A Comprehensive Review of Remote Sensing Technology for Mass-Flowering Crops Extraction

Qingji Meng, Shuying Zang, Bingxue Zhu, Kaishan Song, Miao Li, and Li Sun

***Abstract*—Precise and reliable crop evaluations hold significant value in ensuring agricultural security and fostering agricultural progress. Using the flowering characteristics of crops during their growth period to accurately identify crops is a hot research direction in the field of agricultural remote sensing. This article presents a statistical analysis of 46 articles on flowering crops published between 2004 and 2023. Based on the findings, it is evident that China, the United States, and Ukraine are the primary focus of research in this particular field. The main subjects of study are rapeseed, accounting for 50% of the research, and sunflower, which makes up 19.57% of the study. In the extraction of mass-flowering crops and the observation of their flowering periods, commonly used remote sensing data sources include optical data (Sentinel-2, Landsat 8, Landsat 5, MODIS, etc.) and radar data (Sentinel-1, TerraSAR-X, etc.), and the fusion of multisource data is an effective means to improve the research accuracy in this field. Features such as vegetation indices (notably normalized difference vegetation index (NDVI) and enhanced vegetation index (EVI)), band features, polarization features, and phenological features are essential for analyzing mass-flowering crops. Machine learning and deep learning have proven to be valuable tools for conducting classification research in areas with intricate crop planting structures. Spatiotemporal data fusion is an important way to supplement missing images in crop flowering period identification. Sampling points can be obtained through methods such as combining flowering period characteristics with cloud platforms, sample migration, and crowdsourcing activities. This work explores an efficient approach to quickly generate comprehensive crop classification datasets on a global scale. It also presents an overview of the future development of mass-flowering crop extraction, focusing on data sources, information extraction techniques, training samples, and classification methods.**

Received 13 December 2024; revised 6 March 2025 and 30 April 2025; accepted 30 April 2025. Date of publication 12 May 2025; date of current version 16 June 2025. This work was supported in part by the Key project of National Natural Science Foundation of China (NSFC) under Grant 42430412, in part by the International (Regional) Cooperation and Exchange of the National Natural Science Foundation of China under Grant W2412013, in part by the Science & Technology Fundamental Resources Investigation Program under Grant 2022FY100701, and in part by the Academic Innovation Project of Harbin Normal University under Grant HSDBSCX 2024-05. *(Corresponding authors: Shuying Zang; Miao Li.)*

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Digital Object Identifier 10.1109/JSTARS.2025.3569094

***Index Terms*—Extraction, mass-flowering crops, rapeseed, remote sensing (RS), sunflower.**

I. Introduction

The ongoing rise in the human population and global food demand will pose significant challenges to human development. According to a research report by the United Nations, "the world's population is expected to grow to nearly 10 billion by 2050, and agricultural demand will increase by about 50% compared with 2013" [1]. Over the past few years, the increased occurrence of global warming, extreme weather disasters, and frequent regional conflicts has heightened the vulnerability of global agriculture [2], [3]. Therefore, it is imperative to actively promote the transformation of agricultural development models toward digitalization, precision, and greening. Remote sensing (RS) is an important technological support for the transformation of agricultural development models. Users can access comprehensive information about crop growth status and growth environments quickly and affordably. RS has been applied in agricultural research since the 1970s [4]. The application scope mainly includes planting structure extraction [5], [6], [7], [8], [9], crop growth status assessment [10], [11], [12], [13], [14], crop yield prediction [15], [16], [17], [18], flowering period identification [19], [20], and precision agriculture [21], [22], [23], [24]. The resources readily accessible include a range of image data with different resolutions, cloud processing platforms that utilize artificial intelligence (AI) technology and cloud computing (such as Google Earth Engine and AI Earth) [25], [26], [27], [28], as well as advanced methods in deep learning (DL) and machine learning (ML) such as U-net [29], [30], [31], random forest (RF) [32], [33], [34], [35], and decision tree (DT) [36], [37], [38]. It offers essential information, platform, and methodological assistance for the advancement of all-weather agricultural RS monitoring with high spatiotemporal resolution.

The main objective of agricultural RS research is to provide a clear understanding of how crops are distributed in space. Field surveys are commonly used by researchers to gain an initial understanding of crop distribution. However, it is important to note that this method is most effective for small-scale studies. In large-scale crop classification research, identifying features that can effectively distinguish between different crop types is a key approach to achieving accurate classification. As a critical phenological feature of mass-flowering crops, the flowering period has been widely applied in crop classification research due to its distinctiveness and recognizability [39], [40], [41], [42], [43].

Moreover, data regarding the timing and intensity of flowering can be utilized to evaluate the vitality of crop growth and estimate the crop yield [44], [45]. However, the flowering time of crops is complex and variable. Even if the same crop is grown in the same region (temperature zone, agricultural planting area), there can be multiple flowering times due to differences in planting management techniques, varieties, climate, and soil conditions [46]. Given the significance and intricacy of crop flowering, it is vital to precisely track its duration to promptly gather crop growth data and successfully classify crops based on their flowering period.

Over the past few years, scholars have been examining the advancements made in crop classification mapping through the fusion of optical and radar data. They have focused on data fusion theory and methods to summarize the research progress in this field [47]. Some scholars have also discussed the application of ML and DL methods in agricultural classification from the perspective of classification methods [48]. Examining the literature from the past two decades, it was discovered that RS technology is primarily employed for monitoring soil moisture and crop health during the current season; however, its utilization in other domains is infrequent [49]. Although the abovementioned review articles focus on the application of RS technology in agricultural classification mapping and other fields, they rarely summarize the data, features, and methods for classification applications from the perspective of mass-flowering crops. Furthermore, there was no discussion regarding the selection of data sources for classifying mass-flowering crops, additional methods to compensate for insufficient observation data during the flowering period, or strategies to increase the number of crop sampling points.

Thus, this article begins by examining the flowering period of crops and focuses on two specific types of crops, rapeseed and sunflower, which have distinct flowering periods. The article delves into the extensive research conducted on these crops. Here is the outline of this article (Fig. 1).

1) Section II provides an overview of the criteria for article retrieval and screening, as well as the basic information of research articles and global distribution information of rapeseed and sunflower.
2) Section III discusses the utilization of various RS data for mass-flowering crop extraction and highlights the significance of integrating multiple data sources in studying mass-flowering crops.
3) Section IV summarizes the key classification features in the study of mass-flowering crops—namely, vegetation index features—and the various methods used for identifying sunflower and rapeseed.
4) Section V covers the significance of choosing the right data sources, techniques for acquiring crop sampling points, and efficient methods for creating global multiple crop datasets. It also looks ahead at potential future directions.

II. Materials

A. Article Search Procedure and Selection Criteria

Examining and analyzing the literature will provide valuable insights into the most recent advancements in RS for extracting flowering crops. The literature data source selected for this article comes from the Web of Science Core Collection, which covers the world's leading science and technology journals. For the literature search, the defined criteria were "RS or Optical or SAR" AND "Crop extraction or Classification or Mapping" AND "Flowering." A comprehensive search yielded a total of 929 articles as of 25 March 2024. Irrelevant articles were excluded according to the following criteria: (1) The research field is RS, but the research object is not crops; (2) The research field is RS, and the research object is crops, but the research content is not related to crop extraction or flowering period monitoring; (3) No open access publications; and (4) Articles in languages other than English. After applying various filtering conditions, a total of 46 articles that are relevant to the topic were obtained.

B. Research Article on the Basic Information

Based on the findings, it is evident that there has been a consistent body of research dating back to 2004. Furthermore, the number of articles published remained relatively steady from 2009 to 2019. Since 2020, the number of articles published has increased year by year (Fig. 2). This trend is strongly connected to the utilization of Sentinel data and the increasing use of DL algorithms. Since the research areas of the articles are composed of one or more countries, this results in a total of 85 research areas of the statistical articles. China is the most extensively studied country, with 32 out of 85 studies focusing on it. The United States and Ukraine both have 5 studies, putting them in a tie for second place out of the 85 studies. Many countries in Africa, South America, South Asia, and Southeast Asia have not received much attention. It makes sense to prioritize the development of developing countries to improve their agricultural security and promote economic growth (Fig. 3). In addition, the existing literature covers a variety of crop types (Fig. 4). However, this study focuses on crops that exhibit prominent flowering characteristics during the growing season and are readily identifiable in RS imagery, namely mass-flowering crops such as rapeseed, sunflower, and cotton. Based on the statistical results, rapeseed and sunflower were ultimately selected as the research subjects, accounting for 50% (23/46) and 19.57% (9/46) of the relevant literature, respectively.

C. Main Planting Areas of Sunflower and Rapeseed

When conducting research on mass-flowering crops, it is important to identify the specific areas where they are planted. Thus, this article utilizes the most up-to-date global dataset known as the Spatial Production Allocation Model 2020 dataset (SPAM 2020) [50], and selects the harvested area of sunflower and rapeseed as the area data of crops. The cross-entropy method was employed in SPAM 2020 to enhance the estimation of the distribution of 46 crops. This latest version of SPAM demonstrates a notable advancement compared to its predecessors, SPAM 2005 and SPAM 2010.

Fig. 5 illustrates the distribution of sunflower plantations worldwide, with a significant concentration in various regions of Europe, Asia, Africa, and South America. Russia, Ukraine, Argentina, Romania, Tanzania, China, and Kazakhstan are the

