



Crop Mapping with Combined Use of European and Chinese Satellite Data

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Abstract: Agricultural landscapes are characterized by diversity and complexity, which makes crop mapping at a regional scale a top priority for different purposes such as administrative decisions and farming management. Project 32194 of the Dragon 4 Program was implemented to meet the requirements of crop mapping, with the specific objective to develop suitable approaches for precise crop mapping with combined uses of European and Chinese high- and medium-resolution satellite images. Two sub-projects were involved in the project. The first was to focus on the use of time series high-resolution satellite data, including Sentinel-2 (S2, European satellite data) and Gaofen-1 (GF-1, Chinese satellite data), due to their similar spectral bands for Earth observation, while the second was to focus on medium-resolution data sources, i.e., the European Project for On-Board Autonomy-Vegetation (PROBA-V) and Chinese Fengyun-3 Medium Resolution Spectral Imager (FY-3 MERSI) satellite data, also due to their similar spectral channels. The approach of the European Space Agency (ESA) Sent2Agri project for crop mapping was adapted in the first sub-project and applied to the Yellow River irrigated district (YERID) of Ningxia in northwest China in order to assess its ability to accurately identify crop types in China. The goal of the second sub-project was to explore the potential of both European and Chinese medium-resolution satellite data for crop assessment in a large area. Methods to handle the data and retrieve the required information for the precise crop mapping were developed in the study, including the adaptation of the ESA approach to GF-1 data and the application of algorithms for classification. A scheme for the validation of the crop mapping was developed in the study. The results of implementing the scheme to the YERID in Ningxia indicated that the overall accuracies of crop mapping with S2 and GF-1 can be high, up to 94–97%, and the mapping had an accuracy of 88% with the PROBA-V and FY3B-MERSI data. The very high accuracy suggests the possibility of precise crop mapping with the combined use of time series high- and medium-resolution satellite data when suitable approaches are chosen to handle the data for the classification of crop types.

Keywords: crop mapping; classification; GF; Sentinel; Sent2Agri; Dragon Program

1. Introduction

Agriculture represents one of the major fields in remote sensing applications. Precise crop mapping is needed at various scales for users from individual agricultural companies to national and international entities. Crop mapping has therefore become one of the key



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Copyright: © 2021 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https:// creativecommons.org/licenses/by/ 4.0/). remote sensing applications in agriculture. Due to the high diversity and complexity of agricultural landscapes, accurate identification of crop types is challenging. Moreover, agricultural fields are often divided into multiple cropping patches with different varieties or even different crops. Therefore, mixed targets are commonly seen in an image pixel when the spatial resolution does not allow for separating the patches. This is especially true in China because farmers have parcels of 0.2 ha on average. The number of mixed pixels decreases as the spatial resolution of satellite data improves. However, a high spatial resolution also implies increased costs and a smaller area being covered by one image. In addition, it is crucial to acquire frequent images to accurately differentiate the spectral profiles of different crops across the season [1]. All in all, developing precise crop mapping methods is still a challenging task in remote sensing for agricultural monitoring.

Crop type classification with satellite image time series is an important tool for precise and timely crop mapping. A number of open-source, cloud-based tools have been developed for crop type classification in recent years. The Sen2Agri system is one such open-source tool available for free download, allowing users to generate near-real-time products tailored to their needs at their own premises or using cloud computing infrastructure [1]. A variety of crop classification methods at different scales and with various levels of accuracy can be found in the literature [2–4]. Meng [5] collected all the available cloud-free Sentinel-2 multispectral images for winter wheat and rapeseed growth periods in the study area in southern China and used the random forest (RF) method as the classifier to identify the optimal temporal window. Song [6] presented an approach integrating object-based image analysis with RF for mapping in-season crop types based on multitemporal GF-1 satellite data at a spatial resolution of 16 m. Song [7] proposed a method to examine a total of 13 spectral variables from GF-1 images and three classifiers, the Bayesian discriminant (BD), Mahalanobis distance (MD), and RF, for classification of six LULC types at East Dongting Lake, Hunan, China. Li [8] utilized deep learning-based frameworks, including DenseNet, ResNet, VGG, SegNet, and DeepLab v3+, for cotton crop field identification with GF-1 high-resolution (16 m) images. Fan [4] reported on crop type classification with high-resolution satellite data with a wide field of viewer (WFV) onboard GF-1, the Multispectral Instrument (MSI) onboard Sentinel 2 (S2), and the Operational Land Imager (OLI) onboard Landsat 8 (L8), and found that these satellite data may be used for crop type classification within the growing season with very good accuracy if the training datasets were well-tuned. A combination of S2 and L8 for classification has been confirmed to be suitable for crop type classification [9–12].

