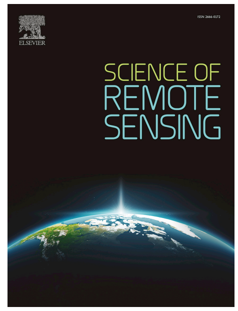

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A review of crop yield estimation on pixel and field scales from remotely sensed data

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Abstract: Crop yield estimation over large regions can provide critical data support for regional agricultural management and global food security assessments. The previous reviews mainly focused on the technological advancements of methods in specific areas such as crop growth, data assimilation, and machine learning. No reviews have summarized the progress in all these areas, particularly at the pixel and field scales. This review comprehensively evaluates various methods for estimating global and regional crop yield from different remotely sensed data, particularly on the pixel and field scales, in the past two decades. All estimation methods are grouped into four categories: empirical statistical, light use efficiency (LUE), data assimilation, and machine learning. We also identify remaining challenges in data consistency, update frequency, and crop type coverage, particularly in data-scarce developing regions. This review provides valuable insights for researchers in the field of remotely sensed data-based crop yield estimation, enabling a deeper understanding of the current status of global and regional datasets, the characteristics and challenges of existing estimation methods, and future research directions.

Keywords: Crop yield estimation, remotely sensed data, machine learning models, data assimilation, LUE models

1 Introduction

Food security refers to the condition in which people have access to sufficient, safe and affordable food to meet their diverse dietary needs . Food security is divided into five specific dimensions (FAO. 1996), including food availability, sustainability of supply, food quality and safety, cultural acceptability (food meets personalized needs), and food access (consumers have the ability to afford it). Currently, Global food security is facing unprecedented challenges (Bose et al. 2016). According to the Food and Agriculture Organization (FAO) (FAO 2017), the global population is projected to reach nearly 10 billion by 2050. Coupled with changing consumption patterns, food demand is expected to increase by more than 50% in the coming decades. However, climate change, environmental pressures, global economic instability, and uncertainties in trade policies are exacerbating the vulnerability of food supply systems (Haufler et al. 2022). Against this backdrop, improving the accuracy and granularity of crop yield estimation has become an urgent task to ensure food and nutritional security (Zhang et al. 2020). Crop yield, defined as yield per unit harvested area, is a critical analytical variable in agricultural, environmental, economic, climatic, and geoinformation sciences. It is essential for understanding regional differences, assessing potential yield gaps, and informing agricultural production and policy decisions (Iizumi and Ramankutty 2015). Unlike relatively stable harvested areas, yields are more sensitive to changes in climatic conditions, soil fertility, management practices, and resource availability. Crop yield estimation is crucial for food security. By estimating the yields of different crops, farmers can adjust the planting structure based on market demand, climate change, and soil conditions, optimizing resource allocation such as irrigation and fertilization to ensure the efficient use of agricultural resources (Taheri et al. 2024). Additionally, yield information can help governments manage food security, assess supply risks, and determine whether food reserves or imports are necessary to ensure a stable market supply (Iizumi et al. 2014; Ray et al. 2012). As the impact of climate change intensifies, yield data can also assist in selecting more resilient crop varieties, adjusting planting times, and providing early warnings for climate-related disasters (Gitz et al. 2016). Governments can use yield data to formulate appropriate agricultural policies and support measures (Iizumi and Ramankutty 2015), ensuring food security and sustainable development.

Traditional crop yield estimation methods based on ground surveys are often time-intensive, labor-intensive, and inadequate in addressing the dynamic variability of climate and environmental factors. With the continuous advancements in remote sensing technologies, an increasing number of advanced satellite sensors have been launched, enabling the acquisition of satellite imagery with higher spatial and temporal resolutions, which lays a solid foundation for crop monitoring, including crop classification (Chen et al. 2025a; Li et al. 2025c). The Landsat program, designed by NASA and operated by USGS since 1972, provides the longest free satellite imagery archive globally and is widely used in land cover, agriculture, and water resource monitoring. The ASTER sensor, launched aboard the Terra satellite in 1999, was developed through collaboration between NASA and Japan's METI, and primarily provides terrain (Hirano et al. 2003) and temperature data (Hulley et al. 2010). China’s HuanJing (HJ) satellites, Fengyun (FY) satellites (Zhang et al. 2024a), and the China-Brazil CBERS satellites have various high-resolution optical and radar sensors for agricultural, natural resource, and disaster monitoring. The European Space Agency’s Copernicus Sentinel series enhances revisit frequency and data consistency through multispectral instruments coordinated with Landsat data (Gascon et al. 2014). WorldView-2, a high-resolution commercial satellite, offers extremely high spatial-resolution imagery and is widely applied in urban planning, agricultural monitoring, and disaster management. ECOSTRESS, mounted on the International Space Station, measures plant temperature to study water demand and stress responses. Other satellite systems, such as PROBA (Barnsley et al. 2004), SPOT (Chevrel et al. 1981), and Cartosat (Radhadevi et al. 2010), also play critical roles in environmental monitoring, resource management, and disaster early warning. By providing diverse and high-quality remote sensing data, these satellite missions have significantly advanced fields such as environmental monitoring, agricultural management, and resource management, providing real-time, large-scale agricultural monitoring capabilities (Liang and Qin 2008). As a result, they effectively address the limitations of traditional ground-based crop yield estimation methods in responding to dynamic climate and environmental changes.

Crop yield estimation based on remote sensing involves acquiring the spectral characteristics of crops in the study area using remote sensing technology. These spectral characteristics reflect the crop growth status, and other environmental factors are also considered. Both are then input into crop yield estimation models to estimate crop yield, supporting agricultural production decisions and the sustainable development of food security (Fig.1). Currently, remote sensing data used in research can be divided into two categories. One category is remote sensing original reflectance data, which reflects changes in the crop canopy structure and photosynthesis through the combination of reflectance in different bands. For instance, Battude et al. (2016) developed a simple agrometeorological model, combining multi-sensor satellite data, including Formosat-2, SPOT-4, Landsat-8, and Deimos-1, to estimate maize yields in the vicinity of Toulouse, southwestern France. At the regional scale, the model outputs exhibited strong consistency with yield statistics. Another category is high-level remote sensing products, such as coarse-resolution multi-source remote sensing products—the Global Land Surface Satellite (GLASS) product. This product is primarily based on long-term data records (LTDR) from NASA's Advanced Very High Resolution Radiometer (AVHRR) (https://ltdr.modaps.eosdis.nasa.gov) and Moderate Resolution Imaging Spectroradiometer (MODIS) data, combined with other satellite data and auxiliary information (Liang et al. 2021). The GLASS product has spatial continuity with cloud-free pixels, and its spatial resolution ranges from 250 meters to 0.5°, depending on the product. The GLASS product includes parameters such as LAI, Absorbed Photosynthetically Active Radiation (APAR), Green Vegetation Fraction, Gross Primary Productivity (GPP), Land Surface Temperature (LST), various radiation measurements, and evapotranspiration. For example, Huang et al. (2023) improved winter wheat yield estimation by assimilating LAI data from the GLASS product into a crop growth model and using the posterior-based ENKF algorithm, achieving better estimation results. Based on GLASS, the HI-GLASS product (30 meters) (He et al. 2018b; Jin et al. 2022; Liang et al. 2025; Zhang et al. 2022b) and HI-GLASS LS20 product (20 meters) (Ma et al. 2025) provide higher spatial resolution and greater detail, making it possible to achieve more accurate and comprehensive crop yield estimation in different agricultural landscapes. Additionally, there are MODIS 8-day or 16-day composite reflectance and thermal products (Jia et al. 2024). For example, Huang et al. (2023) developed a crop yield regression model based on global MODIS 16-day NDVI data, combined with crop planting identification. This method performs well in small areas, particularly in regions where crop types are unknown. The application of the Advanced Very High-Resolution Radiometer (AVHRR) vegetation index product is also widespread. For instance, Prasad et al. (2006) utilized AVHRR data, integrating 19 years of NDVI, soil moisture, surface temperature, and precipitation data from Iowa, USA. By applying a breakpoint segmented linear regression model, they successfully evaluated and predicted crop yields, with the results closely aligning with observed yields of maize and soybean.

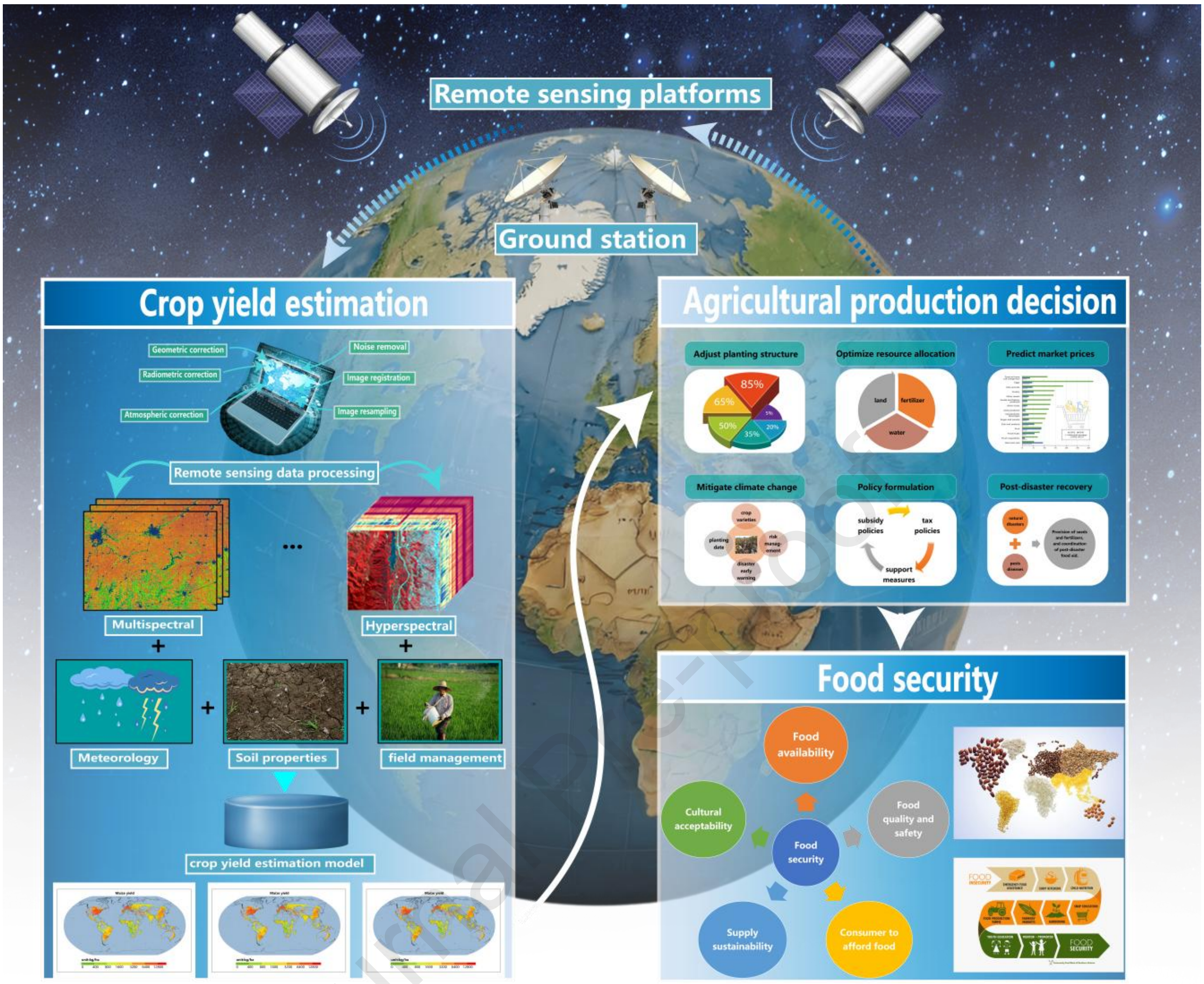

Fig. 1. Crop yield estimation based on remotely sensed data and food security.

Advanced crop yield estimation methods significantly enhance the precision and reliability of agricultural monitoring. Empirical statistical models, among the earliest methods, utilize relationship analyses between historical yields and satellite-based indices such as the Vegetation Canopy Water Index (Anderson et al. 2016; Hatfield 1983; Zhang and Zhang 2016) and vegetation Indices (Qader et al. 2018). As computational capabilities and data availability have advanced, productivity efficiency models, like the Light Use Efficiency (LUE) model, have gained prominence. These models leverage solar radiation and vegetation cover for regional agricultural production and yield estimation (He et al. 2018a; Marshall et al. 2018). Furthermore, integrating remote sensing with crop growth models has garnered attention. Process-based crop growth models are one of the more complex methods in crop yield estimation. They estimate yield by simulating crop physiological processes (such as photosynthesis, respiration, nutrient absorption, and water dynamics). Compared with statistical regression or empirical models, their complexity lies in the need for detailed biophysical parameters and dynamic environmental inputs (such as weather and soil properties). These models can capture the complex nonlinear relationships in the crop growth process and are applicable to a variety of agricultural scenarios, but their accuracy is highly dependent on the quality of input data and the accuracy of model parameters (Grassini et al. 2015). In process-based models, data assimilation technology significantly improves the dynamics and accuracy of predictions by combining remote sensing observation data with crop growth models. Data assimilation methods (such as Kalman filtering, variational methods, or particle filtering) dynamically correct simulation deviations by iteratively optimizing model state variables and parameters to achieve real-time monitoring and early warning of the entire crop growth process (Huang et al. 2019c; Huang et al. 2015b; Jin et al. 2016). Machine learning, especially deep learning, delivers exceptional adaptability and precision across diverse spatial and temporal scales (Cui et al. 2025; Gao et al. 2024; Reichstein et al. 2019; Zhang et al. 2022a). By leveraging multiple data sources such as satellite imagery, weather patterns, and historical yield records, deep learning models are able to effectively capture the complex, nonlinear relationships between environmental factors (such as soil conditions, precipitation, and temperature) and crop productivity. This capability enables accurate forecasts at both broad regional levels and detailed field-specific scales, supporting informed decision-making in agriculture for improved food security and economic planning.

Recent literature reviews have addressed crop yield estimation using remote sensing data. Huang et al. (2019b) reviewed data assimilation in crop modeling, advocating a Bayesian framework and the use of large-scale computing for practical applications. Jin et al. (2018) summarized advancements in crop models and remote sensing, recommending the integration of these data with intelligent optimization for better accuracy at the field scale. Bello (2015) emphasized training in crop growth models and the use of well-calibrated models for research. Dimitrios et al. (2018) discussed integrating remote sensing data with crop models, forecasting improvements with upcoming remote sensing technologies. Oikonomidis et al. (2023) noted the effectiveness of convolutional neural networks (CNNs) in crop yield prediction, though challenged by limited training datasets. van Klompenburg et al. (2020) found that CNNs, LSTMs, and DNNs are effective in crop yield prediction, with features varying by research context. Shingade and Mudhalwadkar (2023) analyzed machine and deep learning methods for crop types and environmental factors. Joshi et al. (2023) reviewed deep learning and remote sensing in crop mapping and yield prediction, highlighting challenges like data scarcity and the need for more effective models. Liang et al. (2024) comprehensively and systematically reviewed the latest progress in inversion algorithms for remote sensing data in various fields, as well as open regional and global data products. In the field of crop yield estimation, they summarized methods for crop yield estimation based on remote sensing data, and proposed feasible development directions for the future. However, due to the wide coverage of the review, the methods of crop yield estimation and the existing product data sets were not fully analyzed.

While extensive literature reviews exist on remote sensing-based crop yield estimation methods, covering crop models, remote sensing technologies, assimilation of satellite data into models, and machine learning with satellite data used as predictors, they often focus on specific aspects of technological advancements, such as remote sensing for agricultural monitoring (Dong and Xiao 2016; Rembold et al. 2013) or process models for climate change impact assessments (Jones et al. 2017; White et al. 2011). Some reviews highlight data gaps in specific applications, such as agricultural monitoring (Atzberger 2013; Fritz et al. 2019), seasonal crop estimation (Ponnaiah et al. 2019), and food security assessments (Brown 2016). However, there are relatively few studies on the combination of grid-based datasets with multi-field crop yield estimation methods. This study aims to address the limitations of existing crop yield estimation reviews and provide a comprehensive overview. We provide a detailed overview of the commonly used crop yield estimation methods, and offer an in-depth analysis of their limitations and advantages. For crop yield studies at the pixel and field scale, we compare the data results obtained from various approaches and explores potential future improvements in the field of yield estimation, with a particular emphasis on the cutting-edge application of ML/DL at the pixel/field level. Additionally, we compare global and regional datasets, emphasizing the importance of precision agriculture and regional agricultural management in enhancing agricultural production efficiency.

