid climate has a low average annual precipitation of 250 mm, and there is significant intra-year variability most rainfall occurs between June and September. Due to the steep terrain and irregular rainfall, long-term and extensive human activities have resulted in serious soil erosion in Yan’an area (Gao et al. 2017). In order to promote ecological restoration, Yan’an was the initial site adopted by the Chinese government to implement the GFG program in 1999 (Chen and Chen 2006). According to current statistics, approximately 7,183.3 km² of cropland has been afforested (Liu et al. 2018).

Maize and wheat are the main food crops in Yan’an area. There are significant spatial differences in the planting patterns of maize and wheat. The terrain in the northern part of Yan’an is dominated by hills and ravines, and the agricultural land is mainly grown with maize. The terrain in the south is dominated by plains and ravines, and the agricultural land adopts the rotation method of summer maize and winter wheat. The growing period for the summer maize typically spans from mid-May to early-October, and that for winter wheat spans from mid-October to early-May in the following year. We mainly estimated the results of maize crop retirement. Generally, the results of summer maize crop retirement could almost reflect the overall cropland retirement results of the cropland adopts the rotation method in this study area.

2.2 Data

The high temporal resolution of daily coverage provided by Moderate Resolution Imaging Spectroradiometer (MODIS) satellites allows detecting seasonal vegetation phenology dynamics. MOD13Q1 16-day synthetic data can effectively reduce the interference of cloud and rain (Ganguly et al. 2010). We used a time-series of NDVI data from MOD13Q1 (Collection 6) in 2001 to construct intra-annual time-series NDVI curves for various surface vegetation types. Then, the phenology metrics (such as the start, middle and end of the growth period) of different surface vegetation types were extrapolated based on the NDVI curves, which were used to indicate the correct Landsat data to collect.

We collected four Landsat footprints (WRS-2 paths/rows 128/34, 127/34, 127/35, and 126/35) covering the Yan’an area for all growing seasons between 2000 and 2020 from the United States Geological Survey (USGS) and obtained reflectance data. We applied a cloud cover threshold of < 20% and

Figure 1. Study area and land cover. (a) Study region in Shaanxi Province. (b) The county distribution of Yan’an region. (c) Land cover types from and proportions Global land cover (GLC) 2017.
obtained terrain-corrected image. Unfortunately, Landsat images showing different land-use stages and phenological metrics were not always available as a result of the influences of clouds. Therefore, based on the modified neighborhood similar pixel interpolator theory (Yang et al. 2020), we used healthy pixels to substitute any pixels with cloud pollution. These replaced pixels were acquired on the same or adjacent dates in nearby years (within a 3-year window). Considering the differences in spectral reflectance of the sensors, we applied previously reported parameters to normalize Operational Land Imager (Landsat8) reflectance to Landsat Thematic Mapper (Landsat5) and Enhanced Thematic Mapper Plus (Landsat7) values (Roy et al. 2016).

We calculated NDVI based on the red band and near-infrared band. The ALOS Global Digital Surface Model “ALOS World 3D – 30 m” (AW3D30) in 2015 was resampled to obtain the slope data of the study area. Here, 0–15° is defined as a gentle slope, and above 15° is defined as a steep slope. We used the global land cover (GLC) data (obtained from http://data.ess.tsinghua.edu.cn) to identify impervious areas and water bodies. The GLC and MCD12Q1 data were used to provide a contrast experiment with our method. Additionally, the support vector machines classifier (SVM) was used to derive land cover maps to capture the transfer of agricultural land use types. According to their respective results of retired cropland, confusion matrices were estimated based on Google Earth historical images samples.

3. Methods

Figure 2 shows the detailed research process. In the first step, we created an annual Landsat NDVI dataset based on crop phenology metrics obtained from the time-series curves of MODIS NDVI. Second, we created a cropland extraction index (CEI) in Section 3.2.1. The construction of the NDVI dataset depends on the type of crops in the study area. This paper only calculated the CEI of the maize crop, we used the results of maize crop retirement to approximate reflected the overall retired results of cropland using the rotation method in this study area. And section 3.2.2 explains the calculation of CEI as a variable of the phenology-based cropland retirement remote sensing model (PCRRS) for deriving the extent of cropland retirement. Considering the effect of climate change on differences in phenological metrics, we therefore evaluated the consistency of annual CEI values by visual interpretation and analytical samples obtained from Google Earth high-resolution imagery. Analytical samples were stable in terms of their land cover type and range; i.e. they were always cropland or forest from 2000 to 2020. Third, the thresholds of CEI and PCRRS were analyzed using Google Earth high-resolution imagery due to their critical role in improving

Figure 2. Flowchart of the cropland retirement extraction. (Spatial: obtain the distribution of cropland area based on CEI; temporal: use inter-annual CEIs based on the PCRRS model to obtain the timing and extent of cropland retirement.)
model accuracy. Finally, we distinguished retired cropland and stable cropland based on the PCRRS model and evaluated the mapping accuracy. And the cropland retirement results obtained by GLC product, SVM model and PCRRS model were cross-validated at 30 m spatial resolution scale.

3.1 Selection of phenological metrics based on a phenological analysis

We used time-series Google Earth imagery to monitor the dynamic processes of land-cover types and gradual cropland retirement in the Yan’an area. For the NDVI curves of crops in this study area, as shown in Figure 3a, there was a significant discrepancy with other vegetation types during the key phenological stages (from DOY161 to DOY289) (Yang et al. 2020). In the NDVI time-series curves, the crop NDVI began to increase on DOY 161 and peaked between DOY 225 and 241, after which crop NDVI values began to decrease, reaching their lowest levels around DOY 273. In our analysis, the NDVI curve for cropland clearly differed from the curves for forests and grasslands.

As shown in Figure 3b, we found that the NDVI time-series curve of the cropland retirement sample was relatively steep from DOY161 to DOY289 when more than 95% crops are covered. Relative to the crop coverage rate lower than 10% (Figure 3d), the NDVI values of this cropland retirement sample at the start and end of the crop growth period were significantly higher, and the NDVI time-series curve was smooth (Qin et al. 2016). The start and end of the crop growth period are the most important phenological parameters that reflect cropland retirement. Therefore, we determined the NDVI values of crops at the start (DOY161), middle (DOY225) and end (DOY273) as phenological metrics, and the length of the periods described above, as shown in Table 1. We used Landsat data from the same or nearby dates as a phenological metric for the analysis of cropland retirement.