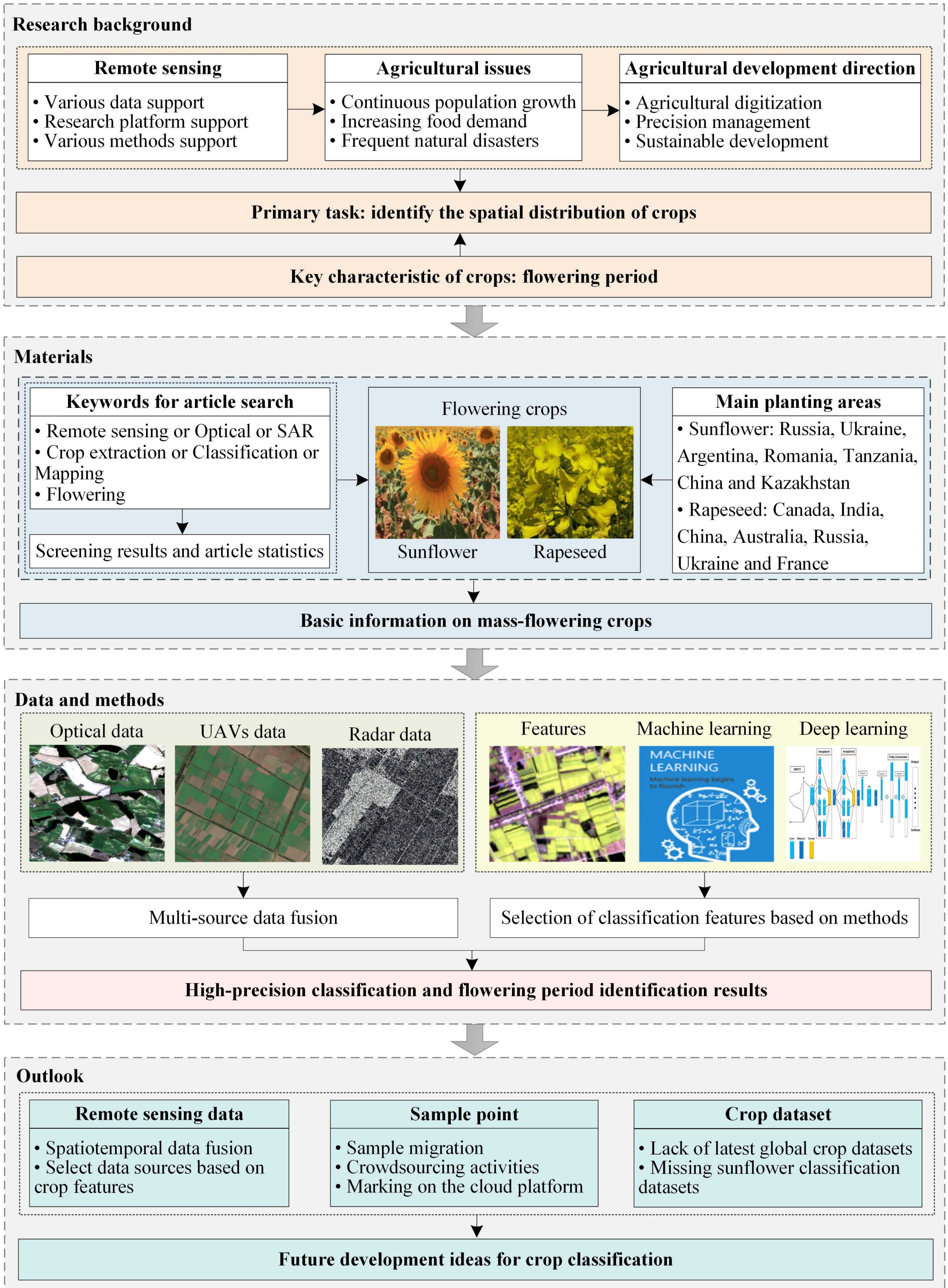

Fig. 1. Flowchart of mass-flowering crop classification and flowering period identification.

seven countries that have the largest planting areas. Although the planting areas in other continents are wider, the areas are generally smaller. From the statistics of sunflower planting area from 2000 to 2022 obtained from the National Bureau of Statistics of China (https://data.stats.gov.cn/) (Fig. 6), China's sunflower planting area fluctuates widely and is shrinking, and the planting area is mainly concentrated in the Inner Mongolia Autonomous Region and Xinjiang Uygur Autonomous Region. The global planting area for rapeseed is primarily found in various regions across the globe, including East Asia, South Asia, Central

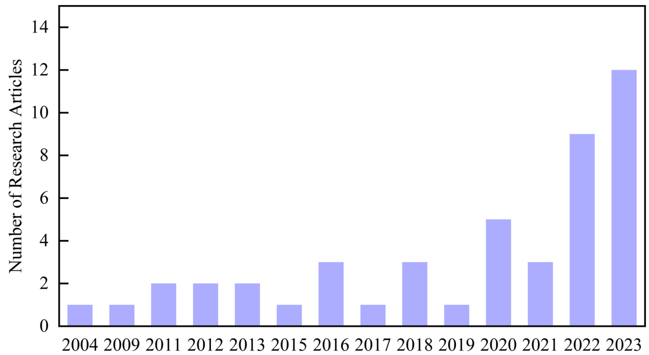

Fig. 2. Annual number of research articles published.

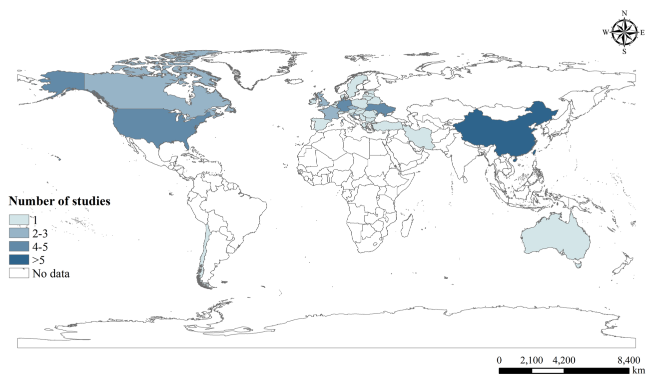

Fig. 3. Frequency of occurrence of research areas in research articles.

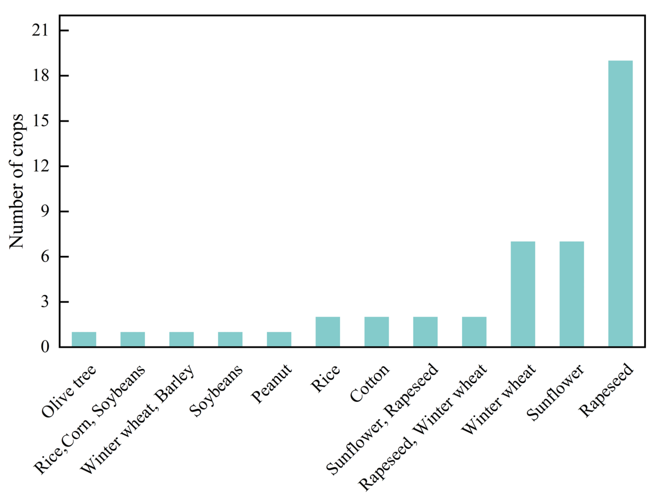

Fig. 4. Frequency of crop occurrence in research articles.

and Western Europe, southern Australia, and northern North America. These regions, as shown in Fig. 7, have countries with rapeseed planting areas exceeding 1 million hectares. Some of these countries include Canada, India, China, Australia, Russia, Ukraine, and France. Rapeseed is also grown in South America and Africa, but in a very small area. Statistics in recent years show that the area planted with rapeseed in China is generally stable, with large fluctuations only in the periods of 2006–2007

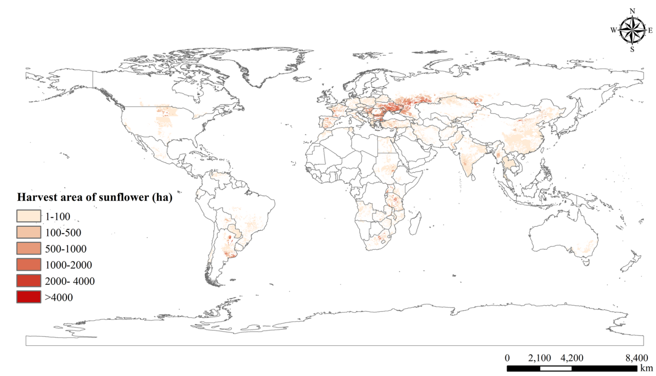

Fig. 5. Harvested area map for global sunflower in SPAM 2020.

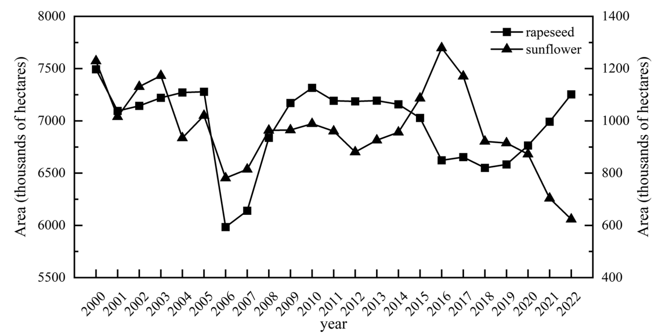

Fig. 6. Changes in rapeseed and sunflower planting area in China from 2000 to 2022.

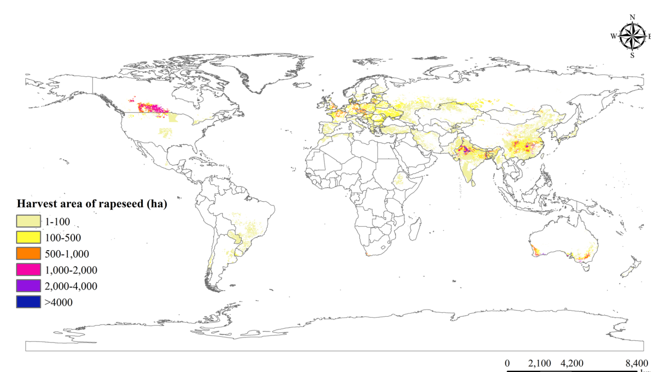

Fig. 7. Harvested area map for global rapeseed in SPAM 2020.

and 2016–2020. Based on the analysis provided, it is readily apparent that China, Russia, Ukraine, and certain countries in Western Europe are the primary regions where rapeseed and sunflower are cultivated on a large scale. These areas also serve as focal points for RS classification studies on these crops.

III. RS Data Sources for Crop Extraction

As RS technology continues to advance, the data sources available for agricultural RS research have become increasingly abundant. Relevant studies have indicated that satellite sensors, characterized by their wide coverage and high accessibility, are the most widely applied [51]. Statistical results regarding

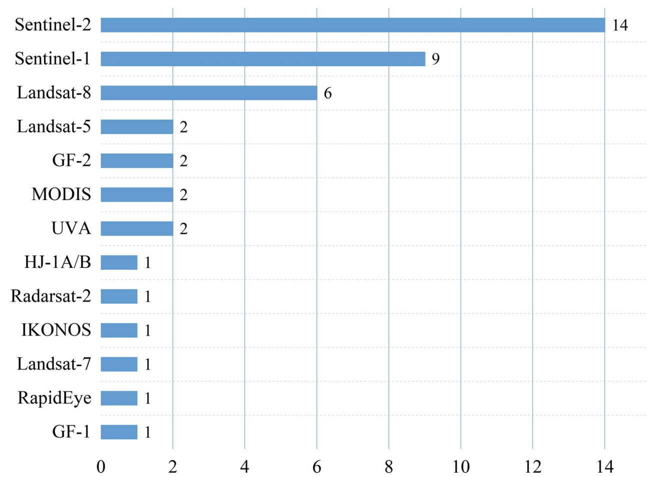

Fig. 8. Frequency of use of commonly used sensors in mass-flowering crop classification.

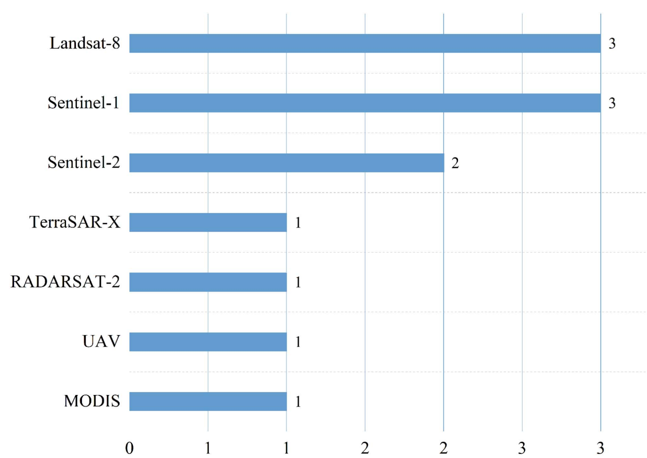

Fig. 9. Frequency of use of commonly used sensors in mass-flowering crop flowering stage identification.

the classification and flowering stage identification of mass-flowering crops further confirm this trend, showing that although both satellite and unmanned aerial vehicle (UAV) platforms have been utilized, the research primarily relies on satellite-based multispectral and radar observation systems. In crop classification tasks, sensors such as Sentinel-2, Sentinel-1, Landsat-8, and Landsat-5 are frequently employed; while in flowering stage identification studies, Landsat-8, Sentinel-1, Sentinel-2, and TerraSAR-X serve as the main data sources (Figs. 8 and 9).

