

The RapeseedMap10 database: annual maps of rapeseed at a spatial resolution of 10 m based on multi-source data

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Abstract. ~~As a major oilseed crop,~~ Large-scale, ~~and~~ high-resolution maps of rapeseed (*Brassica napus* L.), ~~a major oilseed crop,~~ are critical for predicting annual production and ensuring global energy security, ~~but,~~ ~~However,~~ such ~~free~~ maps are still ~~not freely~~ ~~un~~available ~~for~~ ~~in~~ ~~large~~ ~~many~~ areas. ~~In this study, w~~We ~~designed~~ ~~developed~~ a new pixel- and phenology-based algorithm and produced a new data product for rapeseed planting areas (2017–2019) ~~over~~ ~~in~~ 33 countries at 10_m spatial resolution based on multiple data. ~~The~~ ~~Our~~ product ~~showed~~ ~~is~~ ~~strongly~~ ~~good~~ ~~consistency~~ ~~at~~ ~~the~~ ~~national~~ ~~level~~ with ~~the~~ official statistics ~~of~~ ~~the~~ (Food and Agricultural Organization of the United Nations, ~~FAO~~) ~~at~~ ~~the~~ ~~national~~ ~~level~~. ~~Our~~ ~~r~~Rapeseed maps ~~achieve~~ ~~achieved~~ ~~F1~~ ~~spatial~~ ~~consistency~~ ~~scores~~ ~~of~~ at least 0.81 ~~F1~~ ~~scores~~ ~~of~~ ~~spatial~~ ~~consistency~~ when ~~compar~~ed ~~ing~~ with the ~~the~~ Cropland Data Layer (~~CDL~~) in ~~the~~ United States ~~of~~ ~~America~~ (~~USA~~), ~~the~~ Annual Crop Inventory (~~ACI~~) in Canada, ~~the~~ Crop Map of England (~~CROME~~), and ~~the~~ Land Cover Map of France (~~LCMF~~). Moreover, ~~their~~ F1 scores ~~based~~ ~~on~~ ~~independent~~ ~~validation~~ ~~samples~~ ranged from 0.84 to 0.91 ~~2~~ ~~based~~ ~~on~~ ~~the~~ ~~independent~~ ~~validation~~ ~~samples~~, implying a good consistency with ground truth. ~~In~~ ~~almost~~ ~~all~~ ~~countries~~ ~~covered~~ ~~in~~ ~~this~~ ~~study~~, ~~t~~The rapeseed crop rotation ~~interval~~ ~~was~~ ~~is~~ at least 2 years ~~in~~ ~~almost~~ ~~all~~ ~~countries~~ ~~in~~ ~~this~~ ~~study~~. Our derived maps ~~with~~ ~~reasonable~~ ~~accuracy~~ suggest, ~~with~~ ~~reasonable~~ ~~accuracy~~, the robustness of the algorithm in identifying rapeseed over large regions with various climates and landscapes. ~~Scientists~~ ~~and~~ ~~local~~ ~~growers~~ ~~can~~ ~~use~~ ~~t~~The ~~freely~~ ~~downloadable~~, derived rapeseed planting areas ~~freely~~ ~~downloaded~~ ~~will~~ ~~benefit~~ ~~scientists~~ ~~and~~ ~~local~~ ~~farmers~~ ~~to~~ ~~help~~ ~~to~~ predict rapeseed production and optimize planting structures. The product is ~~available~~ publicly ~~available~~ at <http://dx.doi.org/10.17632/ydf3m7pd4j.3> (Han et al., 2021).

1 Introduction

~~Currently,~~ ~~f~~Although fossil fuels are ~~currently~~ the main source of energy (Fang et al., 2016; Shafiee and Topal, 2009), ~~However,~~ ~~their~~ overexploitation ~~is~~ ~~ing~~ ~~fossil~~ ~~fuels~~ ~~will~~ increasing ~~various~~ ~~risks~~ ~~threats~~ ~~to~~ ~~for~~ human survival, such as greenhouse gas emission, and environmental pollution (Fang et al., 2016; Höök and Tang, 2013). Biofuel energy seems to be a promising alternative energy source (Hassan and Kalam, 2013). Rapeseed (*Brassica napus* L.) is an important source of biofuels, edible oil, animal feed, and ~~plant~~ protein powder ~~plants~~ (Firrisa et al., 2014; Malça and Freire, 2009; Sulik and Long,

30 2016). Data products ~~about on the rapeseed~~ planting densities, growth conditions, and productivity ~~of rapeseed~~ are dependent on precise and accurate planting area maps (Zhang et al., 2019). ~~but. However,~~ such maps are ~~yet still~~ unavailable.

Global agricultural statistics on rapeseed in many regions ~~come are derived~~ from field surveys, field sampling, and producer reports (Arata et al., 2020; Fuglie, 2010). Ground-based methods, ~~which~~ are time--consuming and labor--intensive, ~~and fail~~
35 ~~to in describing the provide~~ detailed spatial information ~~on f~~ rapeseed fields (Wang et al., 2020a). ~~In contrast, r~~ Remote sensing technology plays an important role in agricultural monitoring ~~and, yields providing~~ accurate, ~~and~~ objective spatial--temporal crop information (Dong et al., 2016; Salmon et al., 2015).

~~At present, m~~ Many ~~current~~ land cover products ~~from obtained by~~ remote sensing have ~~a~~ publicly ~~provided available a~~ cropland
40 layer. ~~Examples include, e.g.~~ the Fine Resolution Observation and Monitoring of Global Land Cover project (Gong et al., 2013), the Global Land Cover 2000 (GLC2000) map (Bartholomé and Belward, 2005), ChinaCropPhen1km (Luo et al., 2020), and Global Food Security-support data at 30 m (GFSAD30) (Phalke et al., 2020; Xiong et al., 2017). ~~Nevertheless, c~~ ~~However,~~
~~cropland identified by these products is~~ either ~~un failed in distinguishing differentiated as to different~~ crop type, ~~s or has~~ a coarse spatiotemporal resolution (Teluguntla et al., 2018), ~~or excluded does not include~~ rapeseed information. ~~Fill nowadays,~~
45 ~~there are f~~ Few ~~large-scale~~ rapeseed maps ~~on a large scale~~, especially at 10_m_resolution, ~~are currently available. A decision tree classification method based on a large number of training samples has been used to classify various crops for t~~ The 30-m
-resolution Cropland Data Layer (Boryan et al., 2011) ~~in for~~ the USA and ~~the~~ Annual Crop Inventory in Canada (Fisette et al., 2013) ~~did classify various crops using the decision tree classification method based on a large number of training samples.~~
~~However, the but this~~ method is hard to apply to other developing regions ~~due because to a lack of~~ ground training samples ~~are~~
50 ~~lacking~~ (Xiong et al., 2017). A new method ~~is highly required~~ to map large-scale annual maps with ~~a~~ high spatial resolution, ~~which that will would~~ be widely applicable ~~for to the~~ regions with ~~seare few~~ ground training samples ~~is thus strongly needed.~~

Five remote sensing-based methods for rapeseed mapping have been developed in recent decades: ~~1a~~ machine learning methods (Griffiths et al., 2019; Preidl et al., 2020; She et al., 2015; Tao et al., 2020); ~~2b~~ ~~a classification er~~ based on time
55 series data (Ashourloo et al., 2019); ~~3e~~ ~~a~~ threshold segmentation based on phenology (Tian et al., 2019); ~~4d~~ ~~m~~ Multi-rRange ~~s~~ Spectral ~~f~~ Feature ~~F~~itting (MRSFF) (Pan et al., 2013); and ~~5e~~ ~~mapping based on HSV (hue, saturation, and value) transformation and s~~ Spectral ~~f~~ Features (Wang et al., 2018). ~~However, M~~ most ~~of these~~ methods, ~~however~~, only produce rapeseed maps ~~_~~ for a small area ~~based using on~~ very limited imageries taken on ~~the~~ rapeseed ~~peaking~~ flowering dates (Ashourloo et al., 2019; She et al., 2015). ~~Rapeseed~~ The peak flowering dates vary by area and cultivar because of differences
60 in natural conditions and cultivation habits, especially over ~~a~~ large regions (d'Andrimont et al., 2020; Ashourloo et al., 2019; McNairn et al., 2018). ~~Using the above methods to~~ Thus, it is still a big challenge ~~to a~~ automatically map rapeseed areas with a finer resolution over a large region ~~by applying the above methods~~ ~~is thus still a huge challenge.~~

65 ~~Taking into consideration~~ the unique phenological characteristics of ~~different~~ crops, ~~many various researchers~~ studies have
indicated ~~developed the~~ potentially ~~useful~~ ~~phenology-based methods~~ ~~ways based on phenology~~ for crop identification ~~ing~~
~~over~~ in large areas (Ashourloo et al., 2019; Dong et al., 2016; Liu et al., 2018b, 2020a; Zhang et al., 2020). The ~~se~~ algorithms,
~~which based on phenology develops~~ generate classification rules ~~through by~~ analyzing the unique characteristics of the ~~studied~~
70 crop, ~~which~~ have been successfully applied ~~for to~~ mapping rice (Dong et al., 2016), soybean (Zhong et al., 2014), corn (Zhong
et al., 2016), and sugarcane (Wang et al., 2020a); but ~~have~~ rarely ~~been~~ applied to rapeseed. Rapeseed has unique reflectance
and scattering characteristics (Ashourloo et al., 2019; McNairn et al., 2018; Sulik and Long, 2015, 2016); and ~~undergoes~~ ~~has~~
three canopy morphologies ~~(Ashourloo et al., 2019; Rondanini et al., 2014 based on)~~, ~~including~~ leaves, yellow petals, and
85 pods/branches ~~(Ashourloo et al., 2019; Rondanini et al., 2014)~~. Each canopy shape strongly influences how solar radiation ~~is~~
intercepted ~~s~~ (Sulik and Long, 2016). ~~Thus~~ the specific features of reflectance values and scattering coefficients of rapeseed
from S-1/2 data ~~will can thus~~ provide information for ~~the~~ automatic mapping of rapeseed over larger areas and with a finer
75 resolution.

~~Another relevant aspect of rapeseed imaging concerns~~ ~~Also, crop rotation, which is~~ ~~is~~ beneficial ~~for to~~ the management of
pests and disease ~~management~~s in crop production ~~(Harker et al., 2015; Liu et al., 2018a) and~~. ~~Previous studies have shown~~
~~that crop rotation is one of the main a major~~ ~~causes factor in of yield change in~~ rapeseed ~~yield production~~ (Harker et al., 2015;
80 Ren et al., 2015). The physical and chemical properties of ~~the~~ soil ~~will change~~ ~~are altered~~ during crop rotation, and these changes
~~will~~ affect rapeseed growth (Ren et al., 2015). Most ~~of the~~ current studies ~~are~~ ~~have been~~ limited to field observations (Peng et
al., 2015). ~~The~~ ~~The~~ spatial distribution ~~information~~ of rapeseed rotation in different regions is still ~~not un~~clear ~~due because to~~
~~the lack of~~ high-resolution rapeseed maps ~~are lacking~~. ~~To aid cultivation and management, the characteristics of~~ ~~It is necessary~~
~~to explore the r~~ rapeseed rotation ~~need to be explored~~ ~~for cultivation and management~~.

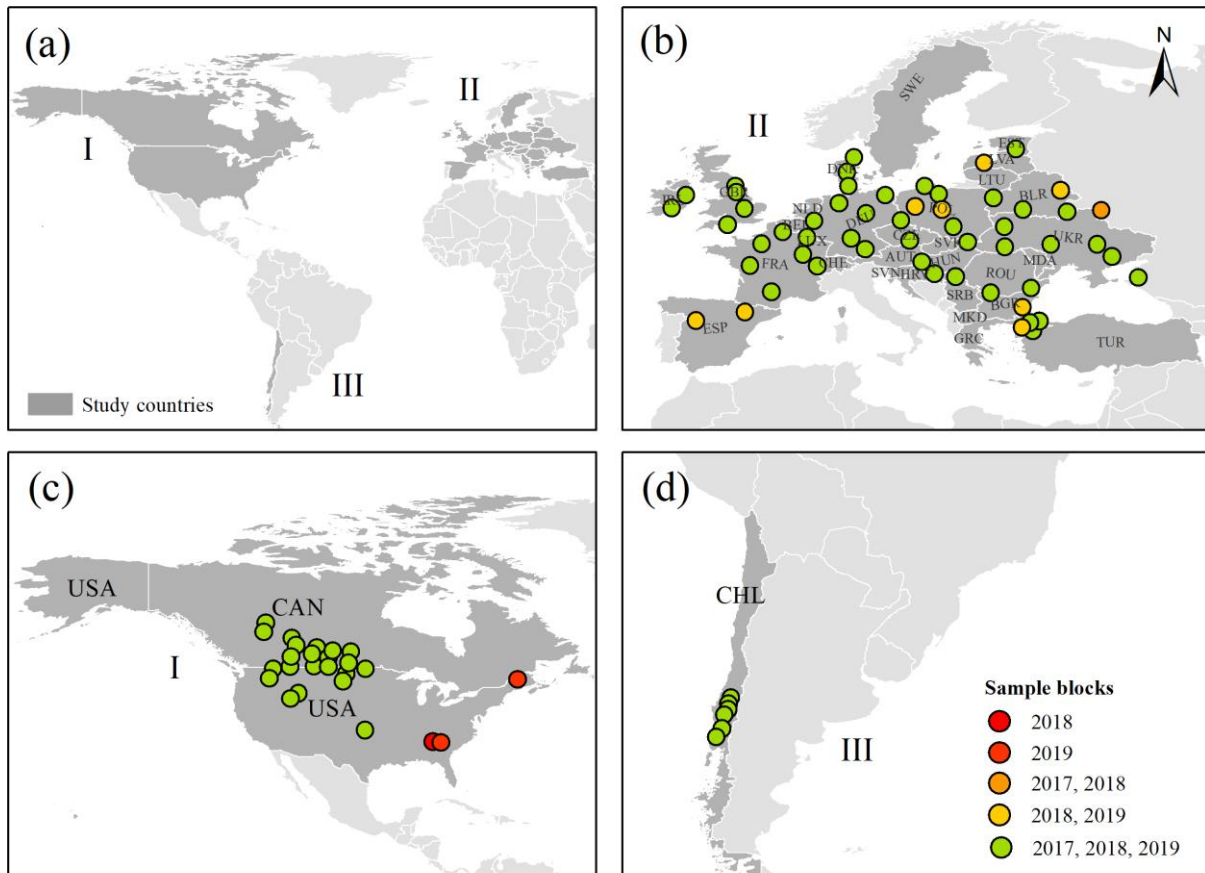
85 ~~Thus~~ ~~Taking into account the above-mentioned issues~~, we integrated multi-source data to ~~1)~~ develop a new method for
identifying rapeseed. ~~We then;~~ ~~2)~~ ~~applied~~ ~~our~~ ~~the~~ new method to generate rapeseed maps with a spatial resolution of 10 m
~~from 2017 to 2019~~ across the main planting areas of 33 countries ~~from 2017 to 2019 and~~; ~~3)~~ analyzed the geographical
characteristics of rapeseed ~~planting cultivation~~ and crop rotation.

90 **2 Materials and Methods**

2.1 Study area

We identified rapeseed planting areas ~~for in~~ 33 countries, ~~the world's main rapeseed producers, on~~ three continents: ~~(North~~
America, South America, and Europe) ~~(as they are the main rapeseed producers in the world~~ (Fig. 1). The ~~largest areas of~~
~~rapeseed cultivation~~ ~~planting areas and production of rapeseed~~ are ~~located~~ ~~large~~ in Canada and the European Union (EU) (Carré
95 and Pouzet, 2014; van Duren et al., 2015; Rondanini et al., 2012). ~~Europe produces a large amount of biodiesel for the world~~

100 every year. In 2008, 79% of the biodiesel feedstock crops in Europe, which produces a large amount of biodiesel for export every year, were rapeseed (van Duren et al., 2015). In Also, Chile, is the main rapeseed producer in South America, and the country with a high the yield of rapeseed in 2018 was (38,877 kg/ha⁻¹). Rapeseed agriculture cultivation in these countries is important for food and energy security (Carré and Pouzet, 2014). The climates of these three continents are different because of factors such as latitude and topography (Peel et al., 2007). The rapeseed planting season varies among countries because of these differences in climate and other natural conditions. Rapeseed planting seasons are distinctive because of differences in natural conditions (such as climate) in different countries (Singha et al., 2019; Wang et al., 2018), which thus brings posing great challenges to the mapping of rapeseed.



105 Figure 1. The Locations of 10 km radius sample blocks for phenological monitoring in the 33 countries and the sample blocks
 for phenological monitoring with a radius of 10 km in this study. The 33 countries include Canada (CAN), United States of
 America (USA), Chile (CHL), Ireland (IRL), United Kingdom of Great Britain and Northern Ireland (GBR), France (FRA),
 Spain (ESP), Netherlands (NLD), Belgium (BEL), Luxembourg (LUX), Germany (DEU), Switzerland (CHE), Denmark
 110 (DNK), Sweden (SWE), Poland (POL), Czechia (CZE), Austria (AUT), Slovenia (SVN), Croatia (HRV), Slovakia (SVK),
 Hungary (HUN), Estonia (EST), Latvia (LVA), Lithuania (LTU), Belarus (BLR), Ukraine (UKR), Republic of Moldova

(MDA), Romania (ROU), Bulgaria (BGR), Serbia (SRB), North Macedonia (MKD), Greece (GRC), Turkey (TUR). ~~(a-d)~~. ~~Country~~The names and codes of the country are prepared are the same as those used by ~~by~~ the Statistics Division of the United Nations Secretariat. The three-digit alphabetical codes assigned by the International Organization for Standardization ~~(ISO)~~ can be found at <https://unstats.un.org/unsd/methodology/m49/>.

115 2.2 Data

2.2.1 Remote sensing data

We collected ~~imagery from the~~ Sentinel-2 (S2) and Sentinel-1 (S1) ~~imagery satellites~~ (Table 1). ~~The S1/2 satellites are~~ launched by the European Space Agency (ESA) (Drusch et al., 2012; Torres et al., 2012). We used red (b4), green (b3), and blue (b2) spectral bands with 10 ~~=~~m spatial resolution ~~t~~Top ~~o~~f ~~a~~Atmosphere (TOA) reflectance observations. The S2 TOA product includes the ~~q~~Quality ~~a~~Assessment (QA) band, which was used to remove most of the ~~poor~~bad-quality images (e.g. cloud-~~obscured~~s information) in this study. ~~However, it is difficult to r~~Removal of all ~~clouds~~ such information was difficult, however, because of ~~due to~~ the quality of the QA band (Wang et al., 2020a; Zhu et al., 2015). We used the ~~i~~Interferometric ~~w~~Wide ~~s~~Swath mode of S1, which provides dual-band cross-polarization (VV) and vertical transmit/horizontal receive (VH) with a 12 ~~-~~day or 6-day repeat cycle and 10 ~~m~~ spatialee resolution (Torres et al., 2012). The S-1/2 images were obtained ~~using~~on the ~~Google~~google eEarth eEngine (GEE) (Gorelick et al., 2017). ~~In addition~~Also, we used QA bands to remove most of the ~~poor~~bad-quality images on GEE. ~~(S~~—(Sample code ~~—~~ can be found at https://code.earthengine.google.com/?scriptPath=Examples%3ADatasets%2FCOPERNICUS_S2). ~~Further details are~~ provided in ~~See~~ Table 1 ~~for more details~~.

2.2.2 Digital elevation model

130 We used a spatial resolution of one arc-second (approximately 30 m) elevation data from the Space Shuttle Radar Terrain Mission (Table 1) (Farr et al., 2007). ~~W~~Then we ~~then~~ calculated the spatial distribution of slope ~~using~~on GEE (~~s~~Sample code ~~can be found~~ at https://code.earthengine.google.com/?scriptPath=Examples%3ADatasets%2FUSGS_SRTMGL1_003). ~~Later~~Finally, we extracted areas with a slope of less than 10° to mask hilly terrain (Jarasiunas, 2016).

2.2.3 Cropland and agricultural statisticals data

135 In this study, cropland data from the GFSAD30 were used to identify major farming areas in different countries (Phalke et al., 2020; Xiong et al., 2017). ~~Existing~~ The existing-crop data products containing rapeseed information ~~include~~ comprise four datasets: 1) the 30-m Annual Crop Inventory (ACI) in Canada (Fisette et al., 2013) ~~and~~; 2) the 30-m Cropland Data Layer (CDL) in ~~the~~ USA (Boryan et al., 2011), ~~both of which~~ (CDL and ACI layers ~~were~~are downloaded from GEE); 3) the Crop Map of England (CROME) ~~was~~ generated in GBR, ~~and~~; 4) the 10-m Land Cover Map of France (LCMF) in France (Inglada ~~et al., 2017~~). These four crop layer products ~~were~~are generated ~~based on~~from satellite images and a large number of training

sample collections. In this study, rapeseed maps in ACI, CDL, CROME, and LCMF were used for accuracy verification at the pixel level. ~~For accuracy verification, we selected statistics~~ ~~The FAO releases annual statistics on major crop~~ ~~the areas for major crops~~ in different countries ~~and~~ regions ~~released annually by the Food and Agricultural Organization of the United Nations (FAO) every year. We selected the statistics from FAO for accuracy verification. Please see~~ Details are provided in Table 1 ~~for more details.~~

2.2.4 Crop calendars

We used two crop phenological data-sets to assist in ~~the extraction of~~ rapeseed phenological parameters: ~~crop calendars in different countries (<https://ipad.fas.usda.gov/ogamaps/cropcalendar.aspx>).~~ ~~and field records of~~ ~~the crop phenology in Germany.~~ The crop calendars ~~come~~ originated from the United States Department of Agriculture, ~~which only records~~ rapeseed ~~the planting and harvest times of rapeseed for in some selected countries.~~ The crop phenology ~~field records of the crop phenology in Germany~~ ~~are were~~ in-situ observations from crop phenological records shared by the Deutscher Wetterdienst (DWD) in Germany (Kaspar et al., 2015). The DWD provides field observations of crop phenological periods throughout Germany following the Biologische Bundesanstalt, Bundessortenamt, and Chemical (BBCH) scale ~~throughout Germany~~ (Table 1). DWD records ~~include the~~ the start date and the end dates of rapeseed flowering (d'Andrimont et al., 2020; Kaspar et al., 2015). ~~Neither~~ ~~ote~~ ~~the two~~ ~~at both~~ crop calendars ~~and nor the~~ DWD records ~~do not~~ contain information on rapeseed ~~the~~ peak flowering dates ~~of rapeseed.~~ To extract rapeseed phenological parameters, ~~w~~ We used all stations that fully recorded ~~the~~ start and end dates of the flowering periods from 2017 to 2019, namely, ~~for extracting rapeseed phenological parameters. Finally,~~ 281, 269, and 253 stations ~~are available~~ in 2017, 2018, and 2019, respectively.

Table 1 Detailed information about the data collected in this work.