The structure of this review is as follows: Section 2 compares various remote sensing-based crop yield estimation methods, with a focus on highlighting the research progress in generating gridded yield data for each method, while discussing their respective advantages and the challenges they currently face. Section 3 presents a comparative analysis of existing publicly available crop yield datasets, with maize as a case study. This section begins by examining global yield datasets and then moves on to a comparison of regional yield datasets. Section 4 synthesizes the current challenges in the field of crop yield estimation and explores potential future directions. Finally, the main conclusions of this review are summarized. Through its broad coverage of research domains and comparative analysis of multiple methods, this study fills the gaps in existing reviews. It provides valuable guidance for future research, contributing to the efficient development of agricultural production.

2. Crop yield estimation methods

2.1 Systematic search

This paper conducted a systematic review of Elsevier ScienceDirect, Web of Science, SpringerLink, Taylor & Francis Online, Scopus, and IEEE. Studies on the application of remote sensing data in field/pixel-scale crop yield estimation from 2000 to 2023 were collected. According to different research needs and application scenarios, crop yield estimation methods can be roughly divided into four categories: empirical statistical models, light use efficiency models, crop growth models assimilated by remote sensing data, and machine learning and deep learning models. Appropriate search keywords, synonyms, abbreviations, and alternative spellings were determined. The search keywords included "field/pixel-scale crop yield estimation or prediction", "yield mapping", "empirical statistical", "light use efficiency model", "data assimilation", "remote sensing", "machine learning", and "deep learning". Boolean operators (AND and OR) were used to construct advanced search strings. A total of 2,654 articles related to crop yield and remote sensing were screened from all databases. According to the research questions, inclusion and exclusion criteria were formulated, excluding non-English literature, gray literature, and literature with an impact factor of less than 4.0. Relevant data and information were extracted from the literature that met the established criteria. To ensure the representativeness of the literature, we covered studies on different crop types (such as wheat, corn, soybeans, etc.), different regions (such as China, Europe, North America), and a variety of methods for crop estimation at the field/pixel-scale. Finally, a total of 60 of the most typical studies on crop yield estimation at the field/pixel scale based on remote sensing data were included in the comparison. We discussed in detail the basic principles and applications of these four methods, the comparison between the methods, and the applicable scenarios, to provide references for future research and practice.

2.2 Empirical statistical methods

2.2.1 Method overview

Empirical statistical models based on remote sensing are widely used in crop yield estimation (Manjunath et al. 2002; Mulianga et al. 2013; Prasad et al. 2006). The core of these models is to use remotely sensed data to achieve continuous yield estimation over a large area and at the pixel scale, through the statistical relationship between remote sensing indicators (such as vegetation indexs) and crop yield. This method assumes that the photosynthetic activity of vegetation captured by remote sensing (such as canopy chlorophyll content) can indirectly reflect crop growth conditions and crop yields, which are affected by environmental and management factors such as fertilization, drought, and precipitation (Tucker 1979). A variety of vegetation indices (VIs) are commonly used (Ma et al. 2024a), including the NDVI, the Vegetation Condition Index (VCI), and the Temperature Condition Index (TCI). Among them, NDVI has become a core indicator due to its strong correlation with crop canopy structure and photosynthetic capacity (Johnson 2014), and is widely used to monitor soil moisture, vegetation productivity, and climate change impacts (Mulianga et al. 2013). By analyzing the temporal changes of NDVI, it is possible to effectively monitor the dynamics of crop canopies, chlorophyll content, and photosynthetic capacity, providing a reliable basis for yield estimation (Jr et al. 1981; Tucker et al. 1980).

The empirical statistical method based on NDVI also faces certain limitations. For example, in areas with high vegetation coverage, NDVI is prone to "saturation", that is, it is impossible to further distinguish the vegetation status, thereby reducing the estimation accuracy of high-yield areas (Gu et al. 2013). Secondly, when the yield is dominated by non-photosynthetic factors (such as high temperature stress during the filling period), the explanatory power of NDVI is weakened, especially under extreme climate events (Lobell et al. 2015). To overcome these limitations, researchers gradually introduced surface reflectance (such as near-infrared and shortwave infrared bands) to capture subtle changes in LAI and canopy structure, and improved spatiotemporal resolution through multi-source remote sensing data fusion (such as Landsat and MODIS) (Jin et al. 2019).

2.2.2 Recent progress

The empirical statistical regression method based on remote sensing data achieves large-area, high-resolution yield mapping by establishing an empirical relationship between vegetation index and yield. It is characterized by high computational efficiency and easy calibration. We conducted a literature search using the themes “pixel or field-scale crop yield estimation”, “remote sensing”, and “statistical regression”, selecting and analyzing several representative studies that employed empirical statistical models based on remote sensing data for crop yield estimation at the pixel/field scale (Table 1). The research methods mainly include regression models based on vegetation indices and meteorological indicators. The research area covers the Midwest of the United States, Tanzania, Kenya, northeastern Australia, etc. The period is from 2000 to 2018, and the spatial resolution ranges from 10 to 250 meters. Currently, gridded crop yield datasets can be sourced from four main types: remote sensing satellites (Iizumi et al. 2014), census data (Ray et al. 2012), survey data (Helber et al. 2023), and models (Müller et al. 2019). Census data refers to statistical data on crop variables (such as yield, area, etc.) for a specific region or country, such as data from national statistical bureaus. Survey data refers to data obtained through sampling surveys of local crop information in certain regions, such as field measurements taken from different farmlands or experimental sites. Model data are generated through simulations using models. In general, gridded crop yield data products are a combination of multiple information sources.

Table 4 shows the performance of several empirical statistical models in practical applications in chronological order. These models use remote sensing data to capture the interaction between vegetation photosynthetic activity and environmental factors, and indirectly reflect the growth status of crops. For example, Becker-Reshef et al. (2010) constructed a regression model based on BRDF-corrected surface reflectance, estimated winter wheat yield at the county scale in the United States, and applied it to Ukraine, showing the cross-regional applicability of simple statistical regression methods in areas with sufficient data. However, this performance is highly dependent on similar climate and management conditions in the two places. Once the environmental background changes significantly, such as when applied to areas with variable climate and large differences in management practices, the predictive ability of the model will rapidly decay. This fragility of cross-regional applicability shows that the empirical relationship of the model is not a universal natural law, but a product limited to specific historical data patterns and lacking adaptability to environmental dynamics. The reliance of empirical statistical regression models on remote sensing data and high-resolution applications also exposes certain vulnerabilities. For example, the S2-Oz-wheat model of Zhao et al. (2020) uses high-resolution multispectral data from Sentinel-2, combined with remote sensing indices and meteorological indices, to achieve high-precision estimates at the field scale, but its success depends on the crop model's accurate simulation of irrigation conditions, and it performs poorly in non-irrigated areas.

The SCYM (a scalable satellite-based crop yield mapper) model combines crop growth models with meteorological and remote sensing data. Using the APSIM (Agricultural Production Systems Simulator), it simulates crop phenological parameters (e.g., LAI and yield) under different climate and management conditions and converts LAI into remote-sensing-observable variables like GCVI (Green Chlorophyll Vegetation Index). Then, it integrates GCVI and gridded meteorological data into a statistical regression model to estimate yield. A generic multiple linear regression can thus be defined for a specified combination of image dates as:

$$yield = \beta_{0,d} + \beta_{1,d} * W + \beta_{2,d} * RM_d + \beta_{3,d} * W * RM_d \tag{1}$$

where W is a vector of weather attributes over the season (e.g., monthly averages of temperature and rainfall), RM is a vector of remote-sensing-based measures (such as GCVI) on dates d, and all coefficients β are specific to the particular image dates. The SCYM model (Azzari et al. 2017; Deines et al. 2021; Jin et al. 2019; Lobell et al. 2015) can achieve large-scale, medium- and high-resolution crop yield mapping by integrating the LAI simulated by APSIM, the green chlorophyll vegetation index (GCVI) extracted by remote sensing, and meteorological data. Azzari et al. (2017) found that the model performed well in the Midwestern Corn Belt of the United States (spatial $R^2 \geqslant 0.50$ and temporal R^2 as high as 0.85). In the application of SCYM in the wheat-growing areas of northern India, the spatial variability capture ability of SCYM is acceptable (R^2 is about 0.45), but the prediction accuracy of temporal variability is significantly reduced. This may be because SCYM uses localized APSIM parameters in India (such as meteorological data, irrigation strategies, and crop masks), but is still limited by the low quality of ground data in India (for example, duplicate reports, missing data, and outliers) and the low temporal variability of the irrigation system (the temporal standard deviation is only 0.2 ton/ha, accounting for 4.5% of the mean). Although the empirical statistical framework of SCYM is flexible, its reliance on high temporal resolution data and accurate ground data makes its generalization ability in data-constrained areas challenging.

Table 1. Studies on crop yield estimation using empirical statistical models.

Method	Spatial resolution	Spatial coverage	Temporal coverage	Variables	Accuracy	Remotely sensed data resource	Ground truth	Reference
Regression	County-level	Kansas, Ukraine	2000-2008	VI, BRDF	R^2=0.74，RMSE=440kg/ha	MODIS	National statistical data	Becker-Reshef et al. (2010)
	Field-level	Northeastern Australia	2016-2017	VI, crop water stressindex	Field: R^2 = 0.9, RMSE =640 kg/ha	Sentinal-2	Field survey data	Zhao et al. (2020)
CM-Reg	250m/30m	Eastern Nebraska	2007-2010	VI, meteorological variables	Field: R^2=0.5, RMSE=2200kg/ha	Landsat	Field survey data	Sibley et al. (2014)
SCYM	30m	Midwest USA	2008-2012	VImax, meteorological variables	Field: corn: R^2 =0.35, soybean: R^2=0.32	Landsat5/7	Field survey data	Lobell et al. (2015)
	30m	Midwest USA, northern India, and southern Brazil	2000-2014	VImax, meteorological variables	County:USA: R^2 = 0.50-0.85， RMSE = 850kg/ha. India:R^2=0.45, RMSE=560kg/ha	Landsat and MODIS	National statistical data	Azzari et al. (2017)
	10m	Tanzania, Kenya	2015-2017	VI harmonic regression max, meteorological variables	Regional: R^2 = 0.39-0.55, RMSE = 690-930kg/ha	Sentinal-1/2	Field survey data	Jin et al. (2019)
	30m	Midwest USA	2008-2018	VI harmonic regression coefficients, meteorological variables	pixel：R2=0.39, RMSE = 2460 kg/ha，MAE = 1920 kg/ha	Landsat 5 TM, 7 ETM+, and 8 OLI	Field survey data	Deines et al. (2021)

Empirical statistical regression models have shown some potential in crop yield prediction. They can efficiently integrate remote sensing data and meteorological information, provide large-scale yield estimates, and perform well in areas with sufficient data. However, they have also exposed several limitations in practical applications, which limit their adaptability to diverse environments and management conditions. First, such models rely on regional historical data for calibration, resulting in unstable performance during spatiotemporal migration. Second, empirical statistical models have limited ability to respond to extreme climate events. For example, heat stress during maize's reproductive stage has a much greater impact on yield than stress during the vegetative growth stage. Due to the lack of scenarios such as extreme droughts or floods in the training data, the model may find it difficult to capture the nonlinear yield changes caused by these events, especially in the absence of sufficient historical data. In addition, such models often simplify yield as a function of vegetation indices. Although this approach achieves some statistical effectiveness, it lacks true agronomic significance (Ren et al. 2009) and fails to adequately simulate the dynamic physiological processes of crop growth and development, such as the critical role of flowering and grain-filling stages. Consequently, these models are unable to capture the timing of in-season stress, for instance, the considerably greater impact of heat stress during the reproductive stage of maize compared to stress during vegetative growth (Pham et al. 2023). Although SCYM partially incorporates these processes through APSIM simulation, its predictions may still be limited by insufficient remote sensing data due to cloud cover during the growing season, especially in high-cloud areas such as India. To improve generalization capabilities, empirical statistical models need to integrate more robust dynamic physiological simulations, optimize cloud processing algorithms, and rely on higher-quality ground data to better cope with the challenges of complex environments and extreme events. Future research can continue to explore the following directions, such as integrating meteorological, soil, and agronomic management data through multi-source data fusion to enhance the sensitivity of the model to environmental changes, introducing the physiological mechanisms of the crop growth models, combining remote sensing data with the crop development stage, and improving the model's ability to capture dynamic processes. In addition, transfer learning technology can also be considered to reduce dependence on data from specific regions and improve the generalization ability of the model. These directions can not only make up for the shortcomings of the current model, but also provide technical prospects for future yield estimation across a wide range of conditions and multiple scenarios..

2.3 Light Use Efficiency Models

2.3.1 Method overview

Light Use Efficiency (LUE) is a crucial parameter that measures the efficiency with which plants convert intercepted light energy into chemical energy. At a macro level, LUE can be understood as the ratio of chemical energy stored during assimilation to absorbed solar radiation (Monteith 1972). At a micro level, LUE emphasizes the carbon assimilation rate at the scale of individual plants or leaves, directly reflecting the efficiency of converting absorbed photons into fixed carbon (Lambers et al. 2008). The LUE model was initially developed to estimate gross primary productivity (GPP) and net primary productivity (NPP) and has been widely applied in these contexts. Its fundamental assumption is that, under non-limiting water and nutrient conditions, vegetation productivity is linearly related to the absorbed photosynthetically active radiation (APAR). Consequently, LUE serves as a critical intermediate variable for estimating GPP and NPP. For agricultural production, the cumulative NPP throughout the growing season corresponds to crop biomass, which is a key variable for yield estimation. The harvest index (HI), defined as the ratio of crop yield to crop biomass, allows crop yield to be estimated by integrating crop biomass with HI (Dong et al. 2020). The LUE model, grounded in crop physiological processes, provides a mechanistic pathway for large-scale yield estimation.

Advancements in remote sensing technology, particularly multi-temporal and multi-resolution satellite observations, have enabled us to estimate a variety of key environmental parameters related to LUE models

(Wang 2019). Many high-level products have been generated to characterize these variables in the Global Land Surface Satellite (GLASS) products suite at a spatial resolution as fine as 250 m (Liang et al. 2023) and the high-resolution GLASS (Hi-GLASS) products suite at 30 m spatial resolution (Liang et al. 2025), such as LAI (Ma and Liang 2022), FAPAR (Jin et al. 2022; Ma et al. 2022), PAR (Zhang et al. 2014), soil moisture (Zhang et al. 2023; Zhang et al. 2022b), and GPP (Huang et al. 2022; Lin et al. 2024b; Zheng et al. 2020). Remote sensing data mainly influence model construction in two modes: assimilation and driving. The assimilation mode involves integrating remotely sensed data to obtain non-remote sensing parameters, such as environmental limiting factors and LUE. The driving mode involves using remote sensing data to inform model parameters when incorporating LUE models, particularly in aspects like land cover types and PAR (Changqiao et al. 2017). Remotely sensed data not only provide fundamental inputs to LUE models, such as photosynthetically active radiation (PAR), LAI, and spectral vegetation indices, but also facilitate the estimation of environmental constraint factors (e.g., drought, extreme temperatures, and soil moisture deficits) that modulate LUE. By integrating these remote sensing-derived variables into LUE models, it is possible to capture the spatial dynamics of crop community growth and vegetation productivity at broad scales. Combined with harvest index and allocation coefficients (e.g., aboveground allocation coefficients, carbon allocation coefficients), these outputs can be further incorporated into empirical statistical models for yield estimation, enabling efficient and accurate large-scale yield mapping (Fig. 2). Moreover, continuous advancements in sensor technology and data processing algorithms, along with the incorporation of new spectral and LiDAR (Light Detection and Ranging) remote sensing data, have provided additional opportunities to enhance the accuracy and applicability of LUE models. For example, the use of near-infrared, shortwave infrared, and even solar-induced chlorophyll fluorescence (SIF) data can offer deeper insights into vegetation's light energy conversion efficiency and stress response mechanisms. These advancements support the extension of LUE models to diverse environmental conditions and crop types, further improving their precision and applicability.

