High-Resolution Mapping of Winter Cereals in Europe by Time Series Landsat and Sentinel Images for 2016–2020

Xiaojuan Huang 1,†, Yangyang Fu 1,†, Jingjing Wang 2, Jie Dong 3, Yi Zheng 1, Baihong Pan 1, Sergii Skakun 4 and Wenping Yuan 1,*

1 School of Atmospheric Sciences, Sun Yat-sen University, Zhuhai 519082, China; huangxj77@mail.sysu.edu.cn (X.H.); fuyy23@mail2.sysu.edu.cn (Y.F.); zhengy263@mail2.sysu.edu.cn (Y.Z.); panbh3@mail2.sysu.edu.cn (B.P.)
2 State Key Laboratory of Multiphase Flow in Power Engineering, Department of Environmental Science and Engineering, Xi’an Jiaotong University, Xi’an 710049, China; jjwang@stu.xjtu.edu.cn
3 College of Geomatics & Municipal Engineering, Zhejiang University of Water Resources and Electric Power, Hangzhou 310018, China; jdongbnu@126.com
4 Department of Geographical Sciences, University of Maryland, College Park, MD 20742, USA; skakun@umd.edu
* Correspondence: yuanwp3@mail.sysu.edu.cn
† These authors contributed equally to this work.

Abstract: Winter cereals, including wheat, rye, barley, and triticale, are important food crops, and it is crucial to identify the distribution of winter cereals for monitoring crop growth and predicting yield. The production and plating area of winter cereals in Europe both contribute 12.57% to the total global cereal production and plating area in 2020. However, the distribution maps of winter cereals with high spatial resolution are scarce in Europe. Here, we first used synthetic aperture radar (SAR) data from Sentinel-1 A/B, in the Interferometric Wide (IW) swath mode, to distinguish rapeseed and winter cereals; we then used a time-weighted dynamic time warping (TWDTW) method to discriminate winter cereals from other crops by comparing the similarity of seasonal changes in the Normalized Difference Vegetation Index (NDVI) from Landsat and Sentinel-2 images. We generated winter cereal maps for 2016–2020 that cover 32 European countries with 30 m spatial resolution. Validation using field samples obtained from the Google Earth Engine (GEE) platform show that the producer’s and user’s accuracies are 91% ± 7.8% and 89% ± 10.3%, respectively, averaged over 32 countries in Europe. The winter cereal map agrees well with agricultural census data for planted winter cereal areas at municipal and country levels, with the averaged coefficient of determination $R^2$ as 0.77 ± 0.15 for 2016–2019. In addition, our method can identify the distribution of winter cereals two months before harvest, with an overall accuracy of 88.4%, indicating that TWDTW is an effective method for timely crop growth monitoring and identification at the continent level. The winter cereal maps in Europe are available via an open-data repository.

Keywords: winter cereals; vegetation index; time-weighted dynamic time warping; Landsat; Sentinel; Google Earth Engine

1. Introduction

Winter cereals, such as wheat, rye, barley, and triticale, are important cereal crops, and approximately 278 million hectares are planted in 2020, accounting for 30% of the world’s grain-crop area and 41% of global grain production (https://www.fao.org/faostat/en/#data, accessed on 10 May 2020). Global grain prices fluctuate during the wheat-growing season, as supply expectations shift and change significantly in response to the amount of planted acreage, the weather, and growing conditions [1]. Winter cereals are also perhaps the most political commodity in the world because they are the main ingredients of bread, which is the most basic food. The Arab Spring of 2010 started as a direct result of bread
riots in Tunisia and Egypt, and then spread across the Middle East [1]. Winter cereals are a major type of grain and dominate grain production in many regions, including Europe, the United States, and China. Therefore, a timely and accurate map of winter cereals is vital for food security assessments, grain production management, and yield forecasting [2–4].

Remote sensing has become the main tool used to effectively identify areas planted with winter crops, and it provides spatially and temporally continuous information over vegetated surfaces [5,6]. The most popular method used to discriminate winter crops from other crops is to build a relationship between satellite-derived information (e.g., vegetation index) and winter crop features such as seasonal growth changes [7–10]. Satellite-based crop mapping is based on machine learning methods (e.g., decision tree, random forests, support vector machines, and neural networks). These methods have been successfully implemented to identify crop types [7,9,11–14]. Based on millions of field samples, the U.S. Department of Agriculture (USDA) have generated Cropland Data Layers (CDL) with 30 m resolution by using a decision tree method [15]. However, machine learning algorithms need large volumes of training samples, which must be updated each year, and depend on the support of the government in most cases [15]. Therefore, the exploration of potentially wide-ranging applications of machine learning algorithms has been hindered by the lack of a huge systematic collection of ground training samples [15,16]. The semi-supervised classification methods require fewer training samples compared with supervised classification, and usually show good performance for smaller areas. However, this method can hardly be used in large areas due to the complexity and time-consuming nature of the process [17].

The curve similarity-based method is an alternative approach, which has been used in previous studies to discriminate winter cereals from other crops through the consideration of major phenological characteristics and spectral signatures [8]. Winter cereals can be identified through their unique phenological features using a metric that reflects the different phenology stages during their lifecycle, as follows: seeding, tillering, greening-up, jointing, heading, grouting, maturity, and harvesting [18]. The growth processes can be inferred from the curve of a vegetation index (e.g., NDVI) that is derived from remote sensing data. For example, Dynamic Time Warping (DTW), a method originally proposed for speech recognition [19], has been used for crop identification [20] and land cover classification [21]. The original DTW method used the Euclidean distance to calculate the optimal alignment between two curves without any restrictions, which usually resulted in an unreasonable alignment [22,23]. To address this unreasonable alignment, warping time constraints and a distortion penalty were introduced to limit the warping range, and a time-weighted DTW (TWDTW) with a penalty was proposed to account for the seasonality of crop types and to improve the classification accuracy [24]. Recent studies have shown that the TWDTW method can successfully classify winter wheat and double-season paddy rice at the country level [5,25]. Compared with the supervised and semi-supervised classification methods, the TWDTW method requires a very small number of ground samples and is suitable for large area classification [5,26].

The winter cereal planting area in Europe accounted for approximately 76.35% of the total cereal area in 2020 (https://www.fao.org/faostat/zh/#data/QCL, accessed on 10 May 2020). Previous studies have shown that only crop-group specific [27] or rough classifications (such as cropland and non-cropland [28], or cropland-use intensity [29]) have been achieved over Europe by using the vegetation index provided by the Moderate Resolution Imaging Spectroradiometer (MODIS) instrument with a spatial resolution of 250 m. The available Landsat and Sentinel-2 satellite images have provided an unprecedented opportunity for the extraction of agricultural land use information with a high resolution in recent years [30–32]. Moreover, high-resolution crop mapping using multi-spectral data has been conducted at regional scales during the past several decades [6,26]. For example, by using the random forest algorithm, significant efforts have been made to generate high-resolution crop maps (e.g., winter cereals) at national and local sites, which were supported by the “Sentinel-2 for agricultural” project [30,33,34]. Under the framework of the agricultural policy of the European Union, the Land Parcel Identification System
Remote Sens. 2022, 14, 2120 (LPIS) opened in France was developed to identify all declared agricultural parcels through aerial photography and a geographic information system (GIS) at a scale of 1:5000 [35]. However, there are still some hindrances in the existing winter cereal maps. Firstly, it is difficult to classify on a larger scale due to the fixity of sites [30]. Secondly, the generation of crop maps based on the LPIS platform is time-consuming [36], so it is difficult to provide real-time maps.