A. Satellite RS Data

1) Optical RS Data: In recent years, optical RS data, with its high spatial resolution, abundant spectral information, various data sources, established data processing techniques, and a well-developed technical framework (Table III), have been widely applied to crop classification, planting structure monitoring, and phenological information extraction. Especially in the study of mass-flowering crops, optical RS imagery, with its advantage of intuitive visualization, can clearly reflect the flowering characteristics of crops such as rapeseed and sunflower. Its visible and near-infrared bands respond well to the color changes in the flowering canopy, making it suitable for constructing vegetation indices for flowering stage detection and crop identification. Therefore, optical RS demonstrates broad application prospects in the classification and flowering stage monitoring of mass-flowering crops.

MODIS (Table I) data has the features of wide coverage, high time resolution, and multiple types of data products. When paired with the well-established NDVI and EVI data products, it has found extensive application in crop classification. For example, MODIS-EVI products and DT algorithms were used to investigate the spatiotemporal distribution pattern of winter rapeseed in the Yangtze River Basin in China from 2003 to 2015. The results showed that the number and density of winter rapeseed fields decreased [52]. MODIS data also has good performance in other crop classifications [53], [54], [55]. Given the limited spatial resolution of MODIS at just 250 m, the issue of mixed pixels becomes a significant concern. Meeting the demand for extracting refined crop information can be quite challenging.

The Landsat series of satellites is the world's longest-running Earth observation program. It has high spatial resolution and rich spectral band information [56] and has been widely used in crop classification. Landsat 9 is the latest satellite launched [57]. During the rapeseed flowering period, various calculations were conducted on Landsat 9 images. The results were then compared using both supervised and unsupervised classification methods. The results indicate that the combination of the canola flower index (CFI) and supervised classification achieved the highest accuracy for rapeseed extraction, with an overall accuracy (OA) of 93.08%, which also shows that Landsat 9 has broad application prospects in rapeseed information extraction [58]. Classifying multiple crops, including sunflowers in Ukrainian agricultural experimental fields, was achieved by utilizing Landsat 8 as the data source and employing convolutional neural networks (CNNs), multilayer perceptron, and RF methods. The results showed that CNNs achieved the highest classification accuracy (OA = 94.6%) [59]. The spatial resolution of Landsat has been greatly improved compared to MODIS data, and it can significantly reduce the impact of mixed pixels on crop classification accuracy. With its extensive data spanning almost 50 years, Landsat data are the preferred option for conducting long-term tracking research on changes in crop planting structures in regions with intricate planting systems.

The red edge band of Sentinel-2 is highly responsive to variations in the growth status of vegetation. As a result, researchers frequently utilize Sentinel-2 data for crop classification studies [60], [61], [62]. In terms of sunflower classification, single-phase Sentinel-2 data were used to determine the best classification window based on the phenological characteristics and NDVI index of the crops, and the Skcnn–Tabnet classification model was used to identify sunflowers, corn, and other crops in the Hetao Irrigation District. The results showed that the Skcnn–Tabnet model performed the best, achieving an OA of 92.70%, outperforming the Deeplabv3+ (81.49%), UNet (82.66%), and

TABLE I
BASIC INFORMATION OF COMMONLY USED MULTISPECTRAL SATELLITES FOR CROP EXTRACTION AND FLOWERING PERIOD OBSERVATION AND OTHER MAINSTREAM MULTISPECTRAL SATELLITES

Satellite	Payload name	Launch time	Revisit cycle	Country
Landsat 5*	Thematic Mapper (TM)	1984	16	United States
EOS-TERRA/AQUA*	MODIS (250 m, 500 m, 1 km)	1999	16	United States
Landsat 7*	Enhanced Thematic Mapper Plus (ETM+)	1999	16	United States
IKONOS*	Panchromatic 1 m Multispectral 4 m	1999	3	United States
Landsat 8*	OLI (15-30 m) TIRS (100 m)	2013	16	United States
Sentinel-2*	Multispectral 10 m/20 m/60 m	2015	5	European Space Agency
HJ-1A/1B*	Multispectral 30 m (1A/1B) Hyperspectral 100 m (1A)	2008	2	China
GF 1*	Panchromatic 1 m Multispectral 4 m and 16 m	2013	4	China
GF 2*	Panchromatic 0.8 m Multispectral 3.2 m	2014	5	China
GF 6	Panchromatic 2 m Multispectral 8 m and 16 m	2018	4	China
RapidEye*	Multispectral 5 m	2008	1	Germany
Quickbird	Panchromatic 0.65 m Multispectral 2.62 m	2001	1	United States
WorldView-1	Panchromatic 0.5 m	2007	1.7	United States
WorldView-2	Panchromatic 0.5 m Multispectral 1.8 m	2009	1.1	United States
GeoEye-1	Panchromatic 0.46mMultispectral 1.84 m	2010	3	United States
WorldView-3	Panchromatic 0.31 m Multispectral 1.24 m SWIR 3.7 m	2014	1	United States
WorldView-4	Panchromatic 0.31 m Multispectral 1.24 m	2016	1	United States
Spot-5	HRS 2.5-20 m HRG 10 m VEG 1 km	2002	5	France
Pleiades-1/2	Panchromatic 0.5 m Multispectral 2 m	2011/2012	1	France
Spot-6	Panchromatic 1.5 m Multispectral 6 m	2012	1	France
CBERS-02B	Multispectral 19.5 m WFI Multispectral 258 m Panchromatic 2.36 m	2007	3	China
ZY-1 02C	Panchromatic 5 m Multispectral 10 m HR 2.36 m	2011	3	China
ZY-3	Panchromatic 2.1 m Multispectral 5.8 m	2012	5	China

Note: The satellites listed above the dashed line in the table are commonly used multispectral satellite data for crop extraction or flowering period observation based on literature statistics, while those below the dashed line are other mainstream multispectral satellites. The "*" symbol indicates multispectral satellites that have been applied in the literature for mass-flowering crops extraction. The revisit cycles listed refer to the nominal values officially provided by satellite operators. In practice, especially for sensors with off-nadir pointing capability, the actual revisit frequency may differ due to observation geometry, acquisition strategy, and environmental conditions.

TABLE II
BASIC INFORMATION ON THE WORLD'S MAJOR HYPERSPECTRAL SATELLITES

Satellites	Sensors	Spatial resolution (m)	Spectral resolution (nm)	Band quantity	Spectral range (nm)	Country	Launch time
EO-1	Hyperion	30	10	242	400-2500	America	2000
PROBA	CHRIS	17/34	5/12	153	400-1050	Belgium	2001
IMS	HySI	506	10	64	400-950	India	2008
ISS	HICO	100	5	128	350-1080	America	2009
FLORA	HSI	30	10	200	380-960	America and Brazil	2016
GF-5	AHSI	30	5/10	330	400-2500	China	2018
OVS-1A/B	OHS	10	2.5	256	400-1000	China	2018
DESIS	DESIS	30	2.5	235	400-1000	Germany	2018
PRISMA	PRISMA	30	10	249	400-2500	Italy	2019
ALOS-3	HISUI	30	10/12.5	185	400-2500	Japan	2019
EnMAP	EnMAP HSI	30	6.5/10	244	420-2450	Germany	2019
ISS	DESIS	30	-	235	400-1000	Germany	2018
-	SHALOM	10	10	275	400-2500	Italy	2021
-	SBG	30	10	214	380-2500	America	2023

Note: The 46 studies analyzed in this review did not involve hyperspectral data. The hyperspectral sensors listed in the table are provided solely as supplementary information for reference.

RF (83.96%) algorithms [63]. Using the support vector machine (SVM) classifier, the spectral features derived from Sentinel-2A data achieved higher mapping accuracy and user accuracy for rapeseed compared to Landsat-8 data under the same conditions. Even after the incorporation of texture information, Sentinel-2A continued to outperform Landsat-8 in rapeseed identification, achieving an OA of 90.1%, compared to 82.4% for Landsat-8 [64]. Furthermore, researchers conducted a comparison between Sentinel-2 data, GF-1 WFV, and SPOT-7. The findings indicated that Sentinel-2 data are well-suited for extracting crop information in regions characterized by intricate ground structures or fragmented plots. At the same time, it also greatly reduces the interference of mixed pixels, which also expands the application scope and scale of satellite sensors.

Advancements in RS technology have greatly enhanced the capabilities of multispectral satellite sensors. However, all current multispectral data cannot balance spatial and spectral resolutions. As a consequence, the high spatial resolution images yield more precise ground object information. However, the image data are plagued by significant issues of "same objects with different spectra" and "same spectra with different objects" due to the constraints of spectral wavelength [65]. This limitation impacts the effectiveness of multispectral data in the identification and mapping of crops, especially when it comes to differentiating between crops that exhibit similar spectral characteristics.

To enhance the application range of optical RS data within agricultural RS, hyperspectral RS technology has been developed. The extensive wavelength range and enhanced spectral resolution of hyperspectral data (Table II) enable it to accurately detect subtle spectral variations among crops at various growth stages and across different crop types. Consequently, hyperspectral data present significant opportunities for enhanced crop classification [66]. Researchers in rapeseed classification utilized Hyperion hyperspectral imagery to propose a multirange spectral feature fitting (MRSFF) method based on the variance coefficient weight. This approach significantly improved the accuracy of rapeseed identification in the study area (Zhejiang Province, China), outperforming traditional methods, including SFF, SAM, and the NDVI-based approach [67]. Additionally, leveraging OHS-2A hyperspectral satellite data and a 3D-CNN DL model, high-precision classification (OA = 94.65%) of crops such as rapeseed and winter wheat was achieved using a single hyperspectral image during the cloudy season. This approach significantly outperformed single-temporal Sentinel-2 and achieved classification accuracy comparable to multitemporal Sentinel-2, offering an efficient, low-dependency solution for crop RS monitoring without the need for time-series data [68]. Research on sunflower classification utilized DLR earth sensing imaging spectrometer (DESIS) hyperspectral images and the Wavelet Attention CNN, resulting in the successful identification of crops, including sunflowers and corn, in southeastern Hungary. The OA reached 97.89%, significantly outperforming the SVM (87.79%) and RF (86.28%) algorithms [69]. Hyperspectral data are crucial in precision agriculture research, particularly for managing sunflower crops, monitoring phenological stages, and managing weeds [70]. Hyperspectral data encompass an important quantity of bands, resulting in significant band redundancy (Table III). In crop classification, it is essential that we initially extract key bands to enhance both efficiency and accuracy in the classification process.