3.2 Cropland retirement recognition

3.2.1 Cropland extraction index based on phenological characteristics

Based on the growth characteristics of vegetation during the growing season, multi-time or time series satellite images have been widely used to extract land cover information (Huang et al. 2017). During the growing period of a crop, differences in phenology between crops and other surface vegetation

![Figure 3](image-url)
categories, such as grass or forest, are huge as a result of the differing sowing and harvesting times among crops (as shown in Figure 3a). We constructed the CEI based on phenological metrics. The parameters were configured as follows:

\[
CEI = \left[ \frac{(NDI_{\text{grow max}} - NDI_{\text{grow begin}})}{\Delta t_{\text{grow max}} - \Delta t_{\text{grow begin}}} \right] \times 10000
\]

where \(NDI_{\text{grow max}}, NDI_{\text{grow begin}},\) and \(NDI_{\text{matu end}}\) represent the NDVI at the middle, start, and end of the growth period, respectively, with \(\Delta t_{\text{grow max}} - \Delta t_{\text{grow begin}}\) and \(\Delta t_{\text{grow max}} - \Delta t_{\text{matu end}}\) representing the corresponding time intervals. The formula \(\frac{(NDI_{\text{grow max}} - NDI_{\text{grow begin}})}{\Delta t_{\text{grow max}} - \Delta t_{\text{grow begin}}}\) is defined based on the difference in growth fluctuations between the target crop and background data, and we selected two periods with a large difference for comparison. To facilitate the calculation and threshold extraction, we multiplied the result by 10,000.

The setting of a reasonable CEI threshold is a key step (Maxwell and Sylvester 2012) in distinguishing between cropland and other features. Extracting pure crop pixels is a relatively simple process. But choosing a reasonable CEI threshold for extracting crop areas from mixed pixels is difficult. To simplify the interference of mixed pixels, a Landsat pixel is defined as “cropland” if more than 50% of the pixel is covered by crops (Yang et al. 2019). The percentage of crops within the pixel was verified by visual interpretation using high-resolution Google Earth images.

### 3.2.2 Recognition of the extent of cropland retirement based on the PCRRS model

Cropland surface phenology can change dramatically due to changes in crop cover proportions or the alteration of land use practices. We constructed a CEI model based on the NDVI values of crop phenology characteristic parameters. Consequently, we explored using the CEI value as a variable in the PCRRS model to map cropland retirement.

The six main steps of our approach are described below. First, we calculated the CEI index of crops (such as corn) in the start year M and end year N (M and N refer to the two years before and after the cropland retirement phenomenon occurred). Then, the CEI thresholds were used to separate cropland from other land-use classes. Second, we used the inter-annual CEI value as an input parameter for the PCRRS model to calculate the PCRRS value Eq. (2). Third, a relationship between PCRRS values and the ratio of cropland retirement area in Landsat pixels was derived by visually interpreting a part of analytical samples (126 samples in total) from Google Earth high-resolution imagery. Then, within the cropland area present in year M, we were able to determine the extent of cropland retirement from M to N based on the appropriate PCRRS threshold. Fourth, it is assumed that other crops (such as wheat) should not be grown in the same area after corn is retired. The interannual variation in phenological parameters caused by alternating cultivation between crop types can cause the misidentification of the model in this paper. Growing other type of crops in the retired area is defined as a shift in crop type. Repeat steps first to fourth to obtain active and abandoned cropland for other crops. Fifth, we distinguished cropland retirement from stable cropland based on the area of cropland in N (The phenomenon of cropland retirement occurs within the scope of farmland and ends in the scope of non-farmland), and eliminated interference from water bodies and built-up areas using land-use data for year N. Finally, in the sixth step, farmland fallow is defined as the early result of cropland abandonment which was marked as active farmland in the next stage, so we can eliminate the impact of fallow land.

\[
PCRRS_i = CEI_i^M - CEI_i^N
\]

where i represents various crops.

In steps 1–3, we characterized the changes in phenomenological parameters caused by changes in crop coverage, extracted the extent and timing of cropland retirement based on an appropriate threshold, as shown in Figure 4. In step 4–5, because alterations in the crop type and land-use category may result in false judgments, we highlighted these changes and provided a solution. In the final step, we removed the

| Parameters | Start | Middle | End | Length |
|------------|-------|--------|-----|--------|
| DOY        | 161   | 225    | 273 | 64/48  |

Table 1. Key phenological metrics of the data used.
interference from fallow cropland. Thus, the extent and timing of cropland retirement could be obtained with high precision.

3.3 Comparison and verification of the model accuracy

3.3.1 Land-cover classification based on support vector machines classifier

SVM is a computer learning method for supervised analysis and classification of high-dimensional data. Equivalent to other learning methods such as neural networks and decision trees, SVM employ non-parametric optimization algorithms to locate optimal boundaries between classes. (Prishchepov et al. 2013).

We used SVM and three NDVI images, such as at the start, middle and end of the crop growth period, to obtain annual coverage maps of crops (maize and wheat) in the study area (Alcantara et al. 2012). Then, we identified active farmland and abandoned farmland based on annual cover transfer results for crops.

Training data were extracted from Global Land Cover (GLC) 2017, and the land cover categories include forest, grassland, water, impervious surface and crops. Among them, the crop types are divided into corn and wheat through Google historical images combined with crop phenological parameters.

3.3.2 Validation of the cropland retirement map

Confusion matrices were used to examine the accuracy of the retired cropland maps by calculated the producer’s accuracy (PA), user’s accuracy (UA), and overall accuracy (OA). Taking into account the sampling bias caused by the sparsity of samples (Card 1982), we adopted disproportionate stratified sampling for verification (Olofsson et al. 2014). We stochastically selected 100 pixels each from the stable farmland (500 samples in total) and stable non-farmland classes, and 150 pixels per year from the retired cropland class (600 samples in total). The sample size is 50 m*50 m, covering one Landsat pixel to reduce the recognition error caused by registration. The sample distribution is shown in Figure 4. These validation points, which record crop percentage and cropland abandonment percentage, was derived from high-resolution Google Earth imagery by visual interpretation.

4. Results

4.1 Parameter extraction of the PCRRS model

We initially evaluated the impact of the Landsat image date selected on the range of CEI values, and the results showed good consistency. All available Landsat images

Figure 4. Partial samples in the google earth images. The red borders correspond to high-resolution google images in different years: a and b are the comparison pictures of the cropland retirement area in 2003 and 2015; c and d are the comparison pictures of the cropland retirement area in 2012 and 2019.
in this paper were showed in Figure 5a. Deviations in the imaging dates may cause fluctuations in the CEI values obtained for vegetation types. The CEI values of forest and cropland were analyzed (Figure 5b). Cropland had higher CEI values than forest, with values exceeding 140. The mean CEI value of crops was highest in 2005 and lowest in 2018. For the same vegetation type, the distribution range of CEI values may differ due to differences in the imaging date. For example, in 2018, an image collected on DOY302 was used to construct the CEI. Because the NDVI value of forests also dropped to its lowest level at that time, forests had larger CEI values than during the other four periods, while the corresponding CEI values for cropland were smaller.

Based on the distribution of CEI values described above, relationships between CEI values and the proportion of cropland within mixed pixels were obtained for both 2005 and 2018 (Figure 6a). The results showed that CEI values increased with increasing the proportion of cropland. Moreover, during different periods, the same CEI value corresponded to

Figure 5. (a) Distribution of Landsat images between pheno-period of start and ending. (b) The range of CEI values for forest and cropland during various epochs based on our CEI algorithm.