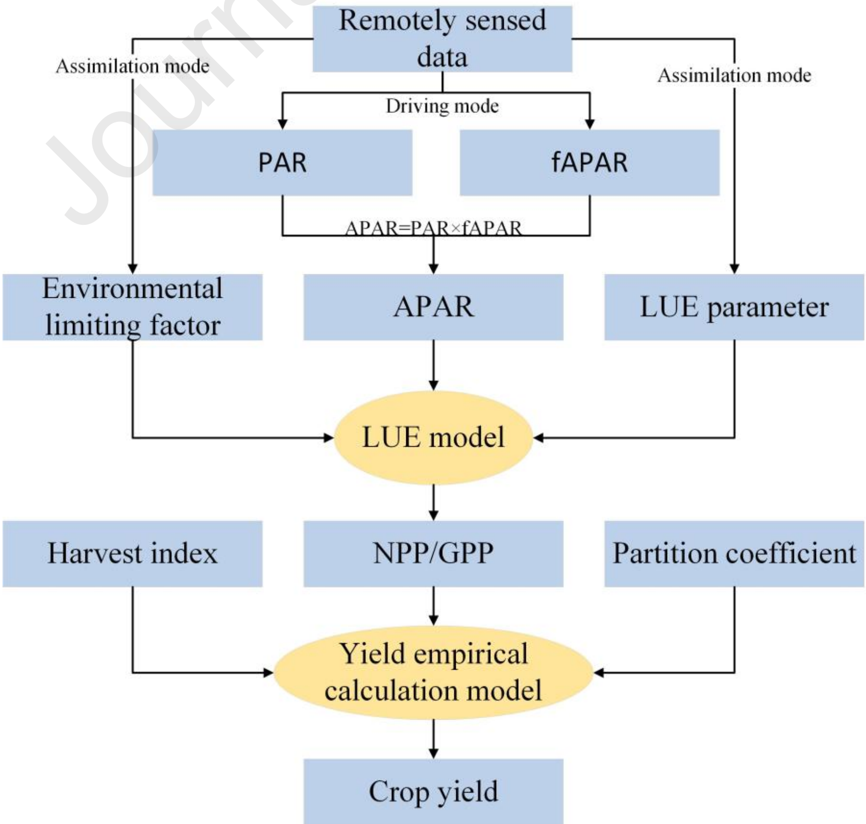

Fig.2 The process of estimating NPP, GPP, and crop yield using the LUE model with remotely sensed data

2.3.2 Recent progress

Light use efficiency (LUE) models have become a core tool for crop yield estimation by relating photosynthetically active radiation (PAR) absorbed by crops to biomass production. These models have evolved from simple empirical formulas to complex frameworks that integrate environmental, management, and physiological factors, showing remarkable diversity. We conducted a literature search using keywords such as "light use efficiency (LUE) model"(Monteith 1972), "production efficiency model", and "crop yield estimation". Several representative studies on crop yield estimation were selected and analyzed. These studies cover multiple regions, including China, India, the United States, and Canada, from 1988 to 2015, with spatial resolutions ranging from 30 meters to 8 kilometers. To systematically present the development of different LUE models, Table 2 lists six LUE models, in chronological order, that combine time-series remote sensing data for crop yield estimation. These studies were selected based on their representativeness and diversity across different geographic areas, time spans, and spatial resolutions, to comprehensively reflect the evolution and current application of LUE models in crop yield estimation.

The earliest LUE model was proposed by Monteith (1972), namely the production efficiency model (PEM), which assumes that NPP is proportional to APAR and LUE is a crop-specific constant. Its simplicity makes it easy to parameterize, requiring only remote sensing data to estimate FAPAR and meteorological data to calculate PAR, and it is suitable for data-scarce areas. For example, Liu et al. (2010) obtained an R^2 of 0.72 in estimating maize yield in Canada, and Pan et al. (2009) achieved an R^2 of 0.86 in estimating wheat in the Loess Plateau. However, the model assumes a fixed LUE value and ignores non-climatic factors such as water, nutrients, or pests and diseases, resulting in reduced accuracy in areas with high environmental heterogeneity, such as farmland with significant changes in irrigation or fertilization. PEM performs well in large-scale preliminary assessments, but is limited in precision agriculture due to its lack of dynamic adaptability. To improve this situation, Xin et al. (2013) introduced crop-specific radiation use efficiency (RUE), showing the potential for development into more sophisticated models. In contrast, the CASA model (Field et al. 1995) significantly improves its ability to capture environmental variability by dynamically adjusting LUE to reflect temperature and water stress. Wang et al. (2019) showed high accuracy in estimating winter wheat yield in Beijing using HJ-1A/B data. However, its reliance on high-quality input data (such as meteorological and environmental scalars) increases computational complexity and may introduce uncertainty in data-sparse areas, limiting its ability to be rapidly deployed.

Table 2 Crop yield estimation studies based on LUE models.

Model	Spatial resolution	Spatial coverage	Temporal coverage	Accuracy	Remotely sensed data resource	Ground truth	Reference
PEM	30m	Canadian Great Lakes Region	2001, 2006	Field: $R^2 = 0.72$, RMSE=720kg/ha	CASI and Landsat TM/ETM+	Field survey data	Liu et al. (2010)
	30m	Loess Plateau and Hills Region, China	2005	Field: $R^2 = 0.86$	QuickBird	Field survey data	Pan et al. (2009)
CASA	30m	Beijing Region, China	2008-2009	Field: R^2=0.56, RMSE=1220kg/ha	Spot-4/5	Field survey data	Wang et al. (2019)
	1.1km	ndian River Basin	1993-1994	County: R^2=0.8, RMSE=551 kg/ha	NOAA-AVHRR	National Statistics	Bastiaanssen et al. (2003)
GLO-PEM	1km	Tibetan Plateau, Three Rivers Source Region, China	1988-2005	Field: R^2=0.541, P<0.001	NOAA-AVHRR	Field survey data	Fan et al. (2010)
	8km	Various Regions in China	1998-2000	Field: R^2 ranges from 0.4-0.5	NOAA-AVHRR	Field survey data	Tao et al. (2005)
MOD17	30m	Continental USA and Montana State	2008-2015	County: $R^2 = 0.96$, RRMSE = 37.0%; field: $R^2 = 0.42$, RRMSE = 50.8%， $p < 0.05$	Landsat 5/7and MODIS	National Statistics (USDA) and Field survey data	He et al. (2018a)
	1km	Midwestern USA	2009-2011	County: corn: R^2 = 0.77； RMSE = 890kg /ha, soybean: R^2 = 0.66； RMSE = 380kg/ha)	MODIS	National Statistics (USDA)	Xin et al. (2013)
EC-LUE	1km	Multiple Global Regions	2000-2012	R^2 =0.61, p<0.01	MODIS	Field survey data	Yuan et al. (2016)
	30m	Nebraska State, USA	2008-2017	ASD: R^2 =0.60, RMSE=556.04kg/ha, MAE=320.73kg/ha	Landsat5/7/8 and MODIS	National Statistics (USDA)	Dong et al. (2020)
PEMOC	250m	Mainland United States	2010-2015	County: R^2 ranges from 0.55-0.77, RMSE ranges from 500-600kg/ha	MODIS	National Statistics (USDA)	Marshall et al. (2018)

Further development of the LUE model is reflected in the integration of more biophysical and management factors. GLO-PEM (Goetz et al. 2000) provides a more detailed analysis of carbon flux by separating GPP and autotrophic respiration. It relies entirely on remote sensing data and is suitable for areas with insufficient ground observations, but it often overestimates low yields and underestimates high yields in areas such as the Qinghai-Tibet Plateau, showing consistency problems. The MOD17 algorithm provides global NPP estimates based on the APAR-NPP relationship, but its coarse resolution makes it perform poorly in complex vegetation areas, although the enhanced version can reach an R^2 of 0.92 at the county scale. Recent models such as EC-LUE (Yuan et al. 2007) estimate daily GPP through universal parameters and the minimum law, which performs well over large areas, but the accuracy of C4 crops is reduced due to calibration bias. PEMOC (Marshall et al. 2018) optimizes PEM parameters, with an R^2 of 0.55-0.7 in the US study, but assumes that the harvest index is constant, which may fail in areas with diverse management practices. These advanced models have improved accuracy but increased the complexity of parameter calibration and data requirements. Comprehensive comparisons show that simple models such as PEM are easy to use but have limited accuracy, dynamic models such as CASA are more realistic but data-intensive, and GLO-PEM and PEMOC attempt to balance the two, but introduce new challenges. Fixed parameter models (such as PEM) have weak generalization capabilities, while models that allow parameter changes (such as CASA and EC-LUE) require a large amount of data support. In terms of spatial resolution, MOD17 is suitable for global assessments, but it ignores the details of precision agriculture; the high-resolution LUE model is computationally data-intensive. In short, LUE models have their own advantages and disadvantages in crop yield estimation. PEM is suitable for data-scarce scenarios, CASA adapts to environmental variability, GLO-PEM and MOD17 are conducive to global monitoring, and EC-LUE and PEMOC pursue refinement. In the future, the integration of remote sensing, ground data, and computing techniques (such as parameter optimization or data assimilation) can improve model performance, resolve the contradiction between global scalability and fine resolution, and promote sustainable agricultural development.

The accuracy of the LUE model is highly dependent on the support of high-resolution remote sensing data. Recently, the application of satellite data such as Sentinel-2 and Landsat-8 has significantly improved the spatial resolution and temporal continuity of the model. For example, Dong et al. (2020) combined the high temporal resolution of MODIS with the high spatial resolution of Landsat through spatiotemporal fusion technology to improve the ability to capture details in crop yield estimation. In addition, multispectral sensors (such as RGB and MSI) carried by drones also provide new tools for field-scale LUE monitoring, especially in the middle and late stages of the crop growth period. Although LUE models have advanced crop yield estimation, they still face many challenges—such as parameter sensitivity, environmental heterogeneity, and limited model generalizability—that point to directions for future research. First, the spatial and temporal variability of the harvest index (HI) requires further investigation. HI, which represents the proportion of crop biomass allocated to economic yield, is influenced by cultivar, soil nutrients, and management practices; it can vary greatly across regions and within growing seasons, introducing uncertainty when translating NPP estimates into yield within LUE frameworks. Second, LUE is affected by crop physiological traits (e.g., C3 versus C4 pathways) and environmental gradients (e.g., temperature and radiation), and its maximum values and response functions remain uncertain across different crops. For example, as shown in Table 2 above, most studies were conducted at small spatial scales with total sample sizes (n) not exceeding 100; at the field scale, reported R2 values are generally above 0.5, and accuracy tends to be higher at the county scale. This performance benefits from the relative ease of optimizing results through in-situ calibration of model parameters during the study, but at larger scales this becomes a major challenge because parameter differences between sites or crops are substantial. Such heterogeneity therefore limits the application of LUE models in large-scale precision agriculture, indicating the need to incorporate dynamic modeling to capture variability. For example, by Xie et al. (2023) proposed the PAR-Ɛmax model, which significantly improved the estimation accuracy under different vegetation types by dynamically adjusting the maximum LUE (annual scale R^2 is 0.44, RMSE is 1.82 g C m^{-2} MJ^{-1} d^{-1}), providing a reference for crop yield estimation. Although the LUE model alone has relatively weak generalization, it is useful for elucidating physiological mechanisms and can serve as a baseline when combined with other approaches. In particular, for large-scale applications it can be coupled with machine-learning algorithms (e.g., random forests) by using LUE model outputs as inputs to these models, thereby enabling large-area yield prediction and reducing estimation errors (Dhillon et al. 2023). Future research should focus on the short-term impact and long-term effects of extreme climate events on crop yields. For example, climate change may affect the dynamic changes of LUE through temperature and water stress, and the adaptability of the model to dynamic environments needs to be improved. Regional-scale LUE measurements also need to flexibly update LUE values for different crop types to adapt to crop heterogeneity. Ensuring the large-scale availability of flux tower site datasets and in situ yield-label data and facilitating their efficient sharing and analysis would lay the groundwork for innovations in LUE models for crop yield estimation.

2.4 Data assimilation methods

2.4.1 Method overview

Crop growth models simulate the effects of meteorological, soil, and field management conditions on crop growth, revealing the constraints of environmental factors on crop yield (Aggarwal and Kalra 1994; Hoogenboom 2000). However, the uncertainty of model parameterization and meteorological input, especially the inherent variability of agricultural systems (such as crop varieties and soil types), limits model accuracy in large-scale applications (Hansen and Jones 2000). Remote sensing data provide high-frequency, multi-scale surface observations , but they alone cannot meet the needs of accurate prediction alone due to cloud contamination and retrieval errors (Wiseman et al. 2014). To address these challenges, data assimilation (DA) techniques have emerged, which integrate process-based crop growth models (as prior information) with remote sensing-derived surface observations (as evidence) using statistical and probabilistic methods (Huang et al. 2019b). This approach enables the dynamic calibration and optimization of model parameters and initial conditions. Compared to traditional point-based field experiments or large-scale statistical data, remote sensing provides diverse and high-frequency growth information over extensive spatiotemporal scales. Through data assimilation, probabilistic methods represented by the Ensemble Kalman Filter (EnKF), 4D-Var, and Particle Filter can iteratively update the model state, gradually bringing the model output closer to the true characteristics and growth conditions of the crop canopy. Through multiple iterations, when the difference between the model's prior simulation results and remote sensing observations is progressively reduced, the system ultimately obtains more accurate posterior information, thereby effectively improving the reliability and stability of crop yield estimations (Huang et al. 2023; Huang et al. 2019a). The specific process of data assimilation of remotely sensed data into crop growth models is shown in Fig. 3.

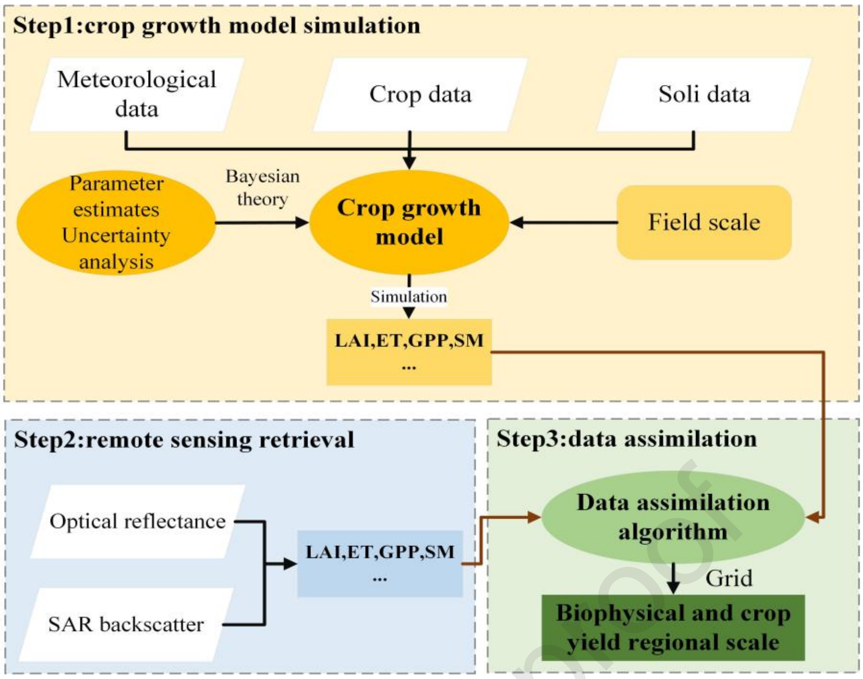

Fig. 3 The basic process of data assimilation of remotely sensed data into crop growth models

The research utilized various data assimilation algorithms, which can primarily be divided into three categories: calibration methods, forcing methods, and updating methods (Delécolle et al. 1992; Dorigo et al. 2007). Calibration methods adjust the initial parameters of the crop model to achieve the best consistency between remotely sensed data and simulated state variables (i.e., simulated data from the crop model). Firstly, recalibrate the model's inputs and parameters using remotely sensed data, then select the optimal solution and run the recalibrated model with the optimized parameters (Baret et al. 2007). There are many studies on the assimilation of remotely sensed data and crop models using calibration methods, and there are various assimilation algorithms, such as the Simplex Search Algorithm (Claverie et al. 2012; Jégo et al. 2012), Maximum Likelihood Solution (MLS) (Hoogenboom 2000), Least Squares Method (LSM) (Mandal and Rao 2020), Powell's Conjugate Direction Method (PCDM) (Chen and Tao 2022; Fang et al. 2011), Shuffled Complex Evolution-University of Arizona algorithm (SCE-UA) (Bai et al. 2019; Cui et al. 2022; Dong et al. 2016; Huang et al. 2015a), and Particle Swarm Optimization (PSO) algorithm (Jin et al. 2017; Li et al. 2015b). In cases where there is a sufficient amount of observational data with small errors, this method utilizes remote sensing data to calibrate crop growth models, thereby reducing the accumulation and diffusion of errors in the data assimilation process to some extent. However, there are two limitations to this approach: (1) it requires a large number of iterations, which is time-consuming, and (2) the calibration settings may not necessarily be reliable parameter settings.

Forcing method: This simpler approach uses observed data to directly replace simulated values in crop models, enhancing model accuracy but potentially introducing errors from remote sensing data inaccuracies. Notable applications include the forced-coupling method with a sugarcane crop model (MOSICAS) and Sentinel-2 satellite-derived FAPAR by Morel et al. (2014), and the calibration of parameters for jujube trees using the WOFOST model with Landsat 8 data (Bai et al. 2020). They utilized Landsat 8 data to perturb the LAI and recalibrate the Transpiration/Dry Weight Index (TDWI) at the field scale for jujube orchards. Their study found that the perturbed LAI resulted in higher accuracy in predicting crop yield. Although the forcing method for assimilating remote sensing crop models and data is relatively simple, strictly speaking, it may not involve data assimilation itself. It merely replaces the state variables or initial input data in the simulation results with the state variables or initial input parameters estimated from remote sensing data. In the case of the forcing method, the crop model does not utilize its own information but instead relies on observed state variables, leading to some errors. Additionally, errors may also exist in remote sensing observational data. Once the forcing assimilation is completed, these errors are introduced into the crop model. Therefore, theoretically, the forcing method is not as effective as the calibration method.

