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Integrating Remote Sensing and Crop Modeling for Real-Time Yield Prediction in Wheat

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Abstract Wheat is one of the most important cereal crops globally, and accurate yield prediction is critical for ensuring food security and supporting precision agriculture. Traditional estimation methods relying on field surveys are often time-consuming, labor-intensive, and limited in spatial coverage. This study integrates remote sensing technologies with crop modeling approaches to establish a real-time and scalable framework for wheat yield prediction. Specifically, we utilized satellite and UAV-based remote sensing data-including NDVI, LAI, and chlorophyll indices-combined with process-based crop models such as WOFOST and APSIM to simulate crop growth dynamics. The integration was achieved through data assimilation techniques that continuously feed remote observations into crop models, enabling dynamic calibration and validation across growth stages. A case study in the Indo-Gangetic Plains demonstrated that assimilating Sentinel-2 data with the WOFOST model significantly improved yield prediction accuracy and provided timely forecasts beneficial for regional decision-making. This integrated approach enhances both spatial and temporal resolution in yield monitoring, offering a more reliable foundation for precision management, early warning systems, and policy development. Future research should focus on incorporating artificial intelligence and machine learning algorithms to refine model performance and expanding open-access platforms for wider application in climate-resilient wheat production.
Keywords Remote sensing; Crop modeling; Wheat yield prediction; Data assimilation; Precision agriculture

1 Introduction

Wheat is almost everywhere on people's dining tables. It is not only a staple food in many countries but also an important source of calories and protein globally (Ma et al., 2024). When it comes to food security, wheat is often an unavoidable topic. Especially in the context of frequent climate change and continuous population growth, whether the yield of wheat can be accurately predicted is no longer just a scientific research issue, but is related to government decision-making, market fluctuations and even farmers' income (Cheng et al., 2022).

However, the prediction methods commonly used in the past, such as field investigations and manual sampling, although seemingly intuitive, were labor-intensive, time-consuming, had small data volumes, and were also easily affected by regional differences. When encountering extreme weather or areas with complex terrain, these methods become even more inadequate. In addition, they have difficulty revealing the intricate relationships among genotypes, environmental conditions and agricultural management, and the prediction accuracy is naturally limited (Gawdiya et al., 2024).

So, researchers began to try a new combination idea: using remote sensing technology and crop models "together". Satellite images can cover large agricultural areas in a very short time, providing dynamic information on crop growth, while models and machine learning algorithms are responsible for integrating these images, meteorological data, soil characteristics, etc., to form more comprehensive yield estimates (Bian et al., 2022). Some of the latest studies show that this approach of combining multi-source data not only makes the prediction results more timely and accurate, but also significantly helps local agricultural management and policy-making (Ashfaq et al., 2024).

2 Remote Sensing Technologies in Crop Monitoring

2.1 Types of remote sensing platforms

When it comes to crop monitoring, the most common "eyes" can be roughly divided into three types: satellites, drones and ground sensors. Satellite platforms, such as Sentinel-2 or Landsat 8, can cover large areas at one go and are frequently revisited, making them particularly suitable for observing macroscopic changes in crop growth (Ibrahim et al., 2023). However, their resolution is limited and sometimes the details are not clear enough. On the contrary, drones can "bend down" to observe the field conditions, with high resolution, flexibility and mobility, and can take off at any time to take pictures. They are especially suitable for monitoring fine indicators such as leaf area index (LAI) or chlorophyll content. As for ground sensors, although they have a small field of view, they are highly accurate. Both handheld and fixed types are available and are often used to calibrate or verify data from satellites and drones (Mukiibi et al., 2024). It can be said that each of the three has its own strengths and weaknesses. When used in combination, the effect is often better.

2.2 Key indices and parameters: NDVI, LAI, chlorophyll content

In remote sensing images, truly valuable information is often hidden in those indices. NDVI is the most commonly used one to determine the "mental state" of vegetation. The higher the value, the more lush the crops (Han et al., 2021). LAI, however, took a different perspective, reflecting biomass and yield potential from the number of leaves (Sishodia et al., 2020). Chlorophyll content is mostly calculated with indices such as SPAD or MCARI, which can reveal the photosynthesis and nitrogen conditions of plants (Shanmugapriya et al., 2022). Of course, not all crops are equally sensitive to these indicators, so sometimes scientists also use "advanced" parameters such as the red border index and multi-band index to make the results closer to reality (Figure 1).