In summary, multispectral data demonstrate significant advantages in the classification of mass-flowering crops, with commonly used data sources (such as Landsat-8 and Sentinel-2) typically achieving OAs ranging from 81% to 95%. However, the specific classification performance varies depending on the

TABLE III
ADVANTAGES AND LIMITATIONS OF VARIOUS RS DATA SOURCES IN THE EXTRACTION OF MASS-FLOWERING CROPS AND THE IDENTIFICATION OF FLOWERING SIGNALS

Data sources	Advantages	Limitations
Satellite optical remote sensing data	•High spatial resolution. •Image-based intuitive visualization facilitates the identification of mass-flowering crops with significant color changes, such as rapeseed and sunflower. •Abundant spectral information, especially the significant response of visible and near-infrared bands to flowering period changes. •Abundant data sources, mature technology, and well-developed processing methods.	•Depends on illumination conditions and cannot capture images at night. Significantly influenced by atmospheric conditions such as clouds and precipitation, which can hinder image acquisition during the flowering period. •Difficulty in penetrating the canopy structure, preventing the acquisition of internal crop growth characteristics. •Hyperspectral data may have band redundancy issues, requiring effective dimensionality reduction to avoid information redundancy.
Satellite radar remote sensing data	•All-weather, all-time operation, unaffected by clouds, rain, or lighting conditions, ensuring image acquisition during the flowering period. •Ability to penetrate vegetation, facilitating the acquisition of crop structural information. •Microwave scattering information, sensitive to changes in crop canopy structure, and can be used for the indirect identification of flowering growth characteristics. •Can be integrated with optical data, enhancing the timeliness and stability of flowering period identification.	•Insensitive to color changes, making it difficult to directly identify significant signals during the flowering period, can only be indirectly inferred through changes in canopy structure. •Complex data preprocessing and requires professional knowledge for interpretation, not as intuitive as optical imagery. •Spatial resolution is usually lower than optical data. •Microwave signals are easily affected by background noise such as surface roughness.
UAVs remote sensing data	•Ultra-high spatial resolution, suitable for fine-scale monitoring of flowering period features in mass-flowering crops, such as flowering ratio and canopy structure changes. •Low cost and flexible deployment, with the ability to plan flight schedules based on specific needs during the flowering period, enhancing observational timeliness. •Various sensors can be integrated, including multispectral, hyperspectral, thermal infrared, and LiDAR.	•The coverage area is constrained, influenced by variables including flight altitude and endurance, which complicates the execution of extensive, prolonged monitoring activities. •Operations are highly restricted due to external factors such as regulations, climate, and airspace management. •The data processing workload is substantial, including tasks such as image-stitching and coordinates correction.

classification methods and crop types. Although this review covers relevant research on hyperspectral data (with OAs ranging from 86% to 98%), the surveyed literature does not address its application in mass-flowering crop identification, and thus, this content is provided for supplementary reference. It is important to note that optical RS relies on lighting conditions during image acquisition and is susceptible to interference from weather factors such as clouds, haze, and precipitation, which may limit data acquisition during the flowering period. Additionally, its inability to penetrate the vegetation canopy limits its capability to detect internal crop structural features (Table III). Consequently, subsequent investigations may integrate optical data with additional data types to address these constraints.

2) Radar RS Data: In contrast to optical data, radar data (Table IV) demonstrate the ability to operate in all weather conditions and at any time of day, remaining unaffected by clouds, rain, and lighting conditions [71], providing continuous and stable observational support during the crop flowering period. In addition, the microwave scattering characteristics of radar data are highly sensitive to changes in crop canopy conditions and can indirectly reflect growth features during the flowering stage through variations in backscatter coefficients (Table III). Leveraging these advantages, radar data demonstrate broad application prospects in the extraction of mass-flowering crops and the identification of flowering periods [72]. For instance, multi-temporal Sentinel-1 data were utilized to extract the backscatter coefficients of VV and VH polarization, along with their ratio. The high-precision classification of rapeseed and wheat across various growth periods and years was accomplished in Ergun, Inner Mongolia, utilizing the RF classification method. Optimal classification outcomes were recorded during the flowering to maturity phase, specifically in July and August (OA = 96%) [73]. Additionally, the DT algorithm was employed to categorize different crops like sunflowers and rapeseed in central Spain, utilizing data from RADARSAT-2 and Sentinel-1. The results show that the classification accuracy of rapeseed is the highest among all crops, with overall classification accuracies exceeding 83% and reaching up to 89.1% [74]. Similarly, RADARSAT-2

TABLE IV
BASIC INFORMATION ON RADAR DATA COMMONLY USED FOR CROP EXTRACTION AND FLOWERING PERIOD OBSERVATION AND OTHER MAINSTREAM RADAR DATA

Satellite	Frequency (band)	Image resolution (m)	Polarization	Repeat rate (days)	Launch time
ENVISAT ASAR	C	30	VV, HH	35	2002
TerraSAR-X	X	0.25-40	HH, HV, VH, VV	11	2007
RADARSAT-2*	C	3-100	HH, HV, VH, VV	24	2007
Sentinel-1*	C	5-40	VV, VH or HH, HV	12	2014
ERS-1	C	30	VV	35	1991
JERS-1	L	18	HH	44	1992
ERS-2	C	25	VV	35	1995
RADARSAT-1	C	8-100	HH	24	1995
ALOS PALSAR	L	10-100	HH, HV, VH, VV	46	2006
COSMO-SkyMed	X	1-100	HH, HV, VH, VV	16	2007
TanDEM-X	X	0.25-40	HH, HV, VH, VV	11	2010
Kompsat-5	X	0.85-20	HH, HV, VH, VV	28	2013
ALOS-2 PALSAR-2	L	1-100	HH, HV, VH, VV	14	2014
GF-3	C	1-500	HH, HV, VH, VV	29	2016
PAZ	X	1-6	HH, HV, VH, VV	11	2018
SAOCOM-1A/B	L	10-100	HH, HV, VH, VV	8	2018
GF-3 02	C	1-100	HH, HV, VH, VV	12	2021

Note: The radar data listed above the dashed line in the table are commonly used for crop extraction or flowering period observation based on literature statistics, while those below the dashed line are other mainstream radar data. The "*" symbol indicates radar data that has been applied in the literature for mass-flowering crops extraction.

data can also be used to identify crop flowering periods. For example, a cutting-edge crop growth estimator was created by integrating RADARSAT-2, TerraSAR-X, and an innovative dynamic filtering framework. It can determine the flowering date of rapeseed with high accuracy [75]. These studies demonstrate that radar data perform exceptionally well in the classification of mass-flowering crops (with OAs ranging from 83% to 96%) and in the identification of flowering stages, facilitating precise differentiation of crop types and recognition of critical growth stages.

The processing of radar data is complex, which includes a substantial volume of data, and the interpretation of images requires specialized expertise. Furthermore, during the acquisition process, radar data may be influenced by noise interference, impacting both image quality and accuracy (Table III) [76]. In addition, radar is insensitive to color changes, making it difficult to directly utilize color signals to identify the flowering period. It typically requires the indirect assessment of flowering features through changes in canopy structure, which increases the complexity of recognition. Therefore, integrating optical data with their spectral advantages for multisource data fusion can compensate for the limitations of radar data, providing an effective means to further enhance the accuracy of crop extraction and improve the timeliness and stability of flowering period identification.

B. UAVs RS Data

Although satellite RS is effective for extensive monitoring, its limitations, including poor mobility, significant initial expenses, and prolonged construction timelines, hinder its flexibility in studies of mass-flowering crops [77]. In contrast, UAVs offer the advantages of low cost and flexible deployment, allowing flight plans to be tailored to different flowering stages, thereby enhancing the timeliness of observations. Meanwhile, the ultrahigh-resolution imagery acquired by UAVs can capture richer geometric structures, textural features, and spatial details (Table III) [78], making UAVs particularly suitable for fine-scale monitoring of flowering stages in localized areas of mass-flowering crops, such as assessing flowering proportions and changes in canopy structure. Furthermore, UAVs can be equipped with multiple types of sensors, and by integrating multisource data, they can effectively overcome the limitations of single-source observations, thereby improving the accuracy of crop identification [80], [81], [82].

UAVs are showing exceptional capabilities in the application of RS technology, particularly in crop extraction, health monitoring, and growth stage identification. For example, Information about lodging in sunflowers can be obtained by analyzing multispectral data collected by UAVs and using advanced deep-learning algorithms. The accuracy of this method surpasses that of the RF algorithm. Quickly and accurately identifying sunflower lodging is of great significance for assessing damage to sunflower crops [30]. Applying image fusion and deep semantic segmentation to UAV images can accurately identify sunflower lodging information, and the accuracy is higher than SVMs [82]. In addition, the growth phase of sunflowers can be identified in UAVs multispectral images using an improved deep-learning algorithm [83]. The studies presented indicate that combining DL with UAV RS offers broad prospective uses in sunflower research, delivering enhanced accuracy and advanced technological support for precision agriculture [84]. UAV RS encounters constraints related to flight altitude and endurance, which complicates large-scale, long-duration monitoring efforts [85]. Furthermore, its performance is extensively influenced by weather conditions, and it may experience operational issues during strong winds, rain, or other adverse weather scenarios. Additionally, the substantial workload associated with data processing and analysis elevates both technological and computational expenses (Table III). Advances in battery technology and enhancements in data processing capabilities are gradually tackling these challenges.

C. Data Fusion for Crop Extraction

Various data sources possess distinct advantages and limitations regarding spatial, spectral, and temporal resolution. Relying on a single data source is frequently inadequate for a thorough and accurate representation of surface information. In practical applications, it is often essential to conduct data fusion from various sources to maximize the benefits of diverse RS data, tackle the limitations of individual data sources, and deliver more precise RS information support, thereby enhancing the reliability and precision of crop information extraction. Over the past few years, numerous experts have provided definitions for the concept of "RS data fusion" [86], [87]. The term "data fusion" in RS has multiple variants, such as image fusion [88], multisensor fusion [89], and RS image fusion [90]. There are three main categories for multisource data fusion methods: pixel-level fusion, feature-level fusion, and decision or symbol-level fusion. In recent years, scholars have conducted extensive research and experiments on methods for multisource data fusion. The research methods mainly include Principal Component Analysis, Intensity, Hue and Saturation, Discrete Wavelet Transform, Brovey Transform, High-pass Filter, Maximum Separability, and Minimum Dependency, among others [47].

In crop extraction research, the fusion of optical and radar data has become a common technical approach [47], [87], [91]. Optical data provide high spatial resolution and detailed spectral information, effectively representing crop spectral characteristics; however, they are significantly affected by clouds, rain, and lighting conditions. Radar data offer several advantages, including the ability to operate in all weather conditions and the use of multipolarization, which enhances its sensitivity to changes in crop growth. However, it does not provide intuitive spectral information. The integration of these two data types can yield more thorough and dependable RS information for accurate crop identification. The data from the Sentinel series, specifically Sentinel-1 (radar data) and Sentinel-2 (optical data) time series, were utilized to classify rapeseed and wheat and determine their phenological stages. The results showed that the classification accuracy obtained by combining the two types of data was higher than that obtained by using either one alone. In addition, the use of both data types can enhance the identification of the phenological stages of wheat and the flowering and maturity periods of rapeseed [92]. In addition, the combination of other types of optical and SAR data can also achieve high-precision identification results of the distribution and flowering period of rapeseed [7], [93], [94]. Data fusion also plays a crucial role in sunflower classification research. For example, by incorporating SAR information into the sunflower classification process, the accuracy of classifying sunflowers can be enhanced, enabling more precise identification of their growth stages [95], [96], [97]. Similarly, HH polarization information has more accurate identification results for dense sunflower canopies than ratio or cross-polarization images [98]. The studies presented indicate that data fusion effectively utilizes the complementary strengths and synergies of various data sources, leading to a notable enhancement in the quality and accuracy of RS data, which in turn improves the precision of crop identification. This not only expands the breadth and depth of RS technology applications in agriculture but also provides more reliable technological support for precision agriculture. In practical applications, it is essential to take into account factors like data fusion methods, data quality, and fusion objectives to guarantee the reliability and effectiveness of the fusion results.