Figure 6. The results of PCRRS model analysis. (a) Variations in the proportion of cropland with changes in the CEI of mixed pixels for cropland and other vegetation types. (b) Google Earth image showing the percentage of cropland retirement obtained using PCRRS. (c) Variations in the proportion of cropland retirement with changes in the PCRRS value.
similar crop proportions. Based on the analysis above, when the proportion of crop area exceeded 50%, we used the same CEI threshold of >70 for all periods.

The PCRRS method by applying the difference among CEI values in different years to each percentage of cropland retirement, obtaining thresholds that relate directly to the percentage of cropland retirement within a pixel. A high-resolution Google Earth image taken on 07/01/2019 of an area of cropland retirement is shown in Figure 6b. For this image, the percentage of cropland retirement was obtained by applying the PCRRS to CEIs for 2001 and 2018. The results showed that the PCRRS method enabled a calculation of the approximate percentage of cropland retirement within a Landsat pixel.

The relationship between a set of PCRRS value and the proportion of cropland retirement is shown in Figure 6c. Land cover changes as small as 25% of a pixel can be effectively monitored (Vargas, Montalban, and Leon 2019). However, estimating the percentage of cropland retirement within a pixel in areas where cropland is highly dispersed is often difficult (Ozdogan and Woodcock 2006). Therefore, we marked the pixels with the proportion of cropland retirement more than 25% as the pixel of retired cropland. Considering the consistency of the constructed datasets and the same calculation method, we used the same PCRRS threshold across periods, with a corresponding PCRRS value of > 20.

4.2 Cropland retirement mapping and accuracy assessment

The OA of active cropland maps throughout the study ranged from 86.8% (2005) to 92.6% (2014). The active cropland category possessed high accuracy, with the UA ranging from 88.1% (2018) to 91.6% (2014) and the PA ranging from 83.2% (2018) to 93.4% (2014). Four annual maps of retired cropland spanning from 2001 to 2018 were obtained using the PCRRS model. The retired cropland class also had a high accuracy, with the PA ranging from 84.2% (2005–2009) to 95.2% (2001–2005) and the UA ranging from 83.9% (2014–2018) to 92% (2001–2005) (Table 2). In Yan’an, land-use policies have played a decisive role in cropland retirement (Lu et al. 2012). The GFG program launched by the Chinese government aimed to restore ecosystems by converting cropland in mountain and barren areas to forests or grasslands.

All cropland retirement samples were used to cross-validate the accuracy of the model. Croplands in mountainous areas are especially likely to be retired because they tend to be unprofitable (Zimmermann 2007). The overall accuracy of the model in steep terrain is as high as 93.4%. The recognition accuracy of the PCRRS model in flat terrain indicated that the impact of crop type changes on OA cannot be ignored. In addition, based on the land use type results obtained by SVM with multi-date images, we obtained the recognition results of the conversion of cropland to woodland and grassland. And the accuracy of the recognition results was still lower than with our method (Table 3), although the result of cropland retirement also had good accuracy.

We identified widespread cropland retirement in the Yan’an region, with the timing and extent of cropland retirement varying greatly from 2001 to 2018. The results showed that of the ~722,800 ha of cropland in 2001, roughly 82.86% had been retired by 2018. We found high rates of cropland retirement after the beginning of the GFG program and a substantial contraction of cropland (Figure 7). And followed by a slow conversion from farmland to woodland since 2009. The highest rates of cropland retirement occurred between 2001 and 2005, when almost 265,051 ha of cropland disappeared. By 2009, another 209,477 ha of previously cultivated cropland were abandoned. From 2009 to 2018, only 124,358 ha were converted from cropland to grassland.

| Year | Producer’s accuracy | User’s accuracy | Overall accuracy |
|------|---------------------|----------------|-----------------|
| 2001 | 92.9                | 89.6           | 91.4            |
| 2005 | 89.2                | 88.7           | 86.8            |
| 2009 | 91.1                | 87.6           | 89.2            |
| 2014 | 93.4                | 91.6           | 92.6            |
| 2018 | 83.2                | 88.1           | 88.0            |

Table 2. Accuracy comparison among years of PCRRS model based on google earth images.
Table 3. Confusion matrices of various models based on google earth images.

| Model     | Class (pixels) | Cropland retirement (CR) | Other changes | Producer’s accuracy |
|-----------|----------------|--------------------------|---------------|---------------------|
| PCRRSdist | CR             | 70                       | 15            | 82.3%               |
|           | Other changes  | 8                        | 257           | 96.9%               |
|           | User’s accuracy| 89.7%                    | 94.5%         | Overall accuracy    |
| PCRRSflat | CR             | 45                       | 26            | 63.3%               |
|           | Other changes  | 16                       | 163           | 91.1%               |
|           | User’s accuracy| 73.8%                    | 86.2%         | Overall accuracy    |
| GLC       | CR             | 56                       | 74            | 43.1%               |
|           | Other changes  | 64                       | 406           | 86.4%               |
|           | User’s accuracy| 46.6%                    | 84.6%         | Overall accuracy    |
| SVMtransfer | CR         | 125                      | 78            | 61.6%               |
|           | Other changes  | 23                       | 374           | 94.2%               |
|           | User’s accuracy| 84.5%                    | 82.7%         | Overall accuracy    |

4.3 Temporal and spatial patterns of cropland retirement

We observed strong differences in cropland retirement among counties in our study area. In particular, the temporal patterns of retirement differed among counties. Six counties had substantial retirement rates before 2005: Zichang, Zhidan, Wuqi, Ansai, Yanchuan, and Yanan in the north, among which Yanchuan had the highest retirement rates (up to 66.8%). On the other hand, southern counties had relatively low retirement rates before 2005 and higher rates after 2005. In general, our analyses revealed that the implementation time of land-use policy differed for each county. All counties in Yan’an showed a slowing trend of cropland retirement, although the extent of the change varied regionally (Figure 8a).

Cropland retirement was also related to terrain (Figure 8b). Before 2005, only 21% and 34% of cropland was converted to forest or grassland on slopes of 0–6° and 6–15°, respectively, while nearly half of cropland on slopes of 15–25° was converted to forests or grassland. The greatest reforestation occurred on slopes > 25°. We found that, compared with flat terrain, cropland retirement occurred earlier and increased more on steeper slopes, reflecting the success of initiatives to restore the ecological environment of the mountainous area. This outcome was in line with the design of the GFG program, which encourages the conversion of cropland to forest on steep slopes. Inter-cropping of shrubs and crops is also common in retired cropland areas with flatter terrain, the phenomenon of gradually cropland retirement is widespread in this study area (Figure 9). We found that 87% and 88% of cropland was converted to forest or grassland on slopes of 0–6° and 6–15°, respectively, from 2001 to 2018. In all topography classes there was a trend for the pace of cropland retirement to slow.