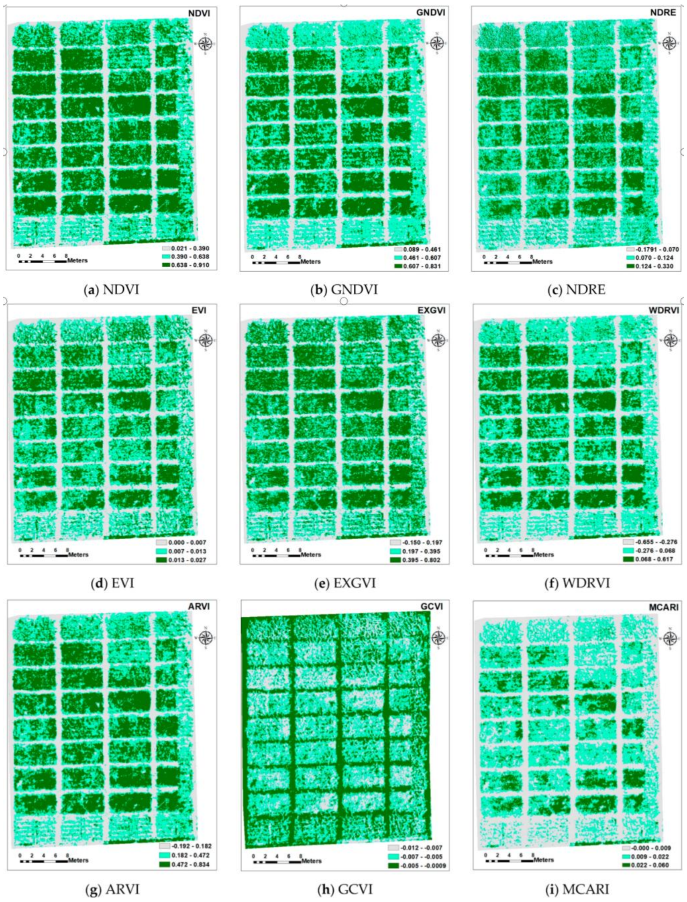

Figure 1 Spatial variability of vegetation indices (VIs) during the *kharif* maize: (a) normalised difference vegetation index (NDVI); (b) green normalised difference vegetation index (GNDVI); (c) normalised difference red-edge index (NDRE); (d) enhanced vegetation index (EVI); (e) excess green vegetation index (ExGVI); (f) wide dynamic range vegetation index (WDRVI); (g) atmospherically resistant vegetation index (ARVI); (h) green chlorophyll vegetation index (GCVI); (i) modified chlorophyll absorption ratio index (MCARI) (Adopted from Parida et al., 2024)

2.3 Advantages: non-invasive, large-scale monitoring, real-time data acquisition

Compared with sampling and measuring each plant one by one, the benefits of remote sensing are too obvious. It can obtain large-scale field data without destructive sampling or a large amount of manual labor (Omia et al., 2023). Moreover, one shot is not enough; it can be taken repeatedly, which is both fast and extensive, allowing you to almost instantly observe the changes in the health of the crops. In this way, both disease signs and nutrient deficiencies can be detected in advance (Li et al., 2023). When this type of data is combined with models or machine learning, the monitoring accuracy and scalability will be further enhanced. For agricultural managers, this means they can intervene earlier, use land more rationally, and achieve the most stable harvest with the least input.

3 Crop Modeling Techniques for Wheat Yield Prediction

3.1 Overview of process-based models: APSIM, DSSAT, WOFOST

In wheat yield prediction, several frequently mentioned models are almost household names: APSIM, DSSAT, and WOFOST (Wajid et al., 2021). Their common point is that they all attempt to use daily meteorological, soil and crop data to restore the entire process of plants from emergence to panicle formation, including growth, development and biomass accumulation. The difference lies in that the algorithmic details of each model are slightly different, and thus their applicable scopes are not exactly the same. Some studies suggest that the prediction results of DSSAT and DAISY are more stable, while APSIM and WOFOST also perform well in complex environments. When it comes to which one is the best, there is actually no definite conclusion. So some scholars simply combine multiple models to make up for the bias of a single model. This kind of "combination punch" is often more stable when dealing with uncertainties.

3.2 Role of input variables: weather, soil data, crop genotype

Whether the model is accurate or not mainly depends on the data "fed" in. Meteorological data, soil properties and variety characteristics - all three are indispensable. The meteorological section generally includes temperature, precipitation, radiation intensity, etc. In terms of soil, it involves texture, nutrient and moisture characteristics; Crop genotypes reflect variety differences. Studies have found that the availability of water and nitrogen is most likely to influence the yield outcome, and precipitation, soil type and nitrogen fertilizer application rate are often sensitive factors (Hao et al., 2024). Of course, if fine calibration can be made for the soil and varieties in different regions, the error will be significantly reduced, especially in arid or barren environments, which is more prominent (Shahid et al., 2024).

