Mapping fallow fields using Sentinel-1 and Sentinel-2 archives over farming-pastoral ecotone of Northern China with Google Earth Engine

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ABSTRACT
The cropland in the farming-pastoral ecotone of Northern China is highly unstable owing to environmental restoration projects, poor soil fertility, poverty, and rural labor loss, and it is characterized by a large number of fallow fields. Mapping fallow fields in a farming-pastoral ecotone can help in evaluating the impact of complex cropland landscapes on the environment and food security. To map the fallow fields using the Sentinel-1 and Sentinel-2 archives, a multi-temporal dataset of vertical transmit–vertical receive + vertical transmit–horizontal receive polarization was established. Moreover, spectral bands and vegetation index datasets were established using Google Earth Engine to classify cropped and fallow fields using the Random Forest classifier. The overall accuracies and Kappa coefficients of different datasets were assessed to examine the dataset with the highest overall accuracy in the main growing season. A 10 m resolution fallow map for 2020 was then generated based on the combined Sentinel-1 and Sentinel-2 datasets with the highest overall accuracy and Kappa coefficients were 95.82% and 0.92, respectively. In addition, the time-series characteristics of the entropy eigenvalues generated via dual-polarization decomposition were quantitatively evaluated to clarify the contribution of the Sentinel-1 synthetic-aperture radar archive to the fallow field mapping. The eigenvalues were more sensitive to the phenological characteristics of cropped and fallow fields than the original backscatter signal of the Sentinel-1 data. Moreover, the mapping method was tested at different time intervals by gradually aggregating the results across an increasing number of months to optimize the fallow field monitoring using the minimum number of observations possible within a short period. Data aggregated over August achieved the highest one-month accuracy; it was also very close to the observations from the whole growing season. The results further emphasize the influence of Sentinel-1 archives on fallow field mapping. Overall, this study clarifies the potential applicability of Sentinel archives for monitoring and mapping managing patterns of agricultural land in a region.

Introduction

The need to meet the food and nutritional demands of the ever-growing human population is exerting immense pressure on agriculture worldwide (Fróna, Szenderá, and Harangi-Rákos 2019). Thus, efficient methods for mapping complex croplands are essential for implementing sustainable agricultural practices and periodically monitoring crops in ecological transition zones (Belgu and Csillik 2018; Yin et al. 2018a). Fallow cropland is widespread in arid farming areas, such as the farming-pastoral ecotone of Northern China, which receives low amounts of precipitation and experiences prolonged drought (Chen et al. 2021a).

The Food and Agriculture Organization of the United Nations (FAO) defines fallow land as a cropland that has been uncropped for 1–5 years (Dara et al. 2018; Prischepov et al. 2013; Yin et al. 2018a). Fallow land is a land management strategy used to restore soil fertility when access to livestock manure or chemical fertilizers is limited (Bégué et al. 2018; Tong et al. 2020). Fallow farming in the farming-pastoral ecotone of Northern China is a voluntary
strategy used by farmers; it is also encouraged by the government (Chen et al. 2021b). However, if fallow land is left unsupervised for long periods, this might result in cropland abandonment, which is a special type of land use change caused by a range of social, economic, and environmental issues (Li and Li 2017).

The practice of leaving land fallow has existed in arid and semi-arid regions for hundreds of years. A previous study conducted in the Sahel of Africa, which is a typical arid and semi-arid region, found that the fallow fields occupied 57–62% of Sahelian agricultural lands in 2017 (Tong et al. 2020). In 2018, fallow fields in the United States of America accounted for 6,888 thousand hectares (KNOEMA 2019), representing approximately 3.5% of the total cropland area. According to two national household surveys conducted in 262 counties located in 29 provinces in China, approximately 13.5% and 15% of the agricultural fields were idle in 2011 and 2013, respectively (Gan, Yin, and Tan 2015). It has also been shown that fallow ratio tends to be higher in the farming-pastoral ecotone of Northern China. Chen et al. (2021b) found that fallow land represented up to 40% of cropland in a transitional zone between pastoral and agricultural areas in the northern part of Ulanqab, which is located in the middle part of the farming-pastoral ecotone of Northern China.

There is a global prevalence of fallow land, but there is currently a lack of continuous global or national-scale fallow field monitoring. The development of timely and accurate mapping methods for fallow cropland might better reveal the impact of fallow land on agricultural production; this could help develop informed government policies regarding fallow and cropped fields, as well as the selection of reserve cropland (Gumma et al. 2018).

Remote sensing has become an important method for characterizing land use and land cover change processes because repeated observations can be obtained by multi-temporal remote sensors. This allows for the capture of seasonal changes in different crop types and fallow patterns (Dong et al. 2016; Prishchepov et al. 2012; Tong et al. 2020). Most previous studies have used the Normalized Difference Vegetation Index (NDVI) to assess fallow cropland, based on the Moderate Resolution Imaging Spectroradiometer (MODIS), Landsat, and Sentinel-2 archives; this vegetation index has been described as the most vital and valuable index for detecting vegetation coverage (Alcantara et al. 2013, 2012; Dara et al. 2018; Kanjir, Đurić, and Veljanovski 2018; Löff et al. 2018; Tong et al. 2020; Yin et al. 2018a). However, using multi-metrics with a higher-dimensional data layer might enhance the ability of remote sensing to identify and classify complex surfaces (Cegielska et al. 2018; Hasituya et al. 2016).

In this context, data from Sentinel-1 and Sentinel-2 satellites might contribute to fallow field monitoring and mapping. Tong et al. (2020) utilized Sentinel-2 data to monitor active crop and fallow fields within agricultural lands, based on five different contemporary cropland products, using Google Earth Engine (GEE). Kanjir, Đurić, and Veljanovski (2018) investigated anomaly observations in an agricultural parcel using a time series of Sentinel-2 NDVI images. Useya and Chen (2019) revealed that the Sentinel-1 time-series archive could detect subtle changes that occur in fields and thus could be utilized to detect cropping patterns over small-scale farmlands. The Sentinel-2 archive is indisputably powerful in typical remote sensing application (D’Amico et al. 2021; Wang et al. 2019); its utility could likely be increased further by integrating it with information from the Sentinel-1 (Synthetic-aperture radar, SAR) archive (Veloso et al. 2017; Slagter et al. 2020). Sentinel-1 and Sentinel-2 combined datasets have been used widely in land use/land cover mapping (Steinhäusen et al. 2018), irrigation area mapping (Gao et al. 2018), soil moisture monitoring (El Hajj et al. 2017; Gao et al. 2017), and crop classification (Van Tricht et al. 2018). Moreover, Sentinel-1 data have been used to detect crop fallowing in a previous study (Chandna and Mondal 2020). However, the Sentinel-1 and Sentinel-2 datasets have yet to be combined to monitor fallow cropland.