Low-resolution satellite data have been applied to agricultural monitoring in the past three decades. It has been commonly understood that the spatial resolution of satellite data is one of the key factors determining the quality and accuracy of their applications for crop monitoring. To improve the accuracy of crop monitoring, the spatial resolution of several types of EO data has been steadily evolving. European satellite, the Project for On-Board Autonomy-Vegetation (PROBA-V) [13], brought the world a new data source for agricultural monitoring. PROBA-V data has a spatial resolution of 100 m and the ability to cover the entire surface of the globe. Moreover, the data may be downloaded free of charge. In addition, PROBA-V provides satellite data with 300 m and 1 km pixel scales under nadir. The Chinese meteorological satellite provides 250-m-resolution data globally and free of charge since late 2008 [14]. FY-3 MERSI [15] is a Medium-Resolution Spectral Imager (MERSI) carried aboard the third FY ("Wind and Cloud") series of meteorological satellites developed in China. FY-3A/B/C MERSI has 20 spectral bands, five bands in 250 m, and 15 bands in 1000 m, while FY-3D MERSI has 25 spectral bands, six in 250 m, and 19 bands in 1000 m. The 250 m bands of FY3 MERSI are similar to PROBA-V in the visible and near-infrared.

PROBA-V supports applications such as land use, worldwide vegetation classification, crop monitoring, famine prediction, food security, disaster monitoring, and biosphere studies. The 100-m PROBA-V data has been widely used for landscape classification. Eberenz [16] demonstrated land cover mapping over West Africa with PROBA-V 100 m

time series data for the 2014–2015 season, using temporal metrics and cloud filtering in combination with in situ training data and machine learning, implemented on the ESA Cloud Toolbox infrastructure. Lambert [17] proposed a fully automated classification method to deliver the first cropland map at a 100 m scale for the Sahel and Sudan region using PROBA-V images with an overall accuracy of 84% and an F-score of 74%. Durgun [18] developed a method inspired by spectral matching techniques (SMTs) and based on phenological characteristics of different crop types using 100-m PROBA-V normalized difference vegetation index (NDVI) data from the 2014–2015 season for crop area mapping. Zhang [19] studied crop classifications based on Iterative Self-Organizing Data Analysis Technique (ISODATA) clustering, the maximum likelihood method (MLC), and a similarity analysis. Roumenina [20] assessed the crop mapping performance provided by the PROBA-V 100 m data in comparison with coarser-resolution data (e.g., PROBA-V 300 m data) in Bulgaria with the maximum likelihood classification (MLC) and Iterative Self-Organizing Data Analysis Technique (ISODATA). Dimitrov [21] presented the results of a subpixel classification of crop types in Bulgaria from PROBA-V 100 m NDVI time series using two subpixel classification methods, an artificial neural network (ANN), and support vector regression (SVR). Moreover, VITO [22] developed an operational Mission Exploitation Platform (MEP) to drastically improve the exploitation of the PROBA-V Earth Observation (EO) data archive. FY-3 MERSI data were also made available through the research cooperation [14] and used to make the crop type map in the North China Plain with the decision tree algorithm [23] as well as to monitor the crop growth [24–35].