Crop maps produced before the harvest, especially in areas with water resources problems, are requested by policy and decision makers for use in agriculture monitoring, simulating crop water use, calculating statistics, and satisfying the timeliness of yield prediction demands [10,37]. The frequency and intensity of drought are projected to increase in Europe in the future as the climate changes, leading to a risk of crop yield losses and even crop failure [36,38,39]. The early-season (as early as possible) mapping of winter cereals is therefore urgently needed for yield forecasting and assessments of food security [5,40]. However, due to the limited input information, it is more difficult to identify the distribution of crops before harvest than at the end of the growing season [5].

In this study, we used a phenology-based method (TWDTW) to detect the geographical locations of winter cereals in Europe and mapped winter cereal distribution for 2016–2020 with the resolution of 30 m. Furthermore, we assessed the performance of the TWDTW method in identifying winter cereals at the early stage of the growing season in Europe. The winter cereal map can be updated annually and used as evidence for agricultural management and policy making.

2. Materials and Methods

2.1. Study Area

Our study area covers 32 European countries (Figure 1). The area has highly diverse climatic and topographic characteristics. The temperate maritime climate and the Mediterranean climate are the main climates in Europe, and the agricultural landscape is characterized by medium sized farms (2–25 ha) [41].

Figure 1. The study area, encompassing 32 countries across Europe. The green triangles show the field survey samples from Google Earth Engine.
2.2. Data

2.2.1. Satellite Data

We used surface reflectance (SR) products, after atmospheric corrections, from the Enhanced Thematic Mapper Plus (ETM+) sensor onboard Landsat 7, the Operational Land Imager (OLI) sensor onboard Landsat 8 (United States Geological Survey), and the Multispectral Instrument (MSI) sensor onboard Sentinel-2 (European Space Agency), to obtain the NDVI from 2016 to 2020. Firstly, to reduce the impact of clouds, the quality bands sourced in Landsat and the QA60 band provided by Sentinel-2 were employed to remove the clouds in their respective images. Then, we used the nearest neighbor method to resample the NDVI of Sentinel-2 to 30 m, so as to keep the same spatial resolution with Landsat. Furthermore, we obtained all valid NDVI values (Landsat 7, Landsat 8, and Sentinel-2) within one month with cloud-free, and chose the maximum value for monthly synthesis for each pixel in each image, which was proved to be effective for crop mapping and to show the growing state. In addition, the monthly cloud-free image frequencies from October to the following July, over 2016–2019, were calculated for each pixel and shown in Figure 2. The monthly maximum composite NDVI was implemented on GEE and then downloaded to the local server. For Sentinel-2, the Level-2A (SR) product cannot be obtained from either GEE or ESA prior to 2018 due to missing data.

Moreover, we used synthetic aperture radar (SAR) data from Sentinel-1 A/B, in the Interferometric Wide (IW) swath mode, to obtain the radar response to the physiological

Figure 2. Number of months with good (cloud-free) observations in Europe, derived from the monthly maximum composite NDVI from October to the following July, 2016–2019. (a–d) show 2018, 2016, 2017, and 2019, respectively.
structural development of crops [42]. The SAR data offered vertical transmittance/vertical receival (VV) and vertical transmittance/horizontal receival (VH) polarization bands with 10 m spatial resolution. Similarly, we resampled the SAR data to 30 m based on the nearest neighbor method and obtained the monthly maximum synthetized values of VH. The above processes were run on the GEE platform.

2.2.2. Field Samples and Agricultural Census Data

Winter cereals are biennial cereal crops sown in the autumn and harvested in the following July. Wheat, winter barley, rye, and triticale are typical winter cereals in Europe and they had similar seasonal change curves of NDVI and phenological characteristics [43]. In this study, we first obtained 50–200 winter cereal field samples for each country in 2018. These samples were selected randomly by visually interpreting the color and textures of images on Google Earth [5] and comparing the NDVI thresholds with empirical values [44]. Further, these samples were evenly distributed in space. Then, the standard NDVI seasonal change curves of winter cereals in each country were obtained by calculating the average NDVI value of field samples in the corresponding countries (Figure 3).

![Figure 3. The standard NDVI seasonal change curves of winter cereals in 32 countries in Europe. Error bars are standard deviations. The other five countries are Albania, Bosnia-Herzegovina, Kosovo, Macedonia, and Montenegro. In this study, we used the same standard curve for these latter countries because they are geographically adjacent.](image)

In addition, we selected 3356 field samples in 32 countries (1502 samples for winter cereals and 1854 samples for other, non-winter cereal crops) in 2018 for validating the identification accuracy at the pixel level. The method of generating these validation samples is similar to the above procedure. In addition, the winter cereal plating area at country and municipal levels in the study area were obtained from the National Bureau of Statistics in each country to assess the accuracy at the regional level (https://www.fao.org/faostat/en/#data, accessed on 25 May 2020). Overall, we obtained the country-level agricultural census data for all 32 countries from 2016 to 2020 and municipal-level data for
11 countries from 2016 to 2019. Therefore, our validation with respect to the municipal-level data was implemented for 11 countries.

2.3. Method

The methodology used in this study is shown in the flow chart (Figure 4). The workflow consists of the following steps: (1) constructing monthly maximum composite NDVI images; (2) using SAR data to distinguish winter rapeseed at each pixel; (3) preparing the standard seasonal change in NDVI-based winter cereal samples; (4) winter cereal identification with the TWDTW method; (5) evaluation of classification accuracies.

![Flow chart of the methodology in this study for winter cereals classification.](image-url)

**Figure 4.** Flow chart of the methodology in this study for winter cereals classification.

2.3.1. Time-Weighted Dynamic Time Warping (TWDTW)

We used the Time-Weighted Dynamic Time Warping (TWDTW) method to identify winter cereals in Europe. The TWDTW method is an improved algorithm of Dynamic Time Warping (DTW), which was originally developed for speech recognition [19]. The details about TWDTW can be found in previous studies [5,24,26].