Xie et al. (2007) and Tong et al. (2020) have shown that masking non-agricultural areas blended with agricultural fields is a critical pre-processing step for distinguishing active cropping and fallow fields regarding remote sensing activities. The fallow fields in the farming-pastoral ecotone of Northern China can be easily confused with cropped fields in multispectral remote sensing data due to climatic and soil conditions (Estel et al. 2015), cropping techniques (Tong et al. 2017), and crop failure (Siebert, Portmann, and Döll 2010). It is also easy to confuse the surrounding ecosystems because of their natural regeneration. Furthermore, it is challenging to map such areas because of the extensive and diverse
fallow practices in the ecological transition zone (Siebert, Portmann, and Döll 2010). Therefore, accurate cropland maps and multi-sensor remote sensing data fusion are essential for mapping fallow fields in such an area.

Typically, fallow fields differ significantly from cropped fields based on the spectral bands in the farming-pastoral ecotone of Northern China. The cropped fields are generally greener than the fallow fields during the growing season, which means that the cropped field had a higher NDVI value; while the NDVI value of the fallow fields in the early growing season is higher than that of the cropped fields. The difference is caused by the traditional cropping practices that characterize the study area, with plowing being conducted before planting in cropping fields. In contrast, the fields that are to be fallow in the following year do not undergo preparatory work, such as plowing and/or fertilization. Hence, weeds grow in the fields due to natural vegetation restoration (Levers et al. 2018; Li and Li 2017), which leads to a higher vegetation cover than in bare soil; therefore, the fallow fields have higher NDVI values than the cropped fields in the early growing season.

In general, the following challenges complicate the identification of fallow and cropped fields using optical data: (i) images should be obtained during a specific period to best capture the difference in phenology between cropped and fallow fields; therefore, high time-resolution remote sensing images are required; (ii) the highly fragmented cropland landscape and the small cropland patches in the farming-pastoral ecotone require high spatial resolution images; and (iii) clouds and rain occur during the critical crop-growing period; therefore, it may be challenging to obtain sufficiently clear optical observations. The open-source high spatio-temporal resolution data of the Sentinel-1 and Sentinel-2 archives, combined with Google’s powerful Earth Engine cloud-computing platform (Mugiranaza, Nascetti, and Ban 2020; Shelestov et al. 2017) can overcome the above-mentioned challenges by combining both Sentinel-1 and Sentinel-2 data.

In the present study, to estimate agricultural land use in 2020, multi-metric data obtained from Sentinel-1 and Sentinel-2 archives were analyzed to establish a method that can accurately identify fallow fields across a large area, using a combined time series dataset of the Sentinel-1 and Sentinel-2 archives and Google Earth Engine. This method was tested over the farming-pastoral ecotone of the northern foot of the Yinshan Mountains, China. In addition, to assess the contribution of SAR data to fallow field mapping, the time-series eigenvalues derived from the Sentinel-1A Single Look Complex (SLC) archive were analyzed over the sampling area to characterize the growing season trajectories of the cropped and fallow fields. Lastly, the accuracy of the developed method was tested under different aggregated strategies, and an optimized strategy for identifying fallow fields was determined that required as few observations as possible over a relatively short period.

Materials

Study area

The farming-pastoral ecotone in northern China is an ecological security barrier located at the front of natural pastoral areas; the vegetation dynamics in this region are influenced by both natural and anthropogenic factors; they have undergone drastic changes in the past few decades. The changes have caused a range of social, economic, and environmental issues. Fallowing is an effective practice for balancing agricultural production and ecology in a region, restoring soil fertility, and increasing field yields (Shen et al. 2019; Chen et al. 2021a, 2021b).

The farming-pastoral ecotone of the northern foot of Yinshan Mountain is located in the central part of the farming-pastoral ecotone of northern China. The area experiences inadequate annual rainfall and high evaporation (Zhang, Ning, and Tong 2020) and has a fragile ecological environment. Poor agricultural production conditions have led to fallowing and abandonment of cropland over the last two decades (Wang 2018). Therefore, this area was selected for developing a method for mapping fallow fields.

The farming-pastoral ecotone of the northern foot of Yinshan Mountain (Figure 1) is located in the central part of the Inner Mongolia Autonomous Region, China; the Yinshan Mountain Range lies to the south, and the Mongolian Plateau pastoral area lies to the north. The ecotone spans a region located at 107°16’38” – 116°55’45” E and 40°43’6” – 43°22’52” N. The ecotone comprises 11 counties in Xilin Gol League, Ulanqab City, Hohhot City, Baotou City, and Bayannaoer City, with a total area of 96,767 km² and
The area has an average altitude of 1600 m. The area has a typical mid-temperate continental monsoon climate that is characterized by an annual precipitation of 200–400 mm, annual evaporation of 1,600–2,000 mm, and an annual average wind speed of 4.7 m·s⁻¹. The landforms mainly comprise hills with gentle slopes, within which the arid cropping fields are distributed. The area’s chestnut soil has a rough texture.

Drought-tolerant crops, such as spring wheat, corn, benne, canola, naked oats, and potatoes, are the main crops planted in a single season in the area, because of the low-accumulated temperature and the unfavorable water and heat conditions (Li et al. 2015). The growing period of the crops is between May and October.

Spring drought is the most common and severe natural disasters in the region; it can lead to a dry soil thickness of more than 20 cm in some fields, and approximately 58% of the cropland can become unavailable for planting. This greatly affects the production of agriculture and animal husbandry (Chen et al. 2002).