The recent development of high- and coarse-resolution satellite data in Europe and China provides an opportunity to investigate the potential of using both types of data for precise crop mapping at a regional scale. In this paper, we present the results of the Dragon 4 project 32194. The aim of the project is to evaluate the potential of crop mapping with the combined use of European and Chinese satellite data. It was divided into two sub-projects, namely, crop mapping with (i) high-resolution Sentinel-2 and Gaofen-1 data and (ii) medium-resolution PROBA-V and FY-3 MERSI data. The main objectives of the first sub-project were to (i) compare S2 and GF-1 time series data in a perspective of crop type mapping, (ii) develop a crop type mapping method based on both high-resolution satellites time series, (iii) validate and extend the crop mapping approach of ESA Sen2Agri in an irrigated area in northwest China, and (iv) improve GF-1 satellite data processing. The aims of the second sub-project were to (i) develop a method for crop mapping with both PROBA-V and FY-3 MERSI data and (ii) improve FY-3 MERSI data processing and product generation.

2. Data and Methods

2.1. High-Resolution Crop Mapping (Sub-Project 1)

2.1.1. Study Area

The study area [4] of the first sub-project was the Yellow River Irrigation District (YERID) in Ningxia Hui Autonomous Region, northwest China [36,37]. The YERID has long been appreciated as the most important agricultural production region in Ningxia, even though the annual rainfall is very low in the district. Two-thirds of Ningxia's total grain production and agricultural production value is generated from YERID, even though it has only one-third of the total farmland in Ningxia. The study area also represents a typical irrigated agricultural region in China. Wheat, rice, and corn are the major crops in YERID. The growing season in YERID is generally from May to September.

2.1.2. Field Data and Training Samples

In the middle of June 2017, a field campaign was carried out for three days with a random sampling approach. In total, ~1500 ground truth photos with spatial reference and associated crop or other land cover classes were collected. Another three field campaigns were carried out again in June, July, and September in 2018. A random block sampling approach was applied to these three field campaigns. Figure 1 shows the distribution of the

sampling points in YERID of Ningxia. During the field campaign, georeferenced pictures were taken along the roads with a GPS camera following predefined itineraries. The land cover and crop type classes were retrieved by visual screening of the pictures using a photo data interpretation tool developed by the Chinese team. The final output of this process is a formatted file gathering all GPS points with corresponding classes, class codes, author, roadside (left or right), collecting dates and times, and the corresponding photo file names.



(**b**) field sample distribution in 2018

Figure 1. The field samples collected in the study area.

In addition to the field campaigns, more spatially well-distributed training samples were obtained by visually interpreting the satellite images. All samples were randomly separated into two datasets at a ratio of 70% (for training) to 30% (for validation). Tables 1 and 2 list the number of samples and the proportion of each crop type for the 15 m GF-1 and 10 m S-2 pixels.

Counts and Proportion	Forage Grass	Corn	Grape	Greenhouse	Sward	Medlar	Rice	Vegetables	Wheat	SUM
Pixel Counts 2017	8171	9584	5476	6036	1780	928	30,600	3692	2272	68,539
Pixel Counts 2018	4201	16,129	4508	4330	338	645	14,117	6359	6205	56,832
Proportion 2017	11.9	14.0	8.0	8.8	2.6	1.4	44.6	5.4	3.3	100
Proportion 2018	7.4	28.4	7.9	7.6	0.6	1.1	24.8	11.2	10.9	100

Table 1. The number of training samples for GF-1 at 15 m and the proportion for each crop type.

Table 2. The number of training samples for S-2 at 10 m and the proportion for each crop type.

