Research Progress on Spatiotemporal Variability of Rice Planting Based on Satellite Remote Sensing Monitoring

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Abstract As a vital food crop, rice is an important part of global food crops. Studying the spatiotemporal changes in rice cultivation facilitates early prediction of production risks and provides support for agricultural policy decisions related to rice. With the increasing application of satellite remote sensing technology in crop monitoring, remote sensing for rice cultivation has emerged as a novel approach, offering new perspectives for monitoring rice planting. This paper briefly outlined the current research and development status of satellite remote sensing for monitoring rice cultivation both at home and abroad. Foreign scholars have made innovations in data sources and methodologies for satellite remote sensing monitoring, and utilized multi-source satellite information and machine learning algorithms to enhance the accuracy of rice planting monitoring. Scholars in China have achieved significant results in the study of satellite remote sensing for monitoring rice cultivation. Their research and application in monitoring rice planting areas provide valuable references for agricultural production management. However, satellite remote sensing monitoring of rice still faces challenges such as low spatiotemporal resolution and difficulties related to cloud cover and data fusion, which require further in-depth investigation. Additionally, there are shortcomings in the accuracy of remote sensing monitoring for fragmented farmland plots and smallholder farming. To address these issues, future efforts should focus on developing multi-source heterogeneous data fusion analysis technologies and researching monitoring systems. These advancements are expected to enable high-precision large-scale acquisition of rice planting information, laying a foundation for future smart agriculture.

Key words Satellite remote sensing; Rice cultivation; Spatiotemporal variability; Monitoring; Research review

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Rice is one of the world's major food crops, and monitoring its spatiotemporal distribution plays a critical role in early warning systems for food security and the formulation of rice cultivation policies. With ongoing global climate changes and population growth, the demand for rice as a staple food continues to rise. Monitoring the spatiotemporal distribution of rice cultivation holds significant importance for the application of remote sensing technology[1]. Traditional ground survey methods face limitations such as high labor requirements and small coverage areas, making them unsuitable for large-scale and repeated monitoring. In contrast, satellite remote sensing monitoring offers advantages such as macro-scale coverage, rapid data acquisition, and low consumption, making it a novel technology for monitoring the spatiotemporal distribution of rice cultivation[2].

Currently, scholars both at home and abroad have conducted extensive research on using remote sensing to monitor rice cultivation. Multi-temporal image data enable the identification of rice planting areas, monitoring of growth conditions, and estimation of yields[3]. In particular, the introduction of multi-source fused satellite data and machine learning models in recent years has further improved accuracy. For example, the effective integration of Sentinel-2 satellite data with crop growth models can significantly enhance the precision of yield forecasting for rice in Northeast China[4]. Meanwhile, advancements in drone remote sensing technology provide high-resolution images at the field scale for monitoring rice growth, enabling more precise judgement[5].

However, remote sensing monitoring currently faces numerous technical challenges, such as cloud coverage of optical images, difficulties in effectively fusing heterogeneous data, and low identification accuracy for small fragmented plots of smallholder farmers, all of which constrain further improvement in monitoring effectiveness[6]. Additionally, the applicability in southern regions characterized by complex terrain, numerous mountainous areas, and fragmented rice fields remains to be enhanced[7]. To address these issues, subsequent research must further advance multi-source heterogeneous data fusion analysis, explore the establishment of automatic analysis process of cloud computing, and refine the "aerial-ground" integrated monitoring methodology[8-9].

This paper summarized the achievements of scholars both at home and abroad in monitoring rice cultivation using satellite remote sensing technology and the primary data sources and methods employed by researchers worldwide, analyzed existing shortcomings and challenges, and prospected future development trends, aiming to offer valuable insights for other scholars. It lays a foundation for making greater contributions to the application of remote sensing in the field of rice cultivation monitoring.

Research Status Abroad

International scholars have also achieved notable results in the field of satellite remote sensing for monitoring rice cultivation. Tanaka *et al.*[5] suggested that "NDVI and the green excess index

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based on multi-rotor drone aerial photography can effectively monitor abnormal growth areas in rice and track yield variations", providing a cost-effective monitoring method for small farmers. In terms of data fusion, Barbieri *et al.*[8] proposed the RIICE technology, which integrates satellite remote sensing with crop models, achieving over 85% accuracy in monitoring rice cultivation areas in Nigeria. This validates the feasibility of multi-source data fusion. The application of machine learning is a key technology for breaking through the limitations of monitoring accuracy. Lu *et al.*[4] achieved prediction results superior to those of traditional methods by combining Sentinel-2 data with the deep learning model BCHA. Zha *et al.*[10] significantly improved the accuracy of NIN (Nitrogen Nutrition Index) estimation using remote sensing data acquired from drones, thereby facilitating the implementation of scientific and precise formula fertilization.