3.3 Output utility: predicting phenology, biomass, and grain yield

The output results of these models are actually very useful. Not only do they provide the final grain yield, but they can also predict the flowering period, maturity period, leaf area index (LAI), and even changes in aboveground and underground biomass. For researchers, this helps to understand the response of wheat under different climatic and management conditions; For farmers or policymakers, these data can be used to plan resources and adjust planting strategies. Furthermore, if the model is combined with remote sensing images or machine learning, real-time yield predictions with geolocation can be generated (Kheir et al., 2023), which makes the application of precision agriculture more operational and also provides a basis for food security planning.

4 Synergistic Integration of Remote Sensing and Crop Models

4.1 Data assimilation methods to feed real-time remote data into models

Data assimilation is a crucial step for the model to "understand" the real-time situation in the field. In simple terms, it is to continuously stuff remote sensing observations into the model to keep the model's state in sync with reality. The commonly used methods include ensemble Kalman filter (EnKF), four-dimensional variational assimilation (4DVar), particle filter, as well as particle swarm optimization (PSO) or Complex Evolutionary Algorithm (SCE-UA), etc. (Jin et al., 2022). These algorithms can dynamically correct the variables in the model based on the leaf area index (LAI) or soil moisture data sent back by satellites. For instance, when MODIS or Sentinel data is input into WOFOST or SAFY models, the predicted yields are often much more accurate than before, with a significant decrease in error, whether at the field or regional scale.

4.2 Calibration and validation using time-series remote observations

No matter how advanced a model is, it still needs to be calibrated and verified to be reliable. Researchers usually fine-tune model parameters using continuous remote sensing time series, such as LAI, NDVI or soil moisture, and then compare the results with the real observed growth process and yield to see if they match (Zhuo et al., 2023). Especially during the critical periods such as jointing, panicle formation or grain filling, integrating the vegetation index into the model in stages yields more obvious results (Bouras et al., 2023). Nowadays, many teams combine remote sensing and ground measurement data to create grid-based or multi-model integrated calibration systems. This approach can significantly enhance spatial resolution and make predictions closer to reality.

4.3 Benefits: enhanced prediction accuracy, dynamic model adjustment

Combining remote sensing with models has quite a few benefits. The most direct one is that the prediction is more accurate. Relevant studies show that the R^2 of wheat yield has increased and the RMSE has decreased (Zare et al., 2022). Meanwhile, the model can "update its status" at any time, promptly reflecting changes in crops or the environment, and is more sensitive to sudden situations such as drought and diseases. Moreover, this system is scalable and updated quickly. It can be of great use whether providing field advice to farmers or serving policy-making and food security assessment.

5 Case Study: Real-Time Wheat Yield Forecasting in the Indo-Gangetic Plains

5.1 Background: wheat production significance, climatic variability

On the vast Ganges Plain of India, wheat is almost the lifeblood of farmers. It is not only one of the main production areas in the country but also closely related to the food supply of hundreds of millions of people. But this seemingly fertile land is not always stable. Frequent climate fluctuations, early arrival and early departure during the rainy season, droughts, heat waves, and sudden cold waves may all disrupt the planting rhythm (Zhao et al., 2020; Qader et al., 2023). Farmers often find it hard to judge the quality of their harvests, and the government is also prone to being "at a loss" when it comes to resource allocation and market regulation. Therefore, if the output can be predicted in advance, it can not only help farmers avoid risks, but also enable the policy level to be better prepared.

5.2 Methods: using Sentinel-2 data and WOFOST model with real-time assimilation

To make the predictions more realistic, researchers attempted to combine the data from the Sentinel-2 satellite with the WOFOST crop model. Sentinel-2 takes fine shots and updates quickly, accurately capturing key parameters such as leaf area index (LAI) and soil moisture. Through methods such as Ensemble Kalman filtering (EnKF), these data were continuously input into the model, enabling it to be "corrected" in real time according to the field conditions throughout the growing season (Figure 2) (Wu et al., 2020). It is worth mentioning that the research also used Sentinel-1 radar data in combination, which can still obtain clear information in cloudy weather. This is particularly crucial for the Indian monsoon region.

