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Exploring the Research Progress of SAR Remote Sensing in Monitoring Rice Planting Area

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Abstract:
As global food security issues become increasingly prominent, accurate monitoring of rice planting areas is particularly important as it is a major food crop. Radar remote sensing has unique advantages in rice planting monitoring due to its all-weather and all-day imaging capabilities. This paper explores the application of SAR remote sensing in rice planting area monitoring and reviews two types of methods that are currently widely used. This paper concludes that the time series-based method has high computational efficiency, but it is difficult to meet the requirements of long-term monitoring; there are many branches of machine learning methods, among which the accuracy of supervised classification and deep learning methods is guaranteed, but there are problems of large computational workload and poor migration ability. In general, the current problems of SAR monitoring of rice planting areas mainly include complex data processing, limited classification accuracy, and low standardization. Future research should focus on improving the versatility of algorithms, enhancing data fusion capabilities, and promoting the widespread application of radar remote sensing in agricultural remote sensing.

Keywords: Rice planting area; SAR; Agricultural remote sensing

1. Introduction

Rice is one of the most important food crops in China. The rice planting area accounts for 30% of China‘s food crop planting area, and the output accounts for about half of the country‘s total grain output [1]. Rice planting is related to the national economy and people‘s livelihood, and plays an important role in ensuring the country‘s overall food security. With the continuous advancement of standardized, large-scale, integrated and scientific food production in my country, my country has now established a relatively complete large-scale rice cultivation and planting system. As the large-scale cultivation and planting of rice matures, the monitoring of rice planting area is particularly important. From the perspective of traditional methods, agricultural statistics by independent

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workers or small-scale sampling surveys organized by local units are difficult to meet the needs of modern agricultural development and the needs of relevant management departments to obtain agricultural information efficiently, immediately and accurately [2]. Remote sensing has the advantages of high efficiency, simplicity, macro, timely and objective, and is widely used in all aspects of agricultural production [3]. Through mathematical and physical methods and computer means, the analysis of rice spectral response obtained by remote sensing can effectively carry out real-time, rapid and high-precision monitoring of the rice planting area.

The weather during the rice ripening season is characterized by frequent clouds, fog and rain. The use of optical remote sensing satellites to monitor rice planting areas will be seriously affected by atmospheric and ground conditions, resulting in low accuracy of monitoring rice planting areas [4,5]. Synthetic aperture radar, as an active microwave sensor, is not restricted by light and climate conditions, and has strong penetration and high resolution. It can achieve all-day and all-weather ground observation, making up for the defect that optical remote sensing satellites are greatly affected by climate conditions. Therefore, satellite-borne synthetic aperture radar has gradually become an important means of monitoring rice planting areas. For example, Huang et al. analyzed the interannual phenological change process and rhythmic characteristics of rice, combined the time series characteristic parameters and the membership of the time series curve, and achieved good results in the detection of rice planting areas of multiple varieties [6]. Lasko et al. combined the random forest algorithm of VV, VH and HH polarization modes to achieve better recognition results in rice planting areas with seasonal floods [7]. Ndikumana et al. applied an RNN classifier to Sentinel-1 images to extract the rice planting area and achieved an F-score of 96% in the study area[8]. Chatterjee et al. combined the VGG16 unsupervised clustering model with the feedforward neural network learning method to extract rice planting area, which improved the generalization ability of the model while ensuring high accuracy[9].

The classic methods for extracting rice planting area through SAR mainly include time series-based extraction methods and machine learning methods. With the continuous development of data open source and cloud computing in the past three decades, rice planting area extraction methods based on multi-phase and multi-source remote sensing data fusion and remote sensing data cloud platforms have been increasingly widely used. This paper aims to summarize the historical development of SAR in monitoring rice planting areas, summarize the popular rice area extraction methods and discuss their advantages and disadvantages, summarize and look forward to the future development direction of SAR monitoring of rice planting area, and provide reference for relevant practitioners and researchers.

