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A comprehensive review of rice mapping from satellite data: Algorithms, product characteristics and consistency assessment

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ABSTRACT

With a growing global population and intensifying regional conflicts, the need for food is more urgent than ever. Rice, as one of the world's major staple crops especially in Asia, sustains over 50 percent of the global population. Accurate rice mapping is fundamental to ensuring global food security and sustainable agricultural development. Remote sensing has become an essential tool for mapping rice cultivation due to its ability to cover large areas and provide timely observation. Existing reviews mainly focus on the paddy rice mapping methods. However, it lacks a comprehensive understanding on the quality of different paddy rice maps from regional to global scales. This paper provides a comprehensive review of existing satellite-based rice mapping methods and products. Firstly, we categorized all previous methods into four classes: 1) spatial statistical method; 2) traditional machine learning method; 3) phenology-based method; and 4) deep learning method. Secondly, we summarized 25 products, including 3 global products and 22 regional products. Furthermore, we examined the consistency and discrepancy among different products in China, Heilongjiang China and Vietnam respectively and explored the underlying reasons. We found that 1) rice fields with simple cropping patterns and intensive cultivation can be correctly recognized using various algorithms; 2) different products share low consistency in fragmented rice fields 3) the prevalence of clouds and complicated rice cropping patterns or diverse growing environments in subtropical and tropical regions poses challenges to accurate rice mapping. Due to these challenges, currently it still lacks paddy rice maps with both large spatial coverage, high spatial resolution, and long time series. Moreover, deficiency of ground-truth samples impedes product development and validation. For improved paddy rice mapping at large scale, we suggest to apply sample-free rice mapping techniques and remote sensing foundation models to leverage the strengths of phenology-based methods and deep learning methods.

1. Introduction

The United Nations has proposed the Sustainable Development Goals (SDGs), with SDG2 - Zero Hunger Goal outlining the food requirements for the global population. Sustained population growth and intensified regional conflicts have burdened the pressure on food production (Kussul et al., 2023; Lin et al., 2023; Mottaleb et al., 2022), leading to increased attention on food security worldwide. Rice is one of the primary staple crops in the world, especially in Asia, thus providing food for more than 50% of the population (Zhang et al., 2015). Accordingly, accurate rice mapping is fundamental to ensuring global food security and sustainable agricultural development. In addition, rice cultivation mapping can also help solve some environmental, climatic, and health concerns. Firstly, rice requires substantial amounts of water for irrigation during growth, with nearly 30% of the world's exploited freshwater resources used for rice cultivation (Chen et al., 2020). Over-irrigation can lead to a decline in groundwater level (Pradhan et al., 2022), which will pose a significant threat to global water security. In addition, rice cultivation in flooded conditions substantially enhances regional evapotranspiration. However, current evapotranspiration models overlook flooded paddy fields, leading to underestimation of evapotranspiration (Teluguntla et al., 2020; Wei et al., 2023). Accurate paddy rice

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distribution datasets can help improve the estimation of evapotranspiration and irrigation water use. Secondly, unlike other staple crops, rice is cultivated in inundated environments, leading to increased greenhouse gas emissions, particularly methane (Suepa et al., 2013), which has a stronger warming effect than carbon dioxide. The 5th IPCC report estimated that methane emissions from paddy fields account for approximately 12% of anthropogenic emissions (Inoue et al., 2020). Therefore, high-resolution paddy rice map was critical to understanding the contribution of rice paddies to atmospheric methane concentrations (G. Zhang et al., 2020a). Last but not least, inundated paddy fields serve as habitats for migrating waterfowl, which carry viruses such as H7N9 (Zhao et al., 2021b). Thus, rice distribution databases are required to establish spatio-temporal modeling of avian influenza transmission for timely prevention.

Traditional rice mapping is labor-intensive and time-consuming (Abdali et al., 2024; Mosleh et al., 2015). Instead, satellite remote sensing can probably achieve global-scale and long-term continuous paddy rice mapping at a low cost, and is thus adopted by most researchers in recent years. Optical remote sensing has been widely utilized as the primary data source in rice mapping (Fernandez-Urrutia et al., 2023). These sensors offer repetitive observations throughout the rice growing season, capturing essential information on the dynamic changes in rice growth patterns and phenological stages. During the transplanting period, paddy fields are inundated prior to the emergence of crop canopy, making the Land Surface Water Index (LSWI) value greater than Normalized Difference Vegetation Index (NDVI) or Enhanced Vegetation Index (EVI) value, which is different from other staple crops (Xiao et al., 2002). Xiao et al. discovered this characteristic and employed it to successfully extract rice using MODIS data (Xiao et al., 2005, 2006). Due to the complex agricultural landscapes and prevalent fragmentation of fields in the Asia, coarse spatial resolution data tend to overestimate or underestimate crop area, representing a problem in practice (Han et al., 2022a). To obtain a finer spatial distribution of rice, Landsat and Sentinel-2 data are suitable data sources. Especially, Sentinel-2 offers higher spatio-temporal resolution and more spectral bands, making it more applicable to complicated agricultural landscapes compared to Landsat (Dong and Xiao, 2016). Hyperspectral data contain much more spectral channels and have irreplaceable advantages in monitoring the distribution and growth status of rice (You, 2020). Unfortunately, there are still difficulties in obtaining large-scale and long time-series hyperspectral data (You, 2020), hindering its widespread application. Although many studies have reported the excellent performance of optical data in identifying paddy rice, the existence of cloudy and rainy weather inevitably limits the application of optical sensors, particularly those on satellites with longer revisit periods (e.g., Landsat), in tropical and subtropical regions.

The alternative is to use Synthetic Aperture Radar (SAR). SAR is active microwave remote sensing that emits microwave signals that can penetrate clouds and interact with objects. Throughout the rice growth cycle, the SAR backscattering coefficient typically exhibits a V-shaped variation, reflecting the sequential changes in the paddy field surface from bare soil to water-covered conditions and finally to rice crop (Chen et al., 2024). Utilization of this dynamic information is the key to identifying rice from other crops (Kustiyo et al., 2019). In regions with high cloud cover frequency, such as Indonesia and southern China, SAR tends to better extract rice than optical sensors (Kustiyo et al., 2019; Yang et al., 2008). In the early days, the high costs and the relatively long revisit cycles of satellites made SAR datasets challenging to use on a wide scale until the advent of free SAR sensors, such as Sentinel-1 (Pan et al., 2021). The integration of optical and SAR data has further improved rice mapping accuracy, and has therefore gained widespread adoption in recent studies (Asilo et al., 2014; Inoue et al., 2020; Torbick et al., 2011).

At present, remote sensing-based rice mapping has achieved great progress. Various remote sensing rice mapping products have been released to fully explore the potential of remote sensing in rice research. These products serve as essential references for further exploration of rice-climate- environment interactions (Ouyang et al., 2023). To clarify the current status of rice mapping and the potential directions of future efforts, this paper systematically summarizes the rice mapping research from the perspective of rice mapping products. Our analysis of these datasets has revealed gaps in current rice mapping efforts. Firstly, finer-resolution rice mapping products are desired at continental to global scales. Secondly, there is a scarcity of long time-series rice maps for many countries or regions. Thirdly, the consistency among different rice maps exhibits considerable spatial variability. These findings can provide valuable insights for future research in this field. The following parts of this review are divided into five parts. First, we divided the existing remote sensing rice mapping methods into four types and discussed the pros and cons of different algorithms. Next, we collected the existing remote sensing rice mapping products, and illustrated the basic characteristics of these products, including: spatial coverage extent, spatial resolution, temporal coverage and temporal resolution. In the third part, we evaluated the consistency and discrepancy among different paddy rice maps in three representative study areas, China, Heilongjiang and Vietnam. Afterwards, we delved into the complexities associated with the diversity in rice growing environments. By discussing the major challenges in large-scale paddy rice mapping, we proposed some potential methods and techniques. Finally, we summarized the primary conclusions.

2. Rice mapping methodology

Researchers have developed various rice mapping algorithms, which can be categorized into four types based on their differences: (1) spatial statistical method, (2) phenology-based method, (3) traditional machine learning method, and (4) deep learning method. The strengths and weaknesses of these methods are described below.