In response to complex environmental conditions, different scholars have employed varied methods. Huang utilized NOAA-AVHRR long-time-series NDVI data to establish a predictive model, which excluded factors such as technological advancements and achieved a prediction accuracy up to 6% for provincial rice yields[3]. Yu *et al.*[11] used drone-based hyperspectral data to invert rice phenotypic parameters. They noted that different components exhibited varying sensitivities to specific spectral bands, offering new insights for precision monitoring.

However, these studies also face certain issues. Barbieri *et al.*[8] noted that accuracy in fragmented planting areas could drop to 75%, while Tanaka's method is more suitable for monitoring within field-scale ranges[5]. There is a need to further refine multi-source data fusion algorithms and enhance cloud-based platform automation to meet the requirements for large-scale monitoring.

Table 1 Comparison of multidimensional technical approaches and characteristics in core remote sensing monitoring research of rice abroad

Author	Research content	Research method	Advantage	Disadvantage
Kei TANAKA	To monitor rice growth and generate maps for fertilization decisions, lodging risk, yield, and protein content using multi-rotor drone low-altitude remote sensing technology.	Orthophotos and digital surface models (DSM) were generated by combining NDVI and 2G_RBi indices and processing aerial images using SfM-MVS technology.	Low cost and high security.	The long-term data stability has not been verified.
Jian Lu	To establish a method for estimating rice yield in Northeast China by integrating multi-source remote sensing data (MODIS + Sentinel-2), the WOFOST crop model, and deep learning.	Sentinel-2 high-resolution LAI was assimilated into the WOFOST model using the EnKF algorithm.	Significantly improved accuracy.	Insufficient prediction stability in high-yield areas/complex terrain.
Fenghua Yu	To retrieve rice phenotypic parameters (LAI, Cab, Cw, Cdm) based on drone hyperspectral remote sensing by combining the PROSAIL model with optimization algorithms.	An improved Sobol global sensitivity analysis was employed to identify parameter-sensitive bands, and the Particle Swarm Optimization algorithm was used to minimize spectral differences for inversion.	High inversion accuracy.	Lower accuracy in Cw inversion.
Jingfeng Huang	To construct a provincial-level rice yield prediction framework based on NOAA AVHRR multi-temporal NDVI data, which eliminates the effects of long-term trends such as technological advancements and fertilizer application, and thus enables high-precision yield estimation.	Linear regression and the moving average method were adopted to decompose historical yield trends and extract 28 NDVI variables for correlation analysis, and Stepwise regression was then applied to build a prediction model, which was validated across five provinces in China.	High prediction accuracy.	Significant local errors.
Haini Zhao	To achieve high-precision dynamic monitoring of the Rice Nitrogen Nutrition Index (NNI) using fixed-wing drone multispectral data combined with machine learning algorithms such as Random Forest (RF)	Single Vegetation Index (SVI), Stepwise Multiple Linear Regression (SMLR) and Random Forest (RF) were applied.	Breakthrough of prediction accuracy.	Limitations in early growth stages.
Massimo Barbieri	To achieve precise estimation of rice planting area, yield, and yield gaps in Jigawa and Benue States by integrating multi-source satellite data and the ORYZA crop model based on RIICE technology	Multi-source Data Fusion + Model Coupling.	High-precision area monitoring.	Limitations in tropical rainforest regions.

Research Status in China

In China, the research on rice production monitoring using satellite imagery has made significant progress, particularly in regional adaptation studies and operational applications. Sun *et al.*[6] proposed a spatiotemporal fusion model (TSFM), which overcomes limitations of traditional methods such as susceptibility to cloud interference and image registration errors. By integrating spatial and temporal information from images, this model enhances the accuracy of rice extraction. Sun *et al.*[7] utilized time-series EVI data from domestic satellite WFV imagery (GF-1 high resolution) and proposed a rice extraction method specifically designed for fragmented planting areas in southern China. This validates the application potential of domestic high-resolution satellite remote sensing in agricultural remote sensing.