Based on the existing literature, the classification of mass-flowering crops and the identification of their flowering stages have utilized RS data from a variety of satellite and UAV platforms, among which multispectral and radar sensors based on satellite platforms are the most widely applied. Multispectral data offer advantages such as high spatial resolution, abundant spectral information, and intuitive image visualization, while radar data, with their all-weather observation capability, demonstrate unique application advantages in cloudy and rainy regions. When deployed on satellite platforms, both types of sensors enable large-scale crop monitoring. According to the statistical results (Figs. 8 and 9), representative sensors include Sentinel-2, Sentinel-1, and Landsat-8. Although the reviewed literature does not involve hyperspectral data, its potential in the study of mass-flowering crops should not be overlooked. Compared with satellite data, UAV-based RS has been more widely applied for the fine-scale monitoring of mass-flowering crops, effectively addressing the limitations of satellite data in terms of spatial resolution and local detail extraction. In summary, various RS data sources each have distinct advantages and can complement one another in practical applications. Therefore, in practice, the selection of data sources should comprehensively consider factors such as research objectives, regional characteristics, and spatiotemporal resolution requirements, in order to avoid affecting the accuracy and quality of classification results due to data-source mismatches.

IV. Features and Methods

A. RS Features

The statistical results from the literature (46 articles in total) show that the commonly used features in crop classification and flowering stage identification research primarily include band features, vegetation index features, texture features, polarization features, and other types of features (Tables V and VI). Among these, vegetation index features are the most widely used, followed by band features, polarization features, and phenological information (Figs. 10 and 11). In the classification of mass-flowering crops, the features used for identifying sunflowers

TABLE V
VARIOUS FEATURES USED FOR CROP CLASSIFICATION

Feature types	Feature
Band features	R, G, B, RE1, RE2, RE3, NIR, Narrow NIR, SWIR1, SWIR2, Water vapour band, Panchromatic, NIRmax
Vegetation index features	NDVI, GNDVI, BNDVI, NDYI, EVI, EVI2, ARI, CCCI, CARI, EAYI, RYI, CI, DYI, VARI, MSAVI, NDVI_max, NDVI_inf, ΔNDVI, PWRI, RRCI, SAVI, OSAVI, SIPI, PSRI, DVI, RVI, NDWI, MNDWI, NDBI, RENDVI, REP, LSWI, NDSVI, NDTI, WRI, GRVI, GCVI, TBVI, TRVI, GLI, NGBDI, EXG, NRFI, CFI, CRI, NRGBI
Texture features	Entropy, Mean, Variance, Contrast, Homogeneity, Angular second moment, Correlation, Dissimilarity
Polarization features	VV, VH, HV, HH, VH_{max}, VH_{cv}
Other features	DEM, Phenological features, HSV transform, J-M distance, RSG-OC

TABLE VI
VARIOUS FEATURES USED FOR FLOWERING STAGE IDENTIFICATION

Feature types	Feature
Band features	R, G, B, NIR
Vegetation index features	NYI, NRFI, NDYI, NDVI, EVI, NDBR, NDMI, LAI, AGB, GNDVI, EVI2, NDRE
Polarization features	VH/VV_{des}, VH/VV_{asc}, VH/VV, VV, VH
Other features	GDD, GLDAS data (DEM, Longitude, Latitude, Meteorological elements, etc.), Rapeseed flowering period data, Phenological features, BBCH, CIred edge

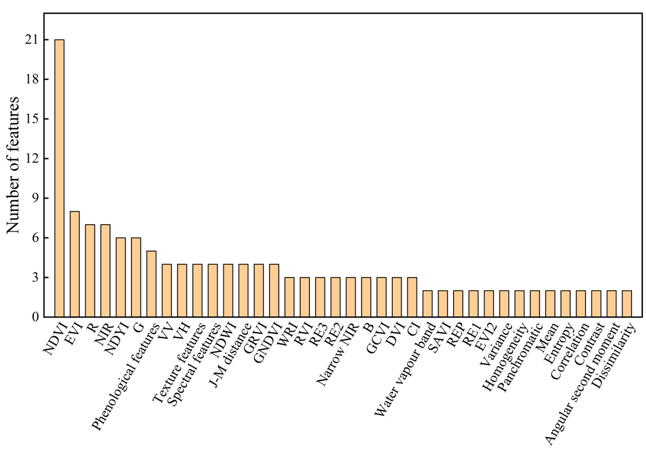

Fig. 10. Frequency statistics of features used in crop classification (frequency ≥ 2).

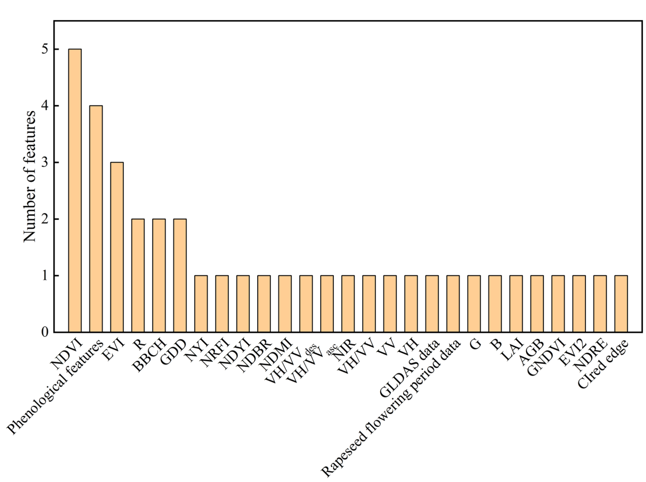

Fig. 11. Frequency statistics of features used in flowering period identification.

mainly include: vegetation index (NDVI), spectral bands (NIR, RE2, RE3, Narrow NIR, R, G), and polarization features (VV) (frequency ≥ 2). The features used for identifying rapeseed mainly include: vegetation index (NDVI, EVI, NDYI, GRVI, GCVI, WRI, CI), spectral bands (R, G, NIR), polarization features (VH), and phenological characteristics (frequency ≥ 2). In the identification of flowering stages for mass-flowering crops, the features that effectively capture the flowering signals of sunflowers include vegetation indices (NDVI, NDBR, NDMI, EVI), polarization features (VH/VV_{des}, VH/VV_{asc}, VH/VV, VV, VH), and phenological characteristics. The features that effectively capture the flowering signals of rapeseed include vegetation indices (NYI, NRFI, NDYI), phenological characteristics, and other auxiliary features (such as GLDAS data, rapeseed flowering stage data, BBCH, and GDD). Overall, vegetation indices demonstrate broad applicability in both the classification and flowering stage identification of mass-flowering crops, serving as the most representative and critical features in current research.

1) Vegetation Index Features: Based on the results earlier, it is evident that among various vegetation indices, NDVI and EVI (Table VII) are the most widely used in current studies on mass-flowering crops. Moreover, existing research has confirmed that these two indices exhibit good applicability in the classification and flowering stage identification of rapeseed and sunflower. For example, using Landsat-8 time-series imagery, the variations in NDVI values across different growth stages of sunflower were analyzed. The results indicated that NDVI had the strongest correlation with the flowering stage of sunflower ($R^2 = 0.966$), demonstrating its high accuracy and significant application potential for flowering stage identification [99]. Furthermore, utilizing the NDVI series data acquired from the HJ-1A/1B images, a fitting technique involving an asymmetric logistic

TABLE VII
VEGETATION INDICES COMMONLY USED FOR CROP CLASSIFICATION AND FLOWERING PERIOD OBSERVATION

Vegetation index	Equation	Reference
NDVI	(NIR-Red)/(NIR+Red)	**[103]**
EVI	2.5[(NIR-Red)/(NIR+6Red-7.5Blue+1)]	**[104]**
NDYI	(Green-Blue)/(Green+Blue)	**[45]**
NRFI	(Red-SWIR2)/(Red+SWIR2)	**[94]**
WRI	[(NIR-Green)/(NIR+Green)]*[Blue/(Green+Red)]	**[42]**
CFI	NDVI*($\text{sum}_{\text{red, green}}$+$\text{diff}_{\text{green, blue}}$)	**[41]**
CRI	Green/Blue	**[46]**
PWRI	RE-GCVI/a	**[64]**
EAYI	($S_{\text{DYI peak}}$/t2-t1)/1−($S_{\text{NDVI valley}}$/t2-t1)	**[105]**
CI	NIR*(Red+Green)	**[106]**
RYI	Green/Blue	**[46]**

curve was employed to analyze the NDVI characteristics and phenological indicators of corn and sunflower. This approach aimed to achieve the most accurate classification outcomes [100]. Research indicates that utilizing the DT classification algorithm, the variance between the NDVI and the green (B) and red (R) bands of TM imagery effectively differentiates between winter wheat and rapeseed. The most effective classification periods are identified as the elongation, flowering, and fruiting stages of rapeseed [101].

It is worth noting that, in addition to commonly used indices (NDVI and EVI), researchers have developed a variety of vegetation indices specifically for rapeseed extraction and flowering stage identification, based on the unique spectral and phenological characteristics of rapeseed. In this study, nine representative rapeseed-specific indices were selected (Table VII), and their application characteristics, advantages, and limitations were briefly summarized as follows. The NDYI, by combining the blue and green spectral bands, effectively compensates for the shortcomings of NDVI during the flowering period, significantly enhances the flowering signal, and enables accurate identification of the rapeseed flowering stage. However, NDYI also misclassifies other crops of the same period (such as winter wheat) as rapeseed, and it is a challenge to distinguish between forest and rapeseed in some areas, and it can only be classified using a narrow date window [20], [41], [64]. An effective method for identifying rapeseed fields is NRFI, which can also be used to detect the flowering date of rapeseed by analyzing the local maxima in the NRFI time series. Based on Landsat 8 data, NRFI performs better than NDYI in identifying the peak flowering date of rapeseed. Studies indicate that NRFI is more precise in detecting rapeseed compared to NDYI, although it is not as accurate as PWRI and WRI [64]. WRI can effectively enhance the separability of rapeseed from other crops, automatically extract rapeseed in cloudless areas, and combine with other methods to further improve the classification accuracy of rapeseed. Even so, WRI may not be the most appropriate choice for regions with intricate land cover types [102], and certain findings suggest that the classification accuracy of WRI is inferior to that of PWRI. CFI only uses blue, green, red, and near-infrared bands for calculation. It has a high degree of automation, which greatly reduces the dimension and volume of RS data and enhances the image information of rapeseed. However, some studies have shown that there are some omission errors in the classification results of CFI [20]. The sensitivity of CRI to changes in vegetation canopy growth is very high. The relationship between the change in index value and the change in flower density is linear. Additionally, it outperforms NIR/Red in accurately determining the crop's flowering state [46]. PWRI expanded the time window to distinguish between winter rapeseed and winter wheat and showed good separability between the two winter crops during the whole flowering period of winter rapeseed. CI, EAYI, and RYI are constructed based on the spectral characteristics of rapeseed during the flowering period or the key features of the time series of other indexes, and they are widely used in rapeseed-related research.

It should be noted that, based on the statistical analysis of existing literature, no indices have been specifically developed for the extraction of sunflowers or the identification of their flowering periods. Therefore, these topics will not be further discussed in this article.

2) Color Features: In the study of mass-flowering crops, color features serve as intuitive indicators of crop growth status and play a vital role, particularly in identifying the flowering stages of sunflower and rapeseed. As a representative mass-flowering crop, the flowering condition of sunflowers is distinctly observable in RS imagery. According to previous studies, it is known that the Hetao Irrigation District in China is a concentrated planting area for sunflowers [100], [107], with the flowering period and maturity period of sunflowers in mid-to-late August and mid-to-late September, respectively [5], [7]. Sentinel-2 offers a comprehensive range of 13 bands, enabling the capture of extensive and intricate land cover data [108], [109]. Therefore, Sentinel-2 true color images of five periods from July to September 2021 in the Hetao Irrigation District were selected to show the color changes of sunflowers in multiple growth stages (squaring, flowering, and maturity) in RS images. Fig. 12 shows the sunflower's color changes over time. On 30 July, the sunflower appeared dark green, indicating it was in the squaring stage. By 9 August and 19 August, the color shifted from dark green to light green, signaling that the sunflower had entered the flowering stage. On 29 August, the sunflower's color resembled that of 30 July, indicating the end of the flowering period. By 8 September, the sunflower had reached the mature stage, with a generally darker color.