2.1. Spatial statistical method

Spatial statistical method based on multi-source data is the dominant method for global-scale crop mapping and can be categorized into two types. The first type is the statistics-to-grid strategy, which usually involves collecting various agricultural and socio-economic statistics to construct spatial allocation models. These models are then combined with remote sensing observation data to assign the statistics to a grid, resulting in gridded maps. Spatial Production Allocation Model (SPAM) is a representative method among them (You et al., 2014). Recently, Yu et al. has improved the methodology and updated the SPAM product (SPAM 2010) (Yu et al., 2020). This update primarily focuses on improving the base year, expanding the crop list, and extending the coverage of local administrative units. Similar strategies were employed to develop different spatial allocation models (Frolking et al., 2002; Wang et al., 2022). The second type is the grid-to-grid strategy, which utilizes existing publicly available, high-quality crop distribution maps. Each type of map is assigned a score based on criteria such as timeliness, spatio-temporal coverage, data validation accuracy, and spatial resolution. These maps are then aggregated into grids. The grids are typically large in scale, and for each grid, high-scoring maps are selected and counted as a percentage of the grid. Becker-Reshef used this strategy to harmonize 24 crop products to develop the most up-to-date global distribution map for staple crops (Becker-Reshef et al., 2023). Tang produced the CROPGRID dataset by integrating 27 crop products (Tang et al., 2024).

The main advantage of spatial allocation method based on multi-source data is that it is applicable to global scale mapping while encompassing a wide range of crop types, with rice being one of them. This contributes significantly to large-scale crop growth monitoring. The disadvantages are also quite obvious. Firstly, the method may encounter missing data in areas where there is a lack of statistical data or remote sensing products. Secondly, the spatial resolution of the obtained products is very coarse, and thus the grid only provides information on crop proportion or area, which greatly limits its application in precision agriculture at small scales.

2.2. Phenology-based method

The transplanting and heading periods are recognized as key stages for rice identification and serve as the foundation for phenology-based methods (Du et al., 2022; L. Zhu et al., 2021a). These algorithms leverage the unique physical properties of rice, which can be easily quantified using temporal profiles of spectral indices such as LSWI and NDVI/EVI. This is because rice fields exhibit a distinct mixture of open water and rice plants during the transplanting stage. Xiao was the first to observe the phenomenon that LSWI minus NDVI/EVI is greater than 0 or a very small threshold (e.g., 0.05) during the rice transplantation stage using remote sensing and ground observations (Xiao et al., 2002). Building on this finding, Xiao proposed the original phenology-based method, which provided a simple and effective algorithm for remote sensing rice mapping. Subsequently, the distribution of rice in the southern region of China, South Asia and Southeast Asia was successfully mapped using this approach (Xiao et al., 2005, 2006). However, in temperate or cold temperate regions, the original phenological method faces challenges due to influence of snow or ice cover in winter and snowmelt in spring on LSWI. Zhang improved the original algorithm by determining the time window of rice transplanting using MODIS nighttime land surface temperature (Zhang et al., 2015). This successfully extended the algorithm to both temperate and cold temperate regions, and laid the foundation for large-scale remote sensing rice mapping. When applying the phenology-based method across various study areas, the effectiveness of rice extraction was found to be sensitive to the selection of threshold value (Fan et al., 2023). In order to enhance the applicability of the phenology-based methods to local areas, adaptive threshold corrections have been introduced (Boschetti et al., 2017; Teluguntla et al., 2015; J. Wei et al., 2022a; Xiaochun Zhang et al., 2018c). Qin et al. justified the general applicability of this method when using Landsat data (Qin et al., 2015), thus providing a feasible solution for fine-scale rice mapping. However, the longer revisit frequency of Landsat satellites somewhat constrains the application of phenology-based method which requires frequent observations, especially when it comes to optical data that is sensitive to cloud interference. Therefore, it is suggested to integrate Landsat data with other optical data retrieved from sensors with shorter revisit periods (Yeom et al., 2021; Zhao et al., 2021a).

Time-series SAR signals are not impeded by cloud cover, making them an invaluable resource for monitoring the phenological changes in rice. Before rice planting, the paddy field typically exhibits bare soil conditions, resulting in a high backscatter. During the rice transplanting period, water coverage on paddy field leads to specular reflection of SAR signals, which in turn leads to a significant decrease in the backscattering coefficient. As the rice reached the heading stage, volume scattering gradually substitutes specular reflection, causing the SAR backscatter to increase again. So, rice phenological change usually contributes to a V-shaped signal in the SAR backscatter time series, which can be effectively utilized in paddy rice mapping (Lestari et al., 2021; S. Xu et al., 2023a; Zhan et al., 2021).

In complex cropping systems, various other crops are cultivated together during the rice growing season. These crops exhibit similar phenological dynamics and vegetation cover change characteristics within the same growing season, making it challenging to distinguish rice from other crops using only one phenological property (Liu et al., 2019). Qiu et al. proposed a novel phenology-based approach called Combined Consideration of Vegetation phenology and Surface water variations (CCVS) (Qiu et al., 2015). The CCVS approach is based on the observation that from tillering to heading period, rice experiences less variation in LSWI, while NDVI increases faster compared to other crops. Since this algorithm takes into account the dynamic characteristics of rice growth from tillering to heading stage, it is more robust than the algorithms that rely solely on the transplanting stage (Qiu et al., 2015). But, the applicability of CCVS algorithm in different regions is currently unproven and needs to be further explored.

The phenology-based method utilizes the spectral or radar signal changes of rice at different phenological stages to construct appropriate indicators and decision rules for rapid rice mapping. Its advantages include efficiency, flexibility, fast computation, independence from ground survey data, and simultaneous capture of rice planting intensity. However, it is susceptible to adverse factors such as rainfall, clouds or pseudo-flooding signals due to spring snowmelt (Zhang et al., 2015). In the absence of effective observations at critical phenological phases, the performance of phenology-based method could be significantly degraded. Moreover, it is difficult to determine proper thresholds when constructing decision rules artificially, and the phenological and spatio-temporal heterogeneity of rice limits the performance of the method to some extent. Progress in mitigating the above uncertainties is very slow at present (C. Zhang et al., 2018b).

2.3. Traditional machine learning method

Traditional machine learning approaches have been used in rice mapping research since a long time ago (Fang, 1998; McCloy et al., 1987), including supervised and unsupervised classification. Unsupervised classifiers, such as K-means, Iterative Self-Organizing Data Analysis Techniques Algorithm (ISODATA), Hierarchical Cluster Analysis (HCA), and Time-Weighted Dynamic Time Warping (TWDTW) categorize data within a feature space into distinct clusters using distance or similarity measurement. After the categorization, researchers can use prior knowledge to identify whether a cluster is rice or not. Fatchurrachman utilized the K-means approach to produce a rice product set for Peninsular Malaysia by stacking monthly median VH backscatters and monthly maximum NDVI (Fatchurrachman et al., 2022). Shen and Pan generated high-resolution single- and double-cropped rice maps in China using the TWDTW method, employing time-series Shortwave Infrared (SWIR) band reflectance and VH backscatters, respectively (Pan et al., 2021; Shen et al., 2023). Unsupervised machine learning methods facilitate rice clustering without the need for ground truth samples. However, they are subject to limited accuracy, necessitating manual interpretation of the classification result. Therefore, compared to unsupervised classifiers, supervised classifiers are more extensively utilized in rice mapping. Representative approaches include the Bayesian models, Maximum Likelihood Classifier (MLC), Decision Tree (DT), Support Vector Machine (SVM), Random Forest (RF), and Artificial Neural Network (ANN) (Huang et al., 2023; Namazi et al., 2023; Torbick et al., 2011; Zhang et al., 2009, 2013). Among these, RF is particularly favored (see Table 1) because it is not prone to overfitting and resistant to noisy data (Gao et al., 2023; Gong et al., 2019). RF classifier integrates multiple decision trees trained using a bootstrapping aggregating strategy, where each individual decision tree is trained using a different training subset. The disadvantage of supervised machine learning is that the classification accuracy relies on the availability of ground samples, highlighting the need of adequate group samples. In addition, the classification accuracy usually decreases when multiple crops were planted simultaneously or when both single- and multi-season rice cultivation occurred at the same time (Blickensdörfer et al., 2022).