2. Research progress on monitoring rice planting area using SAR

New radars such as synthetic aperture radar (SAR) and inverse synthetic aperture radar (SAR) can provide high-resolution images and are widely used in military reconnaissance, terrain mapping and other fields. The development of radar remote sensing mainly includes the single-band single-polarization stage, the multi-band multi-polarization stage, the polarization and interference stage, and the development of four new stages represented by dual/multi-station or constellation, high-time series high-resolution wide-band, and 3D imaging. Its role in earth observation is becoming increasingly prominent and has been widely used in different fields [10]. This section focuses on the current research status of SAR radar for detecting rice planting area.

Food is one of the most important needs for biological survival. Whether food production can be strictly managed and crop planting area can be reasonably and accurately regulated has become the primary condition for the development of individuals and even countries. However, the traditional demarcation of planting areas and growth observation relies on field surveys, which have low timeliness and accuracy, and consume a lot of manpower, material and financial resources, and are extremely inefficient [11]. Remote sensing, with its advantages of rapidity, simplicity, macroscopicity, non-destructiveness and objectivity, has made up for the shortcomings and deficiencies of traditional survey methods. Whether it is ground-based short-range remote sensing, drones, aerial remote sensing, or satellite remote sensing, each has its specific advantages and professional uses. Among them, satellite remote sensing technology has the characteristics of high observation frequency and wide coverage. Through mathematical methods and computer technology, the spectral response of rice obtained by remote sensing can be analyzed to effectively identify the status of rice cultivation and plant growth [12]. However, rice is a typical thermophilic crop. It grows in hot and humid seasons, requires a large amount of water and has high humidity requirements. Optical remote sensing is often interfered with by clouds and fog, especially in low and medium latitudes. It is difficult to obtain high-quality optical images. Satellite-borne synthetic aperture radar SAR (Synthetic Aperture Radar) can achieve target observation by actively emitting electromagnetic waves and recording the characteristics of surface scattered echoes. It can continuously image the ground without being affected by weather conditions, and thus has become an important data source for rice remote sensing monitoring.

In the 1970s, the United States was the first country to carry out crop area remote sensing monitoring and mapping. Starting with remote sensing monitoring of winter wheat area in 1974, the country achieved its first remote sensing spatial distribution mapping of more than 20 crops in 2009, and has been updated annually since then. Now it has achieved monitoring and spatial mapping of more than 100 crops each year [13].

In the early days, China also used remote sensing monitoring of winter wheat area as a breakthrough. In 1983, using MSS images and aerial photographs, and adopting visual interpretation methods, it first obtained the spatial distribution of winter wheat area in the Beijing-Tianjin-Hebei region [14].

By the end of the 1990s, the Remote Sensing Application Center of the Ministry of Agriculture of China and the Chinese Academy of Sciences and other units successively carried out trial operations of crop area remote sensing monitoring services across the country. At present, it has achieved annual remote sensing monitoring of the areas of many major crops in China and the world‘s major grain producing countries [15][16][17]. In 1997, the Chinese Academy of Sciences selected the „China Resources and Environment Remote Sensing Information System and Agricultural Situation Quick Report“ as a major and special support project of the Chinese Academy of Sciences during the „Ninth Five-Year Plan“, which achieved remote sensing monitoring and yield forecasting of wheat, corn, soybeans, rice and other crops over a large area across the country[18].

Between 1991 and 2021, satellite-borne SAR sensors continued to upgrade and iterate, and imaging performance and data acquisition methods were continuously optimized. Rice remote sensing monitoring research based on SAR data has made great progress[19].

3. Overview of the means of obtaining rice planting area

The core of rice planting area extraction is to establish rice interpretation features through manual visual interpretation or computer means to distinguish rice from other land objects in remote sensing images.

3.1 Method for extracting rice planting area based on time series characteristics

Rice has a history of systematic artificial cultivation for thousands of years. With the cooperation of historical breeding process and modern agricultural science, the academic community has now reached a relatively mature understanding of the backscattering characteristics of rice in different growth periods. From planting to maturity, rice is divided into four stages: transplanting period, vegetative growth period, reproductive growth period and maturity period[20]. During the transplanting period, rice seeds germinate into rice seedlings in a large amount of water-irrigated paddy fields, and are then transplanted into rice fields with more abundant fertility to enter the vegetative growth period.