**Database**

**Sentinel-1 data**

The Sentinel-1 archive provides data from the dual-polarization C-band SAR instrument. This collection includes S1 ground range detected (GRD) scenes, which are processed using the Sentinel-1 Toolbox.
to generate a calibrated, ortho-corrected product on the GEE platform. In the present study, both Sentinel-1A and Sentinel-1B data from 2020 were used to map fallow fields, the data have a resolution of 10 m and a temporal resolution of 12 d. Previous studies have pointed out that vertical–vertical (VV) polarization data, in comparison to vertical-horizontal (VH) polarization data, show higher sensitivity to soil moisture (Amazirh et al. 2018). The VH data have higher sensitivity to volume scattering, which depends strongly on the geometrical alignment and characteristics of the vegetation in question (Patel et al. 2006). As fallow fields have different vegetation density and soil conditions, both VV and VH polarizations were utilized here to establish a fallow field mapping method.

**Sentinel-2 data**

Top-of-Atmospheric-corrected Sentinel-2 (MSI Level-1 C) data were obtained for 2020, including data from Sentinel-2A and –2B, and repeat cycle of 5 days was achieved for GEE, which was used to map the fallow fields in this study. In this step, the bands with 60 m resolution (bands 1, 9, and 10) are primarily used to detect atmospheric features and therefore are not included in subsequent research. Details of the Sentinel-2 data are shown in Table 1.

| Name | Description | Resolution | Wavelength |
|------|-------------|------------|------------|
| B2   | Blue        | 10 m       | 496.6 nm (S2A)/492.1 nm (S2B) |
| B3   | Green       | 10 m       | 560 nm (S2A)/559 nm (S2B) |
| B4   | Red         | 10 m       | 664.5 nm (S2A)/665 nm (S2B) |
| B5   | Red Edge 1  | 20 m       | 703.9 nm (S2A)/703.8 nm (S2B) |
| B6   | Red Edge 2  | 20 m       | 740.2 nm (S2A)/739.1 nm (S2B) |
| B7   | Red Edge 3  | 20 m       | 782.5 nm (S2A)/779.7 nm (S2B) |
| B8   | Near-infrared (NIR) | 10 m  | 835.1 nm (S2A)/833 nm (S2B) |
| B8A  | Red Edge 4  | 20 m       | 864.8 nm (S2A)/864 nm (S2B) |
| B11  | SWIR 1      | 20 m       | 1613.7 nm (S2A)/1610.4 nm (S2B) |
| B12  | SWIR 2      | 20 m       | 2202.4 nm (S2A)/2185.7 nm (S2B) |

First, a cloud cover filter (set at <10%) was used to filter out cloudy images from the Sentinel-2 archives. Second, the QA60 band was used to remove cloud pixels and obtain clear observation pixels for the study area. The spatial distributions of the clear observation numbers of Sentinel-1 and Sentinel-2 pixels are shown in Figure 2.

**Reference data**

A cropland base map with an F1 score of 0.94 has been previously used to mask out other land use classes (i.e. impervious surfaces, water, forest, woodland, grassland, and bare soil) in the farming-pastoral ecotone of the northern foot of the Yinson Mountains (Wuyun et al. 2022). Due to the unprecedented dynamic land use changes that have occurred in the area, fallow land and abandoned cropland can be easily confused with the surrounding natural grassland, or with cropland that has been retired under ecological restoration projects, such as the “Grain for Green” project. In a previous study, texture information was shown to have a significant effect on the classification of complex croplands. Hence, croplands in the study area were classified using 2019 data with 30-m resolution spectral bands from the Landsat Operational Land Imager (OLI) archives, and with 15-m resolution texture information from the panchromatic band. Diversified samples were utilized, including fallow, abandoned, and active cropland.

High-resolution GEE images were used as a reference to assess whether land was fallow or cropped, as shown in Figure 1d. One thousand samples were collected separately for both non-cropped and cropped fields using visual interpretations (Estel et al. 2015; Yin et al. 2020). Each sample is labeled as either fallow or cropped, following the principle introduced in Figure 1d. Sentinel-2 time series of clear observations acquired from June 2020 to September 2020 were used for this purpose. The
study area is a typical arid farming area in northern China, with single-season crops being grown throughout the year. Therefore, to avoid misinterpretation due to intra-annual crop growth variability, the images during the crop-growing season were selected and reduced using median values to highlight the spectral differences between the fallow and cropped fields (samples were selected through visual interpretations).

**Methods**

The method introduced in this research can be classified into three main stages: first, multi-sensor data were used to generate multiple metrics with which to identify cropped and fallow fields with GEE. The classification accuracies of different types of datasets were evaluated to create a fallow field map with the highest overall accuracy and Kappa coefficient at 10-m resolution. Second, the PolSARpro software was used to conduct dual-polarization decomposition for the Sentinel-1A SLC time-series archive and to obtain entropy and alpha eigenvalues. Moreover, the time-series characteristics of entropy and alpha were analyzed for cropped and fallow fields that differed from the original SAR backscatter signal, to explain the contribution of the Sentinel-1 archive to the classification. Third, to evaluate the optimal strategy for mapping fallow fields, the accuracy of the developed method was tested under different sensor data and across different time periods.

The overall workflow using the Random Forest classifier is shown in Figure 3.

**Sentinel-1 data processing**

**Backscatter signal of Sentinel-1**

The statistics of the time-series backscatter signal for the selected samples were analyzed, including the cropped and fallow fields on the cropland base map. The backscatter characteristics of soil and vegetation will appear differently in SAR images. Differences in cultivation activity cause differences in vegetation density, which affects the VH polarization backscatter signal. Fallow land features bare soil at the ground surface, which affects the VV polarization backscatter signal. Therefore, the median and variance values were analyzed solely within the selected samples over the fallow and cropped fields.

The restoration of natural vegetation in fallow fields after plowing differs significantly between the east and west of the study area, due to the different water conditions. In addition, the scattering mechanisms of crops in the cropped fields (such as sunflower and corn, which have tall stems and crops, such as potatoes and naked oats, which have short stems)

![Figure 3. Flowchart of the applied method based on Random Forest algorithm in GEE and PolSARpro software; NBR, Normalized Burn Ratio.](image-url)
also have discernible differences. Therefore, to eliminate the interference of such differences on the minimum and maximum values, median values were used to represent the general scattering mechanisms of the samples. The median and variance values of the time-series backscatter signal were also taken for each 10-m cell, and were analyzed based on the entire period of data acquisition.

**Dual-polarization decomposition of Sentinel-1 data**

To illustrate the characteristics and application potential of dual-PolSAR for remote sensing monitoring of fallow fields from a new perspective, the eigenvalues of dual-polarization decomposition are generated in the present study.