Figure 7. Distribution of cropland retirement in the study area from 2001 to 2018 based on the algorithm described in this study. Orange, yellow, green and cyan represent the results of cropland retirement in 2001–2005, 2005–2009, 2009–2014 and 2014–2018, respectively. The three rows (A, B, and C) present close-up images from the map showing cropland retirement, with corresponding Landsat images taken before and after the change. The Landsat images were taken on 29 May 2003 (Landsat5: RGB = 432) and 22 May 2018 (Landsat8: RGB = 543).
Retired cropland may lead to either an abrupt or gradual cessation of cultivation under the combined influence of policies, topography and environmental (Estel et al. 2015). Figure 9 shows the gradual retirement process of cropland in this study area. The land cover type within an approximate MODIS pixel was dominated by maize crops from 2008 to 2014 (Figure 9a-b), and the CEI values of the two periods were larger, 130.32 and 115.63, respectively. Relative to 2008, a slight increase in the proportion of shrub area was the reason for the lower CEI value in 2014. At the same time, the PCRRS value we calculated was as low as 14.69, reflecting a small proportion of cropland retirement area; From 2014 to 2019, the proportion of shrub area in this MODIS pixel increased and exceeded 50% (Figure 9c), and the CEI value in 2019 was as small as 73.48. The increase in the proportion of cropland retirement area corresponds to a larger PCRRS result. It is obvious that there is a positive correlation between the proportion of farmland abandoned area and the results of PCRRS model. The red polygons represent the results of cropland retirement obtained by applying the PCRRS model to the Landsat imagery. A threshold of the PCRRS model can effectively monitor the spatiotemporal distribution of cropland retirement at the pixel level.

![Figure 9. Three plots (a–c) in background high-resolution Google Earth images from 2008 to 2019 at the same location, with approximate MODIS pixel dimensions (black polygons), the recognition results from the PCRRS model for 2009–2018 with Landsat imagery (red polygons), and the time-series curves of MODIS NDVI of the corresponding pixel (blue curves). The gray dots are DOYs of MODIS NDVI data, and the dotted lines are the phenological nodes of this paper. The corresponding model result values are calculated. The three periods of time for the same plot show areas planted with a mix of crops and shrubs.](image-url)
5. Discussion

To accurately estimate the area of cropland retirement, a CEI threshold of crop was used to exclude the interference from vegetation such as woodland and shrubs. Then, how to detect the extent of cropland retirement in the mixed pixels is particularly important. We developed a PCRRS model for identifying and extracting information regarding cropland retirement. Our model eliminated the influence of mixed-pixels problem and allows mapping of retired cropland with high precision for a complex underlying surface.

5.1 Importance of phenological interannual variation for the recognition of retired cropland

Based on the specific phenological cycle of vegetation types, only three images per year are needed to classify land uses, with classification accuracies of up to 80% achieved (Prischepov et al. 2012b). Multiple important phenological periods have been widely used in land use classification (Foerster et al. 2012). Considering that the mixed pixels of cropland also have NDVI fluctuations during the growth cycle, we simulated the proportion of cropland according to the rate of change in NDVI values in the growing and harvesting periods. Based on change reasonable to the value of threshold, the interference caused by other vegetation types could be effectively eliminated. When monitoring changes of agricultural land uses based on inter-annual variation of key phenological “nodes” in farmland, a change of crop type will generate a large change in NDVI values (Xiao et al. 2016). Therefore, we conducted a cooperative analysis of multiple crop types to eliminate the identification error caused by conversion between crop types. Previous studies have shown that the phenological characteristics change with climate (Chmielewski and Ritzer 2001; Khanduri, Sharma, and Singh 2008). Changes in phenological parameters (start, mid and end of the growing season) due to climate can cause misidentification by our model. Considering that the early stage of cropland retirement was characterized by low vegetation coverage, which prevented the phenology of these areas from being significantly advanced or delayed by climate change (Penuelas and Rutishauser 2009). Therefore, a model based on the characteristics of phenological interannual variation can effectively extract the distribution of cropland retirement.

Trees are common in cropland areas (Xu et al. 2018), and the majority of Landsat pixels are a mixture of various land-cover types. Therefore, a mixed pixel analysis is preferred for analyzing changes in regions where cropland is highly fragmented (Jain et al. 2013). The difference in spatial resolution between MCD12Q1 and GLC 30 m may have been the main factor for the large difference between the retired cropland results (Yin et al. 2020) (Figure 10), while the temporal characteristics of gradual cropland retirement should be ignored due to the difficulty of identifying agricultural land retirement via machine learning. This is especially true for the analysis of gradual changes over time, as defined classification rules tend to oversimplify the analysis of the process (Prischepov et al. 2012b), leading to a lag in the temporal results for retired cropland. The rapid cropland loss before 2005 was in line with the initial regulations of an ecological restoration project (Liu et al. 2008). However, following a period of forest expansion at the cost of diminishing grain production, the target for increased forest cover was reduced after 2005 (Xu et al. 2006).

5.2 Uniqueness analysis of the PCRRS model

The cropland retirement in China is unique. In contrast to the natural succession of abandoned agricultural land in other countries (Blair, Shackleton, and Mograbi 2018), Chinese managers have developed afforestation plans on abandoned cropland (Zhou, Rompaey, and Wang 2009). Similar human interventions have resulted in retired cropland being covered with woody vegetation in a relatively short period of time. Compared with the agricultural abandonment caused by social (Prischepov et al. 2012a) and armed conflicts 2019, the agricultural land retirement in China is based on the purpose of improving the ecological environment (Gao et al. 2018). On the premise of ensuring food security (Chen et al. 2015), cropland with low efficiency is planned and purposefully abandoned (Bakker et al. 2011). Obtaining a valid map of cropland retirement from a social, economic, and environmental perspective helps to assess the social, economic, and environmental outcomes of
agricultural land abandonment. Provides a basis for managers to develop sustainable agricultural abandonment plans.

MODIS with high temporal resolution provides a reliable basis for us to obtain phenological parameters of a single crop type. Based on the dates of MODIS phenological parameters (start, middle and end of crop growth period), we collected Landsat data for the corresponding dates. Considering that crops are at the beginning and harvesting stage of the growing season, low vegetation cover corresponds to low NDVI values. Compared with the 16-day synthetic MODIS data, the Landsat image data more realistically reflects the surface vegetation coverage of the corresponding date; in the middle of the growing season, high vegetation coverage corresponds to a high NDIV value. Considering the saturation property of NDVI, the Landsat NDVI image in the middle of crop growth period can approximately reflect the lush growth state of crops. Therefore, it seems reasonable to choose Landsat data from the same date as the MODIS phenological parameters for the study.