Data	Time	Resolution	Institution	Version	Data access	Date of recent access	Descriptions
Sentinel-1 SAR GRD	2017-2019	10m	European Space Agency (ESA)	-	https://developers.google.com/earth-engine/datasets/catalog/COPERNICUS_S1_GRD	2020/11/15	Extracting the backscatter coefficient characteristics of rapeseed
Sentinel-2 MSI	2017-2019	10m	ESA	Level-1C	https://developers.google.com/earth-engine/datasets/catalog/COPERNICUS_S2	2020/11/15	Calculating the spectral indices after removing the cloud
Global Food Security-Support Analysis Data at 30 m (GFSAD30)	2015	30m	United States Geological Survey (USGS), NASA., et al.	V001	https://search.earthdata.nasa.gov/search?q=GFSAD30	2020/11/5	Identifying crop growing areas
The Shuttle Radar Topography Mission (SRTM)	-	30m	NASA Jet Propulsion Laboratory (JPL)	V3	https://developers.google.com/earth-engine/datasets/catalog/USGS_SRTMGL1_003	2020/10/1	Calculating slope map
Cropland Data Layer (CDL)	2017, 2019	30m	United States Department of Agriculture (USDA)	-	https://developers.google.com/earth-engine/datasets/catalog/USDA_NASS_CD_L	2020/12/1	Accuracy verification of rapeseed map at pixel level
Annual Crop Inventory (ACI)	2017, 2018	30m	Agriculture and Agri-Food Canada (AAFC)	-	https://developers.google.com/earth-engine/datasets/catalog/AAFC_ACI	2020/12/1	Accuracy verification of rapeseed map at pixel level
Crop Map of England (CROME)	2018	hexagon cells	Rural Payments Agency (RPA)	V.09	https://data.gov.uk/dataset/fb19d54f-59e6-48e7-820a-fe5fda3019e5/crop-map-of-england-crome-2018	2021/1/15	Accuracy verification of rapeseed map at pixel level
Land Cover Map of France (LCMF)	2018	10m	CNES/DNO/OT/PE	V1-0	https://www.theia-land.fr/en/2018-land-cover-product/?cover-product%2F	2021/3/22	Accuracy verification of rapeseed map at pixel level
Phenological database of Germany	2017-2019	-	Deutsche Wetterdienst (DWD)	-	https://www.dwd.de/DE/leistung/en/cdc/cli/mate-data-center.html?nr=575620&lsbid=646252	2020/10/1	Identifying the phenological characteristics of rapeseed
Agricultural statistics data	2017-2019	-	Food and Agriculture Organization (FAO)	-	http://www.fao.org/faostat/en/#data/QC	2020/12/1	Verifying the accuracy of rapeseed map at national scale
Crop Calendars	-	-	United States Department of Agriculture (USDA)	-	https://ipad.fas.usda.gov/ogamaps/cropeale/ndar.aspx	2020/10/1	Auxiliary reference data for identifying the flowering period of rapeseed

2.3 Methods

2.3.1 Optical and SAR characteristics during the rapeseed growing period of rapeseed

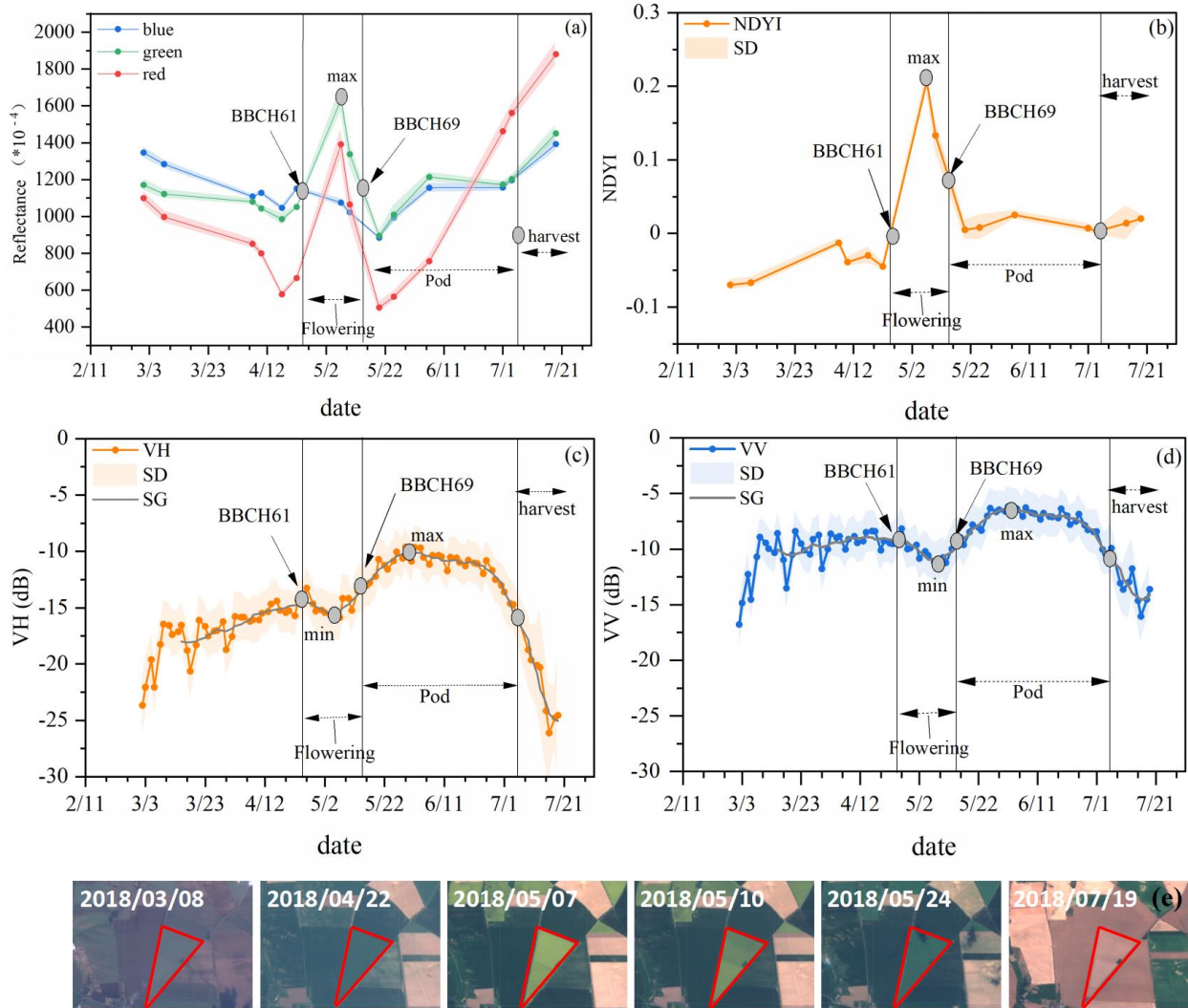
We selected available rapeseed parcels and *in-situ* observations of the DWD from different climate regions and different years to analyze the optical (reflectance and vegetation index) and SAR (VV and VH) characteristics of rapeseed along over time. As an example, Fig. 2 shows the time series of one rapeseed parcel around the DWD station (station id: 13126) in 2018. This rapeseed parcel shows exhibited unique visual characteristics during the flowering period (Fig. 2e). When rapeseed approached peak flowering, the flowers becomes yellow when rapeseed is approaching peak flowering (d'Andrimont et al., 2020; Pan et al., 2013; Tao et al., 2020; Wang et al., 2018). Rapeseed was yellow-green on the true color images of S2 and Google Earth during the flowering period (Fig. S1). The reflectance of the green band and red bands separately increased from 0.09 and 0.06, respectively, (2018/4/17, before flowering (17 Apr 2018)) to 0.16 and 0.14 at peak flowering (7 May 2018/5/7, peak flowering), and then decreased after flowering (Fig. 2a). The reflectance of the blue band was lower than that of the red and green bands during flowering. This outcome is similar to the results of previous research results (Ashourloo et al., 2019; Sulik and Long, 2015). We also calculated the Normalized Difference Yellow Index (NDYI, Eq. 1), which can capture the increasing yellowness in the time series (d'Andrimont et al., 2020; Sulik and Long, 2016), as follows: Also, the NDYI increased from -0.03 on April 17 to 0.21 on May 7 (Fig. 2b). NDYI reaches a peak during the flowering time of rapeseed. This unique spectral feature of rapeseed in the flowering period is caused by the yellow petals.

$$NDYI = \frac{green - blue}{green + blue} \quad (1)$$

where *green* is the TOA reflectance of the green band (b3) of the S2 imagery, and *blue* is the blue band (b2) reflectance. NDYI increased from -0.03 on 17 April to 0.21 on 7 May (Fig. 2b) and reached a peak during rapeseed flowering. This unique spectral feature of rapeseed during the flowering period was due to the yellow petals.

S1 backscattering changes with rapeseed the growth of rapeseed. We used the VV and VH time series smoothed by the Savitzky-Golay (SG) filter (window size 3) (Chen et al., 2004) as inputs to identify the phenological parameters of rapeseed parcels. We used the SG filter algorithm in MATLAB 2020b, which uncovered. The results show that there are local minimums in both the VV (-11.20, 8 May-8) and VH (-15.60, 5 May-5) time series during rapeseed flowering (Fig. 2c,d). Furthermore, VH reached the maximum (-9.64, 1 June-1) during the pod period. Unlike other crops, rapeseed has two distinct green-up phases: the flowering period and the pod period (Ashourloo et al., 2019; Bargiel, 2017; Mercier et al., 2020; Veloso et al., 2017). The petals of rapeseed decrease the scattering of VV and VH, while the pods increase the scattering intensity of VH (d'Andrimont et al., 2020; Bargiel, 2017; McNairn et al., 2009; Mercier et al., 2020). The NDYI and backscattering (VV and VH) time series of rapeseed in different climate regions (Fig. S1) also show exhibited the same characteristics. Therefore, we hence, we therefore used the features in both Optical and SAR features to identify the rapeseed

flowering and pod periods in this study. Due to the differences in the revisit times of the S1/2 satellites, rapeseed peak flowering dates were defined as the median dates extracted using optical and SAR indicators.



210

Figure 2. The time-series profiles of four features of the rapeseed pixels around one DWD station (id = 13126; Longitude: 11.333268424°, Latitude: 52.200000463°) in Germany in 2018. (a) The mean reflectance values (red, green, and blue); (b) Mean NDVI; (c) Mean VH; and (d) Mean VV. The light shaded filled color areas indicate for the standard deviation. The BBCH scale was used for the in-situ observations of rapeseed phenology, with BBCH61 and BBCH69 respectively corresponding to for the start of flowering and the end of flowering, respectively. (e) The rapeseed parcel around the DWD station is shown by bounded in red boundaries (image source: Copernicus Sentinel-2 data 2018).

215

2.3.2 Sample blocks collected for phenological monitoring

As a prerequisite to large-scale mapping ~~rapeseed at a large scale~~, the phenology of rapeseed in different countries ~~needs to~~must be identified and delineated (Dong et al., 2016; Zhang et al., 2020), ~~but~~. ~~However~~, not enough observational records of rapeseed phenology are available on a large scale. ~~Referring to~~In accordance with the DWD method of phenological observation~~ing phenology~~ (Kaspar et al., 2015), we created sample blocks with a radius of 10 km over rapeseed-producing areas of different countries and randomly sampled 10 rapeseed parcels ~~for each~~per block. The rapeseed plots were identified by their phenological characteristics, ~~which were~~ obtained ~~from by the~~ visual interpretation and analysis of reference data, including high-resolution images available in S2 and Google Earth as well as sSpectral reflectance (red ~~band~~ and green bands), ~~and~~ spectral index (NDVI), and scattering coefficient profiles (VV and VH) from the S1/2 time series. ~~It should be noted that the~~ Google Earth images taken during rapeseed flowering were used to assist with the visual interpretation of rapeseed parcels. ~~The~~ rapeseed parcels with no available~~out~~ high-quality time-series imagery ~~available~~ were omitted. Finally, 75 sample blocks in 2017, 84 sample blocks in 2018, and 84 sample blocks in 2019 were uniformly and randomly collected (Fig. 1).

2.3.3 Detection of fFlowering and pod phases ~~detection~~ in different countries

To ~~find~~determine ~~out~~ the flowering dates of rapeseed in different countries, we evaluated each phenological sample block from 2017 to 2019 (Fig. 3). First, we calculated the average values of all pixels ~~in the~~ ~~the~~ 10 previously selected rapeseed parcels in each block ~~we selected before~~ during the rapeseed growth period ~~for each block~~ in conjunction with the crop calendar. VV and VH time series for each sampled rapeseed parcels were smoothed using the SG filter. Second, ~~these~~ S1/2 peak flowering dates and pod dates were derived for all sample blocks ~~based on~~according to the method in Section 2.3.1. We found ~~that~~ the peak flowering dates of rapeseed, especially in Europe, ~~followed~~have an obvious latitudinal gradient, ~~especially in Europe~~ (Fig. 3j).

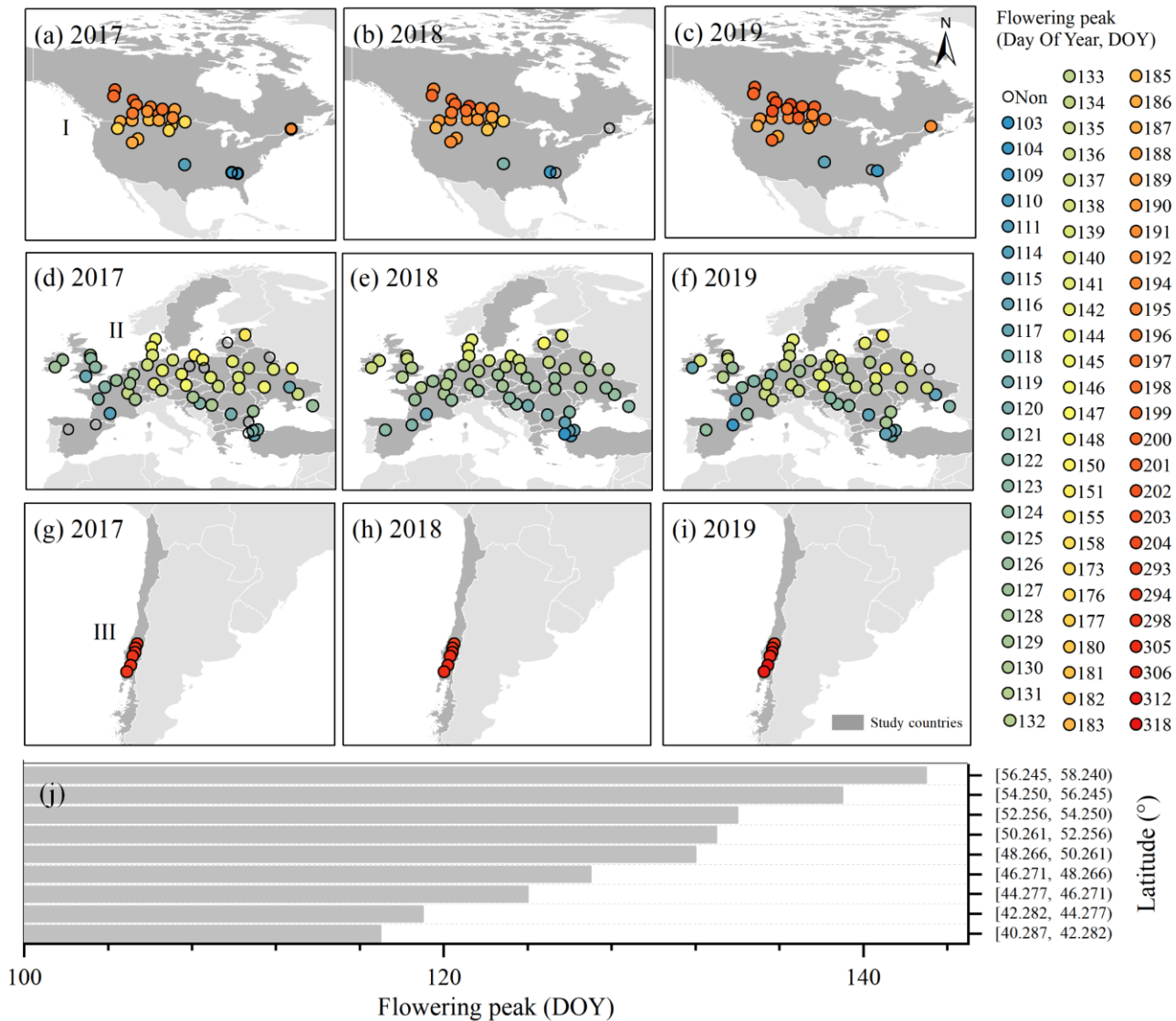
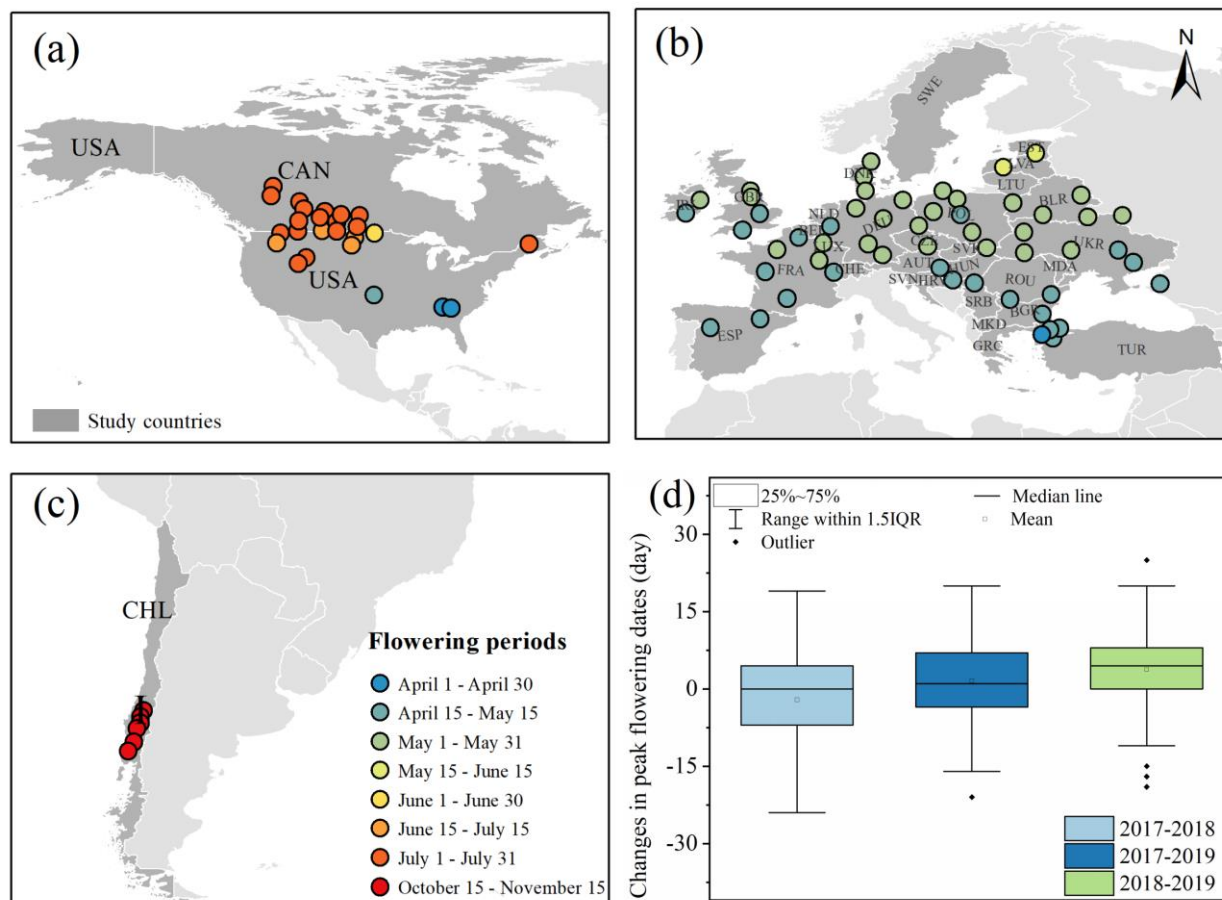


Figure 3. The spatial distribution of rapeseed flowering dates (Julian day). (a-i) Flowering dates (Julian day) was monitored by in different sample blocks in 2017, 2018, and 2019 (a-i). (j) Characteristics of the latitudinal gradient characteristics in Europe (j). The peak flowering date for each latitudinal interval is was calculated by the mean of the flowering dates of all sample blocks in different latitude intervals within that interval.

Also, we also found observed that the signal with the maximum VH occurred identified the signal with the maximum of VH is within 45 days after of the peak flowering date of flowering (Fig. S2). Then we then calculated the difference in the peak flowering date of each sample block between in different years, which revealed that the The results showed that the flowering peak dates of most sample parcels were advanced or delayed by only 10 days (Fig. 4d). Therefore, it is reasonable to use

the same period for rapeseed identification for in different years in the a same given area was thus considered to be reasonable for rapeseed identification in this study. Previous studies and field observation records have indicated show that the flowering period of rapeseed is about approximately 30 days (d'Andrimont et al., 2020; Chen et al., 2019; Kaspar et al., 2015; She et al., 2015). Therefore, we therefore divided each month into two time periods, with (the 15th day serving as the dividing line). Two consecutive half-months were defined as a suitable periods for classifying flowering dates (Fig. 4a-c). Finally, we designated the flowering period for each administrative unit based on the sample blocks. Finally, we designated the flowering period on the basis of the peak flowering dates (Fig. 4a-c).



255 Figure 4. Flowering phenology of rapeseed. (a-c) The spatial distribution of rapeseed flowering periods for among sample blocks. (d) The boxplot showing the changes in peak flowering dates of each sample blocks over in three 3 years.

2.3.4 Development of aing phenology- and pixel-based algorithm for mapping rapeseed

The Our analysis of temporal profiling of rapeseed parcels in this study together with along with the results of many previous studies indicated that the spectrum at the flowering stage and the scattering signal at the pod stage are the key features for

260 identify rapeseed (Ashourloo et al., 2019; Bargiel, 2017; Han et al., 2020; Mercier et al., 2020; Sulik and Long, 2015; Veloso et al., 2017). We developed ~~one a single~~ phenology- and pixel-based rapeseed mapping algorithm ~~that using~~ relies on four features: spectral bands (red and green), spectral indices (NDYI), polarization bands (VH), and terrain (slope). Four primary steps were ~~conducted used to for~~ mapping annual planting areas (Fig. 6).

265 ~~In the first step, we~~ determined the threshold of the feature indicators. We analyzed the histograms of ~~the~~ random samples selected from different countries as ~~suggested by our~~ suggested. ~~We found the similarities of Green band and blue bands and NDYI (Fig. S3) were similar during the flowering stage for in all samples during the flowering stage from the different regions. Most (98%) of the rapeseed pixels (98%) showed had the following values: red > 0.07, green > 0.11, and NDYI > 0.05.~~

270 ~~However, we found~~ observed some pixels, ~~however,~~ with a relatively high NDYI due to contamination by a cloud with a "rainbow" appearance, which would cause them to be misclassified into as rapeseed ~~because they are polluted by the cloud with a "rainbow" appearance~~ (Fig. 5). Because of the limited quality of the QA band and the simple cloud score algorithm, ~~Such misclassifications caused by arising from some poor~~ bad-quality observations from the S2 image ~~can not~~ be removed due to the limited quality of the QA band and simple cloud score algorithm (Wang et al., 2020c; Zhu et al., 2015). The "rainbow" ~~in~~ of the cloud ~~comes is the result of from~~ the push-broom design of S2 (Fig. 5a) and spectral misregistration (~~for~~ For more details, ~~please refer to see~~ ESA, 2015a, and ESA, 2015b). ~~Based on the principle of Taking into account the relative displacement of each spectral channel sensor in the S2 push-broom design (Frantz et al., 2018; Liu et al., 2020b; Zhao et al., 2018), we developed a new spectral index (NRGBI) to reduce the influence of the "rainbow" (Eq. 2): The scatter plot of NDYI and NRGBI of rapeseed parcel samples and "rainbow" samples around clouds (visual interpretation) showed that the NRGBI (threshold is 0.05) can effectively distinguish rapeseed from the "rainbow" (Fig. 5h).~~

$$NRGBI = \frac{red-blue}{red+blue} - \frac{green-blue}{green+blue} \quad (2)$$

where *red*, *green*, and *blue* are the TOA reflectance values of the red ~~band~~ (b4), green ~~band~~ (b3), and blue ~~band~~ (b2) bands of the S2 imagery, respectively. ~~The A scatter plot of NDYI vs. and NRGBI of rapeseed parcel samples and "rainbow" samples around clouds (visual interpretation) showed demonstrated that the NRGBI (threshold is -0.05) can effectively distinguish rapeseed from the the "rainbow" (Fig. 5h).~~ The GEE code for NRGBI index calculation s can be found at <https://code.earthengine.google.com/a39fc699a276d018778d59c5b085d960>. ~~Also~~ In addition, NRGBI can be calculated based on using Eq. 2 in other GIS software programs (e.g. QGIS and ArcGIS) on ~~the a~~ local computer.

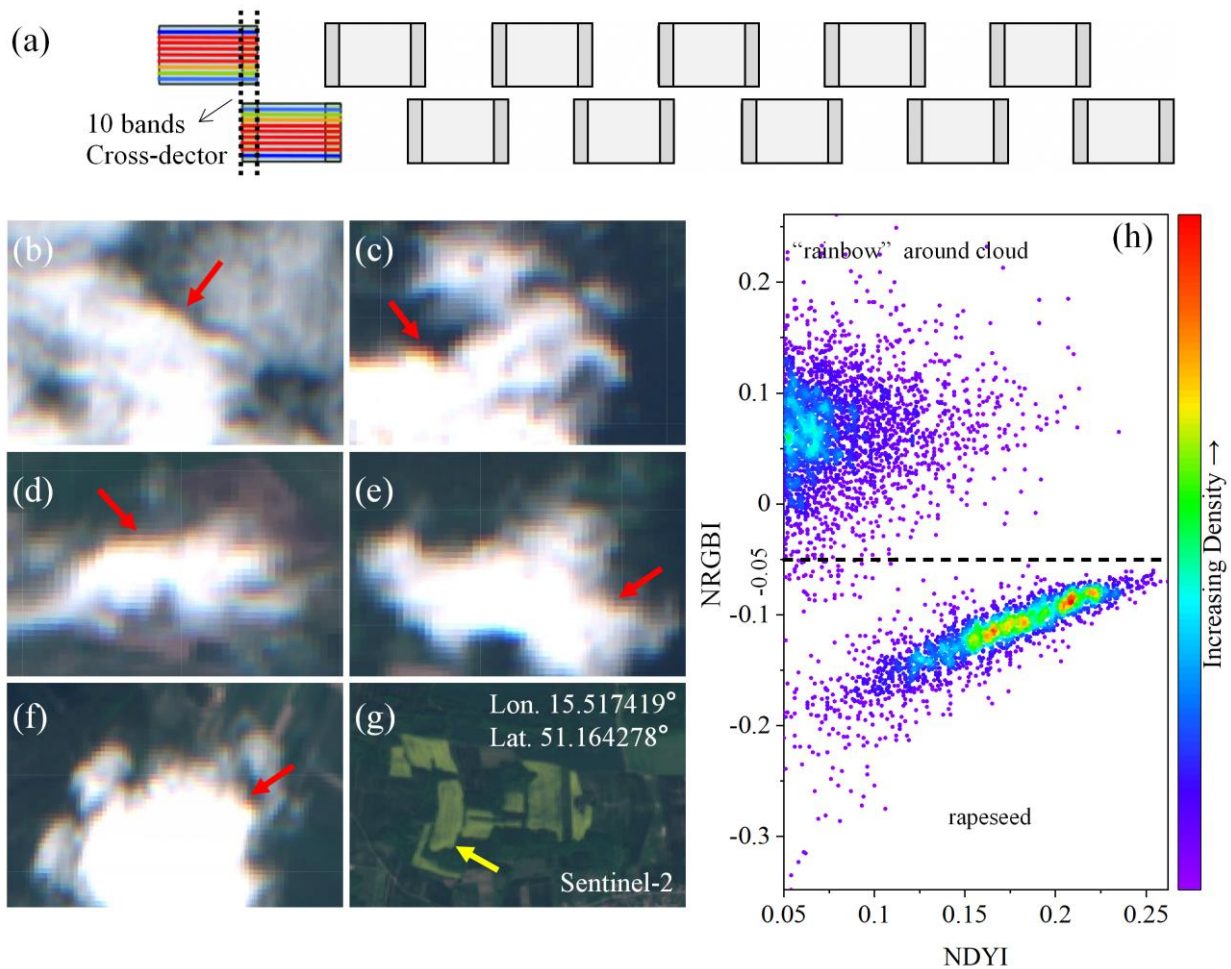


Figure 5. “Rainbow” cloud effect origins Causes, examples, and solutions for the “rainbow” cloud effect. (a) S2 staggered detector configuration of S2 (ESA, 2015a); (b–f) Examples of spectral misregistration effects and the performance of cloud-masking methods. Each image was masked with by the quality assurance band (QA60) for the Sentinel-2 TOA image. With the red arrows indicating the “rainbow” appearing around clouds at high altitudes in the S2 image (image source: Copernicus Sentinel-2 data); (g) Sentinel-2 TOA image of rapeseed at the flowering stage. With the yellow arrow indicates for the rapeseed fields; (h) Scatter plots of NDYI vs. and NRGBI of rapeseed field samples and samples with a “rainbow” around clouds samples from in the S2 images. with Relative pixel density is indicated by the color density for the number of pixels scale on the right.