Polarimetric decomposition theorems have been introduced to investigate the intrinsic physical properties of natural media by evaluating the underlying-scattering mechanisms. Some previous studies interpreted the polarization of backscattered waves and established a relationship between the physical properties of a medium and its polarimetric transformations (Cloude and Pottier 1997; Ferro-Famil, Pottier, and Lee 2001). The use of multifrequency polarimetric datasets has been shown to increase the interpretative capabilities of quantitative remote sensing in natural media.

Cloude and Pottier (1997) originally proposed the H/α decomposition algorithm for quad-PolSAR data. However, to better process dual-polarization PolSAR data, scholars have more recently proposed some decomposition algorithms specific to dual-PolSAR data (Zhou et al. 2011; Ainsworth et al. 2008; Sugimoto, Ouchi, and Nakamura 2012; Guo et al. 2018). Furthermore, Guo et al. (2018) revealed that the two parameters (H and α) derived from H/α decomposition based on VV+VH dual-PolSAR data can also describe the scattering characteristics. However, at present, the dual-polarization decomposition cannot be realized in GEE. Therefore, it is difficult to input H and α as variables into the classification process in large regions, and this process cannot be automated.

Therefore, in this study, one scene of Sentinel-1 image was taken as a test area (Figure 1b) to show the time-series characteristics of the fallow and cropped fields in the SAR data. All available Sentinel-1 SLC images for the main growing season were downloaded from the Copernicus Open Access Hub (https://scihub.copernicus.eu). The H of the scattering characteristics of the cropped and fallow fields was extracted using the growing season time-series Sentinel-1A SLC level 1 standard dual VV+VH polarization images and PolSARpro software. The eigenvalues decomposed from the coherency/covariance matrix constructed from the two vectors are identical, and the parameter H is the same. The only difference observed was that the first element of the decomposed eigenvectors included a constant phase shift of π/4. In other words, it is difficult to establish a relationship between α angle based on dual-PolSAR and volume scattering. Therefore, α was not included in the present study. The data included multi-look, geocoding, speckle filtering, and decomposition values. Therefore, time-series changes in the cropped and fallow fields were comprehensively evaluated using H/α decomposition polarization target analysis. Details of the acquired Sentinel-1 SLC data are shown in Table 2.

Here, the eigenvalue decomposition method is used to decompose the polarization coherence matrix into a weighted sum of two costs: the scattering entropy, H, and the average scattering angle, α. These parameters represent the corresponding physical meanings for distinct eigenvalues and their corresponding eigenmatrices (Cloude and Pottier 1997).

H and α are two essential parameters applied to the polarization scattering characteristics of the target land surface objects. H describes the randomness of the scattering process. When H = 0, the scattering process corresponds to a fully polarized state that is isotropic; increases in H corresponding to increases in the randomness of the target’s polarization. When H = 1, this indicates that the scattering process is wholly random and shows anisotropy, and thus that no polarization information can be obtained. Therefore, 0 < H< 1 indicates the randomness of the scattering, from completely polarized to completely random.

**Sentinel-2 data processing**

The wide range of spectral bands of the Sentinel-2 archive can meet the remote-sensing monitoring and mapping requirements of land-use/land-cover change (LUC). The median values of the Visible, Red Edge, Near-Infrared (NIR), and Short-Wave Infrared (SWIR) bands were included in the combined dataset to accurately represent fallow field mapping. The spectral bands of Sentinel-2 used in this study are listed in Table 1.
Table 2. Descriptions of the acquired Sentinel-1 time-series data for dual-polarization decomposition.

| Date       | Satellite platform | Product type | Mode | Orbit number | Pass direction | Polarization |
|------------|--------------------|--------------|------|--------------|----------------|--------------|
| 2020.05.09 | S1A                | SLC          | IW   | 32487        | Ascending      | VV+VH        |
| 2020.05.21 | S1A                | SLC          | IW   | 32662        | Ascending      | VV+VH        |
| 2020.06.02 | S1A                | SLC          | IW   | 32837        | Ascending      | VV+VH        |
| 2020.06.14 | S1A                | SLC          | IW   | 33012        | Ascending      | VV+VH        |
| 2020.06.26 | S1A                | SLC          | IW   | 33187        | Ascending      | VV+VH        |
| 2020.07.08 | S1A                | SLC          | IW   | 33362        | Ascending      | VV+VH        |
| 2020.07.20 | S1A                | SLC          | IW   | 33537        | Ascending      | VV+VH        |
| 2020.08.01 | S1A                | SLC          | IW   | 33712        | Ascending      | VV+VH        |
| 2020.08.13 | S1A                | SLC          | IW   | 33887        | Ascending      | VV+VH        |
| 2020.08.25 | S1A                | SLC          | IW   | 34062        | Ascending      | VV+VH        |
| 2020.09.18 | S1A                | SLC          | IW   | 34412        | Ascending      | VV+VH        |
| 2020.10.12 | S1A                | SLC          | IW   | 34762        | Ascending      | VV+VH        |
| 2020.10.24 | S1A                | SLC          | IW   | 34937        | Ascending      | VV+VH        |

The fallowing of cropland can significantly change vegetation coverage in a field. Field sampling and ground investigation revealed that during the growing season NDVI values of fallow fields were lower than those of cropped fields in the farming-pastoral ecotone of the northern foot of the Yinshan Mountains, as shown in Figure 5a. Moreover, the NDVI curve shows a single peak because there were no double-season crops in the study area. Here, the time-series median values and the variance of NDVI were both used to characterize the differences between cropped and fallow fields.

Once the active cropland becomes idle, the first year of the idle period can consider the year in which the disturbance event occurred (Kennedy, Yang, and Cohen 2010). Recent remote sensing monitoring research into forest disturbance events has shown that the normalized burn ratio (NBR) is the most sensitive index for such disturbances (Cohen, Yang, and Kennedy 2010), as per equations (1) and (2):

\[
\text{NDVI} = \frac{\text{NIR} - \text{Red}}{\text{NIR} + \text{Red}} \quad (1)
\]

\[
\text{NBR} = \frac{\text{NIR} - \text{SWIR2}}{\text{NIR} + \text{SWIR2}} \quad (2)
\]

The two indices based on Sentinel-2 data present the same changing trend during the growing season. In the study area, the difference between the median values from cropped and fallow field samples was the minimum before July but reached the maximum from August to September; the deviation between the two field types then decreased again after late September.