More importantly, although the annual maximum NDVI increased in gradually retired cropland areas, the trend of the annual maximum NDVI increase may be less significant in the later stages of retirement as a result of the saturation of NDVI signal (Beck et al. 2006). On the contrary, the vegetation growing season in regions of cropland retirement was significantly longer owing to NDVI signal is most sensitive to moderate vegetation coverage (Figure 9) (Debeurs and Henebry 2004). Several studies have found trends of an earlier greening onset and longer growing season through satellite and station observations of phenology (Karlsen et al. 2007). Longer growing periods of surface vegetation will increase drought stress and evapotranspiration with global warming (Barber, Juday, and Finney 2000; Zhang et al. 2009), and the extent of carbon sequestration also increased (White, Running, and Thornton 1999). Therefore, observations of the distribution of cropland retirement might be more effective than maximum NDVI values (or annual mean, growing season integral, etc.) as an indicator of stress or soil restoration on the Loess Plateau (Jong et al. 2011).

The environmental and climatic factors in relatively arid areas are such that the cultivated land is mainly planted with single-season crops. At the same time, the short rainy season makes it possible to capture images of key phenological periods. In addition, poor quality pixels obtained in the key phenological period are also highly substitutable because the NDVI values of single-season crops are relatively stable before sowing and after harvesting. Therefore, in arid and semi-arid regions, our model is able to achieve a high recognition accuracy. However, in wetter regions, our model may not be applicable due to the complexity of farming practices, perennial crops and influence of cloud and rain.

5.3 Uncertainty analysis of the PCRRS model

While its relatively high mapping accuracy highlights the potential of our new approach, there are a few uncertainties. First, although high accuracy was achieved by the PCRRS model in the study area, the model may not be able to accurately simulate areas with complex planting structures in humid regions. Fine transitions between crop types in complex
farming areas will be easily overlooked as a result of the comparatively coarse temporal resolution of Landsat imagery, but with the enrichment of data sources, such as Sentinel series, these interference factors will be greatly reduced. Second, cropland pixels with phenological changes will be marked as cropland conversion, which will impact on the mapping accuracy of cropland retirement. For example, the urban sprawl surrounding the cities in Yan'an was sometimes incorrectly labeled as vegetation restoration caused by an ecological restoration program, despite the use of GLC30 data for masking urban areas. Third, the assumption that phenology and reflectance remain similar over many years may have led to incorrect classifications, so we cannot completely rule out overestimation of the accuracy of the results. At the same time, the use of the same phenological parameters in different regions will cause the model to be disturbed by regional heterogeneity, which will lead to incorrect assessments of the results. By averaging regional phenological parameters, the interference of regional heterogeneity is alleviated to a certain extent. Overall, our analysis demonstrated that cropland retirement can be mapped with a relatively high accuracy at the scale of Landsat imagery using the PCRRS model.

6. Conclusion

The PCRRS model was developed for determining the spatiotemporal pattern of retired cropland in this paper. We eliminated interference from other land-cover types by combining phenological metrics for crops with multi-temporal NDVI images. Then, the phenological change characteristics were used to identify the extent of cropland retirement. The results suggested that our algorithm has a high accuracy of over 85%, and our model was most suitable for sloping cropland areas. Gradual cropland retirement was a common phenomenon in the study area, and our approach successfully mapped its extent and timing. This new approach for satellite-based imagery highlighted the possibility of obtaining more accurate maps of cropland retirement change in areas with small-scale farms and high landscape heterogeneity. Future studies will focus on combining the PCRRS model with MODIS time-series images, applying them at the regional scale to reveal the relationships among interference by human activity, policy implementation, regional environmental differences, and agricultural land-use change.

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Data availability statement

The data presented in this study are available on request from the corresponding author.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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References

Alcantara, C., T. Kuenmerle, A. V. Prishchepov, and V. C. Radeloff. 2012. “Mapping Abandoned Agriculture with multi-temporal MODIS Satellite Data.” Remote Sensing of Environment 124: 334–347. doi:10.1016/j.rse.2012.05.019.

Bakker, H., J. P. G. M. Cromsigt, N. Mpanza, and H. Off. 2011. “Abandonment and Expansion of Arable Land in Europe.” Ecosystems 15 (1): 128–139. doi:10.1007/s10021-011-9497-8.

Barber, V. A., G. P. Juday, and B. P. Finney. 2000. “Reduced Growth of Alaskan White Spruce in the Twentieth Century from temperature-induced Drought Stress.” Nature 405: 668–673. doi:10.1038/35015049.

Beck, P. S. A., C. Atzberger, K. A. Hagda, B. Johansen, and A. K. Skidmore. 2006. “Improved Monitoring of Vegetation Dynamics at Very High Latitudes: A New Method Using MODIS NDVI.” Remote Sensing of Environment 100: 321–334. doi:10.1016/j.rse.2005.10.021.

Benayas, R. 2007. “Abandonment of Agricultural Land: An Overview of Drivers and Consequences.” Cab Reviews Perspectives in Agriculture Veterinary Science Nutrition & Natural Resources 2. doi:10.1079/PAVSNNR200772057.
Bergen, K. M., T. Zhao, V. Kharuk, Y. Blam, D. G. Brown, L. K. Peterson, and N. Miller. 2012. “Changing Regimes: Forested Land-cover Dynamics in Central Siberia 1974 to 2001.” *Photogrammetric Engineering & Remote Sensing* 74: 787–798. doi:10.1002/14498596.2008635141.

Beurs, K. M. D., and G. M. Henegby. 2004. “Land Surface Phenology, Climatic Variation, and Institutional Change: Analyzing Agricultural Land Cover Change in Kazakhstan.” *Remote Sensing of Environment* 89: 497–509. doi:10.1016/j.rse.2003.11.006.

Blair, D., C. Shackleton, and P. Mograbi. 2018. “Cropland Abandonment in South African Smallholder Communal Lands: Land Cover Change (1950–2010) and Farmer Perceptions of Contributing Factors.” *Land* 7: 121. doi:10.3390/land7040121.

Brown, D., K. M. Johnson, T. R. Loveland, and D. M. Theobald. 2005. “Rural land-use trends in the Conterminous United States, 1950–2000.” *Ecological Applications* 15: 1851–1863. doi:10.1890/03-5220.

Buchner, J., Y. He, D. Frantz, T. Kueummerle, and V. C. Radelfoff. 2020. “Land-cover Change in the Caucasus Mountains since 1987 Based on the Topographic Correction of multi-temporal Landsat Composites.” *Remote Sensing of Environment* 248: 111967. doi:10.1016/j.rse.2020.111967.

Cao, S., L. Chen, and X. Yu. 2009. “Impact of China’s Grain for Green Project on the Landscape of Vulnerable Arid and Semi-arid Agricultural Regions: A Case Study in Northern Shaanxi Province.” *Journal of Applied Ecology* 46: 536–543. doi:10.1111/j.1365-2664.2008.01605.x.