For traditional machine learning methods, the input features play a crucial role in determining the classification outcomes. Among these features, spectral bands and spectral indices are particularly significant. It is also possible to reduce the classification errors by combining them with topographic, soil, and meteorological variables (Blickensdörfer et al., 2022). Phenology is indeed an effective feature in rice mapping. For example, Ni et al. proposed an enhanced pixel-based phenology feature (EPPF) approach coupled with an SVM classifier to accurately extract rice in Northeastern China (Ni et al., 2021). EPPF enhances the separation between rice and other crops, thereby improving

Table 1
The characteristics of the rice mapping products.

FID	Spatial extent	Spatial Resolution	Temporal coverage	Temporal resolution	Data Source	Mapping Method	Reference
D1	USA	30m	2008–2022	1 year	Landsat, IRS-p6	decision tree	Boryan et al. (2011)
D2	Global	0.05°	2022	1 year	Multisource	spatial statistic	Becker-Reshef et al. (2023)
D3	Global	0.083°	2010	1 year	Multisource	spatial statistic	You et al. (2014)
D4	Global	0.05°	2020	1 year	Multisource	spatial statistic	Tang et al. (2023)
D5	China	500m	2015–2021	1 year	MODIS	phenology-based	Qiu et al. (2022)
D6	China	1000m	2000–2015	1 year	GLASS-LAI	phenology-based	Luo et al. (2020)
D7	Asian monsoon region	500m	2000–2020	1 year	MODIS	phenology-based	Han et al. (2022b)
D8	Northeast China	30m	2019–2021	1 year	Sentinel1	K-RF,U-Net	(Wei et al., 2022a, 2022b)
D9	Northeast China	30m	2013–2021	1 year	Landsat	RF	Xuan et al. (2023)
D10	Heilongjiang	30m	1990–2020	5 year	Landsat	phenology-based,RF	(C. Zhang et al., 2023)
D11	China	10m/20m	2017–2022	1 year	Sentinel1, Sentienl2	TWDTW	Shen et al. (2023)
D12	Northeast China	10m	2017–2019	1 year	Sentinel2	RF	You et al. (2021)
D13	Vietnam	10m	2020	1 year	Sentinel1, Sentinel2, PALSAR	CNN	Hirayama et al. (2022)
D14	Mainland Southeast Asia	20m	2019	1 year	Sentinel1	U-Net	Sun et al. (2023)
D15	Northeast and Southeast Asia	10m	2017–2019	1 year	MODIS, Sentinel1	phenology-based	Han et al. (2021)
FID	Spatial extent	Spatial Resolution	Temporal coverage	Temporal resolution	Data Source	Mapping Method	Reference
D16	Vietnam	30m	1990–2020	1 year	Landsat, Sentinel1,Sentinel2	RF	Duong et al. (2021)
D17	Greater Mekong region	30m	1987–2018	1 year	Landsat, MODIS	RF	Saah et al. (2020)
D18	Japan	10m	2018–2020	3 year	Sentinel2, PALSAR	CNN	Hirayama et al. (2022)
D19	Bangladesh and Northeast India	10m	2017	1 year	Sentinel1	RF	Singha et al. (2019)
D20	Japan	30m	1985–2019	5 year	Landsat	phenology-based	Carrasco et al. (2022)
D21	Metropolitan France	10m	2018–2021	1 year	Landsat, Sentienl2	RF	Inglada et al. (2017)
D22	China	10m	2016–2020	1 year	Sentinel1	TWDTW	Pan et al. (2021)
D23	Peninsular Malaysia	10m	2019–2020	1 year	Sentinel1, Sentienl2	Kmeans	Fatchurrachman et al. (2022)
D24	South Korea	10m	2017–2021	1 year	Sentinel1	RU-Net	Jo et al. (2023)
D25	Central Vietnam	10m	2007、2017	1 year	Landsat, Sentinel2,PALSAR, AVNIR	Bayesian classifier	Duong et al. (2018)

FID: File ID, IRS-p6: Indian Remote Sensing Satellite-p6; PALSAR: Phased Array L-band Synthetic Aperture Radar; MODIS: Moderate Resolution Imaging Spectroradiometer; GLASS-LAI: Global Land Surface Satellite-Leaf Area Index; AVNIR: Advanced Visible and Near-Infrared Radiometer-2; K-RF: Kmeans-Random Forest, RF: Random Forest, CNN: Convolutional Neural Networks, TWDTW: Time-weighted dynamic time warping, RU-Net: Recurrent U-Net.

classification accuracy. In addition, the remaining rice stubble after harvest possesses unique textural characteristics, which can serve as a basis for rice mapping. Incorporation texture features, such as those derived from Gray Level Co-occurrence Matrix (GLCM) analysis, may enhance the accuracy of mapping to a certain extent (Ngo et al., 2020). Unlike dryland crops, flooded rice fields are characterized by distinct boundaries and irregular shapes, a morphological feature that can be effectively utilized in object-based machine learning rice mapping. In addition to the above features, temporal features are also important. Stacking multiple temporal features, like spectral indexes, is a common approach to enrich the feature set, which effectively captures the dynamic changes in the growth stages of rice (Kontgis et al., 2015; Sukmono and Ardiansyah, 2017). An increased number of features does not guarantee improved accuracy. Feature redundancy may reduce models' performance. To mitigate this problem, dimensionality reduction techniques, such as the Principal Component Analysis (PCA), are recommended before model training (Abdali et al., 2024; Sukmono and Ardiansyah, 2017).

2.4. Deep learning method

Deep Neuron Network (DNN) is one of the research hotspots in remote sensing mapping. More and more researchers are delving into the application of DNN models for rice mapping. Compared to traditional machine learning, DNN models automatically learn various features from remote sensing images, eliminating the process of manually designing feature. Convolutional Neural Network excel at extracting spatial context features through multiple convolutional kernels (Zhang et al., 2018a). Semantic segmentation models, such as U-Net, employ a series of convolutional and pooling layers to learn multilevel features from images (Du et al., 2022). Long Short-Term Memory (LSTM) and Bidirectional LSTM (BiLSTM) network have demonstrated superior performance in learning and predicting time series data (Crisóstomo de Castro Filho et al., 2020). In the context of rice mapping, DNN models have consistently achieved high accuracy, often surpassing 90% within localized regions, and have been found to outperform traditional machine learning approaches (Du et al., 2022; Saadat et al., 2022). To fully leverage the spectral, spatial and temporal characteristics inherent in time-series remote sensing imagery, researchers have integrated multiple DNN modules (CNN + LSTM or LSTM + UNet) and achieved higher accuracy (Nguyen et al., 2020; Yang et al., 2022).

Recently, the Vision Transformer (VIT) has drawn significant attention in the field of remote sensing. VITs have presented remarkable capabilities in image processing by employing the self-attention mechanism, which facilitates superior learning of both local and global features. While there have been research endeavors to recognize cropland using VIT (Sheng et al., 2022), its application in rice extraction remains relatively unexplored. In a comparative study, Xu et al. evaluated the performance of U-Net, DeepLab v3 and Swin Transformer in rice recognition in Arkansas, USA. The results revealed that the Swin Transformer achieved an overall accuracy of 95.47%, outperforming U-Net and DeepLab v3 by margins of 6.13% and 4.67%, respectively (Xu et al., 2023a, 2023b). However, the efficiency of VITs in rice mapping at larger scales need to be further explored.

Deep learning methods are highly extensible and can integrate multiple modules to learn a diverse feature, enhancing model representation. Given an ample supply of training samples, deep learning methods can automatically extract features and generally achieve higher accuracy in rice mapping tasks compared to other approaches. However, acquiring a sufficient number of labeled samples is a significant challenge, especially in large scale. The scarcity of labeled samples can lead to model overfitting, which in turn diminishes the model's spatio-temporal generalization capabilities. Furthermore, the complexity of the hyperparameter tuning and the weak interpretability are also problems that need to be overcome.

3. Rice mapping products

Based on the collected literature, we have put together the current publicly available peer-reviewed rice mapping products, as presented in Table 1. Eleven (D1, D2, D3, D4, D12, D13, D16, D17, D18, D21, D25) products are crop classification or land use cover maps with rice being one of the classes, while remaining 14 are specialized datasets focusing solely on rice identification. Here, characteristics of these rice mapping products are summarized in four aspects: spatial coverage, spatial resolution, temporal coverage and data accuracy.