In terms of technological applications, the research in China emphasizes the integration of multi-source data and algorithms. Wu *et al.*[12] combined GIS with an improved F-UNet model to develop a monitoring method for rice planting areas, achieving detection accuracy above 90% in Yulin City. Liu *et al.*[13] proposed a novel technical approach for remote sensing certification in organic agriculture by analyzing NDVI temporal differences under various fertilization treatments. Li[14] developed a rice growth indicator monitoring model based on drones and random forests, validating the application of low-altitude remote sensing in precision agriculture.

In the field of regional application practices, scholars in China have studied major production areas across various application domains. Fu *et al.*[15] applied HJ satellite data to monitor rice growth in the Heilongjiang reclamation area, demonstrating its applicability in the main rice-producing regions of northern China. Li[16] achieved a yield estimation error of less than 7% in Jiangsu by integrating remote sensing data with crop models. Liu *et al.*[9] developed a RS-P-YEC model to estimate the net primary productivity of early rice in Jiangxi Province, providing technical support for rice production in China's main producing areas. Wu[17] generated high spatiotemporal resolution images using spatiotemporal fusion techniques, and achieved accurate extraction of rice area in cloudy regions (93.3% accuracy) by combining with phenological features and SVM classification. This provides an effective method for agricultural remote sensing monitoring. Zhu[18] revealed the spatial variation patterns of rice growth parameters (correlation at 6–9 m) by integrating geostatistics and machine learning, confirming the superiority of RBFNN in spatial interpolation of farmland data. This offers theoretical support for precise remote sensing irrigation.

However, the research in China also has its limitations. Huang[19] noted that in the mountainous and topographically diverse regions of southern China, where smallholder plots are fragmented, monitoring accuracy tends to be lower. Zhang's study[20] suggested that estimating irrigation water consumption for rice in Northeast China still requires addressing uncertainties in soil parameters. It is therefore imperative to refine methods for multi-source data collaborative analysis to enhance their stability in heterogeneous planting contexts.

Table 2 Comparative analysis of multi-dimensional technical approaches and characteristics in core studies on remote sensing monitoring of rice in China

Authors	Research content	Research method	Advantage	Disadvantage
Peijun Sun	A spatiotemporal fusion model (TSFM) was proposed to address the issues of "cloud contamination" and "salt-and-pepper noise" in rice identification by integrating spatial and temporal information from multi-temporal remote sensing images.	Multi-temporal Landsat 8 images were classified using Support Vector Machine (SVM). Spatiotemporal membership degrees were defined to integrate information across spatial and temporal dimensions. Rice distribution was extracted by a dual-window variable-step-size thresholding method.	Strong anti-interference capability.	Landscape adaptability limitations.
Shujuan Sun	To achieve high-precision extraction of rice planting areas in fragmented terrain regions of southern China based on GF-1/WFV satellite EVI time-series data by integrating the HANTS smoothing algorithm with a decision tree model	An EVI time series covering the entire rice growth period was constructed. The HANTS algorithm was applied to denoise and smooth the data. A decision tree model was then built by integrating phenological features with topographic constraints (slope ≤ 8°).	Significantly improved accuracy.	Resolution limitations.
Yinglan Wu	To achieve high-precision monitoring of dynamic changes in rice planting areas in Yulin City, Guangxi Zhuang Autonomous Region by integrating GIS spatial analysis and an improved F-UNet deep learning model	Multiple indices (NDVI, EVI, LSWI) were jointly used for discrimination. The center-of-gravity migration method was applied to quantify spatial change trends. An F-UNet model, incorporating batch normalization and a Softmax classifier, was constructed to optimize boundary recognition.	Significantly better than traditional SegNet/U-Net models.	Strong data dependency.
Huanjun Liu	A remote sensing identification method for distinguishing between organic and chemical fertilizer application practices was proposed, based on the correlation between NDVI time series differences and yield.	Multi-temporal Landsat 8/Sentinel-2 data were used to construct NDVI time series curves, and the temporal correlation patterns between NDVI and yield were analyzed.	Strong regularity.	Regional limitations.
Songyang Li	To construct a rice growth indicator monitoring model using an unmanned aerial vehicle platform equipped with an active canopy sensor and a consumer-grade digital camera, and validate its applicability in field conditions.	Active sensor mode; digital camera mode.	Dual-mode complementary innovation.	Application scenario limitations.