The research results of Neuygn et al.[21] on the changes in radar echo characteristics of rice from the transplanting period to the vegetative growth period have been widely recognized and applied in the academic community. Since there is a lot of water in the rice field during the germination stage and the water surface changes little, the rice field at this time produces a scattering characteristic close to mirror reflection on the radar signal, and the echo signal received by the radar is extremely weak. After the rice is transplanted into the rice field for growth and enters the vegetative growth period, the diffuse reflection of the radar signal caused by the rice plants and the rice field greatly enhances the echo signal received by the radar. VH polarization is most sensitive to the changes in rice during this period, showing a characteristic of decreasing during the transplanting period and then increasing, and further increasing during the vegetative growth period. Yang Shenbin et al. detected the radar echo change trend of rice during the transplanting period and the vegetative growth period, and further set thresholds at the initial period and the peak period of the radar signal. The accuracy of the extracted rice area can reach about 85% [22].

The advantages of the rice planting area extraction method based on the time series characteristics of rice are that the principle is simple, the calculation amount is relatively low, and it performs well on plots with relatively flat terrain and a single crop type. Its main disadvantages include (1) poor performance in complex and diverse terrains and multi-crop mixed farmland (2) insufficient application potential in the analysis of long time series and large spatial scales (3) the salt and pepper noise of radar images leads to the degradation of the spatiotemporal characteristics of radar data, which interferes with the extraction of phenological change processes and rhythmic characteristics, and easily leads to misclassification (4) the threshold division is affected by subjective factors and prior knowledge. The method of extracting the cultivated area based on the time series characteristics of rice is the most classic method. With the continuous advancement of computer science and technology and the refined development of integrated data processing in academia, it is gradually replaced by more sophisticated methods.

3.2 Rice planting area extraction method based on machine learning

With the continuous development of computer science and technology, the application of machine learning methods in the extraction of rice planting area has also been

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increasingly developed. Machine learning is a technology that enables computers to automatically learn from data and make predictions or decisions through algorithms and models. Its core goal is to allow computers to analyze large amounts of data, identify patterns and rules, and build models that adapt to new data without explicit programming instructions. Machine learning includes different types such as supervised learning, unsupervised learning, and deep learning. In recent years, it has been increasingly widely used in various fields of science and life. In the practice of monitoring rice planting area through machine learning methods, supervised learning, unsupervised learning, and deep learning are also three typical methods.

3.2.1 Supervised classification

In the process of rice planting area extraction, supervised classification usually uses sample pixels of confirmed categories to provide prior information, establishes classification discrimination indicators, algorithms and models, identifies other unknown category pixels, and separates rice pixels from pixels of other categories of objects on SAR images. Its main core process is (1) selecting training samples. Through field surveys or visual interpretation of high-resolution SAR images, known rice and other objects are obtained as training samples. (2) Selection of SAR images and feature channels. Based on the research tendency and climatic conditions, SAR images that meet the experimental needs are selected, and SAR indicators that can reflect rice characteristics are selected. (3) Under different biophysical and geochemical conditions, the best classification method is selected. For example, Mansaray et al. used the VHSI polarization band carried by Sentinel-1A to classify rice cultivation areas with the support of the SVM algorithm, and the accuracy of subtropical fragmented plots can reach about 90% [23].

In general, compared with the traditional method of using rice time series features, supervised classification has indeed greatly improved the accuracy of rice planting area extraction. The improved supervised classification algorithm is more targeted and is particularly important in the increasingly differentiated and diversified application needs of modern agriculture. However, the performance of these improved algorithms still depends on the time window of data input and data collection, which puts higher requirements on the selection of appropriate phenological periods in field surveys and is easily interfered by subjective factors of scientific researchers. Similarly, the selection of optical images as verification samples also requires a complicated process, which affects the efficiency of supervised classification. Due to the small number of original feature bands of SAR images themselves and the influence of radar noise, researchers need to reconstruct multiple independent feature parameters to achieve better classification results. Although this gives the classification a more quantitative mathematical mechanism, it may be difficult to extend to other areas where planting patterns are changing.

3.2.2 Unsupervised Classification

Unsupervised classification is based on the difference in the category features of different objects in the feature space. It is an image classification method without prior category knowledge. In the process of rice planting area monitoring, the most significant difference between unsupervised classification and supervised classification is that unsupervised classification does not require known rice pixels as samples, but directly performs clustering through the algorithm after noise filtering. For example, McGiven et al. used the improved Weka k-means clustering method to identify rice on SAR images provided by Sentinel-1, and achieved a clustering accuracy of 70%-80% in rice-growing areas in East Asia, Northeast Asia and Southeast Asia [24].