3.1. Spatial coverage

In terms of spatial coverage/study area, 3 coarse resolution products (D2, D3, D4) have global coverage. The Cropland Data Layer (CDL) contains over 100 crop types throughout USA (Boryan et al., 2011). It is highly reliable, thus serving as a benchmark in crop classification. Despite not being a major rice-producing or consuming country, France has added the rice category into its newly-released land cover product, probably because its national agriculture department typically requires national-scale crop cultivation monitoring data to support decision-making on international food trade. The remaining 20 products are all concentrated in Asia, the continent that accounts for 90% of the global rice planting area (Dong and Xiao, 2016; Esfandabadi et al., 2022). Apart from one product which covers the entire Asian monsoon region, China possesses a total of 8 of products, 4 of them cover the whole country whereas the other four involve only northeastern China. Regional-scale products primarily focus on primary rice-growing areas that make significant contributions to rice production (Han et al., 2022a). For example, in northeastern China, there has been a significant expansion in the area under rice cultivation to ensure adequate food supply (Qin et al., 2015; Yin et al., 2019). There are 6 products available in the major rice planting region of Vietnam. Japan has two products, while Bangladesh, Malaysia and Korea have one product. However, some countries in Africa do grow a significant amount of rice, they have not released their own rice maps (Manfron et al., 2020). This could be attributed to various reasons such as limited resources, technological constraints, or a lower attention on remote sensing-based agricultural monitoring.

In general, several countries and regions have at least one available product. Nonetheless, numerous regions with extensive rice cultivation remain devoid of comprehensive rice maps, calling for further efforts.

3.2. Spatial resolution

The products listed in Table 1 have been developed over the last 10 years. Three global rice mapping products (D2, D3, and D4) in Table 1 were all obtained using spatial statistics method (Section 2.1). Although with the advantage of global coverage, they are typically available at coarse spatial resolution (0.05°–0.083°). Therefore, unlike the other rice mapping products in the table, these three products only provide the estimate of rice-planting area in each pixel. This deficiency limits their potential to effectively monitoring rice growth. For paddy rice maps in Monsoon Asia, the highest spatial resolution available is 500 m, with the MODIS data serving as the primary data source. Because MODIS offers global coverage once a day, rice maps generated through it usually provide larger coverage. Even in Southeast Asia where clouds and rain are frequent, MODIS has demonstrated the capability to extract paddy rice (Mosleh and Hassan, 2014). In addition, MODIS observations can capture rice crop intensity and crop calendar information besides rice distribution (Asilo et al., 2014; Torbick et al., 2011), which are valuable for estimating rice yields and greenhouse gas emissions. Among all countries in Asia, only China possess products with coarse spatial resolution (500m and 1000m), likely due to the vast land area of this country. But coarse resolution remote sensing products are more severely affected by the presence of mixed pixels, particularly in Asia with prevalent fragmentation of farmland. Liu proposed a sub-pixel estimation method to mitigate this issue to some extent (Liu et al., 2018). However, this method still tends to overestimate rice area in small paddy rice fields and underestimate in large paddy rice fields. Landsat and Sentinel, with spatial resolutions of 30 m and 10 m respectively, help alleviate field fragmentation to some extent. Recently, Shen and Pan mapped single and double rice at an improved spatial resolution to 10m/20m in China (Pan et al., 2021; Shen et al., 2023). The higher spatial resolution provides more spatial details and higher reliability (Waleed et al., 2022). As a result, there is a growing interest in fine-scale rice mapping within the research community using data obtained by Landsat, Sentinel and PALSAR. As presented in Table 1, 19 out of 25 products possess a spatial resolution ranging from 10 to 30 m.

3.3. Temporal coverage and temporal resolution

Three global products are available for a single specific year only. This limitation stems from the fact that these products rely on multiple data sources as inputs for their models. The temporal coverage of the input data sources imposes a constraint on the frequency at which these products can be updated. The D6 dataset spans a period of 15 years, while D7 dataset extends over 20 years. Both D6 and D7 provide data on an annual basis, benefiting from the long-term and high-frequency observation of MODIS. With more than 40 years of Landsat data serving as the primary source, D10, D16, D17 and D20 encompass a longer time coverage of 30 years or greater. Apart from the products mentioned above, the temporal coverage of the remaining products ranges from 3 years to 10 years. Furthermore, 11 products are only available from 2017 onwards because of the integration of Sentinel-2 data, which offers a higher spatio-temporal resolution than Landsat (You et al., 2023).

Apart from D10, D18 and D20, all other products are updated annually. Most studies have adopted the strategy of integrating multi-source datasets or employing SAR data to increase the number of valid observations and avoid the gaps in the resultant map. In the case of the D10 and D20, only Landsat data was utilized as the input. Because it has a long revisit interval (8 or 16 days), the observations are often highly affected by clouds (Duong et al., 2022). Using a common strategy of stacking multi-year data to ensure an adequate number of valid observations, thus the temporal resolution of D10 and D20 is reduced to 5 years.

4. Consistency assessment of different products

To provide a comprehensive understanding and assessment of the similarities and differences among the various existing rice mapping products, we pay attention to three hotspot regions of rice mapping: China; Heilongjiang, China; and Vietnam (Fig. 1). China is the largest producer and consumer of paddy rice (Shen et al., 2023; Yang et al., 2008). In China, rice has been cultivated since thousands of years ago, and now accounts for about 35% of total plant area of all grain crops (Peng et al., 2009). Heilongjiang, located in northeastern China, is a top rice-producing province (Zhang et al., 2018a). Due to its cold temperatures, rice is grown once in a year, usually sown in mid-April and harvested in late September to October, and other dominant crops in this area include corn and soybeans (You et al., 2021). Vietnam is highly

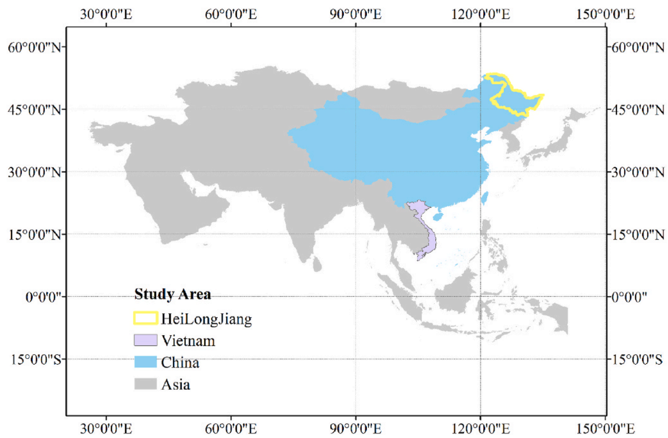

Fig. 1. Study areas.

conducive to rice cultivation, due to abundant water resources and warm temperatures. In Vietnam, rice cultivation pattern is highly heterogeneous, consisting of single, double and even triple rice (Kontgis et al., 2015).

4.1. Assessment methodology

In this paper, a straightforward overlay analysis was employed to assess the consistency among different products. Prior to the assessment, all data were unified into the same coordinate system, followed by the designation of rice fields as 1 and non-rice as 0. In China, three datasets (D5, D6, D7) were compared, which were uniformly resampled to a resolution of 1000m. All three datasets cover 2015, making it the year for consistency assessment. Five datasets (D8, D9, D10, D11, D12) were selected in Heilongjiang province of China, are were resampled to a resolution of 30m. The common period of these datasets is 2019~2020. In Vietnam, five datasets (D13, D14, D15, D16, D17) were compared after resampling to 30 m spatial resolution. The data during the common period of 2018~2020 was chosen for the consistency assessment. All data resampling was performed using the “Resampling” tool in ArcMap 10.6, with the “Resampling Technique” set to MAJORITY. This means that each pixel’s output value is determined by the most prevalent value within a 3x3 window.

To thoroughly understand the consistency and discrepancies among different products, we utilize the following formula for overlay analysis in this paper:

$$\mathrm{Code1} = \mathrm{DST}_1 + \mathrm{DST}_2 + \cdots + \mathrm{DST}_n \tag{1}$$

$$\mathrm{Code2} = \mathrm{DST}_1 * 10^0 + \mathrm{DST}_2 * 10^1 + \cdots + \mathrm{DST}_n * 10^{n-1} \tag{2}$$

Here, DST_i denotes different rice datasets. For China, Heilongjiang and Vietnam, DST_1-DST_n specifically refer to D5-D7, D8-D12, D13-D17, respectively. So, a larger value of code1 indicates that more datasets recognize the pixel as rice. Code 2 records the detailed classification result of each dataset.