Accuracy assessment

The overall accuracy (OA) and Kappa coefficient were employed to evaluate the performance of the dataset and the classifier. OA is defined as the ratio of the total number of correctly classified pixels to the total number of pixels (i.e. the total number of ground truth reference pixels; Foody 2002). In the present study, a random segmentation approach was used to generate training and validation samples from all ground reference samples. A confusion matrix accuracy calculation was performed on the classification results. The samples used for classification were randomly split into two groups: training (70% of the samples) and validation (30% of the samples).

The OA and Kappa coefficients of each dataset were assessed to evaluate the contribution of each dataset, based on the Sentinel-1 and Sentinel-2 archives, for fallow field classification. The datasets were divided into three categories: the median reflectance value of the spectral bands based on Sentinel-2 data; the median and variance values of indices based on Sentinel-2 data; and the median and variance values of the backscatter signal based on dual-PolSAR Sentinel-1 data. Finally, the highest OA and Kappa coefficients were derived to establish the optimal combined dataset in this study.

Evaluation of optimal mapping strategies

When developing an optimal strategy for fallow mapping, there is a tradeoff between early identification and accuracy (You and Dong 2020). To accurately map the fallow fields using as few satellite observations as possible within a short period, the Sentinel archive was aggregated by the month (1 month, 2 months, and 3 months, etc.). The OAs at different time
intervals were calculated to determine the optimal solution for the fallow field mapping, using either different sensor Sentinel data or a combined dataset.

Results

The classification accuracy was tested using increasing steps of 100 trees; the highest accuracy occurred when the tree number was 300. Therefore, a Random Forest classifier with 300 trees was trained and applied to each dataset to identify fallow fields using GEE. All cropland pixels in the study area were previously identified using geoinformation from a pixel-based cropland base map constructed in 2019 (Figure 1; Wuyun et al. 2022). There was a negligible difference in the cropland area between 2019 and 2020. Randomly selected verification samples were used to assess the accuracy of each dataset regarding fallow field classification.

Fallow field map

During the whole growing season, there were more cropped fields (59.95%) than fallow fields (40.05%) within the cropland area, according to the classification map obtained by the combined Sentinel-1 and Sentinel-2 dataset with the highest OA and Kappa coefficient (Table 3). The fallow field percentage in the region is surprisingly high, although a large area of cropland has been converted into shrubbery or woodland due to ecological restoration projects over the last 20 years. Darhan Banner had the greatest percentage of fallow fields (over 65%), followed by the Wuchuan and Guyang counties, with over 50% of cropland being fallow in 2020 in the areas. The cropland in the south of Wulate Middle is at the northern end of the Yellow River Irrigation Zone. It is not an arid farming area; therefore, it had fewer fallow fields in the southern part of the Wulate Middle Banner. Meanwhile, fallow fields were distributed in the northwest part of the Wulate Middle Banner, which is bound by Darhan Banner and Guyang County. Duolun County has the highest annual precipitation of all counties in the farming-pastoral ecotone of the northern foot of Yinshan Mountain. It exhibited the lowest percentage of fallow fields and appeared to be composed almost entirely of scattered cropland in the northern grassland area, as shown in Figure 5.

| County          | Area (km²) | Percentage (%) |
|-----------------|------------|----------------|
| Duolun          | 227.90     | 14.36          |
| Taipuisi        | 450.12     | 21.75          |
| Huade           | 728.93     | 47.39          |
| Shangdu         | 820.52     | 30.55          |
| Chahar Right Rear | 493.26   | 37.93          |
| Chahar Right Middle | 888.26  | 36.83          |
| Sizhwang        | 1488.99    | 41.79          |
| Wuchuan         | 1695.00    | 50.11          |
| Darhan          | 1733.29    | 65.11          |
| Guyag           | 1607.78    | 55.52          |
| Wulate Middle   | 517.09     | 20.72          |
| Total           | 10,651.15  | 40.05          |

Generally, the percentage of fallow fields in the southern part of the study area was lower than that in the northern part. The latter is a transitional zone between traditional pastoral and agricultural areas and has undulating terrain. In addition, the northern part of the study area has lower amounts of precipitation than the southern part, and the soil there is highly barren because of desertification and the fragile ecological environment, which was caused by large areas of natural grassland being reclaimed as cropland at the end of the last century. Thus, farmers in the area have a higher willingness to fallow their fields.

Detailed classification fallow maps generated using three different Sentinel combined datasets are presented in Figure 6.

As shown in Figure 6b, the noise of the fallow field maps generated when using the Sentinel-1 combined dataset was more obvious than of the others; this was caused by the backscatter signal noise from the SAR images. The fallow field map generated using the Sentinel-2 dataset differed slightly from those of the Sentinel-1 and Sentinel-2 combined datasets, between which there were still some mismatches (Figure 6c). The Sentinel-1 and Sentinel-2 combined datasets were able to identify fallow fields more completely than other combined datasets, showing slight improvements in fallow field identification; the noise was reduced significantly by adding Sentinel-1 data to the mapping dataset (Figure 6d).

Classification accuracy

In this study, the confusion matrix and its derived accuracy indicators were used to evaluate the classification accuracy of each dataset.
The Sentinel multi-sensor composite dataset obtained the highest classification accuracy, followed by the Sentinel-2 combined dataset. The validation results are summarized in Figure 7 and Table S-1.

In the spectral bands of the Sentinel-2 archive, the SWIR2 band (B12_med) reflectance showed the highest accuracy (OA = 79.70%), followed by SWIR1 (B11_med; OA = 78.69%). The red band (B4_med) achieved the highest accuracy among the visible bands (OA = 77.52%), followed by the blue (B2_med) and green (B3_med) bands, both of which had accuracies higher than 75%. The Red Edge band is considered to be sensitive to the growth status of green plants (Cui and Kerekes 2018). However, the Red Edge 2–4 bands of Sentinel-2 data (B6_med to B8A_med) showed the lowest accuracy among the spectral bands at 20 m resolution, as shown in Figure 7 and Table S-1, except for the Red Edge 1 band (B5_med). Notably, the resolution did not entirely determine the mapping accuracy of the fallow land for each reflectance band. For example, the accuracy of the SWIR2 band was the highest among the Sentinel-2 spectral bands, and the accuracy of the 20-m resolution SWIR2 reflectance band was generally higher than that of the 20-m resolution Red Edge bands.