The biggest advantage of unsupervised classification is that it does not require on-site acquisition of prior data, which has certain advantages in some areas where data is scarce or scientific and technological support is underdeveloped. However, the independent application of SAR images for unsupervised classification of rice generally has the problem of low classification accuracy (70%-80%), resulting in relatively few related studies on independent application of unsupervised classification. From the perspective of development trends, in recent years, combining optical remote sensing data and SAR image multi-source data for unsupervised classification, or combining the unsupervised classification of rice field SAR images with supervised classification, deep learning and other methods, has become the current hot spot and development direction of unsupervised classification for rice planting area monitoring.

3.2.3 Deep Learning

Deep learning is a branch of machine learning. It is developed based on traditional statistical machine learning, artificial neural network and other algorithm models, combined with big data and computing power. In terms of rice planting area extraction through SAR, compared with traditional machine learning algorithms, deep learning extracts contextual information from the original image, explores and learns the global spatial features and temporal features in multi-phase images in an end-to-end manner, and then obtains high-level features, ultimately achieving the result of improving crop classification accuracy and computational efficiency [25]. The Rice Planting Area Identification Attention Mechanism U-Net (RIAU-Net) model proposed by Ma et al. uses the dual-polarization images obtained by Sentinel-1 in a specific month to mine the rich scattering characteristics of rice in different growth periods. The OA index of its classification results reached 94% [26].

Deep learning methods have made great progress in improving the accuracy, timeliness and transparency of SAR image rice planting area monitoring. By learning the spatial features in time series satellite images, convolutional neural networks (CNNs) have shown better crop classification performance than traditional classification methods. Recurrent neural networks (RNNs) have also shown their potential for rice classification by automatically learning temporal features in time series satellite images [27]. Gradient boosting algorithms such as XGBoost have better transferability; semi-supervised generative adversarial network learners such as GAN can ensure the accuracy of the extraction process under the condition of limited sample size. On the other hand, the current application of deep learning algorithms is still concentrated on the study of smaller plots, which has led to the poor universality of some existing research methods, and the model's ability to handle unbalanced data needs to be further improved. Mixed pixels and SAR image noise also interfere with the classification results of deep learning; in areas with high landscape heterogeneity, the boundaries and contours of land cover classified by deep learning may be deformed. In addition, machine learning methods require a lot of computational and time costs.

In future research on SAR image rice planting area identification through deep learning, the rational use of transfer learning or data enhancement technology to improve the transferability and generalization ability of deep learning models is a key point that scientists need to pay attention to. In addition, in the face of the interference of mixed pixels, the combination of deep learning and spectral unmixing to perform sub-pixel land use/cover classification is also an urgent problem to be solved. In the face of the problem of excessive data calculation and high time cost, the use of dimensionality reduction methods to reduce the amount of calculation is a feasible development direction. Promoting the noise processing and weak supervision classification methods that combine fusion data sources and remote sensing cloud computing platforms can also provide better support for classification results.

4. New progress in extracting rice planting area using SAR

Single SAR image data generally have the problems of radar noise interference and insufficient temporal resolution. Combining optical images (such as Landsat series, MODIS series, SPOT series, and some GF satellites) can not only take advantage of SAR images that are less affected by weather conditions and lighting coverage, but also combine the higher temporal resolution and more mature product processing characteristics of optical satellites to more completely construct a multi-year growth time series of rice and generate reliable, representative and comprehensive training samples in the machine learning process. Tian et al. combined Sentinel-1A and Landsat-8 images and used the K-means unsupervised classification method to extract the rice planting area in Poyang Lake, achieving a classification accuracy of more than 98% [28]. Combining multiple machine learning ensemble learning, weakly supervised classification or semi-supervised classification methods, and combining traditional methods of rice time series characteristics, it can better solve the uncertainty of data fusion and the low accuracy of unsupervised classification in extracting rice planting areas, further reduce human subjective interference in machine learning, and improve the classification accuracy while improving learning efficiency. StructLabX-Net proposed by Cai et al. uses U-TempoNet as the backbone and combines CNN and LSTM algorithms to achieve classification of various crops. Its accuracy can reach more than 90% in multiple research areas, which is better than RF, SVM, CNN, Transformer and other algorithms [29].