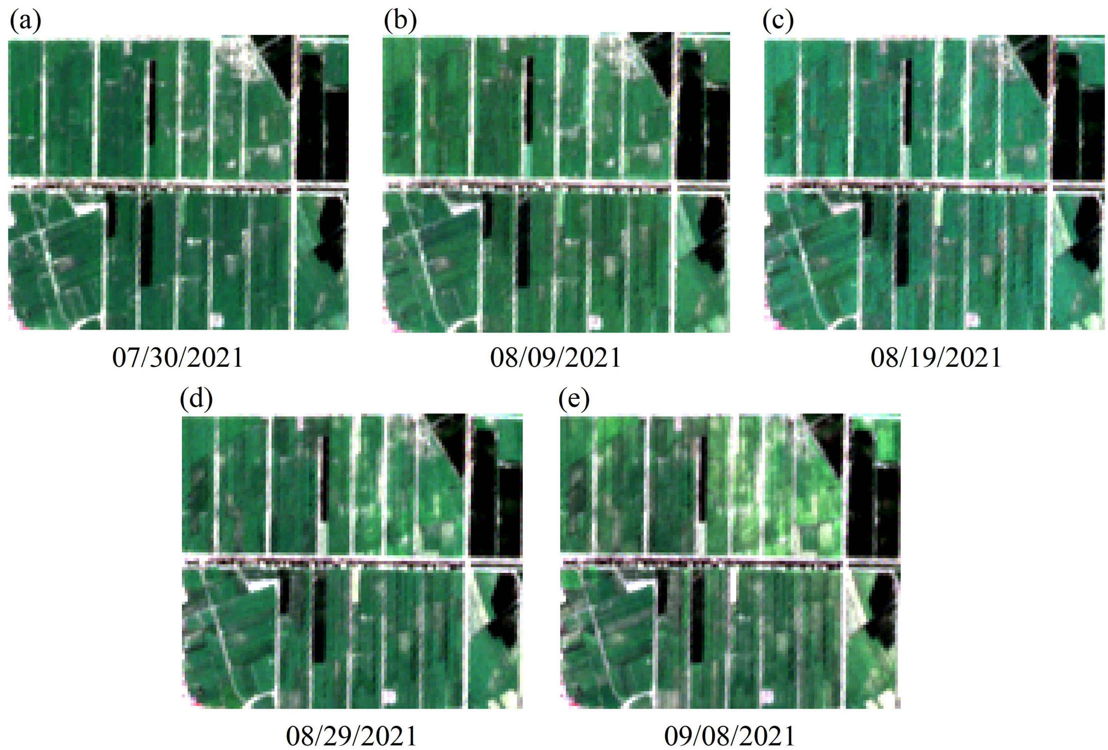

Fig. 12. Sentinel-2 true-color images showing the three growth stages of sunflowers before, during, and after flowering, and the dates they were taken (a)–(e) (images taken in 2021 in the Hetao Irrigation District, China).

The growth status of rapeseed has garnered significant attention as a crucial oil crop worldwide. During the flowering period, rapeseed exhibits unique characteristics that have been extensively studied by researchers to classify rapeseed. According to relevant research results, it can be seen that the Jianghan Plain in China is one of the main rapeseed planting areas, and the flowering and maturing periods of rapeseed are in mid-to-late March and late April, respectively, [110]. As a result, we chose Sentinel-2 true color images from February to April 2020 in the Jianghan Plain. These images effectively showcase the color transformations of rapeseed during different growth stages, including bolting, flowering, pod-setting, and seed-growing, in the RS images. The images on 17 February and 22 February belong to the bolting stage of rapeseed. At this time, rapeseed is generally dark green (Fig. 13). At this stage, rapeseed has similar color characteristics to other vegetation, making it difficult to distinguish. As of March 18, rapeseed has entered the flowering stage. One can observe a noticeable change in the color of the rapeseed, transitioning from its previous stage to a vibrant shade of bright yellow and yellow-green. This stage is also the optimal time window for distinguishing rapeseed from other vegetation [64], [105]. On 7 April and 12 April, rapeseed has entered the pod-setting and seed-growing stages. The color of the rapeseed in the image has changed to bright green, indicating that the flowering period of rapeseed has ended. It should be pointed out that the color variations mentioned in this article are intended solely to assist researchers in identifying the flowering stages of sunflower and rapeseed, and are not discussed as classification features.

B. Classification Methods

According to the reviewed literature (a total of 46 studies), commonly used methods for crop classification and flowering stage identification include supervised and unsupervised classification, ML, DL, threshold-based methods, as well as researcher-defined approaches (e.g., SARM, APPA) (Table VIII). Focusing on mass-flowering crops such as rapeseed and sunflower, Fig. 14 shows that the most frequently used classification methods include ML (RF, SVM, DT), threshold-based approaches, DL, and both supervised and unsupervised classification methods (IsoData, Maximum Likelihood), all of which generally achieve high average OA. It should be noted that, due to the limited number of studies specifically targeting flowering stage identification in mass-flowering crops and the lack of a unified accuracy assessment standard, this article does not provide a systematic statistical analysis of the related accuracy results.

1) Traditional Supervised and Unsupervised Classification Methods: Supervised and unsupervised classification methods are among the earliest approaches applied in RS-based crop classification. Owing to their well-established theoretical foundations and ease of implementation, they are still widely used in the identification of mass-flowering crops. Among them, the Maximum Likelihood Classification (MLC), a representative supervised method, integrates Bayesian theory with prior knowledge and has demonstrated good applicability in the classification of rapeseed and sunflower [106]. For example, using RapidEye and multitemporal Sentinel-1 data, the performance

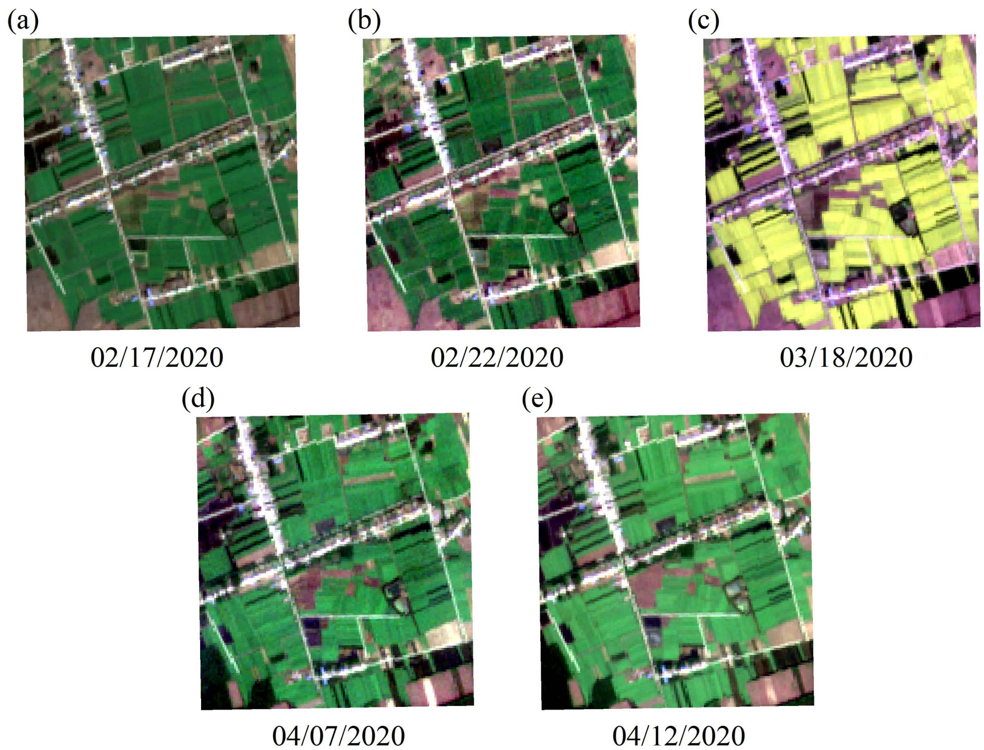

Fig. 13. Sentinel-2 true-color images of rapeseed at multiple growth stages and the dates they were taken (a)–(e) (images taken in 2020 on the Jianghan Plain, China).

TABLE VIII
COMMONLY USED METHODS FOR CROP CLASSIFICATION AND FLOWERING STAGE IDENTIFICATION

Application	Methods
Crop classification	IsoData, Mahalanobis distance, Maximum likelihood, Threshold method, Decision tree, Random forest, Support vector machines, Deep learning, SARM, APPA, Phenology and pixel algorithm
Flowering period identification	Threshold method, Random forest, Deep learning, Crop growth stage estimator, CIred edge time curve

of SVM and MLC was compared in rapeseed extraction. Results showed that after integrating multisource data, the OA of MLC improved to 83.04%. Although its accuracy was slightly lower than that of SVM, MLC produced smoother and more stable classification results [111]. Other studies have also indicated that while MLC performs well with multispectral data and achieves relatively high classification accuracy, its performance is less satisfactory when applied to hyperspectral data [112]. In parallel with supervised classification, unsupervised classification methods are also applied in the classification of mass-flowering crops. For example, based on multitemporal Landsat TM images, the flowering period of rapeseed was selected as the optimal classification period, and various classification methods were compared. The results indicated that the IsoData method, combined with manual visual correction, could achieve better rapeseed extraction accuracy than supervised classification methods under complex surface conditions, demonstrating good potential for application [113]. In summary, both supervised and unsupervised classification methods have their respective advantages and limitations in the classification of mass-flowering crops, as outlined later. Supervised classification methods exhibit distinct category divisions, indicate adaptability to diverse classification requirements, and thoroughly consider the covariance and feature correlations among bands. Nevertheless, these approaches show higher computational complexity and are significantly reliant on high-quality training data. In contrast, unsupervised classification methods operate without the need for training samples, enabling automatic classification and minimizing the necessity for human intervention. The classification results are significantly affected by parameter settings, and there may be uncertainty in category divisions (Table IX). In practical applications, it is essential to carefully choose classification methods that align with the data characteristics and classification needs.

2) Machine Learning: Researchers have proposed various ML algorithms, including SVM, DT, and RF, to improve classification accuracy and analyze crop information in RS images. Algorithms in ML are appropriate for situations involving small datasets, constrained computational resources, and significant prior knowledge. Their high interpretability allows for efficient management of nonlinear problems and high-dimensional data

TABLE IX
COMMONLY USED SUPERVISED AND UNSUPERVISED CLASSIFICATION METHODS

Method category	Method name	Advantages	Limitations
Supervised classification	Maximum likelihood	The covariance between bands and the probability that unknown pixels belong to different categories are taken into account.	Need to set parameters manually, higher computational complexity, slower classification speed.
	Parallel hexahedron	The variance between different categories is considered.	When there are multiple categories, the feature spaces of these categories often overlap.
	Minimum distance	Simple calculation, not limited by data dimensions, is suitable for a variety of classification requirements.	Without considering the internal differences between categories, there is a risk of boundaries overlapping.
	Mahalanobis distance	Considering the correlation between features, it is suitable for processing data with related features.	Vulnerable to the instability of covariance matrix.
Unsupervised classification	K-means	Fast, efficient, simple and intuitive, insensitive to outliers and noise.	The selection of initial clustering centers is often done randomly, which can lead to poor performance when dealing with large datasets.
	IsoData	Less human intervention, high classification accuracy, suitable for dynamic clustering.	It is difficult to grasp the number of iterations; it is difficult to determine the priority parameters.