Existing Challenges and Research Necessity

Currently, the application of satellite remote sensing in rice planting monitoring still faces numerous technical bottlenecks that hinder further improvement in monitoring effectiveness. Optical remote sensing continues to be affected by cloud interference during data acquisition, particularly in southern rice-growing regions where rainy weather leads to short imaging windows. This makes it difficult to ensure the continuity and timeliness of rice monitoring. In this regard, Sun *et al*.[6] noted that "using traditional change detection methods for rice remote sensing identification is subject to cloud interference and image registration errors, resulting in low identification accuracy". At present, there is still a contradiction between spatial resolution and revisit period of satellite data, which makes it difficult to meet both monitoring range and identification accuracy requirements in broken planting areas[18].

At the technical methodology level, fusion algorithms for heterogeneous data are relatively complex, and the spatiotemporal consistency of data from different sensors remains a significant limitation. Huang[19] found that under single-temporal and single-data-source conditions, monitoring accuracy decreased in Cambodia due to its complex planting patterns. While machine learning models improved monitoring accuracy, they suffer from "black-box" issues, reducing model interpretability and limiting their application in agronomic decision-making[4]. Li[14] conducted research using drones and algorithms such as random forests, finding that while these algorithms improved monitoring accuracy, they required extensive sample labeling, which increased costs. Sun[21], by integrating high-resolution remote sensing, GIS, and statistical models, revealed the spatiotemporal pattern of rice area in Jiangsu as "overall slow decline with localized sharp reductions" (50% stable, 42% slow decline, 8% sharp decline) and identified urbanization and aquaculture expansion as the primary drivers. Wang[22] achieved high-precision identification of rice planting structures (double-cropping rice, mid-season rice, and rice-crayfish systems) in Jiangling County by integrating multi-temporal remote sensing feature indices with machine vision clustering techniques. The study also revealed issues such as insufficient data continuity and a lack of in-depth quantification of underlying driving mechanisms.

From the perspective of application status, current methods are not well-suited for fragmented smallholder farming areas. Barbieri *et al*.[8] found in their study that monitoring accuracy in small-scale farming areas in Nigeria was 10%-15% lower than in larger-scale farming areas. Similarly, Wu[12] observed that boundary extraction accuracy for fragmented rice fields in southern China was low, leading to errors in area statistics of rice fields. Consequently, remote sensing monitoring outcomes exhibit clear shortcomings and cannot effectively guide precision agricultural practices.

Strengthening research in this area holds practical significance. For food security, accurately capturing the spatiotemporal distribution of rice production areas is a prerequisite for yield prediction and policy formulation[1]. Li *et al*.[2] highlighted that satellite remote sensing can provide farmers with "high-level timely crop information", which is crucial for optimizing crop distribution and reducing waste. In green agriculture, scientific fertilization and rational irrigation based on remote sensing information can help reduce non-point source pollution and protect the environment[13]. Additionally, scientific and comprehensive monitoring can provide a basis for agricultural insurance, crop disaster assessment, and other aspects, serving the entire agricultural industry chain[9].

Table 3 Comparative analysis of key problem domains and multi-dimensional technical solutions for remote sensing monitoring in major global rice production regions

Author	Research region	Regional characteristics	Existing problems	Solutions
Massimo Barbieri	The three major rice-producing states of Nigeria.	Marked differences in climate and farming practices.	Lagging official statistics; monitoring blind spots; significant yield gaps.	Integration and innovation of RIICE technology and multi-source data collaboration
Chongchong Huang	The whole territory of Cambodia.	Dominance of tropical monsoon climate.	Outdated irrigation infrastructure; fragmented cultivation patterns.	Multi-feature fused time-series remote sensing monitoring.
Yinglan Wu	The Yulin Basin in Guangxi.	Interlaced distribution of paddy and dryland fields.	Conventional methods struggle to delineate small field boundaries, resulting in high rates of misclassification and omission.	Innovative integration of Brovey image fusion technique with an improved F-UNet model.
Ling Sun	The three major agricultural areas of Jiangsu: Xuhuai, Lixiahe, and coastal areas.	Rice area accounting for 70.7% of cultivated land.	A cumulative 13.7% of paddy fields has been converted to non-agricultural land.	Constructing a cultivated land database using high-resolution remote sensing data (RapidEye/GF-1).
Qianqian Wang	Jiangling County, Hubei (core grain-producing area of the Jianghan Plain).	Ample hydrothermal resources but increasingly complex planting structures.	Traditional monitoring methods suffer from time lag.	Multi-feature fusion + machine vision recognition.