The rise of remote sensing cloud computing platforms led by Google Earth Engine (GEE) has provided researchers with a new direction. Users can rely on the powerful computing power of the Google Cloud Platform to achieve the new development of various geographic algorithm models. From the perspective of rice planting area extraction based on SAR images, Medina et al. used the combined images of Sentinel-1 and Sentinel-2 in the GEE platform and adopted the random forest algorithm to extract the rice planting area in the research area. The OA of the results can reach 96%, and the kappa coefficient is higher than 0.92 [30].

5. Discussion

5.1 The Problems Still Existed In Current Research

After decades of exploration and development, satellite-borne synthetic aperture radar has made great progress and mature applications in rice planting area extraction. However, there are still some problems that restrict its development:

(1) Diversified planting conditions lead to the lack of universality of classical methods. During the rice planting process, factors such as rice varieties, planting conditions and methods will affect the long-term characteristics of rice planting. For machine learning methods, differentiated climatic conditions and planting methods lead to the inability to unify the scattering characteristics of rice to radar signals, further limiting the application of traditional machine learning methods in large-scale rice planting area

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extraction.

(2) SAR image noise affects classification accuracy. Noise will cover the original scattering characteristics of the pixel and interfere with the expression of rice scattering characteristics of the corresponding pixel; or affect the feature recognition and edge information extraction between different varieties, resulting in deformation of the edges of different planting areas. For the construction of rice growth time series characteristics, noise will degrade the spatiotemporal characteristics of rice radar data; and for machine learning methods, the presence of noise will make the classifier perform poorly when facing pixels containing noise.

(3) There is an asymmetry problem between the complexity of prior knowledge and the accuracy of the results. The extraction and change analysis of rice planting area over a long time series and at a large scale requires a vast amount of prior knowledge as samples to ensure that the results have a high degree of accuracy to a certain extent. However, the massiveness and complexity of the data and the arduous workload will result in huge cost losses.

5.2 Outlook

Based on the challenges that SAR radar remote sensing monitoring still faces, this paper summarizes the following future development directions:

(1) Lunar-based Earth observation SAR system. As the only natural satellite of the Earth, the Moon can be said to be a „permanent" Earth observation platform. It can not only effectively observe the macroscopic scientific phenomena of the Earth, but also obtain comprehensive scientific information of the atmosphere, land, ocean and multiple layers of the Earth in full band and active and passive joint observation. In addition, the Moon as an observation platform also has the characteristics of stable geological structure, accurate and unique observation capabilities, and wide temporal and spatial coverage.

(2) In-depth study of scattering models. The scattering characteristics of different crops in SAR images are different. By establishing accurate models for different crops, overcoming the limitations of empirical models, analyzing and comparing the effects of different models, the most suitable model for specific regions and crop types can be selected, thereby improving the accuracy of crop growth monitoring[31].

(3) Three-dimensional synchronous observation of aerospace, aviation and ground and the integration of multi-source remote sensing. Whether it is satellite-borne SAR, airborne SAR or ground-based SAR, each has its advantages, disadvantages and applicable scenarios. Combining optical remote sensing and SAR radar monitoring of satellite platforms, unmanned aerial vehicle synthetic aperture radar (UAVSAR), and ground survey and monitoring of ground platforms will be able to further improve the monitoring capabilities of crop areas.

6. Conclusion

This paper discusses the research progress of SAR radar remote sensing in rice planting area monitoring from multiple erspectives, including the temporal characteristics of synthetic aperture radar (SAR) data, polarization information, multi-source data fusion, and the application of deep learning methods. Not only is the rice planting area extraction method analyzed based on the temporal characteristics of rice, but also the rice area extraction method based on machine learning is discussed from three aspects: supervised classification, unsupervised classification, and deep learning. Finally, this paper discusses the problems existing in current research, such as the lack of universality of classical methods, the impact of SAR image noise on classification accuracy, the complexity of prior knowledge and the asymmetry of the accuracy of results, and proposes three possible future development directions.

Authors Contribution

All the authors contributed equally and their names were listed in alphabetical order.

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