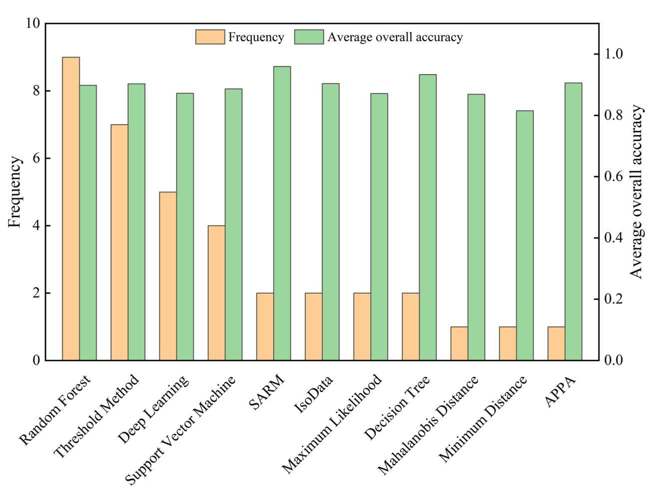

Fig. 14. Frequency of use and average OA of common classification methods for mass-flowering crops.

(Table X), which helps with their widespread application in crop recognition research. For example, the CFI was constructed using Sentinel-2 imagery during the rapeseed flowering period, and the IsoData, SVM, and RF methods were used to classify the Sentinel-2 raw images and CFI images. The results showed that the classification accuracy of the CFI images was higher than that of the raw images. In comparison to other rapeseed indices, the classification accuracy of rapeseed was enhanced by the DT model utilizing the CFI images [41]. In the study of sunflower classification, high-accuracy classification results were achieved for sunflowers in the Hetao Irrigation District using a method that integrates a parameterized phenology-based vegetation indexes classifier with SVM and RF [107]. A study was conducted to compare and analyze different methods for classifying crops. The results showed that SVM and RF had similar usage frequencies, but SVM was found to be significantly more effective as a classification method compared to RF [48]. The studies and statistical results presented indicate that ML algorithms exhibit consistent and outstanding results in the extraction of mass-flowering crops. Image data can be utilized effectively to identify target crops among various crop types, achieving higher classification accuracy than traditional supervised and unsupervised classification methods (e.g., Maximum Likelihood, IsoData) (Fig. 14).

In practical applications, ML often comes across issues with overfitting and struggles to manage missing data (Table X). The processes of feature selection and hyperparameter tuning are intricate, leading to increased computational costs and potentially prolonging model training time [114]. In agricultural areas characterized by diverse crop types, the presence of crops showing similar spectral characteristics complicates the ability of a singular classification approach for precise identification of the intended crops. Consequently, utilizing a combination of two or more methods is frequently employed to enhance the precision of crop information extraction.

3) Deep Learning: As satellite RS technology continues to advance, there has been increasing interest in refining the classification of medium-high resolution images within the RS field. Against the background of increasingly rich programming languages and the continuous development of AI, DL algorithms are born at the right moment, and the types of algorithms have increased unprecedentedly. As per Chollet's

TABLE X
COMMONLY USED ML AND DL [48], [114], [122]

Method category	Method name	Advantages	Limitations
Machine learning	Decision tree	•Can be constructed by directly checking the variables. •It is more convenient than RF in result classification and sample training.	•It is difficult to deal with missing data. •Prone to overfitting problems and ignoring inter-correlations of attributes in the dataset.
	Support vector machin	•Able to solve machine learning problems with small samples. •Proportionately greater than RF as the highest accuracy method for crop classification.	•Model training is long and difficult. •The optimal parameters of the classifier are difficult to obtain and are not suitable for large-scale data training.
	Random forest	•Capable of handling non-linear problems, high latitude data and stable classification results.	•The process of building the model is very time-consuming. •It is difficult to find the best feature selection and optimal segmentation point of the sample.
Deep learning	U-Net	•It can reflect real surface object information and reduce misclassification. •It performs better in areas with complex cropping structures or fragmented farmland.	•The model requires a large number of calculations, which can lead to long training times. •The model requires a large number of calculations, which can lead to long training times.
	CNN	•Have the ability to perform automatic feature extraction and non-linear fitting. •Powerful nonlinear fitting capabilities.	•Requires a large amount of data for training and is computationally expensive. •The types of hyperparameters are various and vary from model to model.
	RNN	•Have a strong ability to learn. •Time-series data is supported, and internal memory is used for storing information and data.	•Vanishing and exploding gradients are one of its serious faults. •A large dataset is required. The training process is difficult to run in parallel.
	DNN	•There are many hierarchical structures and complex non-linear relationships. •Ability to perform transfer learning. It has a wide range of uses and high classification accuracy.	•There is a gradient vanishing and/or explosion. •The model needs to be trained with a large amount of data when running. Training and testing are expensive.

explanation, the concept of "depth" in "DL" pertains to the continuous representation layer, which is also referred to as the model's depth [115]. DL algorithms mainly include CNN, recurrent neural network (RNN), fuzzy neural network, U-Net, U-Net++, Deeplabv series algorithms, SegFormer, and other algorithms [116], [117], [118], [119]. These algorithms exhibit powerful automatic feature extraction capabilities and are well-suited for transfer learning [120], [121]. They indicate known effectiveness in handling large and intricate RS data, and they are capable of modeling complex nonlinear relationships (Table X). As a result, they have shown outstanding performance in tasks such as RS image classification, object detection, and change detection [122]. When examining sunflower classification, it was found that the U-Net algorithm outperformed other DL algorithms (U-Net++, Deeplabv3+, and SegFormer) in terms of classification accuracy for sunflower and other crops in the Hetao Irrigation District [123]. Similarly, using Sentinel-2 as the data source, after comparing multiple DL algorithms, it was found that the U-Net algorithm had the best recognition accuracy for crops such as corn, sunflowers, and pumpkins in the Hetao Irrigation District, and the earliest time window for identifying sunflowers was early July [124]. Additionally, a study integrated DL algorithms (Conv1D and LSTM) with time-series Sentinel-2 data to enable early crop identification in the Shiyang River Basin, comparing their performance with RF and SVM. The results demonstrated that the Conv1D algorithm achieved the highest accuracy when utilizing Sentinel-2 data at a 5-day interval, enabling the identification of sunflowers as early as the flowering stage [125]. DL can be used to accurately classify different types of crops, including rapeseed [126]. In conclusion, DL reveals the capacity to accurately identify sunflower and rapeseed in regions characterized by complex crop planting structures or fragmented plots, exemplified by the Hetao Irrigation District. Despite the various challenges encountered in DL, including complex model design, long computation times, the large amount of labeled data necessary for training, and elevated computational expenses relative to conventional ML techniques [122], its exceptional performance in complex agricultural domains continues to position it as an essential approach for extensive (national or continental-scale) detailed crop classification utilizing medium to high-resolution imagery in the future.

In summary, the selection of features and methods should comprehensively account for crop characteristics, data availability, environmental conditions, research objectives, as well as the applicability and generalization capability of the model. Classification features include spectral characteristics, such as vegetation indices and spectral bands, which are effective for differentiating crops from noncrops. These features enhance the spectral differences between target crops and other crops, and they also aid in identifying flowering periods. Among these, NDVI and EVI are the most commonly used vegetation indices in studies of mass-flowering crops. Additionally, researchers have developed various indices for rapeseed extraction or flowering period identification, such as NRFI, WRI, CFI, and PWRI. Texture and color features can effectively complement spectral characteristics, assisting in the differentiation of crops that exhibit similar spectral properties, especially during the flowering stage. Phenological features, such as peak flowering time and maturity stage, serve as important criteria for determining the ideal identification window. This approach aids in minimizing data volume while simultaneously improving both classification efficiency and accuracy. The polarization characteristics of radar can provide stable information support under overcast or rainy conditions, and can also provide more information for flowering period identification studies and crops that are difficult to distinguish using spectral features alone. ML methods are particularly effective for research scenarios involving small-scale datasets and constrained computational resources. They demonstrate superior classification performance compared to traditional supervised and unsupervised classification methods. DL methods (such as CNN, U-Net, and Transformer) demonstrate superior performance in processing large-scale and multimodal RS data. Furthermore, satisfactory classification outcomes can be achieved in areas defined by complex crop planting arrangements or distributed agricultural land. In practical applications, it is essential to select features and methods that align with the research objectives, while also optimizing data processing workflows to improve the accuracy of crop identification.

V. Outlook

A. Data Source Selection for Crop Classification

It is important to have a diverse range of data sources when extracting crop information using RS technology, particularly when considering data source selection. Currently, most research still relies on single data sources or single-temporal RS data for crop classification. However, single-temporal data are difficult to apply in areas with complex planting structures, and the use of a single data source makes it difficult to reflect rich feature information and obtain high-precision classification results. When choosing data sources, it is crucial to thoroughly evaluate factors including the scale of the research, the objectives of the study, the specific characteristics of the study area (such as crop types, growth cycles, and climatic conditions), and the costs associated with data acquisition (which encompasses both freely available and commercial data). This careful consideration is necessary to ensure the selection of the most appropriate RS data. Fusion of RS data from different sensors, spatial resolution, temporal resolution, and spectral resolution can improve the data's ability to obtain characteristic differences between crops and enhance the accuracy of crop classification. This represents a fundamental strategy for enhancing the selection of data sources. Utilizing a combination of radar data and multispectral data is a common practice in the field of crop classification. Among them, the combination of Landsat and radar data is the most representative. Following the launch of Sentinel-1 (SAR) in 2015, there has been a notable increase in research focused on its integration with multispectral data, such as Sentinel-2. This fusion has demonstrated considerable application potential, especially in the areas of mass-flowering crop classification and the identification of flowering periods. Advancements in RS technology are anticipated to enhance the accuracy of crop classification by exploring the integration of various types of RS data in the future. The use of UAV RS is expanding significantly and has shown promise in the classification of crops. However, limitations such as flight endurance and altitude restrict UAVs to small-scale precision agriculture studies, presenting challenges for large-scale crop classification. As UAV technology advances, the utilization of UAV data for extensive precision agriculture research is anticipated to emerge as a significant area of focus.

B. Spatial and Temporal Data Fusion of RS Data

The flowering period plays an extremely important part during the entire growth stage of crops. The fusion of radar and optical data from multiple sources can provide an estimation of the peak flowering period or the approximate time range when crops start to flower. However, it cannot precisely determine the exact start and end times of flowering [44], [94]. The fundamental reason is that time-series data cannot completely cover the crop flowering period. Spatiotemporal data fusion has the dual advantages of high temporal resolution and high spatial resolution, which can effectively solve the problem of insufficient data caused by single-sensor or multisource data fusion. This can provide sufficient time series data for monitoring crop growth status and flowering period identification. Over the past few years, numerous researchers have made significant advancements in the field of spatiotemporal data fusion. Several methods, including STARFM, FSDAF, SPSTFM, cuFSDAF, RFSDAF, and Unified fusion have been developed [127], [128], [129]. These methods each have their advantages, but when using them, attention needs to be paid to factors such as the types of fused data, characteristics of the study area, and the flowering period of crops to obtain comprehensive time series data. The spatiotemporal data fusion methods of RS data such as MODIS and Landsat, MODIS, and Sentinel-2 are relatively mature and are widely used in crop flowering period and crop growth status identification. However, the capabilities of computers impose restrictions on the extent of research that can be conducted. Addressing the issue of supplementing missing images in crop flowering period identification on large areas through the application of spatiotemporal data fusion algorithms is a pressing concern for the future.