The second step 2- was the identification of all rapeseed pixels from different images during the flowering period and their subsequent aggregation into annual rapeseed planting areas (Fig. 6). Because the peak flowering dates and the number of available images of rapeseed fields vary within a region are different (Fig. S4), rapeseed classifications based on a

single image ~~could~~may fail ~~to~~in capturing rapeseed flowering dynamics (Ashourloo et al., 2019). To avoid ~~the~~ misclassification ~~due to~~from ~~poor~~bad-quality observations during the rapeseed flowering stage, we aggregated all ~~the~~classified results ~~classified~~ from available S2 images ~~during~~the flowering period. ~~Hence~~The use of, a larger number of images ~~will~~ resulted in better performance (Fig. S4).

305

~~In the third s~~Step, we 3: ~~combined~~ing optical data with SAR images to ensure the accuracy of the rapeseed maps. ~~H~~The high VH values during the pod stage are another distinct feature that can distinguish rapeseed from other crops (Mercier et al., 2020; Tian et al., 2019; Van Tricht et al., 2018; Veloso et al., 2017). ~~Taking into c~~onsiderationing the variability of flowering in different fields and the duration of the pod stage (Section 2.3.2), we calculated the maximum VH between the second half of the flowering stage and the next 30 days ~~after the flowering stage (ca. ~45 days); see~~ ~~(See the gray box part~~ in Fig. 6). Within ~~this 45-day interval~~s, at least three S1 satellite images ~~are~~were available in the study areas. ~~Also~~In addition, ~~the~~ areas with a slope $\geq 10^\circ$ were removed (Jarasiunas, 2016). All pixels ~~that~~meeting these requirements ~~are~~were defined as rapeseed.

310

~~In the fourth s~~Step, we 4: ~~removed~~ing the “salt and pepper” noise ~~according by applying a threshold based onto~~ the number of connected components (objects) ~~threshold, that is, (~~ the size of the neighborhood in pixels, ~~)~~ and ~~then~~ filling the gaps inside the parcels (Hirayama et al., 2019). We used an 8-connected rules, which means that the edges or corners of the pixels ~~were~~are connected. If two adjacent pixels ~~are~~were connected, they ~~are~~were considered as part of the same object (<https://www.mathworks.com/help/images/ref/bwareaopen.html>). The bwareaopen function in MATLAB 2020b ~~software~~ was used to remove ~~the~~ objects ~~which are less than~~not meeting ~~the~~ a given threshold. The thresholds of different indicators in ~~different regions~~ ~~can be found~~are given in Table S1.

320

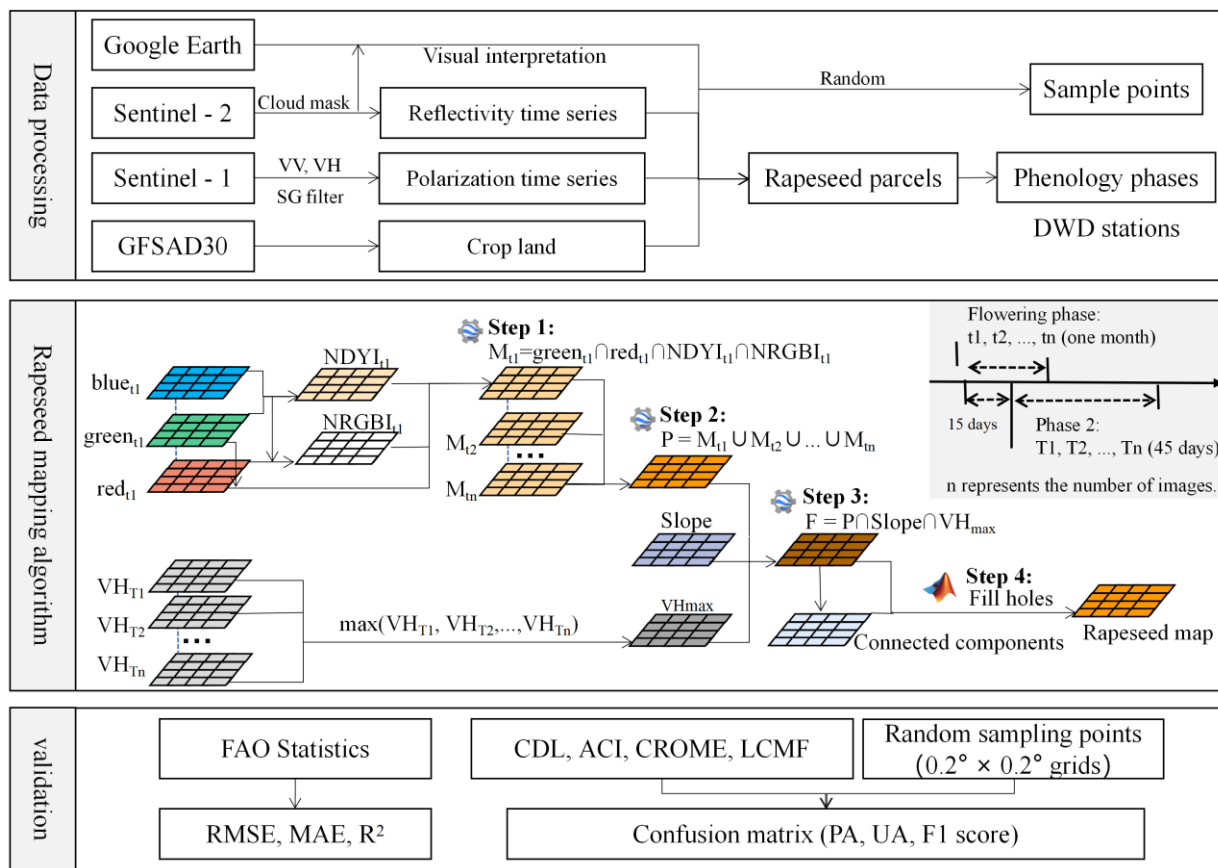


Figure 6. The workflow for mapping rapeseed areas using the proposed phenology- and pixel-based algorithm. GFSAD30, Global Food Security-Support Analysis Data at 30_m (GFSAD30); NDYI, normalized difference yellowness index (NDYI); NRGBI, the new spectral index; (NRGBI); DWD, Deutscher Wetterdienst; (DWD); FAO, Food and Agriculture Organization of the United Nations; RMSE, (FAO), Root mMean square error; MAE, (RMSE), mMean absolute error; (MAE); R², R-squared; CDL, (R²), Cropland Data Layer; ACI, (CDL), Annual Crop Inventory; CROME, (ACI), Crop Map of England; LCMF, (CROME), Land Cover Map of France; UA (LCMF), user's accuracy; PA, (UA), producer's accuracy; (PA), and F1, F1 score (F1).

2.4 Accuracy assessment

To test the accuracy of our proposed algorithm, First, we first compared the rapeseed areas retrieved using by the new method with FAO statistics. Our rapeseed data constituted is a binary (0 or 1) map with a spatial resolution of 10 m. We then can calculated the total area of rapeseed maps in each country and compared these numbers with theFAO national rapeseed statistics. To verify the accuracy of rapeseed mapping, we used the RMSE (Eq. 3), and the MAE (Eq. 4), and the coefficient of determination (R^2 , Eq. 5), which were are used calculated as follows to verify the accuracy of rapeseed mapping:

$$335 \quad RMSE = \sqrt{\frac{\sum_{i=1}^n (y_i - f_i)^2}{n}} \quad (3)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - f_i| \quad (4)$$

$$R^2 = \frac{(\sum_{i=1}^n (y_i - \bar{y}_i)(f_i - \bar{f}_i))^2}{\sum_{i=1}^n (y_i - \bar{y}_i)^2 \sum_{i=1}^n (f_i - \bar{f}_i)^2} \quad (5)$$

where n is the total number of countries, y_i is the mapped rapeseed planting area for country i , \bar{y}_i is the corresponding mean value, f_i is the rapeseed planting areas recorded by the FAO for country i , and \bar{f}_i is the corresponding mean value.

340 We also compared our rapeseed maps with four open-access datasets that include rapeseed layers at the pixel level: (ACI, CDL, CROME, and LCMF) in Canada, the USA, GBR, and France, respectively at the pixel level. We used the data from 2018 and 2019 in these datasets as a reference these datasets as the reference data for 2018 and 2019 (Boryan et al., 2011; Fiset et al., 2013). To unify the spatial resolution of our rapeseed maps, we resampled CDL, ACI, and CROME were resampled to 10 m resolution to allow for comparison. To check the accuracy of our classification, we calculated UA (Eq. 6), PA (Eq. 7), and F1 (Eq. 8) were calculated based on confusion matrices (Table S2) to measure the classification accuracy.

350 Thirdly, we also randomly selected verification samples based on the previous studies (Pekel et al., 2016; Wang et al., 2020b) to validate the our rapeseed maps. A $0.2^\circ \times 0.2^\circ$ latitude-longitude grid (0.2 latitudes by 0.2 longitudes) was generated within the superimposed on our 2018 rapeseed map in 2018 acquired by our method (Fig. S5). Two points—one (rapeseed and the other non-rapeseed)—were generated randomly generated in each grid by visually interpreting images available from S2 and Google Earth, together along with spectral reflectance (red and green bands), spectral index (NDYI), and scattering coefficient (VV and VH) profiles from the S-1/2 time series. The confusion matrices were similarly used to assess the accuracy according to Eqs. 6–8:

$$UA = \frac{x_{ij}}{x_j} \quad (6)$$

$$PA = \frac{x_{ij}}{x_i} \quad (7)$$

$$F1 = 2 \times \frac{UA \times PA}{UA + PA} \quad (8)$$

360 In the above equations, Where x_{ij} is the value of the i -th row and j -th column, x_i is the sum of the i -th row, and x_j is the sum of the j -th column. Although the statistical data and existing products are did not completely the same reflect as the real-actual areas and locations of cultivated rapeseed planted on the ground, these datasets were still beneficial for validating the accuracy of our rapeseed maps at different scales (national and pixel scales).

3 Results

3.1 Accuracy assessment

365 We compared ~~the our~~ derived rapeseed areas with those from ~~the~~ FAO statistics. The total planting areas of rapeseed ~~are~~
~~exhibited good well~~ consistency with the agricultural statistics at the national level, with ~~a~~ RMSE of 1459.64 km², ~~a~~ MAE of
785.25 km², and ~~an~~ R² of 0.88 (Fig. 7). We found ~~that~~ the derived areas in ~~2017-2018 and 2019~~ ~~are were were~~ larger than those
in ~~2018~~ 2017 and 2019, especially ~~for in the~~ countries with ~~the~~ relatively small rapeseed areas. The ~~greater more~~ availability of
S2 images ~~together and with higher better~~ quality of data in 2018 ~~could may have~~ contributed to the ~~derivation of the~~ larger
370 rapeseed areas ~~derived by the our~~ new method (Liu et al., 2020a).

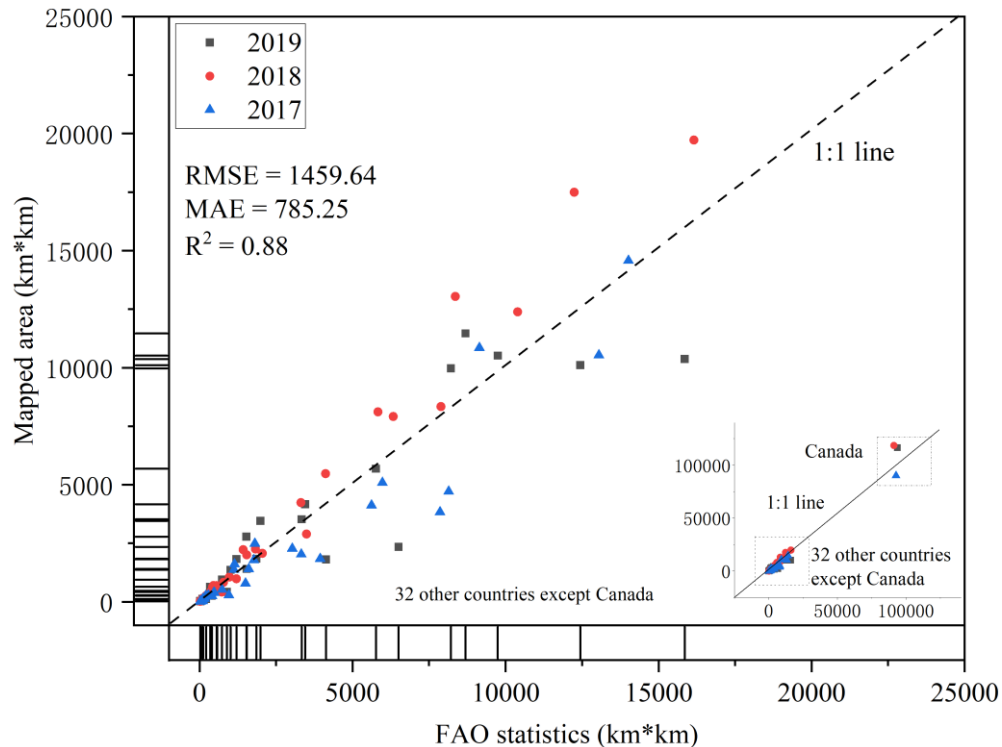
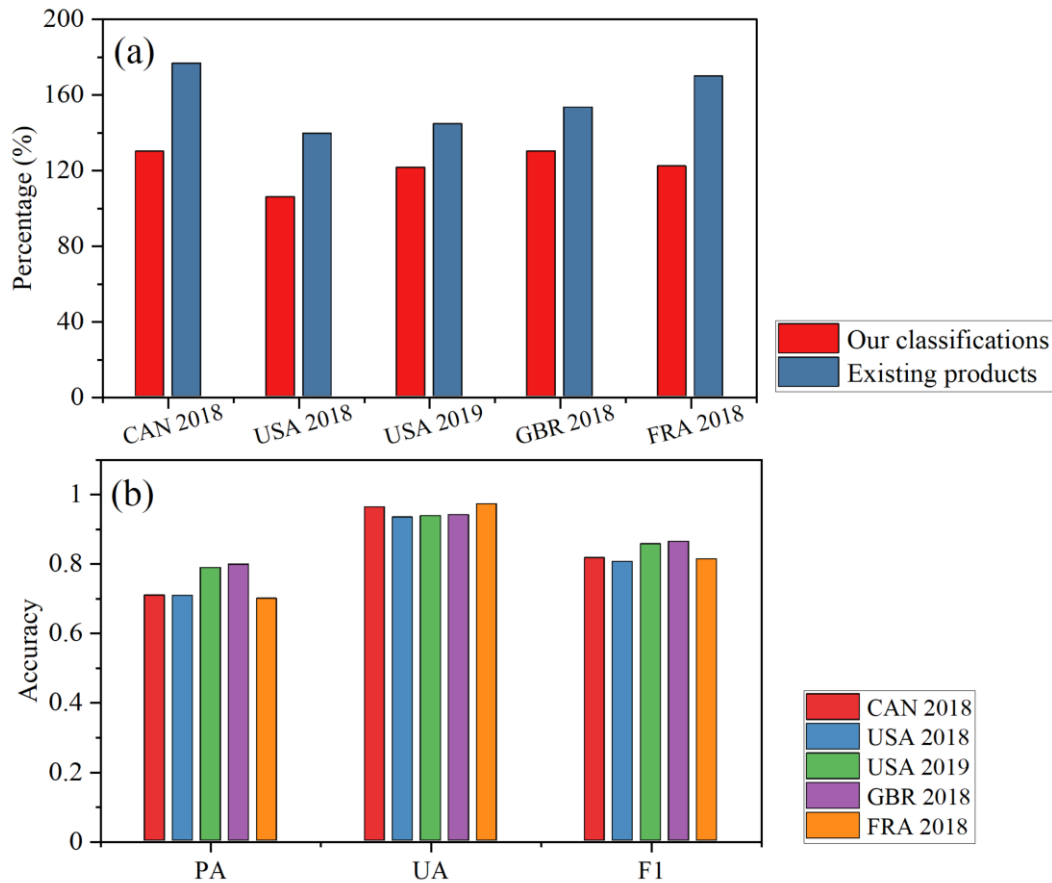


Figure 7. Comparison of rapeseed areas with ~~the~~ FAO statistics at the national level. ~~The names of all 33 countries can be found are listed in Section 2.1.~~

375 ~~As indicated by their higher level of accuracy based on confusion matrix values.~~ ~~The comparison of~~ our rapeseed maps ~~were~~
~~consistent at the pixel level~~ with ~~those maps~~ of ~~the American~~ USA CDL in 2018 ~~and~~ ~~2019~~ ~~and~~ ~~the~~ Canadian ACI,
~~British~~ GBR CROME, ~~and~~ ~~French~~ LCMF in 2018 ~~was consistent at pixel level indicated by a higher accuracy according~~
~~to the confusion matrix values~~ (Table S3). ~~As shown in~~ Fig. 8a, ~~shows that~~ the rapeseed areas calculated from our maps ~~were are~~
consistently more comparable to FAO statistics than ~~were~~ those from existing products. ~~The~~ UA, PA, and F1, ~~which~~ varied by

380 country, ranged from: 0.93–0.97, with PA of 0.70–0.80, and UA of 0.93–0.97, and F1 of 0.81–0.86, respectively (Fig. 8b).
 The rapeseed areas obtained determined using our algorithm by us accounted for around approximately 71% of the 2018 CDL,
 71% of the 2018 ACI, and 80% of the 2018 CROME, and 70% of the 2018 LCMF, and 79% of the 2019 CDL. Furthermore
 In addition, the distributions on our rapeseed maps were our results showed consistent distributions between our rapeseed maps
 and the with those of existing products at the pixel level (Figs. S7 and -S8). The differences in accuracy might may have
 385 been caused due to by the varied number of high-quality images available in different regions (Dong et al., 2016). Despite the
 various different ground conditions, methods, images, and spatial resolutions among the products, the comparison results of
 our comparison further verify the accuracy of our rapeseed maps (Gong et al., 2020; Singha et al., 2019).



390 Figure 8. Classification validation results of the classifications results. (a) The percentage of the rapeseed areas based on
 FAO statistics classified as such in the existing products and classification results in the FAO statistics our rapeseed map
 database. (b) Accuracy of our classifications. The user's accuracy (UA), producer's accuracy (PA), and F1 score (F1) of
 classifications in four countries (Canada, USA, GBR, and France) using the existing products were used as a reference data.
 UA, user's accuracy; PA, producer's accuracy; F1, F1 score.

395 ~~According to~~ The confusion matrix values (Table S4) based on random sampling points, ~~show that~~ the accuracy of ~~the our~~ rapeseed maps varied ~~s~~ in different regions. We ~~obtained the highest~~ ~~found zone II shows the highest~~ accuracy (F1, 0.91) ~~in zone II~~, followed by zone III (F1, 0.9), and zone I (F1, 0.84). ~~These~~ Such disparities ~~y in accuracy might may~~ be ~~ascribed due~~ to ~~the differences in the~~ent availability of ~~high-quality~~S1/2 images ~~among~~in the studied areas. ~~Our~~The results showed ~~indicate~~ that ~~the accuracy of our newly derived rapeseed maps derived by our method~~ ~~ishad~~ a ~~satisfactory~~ing accuracy.

400 3.2 ~~More~~ Additional details features of rapeseed maps derived using ~~by our~~the new method

To ~~show further~~ ~~more details of~~ characterize the rapeseed maps ~~derived~~ generated ~~from in this study~~our method, we selected ~~some various~~ images in ~~some several~~ areas of each country. The rapeseed maps showed ~~ed~~ good spatial consistency with ~~the the~~actual areas of rapeseed cultivation on the ground ~~actual rapeseed planted on the ground~~ (Figs. 9 and Fig.-S6). ~~Fields with various planting densities—ranging f~~From ~~densely planted the~~ areas ~~densely planted by rapeseed~~ in Canada (Fig. 9-a) to relatively sparse ~~planting~~ ones, such as in Chile (Fig. 9-b) and European countries (e.g. Fig. 9-c,d) (Lowder et al., 2016), ~~various shapes—ranging~~ -from regular rectangles (e.g. Fig. 9-a,-h) to irregular parcels (Fig. 9-c,-d), ~~and different climatic conditions—ranging from a~~ ~~from~~ temperate oceanic climate (Fig. 9-c-~~e~~), or even subtropical ~~climate~~ (Fig. 9-b) ~~ones~~, ~~all field details~~ were ~~clearly and comprehensively~~ indicated ~~clearly in on our our~~ maps. ~~The f~~Fragmented pattern of ~~ation of~~ land in some European countries, especially ~~that~~ -in Eastern and Central Europe ~~after due to~~ land reform in 1989 (Hartvigsen, 2013, 2014), ~~such as Estonia (Fig.9f) (Jürgenson and Rasva, 2020; Looga et al., 2018)~~was ~~clearly~~ ~~clearly~~ evident; Fig. 9f shows land in Estonia as an example (Jürgenson and Rasva, 2020; Looga et al., 2018). ~~Although~~ ~~the algorithm was applied to~~ ~~under~~ different climates, terrains, ~~and~~ landscapes, ~~and~~ over ~~a~~ a very larger region, ~~the its algorithm~~ classification accuracy ~~showed a satisfying classification accuracy~~ across 33 countries ~~was~~ satisfactory. ~~Our~~Thus, ~~the~~ rapeseed maps can ~~thus~~ effectively identify ~~the~~ fields in detail with high spatial resolution and clear field boundaries. ~~More~~ rapeseed classification details can be found in Fig. S6.