Updating method: Offering more flexibility and reduced computational demand compared to forcing, updating methods continuously adjust model data using remote sensing inputs. This approach assumes that by combining model simulations and observations, a better estimation of the model state variables on day t will improve the accuracy of the simulated variables for the following days. Techniques include the ENKF (Chakrabarti et al. 2014; Cui et al. 2022; Huang et al. 2023; Ines et al. 2013; Liu et al. 2014; Mishra et al. 2015; Silvestro et al. 2021; Yuan et al. 2020; Zhang et al. 2022c; Zhang et al. 2022d; Zhuo et al. 2019), Particle Filter (PF) (Jiang et al. 2014; Machwitz et al. 2014; Ziliani et al. 2022a, b), and (4D)Var (Dente et al. 2008; Huang et al. 2015b; Jiang et al. 2014; Manivasagam et al. 2021; Zhuo et al. 2022). The ENKF algorithm continuously updates linear state variables. For instance, Zhuo et al. (2019) utilized Sentinel-1 and Sentinel-2 data and soil moisture (SM) maps extracted from hydrological cloud models, assimilating them into the WOFOST model using the ENKF algorithm. This approach successfully improved regional-scale yield estimation for winter wheat in Hengshui City. The ENKF method, as seen in the table, is the most widely used assimilation algorithm and is found to be highly beneficial for integrating crop models with remote sensing data (Bolten et al. 2010; Crow and Wood 2003; de Wit and van Diepen 2007). Unlike the KF, the Particle Filter (PF) algorithm does not assume a Gaussian distribution for nonlinear errors, enhancing its ability to manage nonlinear variations and facilitating parallel computation. Variational methods (3DVar and 4DVar) are more mature than Kalman filter-based ensemble methods, and they have been successfully applied in weather forecasting (Lorenc et al. 2000). 3DVar typically does not take spatial correlation into account (Lorenc 1986; Sasaki 1970). During the assimilation process, 3DVar can use complex observation operators, making it easier to assimilate indirect or nonlinear observations of state variables. However, the high computational cost of 3DVar limits its practical application. To address the limitations of 3DVar, 4DVar was developed, which integrates solutions over time and compensates for the weaknesses of 3DVar in dealing with time-varying state variables and certain initialization issues. This method integrates solutions over time (Le Dimet and Talagrand 1986; Talagrand and Courtier 1987), and 4DVar has been widely applied and gained significant attention since its introduction.

LAI is defined as the total one-sided leaf area per unit ground area (Chen and Black 1992). It is a key parameter that characterizes the structure of the vegetation canopy and plays a crucial role in monitoring regional crop growth, predicting yields, and estimating biomass (Dong et al. 2012; Jiang et al. 2014). Therefore, it is the most commonly used assimilated variable in remotely sensed data assimilation for crop growth models. There are various methods for estimating LAI from remote sensing data (Liang and Wang 2019). The following is an example of the objective function for 4DVar:

$$J(LAI_0)=\frac{1}{2}[LAI_0-LAI_0^{\mathrm{b}}]B^{-1}[LAI_0-LAI_0^{\mathrm{b}}]+\frac{1}{2}\sum_{i=0}^{n}[LAI_i-LAI_i^{obs}]^T O_i^{-1}[LAI_i-LAI_i^{obs}] \tag{2}$$

In the equation, LAI_0 represents the state variable at the initial time of the assimilation window. By substituting LAI_0 into the model operator M and running it to the i-th time step, LAI_i is obtained. LAI_0^b is the background value of LAI at the initial time, which is the simulated LAI at the initial time. LAI_i^{0bs} is the observed LAI value at the i-th time step, B is the error covariance of the simulated LAI, O is the error covariance of the observed LAI, and n is the number of days in the assimilation window. The LAI_0 that minimizes J (LAI_0) is the optimal solution at the initial time, the LAI assimilation value at the initial time.

Once the crop LAI assimilation value is obtained, we can perform linear regression with the measured yield to establish a relationship model, thus enabling crop yield estimation at the regional scale.

2.4.2 Recent progress

Assimilating remote sensing data into crop growth models is an important research direction in the field of agricultural remote sensing, which aims to improve the accuracy and reliability of crop yield estimation by integrating remote sensing observations and model simulations. We conducted a literature search using the keywords "remote sensing data assimilation" and "crop yield estimation," followed by the selection and analysis of several representative studies. These studies assimilated multi-source remote sensing data into crop growth models, such as WOFOST, APSIM, CERES, DSSAT, EPIC, SWAP, and AquaCrop (Table 3). The research areas cover most regions of China, the United States, Canada, Brazil, and several European countries, with a period from 1999 to 2021 and spatial resolutions ranging from 3 meters to 1 kilometer. The models in Table 3 are listed in chronological order of development and provide detailed information on the specific data assimilation methods, spatial resolutions, accuracy, and sources of ground-truth data used in each study.

Table 3. Representative research on data assimilation methods

Crop models	Spatial resolution	Spatial coverage	Temporal coverage	Assimilation algorithm	Assimilation variables	Accuracy	Remotely sensed data resource	Ground truth	Reference
SWAP	500m	Hebei Province and Surrounding Areas, China	2007-2009	SCE_UA	LAI, ET	Regional: R^2=0.86, RMSE=580kg/ha	MODIS	Field survey data	Hao et al. (2010)
EPIC	Field-level	Hebei Province, Hengshui City, China	2004	SCE-UA	LAI	Filed:R^2=0.53, RMSE=600kg/ha	Unkown	Field survey data	Ren et al. (2009)
	500m	Inner Nebraska State, USA	2012,2015	Kalman	LAI, ET	County: corn: R^2=0.7,RMSE=1220kg/ha, soybean：R^2=0.6, RMSE=460kg/ha,	MODIS and Landsat	Statistics and field survey data	Bandaru et al. (2022)
CERES	30m	Hengshui City, Hebei Province, China	2008-2009	PF	LAI	Pixel:R^2 =0.57, RMSE = 447kg/ha Field: R^2=0.87, RMSE=251kg/ha	HJ-1A/B	Statistics and field survey data	Jiang et al. (2014)
	150-300m	Southern Italy	2004	Var	LAI	Field: RMSE=420kg/ha	ENVISAT ASAR and MERIS	Field survey data	Dente et al. (2008)
WOFOST	10m	China Hebei Province, Hengshui City	2017	EnKF	LAI	Field:R^2=0.35, RMSE=934kg/ha	Sentinal-1/2	Field survey data	Zhuo et al. (2019)
	30m	China Zhejiang Province, Deqing County	2013	EnKF	LAI	Field:R^2=0.66, RMSE=1610kg/ha	HJ-1A/B	Field survey data	Wang et al. (2020)
	1km	Winter Wheat Planting Area in North China	2008-2009	EnKF	LAI	Field:R^2=0.49, RMSE=795kg/ha	MODIS	Statistics dataset	Liu et al. (2014)
	1km	Hebei Province, China	2009-2013	4DVar	LAI	Field:R^2 = 0.36, RMSE = 619.73kg/ha	MODIS	Field survey data	Zhuo et al. (2022)
	1km	Southern Hebei Province, China	2009	4DVar	LAI	Field:R^2 = 0.48; RMSE = 151.92kg/ha	Landsat TM and MODIS	Field survey data	Field survey data
	30m	Aral City, Xinjiang, China	2015-2017	SCE-UA	LAI	Field:R^2=0.61, RMSE=805kg/ha	Landsat	Field survey data	Bai et al. (2020)
	1km	Hengshui City, Hebei Province, China	2007-2008	SCE	LAI	Field:R^2=0.326, RMSE=474 kg/ha	MODIS	Statistics and field survey data	Ma et al. (2013)
	16m	Wuhan City, Hubei Province, China	2014-2019	SCE-UA	LAI	Municipal level: R^2>0.94	GaoFen-1	Field survey data	Tang et al. (2022)
	250m	Henan Province, China	2017-2021	ENKF	LAI	Pixel/county scale: R^2 values are 0.41 and 0.57. MAPE values are 7.82% and 10.13%. RMSE values are 688 and 695 kg/ha.	GLASS	Field survey data	Huang et al.（2023）

Table 3. Representative research on data assimilation methods (continued)

Crop models	Spatial resolution	Spatial coverage	Temporal coverage	Assimilation algorithm	Assimilation variables	Accuracy	Remotely sensed data resource	Ground truth	Reference
DSSAT	1km	Iowa, USA	2003-2009	ENKF	LAI, SM	County:R^2=0.41, RMSE=2900kg/ha	MODIS and AMSR-E	National Statistics (USDA)	Ines et al.（2013）
	1km	Iowa, USA	2003-2009	ENKF	LAI, SM	County:R^2=0.64, RMSE=1400kg/ha	MODIS and AMSR-E	National Statistics (USDA)	Mishra et al. (2015)
	1km	Lower Basin of the Parana River, Brazil	2010-2012	ENKF	SM	MAPE=4.37%-16.8%	Unkown	Field survey data	Chakrabarti et al. (2014)
APSIM	3m	Victoria State, Australia	2018-2019	ENKF	LAI	Estimation bias <10%	Sentinel-2/PlanetScope	Field survey data	Zhang et al. (2021b)
	3m	Eastern California, USA	2019	PF	LAI	Field: R^2=0.72, RMSE=1820kg/ha, RRMSE=12.71%	Planet Fusion CubeSat	Field survey data	Ziliani et al. (2022a)
	6.5m	Central Luzon, Philippines	2010	PF	LAI	Field: RMSE=420kg/ha	RapidEye	Field survey data	Machwitz et al. (2014)
	250m	Weishan Irrigation Area, North China Plain	2005-2020	ENKF	LAI, SM, ET	Field:wheat: R^2=0.64, RMSE=913kg/ha, corn: R^2=0.4, RMSE=1079kg/ha	MODIS	Field survey data	Yang and Lei (2024)
DSSAT-CERES	10m	Beijing, Xiaotangshan, China	2009-2013	PSO	LAI, CAN	Field:R^2=0.698，RMSE=726kg/ha	Unkown	Field survey data	Li et al. (2015b)
STICS	30m	Great Lakes Trial Zone, Ontario, Canada	1999-2008	simplex algorithm	LAI	Field: corn: RMSE = 600kg/ha, soybean: RMSE = 600kg/ha, spring wheat: RMSE = 600kg/ha	Landsat TM/ETM+ and SPOT	Field survey data	Jégo et al.（2012）
MOSICAS	10m	Réunion Island	2009-2012	Forcing method	fAPAR	Field：R^2=0.47,RMSE=1260kg/ha	SPOT-4/5	Field survey data	Morel et al. (2014)
SAFY	3m	Saad District, Israel	2017-2018	Forcing method	LAI	Field: R^2=0.45, RMSE=690kg/ha	Sentinel-2 and PlanetScope	Field survey data	Manivasagam et al. (2021)
	10m	Tuscany, Italy	2018	EnKF	LAI	Regional: R^2=0.9, RMSE=730kg/ha	Sentinel-2	Field survey data	Silvestro et al. (2021)
	3m	Beijing, Changping Experimental Zone, China	2017-2019	SP-UCI	AGB	Field: R^2= 0.46, RMSE=1330kg/ha	PlanetScope	Field survey data	Zhao et al. (2022)
AquaCrop	500m	Songnen Plain, China	2000-2020	ENKF	FVC	County:R^2=0.557, RMSE=888kg/ha	GLASS	National Statistics	Cui et al. (2022)
	30m	Yangling Area, Shaanxi Province, China	2014	PSO	Canopy cover (CC), biomass	Field: R^2=0.42, RMSE=810kg/ha	HJ-1A/B, RADARSAT-2	Field survey data	Jin et al. (2017)

Assimilation variables are central to DA, determining how effectively observational data correct model uncertainties. As shown in Table 3, LAI is the most commonly used assimilation variable in DA because it directly reflects canopy structure and photosynthetic capacity (Chen and Black 1992; Dong et al. 2012). However, the selection of assimilation variables must take the observation error covariance matrix into account, and the absence of standardized criteria in practice introduces a high degree of subjectivity (Xiao et al. 2025). Research indicates that using LAI as the assimilation variable can reduce errors in yield estimation (Huang et al. 2023), yet switching to solar-induced fluorescence (SIF) can further enhance accuracy (Guan et al. 2017). Relying on a single variable for assimilation (e.g., LAI alone) overlooks interactions among variables, which may introduce errors in complex farmlands (such as intercropping systems) (Huang et al. 2024). Consequently, the joint assimilation of multiple variables has become a key strategy. For example, in arid regions, variables like soil moisture (SM) and evapotranspiration (ET) better capture the impact of water stress, thereby increasing the model's sensitivity to environmental responses. Effectively integrating these interactive factors represents a core challenge in improving yield estimation accuracy for different crops. For instance, Yang and Lei (2024) employed the ENKF-SSPE algorithm to jointly assimilate LAI, SM, and ET into the APSIM model, successfully optimizing the simulation of water dynamics in wheat on the North China Plain, with LAI and ET yielding the best performance, whereas the optimal combination of assimilation variables for maize was found to be SM and ET. This underscores the necessity of aligning variable selection closely with crop physiological characteristics (such as differences in photosynthetic and water use efficiencies) to avoid predictive biases stemming from parameter mismatches. Future work may involve leveraging multivariable joint assimilation in conjunction with AI algorithms to optimize variable selection.

The accuracy and resolution of remote sensing data further influence the precision of crop yield estimations, as noise in remote sensing variables (e.g., cloud contamination or atmospheric correction errors) can propagate into the models, especially in heterogeneous farmlands (such as smallholder systems). Coarse resolution data typically result in aggregation errors that fail to capture field-scale variations, thereby amplifying model uncertainties and diminishing overall data assimilation performance (Huang et al. 2019a; Luo et al. 2023). To address this issue, fine-resolution data have emerged as a forefront strategy, capable of better capturing intra-field variations and reducing noise effects. For example, Bai et al. (2020) employed the SCE-UA algorithm at 30 m resolution in conjunction with Landsat 8 data, achieving impressive results (R^2 = 0.891, RMSE = 591 kg/ha), which demonstrated the potential of high-resolution data at fine scales, particularly in enhancing the robustness of variable assimilation in heterogeneous farmlands. Similarly, Ziliani et al. (2022a) integrated 3-meter high-resolution CubeSat imagery into the APSIM model to facilitate early prediction of intra-field yield variability, significantly improving accuracy, although high costs and cloud coverage issues still limit its application over large areas. In summary, balancing data quality with the scale of application is critical for improving data assimilation outcomes. In global regions with sparse data, readily available low-resolution data may lead to yield overestimation or underestimation; hence, advanced solutions like multi-source fusion are being developed to bridge the scale gap and optimize the integration of variables.

The choice of assimilation algorithm is crucial to the performance of DA. Its theoretical basis and applicable scenarios determine its performance in crop growth models. Calibration methods, such as SCE-UA (Bai et al. 2020), globally optimize parameters to minimize the deviation between the model and observations, this approach is well-suited for scenarios with high-quality and comprehensive observational data.. However, it relies on a large number of iterations, resulting in high computational costs, which limits real-time, large-scale applications. Forcing methods (Morel et al. 2014) directly replace model state variables with remote sensing observations. They are simple to implement, but because they ignore the internal dynamics of the model, they may amplify the uncertainty of remote sensing data and reduce the stability of long-term predictions. In contrast, update methods balance flexibility and accuracy by iteratively updating the state vector and combining prior models and observational evidence (Huang et al. 2019a). For example, the EnKF assumes that the error is Gaussian and is suitable for linear or near-linear systems. Huang et al. (2023) used EnKF to assimilate LAI data into the WOFOST model and effectively corrected the wheat growth trajectory in Henan Province. However, its ability to handle non-Gaussian errors is limited, and it is easily affected by the nonlinear dynamics of crop growth. The PF avoids the Gaussian assumption through Monte Carlo sampling and is suitable for nonlinear systems. As shown by Li et al. (2015a), it accurately captured the phenological changes of crops in Shenzhou City by assimilating LAI data through PF, but the high computational requirements limit its feasibility in large-scale applications. Variational methods such as 4DVar (Zhuo et al. 2022) optimize the objective function through the time dimension and integrate multi-temporal observations. They are suitable for scenarios that require long-term dynamic correction, but their complex observation operators and high computational costs make them difficult to generalize to resource-constrained environments. When extending grid-based DA models to large regions, selecting an appropriate DA algorithm to enhance computational efficiency and simulation accuracy is critical. High-resolution data on a fine grid can improve accuracy but at the cost of efficiency, as the increased number of grid points leads to exponential growth in computation time; conversely, low-resolution data on a coarse grid is computationally efficient but sacrifices accuracy. For example, EnKF performs exceptionally well in data-intensive small-scale experiments, but may fail in regional-scale predictions where data is sparse or nonlinear. Although PF and 4DVar approaches can tackle nonlinearity, they need to balance computational efficiency and simulation accuracy. In response to these issues, some scholars (Li et al. 2024) have proposed that accelerating convergence can be achieved by implementing a local optimization algorithm through local search or alternative optimization strategies for each solution during each iteration, or by parallelizing the computational tasks of the algorithm using multi-core or distributed computing resources (such as the Spark framework). In the future, hybrid algorithms, such as simulation strategies that integrate SCE-UA with 4DVar or combine machine learning techniques, are expected to alleviate these challenges, thereby promoting the development of a global operational system that ensures high-performance crop yield estimation.