Furthermore, utilizing publicly available rice field samples as presented Table 5, in conjunction with manual interpretations derived from high-resolution Google Earth imagery, we have computed the precision, recall, and F1 scores for different products (see Tables 2-4). During the manual interpretation process, factors such as field shape, texture, and flooding characteristics are all taken into account to assist with identification. Each point has been carefully checked by us, and only pure pixel points were selected and labeled, while points with unclear land cover information were excluded.

Table 2
Accuracy assessment for D5-D7.

	precision	recall	F1
D5	0.99	0.48	0.64
D6	0.98	0.24	0.38
D7	0.98	0.72	0.83

Table 3
Accuracy assessment for D8-D12.

	precision	recall	F1
D8	0.97	0.83	0.90
D9	0.85	0.98	0.91
D10	1.00	0.93	0.96
D11	0.86	0.58	0.69
D12	0.89	0.93	0.91

Table 4
Accuracy assessment for D13-D17.

	precision	recall	F1
D13	0.78	1	0.88
D14	0.74	0.97	0.84
D15	0.96	0.81	0.88
D16	0.78	0.94	0.85
D17	0.56	0.97	0.71

Table 5
Data sources for publicly available rice field samples.

data	count	access date	source
EOMF	5071	2023/9/18	https://www.ceom.ou.edu/photos/browse/
Crop Observe	63	2024/1/1	https://cropobserve.org
USGS	722	2023/11/23	https://www.usgs.gov/apps/croplands/app/data/search
CAWa_Crop_type_samples	171	2023/11/2	https://figshare.com/articles/dataset/A_Crop_Type_D.dataset_for_Consistent_Land_Cover_Classification_in_Central_Asia_and_Beyond/12047478/2
ESA WorldCereal validation	551	2024/4/27	https://zenodo.org/records/7825628#.ZD5YRXZBxPY

$$\mathrm{precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}} \tag{3}$$

$$\mathrm{recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}} \tag{4}$$

$$\mathrm{F1} = 2\frac{\mathrm{precision} \times \mathrm{recall}}{\mathrm{precision} + \mathrm{recall}} \tag{5}$$

where precision is calculated by dividing the number of true positive values by the number of all positive values, recall is calculated by dividing the number of true positive values by total the number of predicted values, and F1 scores is a harmonic mean of precision and recall.

4.2. Assessment results

4.2.1. China

The overlay analysis indicates that the consistency among the different datasets in China is extremely weak, with 5.70% of the code1 corresponding to 3 and 70.85% of code1 being 1. According to the zoom-in subplot (b) in Fig. 2, it is clear that the coarse spatial resolution is the predominant factor responsible for the discrepancy of the datasets. The

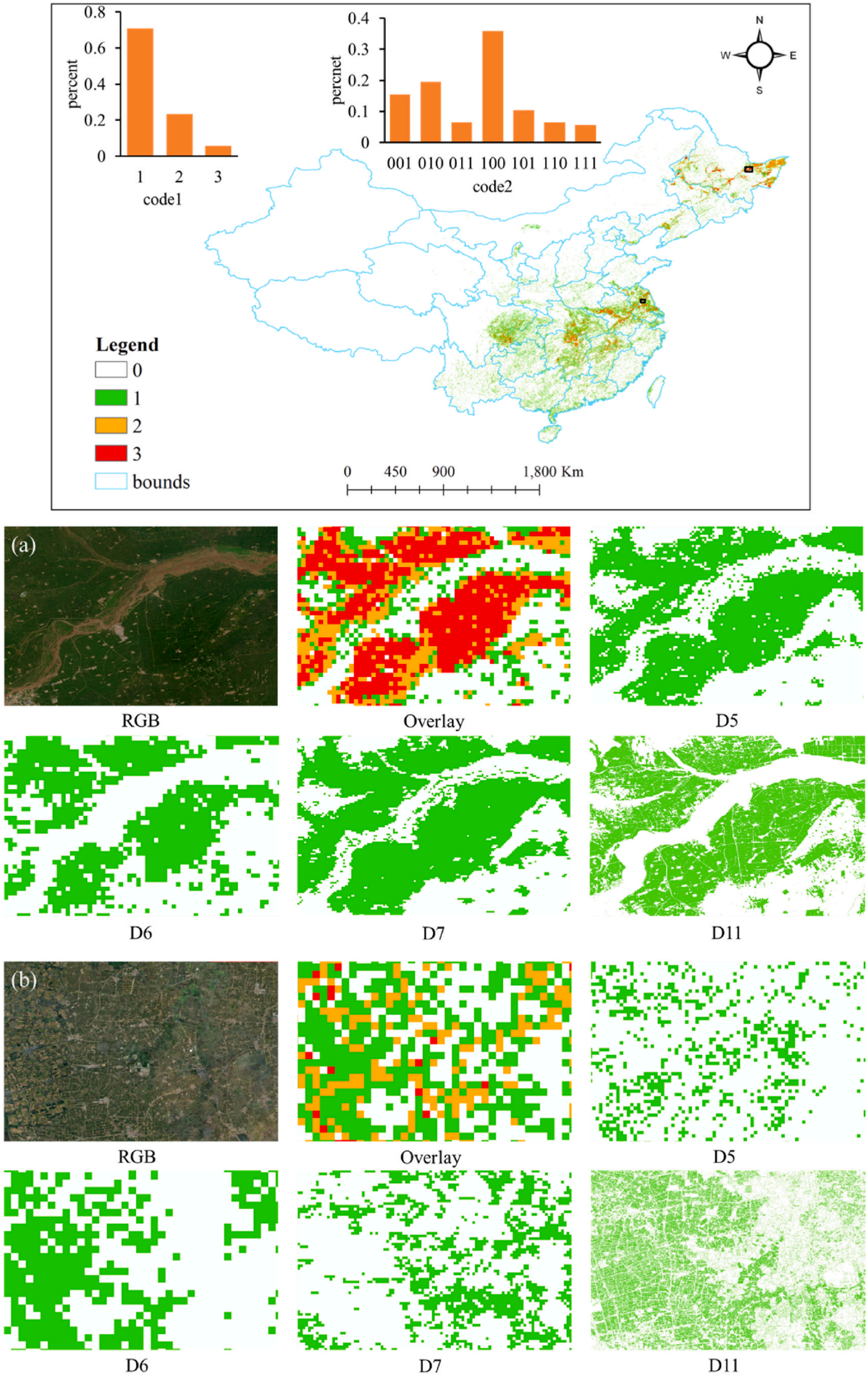

Fig. 2. Results of China overlay analysis with zoom-in plots (D11 as reference for high-resolution data).

spatial resolution of D5, D6 and D7 are 500m, 1 000m, and 500m, respectively. Given the substantial fragmentation of farmland in China, rice maps with coarse resolution suffers more severely from the mixed-pixel issue (Wang et al., 2024). Such conditions are prone to cause identification errors, especially in regions with sparse rice cultivation, which can reduce the consistency of the dataset. Conversely, high spatial resolution data, like D11, provides more detailed representations of rice field distribution, capturing features such as roads, water, and settlements better. Using the 30-m product (D11) as a baseline, we could discover that the products with coarse spatial resolution suffers from significant overestimation or underestimation of rice area within region (a) and (b). Therefore, high spatial resolution rice products are indispensable, which however remain scarce at larger spatial scales. The relative high agreement presented in Northeast China and some parts of central provinces (Jiangxi, Anhui, Hubei, and Hunan) (see Fig. 3) may be related to two main factors, namely the extensive areas of rice cultivation and the intensive farming practices in these areas (Zhou et al., 2023). In situations where fields are fragmented and rice cultivation is sparse, we recommend employing satellite imagery with finer spatial resolution, such as Landsat and Sentinel, to enhance the reliability of the results.

4.2.2. Heilongjiang, China

The rice datasets of Heilongjiang coincide with each other better (Fig. 4). Specifically, code1 values of 5 and 4 secured the top two ranks, taking up 35.07% and 22.13% respectively. This may be associated with several factors, including the simple rice cropping pattern, extended rice growing seasons and more frequent observations attribute to the overlapping of satellite orbit. Altogether, in a simple rice cropping system, various algorithms demonstrate the capability to recognize rice with a high accuracy. Except D12, the F1 scores of the other four datasets range from 0.91 to 0.96 (Table 3).