First, we determined the standard NDVI seasonal change curves [5,25] of winter cereals from the average NDVI values of field samples for each country in 2018. Then, we calculated the distance between the time series of each image pixel and the standard NDVI seasonal change curve of winter cereals by using the TWDTW method. All distance values were ranked from small to large and pixels with low distances were considered to have a higher probability of being winter cereals. In addition, we used the agricultural census area of winter cereals for each country to obtain distance thresholds, which means the total area of winter cereal pixels were consistent with the agricultural census area of each country. Moreover, we presumed that the standard NDVI seasonal change curves for each country did not change from year to year. We employed the curves in 2018 to identify the planting area of winter cereals from 2016 to 2017 and 2019 to 2020, and assessed the potential of the TWDTW method in temporal transferability.

2.3.2. Removing the Disturbance of Winter Rapeseed

Winter rapeseed is sown in early September and harvested the following July or August, which is similar to winter cereals. It is difficult to distinguish between winter cereals and winter rapeseed in optical imagery due to the similarity of the seasonal changes in NDVI. However, rapeseed is taller than other winter cereals and has randomly oriented branches, resulting in high volume scattering and lower attenuation of the signal from the ground [42]. Thus, the high and increasing VH backscatter of rapeseed at late growth stages can be used to discriminate between winter cereals and winter rapeseed [42]. In this study, we referred to Veloso et al. and Dong et al. [5,42], and considered that the VH backscatter values for winter rapeseed in May were above −15.5, and that of other winter cereals were less than −15.5. Accordingly, we assigned higher distance values to the pixels with VH greater than −15.5, which means that those pixels are less likely to be misclassified as winter cereal.
2.3.3. Accuracy Assessment

We evaluated the accuracy of identification of winter cereals at regional and pixel levels by using the census dataset and the field samples. At the regional (municipal) level, the coefficient of determination ($R^2$), relative error (RE), and root mean squared error (RMSE) were used to compare the identified planted area with the agricultural census data for winter cereals. At the pixel level (3393 field samples), the producer’s accuracy (PA), user’s accuracy (UA), overall accuracy (OA), and Kappa coefficient (KC) [45] were used to assess the accuracy of the identified maps. The PA is the percentage of the ground-sampled winter cereal fields that were correctly identified as winter cereals. The UA is the percentage of the identified winter cereal fields that correspond to winter cereal fields in the field samples. The OA shows the overall effectiveness of the identification. In addition, for the Kappa coefficient, higher values indicate better classification accuracy.

3. Results

We examined how early winter cereals can be identified with an overall accuracy reaching 88%. The TWDTW method was used to identify the winter cereals based on the NDVI time series with different lengths starting at November, then increased by monthly increments thereafter. All 3356 validation field samples were used to assess the accuracies of the early-season mapping of winter cereals. With the increase in the length of the time series, the classification accuracy (i.e., OA, PA, and UA) also increased (Table 1). The overall accuracy reached 88.4% in May, close to the maximum overall accuracy (91.8%) at the end of season, with a stable accuracy. These results imply that winter cereals can be identified two months before harvest (i.e., in May) by using the TWDTW method.

Table 1. The classification accuracy of winter cereals using the TWDTW method with monthly increments for all of Europe.

| Time | Producer’s Accuracy of Non-Winter Cereals (%) | Producer’s Accuracy of Winter Cereals (%) | User’s Accuracy of Non-Winter Cereals (%) | User’s Accuracy of Winter Cereals (%) | Overall Accuracy (%) |
|------|---------------------------------------------|------------------------------------------|------------------------------------------|--------------------------------------|----------------------|
| Nov  | 69                                          | 60                                       | 78                                       | 50                                   | 66                   |
| Dec  | 71.4                                        | 65.2                                     | 80.5                                     | 53.6                                 | 69.6                 |
| Jan  | 74.5                                        | 72.3                                     | 85.37                                    | 57.14                                | 73.9                 |
| Feb  | 75                                          | 68                                       | 80.5                                     | 60.7                                 | 72.5                 |
| Mar  | 84.5                                        | 84                                       | 88                                       | 75                                   | 84.1                 |
| Apr  | 86.05                                       | 84.62                                    | 89                                       | 81.6                                 | 85.51                |
| May  | 90.24                                       | 85.11                                    | 91.5                                     | 86.71                                | 88.4                 |
| Jun  | 92.68                                       | 89.6                                     | 92.68                                    | 89.29                                | 91.3                 |
| Jul  | 92.8                                        | 90.29                                    | 92.5                                     | 91                                   | 91.8                 |

We produced early-season winter cereal maps for 2016–2020 with 30 m resolution based on the monthly maximum NDVI from the Sentinel-2 and Landsat data. Figure 5 illustrates the early-season winter cereal distribution for May 2018 for all 32 European countries. Based on the municipal-level agricultural census data, we evaluated the performance of the TWDTW method at the municipal-level for identifying winter cereals. Since the standard NDVI curves for winter cereals were derived from field samples collected in 2018, we examined the accuracy of the method for identifying winter cereals in 2018. The $R^2$ values between the identified planted area and the agricultural census data ranged from 0.53 to 0.99 for the 11 countries, and the slope of the regression lines between the identified areas and the census areas ranged from 0.6 to 1.35, from 2016 to 2020. Meanwhile, the RE ranged from 9% to 85%, and RMSE ranged from $2 \times 10^4$ ha to $23 \times 10^4$ ha, demonstrating that the values of RE and RMSE changed greatly in these 11 countries (Figure 6). We also examined the potential of this approach for other years (i.e., 2016, 2017, and 2019), and the identified winter cereal areas were compared with the agricultural census area for the other
three years (2016, 2017, 2019), except 2020 due to the lack of agricultural census. The results showed that $R^2$ and the slope changed little compared with 2018 in most countries, except for France and Denmark, which implied that the TWDTW method had the ability to apply the standard NDVI seasonal change curve from one year to other years (Figure 6).

In addition, we examined the accuracy of the identification at the pixel level based on the 3356 field samples of winter cereals and other land cover types that were obtained from GEE for 32 countries in Europe (Table 2). The overall accuracies vary from 71.7% to 98.73% in 32 countries, and the Kappa coefficients range from 0.42 to 0.97. The average overall accuracy is above 90% when the 32 countries in Europe are considered together, and the Kappa coefficients are higher than 0.7 in most countries, indicating that the TWDTW method has the potential to identify planted areas of winter cereals in our study area. However, lower identification accuracy still exists in some countries. For example, Bulgaria has the lowest overall accuracy (71.7%) and Kappa coefficient (0.42). In addition, Figure 7 shows zoomed-in images, with rich spatial details for the winter cereals in France and Romania in 2018.

Figure 5. The distribution of winter cereals for 32 European countries in 2018. The red pixels show the geographical locations of identified winter cereals, and white show non-winter cereal areas.
Figure 6. The relationship between the identified and statistical winter cereal areas at the municipal level for 2016–2019.