5.3 Results: improved yield prediction accuracy and early warning benefits for farmers

Practice has proved that the effect of this data assimilation method is quite remarkable. After integrating the LAI and soil moisture data of Sentinel-2 into the WOFOST model simultaneously, the prediction accuracy has been significantly improved. Research shows that when R^2 increases from 0.41 to 0.76, RMSE drops significantly, with the average relative error being as low as 3.17%. Compared with the traditional open-loop model, this joint assimilation can detect the trend of yield changes earlier, providing farmers with the opportunity to intervene in advance and allowing the government to be more composed when dealing with possible crop failures. Ultimately, the predictions not only became more accurate but also more "effective".

6 Benefits of the Integrated Approach

6.1 High spatial-temporal resolution for field-level management decisions

Nowadays, farmland management emphasizes "seeing clearly and acting quickly". By integrating various remote sensing data such as satellite, unmanned aerial vehicle and ground sensors with crop models, researchers can estimate yields on a 20-meter square scale and even track subtle changes in crops at different stages (Yang et al., 2024). This improvement in resolution makes management more specific, and irrigation, fertilization and pesticide application can all be carried out in a targeted manner. Sometimes, just by taking a glance at the anomalies in the spectral time series data, one can identify the problem points in advance. Although it may seem complicated, for farmers, this means more precise decision-making, higher output and more resource conservation.

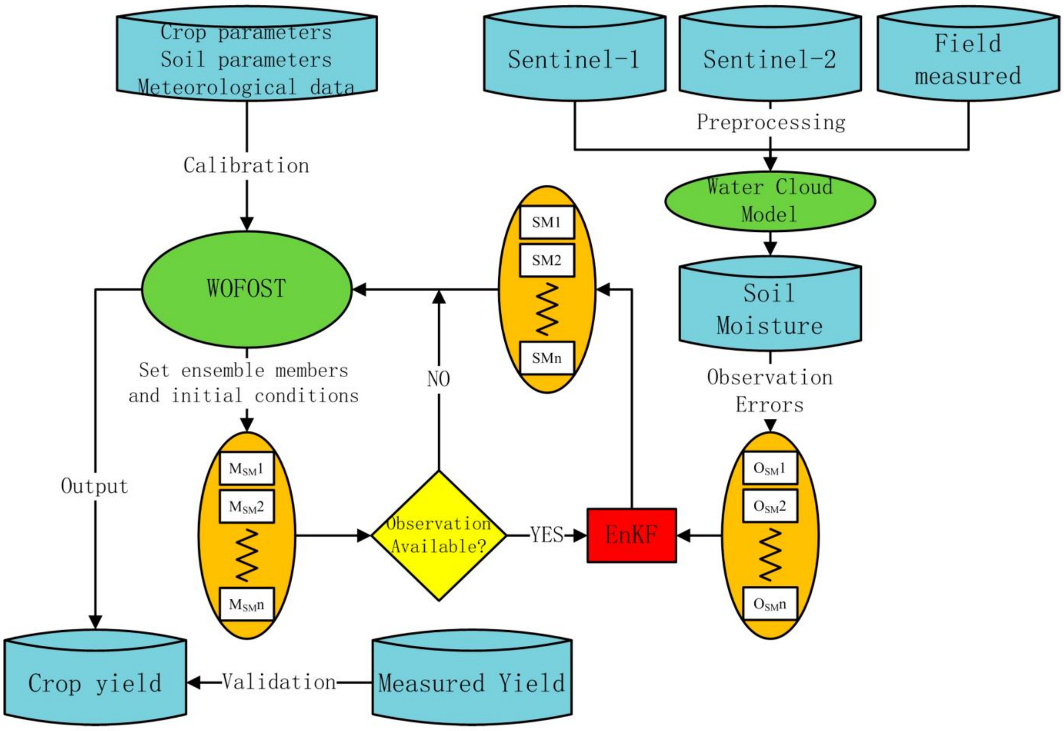

Figure 2 Flowchart for the winter wheat yield estimation using the EnKF-based assimilation algorithm (Adopted from Zhuo et al., 2019)

6.2 Improved accuracy over isolated remote sensing or modeling alone

If relying solely on remote sensing, although the images are clear, it is difficult to explain the physiological processes behind them. Relying solely on models is also easily restricted by input parameters. After the combination of the two, the improvement in prediction accuracy is almost immediate. For instance, after introducing variables such as leaf area Index (LAI), Normalized Vegetation Index (NDVI), or enhanced Vegetation Index (EVI) into the model, R^2 increased, RMSE decreased, and the estimation accuracy of spatial yield variance even improved by 70%, with the error reduced by more than half (Li et al., 2024). With the assistance of artificial intelligence algorithms such as CNN-GRU and ensemble learning, the system remains stable when facing complex and rapidly changing environments (Wang et al., 2023). It can be said that this is a way to make data and models "complement each other's strengths and weaknesses".