Counts and Proportion	Forage Grass	Corn	Grape	Greenhouse	Sward	Medlar	Rice	Vegetables	Wheat	SUM
Pixel Counts 2017	18,846	21,897	11,718	14,778	4446	2529	69,129	8919	4581	156,843
Pixel Counts 2018	10,926	41,031	11,493	11,178	873	1602	38,124	14,499	15,381	145,107
Proportion 2017	12.0	14.0	7.5	9.4	2.8	1.6	44.1	5.7	2.9	100
Proportion 2018	7.5	28.3	7.9	7.7	0.6	1.1	26.3	10.0	10.6	100

2.1.3. Satellite Data

GF-1 was the first satellite of the Chinese High-Resolution Earth Observation System (GF) Program. It consists of four sets of multiple spectral cameras (wide field of viewer, WFV) with a mosaiced swath of 800 km at 16 m spatial resolution and a four-day revisit frequency [38]. The L1B data of GF-1 WFV for this study were downloaded from the website of CRESDA, a main high-resolution satellite data source in China. The rational polynomial coefficients (RPC) orthorectification approach was used for georeferencing the L1B. The Fast Line-of-sight Atmospheric Analysis of Hypercubes (FLAASH) approach was used for the atmospheric correction [39].

Through the Sen2Agri system [40], S-2 L1C (ESA standard product, top of atmosphere) images of six tiles covering the study area were automatically downloaded from the Copernicus Open Access Hub. Using Sent2Agri's L2A processor, the Multisensor Atmospheric Correction and Cloud Screening (MACCS algorithm) [41,42] was applied on S-2 L1C images to generate the L2A images.

Table 3 and Figure 2 show the S2 and GF-1 images used for the study. These images were all acquired in the 2017 and 2018 growing seasons.



Figure 2. The GF-1 and S-2A/B image data used for the study.

Product	Product Type	Number of Data Needed (No. of Archived and New Scenes)
S-2 MSI	L1C	100
S-2 MSI	L2A	100
GF-1 WFV	L1B	100
PROBA-V	S1 TOC 100M	200
PROBA-V	S5 TOC 100M	40
FY3B-MERSI	L1B	300

Table 3. List of European and Chinese EO satellite data used in the project.

2.1.4. Classification Algorithm

Random forest (RF), a supervised machine learning algorithm, was used as the classifier. Based on preliminary tests, the number of features was set to the square root of all input features, and the number of trees was set to 100. All valid satellite images acquired during the crop growing season were used in the classification so that the crop phenology changes were captured as much as possible. Phenology information of different crops is the key to discriminating between crop types in a growing season. More features may also increase the accuracy of the classification [4]. In this study, all possible pairs of spectral bands were used to calculate an NDVI-like index. All possible NDVI-like indices and spectral bands were added as input features for the classification, as proposed in [4].

2.1.5. Validation Method

The confusion matrix (CM) was used for the validation in this study [4]. Overall accuracy (OA), Kappa, and F1 scores [43,44] were calculated based on the matrix. Table 4 shows a typical confusion matrix, in which i represents the ground truth and j the classified result. Nij is the number of pixels that are in class i according to the ground truth but were classified into class j in the resulting image. J is the digital code of each crop type class.

			Classif	ied	
		j = 1	j = 2		j = J
Ground Truth	i = 1 i = 2	N ₁₁ N ₂₁	N ₁₂ N ₂₂		N _{1J} N _{2J}
	 i = J	N _{J1}	N _{J2}		N _{JJ}

Table 4. A typical confusion matrix.

OA is computed as the proportion of correctly classified pixels:

$$OA = \frac{\sum_{i=1}^{J} N_{ii}}{\sum_{i=j=1}^{J} N_{ij}}.$$
(1)

The Kappa coefficient is computed as follows:

Kappa =
$$\frac{M \sum_{i=j=1}^{J} N_{ij} - \sum_{i=j=1}^{J} N_i N_j}{M^2 - \sum_{i=j=1}^{J} N_i N_j}$$
, (2)

where M is the total number of validation samples. The Kappa coefficient is well suited to evaluate imbalanced validation samples. The value of Kappa is always smaller than 1. Kappa = 1 implies perfect agreement in the classification. Normally, a Kappa larger than 0.8 shows a very good classification result.