Cao, Z., Y. Li, Y. Liu, Y. Chen, and Y. Wang. 2017. “When and Where Did the Loess Plateau Turn ‘Green’? Analysis of the Tendency and Breakpoints of the Normalized Difference Vegetation Index.” *Land Degradation & Development* 29: 162–175. doi:10.1002/lrd.2852.

Card, D. H. 1982. “Using Known Map Category Marginal Frequencies to Improve Estimates of Thematic Map Accuracy.” *Photogrammetric Engineering & Remote Sensing* 48: 431–439. doi:10.10013/0031-0182(82)90005-4.2.

Chansheng, C. He, and He. 2016. “Quantifying Drives of the Sediment Load Reduction in the Yellow River Basin.” *National Science Review* 3: 155. doi:10.1093/nsr/nww014.

Chen, O. D., and D. Chen. 2006. “Land-use Change: Impacts of Climate Variations and Policies among small-scale Farmers in the Loess Plateau, China.” *Land Use Policy* 23: 361–371. doi:10.1016/j.lupol.2005.04.004.

Chen, Y., K. Wang, Y. Lin, W. Shi, Y. Song, and X. He. 2015. “Balancing Green and Grain Trade.” *NATURE GEOSCIENCE* 8: 739–741. doi:10.1038/ngeo2544.

Chmielewski, F. M., and T. Rützer. 2001. “Response of Tree Phenology to Climate Change across Europe.” *Agricultural and Forest Meteorology* 108: 101–112. doi:10.1016/S0168-1923(01)00233-7.

Dara, A., M. Baumann, T. Kueummerle, D. Pflugmacher, A. Rabe, P. Griffiths, N. Hözel, J. Kamp, M. Freitag, and P. Hostert. 2018. “Mapping the Timing of Cropland Abandonment and Recultivation in Northern Kazakhstan Using Annual Landsat Time Series.” *Remote Sensing of Environment* 213: 49–60. doi:10.1016/j.rse.2018.05.005.

Debeurs, K. M., and G. M. Henegby. 2004. “Trend Analysis of the Pathfinder AVHRR Land (PAL) NDVI Data for the Deserts of Central Asia.” *IEEE Geoscience & Remote Sensing Letters* 1: 282–286. doi:10.1109/LGRS.2004.834805.

Deng, L., G. B. Liu, and Z. P. Shangguan. 2015. “Land-use Conversion and Changing Soil Carbon Stocks in China’s ‘Grain-for-green’ Program: A Synthesis.” *Global Change Biology* 20: 3545–3556. doi:10.1111/gcb.12508.

Devries, B., M. Decuyper, J. Verbesselt, A. Zeileis, M. Herold, and S. Joseph. 2015. “Tracking disturbance-regrowth Dynamics in Tropical Forests Using Structural Change Detection and Landsat Time Series.” *Remote Sensing of Environment* 169: 320–334. doi:10.1016/j.rse.2015.08.020.

Díaz, G., L. Nahuelhual, C. Echeverria, and S. Marin. 2011. “Drivers of Land Abandonment in Southern Chile and Implications for Landscape Planning.” *Landscape & Urban Planning* 99 (3–4): 207–217. doi:10.1016/j.landurbplan.2010.11.005.

Duveiller, G., and P. Defourny. 2010. “A Conceptual Framework to Define the Spatial Resolution Requirements for Agricultural Monitoring Using Remote Sensing.” *Remote Sensing of Environment* 114: 2637–2650. doi:10.1016/j.rse.2010.06.001.

Estel, S., T. Kueummerle, C. Alcántara, C. Levers, A. Prischepov, and P. Hostert. 2015. “Mapping Farmland Abandonment and Recultivation across Europe Using MODIS NDVI Time Series.” *Remote Sensing of Environment* 163: 312–325. doi:10.1016/j.rse.2015.03.028.

Falcucci, A., L. Maiorano, and L. Boitani. 2007. “Changes in land-use/land-cover Patterns in Italy and Their Implications for Biodiversity Conservation.” *Landscape Ecology* 22: 617–631. doi:10.1007/s10980-006-9056-4.

Foerster, S., K. Kaden, M. Foerster, and S. Itzerott. 2012. “Crop Type Mapping Using spectral–temporal Profiles and Phenological Information.” *Computers and Electronics in Agriculture* 89: 30–40. doi:10.1016/j.compag.2012.07.015.

Ganguly, S., M. A. Friedl, B. Tan, X. Zhang, and M. Verma. 2010. “Land Surface Phenology from MODIS: Characterization of the Collection 5 Global Land Cover Dynamics Product.” *Remote Sensing of Environment* 114: 1805–1816. doi:10.1016/j.rse.2010.04.005.

Gao, G. J., Zhang, Y. Liu, N. Zheng, B. Fu, and S. Murugesu. 2017. “Spatio-temporal Patterns of the Effects of Precipitation Variability and Land use/cover Changes on long-term Changes in Sediment Yield in the Loess Plateau, China.” *Hydrology and Earth System Sciences* 21: 4363–4378. doi:10.5194/hess-21-4363-2017.

Gao, G., B. Fu, J. Zhang, Y. Ma, and M. Sivapalan. 2018. “Multiscale Temporal Variability of flow-sediment Relationships during the 1950s–2014 in the Loess Plateau, China.” *Journal of Hydrology* 563: 609–619. doi:10.1016/j.jhydrol.2018.06.044.
Gomez, C., J. C. White, and M. A. Waldner. 2016. “Optical Remotely Sensed Time Series Data for Land Cover Classification: A Review.” ISPRS Journal of Photogrammetry & Remote Sensing 116: 55–72. doi:10.1016/j.isprsjrs.2016.03.008.

Griffiths, P., D. Müller, T. Kuemmerle, and P. Hostert. 2013. “Agricultural Land Change in the Carpathian Ecoregion after the Breakdown of Socialism and Expansion Of the European Union.” Environmental Research Letters 8: 64–66. doi:10.1088/1748-9326/8/4/045024.

Homer, C., C. Huang, L. Yang, B. Wylie, and M. Coan. 2004. “Development of a 2001 National Land-Cover Database for the United States.” Photogrammetric Engineering & Remote Sensing 70: 829–840. doi:10.14358/PERS.70.7.829.

Huang, H., Y. Chen, N. Clinton, J. Wang, X. Wang, C. Liu, P. Gong, J. Yang, Y. Bai, and Y. Zheng. 2017. “Mapping Major Land Cover Dynamics in Beijing Using All Landsat Images in Google Earth Engine.” Remote Sensing of Environment 202: 166–176. doi:10.1016/j.rse.2017.02.021.

Isbell, F., T. Tilman, P. B. Reich, and A. T. Clark. 2019. “Deficits of Biodiversity and Productivity Linger a Century after Agricultural Abandonment.” Nature Ecology & Evolution 3: 1533–1538. doi:10.1038/s41559-019-1012-1.