Future Research Directions and Development Suggestions

To address the current technical challenges and difficulties in applying satellite remote sensing for rice planting monitoring, future work should prioritize some aspects. Specifically, Li Songyang's use of low-altitude drone platforms and random forest algorithms has shown significant effectiveness in monitoring crop planting at the field scale. Future efforts should explore the fusion of multiple platforms to achieve high coverage from satellite remote sensing platforms to drone remote sensing platforms. For the complex terrain in southern regions and fragmented smallholder farming areas, the spatiotemporal fusion model of Sun *et al.* [6] can serve as a reference to develop adaptive algorithms that integrate multi-source heterogeneous data, thereby enhancing the identification of fragmented planting areas across multiple platforms.

At the methodological and technical levels, breakthrough research in artificial intelligence and remote sensing analysis should be strengthened. Lu *et al.* [4] developed a deep learning model based on BICA and found that combining multi-source data with crop models can better predict crop yields. Future efforts should focus on further improvements to reduce reliance on labeled data. Additionally, Yu *et al.* [11] proposed parameter extraction based on hyperspectral inversion, advocating for the construction of physical and data models to enhance the stability and reliability of results.

The data processing workflow should be advanced towards automation and intelligent upgrading. The RIICE technology developed by Barbieri *et al.* has established an operational cloud computing platform[8]. By developing cloud services for agricultural applications, automation and intelligence in data processing can be achieved, covering steps such as data preprocessing, feature extraction, and model execution. Meanwhile, adopting the GIS-based monitoring system, Wu *et al.* [12] aimed to promote the deep integration of remote sensing agricultural information platforms with agricultural information platforms, thereby constructing an integrated smart agricultural production service platform that encompasses "monitoring, diagnosis, and decision-making". Ground-based validation systems are of significant importance for improving monitoring quality. Huang's study[19] on Cambodia revealed that irrigation is a key factor influencing the spatial pattern of rice in the region. Future efforts should focus on establishing a ground observation network that includes soil moisture, meteorological information, and agricultural parameters to enhance model inversion accuracy through "air-ground" joint validation. Based on the concept of integrating remote sensing with crop models, Li[16] proposed the development of ecological domain adaptation strategies to improve the regional applicability of models.

International collaboration should be strengthened to promote data co-construction and sharing. Guan's study[1] on rice planting monitoring in Vietnam indicates that cross-border monitoring of grain conditions and quality requires synchronized data standards and observation protocols. Establishing a global rice monitoring alliance would facilitate the sharing of validation data and experiences at different scales, thereby enhancing early warning systems for global food security. The exploration of these new directions is expected to drive the transition of global rice planting satellite remote sensing from scientific research to operational applications, achieving breakthroughs and advancements.

Conclusions

Satellite remote sensing holds great potential for monitoring the spatiotemporal variability of rice planting, serving as a timely and effective complement to traditional surveys. A comprehensive analysis reveals that the application of multi-source fusion algorithms is key and central to advancing this field, both domestically and internationally. Scholars abroad have achieved relatively advanced theoretical results in this area of applied research. For instance, Tanaka *et al.* [5] utilized drone platforms for block-wise field monitoring. Barbieri *et al.* [8] proposed the RIICE (Rational Integration of Information for Crop Ecosystems) remote sensing technology, demonstrating the promising application prospects of multi-source data fusion analysis. Multiple studies in China have also developed targeted research models tailored to regional characteristics. For instance, Sun *et al.* [6] introduced a spatiotemporal fusion model to address remote sensing monitoring challenges in complex southern terrains, while Wu *et al.* [12] developed a remote sensing monitoring system based on a GIS platform, suitable for operational applications.

Currently, there remain certain technical challenges, primarily due to cloud interference, difficulties in data fusion, and the identification of fragmented smallholder planting plots, leading to significant uncertainty in monitoring results, especially potential deviations in guiding precision agriculture. Future efforts should further explore the integration of multiple monitoring platforms to achieve a multi-scale "air-ground" integrated monitoring solution, combining low-altitude drone monitoring with satellite surveillance. Additionally, algorithm improvements, such as Li Songyang's random forest algorithm, should be enhanced to increase interpretability and reduce reliance on labeled data.

From an application perspective, establishing a comprehensive remote sensing monitoring system for rice will significantly contribute to early warning for food security, government decision-making, and precision governance. Real-time monitoring of rice planting conditions contributes to resource conservation, prevention of non-point source pollution, and promotion of green agricultural development. Meamwhile, it is essential to expand international cooperation, establish standardized data frameworks and validation mechanisms, and drive the transition of remote sensing applications from scientific research to practical services. Satellite remote sensing holds promising prospects for the future and is expected to become a standard practice in rice planting monitoring, supporting the advancement of intelligent agriculture.

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