In addition, the F1 score [44] is used to evaluate the classified images. Computation of the F1 score requires a computation of the precision and recall for each class, given in the following equations:

Precision =
$$\frac{N_{ii}}{\sum_{j=1}^{J} N_{ij}}$$
 (3)

$$\operatorname{Recall} = \frac{N_{jj}}{\sum_{i = 1}^{J} N_{ij}}$$
(4)

$$F1 \text{ score} = 2 \times \frac{P \text{recision} \times Recall}{P \text{recision} + Recall}.$$
(5)

2.2. Medium Resolution Crop Mapping (Sub-Project 2)

2.2.1. Study Area

For this sub-project, the entire territory of Ningxia Hui Autonomous Region in Northwest China was selected as the study area. The latitude and longitude of Ningxia are 35°14′–39°23′ N and 104°17′–107°39′ E. The total area of Ningxia is ~66,000 km², measuring 250 km from west to east and 450 km from north to south. Ningxia is a typical temperate and semi-arid zone with an annual rainfall of ~200 mm. The landscape of Ningxia is characterized by oasis irrigation agriculture in the north, arid grassland in the center, and mountain forests in the south. In addition, there are rivers, lakes, and deserts. Major crops in the north of Ningxia are winter wheat, spring wheat, corn, soybeans, and rice. Orchards in Ningxia have also developed very quickly in recent decades. Major fruit trees include grape, apple, apricot, and peach. The growing season in Ningxia is from May to September. Although Ningxia is a relatively small region in terms of area, it is characterized by a very diverse landscape. Therefore, it is an ideal site to test the application of optical remote sensing for land cover and land use classification. Figure 3 shows a PROBA-V image of the study area. The red lines in Figure 3 are the county boundaries of Ningxia.

PROBAV S5 TOC 100M 2017-07-06



Figure 3. A 100-m PROBA-V image showing the study area, with bands 321 as RGB.

2.2.2. Field Data and Training Samples

For the medium resolution crop mapping, we only used the field data from the 2017 field campaign (Section 2.1.2). The training samples were visually retrieved from the 100 m PROBA-V and then adapted to the FY-3B MERSI image. All samples were randomly separated into two datasets with a ratio of 70% for training and 30% for validation. Table 5 lists the number of samples and the proportion of each crop type for 100 m PROBA-V pixels.

Table 5. The number of training samples and the proportion of each crop type in 2017 for 100 m PROBA-V.

Counts and Proportion	Forage Grass	Corn	Grape	Greenhouse	Sward	Medlar	Rice	Vegetables	Wheat	SUM
Pixel Counts	295	322	182	233	51	36	1026	137	78	2360
Proportion	12.5	13.6	7.8	9.8	2.2	1.5	43.5	5.8	3.3	100

2.2.3. Satellite Data

The European satellite PROBA-V was launched on 7 May 2013. The optical instrument onboard the PROBA-V provides EO data at 100 m, 300 m, and 1 km spatial resolutions (Table 6). The PROBA-V 100 m (S1 and S5) top-of-canopy reflectance products were downloaded from the VITO's Product Distribution Portal in HDF file format [13]. All images covering the study area with less than 25% cloud cover were selected and processed.

Table 6. The band specification and spatial resolution of PROBA-V and FY3B MERSI.

Band Number	Central Wavelength (nm)	Bandwidth (nm)	Resolution (m)	Central Wavelength (nm)	Bandwidth (nm)	Resolution (m)
		FY3B MERSI			PROBA-V	
1	470	50	250	464	47	100
2	550	50	250			
3	650	50	250	655	82	100
5	865	50	250	837	130	100
5				1603	65	100

For this study, the FY-3B MERSI data were obtained from the platform of the National Satellite Meteorological Center (NSMC), which is officially in charge of the distribution of FY-3B MERSI data in China. A software tool was developed by the Chinese team to process the data specifically for this study.