To examine the effect of SAR data in the identification, we took Germany as an example to identify the winter cereals with and without using SAR data during the implementation of the TWDTW method. The relationship between the estimated and agricultural statistical planted areas of winter cereals with and without SAR data was illustrated in Figure 8. The performance of the TWDTW method with SAR data is better than that without using SAR data. The $R^2$ value increased from 0.49 to 0.81 after using SAR data.

We also used the random forest method to identify winter cereals with the same field samples for further comparison with the TWDTW method. We compared the accuracy of the TWDTW method and random forest method in the classification of winter cereals in a total of 32 European countries. For a fair comparison, the same training samples were used to run the random forest method in GEE and the TWDTW method in the local server, respectively. Moreover, the same field samples were employed to evaluate the accuracy of classification. Overall, the accuracy of the TWDTW method is higher than random forest in identifying winter cereals (Table 3). The overall accuracies are 90.82% and 80.84% for TWDTW and random forest, respectively, while the Kappa coefficients are 0.58 and 0.70,
respectively. Our results demonstrated that the TWDTW method had higher accuracy than the random forest method in classification.

**Table 2.** The confusion matrix of the final winter cereal maps for 32 countries in Europe in 2018.

| Country          | Class               | Non-Winter Cereals | Winter Cereals | User’s Accuracy | Producer’s Accuracy | Overall Accuracy | Kappa Coefficient |
|------------------|---------------------|--------------------|----------------|-----------------|--------------------|------------------|-------------------|
| France           | Non-winter cereals  | 307                | 33             | 90.29%          | 91.10%             | 90.83%           | 0.82              |
|                  | Winter cereals      | 30                 | 317            | 91.35%          | 90.57%             |                  |                   |
| Germany          | Non-winter cereals  | 221                | 18             | 92.47%          | 91.70%             | 92.03%           | 0.84              |
|                  | Winter cereals      | 20                 | 218            | 91.59%          | 92.37%             |                  |                   |
| Romania          | Non-winter cereals  | 108                | 6              | 94.74%          | 93.10%             | 93.86%           | 0.88              |
|                  | Winter cereals      | 8                  | 106            | 92.98%          | 94.64%             |                  |                   |
| Poland           | Non-winter cereals  | 103                | 6              | 94.50%          | 91.15%             | 92.66%           | 0.85              |
|                  | Winter cereals      | 10                 | 99             | 90.83%          | 94.29%             |                  |                   |
| UK               | Non-winter cereals  | 102                | 10             | 91.07%          | 88.70%             | 89.50%           | 0.79              |
|                  | Winter cereals      | 13                 | 94             | 87.85%          | 90.38%             |                  |                   |
| Spain            | Non-winter cereals  | 30                 | 3              | 90.19%          | 71.43%             |                  | 0.69              |
|                  | Winter cereals      | 12                 | 59             | 83.10%          | 95.16%             |                  |                   |
| Bulgaria         | Non-winter cereals  | 24                 | 11             | 68.60%          | 85.70%             |                  |                   |
|                  | Winter cereals      | 4                  | 14             | 77.80%          | 56%                | 71.70%           | 0.42              |
| Hungary          | Non-winter cereals  | 27                 | 3              | 95.00%          | 92.23%             |                  | 0.89              |
|                  | Winter cereals      | 0                  | 24             | 92.00%          | 94.85%             |                  |                   |
| Czechia          | Non-winter cereals  | 13                 | 2              | 86.67%          | 86.67%             |                  | 0.73              |
|                  | Winter cereals      | 2                  | 13             | 86.67%          | 86.67%             |                  |                   |
| Italy            | Non-winter cereals  | 67                 | 3              | 95.71%          | 83.75%             |                  | 0.77              |
|                  | Winter cereals      | 13                 | 57             | 81.43%          | 95%                |                  |                   |
| Lithuania        | Non-winter cereals  | 18                 | 1              | 94.74%          | 85.71%             |                  | 0.83              |
|                  | Winter cereals      | 3                  | 27             | 90%             | 96.43%             |                  |                   |
| Denmark          | Non-winter cereals  | 25                 | 3              | 89.29%          | 92.59%             |                  | 0.83              |
|                  | Winter cereals      | 2                  | 29             | 93.55%          | 90.63%             |                  |                   |
| Austria          | Non-winter cereals  | 49                 | 0              | 100%            | 98%                |                  | 0.97              |
|                  | Winter cereals      | 1                  | 29             | 96.67%          | 100%               |                  |                   |
| Estonia          | Non-winter cereals  | 47                 | 3              | 94%             | 88.68%             |                  | 0.83              |
|                  | Winter cereals      | 6                  | 48             | 88.89%          | 94.12%             |                  |                   |
| Latvia           | Non-winter cereals  | 96                 | 4              | 96%             | 90.70%             |                  | 0.83              |
|                  | Winter cereals      | 3                  | 39             | 92.86%          | 94.64%             |                  |                   |
| Finland          | Non-winter cereals  | 54                 | 0              | 100%            | 81.82%             |                  | 0.79              |
|                  | Winter cereals      | 12                 | 49             | 80.33%          | 100%               |                  |                   |
| Norway           | Non-winter cereals  | 61                 | 0              | 100%            | 85.92%             |                  | 0.82              |
|                  | Winter cereals      | 10                 | 44             | 81.48%          | 100%               |                  |                   |
| Sweden           | Non-winter cereals  | 68                 | 2              | 97.14%          | 81.93%             |                  | 0.54              |
|                  | Winter cereals      | 15                 | 15             | 50.00%          | 88.24%             |                  |                   |
| Slovakia         | Non-winter cereals  | 33                 | 3              | 91.67%          | 86.84%             |                  | 0.76              |
|                  | Winter cereals      | 5                  | 27             | 84.38%          | 90%                |                  |                   |
| Slovenia         | Non-winter cereals  | 12                 | 1              | 92.31%          | 85.71%             |                  | 0.89              |
|                  | Winter cereals      | 2                  | 12             | 85.71%          | 92.31%             |                  | 0.78              |
| Switzerland      | Non-winter cereals  | 19                 | 0              | 100%            | 86.36%             |                  | 0.82              |
|                  | Winter cereals      | 3                  | 13             | 81.25%          | 100%               |                  |                   |
| Greece           | Non-winter cereals  | 31                 | 0              | 100%            | 96.88%             |                  | 0.78              |
|                  | Winter cereals      | 1                  | 2              | 66.67%          | 100%               |                  |                   |
| Portugal         | Non-winter cereals  | 40                 | 0              | 100%            | 88.89%             |                  | 0.78              |
|                  | Winter cereals      | 5                  | 20             | 80%             | 100%               |                  |                   |
| Croatia          | Non-winter cereals  | 10                 | 0              | 100%            | 90.91%             |                  | 0.84              |
|                  | Winter cereals      | 1                  | 4              | 80%             | 100%               |                  |                   |
| Ireland          | Non-winter cereals  | 40                 | 0              | 100%            | 81.63%             |                  | 0.68              |
|                  | Winter cereals      | 9                  | 15             | 62.50%          | 100%               |                  |                   |
| Netherlands      | Non-winter cereals  | 30                 | 0              | 100%            | 83.33%             |                  | 0.75              |
|                  | Winter cereals      | 6                  | 16             | 72.73%          | 100%               |                  |                   |
| Albania, Macedonia, Montenegro, Kosovo, Bosnia and Herzegovina | Non-winter cereals | 23                 | 0              | 100%            | 95.83%             |                  | 0.90              |
|                  | Winter cereals      | 1                  | 6              | 100%            | 96.67%             |                  |                   |
Figure 7. Two examples of pixel-based category maps constructed using the TWDTW method for France and Romania in 2018.