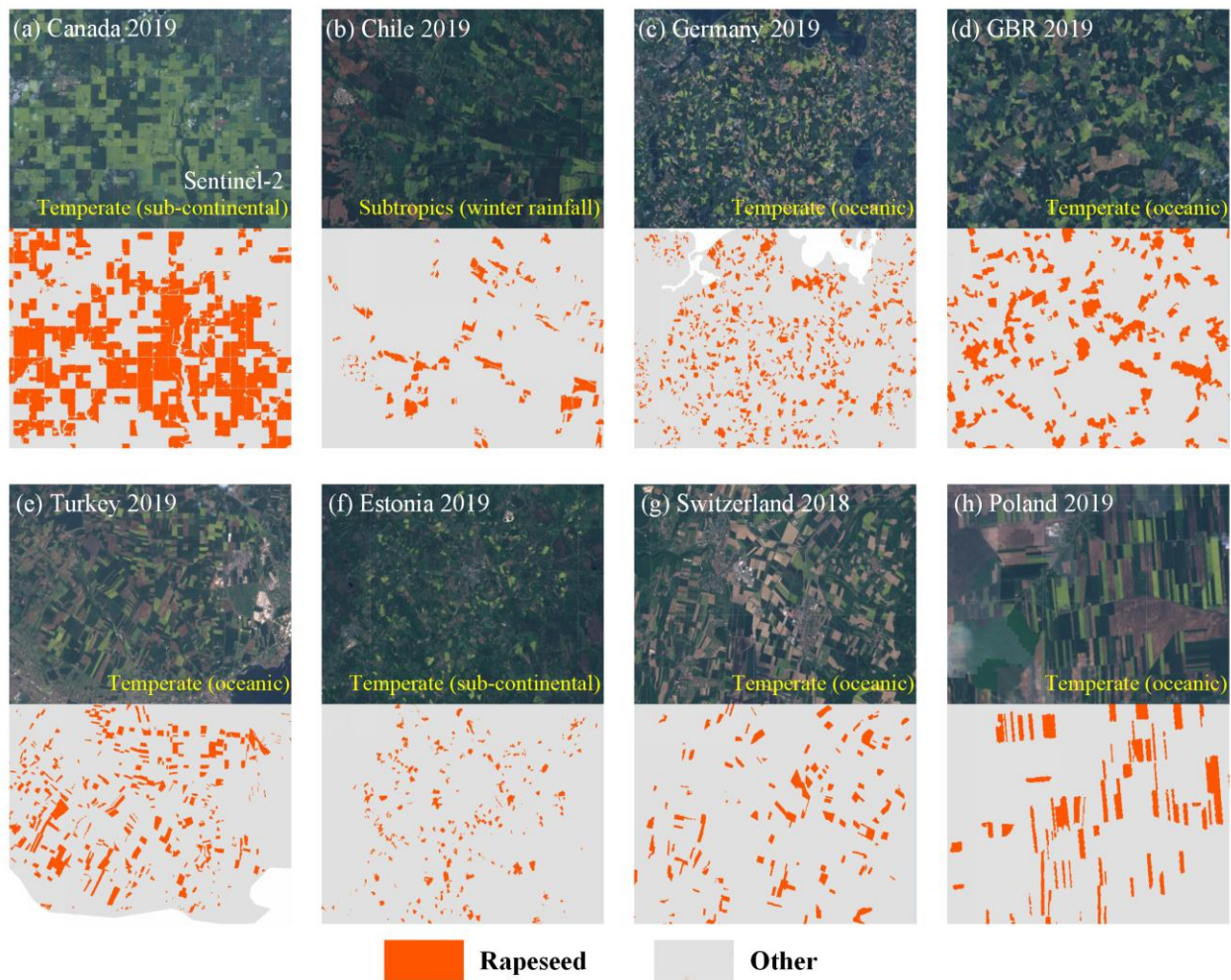


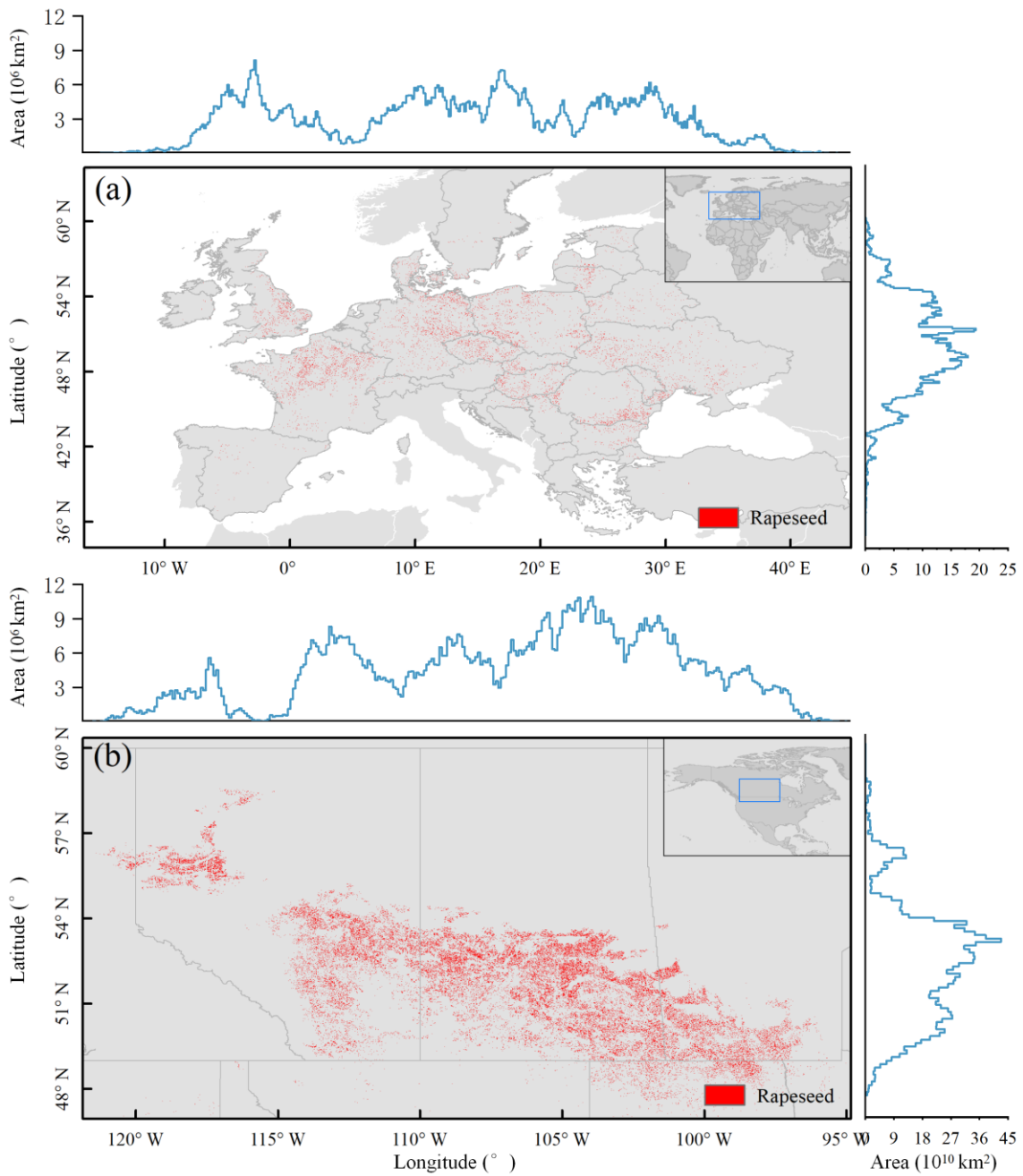
Figure 9. Spatially explicit details of rapeseed maps in eight countries with diverse crop structures in different years. The names of climate zones are given in(the yellow words show the climatic zones). RGB composite images use comprise the red (b4), green (b3), and blue (b2) bands from Sentinel-2 with good-quality observations during the rapeseed flowering period of rapeseed (image source: Copernicus Sentinel-2 data). The climate zone data areis from the Food Insecurity, Poverty and Environment Global GIS Database (FGGD).

3.3 Spatial patterns of rapeseed planting areas

In our maps, the largest total area of rapeseed cultivation worldwide was in Canada shows the largest rapeseed planting area, higher than those in Europe. Along with GBR, Poland, and Ukraine, France and Germany are the two leading rapeseed growing countries in Europe—France and Germany—, accounting for around approximately 66.3% of European rapeseed areas together with the other three countries (GBR, Poland, and Ukraine). The 3-year spatial patterns of three years (2017–2019)

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~~spatial patterns were~~are consistent at the national level (Fig. S9). ~~Moreover, w~~We also plotted the geographic ~~eharacteristics~~ characteristics ~~distribution~~ of rapeseed areas along latitud~~in~~ale and longitud~~inal~~ gradients~~e for in~~ in the study areas (Fig. 10). ~~With the exception of steep mountainous regions and cold northern areas, r~~Rapeseed ~~in Europe~~ is widely planted ~~in European countries in the~~ countries ~~wit~~at latitudes of ~~45~~46~~→~~56~~3~~°N and longitudes of ~~−2°~~W~~→~~4°~~E~~, 9°~~→~~19°~~E~~, and 22°~~→~~27°~~E~~, ~~with exception of the steep mountainous areas and the cold northern areas~~ (Fig. 10a) (~~van Duren et al., 2015~~). In Canada and ~~the~~ USA, ~~the~~ areas with ~~the~~ latitudes of ~~44~~44.5°N, ~~51~~49~~→~~55~~4~~°N, ~~and~~ 56~~→~~57°N and longitudes of ~~−118~~7°W to ~~−117~~8°W and, ~~−114~~98°W to ~~−98~~114°W ~~have high~~are densities of ~~ely distributed~~ planted ~~by~~ rapeseed (Fig. 10b).



435 Figure 10. Spatial distribution of rapeseed areas at 10_m resolution along latitudinal and longitudinal gradients in 2018. (a) Europe and Turkey. (b) Canada and the USA.

4 Discussion

4.1 Investigation of the rapeseed rotation systems

We obtained ~~3~~ three-year rapeseed maps ~~at a spatial resolution of at a 10-m spatial resolution, whose~~ and with a higher accuracy ~~which~~ was validated by annual national statistics books, open-accessed public products, and random sampling points. These rapeseed maps provided a new opportunity to investigate rapeseed rotation systems (Liu et al., 2018a). Crop rotation information is ~~considered~~ an important factor ~~in for~~ crop yield management (Harker et al., 2015; Liu et al., 2018a; Ren et al., 2015; Rudiyanto et al., 2019; Zhou et al., 2015). ~~To analyze rapeseed rotation patterns~~ Thus, we ~~therefore~~ selected 25 representative areas (Fig. S10) ~~to analyze the rapeseed rotation patterns according to that met the following the~~ three criteria: ~~Firstly, the high image quality, of images is high. Secondly, the high rapeseed classification accuracy of rapeseed is high, and. Thirdly, the large extent of planted rapeseed area of rapeseed is large.~~ ~~R~~The rapeseed rotation in these areas was calculated based on the frequency of each rapeseed pixel (Fig. 11).



Figure 11. Spatial distribution of three types of rotation schedules in different areas from 2017 to 2019.

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Because only 3 years (2017–2019) of rapeseed maps were available, please note that the longest observable rapeseed rotation break that can be observed is was 2 years because there are only three years (2017–2019) of rapeseed maps available. Thus, to

more accurately ~~express~~ discern the ~~pattern of~~ rapeseed rotation break, we thus classified the rapeseed rotation breaks in this study into three types: ≥ 2 years, 1 year, and 0 years in this study. ~~M~~We found most countries, especially European ones, show were characterized by a rotation breaks greater than or equal that were ≥ 2 years (mostly the highest ratios of green areas parts) (in Fig. 12), especially for European countries (Fig. 12 b). In Canada, 70% of fields were subjected to The rotation breaks of ≥ 2 years in Canada accounts for 70%, followed with the remainder (30%) following a 1-year break pattern (30%) (Fig. 12-a). As shown in the histogram in Fig. 12d, we identified confirmed that rotation breaks of 20 locations have been identified with ≥ 2 -year rotation breaks, which corresponds to 90% s. The percentage of planting areas with rotation break ≥ 2 years is higher than 90% (Fig. 12 d). Many previous studies have found that a ~~2~~two- or ~~3~~three-year rotation break will significantly reduces the number of fungal spores, especially those of *Rhizoctonia solani* and *blacklegs* *Leptosphaeria maculans*, thus suggesting that a rotation system is an important step component of disease in control in rapeseed ~~ling~~ diseases (Gill, 2018; Harker et al., 2015; Ren et al., 2015; Zhou et al., 2015). ~~R~~Moreover, rapeseed rotation will also benefit improves yield, ~~insects~~, moisture, and fertility, and reduces weeds and pest insects (Bernard et al., 2012; Harker et al., 2015; Pardo et al., 2015; Peng et al., 2015; Ren et al., 2015). Thus, ~~m~~Additional efforts to ~~ore~~ efforts should be input to produce longer time-series rapeseed maps and ~~obtain~~ acquire detailed rotation information are thus needed in the future.

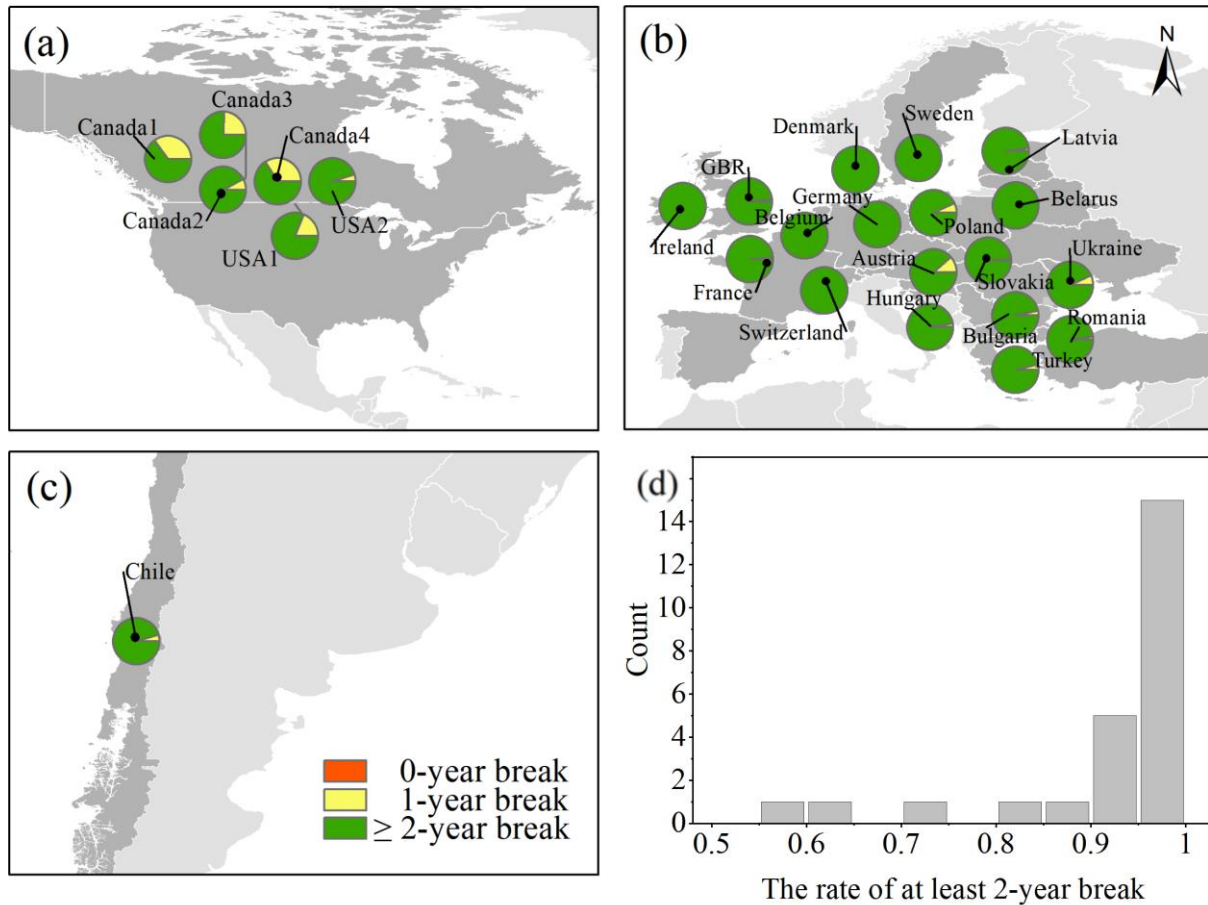


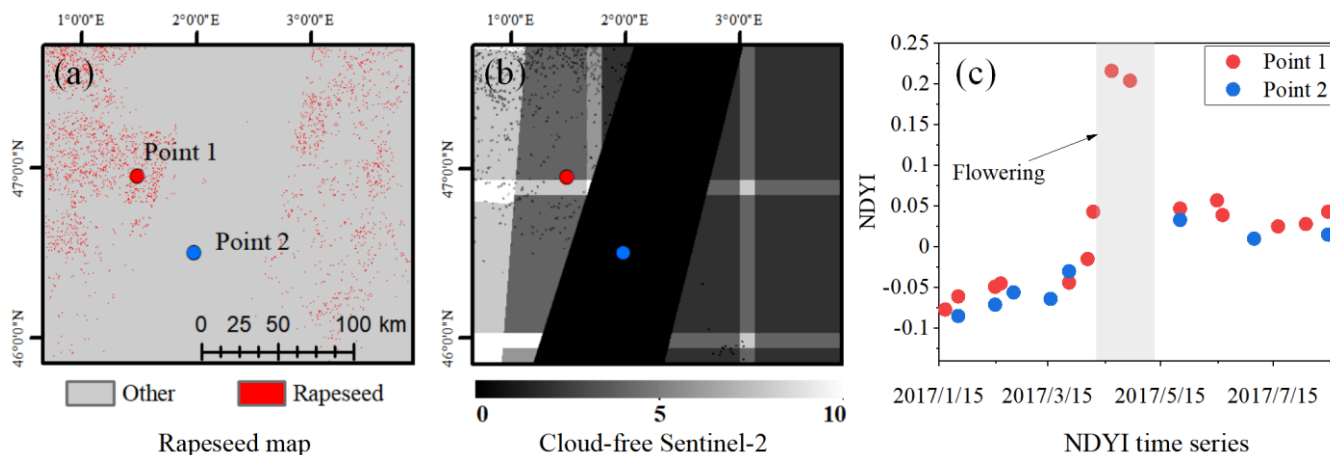
Figure 12. Rapeseed crop rotation. (a–c) The proportions of the rapeseed total area planting areas subjected to three rapeseed rotation breaks of 0, 1, or ≥ 2 years. (d) The numbers of areas in a–c subjected to breaks of with at least ≥ 2 -year breaks in Fig. 12 a–c.

4.2 Uncertainty analysis

The generation of annual high-resolution maps for a specific crop over a large region is a major challenge (Gong et al., 2020; Liu et al., 2018b, 2020a). Pixel- and phenological-based algorithms, multisource remote sensing data, and the GEE are useful for mapping rapeseed at high resolution and over large areas. In addition to these advantages, our proposed algorithm does not need a large number of training sample data and reduces disturbance from agronomic differences by combining images from multiple dates. Nevertheless, the uncertainty still exists from several the following aspects. The first of these factors is the Cropland layer. We used the GFSAD30 datasets to identify croplands; however, the GFSAD30 has its limitations, such as classification errors (Phalke et al., 2020). A second contributory aspect is the number of satellite images available. Although our annual rapeseed maps are

480 consistent with FAO statistics and show higher accuracy compared with existing products, ~~the maps they~~ are limited by the ~~good~~-quality ~~of the~~ observations during ~~the~~ critical growth stages. For example, Fig. 13a shows ~~that there is~~ an error in ~~an~~the area of France in 2017 ~~that, which could~~ be attributed to the lack of clear S2 images during the rapeseed flowering period (Fig. 13b). ~~Because t~~The rapeseed flowering period is generally characterized by high NDVI ~~and high~~ -red band, and green band reflectance, ~~thus~~ rapeseed pixels are likely to be misclassified if ~~the~~ images ~~are missing~~ during the flowering stage ~~were~~ ~~missing~~ (Fig. 13c). ~~A third issue concerns the t~~3) Thresholds for different indicators, ~~which~~. ~~The threshold is a~~ the key factor for mapping crops (Ashourloo et al., 2019; Dong et al., 2016; Liu et al., 2020a; Wang et al., 2020a; Zhang et al., 2015). Although ~~the~~ reference thresholds for ~~the~~ three regions ~~continents in this study~~ are ~~given~~ ~~provided in this study~~, ~~they~~ ~~it~~ should be ~~applied with~~ caution ~~us when applying them~~ to other regions. ~~Finally, 4) Th~~the complexity of the ground environment ~~can~~ ~~contribute to uncertainty~~. For example, landscape types might impact the accuracy of rapeseed maps (Wang et al., 2020a).

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Figure 13. ~~Descriptions~~ Example showing the effect of low-quality observations on ~~for the~~ classification ~~limitation~~ accuracy. (a) Rapeseed map ~~of an area of France in 2017 that contains~~ with an error ~~in France in 2017~~ (Longitude: -2.059824°; Latitude: 46.734987°). (b) Availability of time-series Sentinel-2 images during rapeseed flowering phases. (c) Comparison of the time series of different sites ~~indicating~~ ~~showing~~ how the peak NDVI ~~has been~~ ~~is~~ missed.

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5 Data availability

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The rapeseed maps ~~produced with 10 m resolution~~ ~~produced in this study~~ ~~are~~ ~~is~~ accessible at Mendeley Data (<http://dx.doi.org/10.17632/ydf3m7pd4j.3>) (Han et al., 2021). ~~The rapeseed maps with 10 m resolution are provided in this study~~. The dataset includes a set of GeoTIFF images in the ESPG: 4326 spatial reference system. The values 1 and 0 represent rapeseed and non-rapeseed, respectively. We encourage users to independently verify the rapeseed maps. ~~Also~~ ~~In addition~~, Sentinel 1/2 images, CDL, ACI, and SRTM are available on GEE (<https://developers.google.com/earth-engine/datasets/>). For more detailed information about the data collected in this work, ~~please~~ see Table 1.

6 Conclusions

505 Large-scale, ~~and~~ high-resolution rapeseed maps are the basis for crop growth monitoring and ~~production yield~~ prediction. We ~~designed developed~~ a new method for mapping rapeseed based on ~~the~~ spectral and polarization features and multi-source data. ~~We used the~~ The new algorithm ~~has to produced~~ three annual rapeseed maps (2017–2019) at 10_m spatial resolution in 33 countries. ~~According to the results of t~~ Three different verification methods, ~~indicated that~~ our rapeseed maps ~~have are~~ reasonably ~~accurateey~~ accurate. Compared with existing products at the pixel level in Canada, USA, GBR, and France, PA, UA, and F1 ~~were are~~ 0.70–0.80, 0.93–0.97, and 0.81–0.86, respectively. ~~Also~~ In addition, ~~the~~ F1 ranged from 0.84 to 0.91~~2~~ based on ~~the~~ independent validation samples. Our approach reduces ~~misclassifications disturbances from due to~~ different planting times and ~~low bad~~ low-quality observations to some degree. The 10_m rapeseed maps ~~do~~ provide more spatial details of rapeseed. Finally, we ~~found observed~~ that ~~the~~ rapeseed crop rotation ~~interval~~ interval is ~~at least 2 years or longer~~ at least 2 years ~~or longer~~ in almost all countries in this study. ~~Our proposed~~ The rapeseed mapping method ~~proposed in this work could can~~ be applied to other regions. The derived rapeseed data product is useful for many purposes, including crop growth monitoring and production ~~and~~ rotation system planning.

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Author contributions

ZZ and JH designed the research. JH and LY collected datasets. JH implemented the research and wrote the paper. ZZ, JC, LZ, JZ, and ZL revised the paper.

520 Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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The RapeseedMap10 database: annual maps of rapeseed at a spatial resolution of 10 m based on multi-source data

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Abstract. As a major oilseed crop, large-scale and high-resolution maps of rapeseed (*Brassica napus* L.) are critical for predicting annual production and ensuring global energy security. However, such free maps are still unavailable in large areas. We designed a new pixel- and phenology-based algorithm and produced a new data product for rapeseed planting area (2017-2019) over 33 countries at 10m spatial resolution based on multiple data. The product showed good consistency with the official statistics (Food and Agricultural Organization of the United Nations, FAO) at the national level. Rapeseed maps achieved at least 0.81 F1 scores of spatial consistency when comparing with the Cropland Data Layer (CDL) in [United States of America \(USA\)](#), Annual Crop Inventory (ACI) in Canada, Crop Map of England (CROME), and Land Cover Map of France (LCMF). Moreover, their F1 scores ranged from 0.84 to 0.92 based on the independent validation samples, implying a good consistency with ground truth. The rapeseed crop rotation is at least 2 years in almost all countries in this study. Our derived maps with reasonable accuracy suggest the robustness of [pixel- and phenology-based](#) algorithm in identifying rapeseed over large regions with various climate and landscapes. ~~The proposed algorithm and its derived products may benefit scientists, decision makers, and local farmers to ensure food and energy security.~~ The derived rapeseed planting areas freely downloaded [will benefit scientists and local farmers](#) can be applied to predict rapeseed production and optimize planting structure. The product is available publicly at <http://dx.doi.org/10.17632/ydf3m7pd4j.3> (Han et al., 2021).

1 Introduction

Currently, fossil fuels are the main source of energy (Fang et al., 2016; Shafiee and Topal, 2009). However, overexploiting fossil fuels will increase risks for human survival such as greenhouse gas emission, and environmental pollution (Fang et al., 2016; Höök and Tang, 2013). Biofuel energy seems to be a promising alternative energy source ~~and has become a key concern~~ (Hassan and Kalam, 2013). Rapeseed is an important source of biofuels, edible oil, animal feed, and protein powder plants (Firrisa et al., 2014; Malça and Freire, 2009; Sulik and Long, 2016). ~~As a widely grown winter or spring crop, global rapeseed production has been increasing rapidly in the past few decades.~~ Data products about the planting densities, growth conditions, and productivity of rapeseed are dependent on precise and accurate planting area maps (Zhang et al., 2019). However, such maps are yet unavailable.

30 Global agricultural statistics on rapeseed in many regions come from field surveys, field sampling, and producer reports (Arata et al., 2020; Fuglie, 2010). Ground-based methods are time-consuming and labor-intensive and fail in describing the detailed spatial information of rapeseed fields (Wang et al., 2020a). Remote sensing technology plays an important role in agricultural monitoring, providing accurate and objective spatial-temporal crop information (Dong et al., 2016; Salmon et al., 2015). ~~In previous literature, MODIS and Landsat were used to identify different crop types over large scales (Dong et al., 2016; Gong et al., 2013; Salmon et al., 2015; Xiao et al., 2006; Zhang et al., 2020). With a higher spatial resolution than MODIS and Landsat data, Sentinel 1/2 (S1/2) show a greater power for high resolution crop mapping (Malenovsky et al., 2012; Singha et al., 2019).~~

At present, many land cover products from remote sensing have publicly provided a cropland layer, e.g. the Fine Resolution Observation and Monitoring of Global Land Cover (~~FROM-GLC~~) project (Gong et al., 2013), ~~the GLOBCOVER land cover maps (Arino et al., 2008)~~, the Global Land Cover 2000 (GLC2000) map (Bartholomé and Belward, 2005), ChinaCropPhen1km (Luo et al., 2020), and Global Food Security-support data at 30 m (GFSAD30) (Phalke et al., 2020; Xiong et al., 2017). However, cropland identified by these products either failed in distinguishing different crop types or had a coarse spatiotemporal resolution (Teluguntla et al., 2018) or excluded rapeseed information. Till nowadays, there are few rapeseed maps on a large scale, especially at 10m-resolution. The 30m-resolution Cropland Data Layer (Boryan et al., 2011) for the ~~USA~~ America and Annual Crop Inventory in Canada (Fisette et al., 2013) did classify various crops using the decision tree classification method based on a large number of training samples. However, the method is hard to apply to other developing regions due to a lack of ground training samples (Xiong et al., 2017). A new method is highly required to map large-scale annual maps with high spatial resolution, which will be widely applicable for the regions with scarce ground training samples. Five remote sensing-based methods for rapeseed mapping have been developed in recent decades: a) machine learning ~~methods: supervised classifiers such as Random Forest (RF) (Griffiths et al., 2019; Preidl et al., 2020), and unsupervised classifiers such as Iterative Self-Organizing Data Analysis Technique (;~~ She et al., 2015; Tao et al., 2020); b) a classifier based on time series data: ~~e.g. an automatic rapeseed classification method using sentinel 2 images~~ (Ashourloo et al., 2019); c) a threshold segmentation based on phenology (Tian et al., 2019); d) Multi-Range Spectral Feature Fitting (MRSFF) (Pan et al., 2013); and e) HSV transformation and Spectral Features (Wang et al., 2018). However, most methods only produce rapeseed maps for a small area based on very limited imageries taken on the rapeseed peaking flowering dates (Ashourloo et al., 2019; She et al., 2015). The peak flowering dates vary by area and cultivar because of differences in natural conditions and cultivation habits, especially over a large region (d'Andrimont et al., 2020; Ashourloo et al., 2019; McNairn et al., 2018). Thus, it is still a big challenge to automatically map rapeseed areas with a finer resolution over a large region by applying the above methods. ~~Cloud computing technology is developing rapidly as its powerful computing capability (Gorelick et al., 2017) and has made high resolution rapeseed maps possible over large areas. Google Earth Engine (GEE) can provide unprecedented opportunities to process large amounts of remote sensing data with the most advanced cloud computing and storage capabilities (Gorelick et al., 2017).~~

Considering the unique phenological characteristics of crops, many studies have indicated the potential ways based on phenology for crop identifying in large areas (Ashourloo et al., 2019; Dong et al., 2016; Liu et al., 2018b, 2020a; Zhang et al., 2020). The algorithm based on phenology develops classification rules through analyzing the unique characteristics of the crop, which have been successfully applied to mapping rice (Dong et al., 2016), soybean (Zhong et al., 2014), corn (Zhong et al., 2016), and sugarcane (Wang et al., 2020a), but rarely applied to rapeseed. Rapeseed has unique reflectance and scattering characteristics (Ashourloo et al., 2019; McNairn et al., 2018; Sulik and Long, 2015, 2016), and undergoes three canopy morphologies (Ashourloo et al., 2019; Rondanini et al., 2014), including leaves, yellow petals, and pods/branches. Each canopy shape strongly influences how solar radiation intercepts (Sulik and Long, 2016). ~~Compared with other crops, rapeseed is more easily to be identified, of which the yellow flowers significantly increase the reflectance of red and green bands (Pan et al., 2013; Sulik and Long, 2015). Additionally, when rapeseed grows, the backscatter signal increases because of the rough canopy structure formed by the intertwined pods (McNairn et al., 2018; Mercier et al., 2020; Tian et al., 2019; Veloso et al., 2017).~~ Thus ~~we are sure~~ the specific features of reflectance values and scattering coefficients of rapeseed from S-1/2 data will provide information for automatic mapping of rapeseed over larger areas and with a finer resolution.