Remote sensing data provide extensive spatial information for crop yield estimation, but it is difficult to capture uncontrollable farmland management factors (such as fertilization and irrigation), which are crucial for estimation (Huang et al. 2019a). Therefore, combining remote sensing with crop growth models alone cannot fully solve the complexity of estimation, especially in large-scale applications. Model accuracy is affected by data scarcity and environmental heterogeneity (Ines et al. 2013), and differences in crop growth characteristics further complicate the relationship between LAI and crop yield, increasing uncertainty. Models usually rely on validation data from specific experimental fields, limiting their extrapolation and generalization capabilities (Jégo et al. 2012). DA technology has significantly improved estimation accuracy in small-scale experimental fields (Silvestro et al. 2021), but is limited in large-scale applications due to the lack of management factors and insufficient ground verification data (Cui et al. 2022). Future research should explore multivariate assimilation methods (Yang and Lei 2024), and integrate machine learning optimization algorithms ,such as the combination of Bayesian reasoning and EnKF (Song et al. 2024). to adapt to nonlinear dynamics and improve simulation accuracy. At the same time, researchers should develop high-quality ground datasets to support large-scale verification, and improve remote sensing data processing, such as fusing optical and radar data (Manivasagam et al. 2021) to mitigate the impact of cloud cover, improve data consistency, optimize assimilation algorithms (such as EnKF, 4DVar, SCE-UA, PF, etc.), combine high-temporal and high-spatial resolution remote sensing data with measured data, establish a space-ground integrated observation system, enhance data sharing networks and big data processing capabilities, take advantage of the rapid development of drones and portable sensors, and combine multi-source remote sensing data with intelligent algorithms to further improve the accuracy and practicality of yield forecasts. By balancing variable selection, data quality, and algorithm efficiency, DA can be promoted from rough estimation to fine prediction, providing reliable support for precision agricultural practices and global food security, responding to climate change challenges, and ensuring sustainable agricultural development.

2.5 Machine learning methods

2.5.1 Method overview

Machine learning (ML) and deep learning (DL) play a crucial role in crop yield estimation based on remote sensing data. By capturing the complex relationships between environmental variables and yield, these methods offer higher accuracy compared to traditional empirical and process-based models, provided that sufficient data and high-resolution data are available. The core concept of machine learning is to regard yield as an implicit function of environmental variables, such as soil conditions and meteorological factors, and remote sensing observations, including vegetation indices and spectral reflectance. Models are trained to identify the nonlinear associations between these variables and yield (Reichstein et al. 2019). Unlike light use efficiency models based on physiological processes, machine learning methods do not require explicit simulation of crop growth mechanisms; instead, they rely on statistical patterns from large datasets to directly extract yield-related patterns from input features. As a subset of machine learning, deep learning (DL) employs multilayer neural network architectures to learn complex patterns (Gao et al. 2025a). By iteratively optimizing weights via backpropagation, raw input data (such as NDVI or LST from remote sensing time series) are gradually transformed into higher-scale, more abstract representations, thereby capturing the nonlinear interactions and spatiotemporal dependencies in crop growth dynamics (Cai et al. 2019). In yield estimation, this approach is particularly well-suited for processing high-dimensional, multisource data, for instance, through convolutional layers that extract spatial features and recurrent layers that model temporal changes, thereby revealing underlying yield patterns (Engen et al. 2021; Meghraoui et al. 2024; Yilin et al. 2022).

The fundamental assumption of ML and DL in crop yield estimation is that remote sensing data can reflect the growth status of crops and environmental stresses (such as drought and temperature changes), thereby indirectly characterizing yield potential. Common input variables include spectral indices , meteorological data, and soil characteristics. These data, acquired through satellite observations, offer the advantages of wide-area coverage and high spatio-temporal resolution (Muruganantham et al. 2022). Depending on research objectives, ML and DL models can be categorized as descriptive or predictive: descriptive models are used to analyze patterns in historical data, while predictive models focus on estimating future yields (Alpayd 2014). Remote sensing technology plays a crucial role in machine learning methods, not only providing the foundational data required for training but also enhancing model adaptability through the fusion of multi-source data (such as time-series remote sensing imagery and meteorological grid data). For instance, temporal changes in vegetation indices can capture crop phenology and health status, while the incorporation of multispectral data further enhances the model's sensitivity to dense vegetation or complex environments (Sarker 2021). The rise of large pre-trained foundation models (FM) has significantly advanced the development of crop yield estimation. These models are typically pre-trained on vast amounts of multimodal data (such as remote sensing imagery, weather data, and soil characteristics), possessing strong generalization capabilities that enable cross-regional knowledge sharing to reduce reliance on local training data (Bommasani et al. 2021). For example, in data-scarce regions, the models can utilize knowledge from other areas for prediction, thereby reducing data collection costs. This approach is particularly suitable for global agricultural systems, especially in the context of increasing data heterogeneity due to climate change and land use changes. However, these methods still face challenges in implementation, including issues related to data quality, computational costs, and model interpretability.

From an agricultural perspective, crop yield is determined by the interplay of genotype, environment, and management factors. Consequently, crop yield estimation encompasses various elements such as soil characteristics, climatic conditions, and management practices. Whether it's ML or DL, these factors are essential variables for accurately predicting crop yield. Fig.4 illustrates these factors, which can be categorized into four main types: meteorological data, soil data, crop management data, and multispectral data. Meteorological inputs typically include climate variables such as daily average and extreme temperatures, wind speed, vapor pressure, and precipitation. Studies have shown that climate variables such as temperature, precipitation, and differences in water vapor pressure are closely associated with crop yields and can explain one-third of the variation in global crop yields at the county scale (Guan et al. 2017; Li et al. 2019; Ray et al. 2015). Soil data encompasses key indicators of the crop growth environment, like Available Water Capacity (AWC), Soil Organic Matter (SOM), Cation Exchange Capacity (CEC), and soil texture attributes such as sand and silt content, and pH levels. Multispectral data, primarily sourced from remote sensing satellites, is crucial for extracting feature information via spectral band combinations. Vegetation indices, such as the NDVI and the Enhanced Vegetation Index (EVI), are widely utilized in crop yield prediction. These indices, which leverage the reflective properties of plants, have been proven to effectively indicate plant growth and yield potential (Muruganantham et al. 2022). In terms of environmental variables, factors like LST and SR are also integral to assessing crop conditions. Management data includes historical records of crop yield, planting area, land cover, and the proportion of cultivated fields.

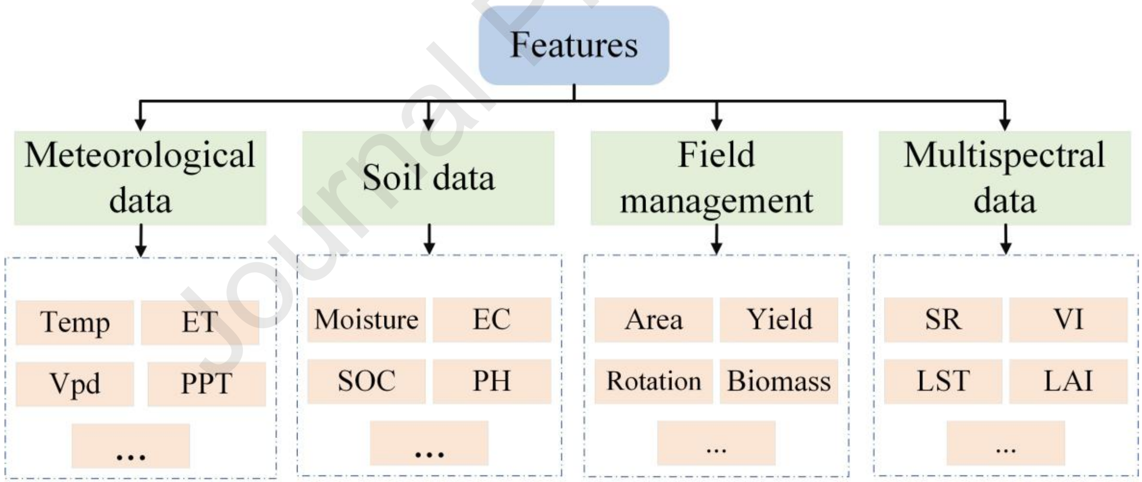

Fig.4 Features used in deep learning models

2.5.2 Recent progress

In recent years, yield mapping using machine learning (ML) and deep learning (DL) methods has garnered significant attention, especially when obtaining field-measured data is challenging. These methods enable large-scale, high-resolution yield estimation by capturing the complex nonlinear relationships between remote sensing data and yield. Compared to traditional empirical regression models, machine learning approaches are more adept at capturing underlying patterns from multi-source data, making them particularly suitable for yield estimation at both point and field scales. We conducted a literature search using the keywords “machine learning, deep learning,” and “subfield yield estimation,” followed by the selection and analysis of several representative studies on pixel or field-scale yield mapping based on traditional machine learning models and deep learning models (Table 4). Primary models such as Random Forest (RF), Extreme Gradient Boosting (XGBoost), Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), and Quantile loss

Domain Adversarial Neural Networks (QDANN) are included, and the study areas cover regions in the United States, Asia, and even global scales, with a period from 1982 to 2022 and spatial resolutions ranging from 0.3 meters to 4 kilometers.

Table 4. Studies on yield mapping using machine learning and deep learning models

Method	Spatial resolution	Spatial coverage	Temporal coverage	Accuracy(scale)	Remotely sensed data resource	Ground truth	Reference
Random Forest	20m/30m	Midwest USA	2008-2018	Pixel:（landsat/sentinel-2）R^2 =0.44/ 0.45, RMSE = 850/820 kg/ha; county: R^2 =0.82, RMSE =240 kg/ha	Landsat, Sentinal-2	Statistical data/field survey data (Corteva AgriScience)	Dado et al. (2020)
	4km	Southeast Asia	1995-2005	Administrative: single rice: R^2=0.88, RMSE = 920 kg /ha; double rice: R^2=0.91, RMSE = 554 kg/ ha; and triple rice: R^2=0.93, RMSE = 588 kg /ha	GLASS	Statistics (FAO)	Wu et al. (2022)
	1km	China	2002-2015	Pixel: R^2=0.65, RMSE=2144.75 kg/ha, County: R^2=0.80	MODIS	Statistical data/ field survey data	Cheng et al. (2022b)
	1km	Midwest USA	2006-2021	County: R^2 range from 0.70 to 0.89; soybean: R^2 range from 0.74 to 0.90	MODIS	National Statistics (USDA)	Dado et al. (2020); Pei et al. (2024)
XGBoost	0.3m	Washington, USA	2019	Field: R^2=0.89, RMSE =542kg/ha, MAE=380kg/ha	UAV-RGB	Field survey data	Qu et al. (2024)
CNN-LSTM	30m	Iowa, USA	2018-2019	MAPE 为 4%-6%	Harmonized Landsat Sentinel-2 (HLS)	Field survey data	Ghazaryan et al. (2020)
LSTM	4km	Global land	1982-2020	R^2=0.82, RMSE=619.8kg/ha	NOAA-AVHRR, GLASS	Statistics (FAO)	Luo et al. (2022)
ALSTM	10m	Northeast China	2022-2023	R^2 = 0.88, RMSE = 341.82 kg/ha	Sentinel-2	Field survey data	Li et al. (2025a)
QDANN	30m	Midwest USA	2008-2022	Pixel: R^2 = 0.48 (Maize) RMSE = 2290 kg/ha, county: R^2 = 0.78, RMSE = 980 kg/ha	Landsat	Field survey data (Corteva AgriScience) and Statistics (USDA)	Ma et al. (2024b)

The RF model is an ensemble learning method based on decision trees. It generates multiple subsamples via bootstrap sampling and randomly selects a subset of features at each decision tree node, thereby constructing a diverse collection of trees to mitigate overfitting and enhance generalization (Breiman 2001). RF shows remarkable robustness when dealing with high-dimensional remote sensing data and has been widely applied in crop yield estimation, effectively handling the noise and nonlinear relationships present in multispectral remote sensing imagery and environmental variables (Virani et al. 2025). At the pixel scale, RF is typically used to capture spatial heterogeneity, thus enabling high-resolution yield mapping; at the field scale, data aggregation supports regional decision-making. For instance, Dado et al. (2020) employed a random forest model combined with Sentinel-2 and Landsat data to predict pixel-scale soybean yield in the U.S. Midwest through NDVI-based harmonic regression, and subsequently extended the application to the field scale via spatial aggregation, demonstrating the utility of RF in multi-source data fusion. Wu et al. (2022) further integrated remote sensing and meteorological data into the RF model to estimate rice yield at a 4 km pixel resolution in Southeast Asia, underscoring the critical role of multi-source data fusion in improving model performance. However, model accuracy is influenced by factors such as sample size, the extent of the study area, data quality (e.g., remote sensing resolution and cloud contamination), and crop type. Under conditions of ample samples and moderate study area sizes, RF generally achieves high accuracy; yet in cases of scarce data or large-scale heterogeneous regions, hyperparameter optimization or integration with other methods may be required to further enhance generalization performance (Padma and Sinha 2023; Salami et al. 2025). XGBoost (Chen and Guestrin 2016), through the use of L1/L2 regularization and a gradient boosting framework, optimizes the handling of sparse remote sensing data and demonstrates excellent adaptability for multi-scale yield estimation in field settings. It enables scalable nonlinear modeling of multi-source features, including remote sensing indices, climatic variables, and soil properties (Cao et al. 2025). In heterogeneous fields, XGBoost is less prone to overfitting and can facilitate early predictions during the initial stages of crop growth by capturing complex interactions and enhancing generalization capabilities, thereby achieving performance improvements of 10%–25% over empirical regression methods (Lionel et al. 2025; Parashar et al. 2024). Both RF and XGBoost have demonstrated significant robustness and scalability in crop yield estimation. Nevertheless, ML methods tend to be less sensitive to mixed pixels and extreme events, and their "black-box" nature often limits interpretability. Although feature importance assessments (e.g., using the Gini index or permutation importance) can help identify key spectral bands—such as the role of NDVI during early phenological stages—in certain cases, these approaches can enhance model interpretability (Huber et al. 2022). In recent years, some studies (Dhillon et al. 2023; Islam et al. 2024; Xie et al. 2025; Yenkikar et al. 2025) have begun exploring the coupling of other machine learning or process models and the integration of multi-source inputs (e.g., remote sensing, climate, and soil data) to improve the modeling capabilities and predictive accuracy for complex agricultural systems, achieving an approximate 15% improvement over approaches that use a single model or variable. Additionally, Brandt et al. (2024) has proposed an ML ensemble-based modeling framework designed for bottom-up scalable yield estimation from parcels to administrative districts. This method integrates multi-source geographic data and employs a majority voting mechanism to generate robust multi-year yield predictions, thereby supporting detailed reporting for official agricultural statistics. In the future, ML can further optimize spatiotemporal dynamic modeling by leveraging cloud computing technologies and integrating them into map-service platforms, consequently providing efficient decision support for multi-scale agricultural management for various stakeholders and fostering the development of smart agriculture and digital agricultural statistical systems.Long Short-Term Memory Networks (LSTM) (Hochreiter and Schmidhuber 1997), as a recurrent variant of deep learning, effectively capture long-term dependencies in time series through gating mechanisms such as the forget gate, input gate, and output gate.

This capability mitigates the vanishing gradient problem and, under complex climatic conditions — such as sequence discontinuities caused by cloud contamination or extreme events — LSTM outperforms traditional machine learning methods by dynamically retaining relevant historical information to predict crop growth curves (Tian et al. 2021; Wang et al. 2022).For example, Luo et al. (2022) used the LSTM model to combine remote sensing, climate, and soil data from the global land area to generate a 4 km resolution wheat yield dataset, thereby illustrating the advantages of multi-source time series fusion. Convolutional Neural Networks (CNN) excel in fine-scale yield estimation due to their local receptive fields that capture detailed spatial information; they are often combined with LSTM to form hybrid models that balance spatial and temporal representations. For example, Ghazaryan et al. (2020) combined a CNN-LSTM model to process multi-source MODIS and HLS data to achieve accurate field-scale estimations for corn and soybean fields in the United States. Compared with traditional methods and single-source data, this multi-source integration improved estimation accuracy by 15%, though model interpretability (e.g., visualization of attention weights) still requires optimization. To address field dynamics under cloud interference, recent LSTM variants have incorporated attention mechanisms to strengthen weight allocation during critical phenological stages. Li et al. (2025a) proposed an attention-based long short-term memory (ALSTM) model for pixel-scale early rice yield estimation in Northeast China. By concentrating on multi-temporal remote sensing data that capture both vegetative growth and reproductive phases, the model reduced error by 20% compared to the LUE model, thereby significantly mitigating fine-scale uncertainty. Similarly, Joshi et al. (2025) introduced a bidirectional LSTM (Bi-LSTM) variant that employs both forward and backward attention to emphasize critical phenological events and environmental drivers (such as temperature/precipitation interactions) in winter wheat, achieving cross-regional predictions with a 10% improvement in generalization compared to a standard LSTM.