6.3 Applications in precision agriculture, food security, and policy-making

The potential of this integrated system is far more than what looks good in the laboratory. It can draw field yield maps and help farmers adjust management plans according to plot differences (Yang et al., 2024); It can also issue early warnings before the signs of reduced crop yields emerge, providing a basis for grain reserves and market regulation (Zhang et al., 2024). For government departments, it can also generate high-precision spatial data for formulating agricultural plans, risk assessments or insurance policies. In other words, from farmland to the policy level, this approach makes it truly possible to "accurately identify and effectively manage".

7 Challenges and Limitations

7.1 Data quality issues: cloud cover, satellite revisit times, input data gaps

No matter how advanced remote sensing is, it cannot escape The Times when the weather is not cooperating. When thick clouds cover the area, the images captured by satellites become incomplete, and data from key growth periods are often missing or distorted as a result. What's more troublesome is that the revisit cycle of satellites does not always happen to coincide with the important growth nodes of crops. Sometimes, missing a few days can greatly reduce the value of information (Wang et al., 2024). However, there are also many problems on the model side: once the input data such as meteorology, soil, and management are incomplete, both the inversion accuracy and the simulation results will be affected (Chen and Tao, 2022). This situation is particularly evident in areas where ground monitoring is weak and production environments vary greatly, and the uncertainty of data is often further magnified.

7.2 Technical complexity in integration, requiring interdisciplinary expertise

Integrating remote sensing with crop models is no easy task. It requires the collaboration of knowledge from multiple fields such as agriculture, remote sensing, data science, and modeling. Data assimilation requires the use of ensemble Kalman filtering (EnKF), 4DVar or machine learning algorithms, and the subsequent calibration and verification processes cannot be taken lightly (Zare et al., 2024). To run models on a regional scale, one still has to deal with huge parameterization tasks and computational pressure. Without a stable data processing procedure and a professional team, it is difficult to do this job well. For some regions with insufficient technological reserves, this interdisciplinary requirement itself has become a bottleneck for promotion.

7.3 Limited access to high-resolution models or sensor data in resource-poor regions

In developed regions, satellites, drones and hyperspectral sensors have long been common, but in areas with limited resources, these devices remain "luxuries". Not only are the purchase and maintenance costs high, but processing and storing big data also require expensive computing power and technical support (Dhakar et al., 2022; Joshi et al., 2023). In addition, due to the lack of high-resolution crop models with open access and the scarcity of datasets for machine learning training, many regions simply cannot run such integrated systems. The result is that the technology seems advanced, but there is still a long way to go before it can be truly popularized.

8 Future Directions and Concluding Remarks

The emergence of artificial intelligence and machine learning is quietly rewriting the way agricultural output is predicted. Nowadays, satellite images, weather records, soil information, and even field management data can all be integrated into a self-adjusting model. Unlike traditional single models, those "hybrid" methods that combine process models such as APSIM with machine learning algorithms (like random forests, XGBoost, and deep neural networks) are more like letting data and mechanisms speak together. The results also prove that this approach is often more stable and accurate, especially showing advantages in environments with variable climates or significant management differences. They can capture complex nonlinear changes, identify trends in advance, and provide stronger support for early prediction. Next, the academic community is increasingly focusing on how to further integrate deep learning and data assimilation technologies, so that "mechanism-driven" and "data-driven" can truly complement each other.

Another direction worth paying attention to is to bring these technologies out of the laboratory and make them more "user-friendly". Now there are open cloud platforms and Web decision-making systems based on Google Earth Engine. Users do not need powerful computing devices to obtain production prediction results online. They integrate remote sensing, meteorological, management and other data on one interface, enabling farmers, agricultural technicians and even government officials to quickly obtain useful information. Meanwhile, low-cost open-source remote sensing tools and simple software also give regions with limited resources the opportunity to use these technologies, helping small-scale farmers reduce risks and improve management efficiency.

Of course, promoting these integrated technologies is not something that can be achieved overnight. To make it truly effective, continuous investment is still needed in data infrastructure, interdisciplinary collaboration and talent cultivation. Only in this way can the integration of AI, remote sensing and modeling be implemented in a broader agricultural system, thereby supporting climate-resilient production, enhancing early warning capabilities, and ultimately providing reliable support for global food security and sustainable development.

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Conflict of Interest Disclosure

The authors affirm that this research was conducted without any commercial or financial relationships that could be construed as a potential conflict of interest.

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