Nonetheless, a certain degree of inconsistency exists as well, with code1 value of 1 accounting for 21.22%. In terms of code2, 11,110 and 01000 exhibit higher proportions of 10.02% and 9.14%, respectively. The code 11,110 indicates that four out of five datasets were classified as rice, with the remaining one dataset classified as non-rice. This discrepancy may suggest an underestimation of the rice cultivation area within that particular dataset. In contrast, the code 01000 implies that one of the datasets may have overestimated the rice cultivation area, given that only one dataset among five classified the pixel as rice. This phenomenon is well illustrated in the zoom-in plot. In area (a), D11 omits a large patch of rice, while D9 holds a slight overestimation, misidentifying some field boundaries and other crops as rice. In area (b), the coexistence of wetlands and rice fields is probably a main source of error there. Upon visual interpretation of high-resolution imagery, we find that D8 and D10 correctly extract rice, D11 severely overestimates rice acreage, and D12 and D9 suffer from moderate and slight overestimation in this region. In general, D11 may be less reliable than the other datasets in Heilongjiang, China. We speculated that this might be related to the mapping algorithms. In their study, the thresholds for the algorithms were established utilizing rice acreage statistics (Shen et al., 2023). If there are errors in the statistical data itself, biases may also be introduced into the remote sensing mapping results. Since this dataset was developed for the whole of China rather than tailored to a specific province such as Heilongjiang, its probable lower accuracy compared to regional products is acceptable. Therefore, we suggest that when producing rice maps, both the robustness of the algorithms and the accuracy of reference data should be considered. To our knowledge, crop area statistics in some Asian countries are not reliable and may not serve as suitable references. Additionally, post-processing is critical. Utilizing reliable cropland products as a mask can help eliminate interference from other land cover types, such as wetlands, which may exhibit characteristics similar to rice fields. This approach contributes to improving the overall quality of the mapping products.

4.2.3. Vietnam

Vietnam planted rice more than once a year to increase production and ensure food security (Duong et al., 2022; Kontgis et al., 2015). Among the five rice products, three are land cover products with rice being one of the categories, reflecting the importance of rice in Vietnam's land use. Because Vietnam lies in the subtropical region where optical remote sensing images are highly affected by cloudy and rainy weather, these rice products mainly rely on SAR data. The evaluation results show a strong consistency among different datasets, but the consistency varied significantly across regions (Fig. 5). In area (a), D17 overestimates the rice planting area. The inconsistency primarily arises from delineating rice field boundaries. Additionally, the codes of 00001, 00010, 01000, 10,000 occupy relatively high proportions, suggesting the presence of overestimation in different datasets across different regions. This may be attributed to the complicated rice cultivation pattern (e.g., multi-cropping) in Vietnam (Han et al., 2022a). In regions characterized by complex agricultural landscapes, such as region (b), the consistency of the products is also markedly lower, probably due to the interference of terrain on SAR data (Ngo et al., 2020; Zhan et al., 2021). Furthermore, Southeast Asia frequently experiences cloud cover

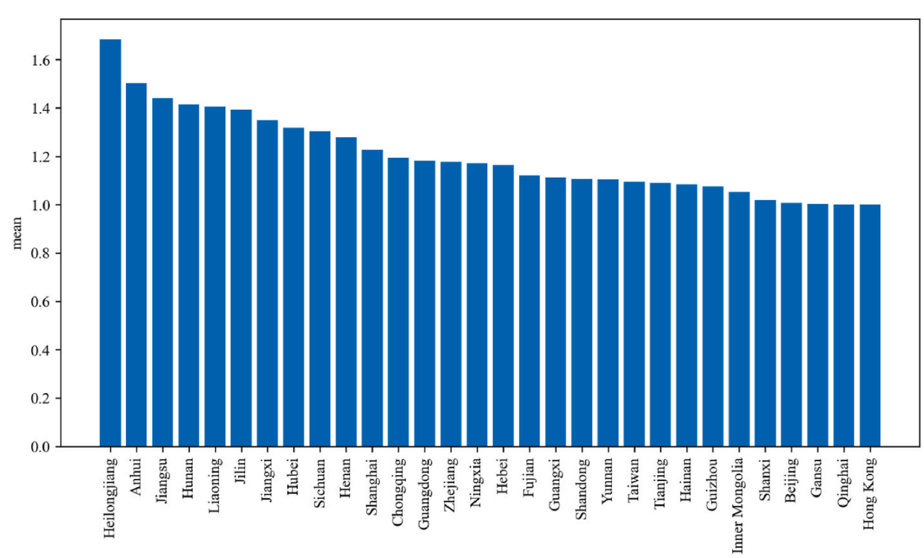

Fig. 3. Mean value per province for code1.

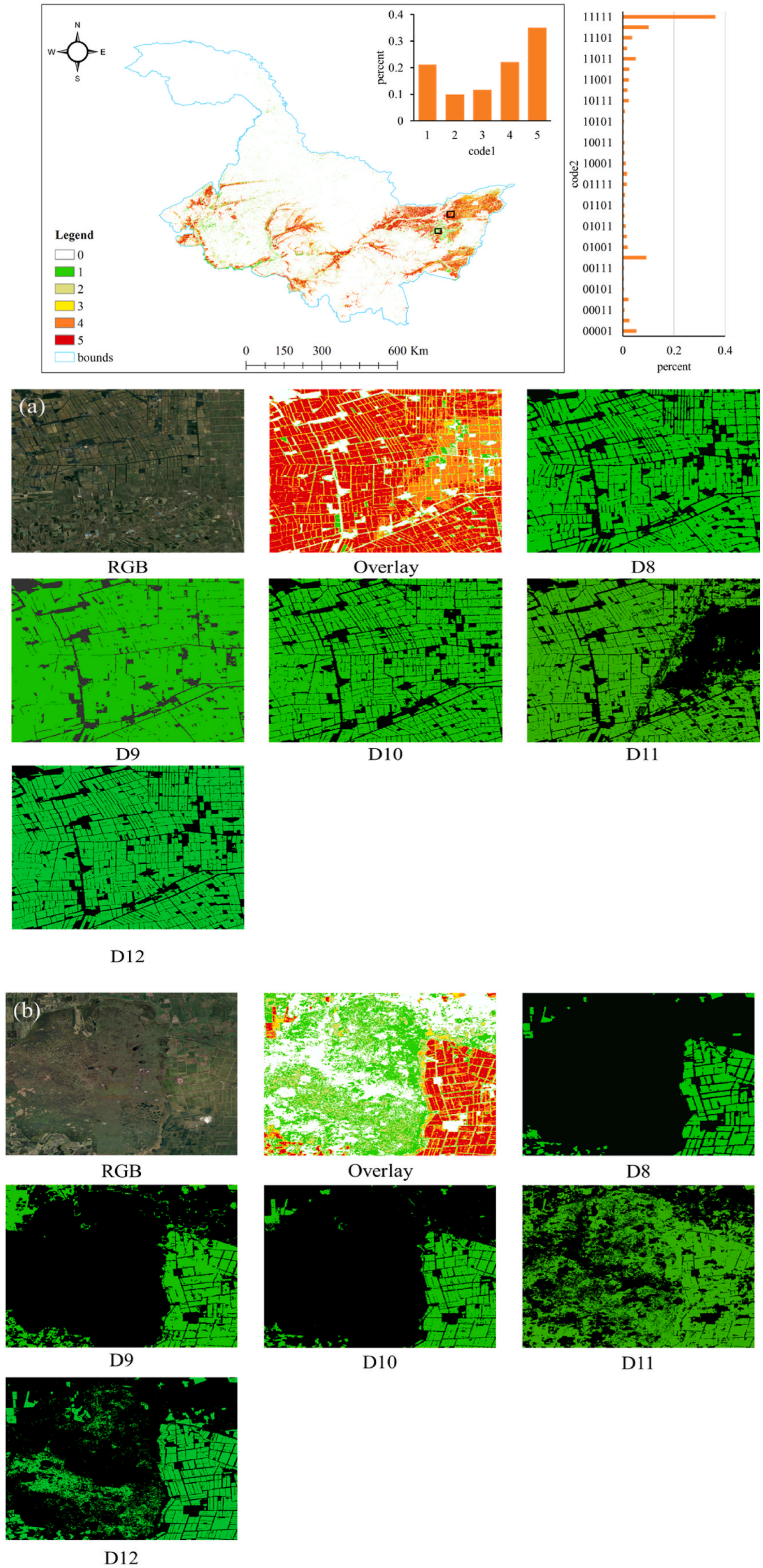

Fig. 4. Results of Heilongjiang overlay analysis with zoom-in plots.