The VV+VH dual-polarization backscattering coefficient achieves higher accuracy than the spectral band. At the same time, the VH polarization showed high importance values regarding the fallow field classification.

All the variances of the index’s datasets achieved a high level of accuracy, with OAs >92%. The variances of indices were significantly more accurate than the median value dataset generated using the Sentinel-2 archive. Among these, the NBR variance dataset achieved the highest accuracy, with an OA of 92.79%, followed by the NDVI variance dataset, which achieved an OA of 92.45%. The accuracy of the NBR median dataset was slightly lower than that of the NDVI median dataset. It can therefore be inferred from these results that NBR and NDVI are the two most effective indices for fallow mapping in the present study.

The two accuracies of the datasets based on VH polarization were higher than those based on VV polarization. This is likely because VH polarization contains more vegetation cover information (Gao et al. 2018). However, the accuracies of the VV and VH polarization median datasets were generally higher than those of the variance datasets, which differed from the indices shown in Figure 7 and Table S-1. Notably, the classification accuracy based on the original Sentinel-1 dual-polarized data was higher than the accuracy of the original spectral band of Sentinel-2.

According to the results displayed by the explanation of Random Forest, the NBR and NDVI variances also showed the highest levels of importance. The VH polarization is ranked third, followed by the median NDVI and NBR median, regarding the importance of NBR, NDVI, and VH polarization for fallow field identification. More details are provided in Figure 8.

Regarding the Sentinel-1 and Sentinel-2 combined datasets, the OA of fallow mapping increased following the introduction of the Sentinel-1 archive into traditional fallow mapping based on the Sentinel-2 single-sensor archive. The accuracy of the combined Sentinel-2 spectral and indices dataset was 95.09%, and the addition of SAR data increased the accuracy by 0.73%, reaching the highest accuracy of 95.82%.

**H/a decomposition of fallow and cropped fields**

The time-series H/a decomposition results of the fallow and cropped fields revealed the differences between the original backscatter signal and the H derived from Sentinel-1 dual-PolSAR (VV+VH) time-series data via the H/a decomposition method.

As shown in Figure 9, H generated by dual-polarization decomposition showed more evident seasonal changes during the growing season than the other values, and the curve in Figure 9c is similar to the index curves obtained during the growing season (Figure 4). Furthermore, the cropped field’s median H value was lower than that of the fallow field before mid-July. There was a continuously increasing trend in the H of the cropped field after August 1 when the crops were in the late growing season. This means that the biomass and vegetation coverage increased. The natural weeds or soil in the fallow fields were maintained in a state with little or no change, which resulted in the median H of fallow fields being lower than of cropped fields after August 1. As the vertical shape of the crops increases, the randomness of scattering becomes higher than that in the fallow fields, showing anisotropy (Hua et al. 2011). However, the transaction points of the cropped and fallow field curves for the three indices appeared in July, slightly earlier than those for entropy.
**Figure 4.** Smoothed Sentinel-2 indices profiles of cropped and fallow fields during the growing season based on the median values of sample pixels identified across the study area with a) Normalized Difference Vegetation Index (NDVI) and b) Normalized Burn Ratio (NBR). Error buffers indicate 95% confidence intervals.

**Figure 5.** Fallow field map at 10-m resolution generated by the most accurate S1-S2 combined dataset, and three frames that show the map in detail.

**Figure 6.** Detailed fallow field mapping results for three combined datasets: a) false color composite Sentinel-2 image at 10 m resolution (RGB = bands 8, 4, 3) on 19 July 2020, b) S1 combined dataset, c) S2 combined dataset, and d) S1-S2 combined dataset.
Figure 7. Classification accuracies of each dataset and the combined datasets: med indicates median value of bands or polarized data, var indicates variance of bands or polarized data, S1_polarized indicates original Sentinel-1 dual-PolSAR (VV+VH) bands, and S1_combined indicates the dataset from Sentinel-1 dual-PolSAR (VV+VH) bands plus the variance of VV and VH bands.

Figure 8. Random Forest variable importance. med indicates median value of bands or polarized data, var indicates variance of bands or polarized data.
The time-series $H$ profile of both cropped and fallow fields in the growing season, as derived by H/a decomposition was successfully obtained in this study, and exhibited significant phenological differences. The experimental results revealed that the polarization decomposition technology helped to capture the phenology of crops and weeds in the fields. Scattering characteristics are more suitable for identification after dual-polarization decomposition for croplands with higher branch crops and fallow fields with low natural vegetation or bare soil. The results displayed in Figure 7 reveal that adding Sentinel-1 archive data improves the classification accuracy and reduces the mismatching during fallow field mapping. The applicability of the Sentinel-1 archive for fallow field monitoring is analyzed in detail in the discussion section below.

As shown in Table S-2, the $H$ of the cropped field was higher than that of the fallow field after mid-July. The higher the branches and the larger the LAI, the stronger the scattering randomness of the vegetation and thus the higher the $H$. This was because the LAI and branch height in the cropped fields were generally higher than those in the fallow fields. However, $H$ was less than 0.7 for both the fallow and cropped fields, indicating that the vertical height of the crops in the samples from the study area was not so high, mainly due to the low crop branches. Furthermore, there was no secondary scattering from the underlying water surface of the crops. This situation also shows that the area mainly comprises arid and semi-arid farming land.

**Optimum Time Interval for Fallow Field Identification**

To determine the most representative period for mapping the fallow field, the accuracies based on different time intervals were tested according to the method introduced in section 3.4. The accuracy assessments are presented in Figure 10.

The highest accuracy was found in the strategy utilizing the Sentinel-1 and Sentinel-2 combined datasets for the whole growing season, with an OA of 95.82% (Figure 10c, Table S-5). In general, the accuracies of the Sentinel-2 combined datasets were higher than those of the Sentinel-1 combined datasets, as shown in Figure 10a and b.