Complementing the temporal modeling strengths of LSTM, Domain-Adversarial Neural Networks (DANN) utilize domain adversarial loss functions and attention mechanisms to perform unsupervised domain adaptation, transferring coarse-scale (e.g., county-scale statistical) knowledge to the sub-field scale. This approach addresses distribution shifts in remote sensing data (such as heterogeneous soils or resolution mismatches), thereby enhancing generalization in low-sample scenarios (Ganin et al. 2016). Ma et al. (2024b), based on the DANN principle, developed the QDANN framework, which uses Landsat GCVI features and meteorological data to transfer county-scale maize yield knowledge to the sub-field scale. At the field scale, the R^2 accuracy increased from 0.44 to 0.48 (RMSE = 2.29 t/ha) relative to a random forest approach, demonstrating its potential in data-scarce regions and its suitability for pixel-scale applications. However, the performance of deep learning models is highly dependent on the scale and quality of the training data, highlighting trade-offs relative to traditional machine learning methods. When sufficient training data are available, machine learning models may be outperformed by deep learning; yet in scenarios with limited training data, machine learning models tend to exhibit relatively stable performance (Liu et al. 2025).For ML and DL, model performance is highly dependent on training data. If there is significant measurement error or uneven distribution of high and low values in the sample, the model will overestimate low values or underestimate high values. In large-scale analyses, commonly used label data are often drawn from public statistical sources such as the USDA-NASS in the United States, renowned for its reliability and accessibility (USDA-NASS 2019). Other sources include regional production statistics from agencies like the Brazilian Institute of Geography and Statistics (http://www.sidra.ibge.gov.br) and official agricultural statistics from countries like India, China, Norway, and Nepal. For example, Luo et al. (2022) pointed out that in data-scarce areas (such as Afghanistan), prediction accuracy is significantly reduced, which is particularly prominent in developing countries because of the lack of high-resolution historical yield data limits the generalization ability of the model. Dado et al. (2020) also found that models trained at the county scale are difficult to generalize to the pixel scale, emphasizing the importance of fine-grained ground data. Additionally, the lack of interpretability of the model has become a major challenge. ML and DL models are often regarded as ‘black boxes’ due to their complex internal mechanisms, and it is difficult to reveal the causal relationship between variables, which limits their application in agricultural decision-making. Pei et al. (2024) tried to introduce SHAP values to analyze feature importance, but SHAP values still cannot fully meet actual needs. Computational cost is also an issue that cannot be ignored, especially deep learning models such as QDANN, which requires high-performance hardware support, which is difficult to deploy in areas with limited resources. Although Ma et al. (2024b) reduced data requirements through transfer learning, their sensitivity to the quality of input features may still affect their stability. Finally, there are significant differences in scale adaptability. The study in Table 4 shows that the accuracy of the pixel and field scales is generally lower than that of the administrative scale, which may be related to the lack of matching between data resolution and model complexity. At the pixel/field scale, the R^2 value of the model ranges from 0.32 to 0.65, while at the administrative unit scale, the R^2 value is higher, ranging from 0.53 to 0.90 (Table 4). This difference in accuracy may be due to the aggregation effect of errors. At the county scale, local random errors are reduced by averaging, while at the pixel scale the model is more susceptible to local variability (Dash 2012). Furthermore, the limitations of remote sensing data resolution and the overfitting problem of the model at the point scale have exacerbated this phenomenon (Atzberger 2013; Lobell et al. 2015).

Remote sensing data play a key role in ML/DL models. The rich spectral information of Sentinel-2 and the long-term sequence data of Landsat provide a solid foundation for feature extraction. Wu et al. (2022) alleviated the cloud contamination problem through harmonic regression, and Luo et al. (2022) used phenological algorithms to enhance the sensitivity to seasonal changes. Pixel-scale (i.e., field- or pixel-scale) yield data play a key role in agricultural remote sensing research as labels for model training and validation. However, such data usually rely on field surveys or mechanical collection, which sre expensive to obtain and are mostly non-public. For example, Dado et al. (2020) used field data obtained in cooperation with Corteva AgriScience, and Qu et al. (2024) relied on private experimental site data. These cooperatively acquired private datasets provide a high-quality training and validation basis for the model, but their scarcity and confidentiality limit the widespread sharing and application of data. To overcome the above limitations, future research can establish a global yield database through international cooperation and adopt semi-supervised learning or transfer learning. Semi-supervised learning uses a small amount of labeled data and a large amount of unlabeled data for training, which can improve model performance when data is limited; transfer learning reduces the dependence on local training data by pre-training the model on a large-scale dataset and then fine-tuning it for specific tasks. At the same time, multi-source data fusion technology is optimized (Gao et al. 2018) to improve the generalization ability and interpretability of the model(Gao et al. 2025b). In short, ML and DL methods have shown great potential in remote sensing-driven yield estimation, but further improvements are needed in data availability, model interpretability, and computational efficiency to meet the application needs of multiple scales and regions.

2.6 Methods summaries

2.6.1 Model accuracy and spatial scale

This study compiles multiple field-scale crop yield estimation studies to systematically reveal the intrinsic relationship between the spatial resolution of remote sensing data and model accuracy (e.g., R^2 and RMSE), thereby filling the gap in the current literature on multi-resolution quantitative comparisons (Figure 3). Most studies utilize medium-resolution remote sensing data (10–100 m), with R^2 values concentrated between 0.35 and 0.7 and RMSE ranging from 200 to 2500 kg/ha. For high-resolution (10 m) remote sensing data, R^2 values range from 0.3 to 0.89, with RMSE approximately between 450 and 1500 kg/ha. In contrast, studies using coarse-resolution data (100–1000 m) report R^2 values between 0.3 and 0.65 and RMSE between 200 and 2200 kg/ha, reflecting the impacts of crop type and regional heterogeneity. Qu et al. (2024) employed 0.3 m UAV RGB imagery, achieving a field-scale yield estimation accuracy with an R^2 of 0.89 and an RMSE of 542 kg/ha. Similarly, Yang et al. (2019) used UAV data with a 5.4 cm resolution to predict wheat yield, obtaining an R^2 of 0.88 and an RMSE of 491.9 kg/ha, which underscores the potential of high-resolution data to capture within-field spatial variations such as differences in soil fertility, moisture distribution, and management practices. Cheng et al. (2022a) compared Sentinel-2 10 m data with ZY-1 02D 30 m data and found that the 10 m imagery was more accurate, while Kayad et al. (2019) tested different resolutions across 59 fields in South Australia and verified that modeling from high-resolution data with subsequent aggregation of outputs performed better than input resampling; they obtained an LCCC of 0.87 and an RMSE of 590 kg/ha, indicating that starting with high-resolution data and aggregating outputs is more effective. However, the accuracy of high-resolution data is significantly influenced by the scales of training and validation, and mismatches between the resolution of training data and aggregated validation at larger scales (such as county-scale statistics) may diminish accuracy (Silvestro et al. 2021; Tang et al. 2022). In contrast, although low-resolution data tend to average out variations and reduce field-scale accuracy, they show significant potential in large-scale estimations by capturing overall trends in a cost-effective manner and avoiding resource waste. Therefore, in crop yield prediction, it is essential to match the resolution and methodology to the target scale to optimize the scientific rigor and practical applicability of yield estimation..

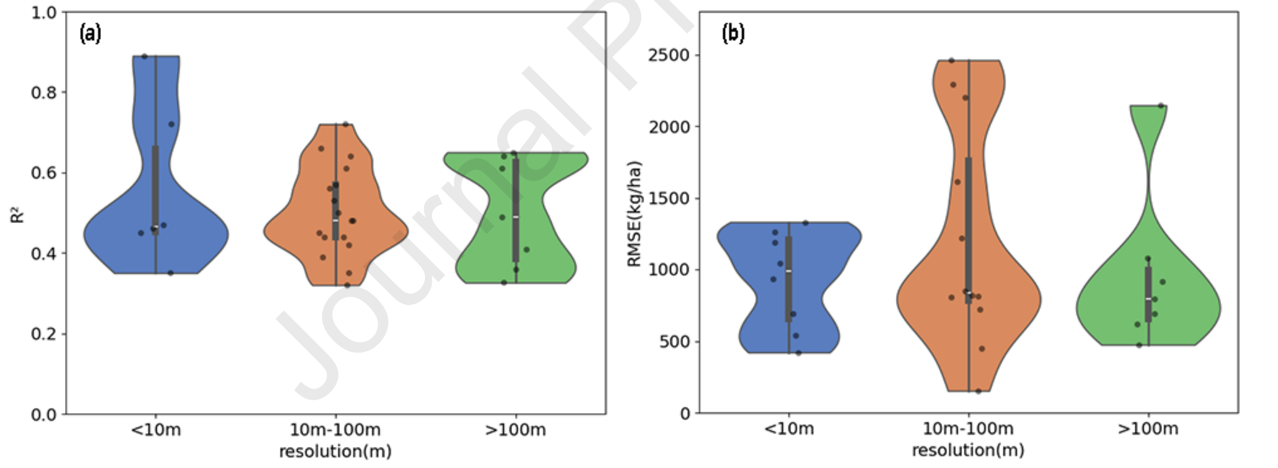

Fig. 5 Relationship between field-scale yield estimation accuracy and spatial resolution of remote sensing data

2.6.2 Model Interpretability

Model interpretability is also key to optimizing crop yield estimation. Quantifying uncertainty and integrating SHAP analysis can enhance the transparency of models (such as ML/DL) and identify the critical technologies driving advancements in the field, thus effectively mitigating the black-box issues of complex models (Doda et al. 2024) and enhancing the reliability of decision-making. Empirical statistical models provide inherent transparency through linear regression coefficients that facilitate direct interpretation of the relationships between variables (Knox et al. 2012); however, focusing solely on inherently interpretable models limits the types of relationships that can be modeled, potentially reducing both accuracy and applicability (Ribeiro et al. 2016). The light use efficiency (LUE) model, on the other hand, can explain physiological parameters through sensitivity analysis. For example, by computing the APAR/GPP ratio, it can reveal dynamic changes in light use efficiency during different phenological phases (such as reproductive and vegetative stages), thereby quantifying the impact of environmental stress on yield (Yuan et al. 2016; Zhou et al. 2016). Data assimilation (DA) techniques support uncertainty propagation; for instance, Monte Carlo simulations are used in EnKF to quantify the sensitivity of assimilated variables (such as LAI or GPP) and to assess the potential impact of model parameter uncertainty on yield estimation accuracy (Chen et al. 2025b; Zare et al. 2024). Machine learning (ML) and deep learning (DL) models benefit from post-hoc interpretation tools, with SHAP being particularly suitable for tree-based models (Lundberg and Lee 2017) due to its localized interpretability based on tree structures. For example, in crop yield estimation, SHAP can quantify the contribution of NDVI or land surface temperature (LST) to XGBoost predictions. Research on the interpretability of deep learning models can be divided into three areas: explaining decision attribution, elucidating logical rules, and interpreting internal structure representations (Zhang et al. 2021a). Decision attribution clarifies the importance of features in predictions; one common method is integrated gradients (Sundararajan et al. 2017), which integrates the gradients from a baseline to the input to enhance transparency (Najjar et al. 2025; Paudel et al. 2023; Sui et al. 2024). For instance, Li et al. (2025b), in a CNN-driven winter wheat yield model that utilized remote sensing data such as VTCI, employed integrated gradients to identify key phenological stages dominated by drought indicators (e.g., the jointing stage), thereby assisting in precise interventions. Moreover, most deep learning yield models focus on deterministic outputs and lack uncertainty quantification, which is crucial for risk management in the context of climate change (Abdar et al. 2021). Bayesian techniques are predominant here, as they derive posteriors from priors and data and enhance model interpretability through uncertainty quantification in crop yield estimation (Lobell et al. 2014). Bayesian neural networks (BNNs) treat weights probabilistically, though they face computational challenges, whereas Monte Carlo (MC) dropout approximates the posterior during inference through random dropout, thus improving interpretability (Kendall and Gal 2017). These interpretability tools not only increase the trustworthiness of yield estimation models and advance the field, but also assist in optimizing variable selection. In the future, integrating multimodal data (such as the fusion of satellite imagery and meteorological information) may further refine these methods to achieve more precise pixel- and field-scale crop yield estimation.

2.6.3 Model quantitative evaluation

To quantitatively evaluate the performance of different models in estimating crop yield at the pixel/field scale, this study compared multiple linear regression, the MOD17 algorithm, a random forest model, and a CNN model (DA models were excluded from the quantitative comparison because they involve numerous practical management parameters that are difficult to obtain). Nearly 4,000 corn yield points for 2019–2024 were collected from corn-growing areas in 18 U.S. states (Kang and Özdoğan 2019). For each year, feature data from May–August were selected (Ma et al. 2024b), including monthly maximum composites of NDVI from the HLS dataset (Masek et al. 2021). Meteorological inputs—monthly means of precipitation, daily maximum temperature, and daily minimum temperature—were obtained from the PRISM dataset (Daly et al. 2015). CONUS 30 m gross primary productivity (GPP) data derived from an improved MOD17 algorithm (Robinson et al. 2018) were converted to yield indirectly using empirical formulas; the autotrophic respiration fraction, harvest index, and carbon content used in those formulas were taken from the literature (Prince et al. 2001; Waring et al. 1998; Yu et al. 2009). Results are shown in Table 5. Multiple linear regression performed poorly among the four methods, with R^2 = 0.12 and RMSE = 2386.37 kg/ha, indicating that it cannot adequately capture the complex relationships between remote sensing and meteorological variables and corn yield at the pixel scale. The results based on the improved MOD17 algorithm were the worst of the four, with R^2 = 0.03 and RMSE = 3677.78 kg/ha, because the algorithm yields poor GPP estimates for crops (Robinson et al. 2018), He et al. (2018a) also demonstrated low estimation accuracy for corn, reporting a Pearson correlation of only 0.38. The XGBoost model achieved the highest accuracy among the four methods, with R^2

= 0.35 and RMSE = 2112.78 kg/ha, indicating that, relative to multiple linear regression, it can better capture the nonlinear relationships between corn yield and vegetation indices and meteorological variables, and is well suited to large-scale crop yield estimation when sample quality is good. The CNN model ranked second, with R^2 = 0.31 and RMSE = 2128.03 kg/ha; however, CNNs involve complex parameter settings and multiple network layers, and the ~4,000 collected samples may not be sufficient to fully exploit a CNN's advantage in capturing complex geospatial features.

Table 5 Quantitative evaluation among models at pixel/field scale

Models	R^2	RMSE（kg/ha）
Multiple linear regression	0.12	2386.37
MOD17	0.03	3677.78
XGBoost	0.35	2112.78
CNN	0.31	2128.03

2.6.4 Model Comparison and Scenario Selection

This study outlines four crop yield estimation methods — empirical-statistical models, light use efficiency (LUE) models, remote sensing data assimilation models, and machine learning models — each of which offers distinct advantages in different scenarios due to their unique characteristics（Table 6）. Empirical-statistical models rely on historical statistical data and readily available remote sensing information; they are computationally simple, low-cost, and capable of rapidly generating regional-scale yield estimates. In practice, these models are particularly well suited for large-scale (national or global) preliminary trend analyses and resource optimization, as they offer high computational efficiency and wide-area coverage without requiring high-resolution details. For example, international organizations employ empirical-statistical models in global monitoring: the FAO integrates MODIS NDVI data with historical yield records to predict trends in major crops worldwide (Basso et al. 2013), thereby supporting the UN famine early warning system. Similarly, the U.S. farming commercial network (Meisner 2017) processes real-time data transmitted from extensive areas through precision agriculture contract management to provide early yield forecasts to the USDA. the pronounced spatial heterogeneity among fields leads to substantial model uncertainty, making LUE models more suitable for small-scale, field-level yield estimation and less often applied to large-area, plot-scale assessments. For example, Wang et al. (2019) applied a locally calibrated CASA model in the Beijing region of China to estimate winter wheat yield and reported favorable results. Data assimilation (DA) models can bridge observational data with process models by quantifying the sensitivity of assimilated variables through uncertainty propagation (e.g., Monte Carlo simulation within the EnKF, thereby enhancing yield estimation accuracy. Particularly under extreme climatic conditions (such as drought or flood) or in contexts with high environmental variability, these models allow for within-season adjustments (e.g., yield predictions 1–3 months after sowing) by dynamically integrating remote sensing data with process models to correct prediction biases in real time (Huang et al. 2019c), outperforming static methods. In practice, DA models are especially suitable for small-scale applications (sub-national or regional scales) where multi-source data are available, uncertainty is high, and real-time monitoring is required. For example, precision field management for farmers also benefits when uncertainties in fertilization and irrigation are high, as it enables optimized allocation of water and fertilizer at the field scale.When sample sizes are sufficiently large and of high quality, machine learning (ML) and deep learning (DL) models can effectively capture complex non-linear relationships to achieve efficient yield estimation. With ample in-field yield measurements, ML/DL algorithms demonstrate substantial potential at smaller, more detailed scales (e.g., pixel or field scale) (Ma et al. 2024a; Sagan et al. 2021). Moreover, when administrative-scale historical yield data are abundant, these methods are well suited for large-area yield assessments (Qiao et al. 2021; Zhang et al. 2025). For instance, the Agricultural Production Anomalies Hotspots (ASAP) system of the European Union Joint Research Centre (JRC) (https://agricultural-production-hotspots.ec.europa.eu/) employs machine learning algorithms and agrometeorological data to monitor crop anomalies in African countries. During the 2022–2023 East Africa drought, the system detected that vegetation biomass for maize and millet was 25–40% below average, thereby triggering warnings of potential yield deficits and supporting FAO aid allocation efforts.