Table 2. The confusion matrix of the final winter cereal maps for 32 countries in Europe in 2018.

| Country   | Class          | Non-Winter Cereals | Winter Cereals | User's Accuracy | Producer's Accuracy | Overall Accuracy | Kappa Coefficient |
|-----------|----------------|--------------------|----------------|-----------------|---------------------|------------------|------------------|
| France    | Non-winter     | 307                | 33             | 90.29%          | 91.10%              | 90.83%           | 0.82             |
|           | Winter         |                    |                |                 |                     |                  |                  |
| Germany   | Non-winter     | 221                | 18             | 92.47%          | 91.70%              | 92.03%           | 0.84             |
|           | Winter         |                    |                |                 |                     |                  |                  |
| Romania   | Non-winter     | 108                | 6              | 94.74%          | 93.10%              | 93.86%           | 0.88             |
|           | Winter         |                    |                |                 |                     |                  |                  |
| Poland    | Non-winter     | 103                | 6              | 94.50%          | 91.15%              | 92.66%           | 0.85             |
|           | Winter         |                    |                |                 |                     |                  |                  |
| UK        | Non-winter     | 102                | 10             | 91.07%          | 88.70%              | 89.50%           | 0.79             |
|           | Winter         |                    |                |                 |                     |                  |                  |
| Spain     | Non-winter     | 30                 | 3              | 90.19%          | 71.43%              | 85.58%           | 0.69             |
|           | Winter         |                    |                |                 |                     |                  |                  |
| Bulgaria  | Non-winter     | 24                 | 11             | 68.60%          | 85.70%              | 71.70%           | 0.42             |

To examine the effect of SAR data in the identification, we took Germany as an example to identify the winter cereals with and without using SAR data during the implementation of the TWDTW method. The relationship between the estimated and agricultural statistical planted areas of winter cereals with and without SAR data was illustrated in Figure 8. The performance of the TWDTW method with SAR data is better than that without using SAR data. The R^2 value increased from 0.49 to 0.81 after using SAR data.

Figure 8. Correlations between the estimated and statistical areas of winter cereals with SAR data (a) and without SAR data (b) at the municipal level in Germany in 2018.
Table 3. The confusion matrix of the winter cereal maps for 32 countries in Europe in 2018 using the random forest and TWDTW method, respectively.

| Methods     | Class               | Winter Cereals | Non-Winter Cereals | User's Accuracy | Producer’s Accuracy | Overall Accuracy | Kappa Coefficient | Computing Time |
|-------------|---------------------|----------------|--------------------|-----------------|--------------------|------------------|-------------------|----------------|
| Random forest | Winter cereals     | 1128           | 269                | 80.74%          | 75.10%             | 80.84%           | 0.58              | 5.88 h         |
|             | Non-winter cereals | 374            | 1585               | 80.91%          | 84.59%             |                  |                   |                |
| TWDTW       | Winter cereals     | 1390           | 196                | 87.64%          | 92.54%             | 90.82%           | 0.70              | 15.36 h        |
|             | Non-winter cereals | 112            | 1658               | 93.67%          | 89.43%             |                  |                   |                |

To further examine the details of classification with the TWDTW method and random forest, we selected a small place in Romania to check the classification (Figure 9). Compared with the TWDTW method, random forest had a large misclassification of non-winter cereals, which was identified for winter cereals. For random forest, the overall accuracy is 85.44%, and kappa coefficient is 0.75, while for TWDTW, the overall accuracy is 93.86%, and kappa coefficient is 0.88.

Figure 9. The comparison of the TWDTW method (a) and random forest method (b) for winter cereal classification in Romania.

4. Discussion

In this study, we used a phenology-based TWDTW method for identifying winter cereals by comparing the similarity of seasonal changes in NDVI at a given pixel with a standard NDVI curve for winter cereals. We produced the distribution maps for winter cereals with 30 m spatial resolution for 32 countries in Europe and the average overall accuracy was 91.8%. We also used the random forest method to identify winter cereals with the same field samples for further comparison with the TWDTW method.

Our results demonstrated that the random forest method had lower accuracy than the TWDTW method in the classification of winter cereals, although random forest is faster in GEE than the TWDTW method in local server. A small number of samples was the main cause of low accuracy for random forest and less vegetation types of non-winter cereals directly led to the misclassification that non-winter cereals were identified as winter cereals. Compared with the machine learning algorithms, the TWDTW method requires only a few
training samples and is beneficial for large scale crop identification, even if the samples are insufficient [5,46]. A previous study used 30,000 samples as the training dataset to classify the cropland in Europe by using the machine learning method [41]. However, the overall accuracy only ranged from 79.2% to 88.8% in most of the countries. Based on 58,178 input samples, a recent study used the random forest classifier to generate the crop type map in Europe. For wheat, the producer’s accuracy and user’s accuracy were 78.2% and 49.6%, respectively [47]. Moreover, the standard NDVI seasonal change curves (calculated from the filed samples in 2018) were successfully applied to identify winter cereals for other years (2016, 2017, 2019) by using the TWDTW method. The $R^2$ between identified areas and agricultural census areas were greater than 0.5 in most of the countries, indicating that the TWDTW method was effective even though there are no training samples in other years [26]. A previous study trained the classifier based on samples from 2008 to 2011 and applied the trained classifier from 1894 to 2007 to identify crops by using the Classification and Regression Tree (CART) algorithm [48]. However, the results showed that the $R^2$ between identified areas and census areas only ranged from 0.142 to 0.192 in different crops.