Also, crop rotation is beneficial to the management of pests and diseases in crop production (Harker et al., 2015; Liu et al., 2018a). Previous studies have shown that crop rotation is one of the main causes of yield change in rapeseed production (Harker et al., 2015; Ren et al., 2015). The physical and chemical properties of the soil will change during crop rotation, and these changes will affect rapeseed growth (Ren et al., 2015). Most of the current studies are limited to field observations (Peng et al., 2015). The spatial distribution information of rapeseed rotation in different regions is still not clear due to the lack of high-resolution rapeseed maps. It is necessary to explore the rapeseed rotation for cultivation and management.

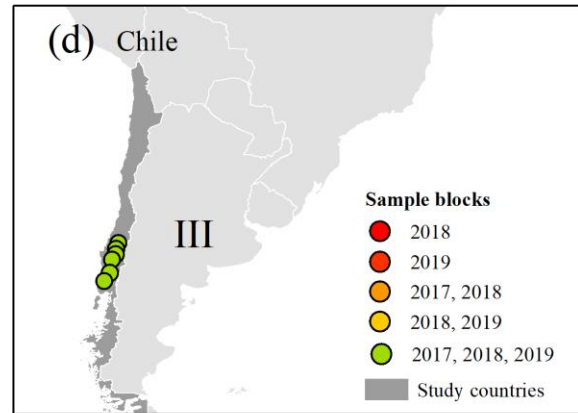
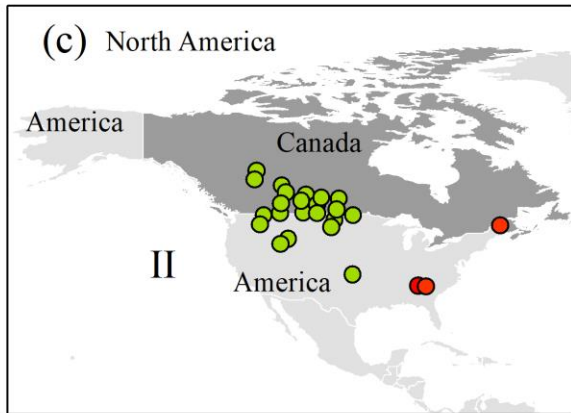
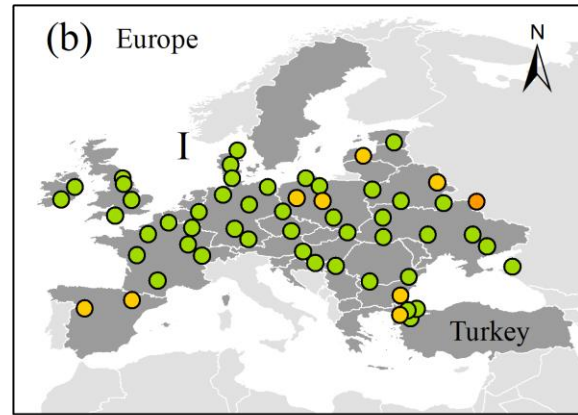
Thus, we integrated multi-source data to 1) develop a new method for identifying rapeseed; 2) apply the new method to generate rapeseed maps with a spatial resolution of 10 m from 2017 to 2019 across the main planting areas of 33 countries; 3) analyze the geographic characteristics of rapeseed planting and crop rotation. ~~The proposed algorithm and its derived products may benefit scientists, decision makers, and local farmers to ensure food and energy security.~~

2 Materials

2.1 Study area

We identified rapeseed planting areas for 33 countries in three continents (North America, South America, and Europe) as they are the main rapeseed producers in the world (Fig. 1). The planting areas and production of rapeseed are large in Canada and the European Union (EU) (Carré and Pouzet, 2014; van Duren et al., 2015; Rondanini et al., 2012). ~~According to the report by Statistics Canada, from 2000 to 2019, the sown area of rapeseed in Canada increased by 1.7 times, and the production increased by 2.7 times (<https://www.canolacouncil.org/>). Rapeseed is grown in most European countries. The EU's rapeseed production of 2017 was approximately 1.92 times that in 2000 (d'Andrimont et al., 2020).~~ Europe produces a large amount of biodiesel for the world every year. In 2008, 79% of the biodiesel feedstock crops in Europe were rapeseed (van Duren et al.,

95 2015). Also, Chile is the main rapeseed producer in South America and the country with a high yield of rapeseed in 2018
(38877 kg/ha). Rapeseed agriculture in these countries is important in food and energy security (Carré and Pouzet, 2014). The
climates in these three continents are different because of factors such as latitude and topography (Peel et al., 2007). Europe
includes three climatic types: subtropics, boreal, and temperate (Fig. S1b) (Peel et al., 2007). The climate in the rapeseed
growing areas in Canada and northern America is temperate and boreal (Fig. S1a). Chile has the main subtropics climate (Fig.
100 S1e). Rapeseed planting seasons are distinctive because of differences in natural conditions (such as climate) in different
countries (Singha et al., 2019; Wang et al., 2018), which brings great challenges to mapping rapeseed.



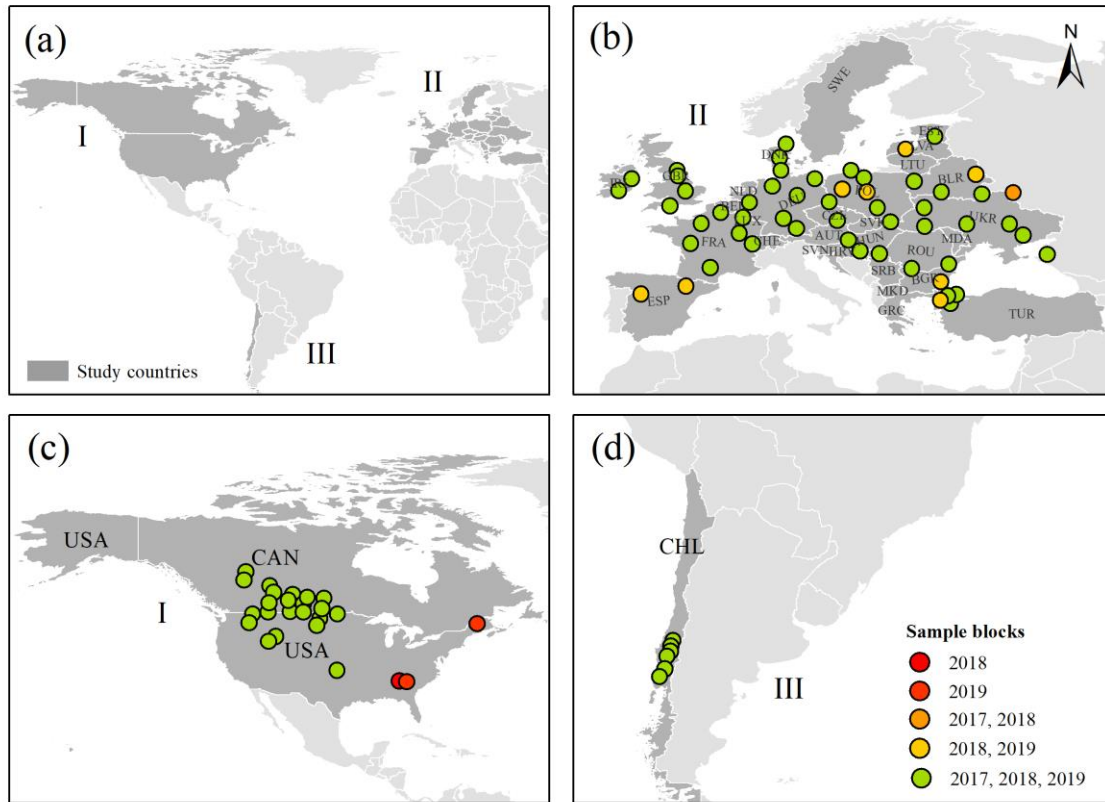


Figure 1. The locations of 33 countries and the sample blocks for phenological monitoring with a radius of 10 km (a-d). The 33 countries include Canada (CAN), United States of America (USA), Chile (CHL), Ireland (IRL), United Kingdom of Great Britain and Northern Ireland (GBR) England, France (FRA), Spain (ESP), Netherlands (NLD), Belgium (BEL), Luxembourg (LUX), Germany (DEU), Switzerland (CHE), Denmark (DNK), Sweden (SWE), Poland (POL), Czechia (CZE) Czech Republic, Austria (AUT), Slovenia (SVN), Croatia (HRV), Slovakia (SVK), Hungary (HUN), Estonia (EST), Latvia (LVA), Lithuania (LTU), Belarus (BLR), Ukraine (UKR), Republic of Moldova (MDA), Romania (ROU), Bulgaria (BGR), Serbia (SRB), North Macedonia (MKD), Greece (GRC), Turkey (TUR). The name and code of the country are prepared by the Statistics Division of the United Nations Secretariat. The three-digit alphabetical codes assigned by the International Organization for Standardization (ISO) can be found at <https://unstats.un.org/unsd/methodology/m49/>.

2.2 Data

2.2.1 Remote sensing data

We collected the Sentinel-2 (S2) and Sentinel-1 (S1) imagery (Table 1). The S1/2 satellites are launched by the European Space Agency (ESA) (Drusch et al., 2012; Torres et al., 2012). The highest spatial resolution of S2 images is 10 m. We used

red (b4), green (b3), and blue (b2) spectral bands with 10-m spatial resolution Top-Of-Atmosphere (TOA) reflectance observations. The S2 TOA product includes the Quality Assessment (QA) band, which was used to remove most of the bad-quality images (e.g. clouds information) in this study. However, it is difficult to remove all clouds due to the quality of the QA band (Wang et al., 2020a; Zhu et al., 2015). ~~The S1 includes four modes: Stripmap (SM), Interferometric Wide Swath (IW), Extra Wide Swath (EW), and Wave (WV) (Torres et al., 2012).~~ We used the ~~Interferometric Wide Swath IW~~ mode of S1, which provides dual-band cross-polarization (VV) and vertical transmit/horizontal receive (VH) with a 12 day or 6-day repeat cycle and 10m space resolution (Torres et al., 2012). The S-1/2 images were obtained on ~~Google Earth Engine (GEE) (Gorelick et al., 2017)GEE~~. Also, we used QA bands to remove most of the bad-quality images on GEE (Sample code can be found at https://code.earthengine.google.com/?scriptPath=Examples%3ADatasets%2FCOPERNICUS_S2). See Table 1 for more details.

2.2.2 Digital elevation model

We used a spatial resolution of one arc-second (approximately 30 m) elevation data from the Space Shuttle Radar Terrain Mission (Table 1) (Farr et al., 2007). Then we calculated the spatial distribution of slope on GEE (Sample code can be found at https://code.earthengine.google.com/?scriptPath=Examples%3ADatasets%2FUSGS_SRTMGL1_003) ~~(Fig. S1d-f)~~. Later, we extracted areas with a slope less than 10° to mask hilly terrain ~~where rapeseed is unlikely to be planted~~ (Jarasiunas, 2016).

2.2.3 Cropland and agricultural statistics data

In this study, cropland data from the GFSAD30 were used to identify major farming areas in different countries (Phalke et al., 2020; Xiong et al., 2017). The existing crop data products containing rapeseed information include four datasets: 1) the 30-m Annual Crop Inventory (ACI) in Canada (Fisette et al., 2013), 2) the 30-m Cropland Data Layer (CDL) in ~~America-USA~~ (Boryan et al., 2011) (CDL and ACI layers are downloaded from GEE). 3) the Crop Map of England (CROME) was generated in ~~GBR-England~~. 4) the 10-m Land Cover Map of France (LCMF) in France (Inglada et al., 2017). These four crop layer products are generated based on satellite images and a large number of training sample collections. In this study, rapeseed maps in ACI, CDL, CROME, and LCMF were used for accuracy verification at the pixel level. The FAO releases annual statistics on the area for major crops in different countries or regions every year. We selected the statistics from FAO for accuracy verification. Please see Table 1 for more details.

2.2.4 Crop calendars

We used two crop phenological data sets to assist in extracting rapeseed phenological parameters, crop calendars in different countries (<https://ipad.fas.usda.gov/ogamaps/cropcalendar.aspx>) and field records of the crop phenology in Germany. The crop calendars come from the United States Department of Agriculture (~~USDA~~) which only records the planting and harvest time of rapeseed in some countries ~~(Table S1)~~. The field records of the crop phenology in Germany are ~~in~~-situ observations from

crop phenological records shared by the Deutsche Wetterdienst (DWD) in Germany (Kaspar et al., 2015). The DWD provides field observations of crop phenological periods following the Biologische Bundesanstalt, Bundessortenamt, and Chemical (BBCH) scale throughout Germany (Table 1). DWD records the start date and the end date of rapeseed flowering (d'Andrimont et al., 2020; Kaspar et al., 2015). Note that both crop calendars and DWD do not contain information on the peak flowering dates of rapeseed. We used all stations that fully recorded the start and end of the flowering periods from 2017 to 2019 for extracting rapeseed phenological parameters. Finally, 281, 269, and 253 stations are available in 2017, 2018, and 2019, respectively. ~~(the spatial distribution of the DWD rapeseed stations can be found in Fig. S2.~~

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Table 1 Detailed information about the data collected in this work.

Data	Time	Resolution	Institution	Version	Data access	Date of recent access	Descriptions
Sentinel-1 SAR GRD	2017-2019	10m	European Space Agency (ESA)	-	https://developers.google.com/earth-engine/datasets/catalog/COPERNICUS_S1_GRD	2020/11/15	Extracting the backscatter coefficient characteristics of rapeseed
Sentinel-2 MSI	2017-2019	10m	ESA	Level-1C	https://developers.google.com/earth-engine/datasets/catalog/COPERNICUS_S2	2020/11/15	Calculating the spectral indices after removing the cloud
Global Food Security-Support Analysis Data at 30 m (GFSAD30)	2015	30m	United States Geological Survey (USGS), NASA., et al.	V001	https://search.earthdata.nasa.gov/search?q=GFSAD30	2020/11/5	Identifying crop growing areas
The Shuttle Radar Topography Mission (SRTM)	-	30m	NASA Jet Propulsion Laboratory (JPL)	V3	https://developers.google.com/earth-engine/datasets/catalog/USGS_SRTMGLO_003	2020/10/1	Calculating slope map
Cropland Data Layer (CDL)	2017, 2019	30m	United States Department of Agriculture (USDA)	-	https://developers.google.com/earth-engine/datasets/catalog/USDA_NASS_CD_L	2020/12/1	Accuracy verification of rapeseed map at pixel level
Annual Crop Inventory (ACI)	2017, 2018	30m	Agriculture and Agri-Food Canada (AAFC)	-	https://developers.google.com/earth-engine/datasets/catalog/AAFC_ACI	2020/12/1	Accuracy verification of rapeseed map at pixel level
Crop Map of England (CROME)	2018	hexagon cells	Rural Payments Agency (RPA)	V.09	https://data.gov.uk/dataset/fb19d34f-59e6-48e7-820a-fe5fda3019e5/crop-map-of-england-crome-2018	2021/1/15	Accuracy verification of rapeseed map at pixel level
Land Cover Map of France (LCMF)	2018	10m	CNES/DNO/OT/PE	V1-0	https://www.theia-land.fr/en/2018-land-cover-product/?cover-product%2F	2021/3/22	Accuracy verification of rapeseed map at pixel level
Phenological database of Germany	2017-2019	-	Deutsche Wetterdienst (DWD)	-	https://www.dwd.de/DE/leistungen/cdc/cli-mate-data-center.html?nn=575620&lsbid=646252	2020/10/1	Identifying the phenological characteristics of rapeseed
Agricultural statistics data	2017-2019	-	Food and Agriculture Organization (FAO)	-	http://www.fao.org/faostat/en/#data/QC	2020/12/1	Verifying the accuracy of rapeseed map at national scale
Crop Calendars	-	-	United States Department of Agriculture (USDA)	-	https://ipad.fas.usda.gov/ogamaps/cropcaleNDAR.aspx	2020/10/1	Auxiliary reference data for identifying the flowering period of rapeseed

2.3 Methods

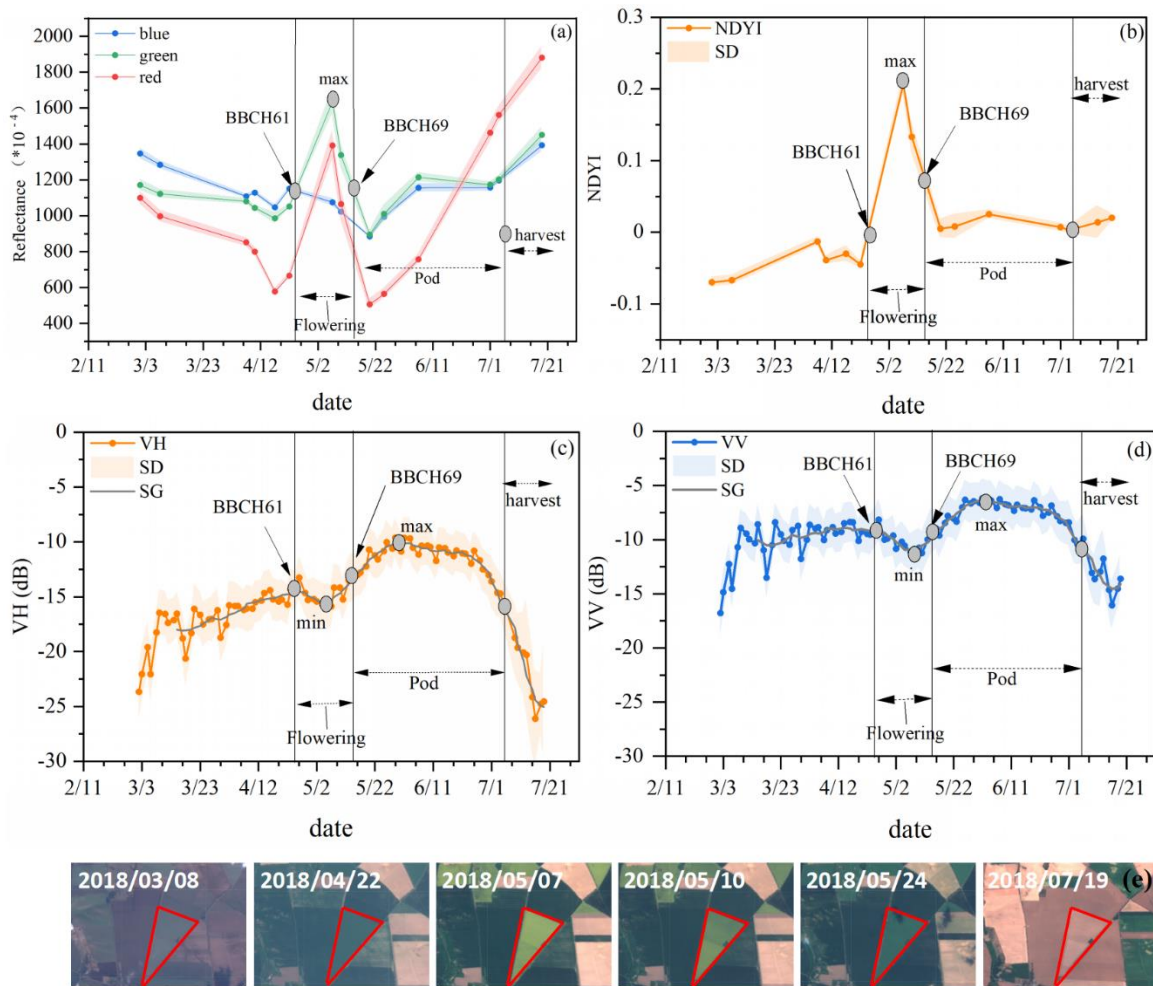
2.3.1 Optical and SAR characteristics during the growing period of rapeseed

We selected available rapeseed parcels and in-situ observations of DWD from different climate regions and different years to
185 analyze the optical (reflectance and vegetation index) and SAR (VV, VH) characteristics of rapeseed along time. For example,
Fig. 2 shows the time series of one rapeseed parcel around the DWD station (station id: 13126) in 2018. The rapeseed parcel
shows unique visual characteristics during the flowering period (Fig. S32e). The flower becomes yellow when rapeseed is
approaching peak flowering (d'Andrimont et al., 2020; Pan et al., 2013; Tao et al., 2020; Wang et al., 2018). Rapeseed is
yellow-green on the true color images of S2 and Google Earth during the flowering period (Fig. S4S1). The reflectance of the
190 green band and red band separately increased from 0.09 and 0.06 (2018/4/17, before flowering) to 0.16 and 0.14 (2018/5/7,
peak flowering), and decreased after flowering (Fig. 2a). The reflectance of the blue band is lower than red and green bands
during flowering. ~~The reflectance of the red band increased again and higher than the green band during the rapeseed harvest
period.~~ This is similar to previous research results (Ashourloo et al., 2019; Sulik and Long, 2015). The Normalized Difference
Yellow Index (NDYI, Eq.1) can capture the increasing yellowness in the time series (d'Andrimont et al., 2020; Sulik and Long,
195 2016). Also, the NDYI increased from -0.03 on April 17 to 0.21 on May 7 (Fig. 2b). NDYI reaches a peak during the flowering
time of rapeseed. This unique spectral feature of rapeseed in the flowering period is caused by the yellow petals.

$$NDYI = \frac{green-blue}{green+blue} \quad (1)$$

where *green* is the TOA reflectance of the green band (b3) of the S2 imagery, *blue* is the blue band (b2) reflectance.

S1 backscattering changes with the growth of rapeseed. We used the VV and VH time series smoothed by the Savitzky–Golay
200 (SG) filter (window size 3) (Chen et al., 2004) as input to identify the phenological parameters of rapeseed parcels. We ran the
SG filter algorithm on MATLAB 2020b. The results show that there are local minimums in both the VV (-11.20, May 8) and
VH (-15.60, May 5) time series during rapeseed flowering (Fig. 2c-d). Furthermore, VH reaches the maximum (-9.64, June 1)
during the pod period (~~Fig. 2d~~). Unlike other crops, rapeseed has two distinct green-up phases: the flowering period and the
pod period (Ashourloo et al., 2019; Bargiel, 2017; Mercier et al., 2020; Veloso et al., 2017). The petals of rapeseed decrease
205 the scattering of VV and VH, while the pods increase the scattering intensity of VH (d'Andrimont et al., 2020; Bargiel, 2017;
McNairn et al., 2009; Mercier et al., 2020). The NDYI and backscattering (VV, VH) time series of rapeseed in different climate
regions (Fig. S4S1) also show the same characteristics. Hence, we used the features in both Optical and SAR to identify the
rapeseed flowering and pod period in this study. Due to the difference in the revisit periods of S1/2 satellites, rapeseed peak
flowering dates are defined as the median dates extracted by optical and SAR indicators.



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Figure 2. The time-series profiles of four features of the rapeseed pixels around one DWD station (id = 13126, Longitude: 11.333268424°, Latitude: 52.200000463°) in Germany in 2018. (a), the mean reflectance values (red, green, and blue); (b), mean NDYI; (c) mean VH; and (d) mean VV; the filled color areas for standard deviation; BBCH for the in-situ observations of rapeseed phenology, with BBCH61 and BBCH69 for the start of flowering and the end of flowering, respectively. (e), The rapeseed parcel around the DWD station is shown by red boundaries (image source: Copernicus Sentinel-2 data 2018).

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2.3.2 Sample blocks collected for phenological monitoring

As a prerequisite to mapping rapeseed at a large scale, the phenology of rapeseed in different countries needs to be identified and delineated (Dong et al., 2016; Zhang et al., 2020). However, not enough observation records of rapeseed phenology are available on a large scale. Referring to the DWD method of observing phenology (Kaspar et al., 2015), we created sample blocks with a radius of 10 km over rapeseed producing areas of different countries and randomly sampled 10 rapeseed parcels for each block (Fig. S5). The rapeseed plots were identified by phenological characteristics obtained from the visual

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interpretation and reference data including high-resolution images available in S2 and Google Earth as well as Spectral reflectance (red band and green band) and spectral index (NDYI) and scattering coefficient profiles (VV and VH) from the S1/2 time series. It should be noted that the Google Earth images during rapeseed flowering were used to assist with the visual interpretation of rapeseed parcels. The rapeseed parcels without high-quality time-series imagery available were omitted. Finally, 75 sample blocks in 2017, 84 sample blocks in 2018, and 84 sample blocks in 2019 were uniformly and randomly collected (Fig. 1). ~~The sample blocks are shown in Fig. 1. We extracted the growth phenology information of rapeseed by calculating the average of the pixels of all rapeseed parcels in each block for different regions.~~

230 2.3.3 Flowering and pod phase detection in different countries

~~The phenology of rapeseed is different among regions.~~ To find out the flowering dates of rapeseed in different countries, we evaluated each phenological sample block from 2017 to 2019 (Fig. 3). First, we calculated the average values of all pixels in the 10 rapeseed parcels we selected before during the rapeseed growth period for each block in conjunction with the crop calendar. VV and VH time series for each sample rapeseed parcels were smoothed using the SG filter. Second, these S1/2 peak flowering dates and pod dates were derived for all sample blocks based on the method in Section 2.3.1. We found the peak flowering dates of rapeseed have an obvious latitude gradient, especially in Europe (Fig. S63j).