Jain, M., P. Mondal, R. S. Defries, C. Small, and G. L. Galford. 2013. “Mapping Cropping Intensity of Smallholder Farms: A Comparison of Methods Using Multiple Sensors.” Remote Sensing of Environment 134: 210–223. doi:10.1016/j.rse.2013.02.029.

Jong, R. D., S. D. Bruin, A. D. Wit, M. E. Schaepman, and D. L. Dent. 2011. “Analysis of Monotonic Greening and Browning Trends from Global NDVI time-series.” Remote Sensing of Environment 115: 692–702. doi:10.1016/j.rse.2010.10.011.

Karlssen, S. R., I. Solheim, P. S. A. Beck, K. A. Hgda, F. E. Wielgolaski, and H. Tmmervik. 2017. “Variability of the Start of the Growing Season in Fennoscandia, 1982–2002.” International Journal of Biometeorology 51: 513–524. doi:10.1007/s00484-007-0091-x.

Khanduri, V. P., C. M. Sharma, and S. P. Singh. 2008. “The Effects of Climate Change on Plant Phenology.” The Environmentalist 28: 143–147. doi:10.1007/s10669-007-9153-1.

Klooster, D. 2003. “Forest Transitions in Mexico: Institutions and forests in a Globalized Countryside.” Professional Geographer 55: 227–237. doi:10.1111/j.0033-1249.2002.005020010.

Kraemer, R., A. V. Prischepov, D. Müller, T. Kuemmerle, V. C. Radellof, A. Dara, A. Terekhov, and M. Frühauf. 2015. “Long-term Agricultural land-cover Change and Potential for Cropland Expansion in the Former Virgin Lands Area of Kazakhstan.” Econstor Open Access Articles 10. doi:10.1088/1748-9326/10/5/054012.

Li, A., G. Lei, X. Cao, W. Zhao, W. Deng, and H. L. Koirala. 2017. Land Cover Change and Its Driving Forces in Nepal since 1990. Singapore: Springer. doi:10.1007/978-981-10-2890-8_3.

Liu, J., S. Li, Z. Ouyang, C. Tam, and X. Chen. 2008. “Ecological and Socioeconomic Effects of China’s Policies for Ecosystem Services.” Proc Natl Acad Sci U S A 105: 9477–9482. doi:10.1073/pnas.0706436105.

Liu, S., X. Niu, B. Wang, Q. Song, and Y. Tao (2018). “An Ecological Benefit Assessment of the Grain for Green Project in Shaanxi Province.” Acta Ecologica Sinica 38: 5759–70.

Liu, W., J. Liu, and W. Kuang. 2020. “Spatio-temporal Characteristics of Soil Protection Efforts of the Grain for Green Project in Northern Shaanxi Province.” Journal of Geographical Sciences 30: 401–422. doi:10.1007/s11442-020-1734-7.

Lu, Y., B. Fu, X. M. Feng, and Y. Zeng. 2012. “A Policy-Driven Large Scale Ecological Restoration: Quantifying Ecosystem Services Changes in the Loess Plateau of China.” PLOS ONE 7: e137182. doi:10.1371/journal.pone.0031782.

Lü, Y., S. Wang, B. Fu, G. Gao, and J. Zhou. 2017. “An Integrated Probabilistic Assessment to Analyse Stochasticity of Soil Erosion in Different Restoration Vegetation Types.” Hydrology and Earth System Sciences 21: 1491–1514. doi:10.5194/hess-21-1491-2017.

Ma, S., G. Churkina, and K. Trusilova. 2012. “Investigating the Impact of Climate Change on Crop Phenological Events in Europe with a Phenology Model.” International Journal of Biometeorology 56: 749–763. doi:10.1007/s00484-011-0478-6.

Maxwell, S. K., and K. M. Sylvester. 2012. “Identification of “ever-cropped” Land (1984–2010) Using Landsat Annual Maximum NDVI Image Composites: Southwestern Kansas Case Study.” other 121. doi:10.1016/j.rse.2012.01.022.

Nguyen, L. H., D. R. Joshi, D. E. Clay, and G. M. Henebry. 2018. “Characterizing Land cover/land Use from Multiple Years of Landsat and MODIS Time Series: A Novel Approach Using Land Surface Phenology Modeling and Random Forest Classifier.” Remote Sensing of Environment. doi:10.1016/j.rse.2018.12.016.

Olofsson, P., G. M. Foody, M. Herold, S. V. Stehman, C. E. Woodcock, and M. A. Waldner. 2014. “Good Practices for Estimating Area and Assessing Accuracy of Land Change.” Remote Sensing of Environment 148: 42–57. doi:10.1016/j.rse.2014.02.015.

Ozdogan, M., and C. E. Woodcock. 2006. “Resolution Dependent Errors in Remote Sensing of Cultivated Areas.” Remote Sensing of Environment 103: 203–217. doi:10.1016/j.rse.2006.04.004.

Pax-Lenney, M., and C. E. Woodcock. 1997. “Monitoring Agricultural Lands in Egypt with Multitemporal Landsat TM Imagery: How Many Images are Needed?” Remote Sensing of Environment 59: 522–529. doi:10.1016/S0034-4257(96)00124-1.

Pazur, R., J. Lieskovsk, M. Bürjg, D. Müller, T. Lieskovsk, Z. Zhang, and A. Prischepov. 2020. “Abandonment and Recultivation of Agricultural Lands in Slovakia: Patterns and Determinants from the past to the Future.” Econstor Open Access Articles. doi:10.3390/land9090316.

Penuelas, J., and Rutishauser. 2009. “Ecology. Phenology Feedbacks on Climate Change.” Science (New York, N.Y.) 324 (5929): 887–888. doi:10.1073/pnas.0706436105.