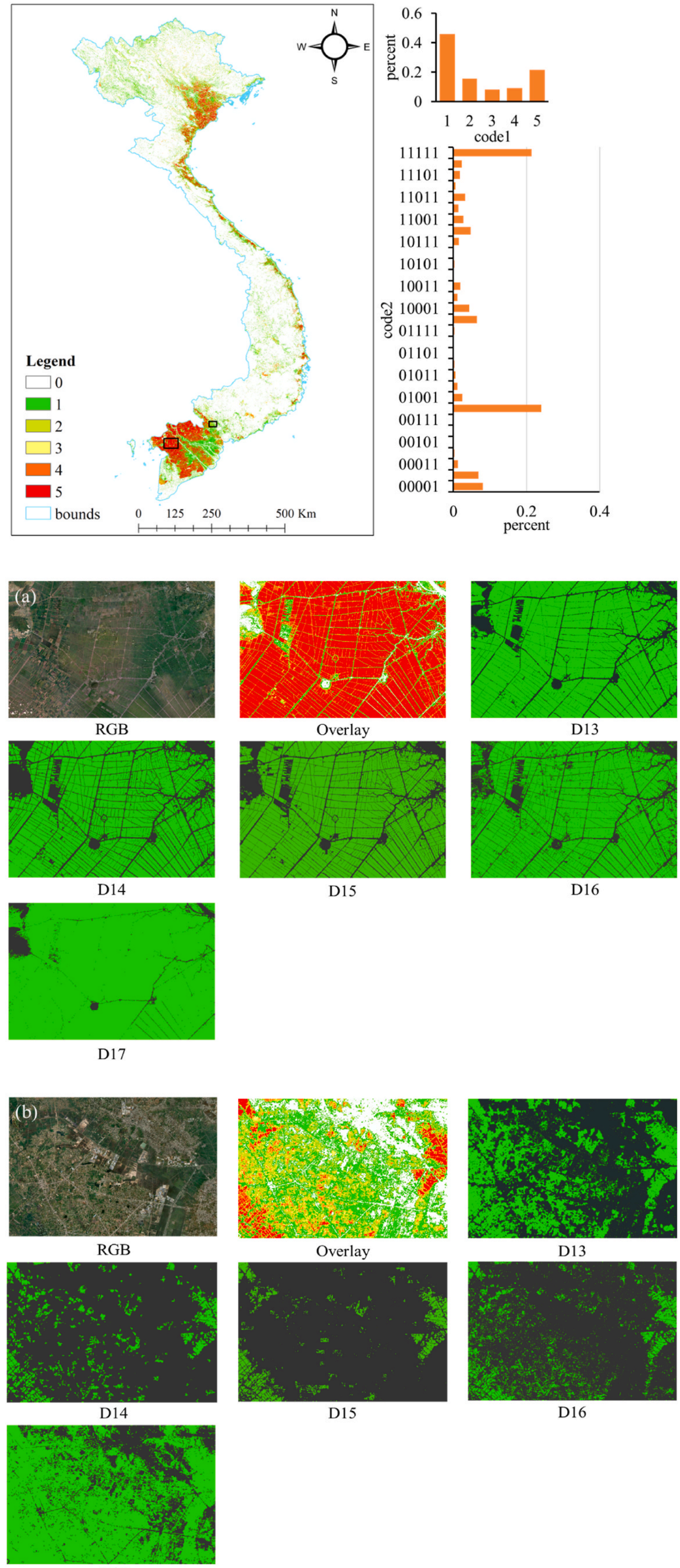

Fig. 5. Results of Vietnam overlay analysis with zoom-in plots.

(Kuenzer and Knauer, 2013), which introduces significant noise into optical remote sensing images, leading to variability in classification results depending on the processing methods used. We advise that employing multi-source remote sensing data is a viable solution in these regions. Combining data from various sources not only offers more effective observations and reduces cloud interference, but also allows different sensors to capture distinct surface attributes, improving rice identification accuracy under complex landscape.

5. Challenges and opportunities

Although excellent progress has been made in satellite-based rice mapping, quite a few challenges persist. The factors contributing to these challenges and possible solutions are discussed below.

5.1. *Diversity of rice cropping systems*

Rice, as one of the primary sources of food for human beings, has a long history of cultivation and a diversity of variety. The International Rice Research Institute (IRRI) grouped rice into four types: irrigated, rainfed lowland, upland, and deepwater (Kuenzer and Knauer, 2013). They are cultivated extensively worldwide, with irrigated rice occupying the largest cultivation area, accounting for more than half of global rice area. The diversity of rice variety allows for adaptation to various cropping conditions. Rice can thrive in regions with mean annual precipitation ranging from less than 100 mm to more than 5000 mm per year, and with mean temperature during the growing season varying from less than 17 °C to more than 33 °C (Boschetti et al., 2017). Rice is predominantly cultivated in plains but can also be grown at altitudes of up to 2600 m (Zhang et al., 2017). Transplanting and wet broadcasting are the most dominant rice planting methods, while dry seeding is also traditionally practiced in some rainfed or upland rice ecosystems in Asian countries, as well as southern Europe (Boschetti et al., 2017). Due to diverse growing conditions and cropping practices, there are significant differences in rice phenology. These complexities pose challenges for remote sensing-based rice mapping, especially at large spatial scales. Orynbaikyzy et al. reported that most crop classification studies still focus on smaller scales (Orynbaikyzy et al., 2019), because existing algorithms often exhibit only regional adaptability. Machine learning methods have rarely been used to generate large-scale rice maps, probably because it is difficult to establish a robust classifier that considers all these complexities. Even a classifier constructed for a specific region may exhibit performance degradation when applied to different time period (Wei et al., 2021; Yang et al., 2022; Zhang et al., 2020a, 2020b). The greater the spatio-temporal heterogeneity, the sharper decline in the machine learning model performance (Xu et al., 2021). Phenology-based algorithms are more flexible to cope with complex rice cropping systems. These algorithms rely on flooding signals during transplanting periods, which are effective for identifying the transplanted and irrigated rice, but not for dry-broadcasted, rainfed or upland rice which are hardly inundated prior to the emergence of rice canopy (Xiao et al., 2022).

The Global Rice Science Partnership (GRiSP) estimated that upland rice covered 15 million hectares, around 10 percent of the global rice area, making it an important contributor to rice production (Tatsumi et al., 2015). Upland rice is often overlooked by researchers in studies due to its lower acreage and yield compared to irrigated rice. For example, Yuan's study in Southeast Asia excluded both upland rice and deepwater rice (Yuan et al., 2022). However, it is important to note that the area of upland rice varies from region to region. In Central and West Africa, upland rice accounts for about 35% of the total area of rice (Boschetti et al., 2017). In Brazil's Cerrado region and China it covers 250,000 ha and 1 million hectares, respectively (Boschetti et al., 2017). Upland rice should not be ignored when investigating rice in these regions. In addition, differentiating ratoon rice from other rice cropping systems presents a challenge, because ratoon rice would be easily classified as double-season rice using remote sensing (Liu et al., 2020). However, it is estimated that ratoon rice now takes up approximately 30, 000 km^2 in China (Zhao et al., 2023), because it grows fast and is balanced in terms of productivity, cost, environmental impact and labor requirements (Liu et al., 2020). Therefore, further research can be conducted on ratoon rice identification in the future.

Overall, the diversity of rice species and growing conditions poses a challenge for rice mapping. While current methods predominantly focus on irrigated rice, the contribution of other rice types to rice production and the environment should not be ignored. Further exploration on satellite-based rice monitoring will facilitate better agricultural practices towards achieving the SGD2.