The mapping accuracy determined using Sentinel-1 combined datasets aggregated by the whole growing season showed the highest accuracy (OA = 90.77%; Figure 10a and Table S-3). This indicates that fallow mapping over the whole growing season, based on Sentinel-1 data, can deliver competitive results. Moreover, the highest accuracy obtained by aggregating data over a one-month interval appeared in September, when the $H$ values of the cropped and fallow fields extracted from Sentinel-1 data demonstrated the most significant differences (Figure 9c). Thus, the whole growing season fallow mapping accuracy obtained using Sentinel-1 data outperformed that of early-season mapping, and the mapping accuracy aggregated from August to September was almost as accurate as that of the whole growing season. Therefore, September was the earliest time at which fallow field mapping could be accurately performed based on the Sentinel-1 dataset.
According to the Sentinel-2 classification accuracy assessments, as shown in Figure 11b and Table S-4, the highest one-month interval accuracy was obtained in August (OA = 93.35%), which was slightly lower than that obtained in the whole growing season using the combined Sentinel-1 and Sentinel-2 datasets. However, similar to the trend observed with the Sentinel-1 combined dataset test accuracy, early season mapping was generally less accurate than the late growing season mapping. Moreover, accurate fallow field monitoring using the Sentinel-2 combined dataset can be performed earlier (August) than using the Sentinel-1 dataset (September). The obtained results suggest that accurate and timely fallow field mapping is possibly based on the Sentinel-2 dataset from August to September, with an OA of 94.18%; more details in are shown in Table S-4.

The classification accuracy obtained when utilizing both Sentinel-1 and Sentinel-2 archives was also assessed to investigate the best performance of the combined dataset when aggregated across different time intervals. As shown in Figure 10c and Table S-5, the highest one-month mapping accuracy was obtained in August (OA = 93.55%); late growing season mapping was more accurate than early growing season mapping.

Different regions have different climatic conditions and data availabilities. The methods introduced in this section can provide the best solutions for fallow field monitoring in different areas.

**Discussion**

**Practice of fallowing in farming-pastoral ecotone in northern China**

The practice of fallowing has existed in the farming-pastoral ecotone at the northern foot of Yinsan Mountain for hundreds of years. Farmers leave a field fallow for 1 year after several years of continuous cultivation and then plow the ground biomass and mix it into the soil at a specific time during the fallow period, thus contributing to the maintenance of soil moisture and nutrients (Chen et al. 2021a, 2021b). Thus, croplands that lie idle for 1 year are most commonly used to increase agricultural productivity in fields, with croplands that are idle for two or more years also being widespread. Due to the large areas of croplands that were cultivated during the 1990s and 2000s, the area of cropland in the area has increased rapidly over a short period. After 2000, the dry climate, barren soil, and the sharp growth in urbanization in Middle Inner Mongolia (Li, Bagan, and Yamagata 2018) led to the migration of a large number of rural laborers to cities. This led to a sharp decrease in the number of agricultural laborers (Zhang et al. 2016) and thus an increase in the area of fallow or abandoned cropland (Wang et al. 2016; Wang 2018). This phenomenon is particularly prominent in the farming-pastoral ecotone in the northern foot of the Yinsan Mountains. In fact, the study area features the worst ecological environment and the lowest agricultural productivity within the farming-pastoral ecotone of
northern China. Fallowing is considered to be a spontaneous cropping pattern conducted by farmers because of its environmentally friendly characteristics, which increase crop yields and promote the harmonious development of the human-land relationship. The government has also encouraged fallowing to ensure the sustainable development of ecologically fragile areas. Therefore, a strategy for accurately monitoring fallow fields on a regional scale is fundamental for addressing the ecological and agricultural production challenges that threaten the farming-pastoral ecotone of northern China.

**Capability of Sentinel-1 and Sentinel-2 archives for fallow field mapping**

The emergence of SAR can eliminate the interruption of cropland monitoring by clouds, fog, and rain, allowing continuous operation. Sentinel-1 dual-PolSAR can provide stable and reliable data, making it a vital data source for enhancing fallow field mapping accuracy. Using only Sentinel-1 can achieve a superior classification accuracy, as shown in Figure 10a and Table S-3. Alternatively, the accuracy of the multi-sensor Sentinel archive for August, as shown in Figure 10c and Table S-5, could fully meet the needs of fallow

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**Figure 11.** Smoothed Sentinel-2 spectral bands profiles of cropped and fallow fields during the growing season, based on median values of sample pixels identified across the study area with a) Red band, b) Red Edge1 band, c) Red Edge2 band, d) Red Edge3 band, e) NIR band, and f) Red Edge4 band.
land monitoring while using fewer observations and requiring a short period and wide coverage data. Thus, it is sufficient for land use mapping over large spatial scales (Wei et al. 2019).

The original Sentinel-1 data can be polarized and decomposed to better explain the differences between land use classes from a mechanistic perspective, as shown in Section 4.3. Quad-polarized PolSAR and dual-polarized PolSAR data considerably improve the scattering information of ground object radar waves and the identification accuracy of different land use types (Guo et al. 2018; Liu et al. 2019; Valcarce-Diñeiro et al. 2019). Many targets of interest in PolSAR require multivariate statistical descriptions, owing to the combination of coherent speckle noise and surface and volume random vector scattering effects (Pottier, Boerner, and Cloude 2003). The results prove that Sentinel-1 derived eigenvalues, after dual-polarization decomposition, are advantageous for capturing phenological changes in fallow and cropped fields.

Apparent low values of OA and Kappa coefficient can be seen on B6 (Red Edge2), B7 (Red Edge3), B8 (NIR), and B8A (Red Edge4) in Figure 7 and Table S-1. A decreasing trend in accuracy was observed, when these four bands were not considered, ranging from 95.09% to 95.64%, and Kappa coefficients were between 0.90 and 0.91 in the whole growing season. However, the B4 (Red) and B5 (Red Edge1) band accuracies were significantly higher than those of the four bands mentioned above even though they had a similar wavelength. This result can be explained by analyzing the time-series characteristics of cropped and fallow field samples on B4 (Red), B5 (Red Edge1), B6 (Red Edge2), B7 (Red Edge3), B8 (NIR), and B8A (Red Edge4). On the Red band and Red Edge1, cropped fields had a higher absorption rate of the spectrum throughout the growing season, while the reflectance was lower than that of fallow fields. In contrast, Red Edge2, Red Edge3, NIR, and Red Edge4 had higher reflectance than the fallow field between July and September, which conformed to the characteristics of the NIR platform band with a high reflectance for healthy vegetation. However, the reflectivity of cropped fields before the beginning of July and after the end of September was lower than that of fallow fields (Figure S-1). This seasonal change caused interference in the monitoring based on the whole growing season data, significantly reducing the accuracy of B6-B8A, and the accuracy of the B6-B8A bands based on the data from July to September was much higher than the accuracy of the whole growing season.