Prischepov, A. V., V. C. Radellof, M. Baumann, T. Kuemmerle, and D. Müller. 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.” Environmental Research Letters 7: 024021. doi:10.1088/1748-9326/7/2/024021.
Prishchepov, A. V., V. C. Radeloff, M. Dubinin, and C. Alcantara. 2012b. “The Effect of Landsat ETM/ETM + Image Acquisition Dates on the Detection of Agricultural Land Abandonment in Eastern Europe.” Remote Sensing of Environment 126: 195–209. doi:10.1016/j.rse.2012.08.017.
Prishchepov, A. V., D. Müller, M. Dubinin, M. Baumann, and V. C. Radeloff. 2013. “Determinants of Agricultural Land Abandonment in post-Soviet European Russia.” Land Use Policy 30: 873–884. doi:10.1016/j.landusepol.2012.06.011.
Qin, Y., X. Xiao, J. Dong, G. Zhang, P. S. Roy, P. K. Joshi, H. Gilani, M. Murthy, C. Jin, and J. Wang. 2016. “Mapping Forests in Monsoon Asia with ALOS PALSAR 50-m Mosaic Images and MODIS Imagery in 2010.” Rep 6: 20880. doi:10.1038/srep20880.
Roy, D. P., V. Kovalsky, H. K. Zhang, E. F. Vermote, L. Yan, S. S. Kumar, and A. Egorov. 2016. “Characterization of Landsat-7 to Landsat-8 Reflective Wavelength and Normalized Difference Vegetation Index Continuity.” Remote Sensing of Environment 185: 57–70. doi:10.1016/j.rse.2015.12.024.
Scott, R. L., E. P. Hamerlynck, G. D. Jenerette, M. S. Moran, and G. Barron-Gafford. 2015. “Carbon Dioxide Exchange in a Semidesert Grassland through Drought-induced Vegetation Change.” Journal of Geophysical Research: Biogeosciences 115. doi:10.1029/2010JG001348.
Tong, X, M Brandt, P Hiernaux, SM Herrmann, F Tian, AV Prishchepov, R Fensholt. 2017. “Revisiting the Coupling between NDVI Trends and Cropland Changes in the Sahel Drylands a Case Study in Western Niger.” Remote Sensing of Environment 191: 286–296. doi:10.1016/j.rse.2017.01.030.
Tong, X., M. Brandt, P. Hiernaux, M. Stefanie, S. M. Herrmann, Prishchepov, A. V. Feng, and R. Fensholt. 2017. “Revisiting the coupling between NDVI Trends and Cropland Changes in the Sahel Drylands: A Case Study in Western Niger.” Remote Sensing of Environment 191: 286–296. doi:10.1016/j.rse.2017.01.030.
Vargas, C., J. L. Montalban, and A. A. Leon. 2019. “Early Warning Tropical Forest Loss Alerts in Peru Using Landsat.” Environmental Research Communications 1 (12): 121002. doi:10.1088/2515-7620/ab4ec3.
Wang, C., Q. Gao, X. Wang, and M. Yu. 2015. “Decadal Trend in Agricultural Abandonment and Woodland Expansion in an Agro-Pastoral Transition Band in Northern China.” PLOS ONE 10: e0142113. doi:10.1371/journal.pone.0142113.
White, M. A., S. W. Running, and P. E. Thornton. 1999. “The Impact of growing-season Length Variability on Carbon Assimilation and Evapotranspiration over 88 Years in the Eastern US Deciduous Forest.” International Journal of Biometeorology 42: 139–145. doi:10.1007/s004840050097.
Xiao, D., Y. Qi, Y. Shen, F. Tao, J. P. Moiwo, J. Liu, R. Wang, H. Zhang, and F. Liu. 2016. “Impact of Warming Climate and Cultivar Change on Maize Phenology in the Last Three Decades in North China Plain.” Theoretical & Applied Climatology 124: 653–661. doi:10.1007/s00704-015-1450-x.
Xu, Z., J. Xu, X. Deng, J. Huang, S. Rozelle, and S. Rozelle. 2006. “Grain for Green versus Grain: Conflict between Food Security and Conservation Set-Aside in China.” World Development 34: 130–148. doi:10.1016/j.worlddev.2005.08.002.
Xu, Y., L. Yu, R. Z. Feng, X. Cai, J. Zhao, H. Lu, and P. Gong. 2018. “Tracking Annual Cropland Changes from 1984 to 2016 Using time-series Landsat Images with a change-detection and post-classification Approach: Experiments from Three Sites in Africa.” Remote Sensing of Environment 218: 13–31. doi:10.1016/j.rse.2018.09.008.
Xu, Z., W. Fan, H. Wei, P. Zhang, J. Ren, Z. Gao, S. Ulgiati, W. Kong, and X. Dong. 2019. “Evaluation and Simulation of the Impact of Land Use Change on Ecosystem Services Based on A Carbon Flow Model: A Case Study of the Manas River Basin in Xinjiang, China.” The Science of the Total Environment 652: 117–133. doi:10.1016/j.scitotenv.2018.10.206.
Yan, L., and D. P. Roy. 2015. “Improved Time Series Land Cover Classification by missing-observation-adaptive Nonlinear Dimensionality Reduction.” Remote Sensing of Environment 158: 478–491. doi:10.1016/j.rse.2014.11.024.
Yang, Y., T. Wu, S. Wang, J. Li, and F. Muhammad. 2019. “The NDVI-CV Method for Mapping Evergreen Trees in Complex Urban Areas Using Reconstructed Landsat & Time-Series Data.” Forests 10: 139. doi:10.3390/f10020139.
Yin, P., A. V. Kuemmerle, B. Bleyhl, and Radeloff; VC. 2018a. “Mapping Agricultural Land Abandonment from Spatial and Temporal Segmentation of Landsat Time Series.” REMOTE SENS ENVIRON 210: 12–24. doi:10.1016/j.rse.2018.02.050.
Yin, H., D. Pflugmacher, A. Li, Z. Li, and P. Hostert. 2018b. “Land Use and Land Cover Change in Inner Mongolia - Understanding the Effects of China’s re-vegetation Programs.” Remote Sensing of Environment 204: 918–930. doi:10.1016/j.rse.2017.08.030.
Yin, H., Butsic, V., J. Buchner, T. Kuemmerle, A. V. Prishchepov, M. Baumann, and E. V. Bragina. 2019. “Agricultural Abandonment and re-cultivation during and after the Chechen Wars in the Northern Caucasus.” Global Environmental Change 55: 149–159. doi:10.1016/j.gloenvcha.2019.01.005.
Yin, H., A. Brando, J. Buchner, D. Helmers, and V. C. Radeloff. 2020. “Monitoring Cropland Abandonment with Landsat Time Series.” Remote Sensing of Environment 246: 111873. doi:10.1016/j.rse.2020.111873.
Zhang, K., J. S. Kimball, Q. Mu, L. A. Jones, S. J. Goetz, and S. W. Running. 2009. “Satellite Based Analysis of Northern ET Trends and Associated Changes in the Regional Water Balance from 1983 to 2005.” Journal of Hydrology 379: 92–110. doi:10.1016/j.jhydrol.2009.09.047.
Zheng, B., S. W. Myint, P. S. Thenkabail, and R. M. Aggarwal. 2015. “A Support Vector Machine to Identify Irrigated Crop Types Using time-series Landsat \(\text{NDVI}\) Data.” International Journal of Applied Earth Observation and Geoinformation 34: 103–112. doi:10.1016/j.jag.2014.07.002.
Zhou, H., A. V. Rompaey, and J. A. Wang. 2009. “Detecting the Impact of the “Grain for Green” Program on the Mean Annual Vegetation Cover in the Shaanxi Province, China Using SPOT-VGT NDVI Data.” Land Use Policy 26 (4): 954–960. doi:10.1016/j.landusepol.2008.11.006.

Zimmermann, G., and N. E. Zimmermann. 2007. “Investigating the regional-scale Pattern of Agricultural Land Abandonment in the Swiss Mountains: A Spatial Statistical Modelling Approach.” Landscape and Urban Planning 79: 65–76. doi:10.1016/j.landurbplan.2006.03.004.