2.2.4. Classification Algorithm and Validation

Random Forest (RF) was also used as a classifier for the second sub-project. The parameter setting as described in Section 2.1.4 was applied here as well. As in the first subproject, all possible combinations of two spectral bands were used to compute the NDVI-like index. All NDVI-like indices and spectral bands were used as input for the random forest classification.

The same indices (described in Section 2.1.5), namely OA, Kappa, and F1 score, were used to validate the medium-resolution classification.

3. Results and Analysis

3.1. Crop Mapping with High-Resolution Sentinel-2 and Gaofen-1

As mentioned above, the highest accuracy is expected when all the spectral bands of the S-2 and GF-1 images and their derived indices are used in the classification as input features. Figure 4 clearly confirms this expectation. GF-1 WFV only has four bands, blue, green, red, and near-infrared [4]. In ref. [45], only the NDVI time series were used for classification. Previous studies [46,47] showed that the normalized difference water index (NDWI) and brightness are often added as the input features for classification. In this study, we compared four cases for crop type classification with the same suite of training samples but different input features. As shown in Figure 4, for both years, classification accuracies

were the lowest when only NDVI images were used. The accuracy increases as the input features increase. The most accurate classification was obtained using the four spectral bands of GF-1 and all the derived NDVI-like indices. When using just the four bands or the four bands and 3 NDVI-like indices, the OA is slightly lower than with all indices (less than 1% difference).



(a) The accuracies of crop type maps in 2017



(b) The accuracies of crop type maps in 2018

Figure 4. The accuracy improved with an increasing number of features for the GF-1 time series data.

The best-performing crop type classification method was implemented for crop type classification with S2 and GF-1 time series. The resulting crop type maps are shown in Figure 5. Table 7 shows the OA, Kappa, and F1 scores for the images, and Figure 6 shows the F1 score for each crop type. Nine types of crops were successfully classified in 2017 and 2018. The major crop types, such as rice, were classified with very high accuracy (F1 score of 98.3–100%). Forage grass, corn, grapes, greenhouse, and vegetables were always classified quite accurately (F1 score of >85%). Lower accuracies were obtained for wheat, sward, and medlar in 2017 with GF data. In 2018, sward was classified less accurately with S2. Wheat was a major cereal crop in this region but is now decreasing due to the cultivation cost. Sward and medlar are relatively rare crops in the region. The training samples for these three types were difficult to collect, and the final number of samples was

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low. The lower accuracy is most likely related to the appearance of cloudy images and the low availability of the training samples. Overall, the crop type classification performances were lower with GF-1 than with S-2.



Figure 5. The best crop type map from S-2 and GF-1 for this study.

Accuracy	GF-2017	S2-2017	GF-2018	S2-2018
OA	94.4	98.4	93.9	96.7
Kappa	93.0	98.0	93.0	96.0
F1 score	84.6	97.0	91.2	94.0

Table 7. The accuracy of the classified results from GF-1 and S-2 for the two years.



Figure 6. The accuracy of F1 score for each crop type from GF-1 and S-2 for the two years.