C. Obtaining Sampling Points for Crop Classification

Sampling points from crops can be utilized in the classification process for both training and verification purposes. Nevertheless, conducting extensive field surveys requires significant time and financial resources, and relies heavily on government or relevant organizational assistance. Currently, research plans to obtain long-term field sampling point data include European Union Land Use and Coverage Area Frame Survey data, CropScape-cropland data layer from the United States Department of Agriculture, etc. These research plans save researchers the cost of obtaining sample points. Sampling point data can be obtained by analyzing the characteristics of the crop flowering period. For example, rapeseed has a distinct color characteristic during the flowering stage, flowers are yellow–green. Based on the high-resolution image resources of cloud platforms such as GEE and AI Earth, the color characteristics of rapeseed can be combined with multiple vegetation indices that are sensitive to the flowering period of rapeseed, and the sampling points can be marked on the cloud platform. This method has been shown to yield more precise annotation outcomes [20]. Some studies use high-resolution images to replace or supplement field survey data based on prior knowledge, but the limited coverage of high-resolution images restricts the application scope of this method [130], [131]. Furthermore, survey data can be acquired through crowdsourcing activities. For example, the crowdsourcing activity initiated by Geo-Wiki has demonstrated its great potential in field survey data acquisition. Additionally, there has been research conducted on global reference datasets related to farmland and efforts to enhance the accuracy of Earth source data [132], [133]. Sample migration is a newly emerging method for obtaining sample points. Researchers have proposed a method for migrating training samples by exploiting the similarity of spectral feature profiles of historical samples and have found that crop classification accuracy is proportional to the number of input migration samples [134]. Researchers have devised a method for automatically migrating training samples by evaluating the similarity and distance between reference and image spectra. This approach enables the successful completion of sample migration [135]. Both studies obtained high-precision results using sample migration results for classification. Sample migration has also been widely used in noncrop classification [136], [137], [138].

D. Global Multicrop Classification Dataset Requirement

Over the past few years, there has been a significant increase in the production of datasets related to crop RS classification. For example, datasets related to rapeseed [39], [139]; and datasets related to grain crops such as rice, corn, and wheat [140], [141]. According to the authors' knowledge, there is a scarcity of extensive classification datasets available for sunflowers. Therefore, the creation of such datasets is a key research direction for oil crops and mass-flowering crops in the future. On a global scale, the latest datasets have not been produced, which hinders the formulation and implementation of agricultural policies. Global-scale crop classification datasets are updated at a slow pace due to the multitude of crop types and the high similarity in classification characteristics among various crops. It is difficult to use simple characteristics to establish classification standards for crop classification. Factors such as the phenological period and key characteristics of the growth process can be influenced by various factors, including rotation, intercropping, planting management technology, crop varieties, and climatic conditions. This negatively impacts the precision and effectiveness of creating crop classification datasets on a global level. DL algorithms perform well in crop classification in areas with complex planting structures, but the scale of training samples limits the scope of research. To solve the abovementioned problems, crop sampling point data can be shared through cooperation among various agricultural organizations, and the update of global crop sampling point data can be accelerated. Simultaneously, the DL algorithm undergoes updates to enhance the accuracy and efficiency of the classification method. Therefore, multisource data fusion and spatio-temporal data fusion methods are used to provide high-quality data sources. By utilizing a vast amount of crop sampling point data, incorporating various classification characteristics of crops, and leveraging advanced DL algorithms, it is possible to efficiently generate multiple crop classification datasets on a global scale.

E. Future Development Ideas for Mass-Flowering Crops Extraction

This article provides a brief introduction and future vision for the development of mass-flowering crop extraction. It discusses three key aspects: data sources, information extraction and training samples, and classification methods (Fig. 15). The increasing diversity of RS data and supplementary data enables a more comprehensive depiction of ground features, which in turn improves the stability and precision of crop classification. Utilizing feature selection algorithms on a range of features—including band information, vegetation indices, phenological features, and texture features—enables the identification of an optimal feature set for differentiating between various crop types. Sample data of high quality are essential to improve classification accuracy. Their acquisition must align with research objectives and follow principles of efficiency, cost-effectiveness, and high quality to guarantee data authenticity and usability. Enhancing existing classification methods and innovating new approaches are both critical strategies for increasing the accuracy and quality of crop classification. RS classification using Transformer leverages the self-attention mechanism to extract deep features from RS images. This approach addresses the limitations of traditional methods that depend heavily on manual features and face challenges in modeling complex nonlinear relationships. This method enhances the ability of the classification to generalize effectively [142], [143]. Meanwhile, the fusion of multimodal data features (such as spectral features, polarization features, texture features, and phenological features) can comprehensively utilize the advantages of different feature types, enhancing the accuracy and stability of crop identification in complex environments. Moreover, it improves the separability of different crop categories [144]. In the future, the integration of techniques like self-supervised learning and few-sample learning has the

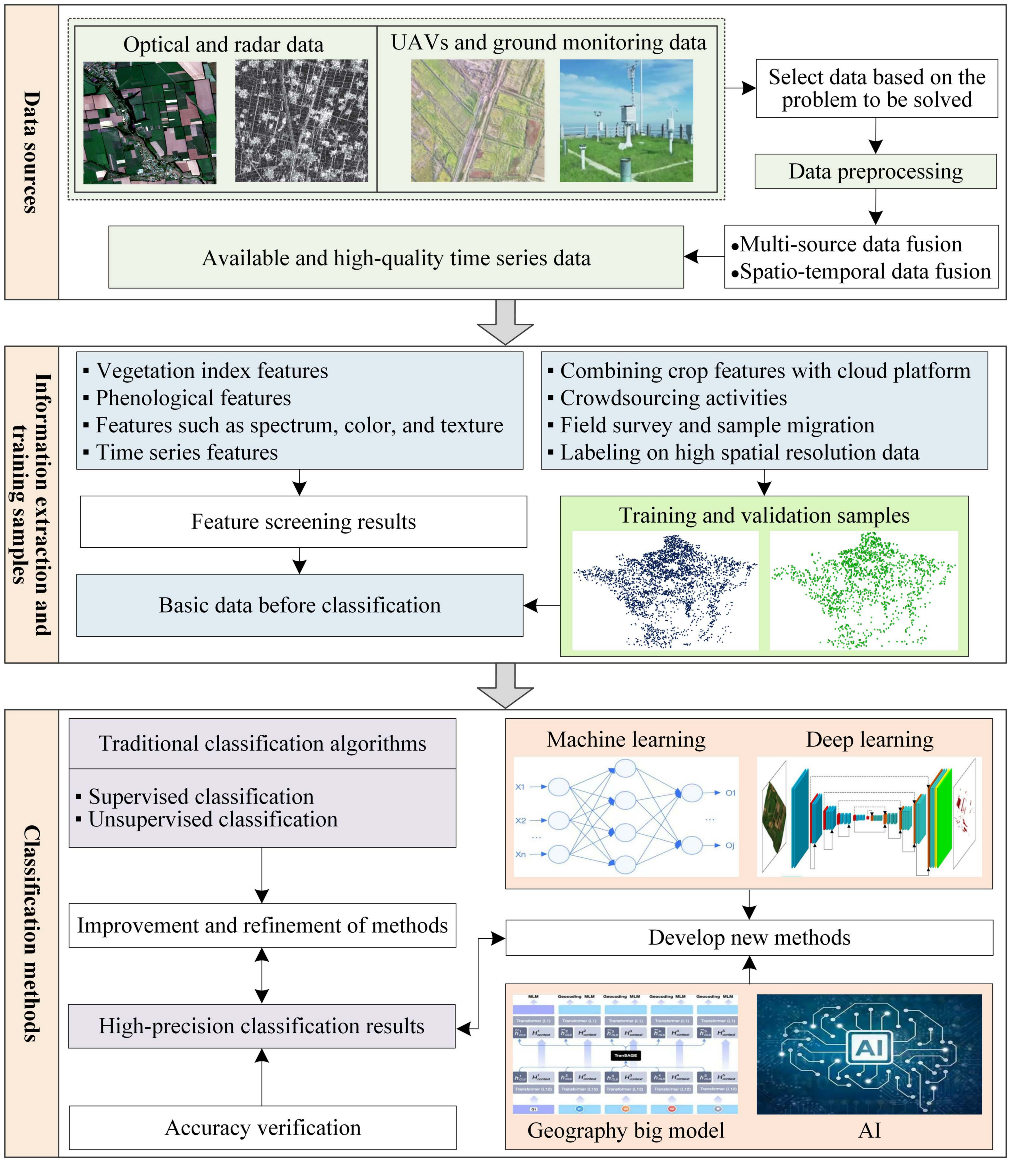

Fig. 15. Map of the future development direction of mass-flowering crops.

potential to decrease labeling costs and enhance model adaptability, thereby increasing the efficiency and accuracy of crop classification.

VI. Conclusion

RS plays an essential part in revolutionizing the agricultural development model. The main focus of agricultural RS research is to accurately determine the spatial distribution of crops. This article provides an overview of the research advancements in extracting RS information from mass-flowering crops (rapeseed and sunflower). After analyzing the filtered results of the articles, it was found that China, the United States, and Ukraine are the main research areas in this field, with articles focusing on rapeseed and sunflower accounting for 50% (23/46) and 19.57% (9/46), respectively. China, Russia, Ukraine, and several countries in Western Europe are significant regions for cultivating rapeseed and sunflower crops. RS data used for the study of mass-flowering crops primarily originates from satellite sensors (including multispectral and radar) and UAVs, with each data type offering distinct advantages and limitations. To further improve classification accuracy, this article proposes that multisource data fusion is an effective strategy, as it not only enhances data quality but also compensates for the limitations of individual data sources. In terms of classification features, vegetation index features are most widely used in mass-flowering crops studies, particularly NDVI and EVI, while other types of features, such as band features, polarization features, and phenological information, also play significant roles. Regarding classification methods, ML outperforms both supervised and unsupervised classification techniques. DL offers substantial advantages for crop classification in areas with complex crop planting structures or fragmented farmland. Furthermore, the selection of features and methods should take into account factors such as crop characteristics, data availability, and research objectives.

This study emphasizes the significance of carefully selecting data sources by taking into account factors such as the scale of the research, the objectives of the study, regional characteristics, and the costs associated with data acquisition. Furthermore, advancements in RS technology are anticipated to enhance the accuracy of crop classification by exploring the integration of various types of RS data in the future. Algorithms that fuse spatiotemporal data can effectively fill in missing images in crop flowering period recognition. However, their application is restricted by the capabilities of the computer. In the future, it will be essential to address the numerous challenges that arise in large-scale applications. Crop sampling point data can be obtained using crop flowering period features and cloud platform imagery resources. Additionally, data can be supplemented or replaced through crowdsourcing activities, sample migration, and annotations using high-resolution imagery. The high similarity of classification features among various crops, along with the complexity of crop growth, planting, and management environments, are major obstacles to the latest global multicrop classification datasets. In years to come, the integration of DL techniques with a large number of crop sampling points and diverse classification features could offer a dependable approach for swiftly generating global crop classification datasets. In addition, improving traditional methods and developing new methods are both beneficial for enhancing the accuracy and quality of crop classification.

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