The northern foot of Yinshan Mountain is located in the middle part of the farming-pastoral ecotone in northern China. The farming-pastoral ecotone in northern China is distributed in an area with annual precipitation of 200–450 mm, with an annual precipitation variability of 15–30% and dryness ranging 1–2, covering approximately 14.66% of the total area of China. Long-term drought and water shortage have limited agricultural development in this area and formed fallow or abandoned agricultural land, which generally shows a significant difference in vegetation coverage from the cropped field. Therefore, the proposed approach avoids erroneous detection in areas with arid and semi-arid climatic conditions and only single-season crops in northern China, particularly in ecologically fragile area with extensive distribution of unstable agricultural land.

Prior studies discussed the remote sensing monitoring of unmanaged fields in South Africa (Tong et al. 2020), Eastern Europe (Yin et al. 2018a), and Poland (Kolecka 2021). These studies reported significant differences between vegetation index in unmanaged and managed fields, and they could be mapped using machine learning algorithms and proper training samples. Hence, this difference is the basis of fallow field classification in a region.

Moreover, the proposed method should be modified according to the local characteristics of the area, where the difference between fallow and cropped fields is not conspicuous because of favorable hydrothermal conditions for vegetation growth, leading to an overall better restoration of nature in the unmanaged fields. Although the vegetation coverage of fallow fields has different characteristics in different regions, the proposed method could still detect fallow agricultural land using combined Sentinel-1 and Sentinel-2 datasets in a region with substantially different conditions between VIs of unmanaged and managed fields in the growing season. However, the method’s potential for monitoring and mapping fallow fields in areas with double-season crops has not been clarified.
Uncertainty of fallow field mapping in farming-pastoral ecotone

Previous studies have shown that the climate of the farming-pastoral ecotone in Inner Mongolia has experienced increasing drought and warming trends over the past 50 years (Zhao et al. 2012). The Chinese Government is emphasizing the need to develop and restore agriculture using fallow systems. Thus, the ability to remotely monitor fallow fields is vital. Here, both optical and PolSAR were used to accurately monitor the spatial distribution of fallow land over the northern foot of Yinshan Mountain, Inner Mongolia. However, there are still some uncertainties regarding fallow field monitoring in the area, mainly due to the reflection and scattering signals of crop failure fields, which can be easily confused with fallow fields in the late growing season.

Crop failure is pronounced during the late growing season in arid agricultural areas with low vegetation coverage. Crop failure commonly occurs in hilly, water-scarce, and dry regions in the northern part of the study area; it is caused by poor field management and prolonged drought. Furthermore, the regular occurrence of crop failure can lead to lower ground biomass and yields in fields than under general growing conditions. Here, the differences between crops tended to decrease and crops under general conditions became more extensive as the growing season progressed. Typically, fields with failing crops are closer to the fallow field with regard to their spectral reflectance and scattering signals. Therefore, the impact of crop failure was not well reflected in the classification results obtained in September based on only the Sentinel-1 combined dataset; this issue is worthy of further investigation.

As shown in Figure 10a, the highest accuracy achieved using the Sentinel-1 combined dataset occurred in September, whereas that of the Sentinel-2 combined dataset occurred in August. This was likely because crop failure would have been more evident in September (late growing season) in the study area, leading to misidentification between fallow and cropped fields. Therefore, the fallow field monitoring based on the Sentinel-2 dataset obtained in September revealed that the reflectance characteristics of crop failure interfered with the classification results. This is why the classification results based on the Sentinel-2 dataset were the most accurate in August.

Regarding the scattering signal of the PolSAR, the largest differences in H between the cropped and fallow fields (Figure 9 and Table S-2) were observed in September. Thus, the highest classification accuracy was obtained in September (Figure 10) when aggregating the dataset over 1 month. In the late growing season, areas with crop failure showed more obvious diffuse scattering characteristics in PolSAR than areas with high vegetation coverage, due to poor growth conditions. The LAIs and branch heights of crops with general or good growing conditions peaked in September. The difference between the cropped and fallow fields in September was more significant than in August, according to the H time-series values extracted from dual-polarization decomposition. At the same time, the overall values of the cropped fields for the H were not as high as those of cropped fields in the agricultural irrigation area. Within PolSAR, this difference led to a specific penetration effect over low vegetation fields, which permitted the monitoring of the underlying surface and presented more apparent diffuse scattering characteristics.

Conclusion

To exploit the potential of multi-sensor data for fallow field mapping, here, a method for classifying cropped and fallow fields using Sentinel-1 and Sentinel-2 archive data was established using GEE and the Random Forest classifier. The combined Sentinel-1 and Sentinel-2 datasets demonstrated the best overall performance with regard to classification, followed by the Sentinel-2 combined dataset (which aggregated spectral bands and indices). The Sentinel-1 combined dataset showed the lowest accuracy, with obvious signal noise.

Due to the essential role of Sentinel-1 SAR data in fallow field mapping, the H eigenvalue of the Sentinel-1 VV+VH backscatter signal generated by dual-polarization decomposition was used to illustrate the time-series characteristics of cropped and fallow fields. The obtained results show that H can capture the details of phenological changes in cropped and fallow fields by comparing the original VV and VH backscattering signals. Thus, the dual-polarization decomposition of VV + VH polarization can be used to supplement optical images; it has great application prospects in areas where obtaining continuous clear optical observations is challenging.
In addition, the optimal time interval for fallow field identification and mapping was determined by optimizing the least number of observations needed to deliver competitive results in early assessments. Fallow fields could only be identified accurately with one-month data (using the Sentinel-1 and Sentinel-2 combined datasets) from August (OA = 93.55%) onwards; this value was very close to that obtained by aggregating the whole growing season’s observations. Thus, this study can serve as a reference for remote sensing monitoring of fallow fields, regarding both data acquisition and mapping. Furthermore, the methods and strategies introduced in this study can be applied across larger regions.

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Data availability statement

GEE (https://code.earthengine.google.com/) is a free and open platform. All data, models, or codes generated or used during this study are available from the corresponding author upon request.

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