3.2. Crop Mapping with Medium Resolution PROBA-V and FY-3 MERSI

Thanks to the daily coverage, the number of valid images from the medium-resolution satellite is high. Therefore, it is able to map the crop along the season. In this study, four scenarios were set up to use the medium-resolution satellite data for crop assessment. The first approach (MVC) was to make a composite of all the S5 100 m PROBA-V data in the growing season by Maximum NDVI Value Composite (MVC) and then classify the image. The second (Mean) was to classify every image and average the accuracies of all classified images as the final accuracy of the crop type map. The third (Fusion in Figure 7, right) was to classify every image and fuse by a majority vote the classified images as the final crop type map. The fourth (Fusion in Figure 7, left) was to classify the time series of all S5 100 m PROBA-V images in the growing season. Figure 7 shows the accuracies of different scenarios for the crop type mapping in the study area. The accuracy of scenario 1 (MVC) was the lowest as only one composite image was used in the classification, and the temporal information was lost. Various accuracies were reached using individual images in scenario 2, and the mean accuracies of individual images were low (OA of 76.6%), while no single image reached an overall accuracy higher than 83%. The accuracies of scenarios 3 (majority vote fusion) and 4 (full time series input) were very similar. Both classifications used all spectral and temporal information of 100 m PROBA-V S5 data, reaching an OA of 88%. Figure 7 also shows that the accuracy already reaches its maximum when using only the images until the end of June.

Figure 8 shows the crop maps from individual FY3B MERSI images and PROBA-V images with the approach proposed in this study.



Figure 7. The accuracies of different approaches for crop type mapping.



(a) Crop type maps from FY3B MERSI

Figure 8. Cont.



(b) Crop type maps from 100m and 333m PROBA-V

Figure 8. Crop type maps from individual medium-resolution satellite images of FY3B MERSI and PROBA-V.

4. Discussion

In the big data era, various kinds of satellite data are increasingly made easily and/or freely available. These satellite images have become rich data sources for crop type mapping with machine learning algorithms. As an open sources tool, the Sen2Agri system has the user community benefiting from the automatic downloading, processing, and applying of sentinel satellite data for the crop type classification, but the Chinese GF satellite data is not yet ready to be explored in this system. After the implementation of the Sen2Agri system in this study area, we observed that training datasets, input features, and classifier algorithms are three key factors that determine the quality and accuracy of the classified results. Thus, we made improvements for our approach of crop type classification with GF-1 and S2 in this study to quickly achieve peak accuracy.

We observed that some studies paid more attention to the evaluation and comparison of various classifier algorithms [48–50], while others paid more attention to the selection of [5,46,51], or adding more [52,53], input features. In general, the RF did perform better than other conventional classifiers, like Maximum Likelihood, Neural Network, Support Vector Machine, etc. [49]. The algorithms of various deep learning methods also perform well, but the computation time for tuning and implementing is often unexpectedly long for the crop type classification of large areas. We followed the Sen2Agri system approach in our study and used the RF [54] as the classifier in this project. We did not intensively test other conventional classifiers and deep learning algorithms since the RF worked well in our study area. Although, there are many options to create and increase the features from the input satellite images, we found in our studies that the classification of all NDVI-like indices combined with the input bands gained higher accuracy than those that used the same spectral bands and only a few selected indices, like NDVI, NDWI, and brightness, that the Sen2Agri system used [1]. The studies [52,53] and the review on crop classification [55] also concluded that the use of vegetation indices improves classification performance, but there is no conclusion which indices have positive contributions on the classification. Therefore, we recommend using all proposed indices if the computation is allowed since

RF is able to deal with high dimension data arrays and neglect the duplications of input data by the random selection of input features.

The preparation of the training dataset is the most time-consuming task in the process of classification. A field survey is often necessary for crop type classification, and the field data collection may help the experts gain the experience of visually interpreting the satellite images. The spatially even distribution and statistical balance of the training datasets for setting up the model should be seriously taken into account. It is difficult to achieve the spatially even distribution for the field samples due to access to fields and time consumption, but this can be improved at home in the process of visually interpreting training samples on the images with a grid frame. For the majority of crop types, training samples may be identified as numerously as possible. However, the minority crop types are difficult to identify, and these classes are poorly represented in the training dataset. This results in a statistically imbalanced dataset for the training sample. In some cases, we had better group some classes to increase the representativeness. This kind of problem can be found after we check the input images and the result from the first-round classification. The impact reduction with the imbalanced dataset for building the classification model is one of the main concerns in the field of machine learning. The effects of imbalanced training samples for the classification in this study were neglected and should be investigated in further studies. There is still another question without a clear answer, which is how many training samples are optimal for the classification. At this moment, what we can do is to collect training samples as numerously as possible.