The TWDTW method can identify winter cereals two months before harvest. This is an important benefit of the method that makes it useful for the early and continuous prediction of winter cereal production [49]. Knowing the distribution of crops ahead of the harvest, we could determine in a timely manner the regions that may suffer food crisis and provide information for local governments to take action and provide assistance [30,50]. Here, we compared the accuracy of early season maps and end of season maps to further evaluate the performance of our method. The end of season (i.e., July) winter cereal maps meant that all growing season images were used to generate the maps and the overall accuracy was 91.8%. The overall accuracy of early season winter cereal maps (88.4%) was stable in May and only 3.4% lower than that of end of season maps. A recent study [5] has also examined the ability of the TWDTW method for early-season mapping and revealed that winter wheat can be identified at the end of April with an overall accuracy of 89.88%, which is comparable to our results. In addition, some studies have conducted early-season winter crop mapping based on other methods. Skakun et al. [8] used a phenology-based method for winter crop identification and demonstrated that the winter crop maps could be achieved 1.5–2 months before harvest with an overall accuracy of 90%, but the spatial resolution (250 m) was relatively coarse. Tian et al. [51] employed the decision tree classification model to map winter crops in some counties and found that winter crops could be distinguished at an average of three months before harvest with an accuracy greater than 90%. However, this requires a large amount of training samples, which will limit the areas lacking samples and is not conducive for large scale mapping [52]. In addition, previous studies have noted that computing time is one of the challenges when using the TWDTW method [24,26]. In this study, the TWDTW method was run on a configuration using 8 cores, with 2.70 GHz and 512 GB memory. In Finland (the area was approximately 33.8 million ha), the processing time was 38 min when classifying winter cereal in 2018 (10 images). This process is significantly faster than that recorded in the previous study, which consumed 9 h when performing crop mapping with 13 images (4 cores and the area of study region was 24,256 ha) [26]. Therefore, the calculation procedure of the TWDTW method used in this study can provide support for real-time crop mapping. Furthermore, incorporating SAR data into the TWDTW method can efficiently remove the rapeseed from other winter cereals and the resulting classification depended on the rapeseed planting area.

In this study, the accuracy of the TWDTW method is comparable for all countries except Bulgaria, where it has a relatively poor overall accuracy of 71%. This is probably because Bulgaria has a Mediterranean climate in the south and a continental climate in the north, creating variability in the phenological features and growing status of winter cereals. In addition, there are some limitations for the TWDTW method. First, the threshold of Euclidean distance used to judge whether a pixel is a winter cereal relies strongly on statistical agricultural census data. Therefore, the accuracy of the method is closely related
to the reliability of agricultural census data. However, the agricultural census data usually have hysteresis, which is still a challenge for real-time crop identification [5,53]. Secondly, the effectiveness of retrieving seasonal changes in crop growth is largely determined by the quantity of cloud-free image data, which directly affects the accuracy of identification. Although we used the monthly maximum merged NDVI values from Landsat and Sentinel-2 to obtain more effective observation data, the TWDTW method performed poorly in identifying winter cereals when the cloud percentage was up to 60%. A previous study has demonstrated that the accuracy of crop identification will be reduced when lacking effective satellite data [54]. In addition, the difference in the wavelength between the Sentinel-2 and Landsat sensors may affect the quality of the synthetic NDVI data. It is still a challenge to reduce the impact from this difference [5,55]. In the future, development of the TWDTW method without the limitation of agricultural census area and a higher applicability of effective satellite data will help to improve the identification accuracy of crops.

5. Conclusions

In this study, we used the TWDTW method to produce winter cereal maps with 30 m spatial resolution in Europe for the period of 2016 to 2020 by combining Landsat and Sentinel data. The TWDTW method performed well in Europe for winter cereal identification, with an average overall accuracy of 91.8% and producer’s and user’s accuracies of 91% ± 7.8% and 89% ± 10.3%, respectively. The Kappa coefficients are more than 0.7 in most countries. Compared with the agricultural census area, the TWDTW method explained 77% ± 15% of spatial variability in the planted area at the municipal level for 11 countries. More importantly, the TWDTW method can effectively provide winter cereal maps two months before harvest with stable accuracy. In general, our study mapped the planted area of winter cereals with a high spatial resolution in Europe, which will provide a resource for decision makers to timely monitor the growth of winter cereals.

Author Contributions: Conceptualization, W.Y.; methodology, X.H. and W.Y.; software, X.H.; validation, J.W.; formal analysis, J.D.; resources, W.Y.; writing—original draft preparation, X.H. and W.Y.; writing—review and editing, Y.F., B.P., Y.Z., S.S. and W.Y.; visualization, X.H. All authors have read and agreed to the published version of the manuscript.

Funding: This research has been supported by the China National Funds for Distinguished Young Scientists (grant no. 41925001), the National Youth Top-Notch Talent Support Program (grant no. 2015-48), the Changjiang Young Scholars Program of China (grant no. Q2016161), and the Fundamental Research Funds for the Central Universities (grant no. 19lgjc02).