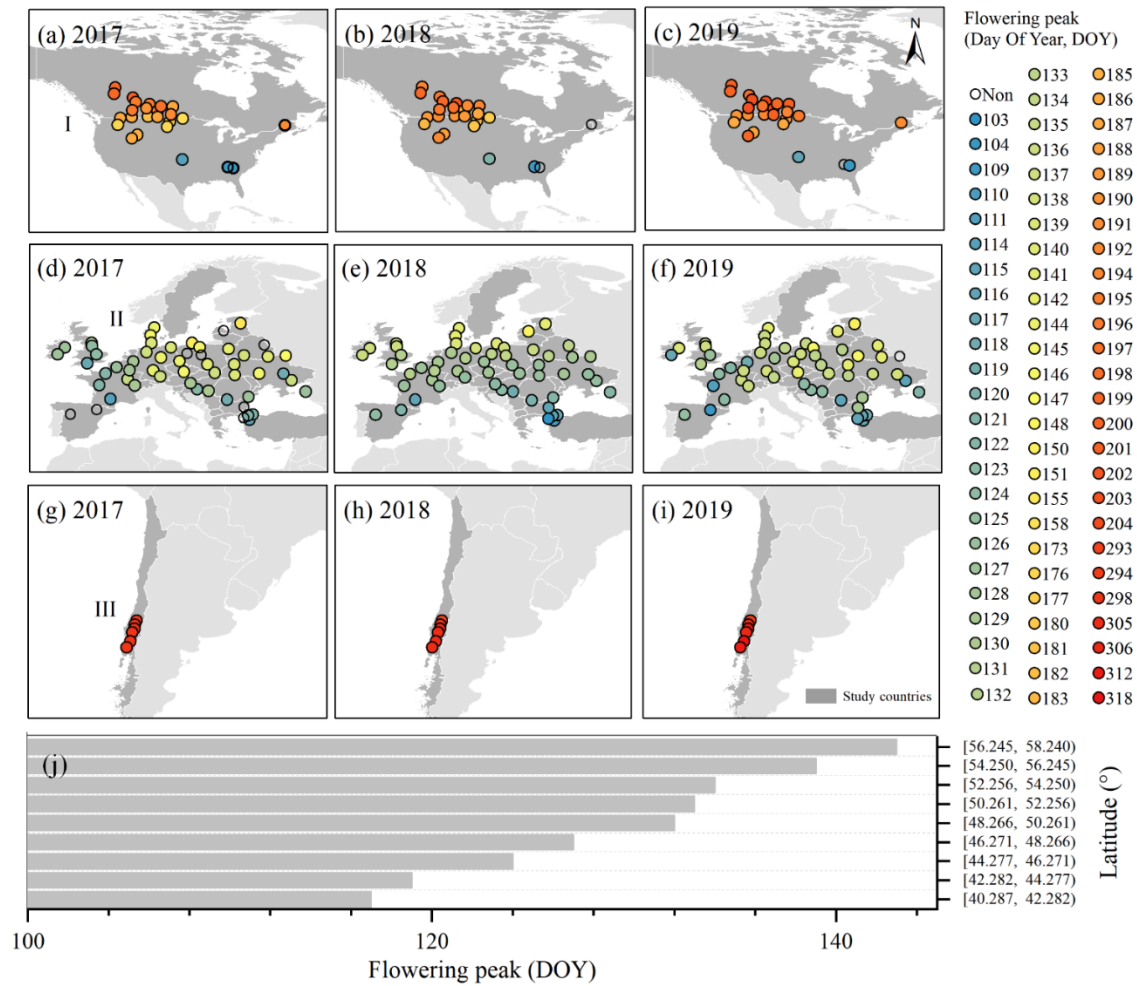
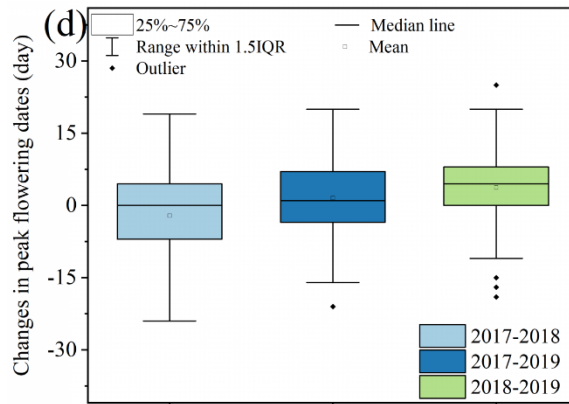
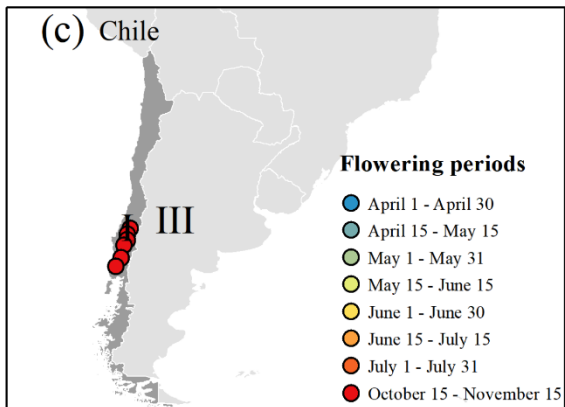
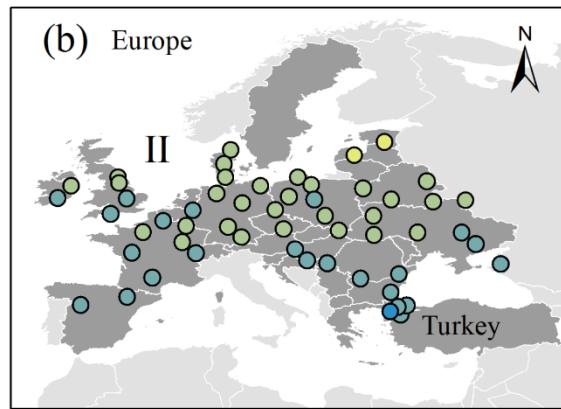
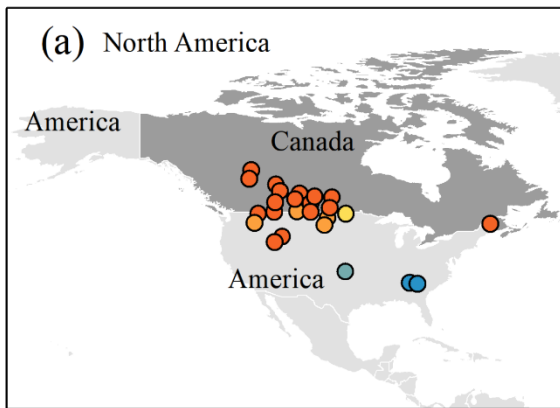


Figure 3. The spatial distribution of flowering dates (Julian day) was monitored by different sample blocks in 2017, 2018, and 2019 (a-i). The latitude gradient characteristics in Europe (j). The date was calculated by the mean of the flowering date of all sample blocks in different latitude intervals)

Also, we found the signal with the maximum of VH is within 45 days after the peak date of flowering (Fig. S72). Then we calculated the difference in the peak flowering date of each sample block in different years. The results showed that the flowering peak dates of most sample parcels were advanced or delayed by 10 days (Fig. 3d4d). Therefore, it is reasonable to use the same period for rapeseed identification in different years in the same area in this study. Previous studies and field observation records show that the flowering period of rapeseed is about 30 days (d'Andrimont et al., 2020; Chen et al., 2019; Kaspar et al., 2015; She et al., 2015). Therefore, we divided each month into two time periods (the 15th is the dividing line). Two consecutive half-months are defined as suitable periods for classifying flowering dates (Fig. 4a-c). Finally, we designated

the flowering period for each administrative unit ~~for each sample block~~ based on the ~~peak flowering dates~~ sample blocks (Fig-
250 3a-e).



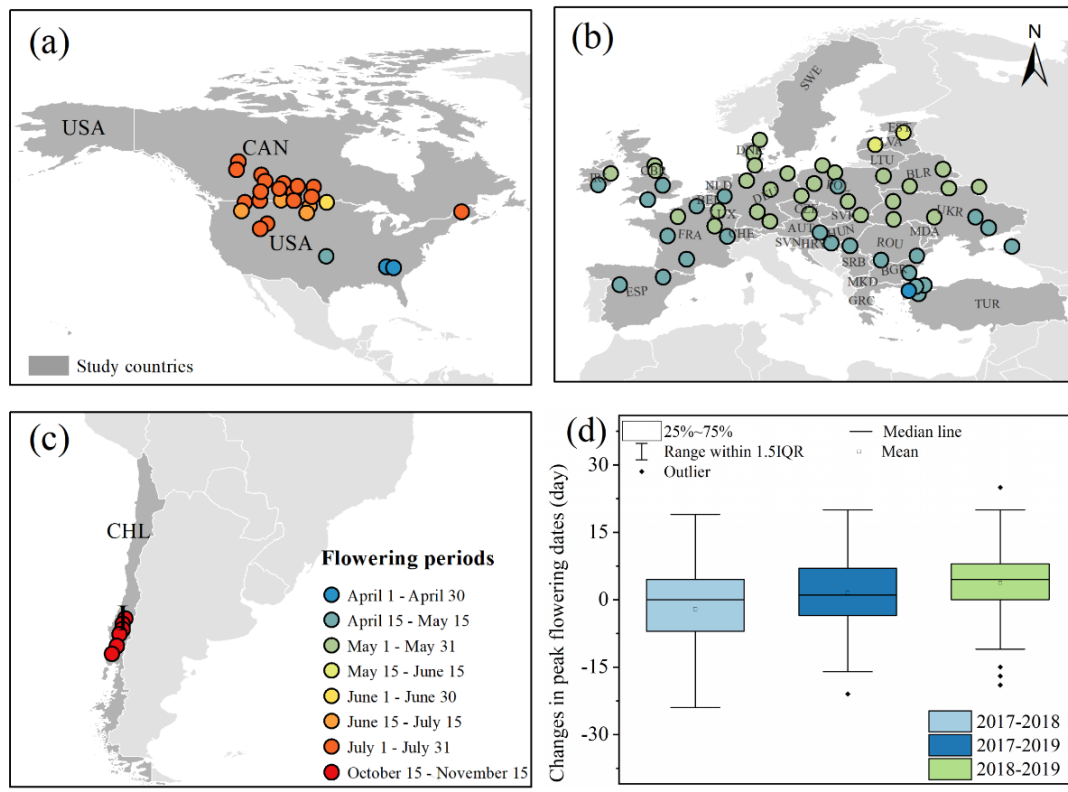


Figure 34. Flowering phenology of rapeseed. (a-c) The spatial distribution of rapeseed flowering periods for sample blocks. (d) The boxplot showing the changes in peak flowering dates of each sample block in three years. 还需要写国家缩写吗

255 2.3.4 Developing phenology- and pixel-based algorithm for mapping rapeseed

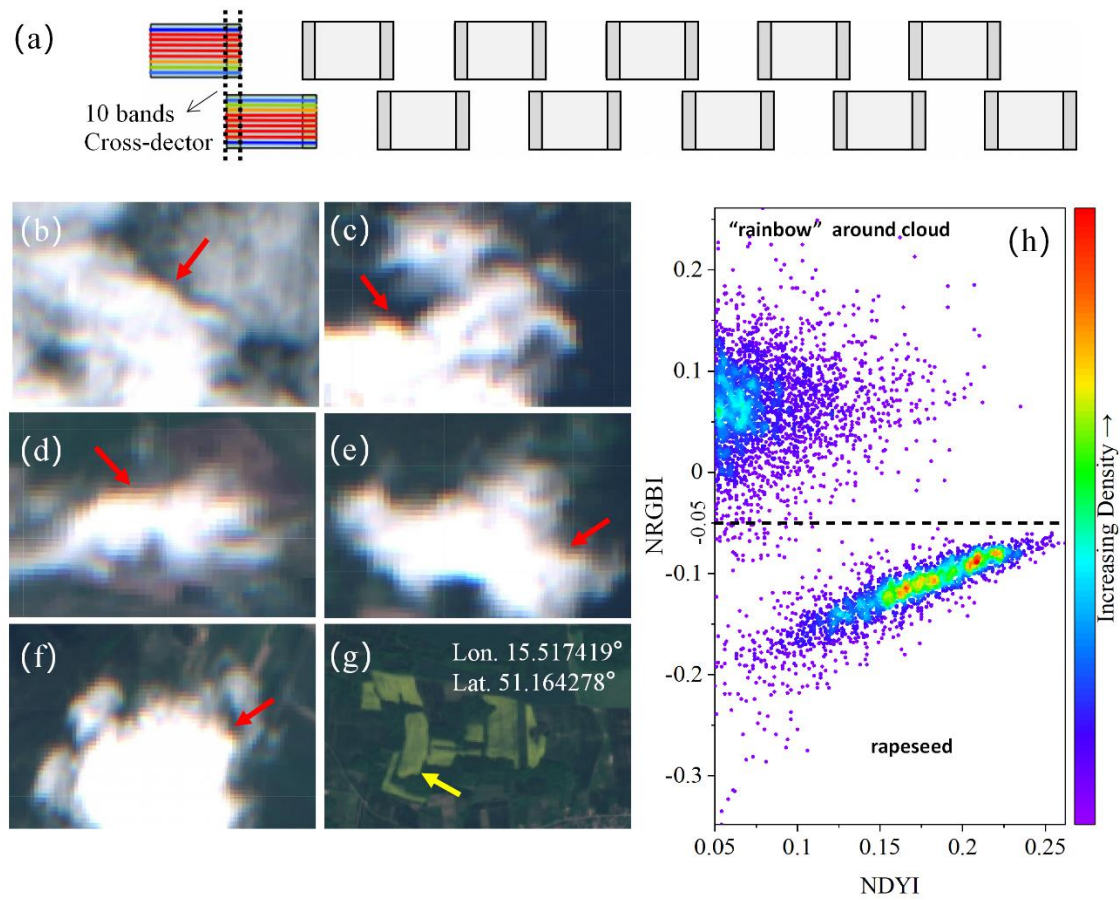
The analysis of temporal profile at rapeseed parcels in this study together with many previous studies indicated that the spectrum at flowering stage and the scattering signal at pod stage are the key features to identify rapeseed (Ashourloo et al., 2019; Bargiel, 2017; Han et al., 2020; Mercier et al., 2020; Sulik and Long, 2015; Veloso et al., 2017). ~~Previous studies have found the high reflectance values of the green band and red band at the flowering stage for rapeseed are the main spectral factors to distinguish from other crops (Ashourloo et al., 2019).~~ We developed one phenology- and pixel-based rapeseed mapping algorithm using four features, spectral bands (red and green), spectral indices (NDYI), polarization bands (VH), and terrain (slope). Four primary steps were conducted for mapping annual planting areas (Fig. 65).

Step 1: determining the threshold of the feature indicators. ~~Thresholds of indicators are the key parameters to determine the area accuracy.~~ We analyzed the histograms of the random samples selected from different countries as the previous studies (Zou et al., 2018) suggested. We found the similarities of green band, blue band, and NDYI (Fig. S39) for all samples during the flowering stage from different regions. Most (98%) of the rapeseed pixels showed red > 0.07, green > 0.11, and NDYI > 0.05.

270 However, we found some pixels with a relatively high NDYI, which would be misclassified into rapeseed because they are
polluted by the cloud with a “rainbow” appearance (Fig. 5). Such misclassifications caused by some bad-quality observations
from the S2 image can’t be removed due to the limited quality of the QA band and simple cloud score algorithm (Wang et al.,
2020c; Zhu et al., 2015). The “rainbow” of the cloud comes from the push-broom design of S2 (Fig. 4a5a) and spectral
misregistration (For more details, please refer to ESA, 2015a, and ESA, 2015b). Based on the principle of the relative
displacement of each spectral channel sensor in the S2 push-broom design (Frantz et al., 2018; Liu et al., 2020b; Zhao et al.,
2018), we developed a new spectral index (NRGBI) to reduce the influence of "rainbow" (Eq.2). The scatter plot of NDYI and
275 NRGBI of rapeseed parcel samples and "rainbow" samples around clouds (visual interpretation) showed that the NRGBI
(threshold is -0.05) can effectively distinguish rapeseed from the "rainbow" (Fig. 4h5h).

$$NRGBI = \frac{red-blue}{red+blue} - \frac{green-blue}{green+blue} \quad (2)$$

where *red*, *green*, and *blue* are the TOA reflectance values of the red band (b4), green band (b3), and blue band (b2) of the S2
imagery, respectively. The GEE code for NRGBI index calculation can be found at
280 <https://code.earthengine.google.com/a39fc699a276d018778d59c5b085d960>. Also, NRGBI can be calculated based on Eq.2 in
other GIS software (e.g. QGIS and ArcGIS) on the local computer.



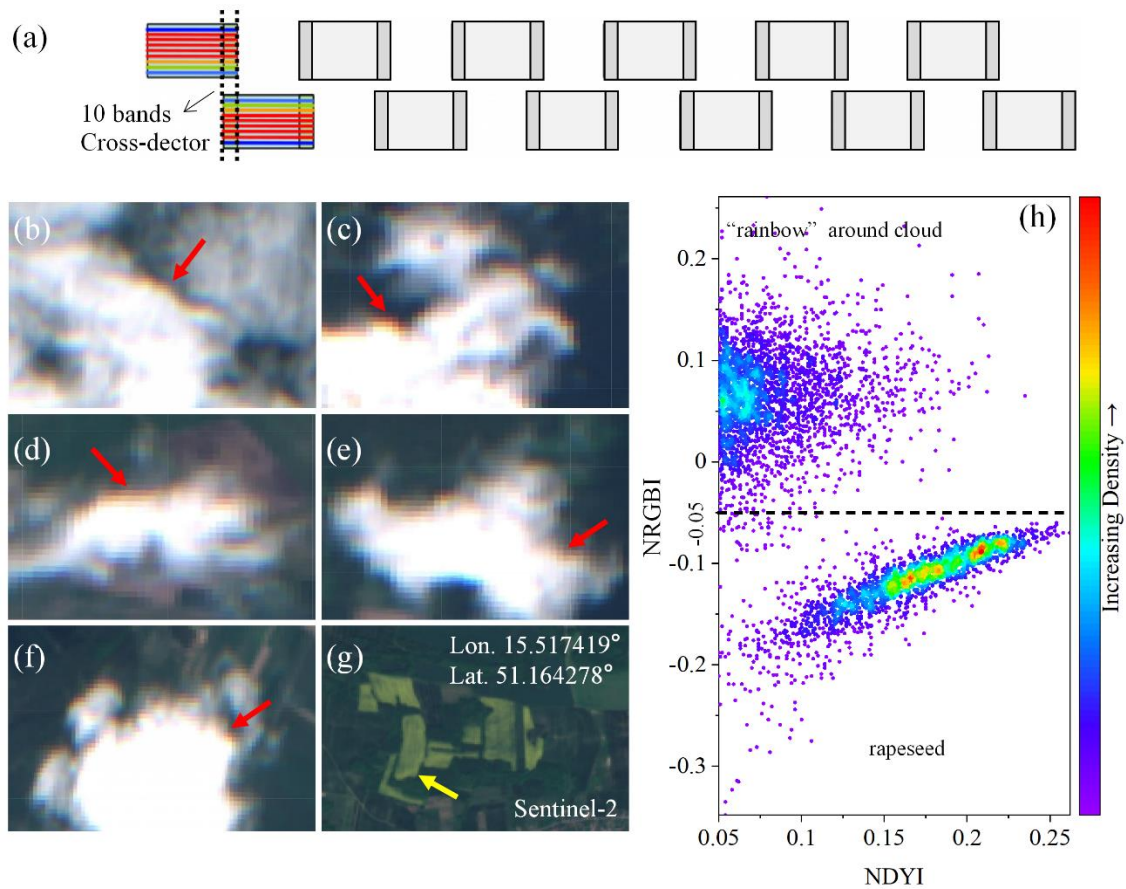
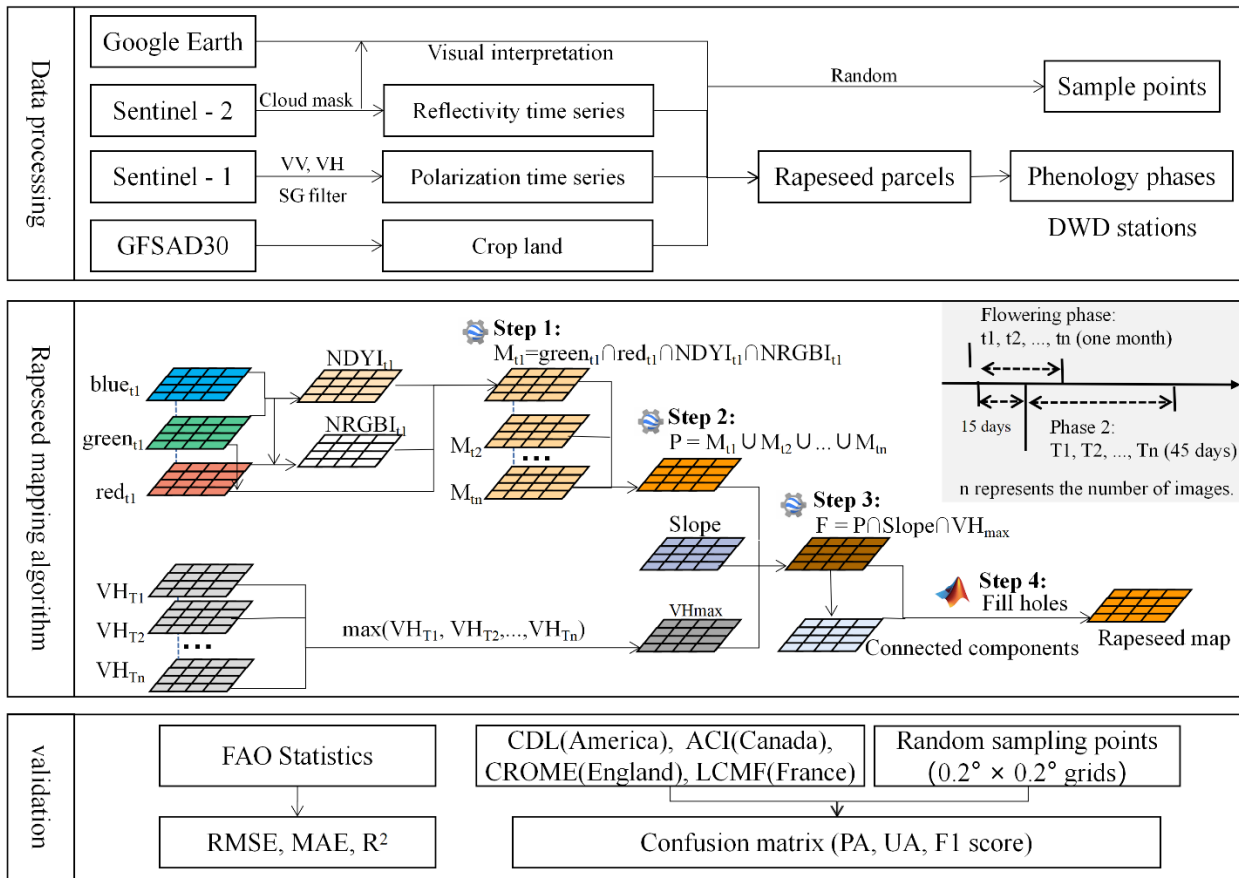


Figure 4.5. Causes, examples, and solutions for the “rainbow” cloud effect. (a) staggered detector configuration of S2 (ESA, 2015a); (b-f) examples of spectral misregistration effects and performance of cloud masking methods (each image was masked by quality assurance band (QA60)) for Sentinel-2 TOA image, with the red arrows indicating the cloud “rainbow” appearance at high altitude in the S2 image (Image source: Copernicus Sentinel-2 data); (g) Sentinel-2 TOA image of rapeseed at the flowering stage, with the yellow arrow for the rapeseed fields; (h) scatter plots of NDYI and NRGBI of rapeseed field samples and “rainbow” around clouds samples from the S2 images, with the color density for the number of pixels.

Step 2: identifying all rapeseed pixels from different images during the flowering period and aggregating them into annual rapeseed planting areas (Fig. 5.6). Because the peak flowering dates and the number of available images of rapeseed fields in a region are different (Fig. S10S4), rapeseed classifications based on a single image could fail in capturing rapeseed flowering dynamics (Ashourloo et al., 2019). To avoid the misclassification from bad-quality observations during the rapeseed flowering stage, we aggregated all the classified results from available S2 images during the flowering period. Hence, a larger number of images will result in better performance (Fig. S10S4).

Step 3: combining optical with SAR images to ensure the accuracy of the rapeseed maps. The high VH values during the pod stage are another distinct feature that can distinguish rapeseed from other crops (Mercier et al., 2020; Tian et al., 2019; Van Tricht et al., 2018; Veloso et al., 2017). Considering the variability of flowering in different fields and the duration of the pod stage (Section 2.3.2), we calculated the maximum VH between the second half of the flowering stage and the next 30 days after the flowering stage (~ 45 days) (See the grey part in Fig. 56). Within 45 days, at least three S1 satellite images are available in the study areas. Also, the areas with a slope $\geq 10^\circ$ ~~(where rapeseed is unlikely to be planted)~~ were removed (Jarasiunas, 2016). All pixels that meet the requirements are defined as rapeseed.