Table 6 Algorithm Selection Based on Different Scenarios

Preferred Method	Conditions/Scenarios	Empirical Cases
Empirical Statistics	Preliminary trend analysis and resource optimization on a large scale (national or global) without the need for high-resolution details	Global monitoring by international organizations; commercial networks of farmers in the United States
LUE	Small scale, with sufficient flux tower data for model calibration	Wheat yield estimation in the Beijing region of China.
DA	Small scale where multiple data sources are available, uncertainty is high, and real-time monitoring is required	Precision field management by farmers
ML/DL	Situations with ample, high-quality data samples and abundant equipment resources	Monitoring and assessment by ASAP in food-insecure regions

3 Crop yield datasets

With the rapid development of remote sensing technology, crop yield estimation methods based on remote sensing data have been widely applied worldwide. These methods obtain and analyze satellite imagery, vegetation indices, and net primary productivity (NPP) indicators, enabling high-precision yield predictions at field and pixel scales. Compared with traditional ground survey methods, remote sensing-based yield estimation offers advantages such as wide coverage, high update frequency, and fine spatial resolution, making it suitable for large-scale real-time monitoring of agricultural fields. However, there are significant differences among various remote sensing yield estimation datasets in terms of data sources, processing methods, and spatial resolution, which pose challenges to data consistency and the reliability of the estimation results. Therefore, conducting a comparison of data consistency is particularly important. This study selected seven representative global crop yield datasets, including M3Crops, SPAM, GAEZ, Ray2012, GGCP10, GDHY, and GGCMI (Table 5). These datasets estimate crop yield using different methods, ranging from macro-scale national statistics to fine-grained pixel-scale estimations, providing multi-dimensional yield information (Figure 3). Among these, M3Crops, SPAM, GAEZ, and Ray2012 mainly use empirical statistical models, GGCP10 applies machine learning methods, and GDHY and GGCMI combine remote sensing data assimilation techniques with empirical statistical models. In addition, this study also includes the 30-meter resolution maize yield dataset compiled by Ma et al. (2024b) to further evaluate the performance of high-resolution data in the comparison of data consistency.

To assess the reliability and consistency of these datasets, this study provides a detailed introduction to the major global crop yield datasets in Section 3.1, followed by a data consistency comparison in Section 3.2. Specifically, Section 3.2.1 compares the global spatial distribution characteristics of maize yield in 2010 across the seven datasets, while Section 3.2.2 focuses on maize yield distribution in three states in the United States. By combining qualitative analysis and quantitative comparison, the accuracy and consistency of each dataset are evaluated. Through this systematic comparative analysis, the aim is to identify the strengths and weaknesses of each dataset, reveal their applicability and consistency issues at different spatial scales, and provide a reliable reference for field and pixel-scale crop yield estimation based on remote sensing data. This ensures the scientific validity and practical value of the estimation results. This process not only helps improve the accuracy and robustness of yield estimation models but also provides solid data support for precision agriculture practices and the formulation of global food security policies.

3.1 Global crop yield dataset

Table 7. Examples of gridded yield mapping products.

Product name	Data source	Crop coverage	Spatial coverage	Temporal range	Spatial resolution	Methods	Website	Reference
M3Crops	satellite and census	175 crops	Global land	Circa 2000	0.083° (10 km)	ESM	http://www.earthstat.org/harvested-area-yield-175-crops/	Monfreda et al. (2008)
SPAM	census, satellite and model	42 crops	Global land	2000, 2005, 2010, 2020	0.083° (10 km)	ESM	https://mapspam.info/data/	Yu et al. (2020)
GAEZ	census, satellite and model	23 crops	Global land	2000, 2010, 2015	0.083° (10 km)	ESM	https://gaez.fao.org/	Fischer et al. (2021)
Ray2012	satellite and census	4 crops	Global land	1995, 2000, 2005	0.083° (10 km)	ESM	http://www.earthstat.org/harvested-area-yield-4-crops-1995-2005/	Ray et al. (2012)
GGCP10	satellite and census	4 crops	Global land	2010-2020	0.083° (10 km)	ML	https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/G1HBNK	(Qin et al. 2024)
GDHY	census, satellite and model	4 crops	Global land	1982 - 2016	0.5° (55 km)	RS-DA, ESM	https://search.diasjp.net/en/dataset/GDHY_v1_2	Iizumi and Sakai (2020)
GGCMI	satellite and model	19 crops	Global land	1901 - 2012	0.5° (55 km)	RS-DA, ESM	https://agmip.org/aggrid-ggcmi/	Müller et al. (2019)

Crop yield serves as a core indicator for measuring agricultural productivity and resource use efficiency. It directly impacts global food security, farmer income, and the supply-demand balance in food markets. To date, numerous scholars have developed global spatially explicit crop yield datasets by integrating remote sensing satellite data with other sources of information (Table 7). These datasets vary in spatial resolution, ranging from 0.083° to 0.5°. M3Crops (Monfreda et al. 2008) is a dataset based on global agricultural census and statistical data. It combines global and local agricultural census data from 1997 to 2003 (e.g., FAO and national statistics), global land cover datasets from satellites, regional agricultural data from the Agro-MAPS project, and other national and provincial agricultural survey data, using techniques such as interpolation and proportional allocation. This dataset includes harvested area, yield, and physiological types of 175 major crops worldwide in 2000, with a spatial resolution of 0.083° × 0.083° (10 km × 10 km). The Spatial Production Allocation Model (SPAM) dataset (Yu et al. 2020) is derived from crop planting area, yield, irrigation area, and population density data collected from sources such as FAOSTAT. Using a cross-entropy optimization algorithm, it performs spatial allocation by combining information on crop suitability, irrigation conditions, protected areas, and population density. Supported by remote sensing, SPAM datasets utilize multiple sources, such as GLC2000/MODIS and IIASA-IFPRI for SPAM2000 (International Food Policy Research 2019a) and SPAM2005 (International Food Policy Research and International Institute for Applied Systems 2016). SPAM2010 (International Food Policy Research 2019b) and SPAM2020 (International Food Policy Research 2024) use Global Cropland Harmonized Maps, GlobeLand30, CCI-LC, GlobCover 2009, and MODIS C5 datasets. Over successive versions, the spatial resolution has improved to a 0.083° grid, covering more crop types and refining the global agricultural production distribution. The Global Agro-Ecological Zones (GAEZ) dataset (Grogan et al. 2022), based on satellite data, models, and census data, is generated at the pixel scale using interpolation techniques, bioclimatic models, and GIS spatial analysis methods, combined with historical and future climate data (such as CRU, GPCC, and CMIP5 models), soil databases (HWSD), global land cover data from satellites (GLC-Share), and agricultural statistical data (such as FAOSTAT). It considers multiple crop types and management levels. Since its initial release in the 1980s, the GAEZ dataset has been updated to version v4 and GAEZ+, with increasing accuracy and reliability in yield estimation. The Ray2012 dataset (Ray et al. 2012) combines FAO national, state, and county census statistics with global farmland data from remote sensing satellites on a 0.083° × 0.083° (10 km × 10 km) grid. The dataset depicts the harvested area and yields of wheat, maize, rice, and soybeans as five-year averages for 1995, 2000, and 2005. However, a major drawback of this dataset is the lack of quantitative information on the inherent errors in the data. Factors such as spatial aggregation, measurement, and rounding during farm sampling can introduce errors, making it difficult to accurately quantify the uncertainties in the yield statistics. The GGCP10 dataset (Qin et al. 2024) was developed by integrating multiple data sources, including statistical data, raster production data, agricultural climate indicators, agronomic indicators, global land surface satellite products, and ground-based data. It uses advanced machine learning techniques to estimate global crop yields for the period 2010-2020 at the grid scale. This approach leverages time series data of environmental factors and crop growth indicators, capturing intra-annual variations in climate and crop conditions that significantly impact crop yields. The spatial resolution is 0.5° × 0.5°, covering four major crops: maize, wheat, rice, and soybeans. The Global Historical Yield Dataset (GDHY) (Iizumi and Sakai 2020) is based on multiple data sources, including FAO agricultural census statistics, MODIS satellite remote sensing, JRA-55 reanalysis, the SAGE crop calendar, and M3-Crops harvested area data. It combines population census statistics with satellite-derived net primary productivity (NPP) to estimate the historical yields of maize, rice, wheat, and soybeans at the grid scale. The dataset uses crop calendars and various crop information to distinguish planting seasons, providing yield data for the four major crops globally from 1981 to 2016, and its spatial resolution is 0.5°. The Global Gridded Crop Model Intercomparison (GGCMI) dataset (Franke et al. 2020a; Franke et al. 2020b) was generated by 14 global crop models (GGCMs). It covers the yields of major global crops (such as maize, wheat, rice, and soybeans) under different climate, soil conditions, and management strategies. The model uses 11 historical climate datasets along with multiple management and irrigation conditions, and simulations are conducted following the AgMIP protocol, with a spatial resolution of 0.5° × 0.5°.

3.2 Dataset consistency comparison

3.2 1 Global dataset comparison

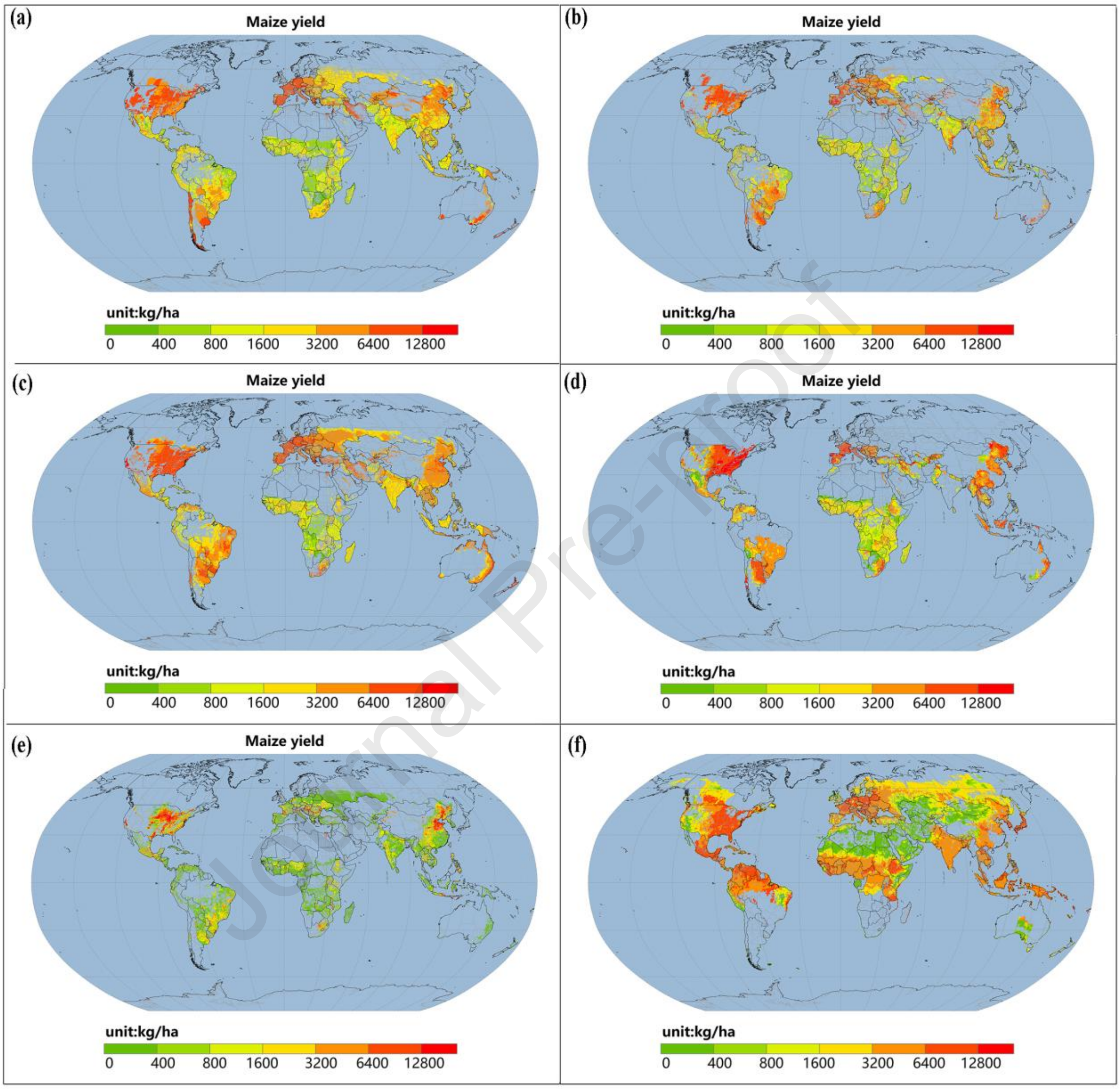

Fig. 6 The spatial distribution of the 2010 global maize yield datasets (M3Crops, SPAM, GAEZ, GDHY, GGCP10, and GGCMI) as well as the 2000 M3Crops maize yield dataset.

Fig. 6 shows the spatial distribution of maize yield in 2000 across five datasets: M3Crops, SPAM, GAEZ, GDHY, GGCP10, and GGCMI. M3Crops, by integrating remote sensing data and climate variables, provides relatively accurate maize yield estimates, particularly excelling in major production areas such as the U.S. Midwest and eastern China. SPAM, utilizing spatial production allocation methods based on administrative divisions and land use information, can accurately reflect regional yield distributions and is suitable for cross-country comparative analyses. With factors related to agricultural suitability, such as climate, soil, and topography, taken into account, GAEZ highlights high-yield areas for maize cultivation, such as the Indian plains and western Europe. GGCMI has the broadest coverage, providing maize yield estimates in Africa, South America, and Australia. However, in central and southern Africa, GGCMI tends to overestimate maize yields compared to the other datasets, probably due to differences in models or data sources. The high estimated corn yields based on the GGP10 dataset are primarily concentrated in the North American Corn Belt, Northeast China, and the North China Plain, as well as the Pampas region in South America. In contrast, corn yields in other regions are generally lower. In contrast, GDHY has the smallest coverage, the lack of data in maize-growing regions such as southeastern China, southwestern Russia, India, and parts of Kazakhstan limits its utility for global maize yield analysis. Overall, these datasets exhibit broadly similar spatial distributions, with high maize yields concentrated in areas with favorable climatic conditions and soil types for maize growth, such as the U.S. Midwest and South, western Europe, eastern China, and the Indian plains Despite differences in coverage and estimation methods, these datasets collectively depict the spatial distribution of maize production in major global regions, providing critical data support for related research and agricultural decision-making.

3.2.2 Regional comparison of datasets

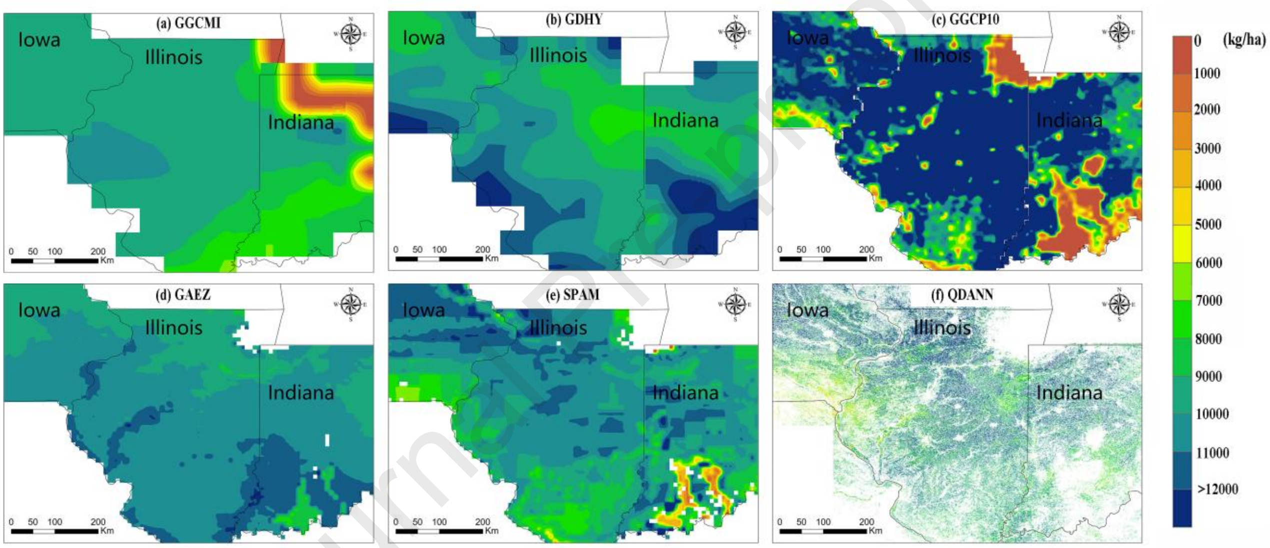

Fig. 7. Observed spatial distribution of 2010 maize yields in Iowa, Illinois, and Indiana, USA, from GGCMI (a), GDHY (b), GGCP10(c), GAEZ (d), SPAM (e), and QDANN (d) datasets.