Data Availability Statement: The 30-m winter cereals distribution map dataset from 2016–2020 at 32 European countries is available at https://doi.org/10.6084/m9.figshare.14614818.v2 (accessed on 28 July 2021). The dataset is provided in tif format with pixel values of 1 for winter cereals and 0 for non-winter cereals.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Sternberg, T. Chinese drought, bread and the Arab Spring. *Appl. Geogr.* 2012, 34, 519–524. [CrossRef]
2. Becker-Reshef, I.; Justice, C.; Barker, B.; Humber, M.; Rembold, F.; Bonifacio, R.; Zappacosta, M.; Budde, M.; Magadzire, T.; Shitote, C.; et al. Strengthening agricultural decisions in countries at risk of food insecurity: The GEOGLAM Crop Monitor for Early Warning. *Remote Sens. Environ.* 2020, 237, 11553. [CrossRef]
3. Franch, B.; Vermote, E.F.; Skakun, S.; Roger, J.C.; Becker-Reshef, I.; Murphy, E.; Justice, C. Remote sensing based yield monitoring: Application to winter wheat in United States and Ukraine. *Int. J. Appl. Earth Obs. Geoinf.* 2019, 76, 112–127. [CrossRef]
4. Zhao, W.; Huang, J.; Li, L.; Zhang, X.; Ma, H.; Gao, X.; Huang, H.; Xu, B.; Xiao, X. Assimilating Soil Moisture Retrieved from Sentinel-1 and Sentinel-2 Data into WOFOST Model to Improve Winter Wheat Yield Estimation. *Remote Sens.* 2019, 11, 1618. [CrossRef]
5. Dong, J.; Fu, Y.; Wang, J.; Tian, H.; Fu, S.; Niu, Z.; Han, W.; Zheng, Y.; Huang, J.; Yuan, W. Early-season mapping of winter wheat in China based on Landsat and Sentinel images. *Earth Syst. Sci. Data* 2020, 12, 3081–3095. [CrossRef]
6. Griffiths, P.; Nendel, C.; Hostert, P. Intra-annual reflectance composites from Sentinel-2 and Landsat for national-scale crop and land cover mapping. *Remote Sens. Environ.* 2019, 220, 135–151. [CrossRef]
7. Atzberger, C.; Rembold, F. Mapping the spatial distribution of winter crops at sub-pixel level using AVHRR NDVI time series and neural nets. Remote Sens. 2013, 5, 1335–1354. [CrossRef]
8. Skakun, S.; Franch, B.; Vermote, E.; Roger, J.C.; Becker-Reshef, I.; Justice, C.; Kussul, N. Early season large-area winter crop mapping using MODIS NDVI data, growing degree days information and a Gaussian mixture model. Remote Sens. Environ. 2017, 195, 244–258. [CrossRef]
9. Yu, L.; Wang, J.; Clinton, N.; Xin, Q.; Zhong, L.; Chen, Y.; Gong, P. FROM-GC: 30 m global cropland extent derived through multisource data integration. Int. J. Digit. Earth 2013, 6, 521–533. [CrossRef]
10. Fu, Y.; Huang, J.; Shen, Y.; Liu, S.; Huang, Y.; Dong, J.; Han, W.; Ye, T.; Zhao, W.; Yuan, W. A Satellite-Based Method for National Winter Wheat Yield Estimating in Remote Sens. 2021, 13, 4680. [CrossRef]
11. Zhong, L.; Hu, L.; Zhou, H. Deep learning based multi-temporal crop classification. Remote Sens. Environ. 2019, 221, 430–443. [CrossRef]
12. Wang, S.; Azzari, G.; Lobell, D.B. Crop type mapping without field-level labels: Random forest transfer and unsupervised clustering techniques. Remote Sens. Environ. 2019, 222, 303–317. [CrossRef]
13. Zheng, B.; Myint, S.W.; Thanekabail, P.S.; Aggarwal, R.M. A support vector machine to identify irrigated crop types using time-series Landsat NDVI data. Int. J. Appl. Earth Obs. Geoinf. 2015, 34, 103–112. [CrossRef]
14. Wardlow, B.D.; Egbert, S.L. Large-area crop mapping using time-series MODIS 250 m NDVI data: An assessment for the U.S. Central Great Plains. Remote Sens. Environ. 2008, 112, 1096–1116. [CrossRef]
15. Boryan, C.; Yang, Z.; Mueller, R.; Craig, M. Monitoring US agriculture: The US department of agriculture, national agricultural statistics service, cropland data layer program. Geocarto Int. 2011, 26, 341–358. [CrossRef]
16. Petitjean, F.; Inglaela, J.; Gańcarski, P. Satellite image time series analysis under time warping. IEEE Trans. Geosci. Remote Sens. 2012, 50, 3081–3095. [CrossRef]
17. Solano-Correa, Y.T.; Bovoilo, F.; Bruzzzone, L. A Semi-Supervised Crop-Type Classification Based on Sentinel-2 NDVI Satellite Image Time Series and Phenological Parameters. In Proceedings of the IGARSS 2019—2019 IEEE International Geoscience and Remote Sensing Symposium, Yokohama, Japan, 28 July–2 August 2019; pp. 457–460. [CrossRef]
18. Dong, Q.; Chen, X.; Chen, J.; Zhang, C.; Liu, L.; Cao, X.; Zang, Y.; Zhu, X.; Cui, X. Mapping winter wheat in north China using sentinel 2A/B data: A method based on phenology-time weighted dynamic time warping. Remote Sens. 2020, 12, 1274. [CrossRef]
19. Sakoe, H.; Chiba, S. Dynamic Programming Algorithm Optimization for Spoken Word Recognition. IEEE Trans. Acoust. 1978, 26, 43–49. [CrossRef]
20. Guan, X.; Huang, C.; Liu, G.; Meng, X.; Liu, Q. Mapping rice cropping systems in Vietnam using an NDVI-based time-series similarity measurement based on DTW distance. Remote Sens. 2016, 8, 19. [CrossRef]
21. Costa, W.S.; Fonseca, L.M.G.; Kortingle, T.S.; Bendini, H.D.N.; De Souza, R.C.M. Spatio-temporal segmentation applied to optical remote sensing image time series. IEEE Geosci. Remote Sens. Lett. 2018, 15, 1299–1303. [CrossRef]
22. Jeong, Y.S.; Jeong, M.K.; Omitaoum, O.A. Weighted dynamic time warping for time series classification. In Pattern Recognition; Academic Press: Cambridge, MA, USA, 2011; pp. 2231–2240.
23. Rabiner, L.; Jiang, B.-H. Fundamentals of Speech Recognition; Prentice-Hall, Inc.: Hoboken, NJ, USA, 1993; ISBN 0130151572.
24. Maus, V.; Cámara, G.; Cartaxo, R.; Sanchez, A.; Ramos, F.M.; De Queiroz, G.R. A Time-Weighted Dynamic Time Warping Method for Land-Use and Land-Cover Mapping. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 2016, 9, 3729–3739. [CrossRef]
25. Pan, B.; Zheng, Y.; Shen, R.; Ye, T.; Zhao, W.; Dong, J.; Ma, H.; Yuan, W. High Resolution Distribution Dataset of Double-Season Paddy Rice in China. Remote Sens. 2021, 13, 4609. [CrossRef]
26. Belgů, M.; Csillik, O. Sentinel-2 cropland mapping using pixel-based and object-based time-weighted dynamic time warping analysis. Remote Sens. Environ. 2017, 204, 509–523. [CrossRef]
27. Weisssteiner, C.J.; López-Lozano, R.; Manfron, G.; Duveiller, G.; Hooker, J.; van der Velde, M.; Baruth, B. A Crop group-specific pure pixel time series for Europe. Remote Sens. 2019, 11, 2668. [CrossRef]
28. Estel, S.; Kuemmerle, T.; Alcantara, C.; Levers, C.; Prischepov, A.; Hostert, P. Mapping farmland abandonment and recultivation across Europe using MODIS NDVI time series. Remote Sens. Environ. 2015, 163, 312–325. [CrossRef]
29. Estel, S.; Kuemmerle, T.; Levers, C.; Baumann, M.; Hostert, P. Mapping cropland-use intensity across Europe using MODIS NDVI time series. Environ. Res. Lett. 2016, 11, 024015. [CrossRef]
30. Defourny, P.; Bontemps, S.; Bellemans, N.; Cara, C.; Dedieu, G.; Guzzonato, E.; Hugol, O.; Inglaela, J.; Nicola, L.; Rabate, T.; et al. Near real-time agriculture monitoring at national scale at parcel resolution: Performance assessment of the Sen-2Agri automated system in various cropping systems around the world. Remote Sens. Environ. 2019, 221, 551–568. [CrossRef]
31. Pan, L.; Xia, H.; Zhao, X.; Guo, Y.; Qin, Y. Mapping Winter Crops Using a Phenology Algorithm, Time-Series Sentinel-2 and Landsat-7/8 Images, and Google Earth Engine. Remote Sens. 2021, 13, 2510. [CrossRef]
32. Guo, Y.; Xia, H.; Pan, L.; Zhao, X.; Li, R. Mapping the Northern Limit of Double Cropping Using a Phenology-Based Algorithm and Google Earth Engine. Remote Sens. 2022, 14, 1004. [CrossRef]
33. Bontemps, S.; Arias, M.; Cara, C.; Dedieu, G.; Guzzonato, E.; Hugol, O.; Inglaela, J.; Matton, N.; Morin, D.; Popescu, R.; et al. Building a data set over 12 globally distributed sites to support the development of agriculture monitoring applications with Sentinel-2. Remote Sens. 2015, 7, 16062–16090. [CrossRef]
34. Bontemps, S.; Arias, M.; Cara, C.; Dedieu, G.; Guzzonato, E.; Hugol, O.; Inglaela, J.; Morin, D.; Rabate, T.; Savinaud, M.; et al. “Sentinel-2 for agriculture”: Supporting global agriculture monitoring. IEEE Int. Geosci. Remote Sens. Symp. 2015, 4185–4188.
Remote Sens. 2022, 14, 2120