Step 4: removing the “salt and pepper” noise according to the connected components (objects) threshold (the size of the neighborhood in pixels) and filling the gaps inside the parcels (Hirayama et al., 2019). ~~In this study, w~~We used 8-connected rules, which means that the edges or corners of the pixels are connected. If two adjacent pixels are connected, they are part of the same object (<https://www.mathworks.com/help/images/ref/bwareaopen.html>). The bwareaopen function in MATLAB 2020b software was used to remove the objects which are less than the threshold. The thresholds of different indicators in different regions can be found in Table [S3S1](#).



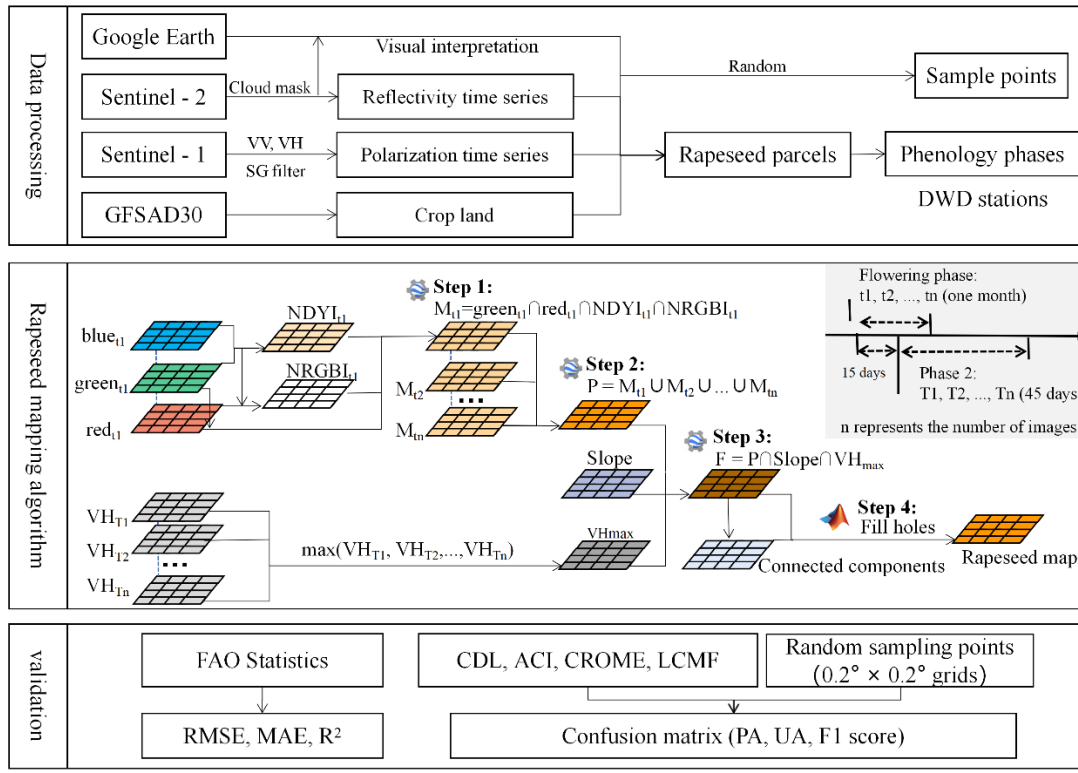


Figure 56. The workflow for mapping rapeseed areas using the proposed phenology- and pixel-based algorithm. Global Food Security-Support Analysis Data at 30m (GFSAD30); normalized difference yellowness index (NDYI); The new spectral index (NRGBI), Deutsche Wetterdienst (DWD), Food and Agriculture Organization of the United Nations (FAO), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), R-squared (R^2), Cropland Data Layer (CDL), Annual Crop Inventory (ACI), Crop Map of England (CROME), Land Cover Map of France (LCMF), user's accuracy (UA), producer's accuracy (PA), and F1 score (F1).

2.4 Accuracy assessment

First, we compared the rapeseed areas retrieved by the new method with FAO statistics. Our rapeseed data is a binary (0 or 1) map with a spatial resolution of 10 m. We then can calculate the total area of rapeseed maps in each country and compare them with the national rapeseed statistics. The RMSE (Eq.3), and the MAE (Eq.4), and the coefficient of determination (R^2 , Eq.5) are used to verify the accuracy of rapeseed mapping.

$$RMSE = \sqrt{\sum_{i=1}^n \frac{(y_i - f_i)^2}{n}} \quad (3)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - f_i| \quad (4)$$

$$R^2 = \frac{\sum_{i=1}^n (y_i - \bar{y})(f_i - \bar{f})^2}{\sum_{i=1}^n (y_i - \bar{y})^2 \sum_{i=1}^n (f_i - \bar{f})^2} \quad (5)$$

where n is the total number of countries. y_i is the mapped rapeseed planting areas, \bar{y}_i is the corresponding mean value, f_i is the records rapeseed planting areas from FAO, \bar{f}_i is the corresponding mean value.

330 Also, we compared the rapeseed maps with four open-access datasets that include rapeseed layers (ACI, CDL, CROME, and LCMF) in Canada, [AmericaUSA](#), [GBREngland](#), and France at the pixel level. We used them as the reference data for 2018, 2019 (Boryan et al., 2011; Fiset et al., 2013). To unify the spatial resolution of the rapeseed maps, CDL, ACI, and CROME were resampled to 10m resolution for comparison. UA (Eq.6), PA (Eq.7), and F1 (Eq.8) were calculated based on confusion matrices (Table S22) to measure the classification accuracy.

335 Thirdly, we also randomly selected verification samples based on the previous studies (Pekel et al., 2016; Wang et al., 2020b) to validate the rapeseed maps. A grid (0.2 latitudes by 0.2 longitudes) was generated within the rapeseed map in 2018 acquired by our method (Fig. S5). Two points (rapeseed and non-rapeseed) were generated randomly in each grid by visually interpreting images available from S2 and Google Earth, together with spectral reflectance (red and green bands), spectral index (NDYI), and scattering coefficient (VV and VH) profiles from the S-1/2 time series. The confusion matrices were similarly used to assess the accuracy according to Eqs 6~8.

$$UA = \frac{x_{ij}}{x_j} \quad (6)$$

340 $PA = \frac{x_{ij}}{x_i} \quad (7)$

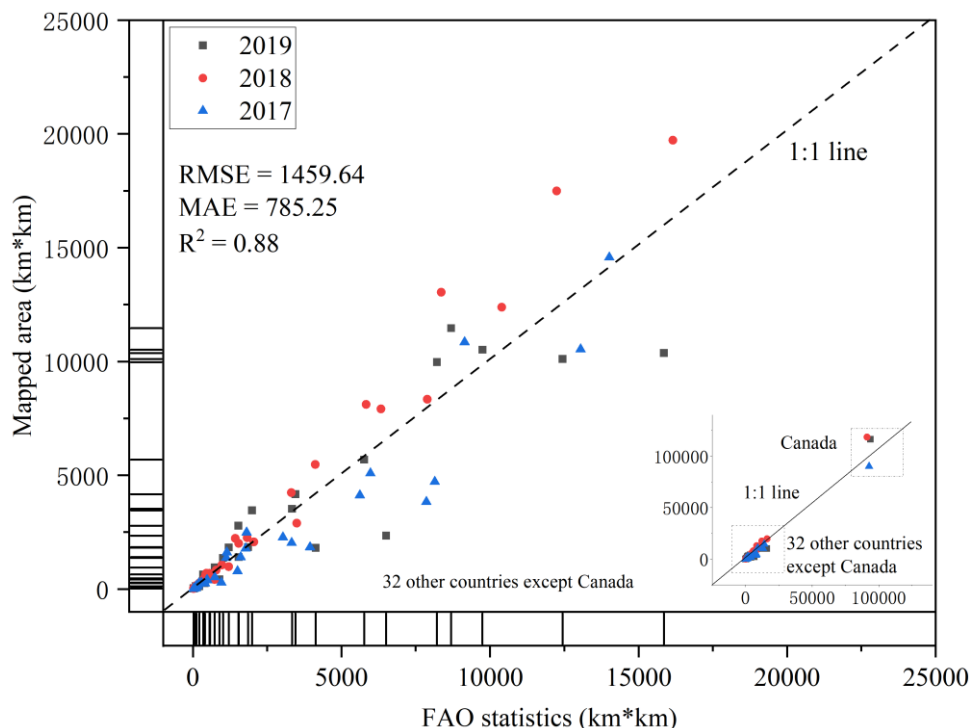
$$F1 = 2 \times \frac{UA \times PA}{UA + PA} \quad (8)$$

Where x_{ij} is the value of the i -th row and j -th column; x_i is the sum of the i -th row; x_j is the sum of the j -th column. Although the statistical data and existing products are not completely the same as the real areas and locations of rapeseed planted on the ground, these datasets do benefit to validating the accuracy of rapeseed maps at different scales (national and pixels).

345 3 Results

3.1 Accuracy assessment

350 We compared the derived rapeseed areas with those from the FAO statistics. The total planting areas of rapeseed are well consistent with the agricultural statistics at the national level, with RMSE of 1459.64 km², MAE of 785.25 km², and R² of 0.88 (Fig. 67). We found the derived areas in 2017 and 2019 are larger than those in 2018, especially for the countries with the relatively small rapeseed areas (e.g. many European countries indicated by the subgraph located at the bottom right of Fig. 6). The more availability of S2 images together with better quality of data in 2018 could contribute to the larger rapeseed areas derived by the new method (Liu et al., 2020a).

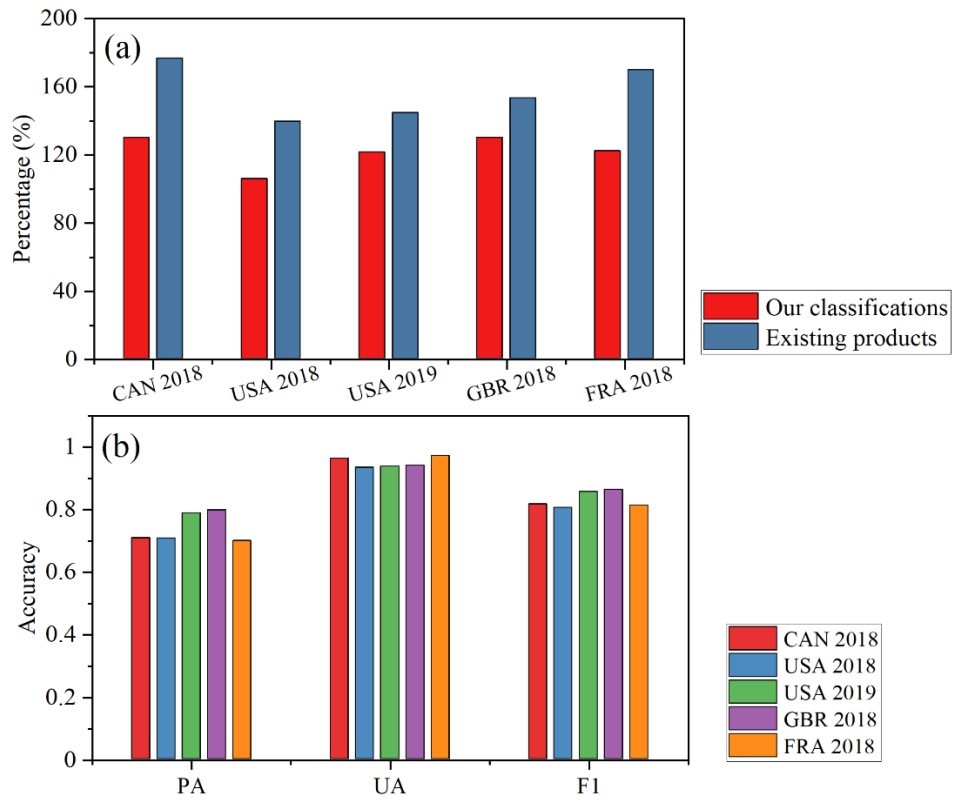


355 Figure 67. Comparison of rapeseed areas with the FAO statistics at the national level. The names of all countries can be found in Section 2.1.

The comparison of our rapeseed maps with those of [America-USA](#) CDL in 2018, 2019, [Canada ACI](#), [England-GBR](#) CROME, France LCMF in 2018 was consistent at pixel level indicated by a higher accuracy according to the confusion matrix values (Table [S4S3](#)). Fig. [7a-8a](#) shows that the rapeseed areas calculated from our maps are consistently more comparable to FAO statistics than those from existing products. The UA, PA, and F1 varied by country, with PA of 0.70–0.80, UA of 0.93–0.97, and F1 of 0.81–0.86 (Fig. [7b8b](#)). The rapeseed areas obtained by us accounted for around 71% of 2018 CDL, 71% of 2018 ACI, and 80% of 2018 CROME, and 70% of 2018 LCMF, and 79% of 2019 CDL. Furthermore, our results showed consistent distributions between our rapeseed maps and the existing products at the pixel level (Fig. S7-S8). The difference in accuracy might be caused by the number of high-quality images available in different regions (Dong et al., 2016). Despite the various ground conditions, methods, images, and spatial resolutions among the products, the comparison results further verify the accuracy of our rapeseed map (Gong et al., 2020; Singha et al., 2019).

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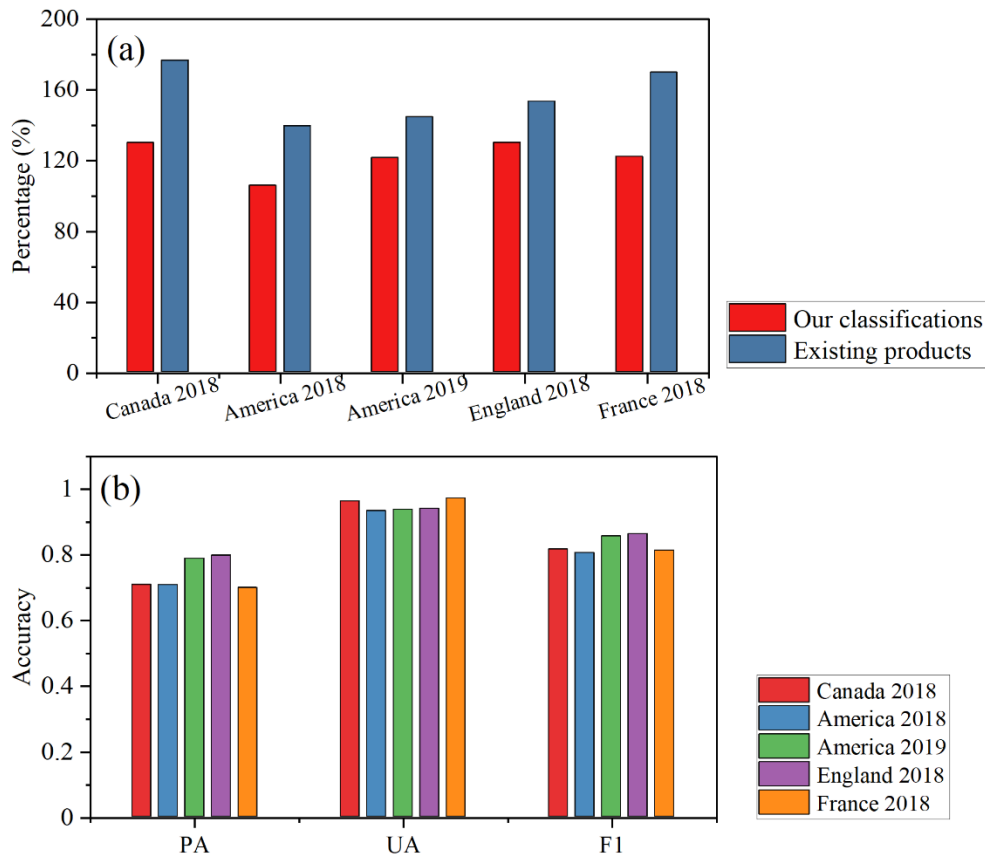


Figure 78. Validation results of the classifications. (a) The percentage of the rapeseed area of the existing products and classification results in the FAO statistics. (b) The user's accuracy (UA), producer's accuracy (PA), and F1 score (F1) of classifications in four countries (Canada, [AmericaUSA](#), [EnglandGBR](#), and France). The existing products were used as reference data. 还需要写国家缩写吗

The confusion matrix values (Table [S5S4](#)) based on random sampling points show that the accuracy of the rapeseed maps varies in different regions. We found [zone IIEurope](#) shows the highest accuracy (F1, 0.91), followed by [zone IIIChile](#) (F1, 0.9), and [zone INorth America](#) (F1, 0.84). Such disparity in accuracy might be ascribed to the different availability of high-quality images in the studied areas. The results showed that the rapeseed maps derived by our method had a satisfying accuracy.

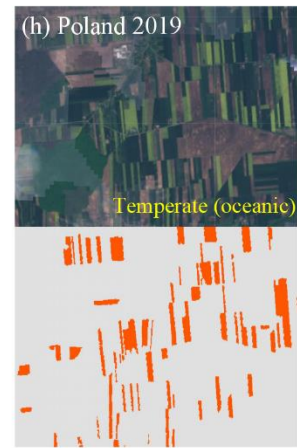
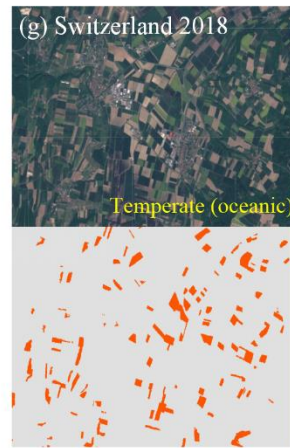
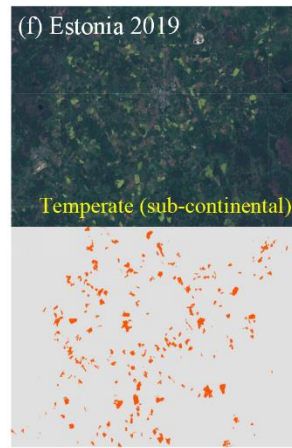
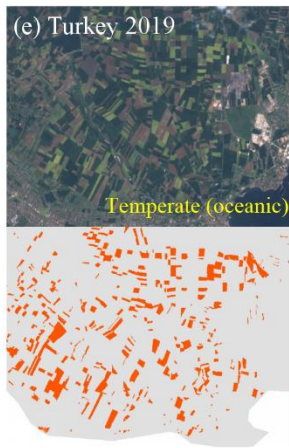
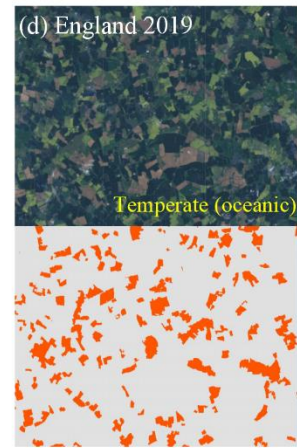
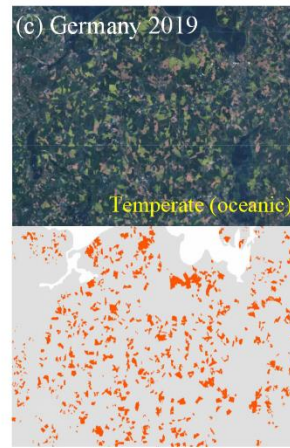
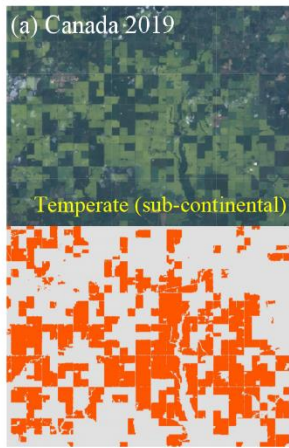
3.2 More details of rapeseed maps derived by the new method

To show more details of rapeseed maps derived from our method, we selected some images in some areas of each country. The rapeseed maps show good spatial consistency with the actual rapeseed planted on the ground (Fig. [89](#) and Fig. [S6](#)). From the area densely planted by rapeseed in Canada (Fig. [89--a](#)) to relatively sparse planting ones such as in Chile (Fig. [89-b](#)) and

European countries (e.g. Fig. 89-c,d) (Lowder et al., 2016), from regular rectangles (e.g. Fig. 89-a, h) to irregular parcels (Fig. 89-c, d), from temperate oceanic climate (Fig. 89- c-e) to temperate sub-continental (Fig. 89-a, f), or even subtropic climate (Fig. 89-b), all field details were indicated clearly in our maps. Fragmentation of land in some European countries, especially in Eastern and Central Europe after land reform in 1989 (Hartvigsen, 2013, 2014), such as Estonia (Fig. 89f) (Jürgenson and Rasva, 2020; Looga et al., 2018). Although under different climates, terrain, landscapes, and over a very larger region, the algorithm ~~proposed in our study~~ showed a satisfying classification accuracy across 33 countries. Thus, the rapeseed maps ~~based on S 1/2 data~~ can effectively identify the fields in detail with high spatial resolution and clear field boundaries. ~~More rapeseed classification details can be found in Fig. S12 and Fig. S19.~~

385

390 ~~Furthermore, our results showed consistent distributions between our rapeseed maps and the existing products at the pixel level (Fig. S13-S14). The yellow grids (70%–80%) mean they are identified as rapeseed areas both by our method and ACI/CDL/CROME/LCMF datasets, while red grids indicate disagreement. The difference in accuracy might be caused by the number of high quality images available in different regions (Dong et al., 2016). Despite the various ground conditions, methods, images, and spatial resolutions among the products, the comparison results further verify the accuracy of our rapeseed map (Gong et al., 2020; Singha et al., 2019).~~



 Rapeseed

 Other

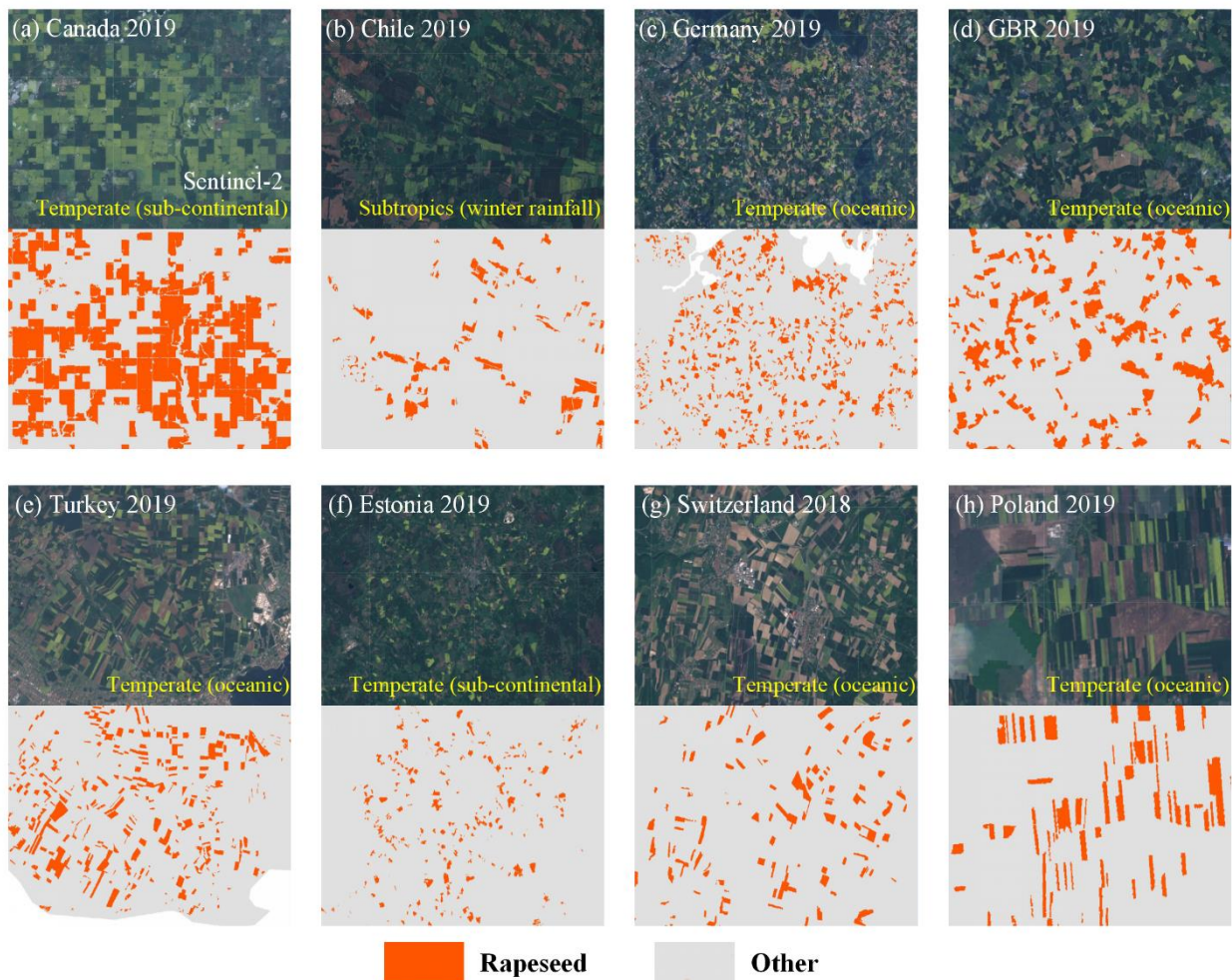
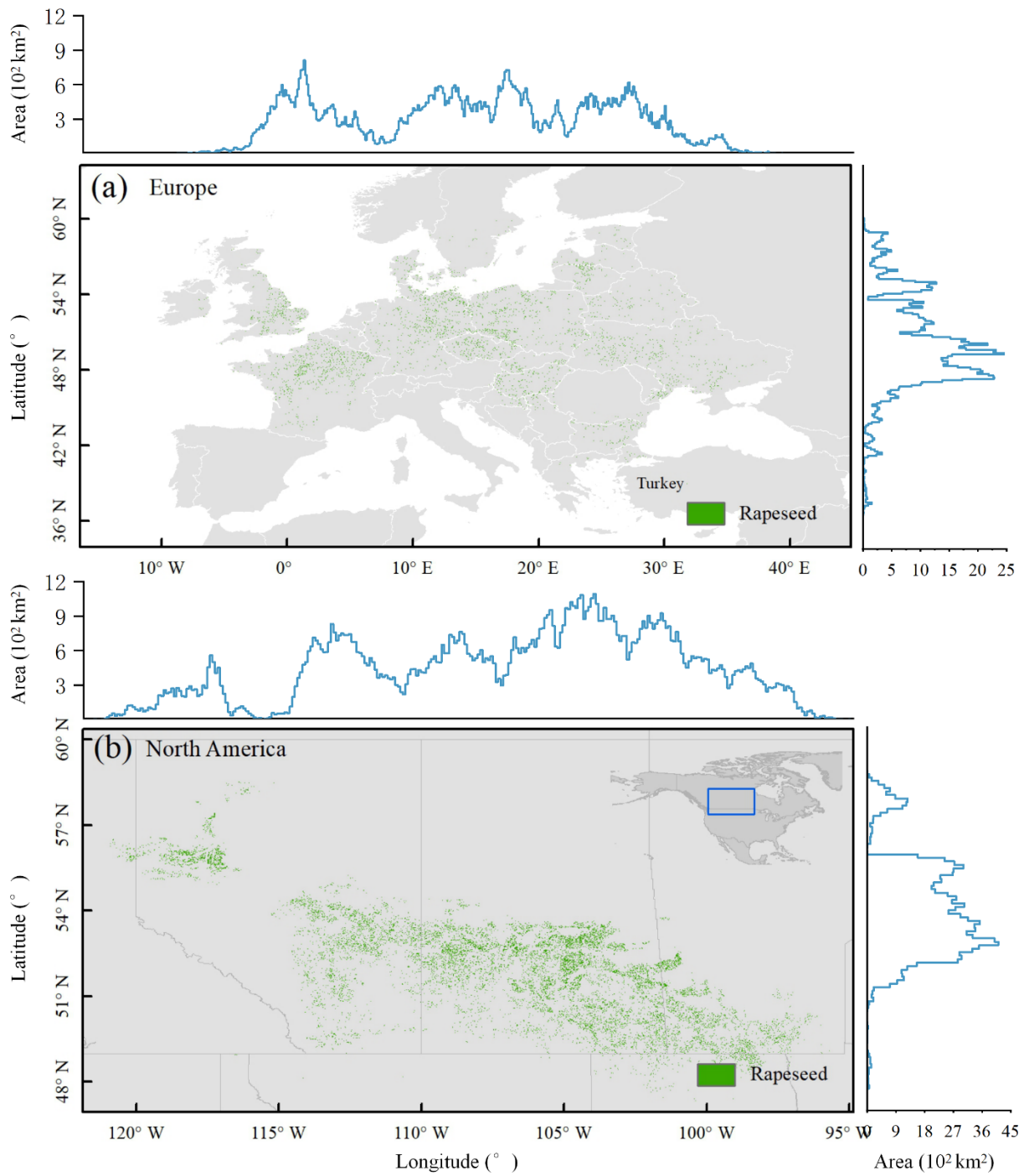