5.2. *Scarcity of ground-truth*

Advanced machine learning classifiers have achieved good results in rice mapping, while the integration of multiple classifiers can further enhance both precision and generalizability (Duong et al., 2022). The assumption of sufficient samples to train powerful classifiers is a common theme that exists in machine learning models. In recent years, the bottleneck for achieving high-resolution, high-precision crop mapping has shifted. It is no longer the deficiency in observation data or image processing capabilities, but a shortage of ground-truth (Lin et al., 2022). This shift can be attributed to the rapid growth in data volume and accessibility, coupled with advances in efficient algorithms and cloud computing platforms.

From our reviewed literature, machine learning classifiers draw samples from several sources. The first one is manual collection in the field which involves precise measurement of paddy field locations using GPS devices (Liu et al., 2019; Rawat et al., 2021; Sukmono and Ardiansyah, 2017; Torbick et al., 2011). This approach, although yielding reliable samples, is labor-intensive, costly, and time-consuming. Moreover, the manually-collected samples are usually limited and distributed within a restricted spatial area, which could not suffice for large-scale rice mapping applications. In addition, the collected samples are also time-sensitive. For historical rice mapping, there is no way to go back and collect them. Therefore, alternative methods must be relied upon.

First, publicly available field reference samples listed in Table 5 can be utilized, although the number is still quite limited. EOMF, a crowd-sourced global geographic reference field photo library developed by a research team from the University of Oklahoma. Users worldwide capture and upload photos to the database using GPS cameras or smartphones. Each photo is accompanied by detailed geographic location information and tags, with crop type being one of the recorded tags. Crop Observe, the website provides a mobile application and an accompanying map. The application focuses on collecting data on crop types, phenological stages, visible damage, and management practices. The collected data serves to train and validate models and algorithms, facilitating research aimed at assessing crop area and yield-related aspects. This data is made freely available to users on the website. USGS, a vast array of reference data collected from across the globe, encompassing diverse landscapes and crop types. The reference data is collected from diverse sources, including customized mobile applications, field surveys, very high-resolution imagery, and secondary sources from other projects and research. CAWa_CropType_samples, the dataset compiled polygon samples for 40 different crop types, with a focus on the Central Asian region. The data was collected between 2015 and 2018 and has been meticulously verified with expert knowledge and remote sensing data. ESA WorldCereal validation, the dataset from the ESA WorldCereal System is utilized for the validation of global crop types. It has been created using a novel IIASA tool called "Street View from Space" (https://svweb.cloud.geo-wiki.org/). And this dataset is entirely independent of all existing maps and reference datasets.

The second method is interpretation via high-resolution imagery (Huang et al., 2023; Mosleh and Hassan, 2014; Okamoto and

Kawashima, 2016). With the rapid development of commercial satellite and unmanned aerial remote sensing, the spatial resolution of acquired images has reached sub-meter level. Experts in image interpretation can easily obtain reliable samples from the images based on domain knowledge and auxiliary information. Samples acquired in this way offer advantages in terms of spatial and temporal distribution, as well as abundance. Although manual interpretation carries the risk of incorrect interpretation, current classifiers demonstrate a certain degree of resilience to such errors (Gong et al., 2019).

The third approach is to collect samples from existing rice maps (Lin et al., 2022; Nguyen et al., 2020; Pang et al., 2021). For instance, Kang et al. developed spatially consistent rice cultivation areas by overlaying multiple maps and subsequently conducting random sampling within these consistent regions to acquire rice samples (Kang et al., 2022). This approach is highly automated and convenient, does not require any additional manual labor. Despite the potential uncertainty associated with the samples obtained in this manner, it serves as a way of additional sample collections. In fact, the approach of extracting samples from existing products is commonly utilized in the realm of large-scale land surface mapping studies (Yang and Huang, 2021; Zhang et al., 2021). Moreover, because CDL data in the United States is generally considered reliable, a number of studies have collected reference samples from it. However, crop classification products with such high accuracy are lacking in other countries and regions, limiting the application of this approach.

5.3. *Sample-free rice mapping*

As mentioned above, the phenology-based method does not require samples but suffers from more uncertainty, while the machine learning method could be more accurate but dependent on samples, both presenting drawbacks when applied independently. Researchers have proposed the idea of incorporating the strengths of phenology-based and machine learning methods to compensate for their respective shortcomings, and surprising progress has been achieved in sample-free rice mapping recently (Zhang et al., 2023). In this paper, we refer to this approach as the hybrid method. The process of the hybrid approach involves estimating the preliminary rice distribution using phenology-based method and then selecting reliable pixels from it as samples to train the machine learning classifier for the final classification. For examples, Qiu et al. divided the whole study area into disturbed and non-disturbed zones based on the data availability during the critical rice growth period. The CCVS method was applied to the non-disturbed zone to directly extract rice and provide a sample source for the machine learning method. The machine learning classifier was then trained and performed in disturbed zone, resulting fully automated rice mapping (Qiu et al., 2017). Zhang et al. implemented the hybrid method to achieve sample-free automated rice mapping in the Jianghan Plain (Zhang et al., 2018a). Zhu et al. found that the mean overall accuracy of the hybrid method was 88.8% and that of deep learning with samples was 91.2%, indicating comparable performance (Zhu et al., 2021a, 2021b). These studies demonstrate the effectiveness and rationality of the hybrid method, providing a feasible way for fully automated sample-free rice mapping. However, the impact of the samples selected from the preliminary results on the machine learning model's performance is not well explored. In addition, the scalability of the approach to larger areas and its effectiveness in more complex rice-growing regions remain to be established. Further exploration into these aspects is essential. Although the hybrid method remains room for improvement, the high level of automation and the absence of the need for ground samples have attracted attention from researchers.

Recently, NASA and IBM have publicly released a geospatial AI (Aritificial Intelligence) foundation model called Prithvi (Jakubik et al., 2023). This model is a first-of-its-kind temporal Vision Transformer pretrained using continental US Harmonized Landsat-Sentinel 2 (HLS) dataset. This pretrained foundation model can serve various downstream tasks, with crop classification being one of them. Users simply need to provide multispectral satellite images from three distinct growing seasons of crops, and the model is able to distinguish different crops. The model is deemed just adequate for conducting large-scale rice mapping at a 30-m resolution. Moving forward, further exploration of the foundation model is essential to realizing the potential of fine-scale sample-free rice mapping, which holds great promise.

6. Conclusions

Rice not only supplies food for human beings but also emits greenhouse gases and consumes large amounts of water during growth, causing profound impacts on the climate and the environment. Precise information on the distribution of rice is the basis for these investigations. Remote sensing has the advantages of all-weather, global coverage, and high-frequency repeated observations, making it a widely used tool in rice mapping. Here we conduct a literature review of remote sensing rice mapping research, with a focus on spatio-temporal coverage, spatio-temporal resolution, and methodology. Our analysis aims to evaluate the current progress of remote sensing rice mapping and assess the consistency among different products across three representative rice planting areas. The challenges of satellite-based rice mapping, possible causes and solutions are then discussed. The main conclusions are as follows:

(1) Current products are typically characterized by short temporal spans, with few regions occupied with long time-series rice maps. Extending these long time-series products from specific regions to larger scales remains challenging.
(2) Rice mapping at large scales still relies heavily on MODIS as the primary data source. Problems such as rice field fragmentation contribute to significant inconsistencies among different products. (3) Finer resolution rice maps at continent to global scale are yet to be developed.

In regions characterized by simple rice cultivation system, existing methods demonstrate the ability to accurately identify rice. However, in regions with multiple rice cropping systems, rice mapping is challenging, and the consistency among different products is low.

(4) Current algorithms are developed in local regions and are difficult to apply directly on continental or global scales. The diversity of rice growing environment and cropping system hinders the development of a universal algorithm.
(5) The scarcity of ground truth data for training and validation is another challenge. Inadequate samples tend to cause misclassification. Fortunately, the combination of sample-free rice mapping methods and AI foundation models is promising in coping with this challenge.

CRediT authorship contribution statement

Husheng Fang: Writing – review & editing, Writing – original draft, Methodology, Data curation, Conceptualization. **Shunlin Liang:** Writing – review & editing, Supervision, Resources, Funding acquisition, Conceptualization. **Yongzhe Chen:** Writing – review & editing, Validation. **Han Ma:** Writing – review & editing, Visualization. **Wenyuan Li:** Writing – review & editing. **Tao He:** Writing – review & editing, Resources. **Feng Tian:** Writing – review & editing. **Fengjiao Zhang:** Writing – review & editing, Visualization.

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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Data availability

Data will be made available on request.

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