35. Vaudour, E.; Noirot-Cosson, P.E.; Membrive, O. Early-season mapping of crops and cultural operations using very high spatial resolution Péliades images. Int. J. Appl. Earth Obs. Geoinf. 2015, 42, 128–141. [CrossRef]

36. Trnka, M.; Rötter, R.P.; Ruiz-Ramos, M.; Kersebaum, K.C.; Olesen, J.E.; Žalud, Z.; Semenov, M.A. Adverse weather conditions for European wheat production will become more frequent with climate change. Nat. Clim. Chang. 2014, 4, 637–643. [CrossRef]

37. Chipanshi, A.; Zhang, Y.; Kouadio, L.; Newlands, N.; Davidson, A.; Hill, H.; Warren, R.; Qian, B.; Daneshfar, B.; Bedard, F.; et al. Evaluation of the Integrated Canadian Crop Yield Forecaster (ICCYF) model for in-season prediction of crop yield across the Canadian agricultural landscape. Agric. For. Meteorol. 2015, 206, 137–150. [CrossRef]

38. Trnka, M.; Hlavinka, P.; Semenov, M.A. Adaptation options for wheat in Europe will be limited by increased adverse weather events under climate change. J. R. Soc. Interface 2015, 12, 20150721. [CrossRef]

39. Senapati, N.; Stratonovitch, P.; Paul, M.J.; Semenov, M.A. Drought tolerance during reproductive development is important for increasing wheat yield potential under climate change in Europe. J. Exp. Bot. 2019, 70, 2549–2560. [CrossRef]

40. Inglova, J.; Vincent, A.; Arias, M.; Marais-Sicre, C. Improved early crop type identification by joint use of high temporal resolution SAR and optical image time series. Remote Sens. 2016, 8, 362. [CrossRef]

41. Phalke, A.R.; Özdoğan, M.; Thenkabail, P.S.; Erickson, T.; Gorelick, N.; Yadav, K.; Congalton, R.G. Mapping croplands of Europe, Middle East, Russia, and Central Asia using Landsat, Random Forest, and Google Earth Engine. ISPRS J. Photogramm. Remote Sens. 2020, 167, 104–122. [CrossRef]

42. Veloso, A.; Mermoz, S.; Bouvet, A.; Le Toan, T.; Planells, M.; Dejoux, J.F.; Ceschia, E. Understanding the temporal behavior of crops using Sentinel-1 and Sentinel-2-like data for agricultural applications. Remote Sens. Environ. 2017, 199, 415–426. [CrossRef]

43. Xu, X.; Conrad, C.; Doktor, D. Optimising phenological metrics extraction for different crop types in Germany using the moderate resolution imaging Spectrometer (MODIS). Remote Sens. 2017, 9, 254. [CrossRef]

44. Fan, C.; Zheng, B.; Myint, S.W.; Aggarwal, R. Characterizing changes in cropping patterns using sequential Landsat imagery: An adaptive threshold approach and application to Phoenix, Arizona. Int. J. Remote Sens. 2014, 35, 7263–7278. [CrossRef]

45. Olofsson, P.; Foody, G.M.; Herold, M.; Stehman, S.V.; Woodcock, C.E.; Waldner, M.A. Good practices for estimating area and assessing accuracy of land change. Remote Sens. Environ. 2014, 148, 42–57. [CrossRef]

46. King, L.A.; Adusei, B.; Stehman, S.V.; Potapov, P.V.; Song, X.P.; Krylov, A.; Di Bella, C.; Loveland, T.R.; Johnson, D.M.; Hansen, M.C. A multi-resolution approach to national-scale cultivated area estimation of soybean. Remote Sens. Environ. 2017, 195, 13–29. [CrossRef]

47. Andrimont, R.; Verhegghen, A.; Lemoine, G.; Kempeneers, P.; Meroni, M.; van der Velde, M. From parcel to continental scale—A first European crop type map based on Sentinel-1 and LUCAS Copernicus in-situ observations. Remote Sens. Environ. 2021, 266, 112708. [CrossRef]

48. Johnson, D.M. Using the Landsat archive to map crop cover history across the United States. Remote Sens. Environ. 2019, 232, 111286. [CrossRef]

49. McNairn, H.; Kross, A.; Lapen, D.; Caves, R.; Shang, J. Early season monitoring of corn and soybeans with TerraSAR-X and RADARSAT-2. Int. J. Appl. Earth Obs. Geoinf. 2014, 28, 252–259. [CrossRef]

50. You, N.; Dong, J. Examining earliest identifiable timing of crops using all available Sentinel 1 / 2 imagery and Google Earth Engine. ISPRS J. Photogramm. Remote Sens. 2020, 161, 109–123. [CrossRef]

51. Tian, H.; Wang, Y.; Chen, T.; Zhang, L.; Qin, Y. Early-Season Mapping of Winter Crops Using Sentinel-2 Optical Imagery. Remote Sens. 2021, 13, 3822. [CrossRef]

52. Johnson, D.M. A comprehensive assessment of the correlations between field crop yields and commonly used MODIS products. Int. J. Appl. Earth Obs. Geoinf. 2016, 52, 65–81. [CrossRef]

53. Song, X.-P.; Potapov, P.V.; Krylov, A.; King, L.; Di Bella, C.M.; Hudson, A.; Khan, A.; Adusei, B.; Stehman, S.V.; Hansen, M.C. National-scale soybean mapping and area estimation in the United States using medium resolution satellite imagery and field survey. Remote Sens. Environ. 2017, 190, 383–395. [CrossRef]

54. Dong, J.; Xiao, X.; Kou, W.; Qin, Y.; Zhang, G.; Li, L.; Jin, C.; Zhou, Y.; Wang, J.; Biradar, C. Tracking the dynamics of paddy rice planting area in 1986–2010 through time series Landsat images and phenology-based algorithms. Remote Sens. Environ. 2015, 160, 99–113. [CrossRef]

55. He, M.; Kimball, J.S.; Maneta, M.P.; Maxwell, B.D.; Moreno, A.; Beugueria, S.; Wu, X. Regional crop gross primary productivity and yield estimation using fused landsat-MODIS data. Remote Sens. 2018, 10, 372. [CrossRef]