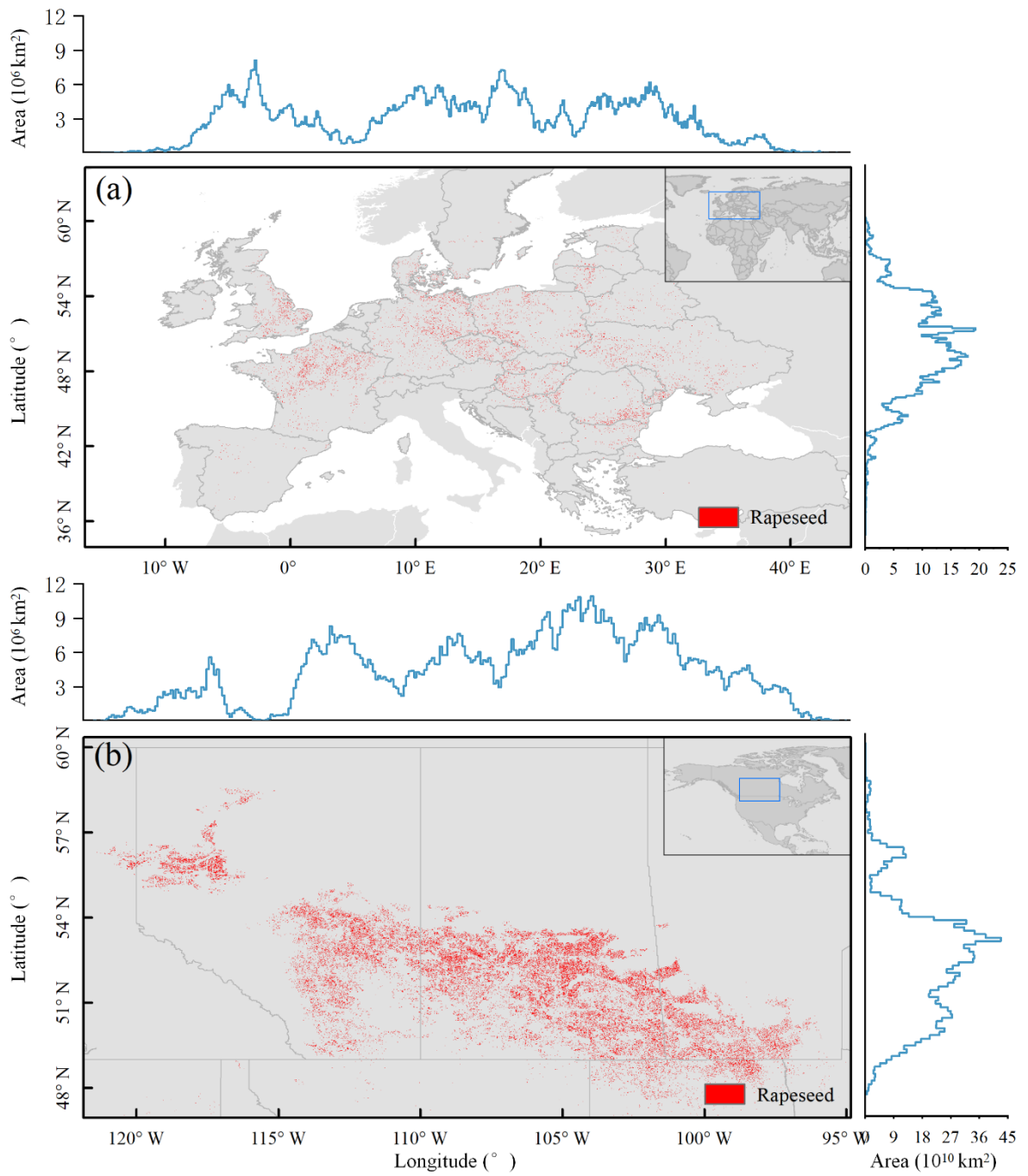
Figure 89. Spatially explicit details of rapeseed maps in eight countries with diverse crop structures in different years (the yellow words show the climatic zones). RGB composite images use the red (b4), green(b3), and blue (b2) bands from Sentinel-2 with good-quality observations during the flowering period of rapeseed (image source: Copernicus Sentinel-2 data). The climate zone data is from the Food Insecurity, Poverty and Environment Global GIS Database (FGGD).

3.3 Spatial patterns of rapeseed planting areas

Canada shows the largest rapeseed planting area (Fig. 9, Fig. S15), with a total area of 118,489.73 km² in 2018, higher than those in Europe (106,814.67 km²). France and Germany are two leading rapeseed growing countries in Europe, accounting for around 66.3% of European rapeseed areas together with the other three countries (EnglandGBR, Poland, and Ukraine). The country wide rapeseed areas in all 33 countries were further normalized to show clearly the spatial patterns (Fig. S15). The spatial patterns of three years (2017~2019) are consistent at the national level (Fig. S9). Moreover, we also plotted the

geographic characteristics of rapeseed areas along latitude and longitude for ~~three regions~~ the study areas (Fig. 910). Rapeseed in Europe is widely planted in the countries with latitudes of 45~56°N and longitudes of -2°~4°, 9°~19°, and 22°~27°, with exception of the steep mountainous areas and the cold northern areas (Fig. 9a10a) (van Duren et al., 2015). In Canada and USA ~~North America~~, the areas with the latitudes of 44~44.5°N, 51~55°N, 56~57°N and longitudes of -118°~-117°, -114°~-98° are densely distributed by rapeseed (Fig. 9b10b).





415 Figure 910. Spatial distribution of rapeseed areas at 10m resolution along latitude and longitude gradients in 2018. (a) Europe and Turkey. (b) Canada and [AmericaUSA](#).

4 Discussion

4.1 Investigating the rapeseed rotation systems

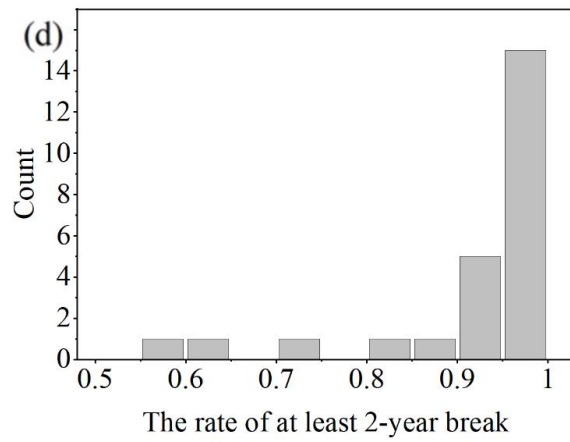
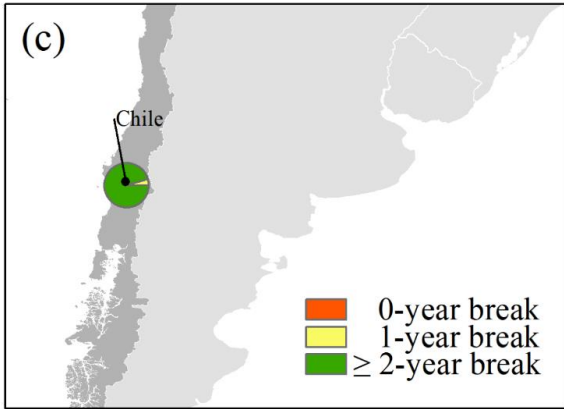
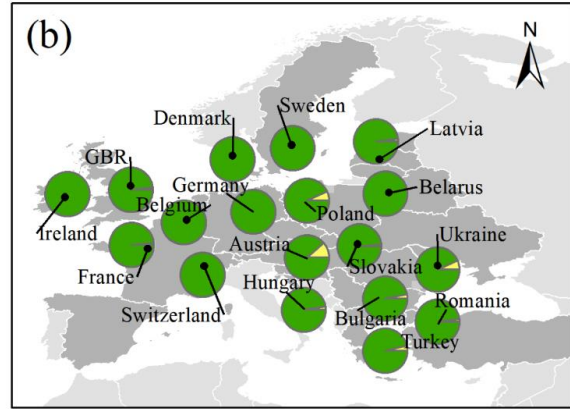
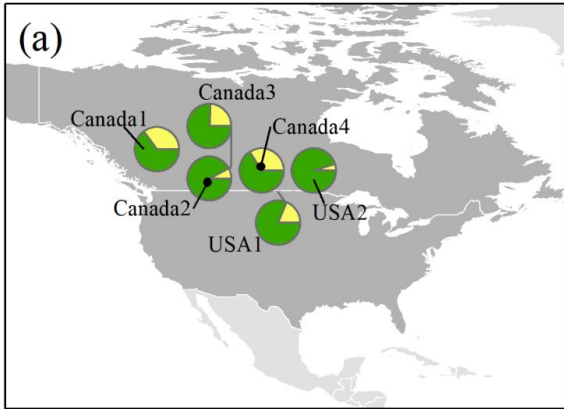
We obtained three-year rapeseed maps at a 10-m spatial resolution, and with a higher accuracy which was validated by annual national statistic books, open accessed public products, and random sampling points ~~at $0.2^{\circ} \times 0.2^{\circ}$ grids~~. These rapeseed maps, ~~with good quality for three consecutive years~~, provide a new opportunity to investigate rapeseed rotation systems (Liu et al., 2018a). Crop rotation information is considered an important factor for crop yield (Harker et al., 2015; Liu et al., 2018a; Ren et al., 2015; Rudiyanto et al., 2019; Zhou et al., 2015). Thus, we selected 25 representative areas (Fig. ~~S16~~**S10**) to analyze the rapeseed rotation patterns according to the three criteria. Firstly, ~~the~~ quality of images is high. Secondly, the classification accuracy of rapeseed is high. Thirdly, the area of rapeseed is large. The rapeseed rotation was calculated by the frequency in each rapeseed pixel (Fig. ~~S17-18~~**S1**).



Figure 11. Spatial distribution of three types of rotations in different areas from 2017~2019.

430 Please note that the longest rapeseed rotation break that can be observed is 2 years because there are only three years (2017-
 2019) of rapeseed maps available. Thus, to more accurately express the pattern of rapeseed rotation break, we classified the
 rapeseed rotation break into three types: ≥ 2 years, 1 year, 0 years in this study (Fig. 10 and Fig. S17-18). We found most
 countries show a rotation break greater than or equal to 2 years (the highest ratios of green parts) (Fig. 10-12), especially for
 European countries (Fig. 10-12-b). The rotation break ≥ 2 years in Canada accounts for 70%, followed by 1-year break (30%)
 435 (Fig. 10-12-a). The histogram confirmed that rotation breaks of 20 locations have been identified ≥ 2 years. The percentage of

planting areas with rotation break ≥ 2 years is higher than 90% (Fig. [4012-d](#)). Many previous studies have found that a two- or three-year rotation break will significantly reduce the number of spores, especially rhizomes and blacklegs, suggesting rotation system is an important step in controlling diseases (Gill, 2018; Harker et al., 2015; Ren et al., 2015; Zhou et al., 2015). Moreover, rapeseed rotation will also benefit yield, insects, moisture, fertility, and reducing weeds (Bernard et al., 2012; Harker et al., 2015; Pardo et al., 2015; Peng et al., 2015; Ren et al., 2015). Thus, more efforts should be input to produce longer time-series rapeseed maps and obtain detailed rotation information in the future.



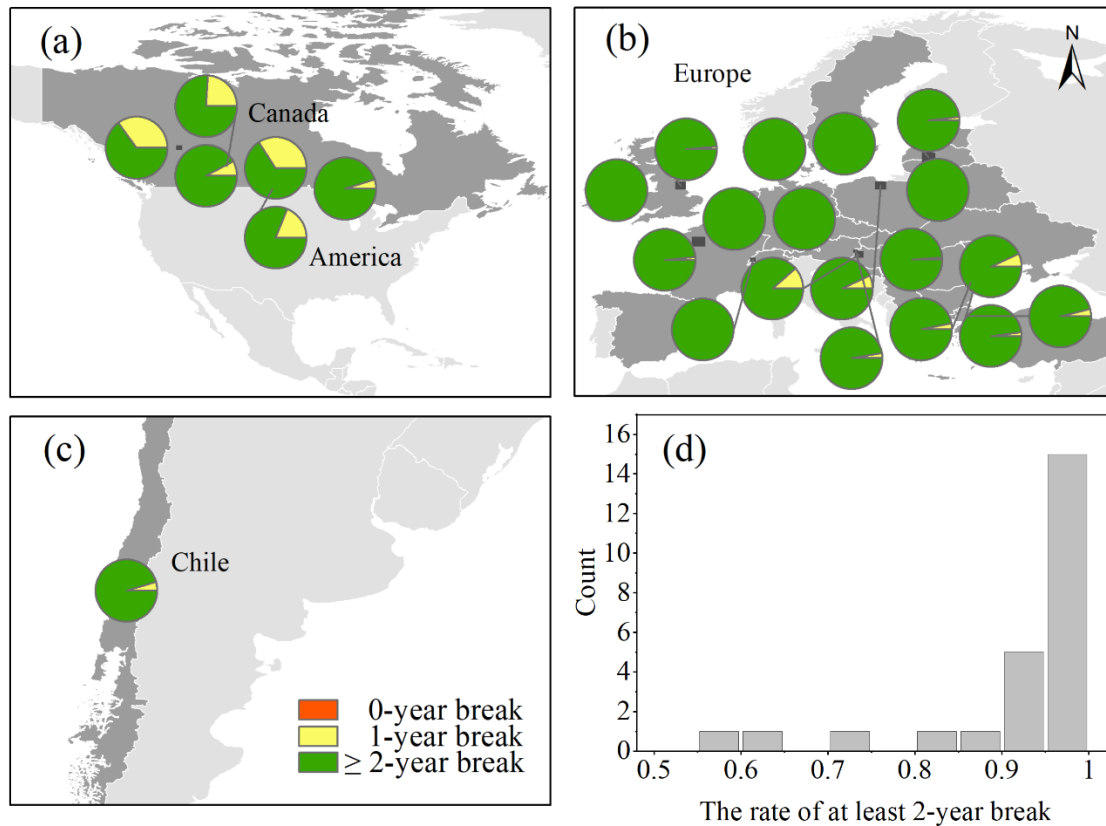


Figure 10-12. Crop rotation. (a-c) The proportions of the total area planted by rapeseed for three rapeseed rotation breaks. The sample blocks selected for each area are red in Fig. S16. (d) The numbers of areas with ≥ 2 -year break in Fig. 10-12 a-c.

4.2 Uncertainty analysis

Generating annual high-resolution maps of a specific crop over a larger region is a big challenge (Gong et al., 2020; Liu et al., 2018b, 2020a). Pixel-and phenological-based algorithms, multisource remote sensing data, and the GEE are useful to map rapeseed at high resolution and over larger areas. Besides, the proposed algorithm does not need a large number of training sample data and reduces disturbance from agronomy differences by combining images of multiple dates. However, the uncertainty is from the following aspects. 1) *Cropland layer*. We used the GFSAD30 datasets to identify croplands. However, GFSAD30 has its limitations such as classification error (Phalke et al., 2020). 2) *The number of satellite images available*. Although our annual rapeseed maps are consistent with FAO statistics and show higher accuracy comparing with existing products, the maps are limited by the good-quality observations during the critical growth stages. For example, Fig. 11a-13a shows that there is an error in the area of France in 2017, which could be attributed to the lack of clear S2 images during the rapeseed flowering period (Fig. 11b-13b). The rapeseed flowering period is generally characterized by high NDYI, red band, and green band reflectance, thus rapeseed pixels are likely to be misclassified if the images during the flowering stage were

missing (Fig. 4e13c). 3) *Thresholds for different indicators*. The threshold is the key for mapping crops (Ashourloo et al., 2019; Dong et al., 2016; Liu et al., 2020a; Wang et al., 2020a; Zhang et al., 2015). Although the reference thresholds for three regions are given in this study, it should be cautious when applying them to other regions. 4) *The complexity of the ground environment*. For example, landscape types might impact the accuracy of rapeseed maps (Wang et al., 2020a).

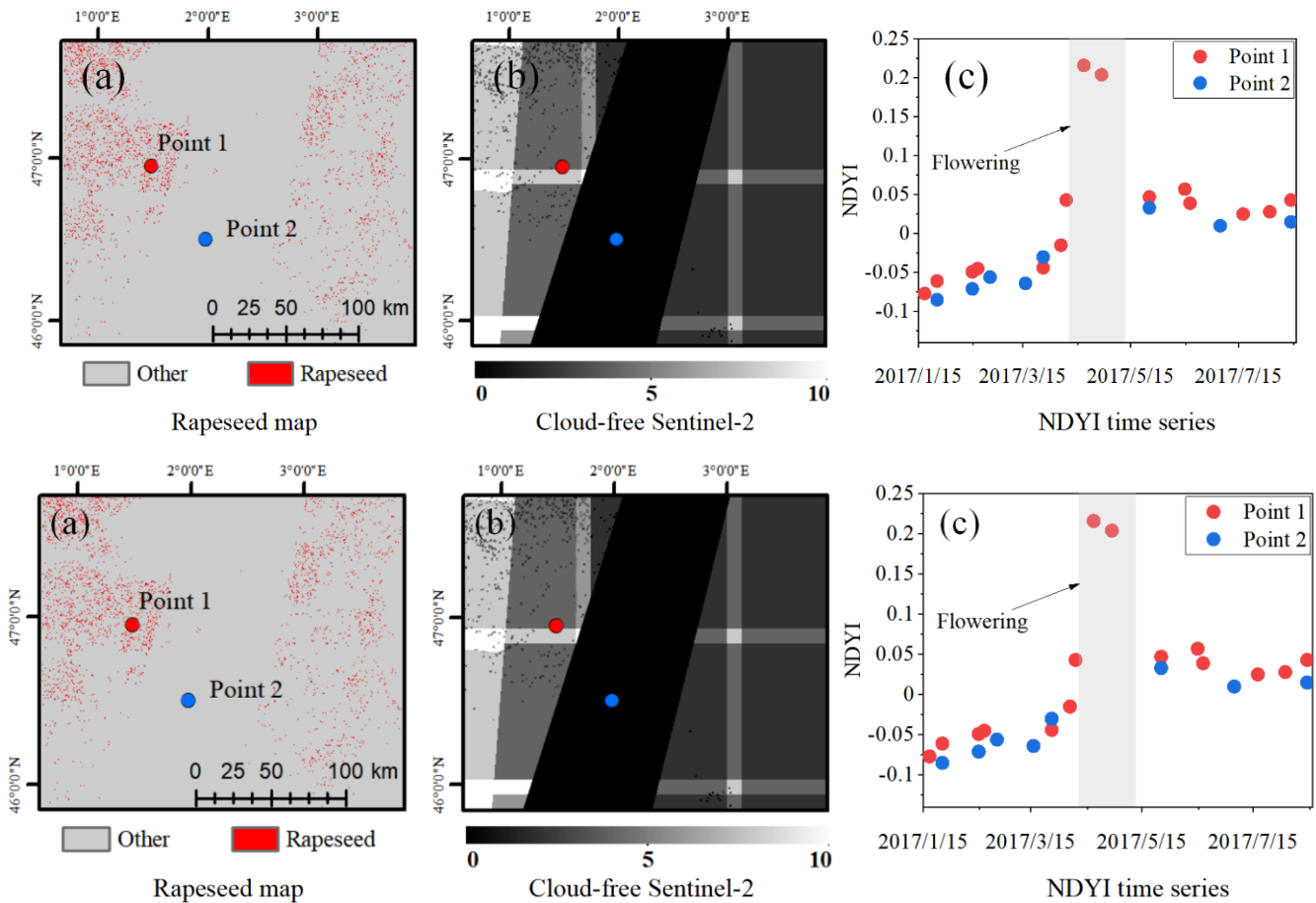


Figure 4e13. Descriptions for the classification limitation. (a) Rapeseed map with an error in France in 2017 (Lon. 2.059824°, Lat. 46.734987°). (b) Availability of time series Sentinel-2 images during rapeseed flowering phases. (c) Comparison of the time series of different sites indicating how the peak NDYI is missed. 修改序号

4.3 Implications and improvements

Despite the above limitations, the new phenology-based method proposed by us has the potential to extend to other regions by modifying the phenology metrics. Recently, the Harmonized Landsat and Sentinel-2 database has improved spatial resolution and shortened the revisit cycle of images (Claverie et al., 2018; Shang and Zhu, 2019). Similar or even higher rapeseed classification accuracy can be expected. Furthermore, remote sensing data fusion algorithms have been continuously developed

(e.g., STARFM and ESTARFM) (Zhu et al., 2010). Finally, various deep learning models have been explored for classifying crops and lowering errors (Hu et al., 2019; Zhong et al., 2019). Integrating phenological metrics and deep learning models might further improve rapeseed mapping accuracy. Thus, such rapeseed products will objectively track the dynamics of rapeseed planting areas as well as agricultural management in the future.

5 Data availability

The rapeseed map produced is accessible at Mendeley Data (<http://dx.doi.org/10.17632/ydf3m7pd4j.3>) (Han et al., 2021). The rapeseed maps with 10 m resolution are provided in this study. The dataset includes a set of GeoTIFF images in the ESPG: 4326 spatial reference system. The values 1 and 0 represent rapeseed and non-rapeseed, respectively. We encourage users to independently verify the rapeseed map. Also, Sentinel 1/2 images, CDL, ACI, and SRTM are available on GEE (<https://developers.google.com/earth-engine/datasets/>). For more detailed information about the data collected in this work, please see Table 1.

6 Conclusions

Large-scale and high-resolution rapeseed maps are the basis for crop growth monitoring and production prediction. We designed a new method for mapping rapeseed based on the spectral and polarization features and multi-source data. The new algorithm has produced three annual rapeseed maps (2017~2019) at 10m spatial resolution in 33 countries. Three different verification methods indicated that our rapeseed maps have reasonable accuracy. Compared with existing products at the pixel level in Canada, [AmericaUSA](#), [EnglandGBR](#), and France, PA, UA, and F1 are 0.70–0.80, 0.93–0.97, and 0.81–0.86, respectively. Also, the F1 ranged from 0.84 to 0.92 based on the independent validation samples. Our approach reduces disturbances from different planting times and bad-quality observations to some degree. The 10m rapeseed maps do provide more spatial details of rapeseed. Finally, we found that rapeseed crop rotation is 2 years or longer in almost all countries in this study. The rapeseed mapping method proposed in this work could be applied to other regions. The derived rapeseed data product is useful for many purposes including crop growth monitoring and production, rotation system planning.

Author contributions

ZZ and JH designed the research. JH and LY collected datasets. JH implemented the research and wrote the paper. ZZ, JC, LZ, JZ, and ZL revised the paper.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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