In this study, the classification was separately conducted with each individual data source. The accuracy of the resulting classification reflected individual performances of targeted satellite data in the given growing season. For optical satellite images, the cloud is a major issue hampering the application. This study did not investigate the data fusion or simulation to make two similar satellite data sources compatible, and the time series can be increased to have more cloud-free images for better classification. In a further study, the joint application of similar satellite data should be enhanced.

5. Conclusions

Project 32194 under the Dragon 4 Program was successfully executed with a focus on crop type mapping, using high- and medium-resolution European and Chinese satellite data for YERID, Ningxia, northwest China. First, the Sen2Agri system was conducted in the study area so that the collection and processing of S2 satellite data were fully benefited from the system. The results demonstrated the good performance of the Sen2Agri system in the fully irrigated area of Ningxia. The medium-term report [27] revealed that nine types of crops were classified, and the crop type map in 2017 was produced based on 35 S-2A/B images. The OA of the crop type map was high, up to 88%. Second, a further study was conducted with the increased input features of GF-1 WFV, S2, and other third-party data after the training dataset was well-tuned with expert knowledge and the ground truth samples. The results showed that crop type mapping with any of these satellite data types could achieve acceptable accuracy. The lowest OA in the tests was 94%, high enough to be acceptable. The relatively lower accuracy with the GF-1 WFV data was due to the limited spectral bands. Third, crop classification with medium-resolution satellite data, 100 m PROBA-V, and 250 m FY-MERSI data was implemented. The preliminary results demonstrated the promising crop assessment capability using 100 PROBA-V or 250 m FY-3B MERSI data as the medium-resolution satellite data produced crop type maps with reasonable accuracy at a regional scale. Classification with these data may produce crop type maps early in the season, as desired by many users. With a very high revisit rate (twice a day), the medium-resolution EO satellite can offer more valid optical satellite images for various applications, including agricultural monitoring.

In this study, Random Forest (RF) was used as the classifier, but the training datasets and input features were paid more attention and finally improved after we gained the experience from the Sen2Agri system. The results proved again that the accuracy of crop type mapping increases with the number of input features used for the classification. The acceptable and peak accuracy of the crop type map was achieved after all the special bands, and the potential associate indices (NDVI like) were jointly used as input features for the classification. The spatially even distribution and the statistical balance of the reference sample are of importance for building a classifier model. Classifications based on individual images result in varying accuracies due to the limited signatures for correctly identifying the crop types on each image. Satellite image time series, used together as the input, is the best option to produce a good classification with high accuracy because such use would ensure that all available information for the whole growing season is involved in the classification for crop type mapping.

Finally, crop type mapping is not only useful for agricultural production management. The classified images or crop type maps may also be very useful for purposes such as environmental studies and irrigation management. Results from coarse resolution crop type classification may, for example, be helpful for the quick running of a crop-specific yield model or pest diseases forecast. Irrigation management is of great importance in Ningxia. Information from the crop type mapping is required to accurately compute the water demand for irrigation in specific growing stages of crops at a regional scale. The methods developed in this study may contribute to making better water management decisions so that the water use efficiency in the area can be significantly improved. Moreover, precision agro-meteorological services also require crop type maps at a regional scale to create better agrometeorological forecasts for the various crop growing stages. In addition, crop type mapping can also provide useful information for early warning of potential agricultural or meteorological disasters occurring at a regional scale. The combination of high- and coarse-resolution satellite data for crop type classification would thereby be useful for these research and operation services. With this understanding and experience, we are able to apply the required crop type mapping practices in various ways. Therefore, our understanding and experience of crop type mapping with high- and medium-resolution satellite data have been widened and sharpened through the implementation of the Dragon 4 Program project.

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