Fig. 7 presents the spatial distribution of maize yields in 2010 from five datasets — GGCMI, GDHY, GAEZ, SPAM, and QDANN — across Iowa, Illinois, and Indiana, the primary maize-producing states in the U.S. GGCMI and GDHY, with spatial resolutions of 55 km, can capture yield differences between these states, showing higher maize yields in Iowa and Illinois compared to Indiana. However, their low spatial resolution limits their ability to capture the yield's spatial variation at finer scales. GGCP10, GAEZ and SPAM, with a spatial resolution of 10 km, provide greater spatial detail, allowing medium-scale yield variations to be more clearly displayed and better identifying transitions between high- and low-yield areas, though some smoothing effects may still occur in certain regions. QDANN, with the highest spatial resolution of 30 meters, captures extremely fine spatial variations, exhibiting high spatial detail. These datasets show significant differences in maize yield spatial distributions, primarily due to differences in spatial resolution and estimation methods. GGCMI and GDHY are suitable for large-scale yield overviews and qualitative analyses of differences among regions, while GGCP10, GAEZ, and SPAM, offering higher spatial detail, are better suited for medium-scale yield analyses. QDANN, with its high resolution, is ideal for studies requiring fine spatial information.

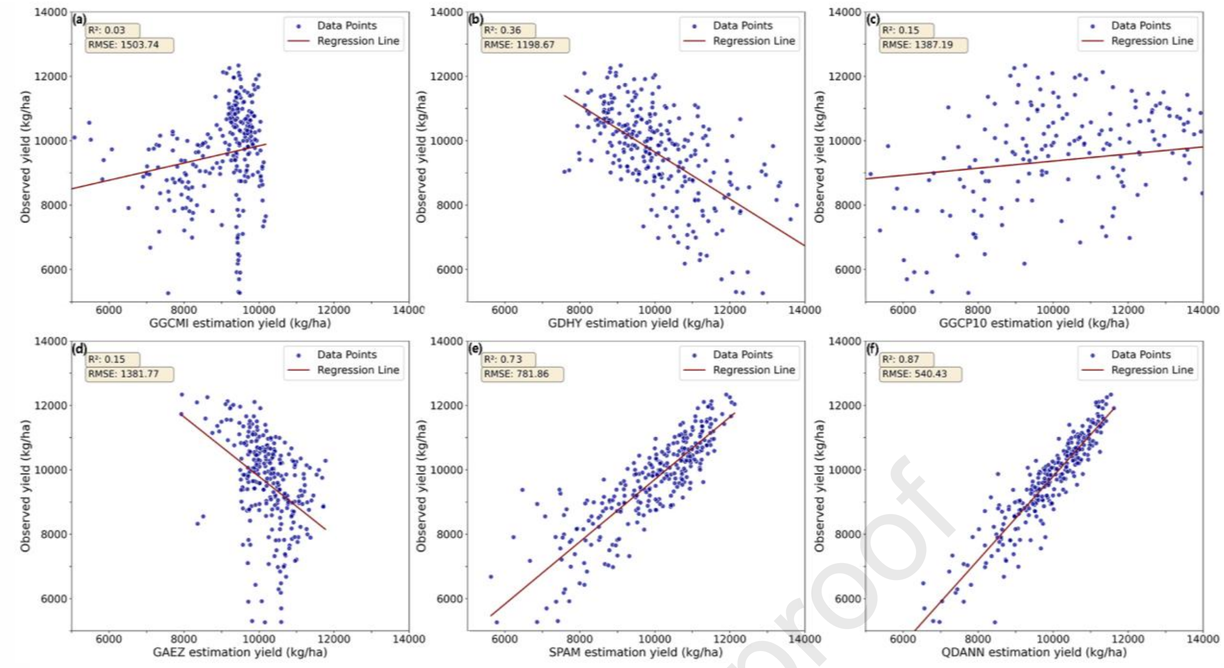

Fig.8. Quantitative comparison of 2010 maize yield from GGCMI (a), GDHY (b), GGCP10 (c), GAEZ (d), SPAM (e), and QDANN (f) datasets with county-scale maize yields in Iowa, Illinois, and Indiana, USA.

We collected county-scale maize statistics from Iowa, Illinois, and Indiana—the top three maize-producing states in the U.S.—for 2010 and aggregated five datasets (GGCMI, GDHY, GAEZ, SPAM, and QDANN) to the county scale for quantitative comparison (Fig. 8). The results show that the QDANN dataset achieves the highest correlation with county-scale statistics (R^2 = 0.87, RMSE = 540.43 kg/ha), making it the most accurate among the six maize yield datasets. The SPAM dataset ranks second, with a correlation coefficient of 0.73 and RMSE of 781.86 kg/ha, demonstrating good alignment with the statistics. However, GGCMI, GDHY, and GAEZ show poorer performance. GGCMI has a correlation coefficient of only 0.03 and an RMSE of 1503.74 kg/ha, exhibiting significant "underestimation of high values" and "overestimation of low values." GDHY shows a correlation coefficient of 0.36 and RMSE of 1198.67 kg/ha, similarly displaying a significant overestimation of low values. The correlation coefficients between the GGCP10 dataset and the GAEZ dataset are both 0.15, with RMSE values of 1387.19 and 1381.77 kg/ha, respectively. The yield distribution estimated by the GGCP10 dataset is more scattered, while the yield estimates from the GAEZ dataset are predominantly concentrated between 9000 and 11000 kg/ha. These differences are mainly attributed to the spatial resolution and data sources of each dataset. High-resolution datasets like QDANN better reflect county-scale agricultural production conditions, while low-resolution datasets fail to capture subtle regional differences, leading to larger yield estimation biases. This quantitative comparison provides a valuable reference for future research in selecting appropriate datasets and methods.

4 Challenges and future directions

4.1 Challenges

In this study, we reviewed four commonly used crop yield estimation methods. However, different studies utilize varied datasets, crop types, geographic regions, and experimental designs. Given these disparities in research contexts, making direct quantitative comparisons among different yield estimation approaches is challenging (Morales et al. 2023). Although this study quantitatively evaluated the multiple linear regression, CASA model, random forest model, and CNN model, the advantages of the model itself could not be fully utilized due to the limited sample size. Recently, several researchers have introduced yield benchmark datasets (Höhl et al. 2023; Kamangir et al. 2025; Lin et al. 2024a) that encompass subnational and county-scale multimodal data, serving as baselines for model performance evaluation. Paudel et al. (2025) proposed a standardized framework, CY-Bench, for subnational maize and wheat yield prediction covering 42 major producing countries. CY-Bench standardizes dataset selection, processing, and the spatiotemporal integration of meteorological, soil, and remote sensing indicators, thus supporting parallel evaluations across methods. By employing predefined in-season prediction tasks and data splits, it enables cross-regional and cross-year generalizability tests. However, these benchmark datasets focus primarily on county-scale yield predictions and lack field-scale yield measurements, even though their design objective is to offer generalizability and trainability at finer spatial resolutions. If future researchers or practitioners can access field-scale yield measurement data, this framework could easily be applied to field crop yield prediction, thereby providing a scalable solution for high-resolution agricultural monitoring (Kamangir et al. 2025).

The quality of remote sensing data poses multiple challenges for yield estimation at the field scale. In regions characterized by frequent cloud cover and rainfall, obtaining high-resolution remote sensing data during critical crop phenological stages is difficult, thereby limiting the accuracy of yield assessments. Moreover, the spatial resolution of remote sensing data directly influences the precision with which field-scale variability is captured; high-resolution data can detect intra-field heterogeneity and improve yield estimation accuracy, although such data tend to be complex to process and costly. In contrast, moderate- to low-resolution data, while more economical and suitable for large-area yield estimation, are prone to spatial error averaging that can obscure detailed information in highly variable fields. For instance, Cheng et al. (2022a) demonstrated that using MODIS to estimate wheat yield at a one-kilometer scale in China yielded an R^2 of 0.80 at the county scale, but the accuracy decreased to an R^2 of 0.65 at the field scale. In addition, the temporal resolution of remote sensing data will also affect the accuracy of yield estimation. For example, Al-Shammari et al. (2021) found that reducing the temporal resolution of the data (from 55 images to 10) will increase the prediction error.Existing crop yield datasets significantly influence the effectiveness of precision agriculture applications in terms of spatial resolution, spatiotemporal coverage, and completeness of crop types. High spatial resolution data can meticulously capture production variations at the field scale, especially in diversified agricultural landscapes, which substantially improves yield estimation accuracy. In contrast, low-resolution data has a wide coverage, but cannot reflect micro-agricultural differences, resulting in inaccurate estimates of fine-grained regions. Temporal coverage and update frequency are also critical. Long-term series and timely updates are better able to reflect climate changes in climates, technological progress and management adjustments, and enhance application value; while lagged data cannot capture recent trends and are limited in practicality. Regarding the completeness of crop types, datasets covering a wide range of crop types support comprehensive analysis, but consistency is difficult to ensure when integrating multi-source data, which increases the difficulty of application.

4.2 Further directions

High-quality data are the basis for accurate crop yield estimation. The accuracy and completeness of high-resolution remote sensing data, weather data, soil data and crop management data are crucial to the estimation results. In regions characterized by persistent cloud cover and frequent rainfall, obtaining high-resolution remote sensing data is challenging. A feasible solution to alleviate this issue is to integrate multiple data sources, particularly synthetic aperture radar (SAR) with optical remote sensing data. Due to its insensitivity to cloud interference, SAR is especially valuable in agricultural areas where optical data are limited. The scarcity field-collected yield data is one of the main constraints in precise crop yield estimation at fine scales. This limitation can be mitigated by obtaining higher precision and higher resolution regional records, such as yield data at the county or village scale. Combining these with large-scale, high spatiotemporal resolution information provided by remote sensing observations can more accurately reflect regional realities and compensate for the spatial coverage limitations of ground data. Additionally, generating synthetic data using alternative methods is considered an effective means of supplementing the deficiencies in observed data (Hongyu et al. 2023). For instance, techniques such as generative adversarial networks (GANs) can be employed to produce simulated data, alleviating the issue of data scarcity in the agricultural field, especially in tasks requiring pixel-scale or instance-scale annotations. Combining these approaches with physical simulations to generate more realistic synthetic data (Hongyu et al. 2023) is also a viable strategy, with research ongoing on how to maintain data diversity while ensuring consistency with the real data distribution. Lastly, the increasing importance of cross-national data standardization and sharing is underscored by current studies, which emphasize the establishment of robust data sharing networks and the optimization of big data processing infrastructures to address global food security challenges.

When discussing the technological progress of crop yield estimation, in addition to focusing on the estimation model itself, it is also necessary to pay attention to the necessity and challenges of crop classification, because accurate crop type identification is a prerequisite for accurate yield estimation. Crop classification can provide information on the spatial distribution of different crops, which is crucial for selecting a yield estimation model that is suitable for each crop's unique growth pattern, environmental response, and yield potential. However, crop classification faces many challenges, such as the diversity of crop phenology, the similarity of spectral characteristics between different crops, and the need for high-resolution, multi-temporal data to capture the dynamic changes in agricultural landscapes. Recent studies have made significant progress in addressing these challenges, especially in rice and wheat classification in Asia. For example, Fang et al. (2024) conducted a comprehensive review of algorithms for rice classification using satellite data, analyzed product characteristics and consistency assessment, and laid a theoretical foundation for this field. On this basis, Fang et al. (2025) (submitted for review) used coordinated data from Landsat and Sentinel-2 and the NASA-IBM geospatial foundation model to develop a 30-meter resolution annual rice distribution product covering monsoon Asia (2018-2023), which greatly improved the classification accuracy. Similarly, Chen et al. (2025a) proposed a sample-free algorithm to map the rice planting intensity and planting calendar in monsoon Asia (2018-2021) at a resolution of 20 meters using multi-source satellite data, providing a new method for dynamic rice monitoring. In terms of wheat classification, Li et al. (2025c) launched AsiaWheat, the first 250-meter annual wheat coverage ratio time series product covering Asia (2001-2023). They used convolutional neural networks and Transformer models to achieve high-precision classification. These advances in crop classification not only demonstrate innovative solutions to long-standing challenges but also provide a solid data foundation for yield estimation models. By combining accurate crop type distribution maps with yield estimation techniques, researchers can achieve more precise and spatially explicit crop yield forecasts, thus providing stronger support for agricultural management, policy making, and food security.

The foundation models (FMs) provide new solutions for crop yield estimation (Mendieta et al. 2023). Built on pre-trained large Transformer architectures, FMs are capable of making high-precision predictions across a wide range of fields and applications. For instance, TimeGPT (Garza and Mergenthaler-Canseco 2023) is the first foundation model specifically designed for time series forecasting. Additionally, NASA and IBM Research have developed an open-source geospatial AI foundation model (Prithvi) (Moor et al. 2023). This FM is pre-trained in a self-supervised manner on large, unlabeled datasets from the Harmonized Landsat-Sentinel 2 (HLS) dataset and is later fine-tuned in a supervised manner on domain-specific datasets for downstream tasks (Zhang et al. 2024b). In adapting to the dynamic agricultural environment and production, FMs exhibit exceptional adaptability and robustness, mitigating the challenge of scarce labels in geospatial contexts. This is especially relevant in broad-scale crop yield estimation, as the model can precisely capture crop growth dynamics, combining both climatic and remote sensing characteristics to provide predictions for monitoring agricultural production in various regions. Transfer learning reduces the need for new data through cross-domain knowledge transfer, which is particularly significant in data-scarce regions such as Africa or South Asia (Al Sahili and Awad 2022; Joshi et al. 2024). Research has demonstrated (Ma et al. 2021; Priyatikanto et al. 2023) that techniques such as fine-tuning and Domain-Adversarial Neural Networks (DANN) can transfer models trained in data-abundant regions (e.g., the US Midwest) to data-scarce areas, significantly improving the accuracy of crop yield predictions. Future research should focus on optimizing domain adaptation techniques, such as the development of Multi-Source Domain Adaptation algorithms, to better handle the heterogeneity of agricultural environments while also exploring ways to retain specific characteristics of the agricultural context (e.g., crop types, growth stages) during the transfer process. Furthermore, there is potential in integrating foundation models with transfer learning to further enhance their generalization capabilities in diverse agricultural settings.

5 Conclusions

In the context of globalization, high-quality crop yield datasets are crucial for food security. High-resolution datasets can capture agricultural production differences at the county scale or finer scales. In contrast, lower-resolution datasets provide broad geographical coverage, but they fall short in capturing subtle spatial differences. Furthermore, the frequency of dataset updates and data completeness significantly influence their applicability in dynamic agricultural environments, such as in analyzing the temporal dynamics of crop yield. Different yield estimation methods have different data requirements, reflecting the complex interaction between data and methods. Machine learning models rely on a large amount of high-quality data to capture complex patterns, while statistical regression models need to ensure the robustness of parameter estimation and rely heavily on historical yield data, meteorological data, and soil data to establish robust statistical relationships. The LUE model mainly relies on remote sensing data to estimate biomass and reflects crop growth status through indicators such as NDVI and LAI, while the DA model requires real-time multi-source data to optimize dynamic predictions. Although these methods impose varying requirements on data quality, they all underscore the importance of high resolution, timeliness, and completeness.

In the future, emerging technologies will inject transformative potential into crop yield estimation by synergistically innovating estimation methods and developing datasets, thereby fully leveraging the advantages of remote sensing data to markedly enhance the accuracy and applicability of crop yield estimates at both pixel and field scales. The deep integration of multiple models and heterogeneous data sources will further unleash the potential of artificial intelligence: fine-tuning base models for heterogeneous field conditions to boost cross-regional adaptability; simultaneously embedding physical constraints and agronomic prior knowledge, and guiding network training with custom loss functions to improve forecast precision and generalizability; and integrating classical methods such as the EnKF with deep learning within a real-time data assimilation framework, dynamically merging SIF and VI time series to enhance intra-seasonal robustness. Additionally, incorporating interpretability tools to elucidate the decision-making process will foster greater user trust. These strategies will convert remote sensing observations into practical decision-making tools, ultimately reinforcing the sustainability of global food security.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Data availability statement

No new data were created or analyzed in this study. Data sharing is not applicable to this article.

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Declaration of interests

☒ 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.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: