Remote sensing of quality traits in cereal and arable production systems: A review

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The Crop Journal 12 (2024) 45–57

Contents lists available at ScienceDirect

The Crop Journal

journal homepage: www.keaipublishing.com/en/journals/the-crop-journal/

Remote sensing of quality traits in cereal and arable production systems: A review

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A R T I C L E I N F O

Article history:
Received 10 May 2023
Revised 12 October 2023
Accepted 16 October 2023
Available online 11 November 2023

Keywords:
Remote sensing
Quality traits
Grain protein
Cereal

A B S T R A C T

Cereal is an essential source of calories and protein for the global population. Accurately predicting cereal quality before harvest is highly desirable in order to optimise management for farmers, grading harvest and categorised storage for enterprises, future trading prices, and policy planning. The use of remote sensing data with extensive spatial coverage demonstrates some potential in predicting crop quality traits. Many studies have also proposed models and methods for predicting such traits based on multi-platform remote sensing data. In this paper, the key quality traits that are of interest to producers and consumers are introduced. The literature related to grain quality prediction was analyzed in detail, and a review was conducted on remote sensing platforms, commonly used methods, potential gaps, and future trends in crop quality prediction. This review recommends new research directions that go beyond the traditional methods and discusses grain quality retrieval and the associated challenges from the perspective of remote sensing data.

Contents

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https://doi.org/10.1016/j.cj.2023.10.005

1. Introduction

With the development of the economy, society and technology and the improvement of life quality, food quality and safety have received much attention in recent years [1,2]. For instance, agricultural products from China face not only enormous competitive pressures at the international level but also the strong impact from foreign agriculture products being sold at the domestic market. The high-quality industrialised production of cereals has received special attention in Chinese crop production and processing [3,4]. A fast and instantaneous delivery of early-stage predictive information on crop yield and quality at both regional and national scales is therefore essential to optimise management for farmers, grading harvest and categorised storage for enterprises, future trading prices, policy planning and effective management of harvest, stockpile and market prices [5].

Traditional laboratory tests and analytical methods for grain protein content (GPC), such as Kjeldahl's test, have been widely adapted in the literature due to their accuracy. These methods mostly involve point sampling at the post-harvest stage and often involve tedious chemical testing. Additionally, in practical applications, these methods are generally not applicable for optimizing pre-harvest management and monitoring large areas [6,7]. With the development of spectral technology, researchers have started using near-infrared spectrometers for near-infrared tests (NIR-test) [8,9]. For instance, Igne et al. tested few original samples of cereal grain with non-destructive qualities by using a spectrometer and results of the quality model were showed the direct relationship between sensitive spectral and quality traits [10]. However, the NIR-test has limited applications in point sampling and post-harvest tests. In sum, traditional laboratory tests and NIR-tests are unable to generate satisfactory predictions of pre-harvest wheat quality.

Over the past few decades, remote sensing with instantaneous and spatial continuity has demonstrated its potential in estimating crop grain quality across regions [11,12]. Remote sensing data with different spectral, spatial and temporal features exhibit a huge potential in diagnosing canopy traits, such as nitrogen content [6], biomass [13], leaf area index [14] and leaf pigment [15]. Unlike grain tests at the post-harvest stage, remote sensing predicts grain quality by monitoring sensitive spectral information on the canopy carbon/nitrogen traits during the critical growing stage, the translocation of carbon and nitrogen from vegetative organs to the grain and the environmental factors that can improve grain modelling performance (Fig. 1) [5]. Therefore, numerous scholars have collected early-stage predictive information on grain quality during the growing stage at the regional scale [1,5,9,16].

The review provides a comprehensive analysis of methods and applications in grain quality prediction, highlighting the current problems and challenges faced by research in this field, while proposing new directions for utilizing remote sensing technology in grain quality forecasting. The rest of this paper is organised as follows. Section 2 presents an overview of the key quality attributes that are of interest to producers and consumers. Section 3 reviews the literature on the quality traits and arable production of cereal. Section 4 presents an overview of the observations and sensing platforms. Section 5 analyses the approaches for directly measuring or inferring cereal quality attributes from remote sensing platforms. Section 6 describes how the crop quality attributes can be derived from the observations. Section 7 discusses the technical challenges and opportunities for development.

2. Key crop quality attributes

Crop quality has different classification criteria according to various requirements and applications, including appearance, nutrition, milling, and food processing quality traits. This study focuses on nutrient quality traits as an important evaluation index in quality classification.

2.1. Grain protein (N) content

The content of grain protein (N), also called crude protein, is one of the most significant indices determining the nutritional value of cereals. GPC denotes the ratio of total grain protein in cereal grain and grain yield. The mechanism of crop grain protein is related to nitrogen translocation after anthesis. Grain N sources can be divided into two types. The first type, re-transportation from the aboveground organs, accounts for 70% to 80%. Meanwhile, the second type is reabsorption from the soil after anthesis, which accounts for 20% to 30%.

GPC is a complex and comprehensive feature that is impacted not only by genetic factors but also by some environment and

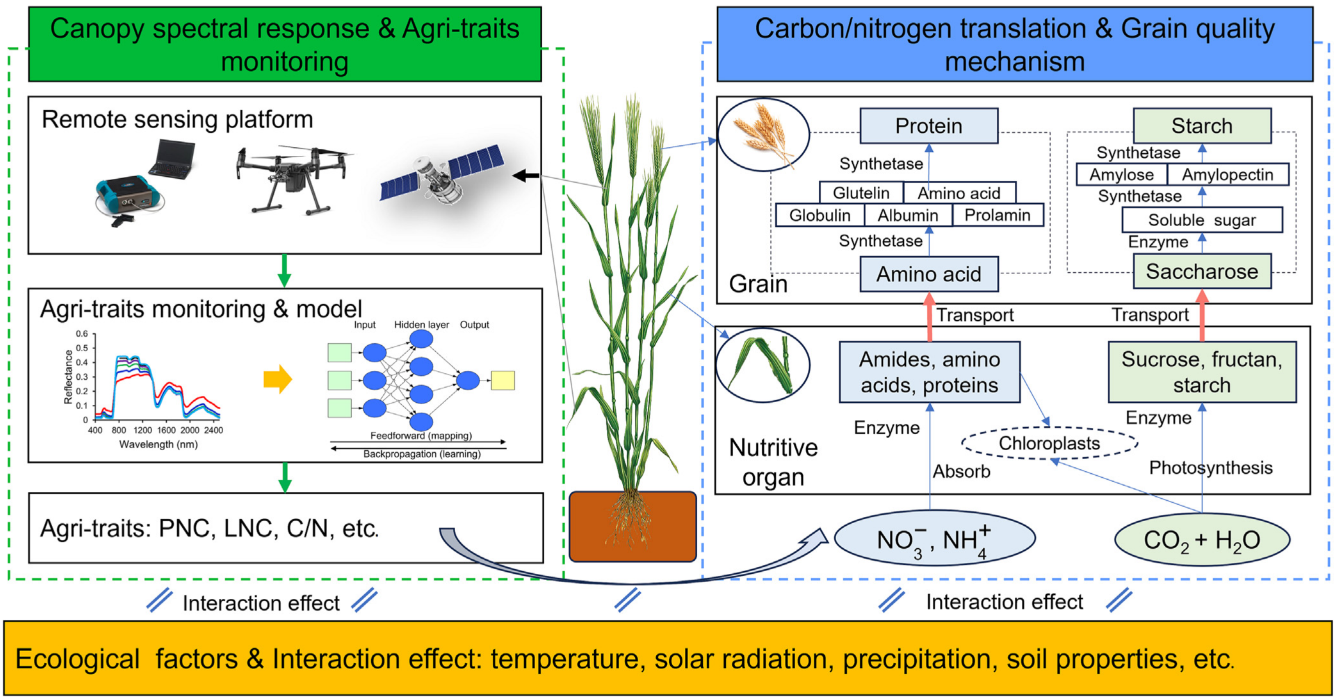

Fig. 1. Grain quality prediction based on remote sensing and mechanism of carbon and nitrogen transfer in crops.

management techniques and even their interaction [17]. Meteorological data with different temporal resolutions, including daily and monthly meteorological data, are often used to analyse the influence of meteorological differences on GPC [16]. Previous studies have highlighted the positive influence of higher temperatures and radiation in the grain-filling phase on wheat GPC [1,18]. However, the influence of higher precipitation on GPC is either positive or negative. Zhao et al. showed that county winter wheat GPC increases by 0.29% for every 1° increase in latitude in the Huang-Huai-Hai region of China. The meteorological data affecting GPC in different regions also differ in time series [16].

2.2. Starch/CHO content

Starch is a polymeric carbohydrate (CHO) comprising a large number of glucose units joined by glycosidic bonds. This CHO is the main product of plant photosynthesis and serves as the primary storage substance in most cereal crops. By hyperspectral analysis, Crude Starch and Amylose of rice showed good spectral characteristics in short wave infrared band [19]. Both direct and indirect prediction models of satellite scale based on vegetation index can accurately predict the starch content of winter wheat.

2.3. Gluten

Gluten, which accounts for 85% to 90% of the total protein in wheat, is the main composite of gliadin and glutelin that is widely found in wheat, barley, rye and oat [20]. Gluten in grains is a major staple food. Gluten is appreciated for its moisture retention, viscoelastic and extending agent and its important role in determining the dough quality of bread and other baked products. Wet gluten content (WGC) is an important factor for grain quality, and detection of WGC for winter wheat by remote sensing satellites is of great significance for evaluating grain quality [21].

2.4. Harvest index

Harvest index (HI) is defined as the ratio between economic yield (grain or fruit yield, etc.) and biological yield at harvest, which reflects the ability of the photosynthetic assimilates of crop population to be converted into economic products [22]. The nitrogen HI (NHI) [23] has also been proposed to describe the translocation ability of absorbed N from vegetative plant parts to grain, which is closely related to nitrogen management, the yield of harvesting organs and grain protein yield. The ratio of NHI to HI is positively and significantly correlated with GPC, thereby indicating that the transfer of dry matter and nitrogen from nutrients to grains are two important factors determining GPC. In recent years, many studies combined the biomass with the growth period of wheat, and used remote sensing data to accurately estimate the harvest coefficient of winter wheat [24,25]. Therefore, exploring the relationship amongst biomass allocation, nitrogen allocation and genotype holds great theoretical and practical significance for high-yield, high-quality and high-efficiency crop cultivation and breeding.

2.5. Oil

Oil is another important quality index for soybean, peanut, corn or rapeseed. High-oil maize helps improve feed quality and feed utilisation efficiency. Vegetable oil is a main edible oil suited for human consumption. In recent years, many scholars have explored the impact of climate change on oil crops and found that high temperature accelerates the respiration and development process of original oil crop varieties, thereby leading to yield reduction [26]. In addition, elevated CO_2 concentration reduces crop quality, which is not conducive to the accumulation of protein and fat in oil crops.

2.6. Moisture

The grain moisture content (GMC) of cereal or oilseed is expressed as a percentage of water weight contained in wet grain. GMC is critical during harvest time and has a direct effect on grain quality throughout storage. For instance, an excessively high GMC will increase the risk of mould development and insect infestation. In addition, the discoloration or yellowing in paddy grain due to

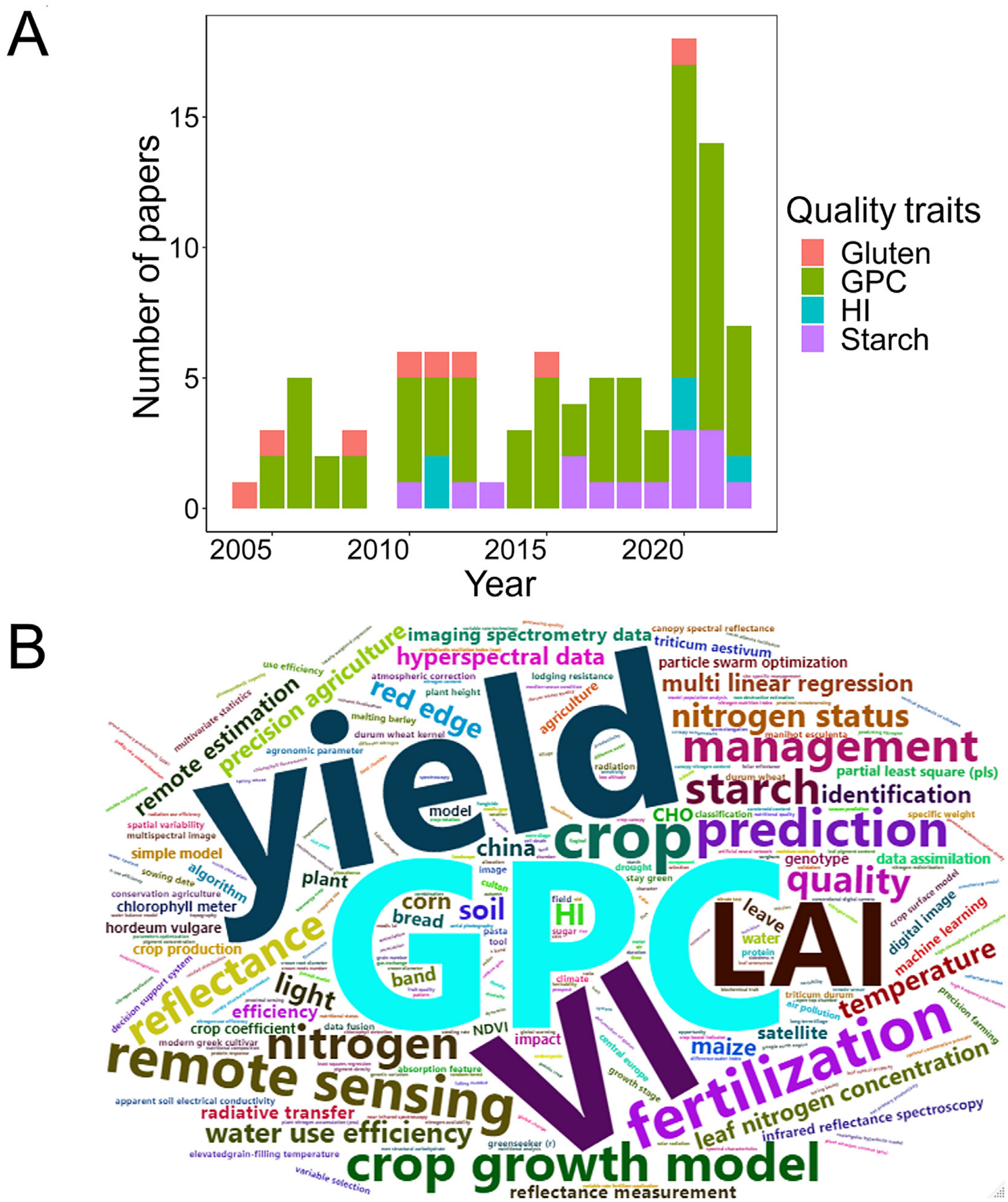

Fig. 2. Literature on grain quality traits from 2002 to 2022 (A) and word cloud (B).

high GMC and heat build-up reduces its market sale given that whiteness is a key quality Indicator for rice consumers.

2.7. Other attributes

Cereal crops are rich in protein, fat, iron, carotenoids, cellulose and vitamins. Carotenoids are the main yellow substances found in millet, and their content is significantly related to appearance quality. Varieties with high carotenoid content are conducive to improving the health function of the millet diet and present an important direction for quality breeding. Under different breeding objectives, the quality characters of different varieties of the same crop can significantly differ. Genes largely determine the performance of quality traits, and different geographical, soil and cultivation conditions and other external factors and genes altogether affect the performance of crop quality characters [27].

3. Review of the literature on quality traits in cereal and arable production

Related papers published between 2002 and 2022 were retrieved from the ISI Web of Knowledge in the Core Collection Database for a systematic literature review. In all the relevant studies conducted so far, the focus of this review is on the utilization of RS technology at the field scale for predicting grain quality. The review does not take into account the research that involves the use of instruments such as Raman spectroscopy or near-infrared spectrometers in laboratory settings for predicting grain quality. Several keywords were used, including ‘spectral index’, ‘vegetation index’, ‘remote sensing’, ‘grain quality’, ‘grain protein’, ‘gluten’, ‘harvest index’ and ‘starch’. A total of 106 articles were eventually included in the analysis. As shown in Fig. 2, GPC appeared in 74 articles, making it a dominant topic in the remote sensing of grain quality traits. Monitoring GPC based on remote sensing data relies heavily on the relationship between GPC and nitrogen (N) or chlorophyll content (Fig. 1). Few articles also focused on quality traits other than GPC, such as gluten (n = 8), HI (n = 6) and starch (n = 18), but grain quality should not be limited to these traits. Grain quality, or the components of the grain organ wrapped in chaff, is inconsistent with the canopy information captured by remote sensing data directly before harvest. Numerous studies have related grain quality to different spectroscopic estimations of physiological and biochemical indexes, relying on the fact that grain quality is related to the translocation and redistribution of carbon and nitrogen [25,28,29]. Remote sensing data reflect the spatial and temporal heterogeneity of crop growth during growing seasons, hence allowing for a real-time management [30]. Cereal production in heterogeneous regions is affected by different environmental factors, with meteorological factors exerting the greater influence. Therefore, the effect of environmental conditions on grain quality prediction should be studied using remote sensing data.

4. Overview of observations and sensing platforms

4.1. Ground-based platform

Over the past two decades, remote sensing on a ground-based platform has been widely used in agricultural applications, such as in estimating crop plant parameters, mapping crop yields and diagnosing soil information (Fig. 3). The quality of various crops was examined by combining this indicator with carbon and nitrogen translocation [31,32]. Hyper-spectrometers (e.g., FieldSpec Pro FR spectroradiometer (Analytical Spectral Devices, Boulder, CO, USA)) or multi-spectrometers (e.g., CropScan MSR-16 (Cropscan Inc., USA)) provided ample waveband information from visible bands to near-infrared bands, thereby producing a rich amount of spectrum information related to crop quality. Important plant indices extracted from spectral information serve as effective indicators of grain quality. Spectral features, including reflection peak depth (P_Depth560) [33], red edge position (linear extrapolation method or REPle), ratio vegetation index (RVI; comprising the sum of the first derivative value within the red and blue edges; SDr/SDb) and the first derivative value at 742 nm (FD742). Vegetation indices (vIs), including the RVI (1480, 870), plant pigment ratio (550, 450) [34] and normalised difference VI (NDVI (800,630)) [35].

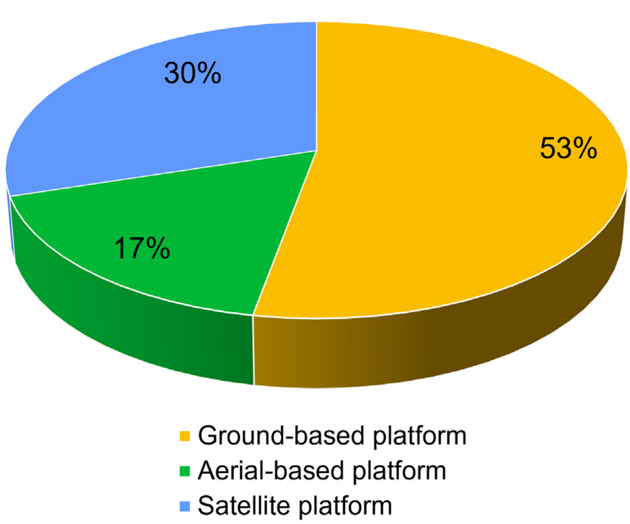

Fig. 3. Proportion of literature published from 2002 to 2022 on remote sensing platforms for grain quality.

For GPC monitoring in winter wheat as an example, based on the physiological and ecological processes and methods of grain protein formation, researchers have monitored the agronomic parameters related to grain quality by using remote sensing information and then achieved the effect of monitoring GPC [36]. Spectral saturation, observed in grain protein-related variable inversion [37], hampers GPC monitoring accuracy and affects crops quality monitoring like potatoes. In recent years, the active remote sensing imaging technology LiDAR has shown incomparable advantages in obtaining the vertical structure information of crops and can achieve an anti-saturation effect to a certain extent. However, only few studies have monitored crop quality using LiDAR, which is still at its primary stage of development and warrants further in-depth study.

The improvement of crop quality depends not only on planting management but also on the breeding of high-quality varieties. Obtaining and analysing phenotypic information serve as the basis of crop breeding research. However, obtaining high-quality phenotypic data, selecting a suitable population size and studying the extent of linkage disequilibrium remain a challenge as long as low structured populations are provided [38]. Previous studies show that high-throughput and high-resolution remote sensing technology can accurately monitor crop phenotypes, provide the necessary conditions for the efficient and large-scale identification and evaluation of germplasm resources and offer a foundation for excavating excellent germplasms and allelic genes [39].

4.2. Aerial-based system

In agricultural remote sensing monitoring, the unmanned aerial vehicle (UAV) platform successfully transforms agricultural information from ‘point’ to ‘area’. In recent years, various sensors carried by UAVs have been widely used in agricultural production and management [40]. In addition to directly and indirectly constructing quality monitoring models, the UAV platform also improves crop harvest quality by guiding field fertilisers and water management and crop harvest periods. Nette et al. reported that system analysis based on colour infrared aerial images, GIS and GPS can provide a decision-making basis for fibre flax quality management. Remote sensing technology can also be used to ensure an appropriate harvest time and improve harvest quality. According to Herwitz et al. [41], JPL Laboratories in the United States used UAVs loaded with digital multispectral cameras to guide the harvest period of coffee beans. The best harvest time can improve the yield and quality of sugar beets. Olson et al. [42] found that in-season yield estimates (red edge normalised difference vegetation/growing degree days) can explain sugar beet yields and recoverable sugar yields. Pesticide and weeding management have also been used in UAV and have certain significance in ensuring high yield and quality.

During the crop growth process, UAV can serve as important tools for recommending the use of crop growth regulators. Cotton has different appearance features at the budding, boll and boll opening stages. In the future, we can analyse the texture characteristics of UAV data collected across the different growth stages of cotton and recommend the use of growth regulators to improve cotton yield and quality. The main function of plant growth regulators for tobacco is topping, which regulates the metabolic process of tobacco plant growth and development, promotes the high-quality production of tobacco leaves. However, the number of recommended UAVs for plant growth regulators remains limited. This gap should be filled in future crop quality research to improve the utilisation of UAVs in agricultural production.

In the field of agriculture, with the development and application of UAVs, there have been continuous innovation and progress in the field of spectral sensors as well. Multispectral and hyperspectral sensors can simultaneously capture spectral information in multiple discrete or continuous bands that cover both visible and near-infrared ranges. They have good applicability in monitoring crop health, nutrient levels, and pest and disease conditions. They also have great potential in the development of crop quality prediction. In terms of sensor, UAV has lower spectral resolution than ground platform, but UAV data has the characteristics of both image and spectrum, which has higher application value and intuitively in monitoring crop growth and predicting quality [43]. In recent years, many studies have used UAV and meteorological data to achieve quality prediction of wheat and rice crops at field scale [44,45]. Images with high spatial resolution and spectral resolution are an important guarantee for accurate prediction of crop quality in the future.

4.3. Satellite platforms

Compared with ground remote sensing and UAV platforms, satellite remote sensing has incomparable advantages in large-scale crop growth monitoring, crop industrial structure planning and crop quality compartment. Satellite image is the lowest cost, the most convenient and large-scale data source for early remote sensing monitoring application in the agricultural field. Previous satellite remote sensing data based on single or multiple data sources use satellite band reflectance or vegetation index as input variables to monitor and forecasts crop quality either directly or indirectly combined with other non-remote sensing data [46,47]. MODIS, Landsat, Sentinel and other satellite image data have been widely used in crop growth monitoring, pest monitoring and other aspects. These data can also improve crop quality and promote economic benefits by guiding field management with remote sensing images. In regions with strong spatial differences, Sentinel-2A data still maintain certain reliability in winter wheat GPC prediction, which has certain reference significance in large-scale crop quality prediction research [48]. By coupling remote sensing data with meteorological data (such as ECMWF) and combining with the growth mechanism of related crops, the crop quality prediction model built has good accuracy and stability, and has good application in time and space expansion [49]. However, due to its limited resolution, low spectral variability and mixed pixels, satellite remote sensing shows obvious shortcomings in the study of small-scale (field, sample plot and plant) crop growth, especially crop quality.

5. Approaches for directly measuring or inferring cereal quality attributes from RS platforms

Many crop quality approaches have been proposed based on the characteristics of crops and different parameters, and these approaches could be classified into three groups approaches (Fig. 4), namely, empirical, semi-physical and physical approaches [50]. Each approach is described in detail in Fig. 4.

5.1. Empirical approach

5.1.1. RS-quality approach

The RS-Quality approach directly builds a relationship between crop quality and spectral information (e.g., sensitive wavebands, vegetation indices and spectral features) at some critical growth stages (Fig. 4A) [34,35]. The RS-Quality approach for cereals is simple (only according to the statistical relationship between quality and remote sensing information) and easy to realise across different areas and different types of cereals, and some models have shown good estimation precision [51]. Wang et al. determined an accumulated spectral index from the jointing to the initial filling stages for predicting GPC in wheat by fusing multi-sensor and multi-temporal remote-sensing images [37]. Hansen et al. chose 8 reflectance wavelengths and 10 vegetation indices to predict GPC in wheat and barley. Magney et al. examined the rate of heading NDVI (i.e., change in NDVI per day at heading, R^2 = 0.64), and the rate of ripening NDVI (R^2 = 0.45) showed a good relationship with wheat GPC [35]. The RS-Quality approach has also been widely used in predicting gluten, starch concentration, grain water content and sedimentation values based on different sensors [19,52,53]. However, this approach does not consider the crop quality mechanism in detail, and the models employed for various areas and crops are different. Therefore, this approach cannot be easily expanded interannually and interregionally.

5.1.2. RS-AgriVar-Quality approach

The empirical RS-AgriVar-Quality approach does not estimate crop quality directly by using remote sensing information. Instead, this approach initially detects the relationship between crop qual-

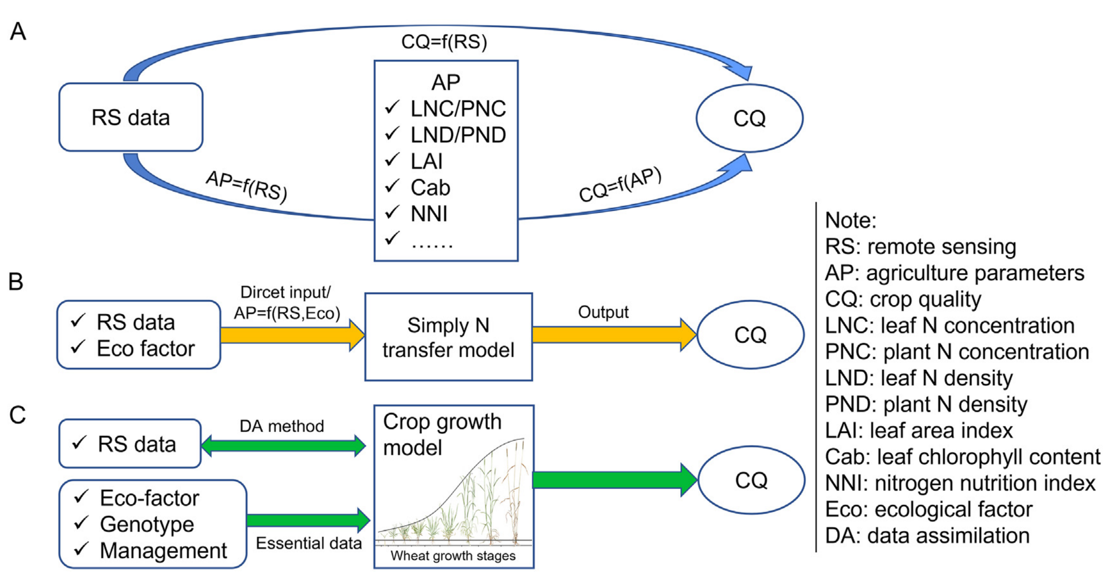

Fig. 4. Three approaches for assessing cereal quality attributes from remote sensing platforms.

ity and the key agriculture variable (AgriVar) at some critical growth stage and then uses the role of remote sensing to retrieve AgriVar [36]. This approach has been widely used by studies on cereals, including wheat, rice and corn. For instance, Wang et al. selected LNC as the key AgriVar to build the GPC model and then constructed the best LNC model from spectral information [34,54,55]. Chen et al. found that NNI can accurately indicate the nitrogen status and then applied the RS-NNI-GPC approach to evaluate grain quality in wheat [56]. Other algorithms, such as principal component regression (PCR), radiation transfer model and optimal combination (OC), have also been applied in crop quality monitoring. For instance, Chen et al. used PCR to establish NNI in winter wheat and to build a GPC prediction model based on the relationship between NNI and GPC. Xu et al. applied the OC method whilst considering different contributions from various growth stages to predict GPC in winter wheat [34]. Xu et al. used the radiative transfer model to estimate chlorophyll, analysed the change in GMC through the change law of chlorophyll and provided a basis for grain harvesting [57]. This approach is more suitable and consistent with the grain quality mechanism and carbon/nitrogen translocation given that a quantitative expression, as a linear or non-linear statistical model, was already built between crop quality and AgriVar. However, crop quality traits are comprehensive characters affected by genetics, environment and management techniques [17]. Therefore, the interannual and interregional extension of the RS-AgriVar-Quality approach warrants further study.

5.2. Semi-physical method

A crop quality model was developed by integrating remote sensing information and some ecological (e.g., environmental or soil) factors to calibrate the bias from interannual and integration (Fig. 4B). This method can be also summed up as two approaches. The first approach considers the impact of ecological factors on crop quality and remote sensing as independent variables based on which crop quality models are built. Predicting GPC by integrating remote sensing data and ecological factors is more accurate than by using remote sensing or ecological factors independently [54]. The hierarchical linear model obtains favourable GPC and gluten predictions between years and regions after coupling ecological factors and remote sensing data [5,49]. The second approach simplifies the process of crop quality formation based on carbon and nitrogen translocation. This approach, which combines remote sensing data with the law of temperature response, the vertical distribution of nitrogen and nitrogen and carbon re-transportation, has been widely used in crop quality analysis [25]. The semi-physical method infers the current growth status based on remote sensing information, and the critical ecological factors related to crop quality offers a solid basis for predicting crop quality. Therefore, this approach can be easily extended to other regions or climate conditions. However, whether some models only consider one or two ecological factors remains unknown, and a comprehensive crop quality model that takes many impact factors into account may be worth pursuing.

5.3. Crop growth model

The physical approach (Fig. 4C) monitors and predicts crop quality by combining a crop growth model and remote sensing data with a data assimilation method [9]. A crop growth model (Table 1) is a physiological and processed simulation of crop or soil variables (e.g., leaf area index, grain yield and GPC) that integrates the effects of meteorological, soil conditions, crop genotype information and management types. However, some crop growth models are point based and demonstrate poor prediction performance when extended to a large-scale area, whereas remote sensing data with instantaneous and spatial continuity can overcome these shortcomings and complement the advantages of each other [58]. Therefore, data assimilation by using the coupling crop growth model and remote sensing data has been widely applied in crop growth monitoring and yield estimation [24,59]. For crop quality prediction, Li et al. [9,60] developed a particle swarm optimisation algorithm to integrate remotely sensed PNA and LAI into the DSSAT-CERES model for estimating GPC in winter wheat with R^2 values of 0.758. Compared with another approach for estimating crop quality, the physical method simulates crop quality based on the crop quality mechanism and whilst considering different ecological factors. The output of the data assimilation algorithm must be one of the output parameters of the crop growth model. However, the crop growth model does not completely express the crop quality characteristics [61]. In sum, complex input parameters and computational inefficiency limit the application of crop growth models.

6. Retrieving crop-quality-related traits from remote sensing data

Different remote sensing information can be acquired using various sensors (Section 4), and three approaches to crop quality estimation have been discussed in Section 5. One of the key processes is retrieving crop quality variables or critical agriculture parameters, such as LNC, PNC, LAI and NNI, from remote sensing data. For this purpose, various algorithms have been developed along with numerical algorithms and computer techniques (Fig. 5).

Table 1
Research status of crop growth model.

Crop growth model	Country	Application scope	Crop	Parameter	Reference
DSSAT	USA	Crop growth simulation	Wheat, Maize	Grain protein, Grain nitrogen	Jones et al. [62]
WOFOST	Netherlands	Crop yield prediction, Management, Disaster assessment	Wheat, Rice	Yield	Van Diepen et al. [63]
APSIM	Australia	Crop, Livestock, Soil, Water resource management simulation	Wheat, Canola	Grain protein, Grain nitrogen	Keating et al. [64]
CropGrow	China	Crop growth simulation, Irrigation management, Disease assessment	Wheat, Rice	Grain protein, Yield	Zhu et al. [65]
FASSET	Denmark	Crop yield prediction, Production management	Wheat, Spring-barley	Grain nitrogen	Berntsen et al. [66]
InfoCrop	India	Crop yield prediction, Pest assessment	Rice, Wheat, Sorghum	Grain protein, Grain nitrogen	Aggarwal et al. [67]
SALUS	USA	Crop rotation simulation, land management strategies, Crop yield prediction	Maize, Peanut, Wheat	Grain nitrogen	Basso et al. [68]

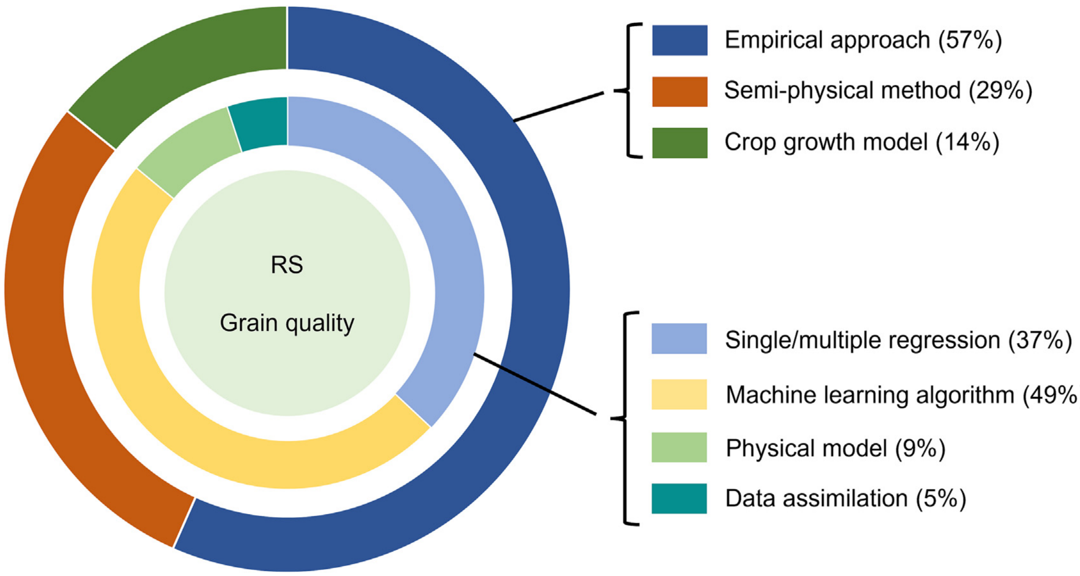

Fig. 5. Statistical map of crop quality prediction methods by remote sensing.

6.1. Single/multiple regression model of quality-related parameters for multiple periods

The mathematical expression of crop agronomic parameters based on spectral bands, vegetation indices or radar information is the initial inversion method and a method with a relatively wide range of applications [2,13]. VIs have been widely used to monitor critical agriculture parameters at different growth stages [107]. Most VIs are constructed based on Red-NIR isolines, such as NDVI, the enhanced VI (EVI) and the soil-adjusted VI (SAVI) [69–71]. NDVI enhances the contrast of reflectance between NIR and Red by means of non-linear stretching. The SAVI constructed by Huete et al. determines the soil coefficient L to adjust the influence of soil brightness according to the actual situation. In the construction of a VI to eliminate the influence of soil, in addition to examining the soil adjustment coefficient (L), Richardson and Wiegand proposed the PVI based on the concept of soil line, which also eliminates the influence of soil background [72]. To further monitor vegetation parameters such as chlorophyll, carotenoids and plant moisture, the spectral bands of the VI are no longer limited to the red and near-infrared bands. In recent years, combined classic VIs have been used to monitor key agronomic parameters related to crop quality [51,73,74].

Given that two or more independent variables usually offer more accurate explanations compared with only one spectral information, multiple linear regressions (MLR) (e.g., stepwise linear regression) generally obtain high estimation accuracy [75]. Pettersson et al. used the MLR model to predict the GPC of barley and improved its prediction with an R^2 value of 0.73. Zhang et al. predicted the GPC in rice grain by using the MLR method, and the R^2 value reached 0.81. Magney et al. showed that MLR analysis can predict GPC in wheat (R^2 = 0.67) more accurately than the single regression model (R^2 = 0.45 by the rate of ripening NDVI) [35]. Whilst MLR has high modelling accuracy, the problems of overfitting and band intercorrelation greatly limit its usage. Most studies that use optical data to monitor agronomic parameters often develop and test their models at specific growing stages and sites [76,77], thereby limiting the spatiotemporal generalisability of these models. The phenological period, plant height and texture characteristics of crop components can be used to address the poor model extrapolation caused by phenological differences [13,78]. When using VI to invert leaf agronomic parameters (e.g., LAI, LNC and leaf chlorophyll content) and plant agronomic parameters (e.g., AGB and PNC), the former models can achieve better accuracy with only VI, whereas the latter models require the use of phenological variables to complete the extrapolation of different growth periods [16]. Remote sensing has been proven as an effective alternative for mapping crop AGB or LAI at multiple regional scales [79,80]. Although the simple regression model based on vIs has a simple structure, the performance of the remote sensing monitoring model has been improved in both spatiotemporal expansions when combined with reasonable crop growth laws.

6.2. Machine learning algorithm

Machine learning methods, such as support vector machine (SVM), artificial neural network (ANN) and random forest (RF) analyses, have been widely used to integrate multi-source input variables, including the fusing of vIs and SAR/LiDAR-derived crop height, structural metrics [77,81] or imagery textures [78]. There is a linear correlation between grain yield and the spectral reflectance of winter wheat, as well as biomass. However, there is a nonlinear relationship between protein content and grain yield. This characteristic contributes to the higher accuracy of machine learning algorithms such as RF and ANN in predicting crop quality [82]. Despite the excellent performance of deep learning algorithms, a well-trained network depends on a wealth of training datasets that are expensive to collect, and their generality for image quality has not been thoroughly tested. The use of time-series-based deep learning models has provided new insights into predicting wheat GPC [83]. The development of new ML and DL algorithms has contributed to accurate and efficient predictions of crop quality. Partial least squares regression (PLSR) is an optimal choice for many researchers [51,52,84]. This powerful modelling tool predicts several dependent variables from a large set of independent variables and constructs a regression model even if the number of samples is less than the number of independent variables [51]. Meanwhile, the ANN method needs to be trained with samples prior its use, and the sample size influences its prediction accuracy. Li et al. claimed that ANN is not an ideal approach for estimating LNC in winter wheat when the sample size is less than 80 [28]. To solve this problem, the support vector regression (SVR) based on statistical learning theory provides a more robust model for retrieving agriculture variables with limited training data.

Although advanced mathematic algorithms have developed to address the problems in single or multiple regressions, a unique relationship between the spectral information and biophysical or biochemical variables is lacking [60]. This limitation hinders the application of high-accuracy models across different situations and periods. By combining spectral information and biochemical parameters [85], the construction of machine learning model will make wheat quality prediction more interpretable. Developing a methodology that utilizes soil, topographic, and yield data to predict grain protein content helps address the impact of environmental factors on prediction accuracy [86].

6.3. Physical model and optimisation

The physical spectral model stimulates the interactions between key biophysical or biochemical elements constituting the canopy and solar radiation with physical rules [87]. This model mainly includes the leaf optical model and canopy model. The leaf optical model stimulates the directional-hemispherical reflectance and transmittance of different leaves by considering the leaf structure parameters and leaf biochemical contents. Some representative models include the PROSPECT model [88], the algorithm BDF model [89] and the SLDP model [90]. At the canopy scale, when the radiation transfer model is used in the simulation, canopy and environmental parameters, in addition to blade structure and composition, need to be inputted along with the radiation transmission model. The main canopy radiation transfer models include SAIL, NADIM, MCRM and DART.

During the development of 2D and 3D radiative transfer models, great progress has been made in inverting LAI, chlorophyll, pigment and AGB. Physical-based methods that directly involve N have been rarely used, whereas plant nitrogen is directly related to crop quality attributes, such as GPC. The few studies that use radiative transfer models to analyse N generally rely on the correlation between leaf chlorophyll content and N [49,91]. To guarantee the transferability and robustness of monitoring different quality-related agronomic parameters, these mechanistic approaches are urgently needed. The powerful deductive capabilities of RTM models can be used to build large training datasets for machine learning models to infer parameter predictions that are not present in existing RTM models [92]. These advancements will motivate researchers to further develop customised RTMs to simulate agronomic traits that are related to crop grain quality.

6.4. Data assimilation

The data assimilation system generally comprises a simulation model, observation data and assimilation algorithm. Compared with other remote sensing monitoring models, the crop growth model shows more advantages in simulating AGB and LAI [80,91]. The assimilation algorithm plays a critical role in the coupling of the crop growth model and remote sensing data, which directly affects the efficiency and accuracy of the assimilation system. At present, assimilation algorithms mainly include parameter optimisation algorithms [93,94] and filtering algorithms [95,96]. Some studies directly assimilate the reflectance, VI or backscatter coefficients using the radiation transfer model. The optimisation algorithms for crop model assimilation include the simple search algorithm, maximum likelihood method [97], shuffled complex evolution method developed at the University of Arizona [94] and Powell conjugate direction method [98]. The cost function is constructed in the form of root mean square errors, least squares and 3D and 4D variations. The most commonly used sequential filtering algorithms include the extended Kalman filter [99], ensemble Kalman filter [100] and particle filter [95].

When simulating crops with different scales, a reasonable selection of pixel size not only affects the accuracy of assimilation results but also determines the calculation speed. Previous studies have effectively improved the efficiency of assimilation calculation by using look-up tables [101] and dividing texture units [102]. However, spatial scale conversion is a difficult scientific problem that needs to be solved urgently when remote sensing and crop model data assimilation systems are applied at regional scales. The scale expansion of a data assimilation system depends on the conversion of information with high and low spatial–temporal resolutions [103]. The conversion of information to high spatial–temporal resolutions (downward conversion) is complex and cannot be easily programmed or applied in practice [104]. Scale-up conversion, which converts information upward, is commonly used to solve the scale mismatch. Huang et al. combined phenological information with low spatial resolution remote sensing data and then adjusted the track of assimilation parameters generated by the crop growth model via the inversion of relatively accurate values from medium- and high-resolution images so as to improve the assimilation accuracy [105]. Although the application of data assimilation systems in large areas continues to face many challenges, Huang et al. derived a 1 km daily AGB dataset of the main winter wheat producing areas in China based on this system [80]. The construction of crop growth variable datasets combined with crop growth models and satellite remote sensing data will further advance the large-scale prediction of crop quality.

7. Technical challenges and opportunities for development and translation

7.1. Challenges and opportunities

At present, grain crops, such as maize, wheat and rice, are the main objects of remote sensing quality monitoring. Amongst them, GPC has received much research attention, whereas studies on the remote sensing monitoring of dry and wet gluten content, gelatinisation degree and grain sedimentation rate remain scarce. Few articles also focused on quality traits other than GPC, but grain quality should not be limited to these traits. Monitoring GPC based on remote sensing data relies heavily on the relationship between GPC and nitrogen or chlorophyll content. The formation mechanism of other traits is not only related to the movement of carbon and nitrogen, but also affected by many other factors, so it Is difficult to establish the relationship between remote sensing data and these traits through a simple algorithm. It is usually necessary to combine ground observation data, environmental factors, as well as abundant agronomic expertise and experience to conduct comprehensive analysis and adopt more complex and precise modellingg methods to simulate the formation mechanism and interaction mechanism of multiple traits. This is also a challenge and important direction for remote sensing technology in agronomic trait research. Therefore, there is a lack of research on other quality traits. Studies on the remote sensing monitoring of the quality traits of cash crops, forage crops, green manure crops and medicinal crops are even less. Monitoring and studying more crop varieties and quality traits and improving them will help generate additional economic benefits for producers and benefit the quality of life of people. In remote sensing monitoring, the physical model shows the strongest mechanism and stability. However, the existing physical models lack the monitoring simulation of nitrogen, which presents a great challenge for future quality monitoring research.

Crop information acquisition devices are rapidly developing, and crop quality research is also on the rise. However, the monitoring and prediction of crop quality will also put forward stronger and stricter requirements for information acquisition devices. Scholars have carried out comprehensive and extensive research on satellites, UAVs and ground remote sensing data platforms, which play important roles in quality monitoring and prediction. Satellite data have great advantages in crop monitoring at the global, national and regional scales. However, they often face difficulties in providing high-quality remote sensing data that are needed in the field in time due to climate factors (e.g., clouds and precipitation), revisiting cycles and spatial and temporal resolutions [106]. Meanwhile, UAVs and ground-based remote sensing monitoring platforms play an irreplaceable role in the dynamic monitoring of crop long time series, crop subdivision and acquisition of field information. In view of the spatial dispersion and spatial–temporal variability of agricultural production, the use of multiple data sources warrant attention in future research. In addition, with the gradual development of the Internet of Things, intelligent robots and crop growth simulation systems, the development of data fusion technologies is also urgently needed.

The goal of data fusion is to obtain higher quality, more optimised and more reliable remote sensing data through the processing and analysis of two or more data sources with complementary synergistic advantages for the same scene. Data fusion includes three levels, namely, the data, feature and decision levels. Homogeneous remote sensing, heterogeneous remote sensing, remote sensing-site and remote sensing-non-observation data fusions form the four categories of remote sensing data fusion. Fusion technologies, such as panchromatic-multispectral, have formed standard technical processes and been widely used. However, many uncertainties remain in heterogeneous remote sensing data fusion, especially in space-space data with large-scale differences in their sensor designs and observation mechanisms. For specific observation scenarios, further mining the correlation and fusion characteristics of heterogeneous data sources to achieve data fusion at different scales presents a great challenge for agricultural remote sensing applications.

7.2. Outlook

7.2.1. The potential application of UAV for cereal quality predicting

The ultimate goal of previous remote sensing research is to serve the agricultural production practice. Compared to remote sensing satellites and ground platforms, UAVs offer several advantages, including high spatial resolution, accurate observations, and convenience. UAVs have great potential in data acquisition and field management due to their advantages, such as their lightness, agility, low cost and high operational efficiency. Airborne sensors, such as digital cameras, multispectral cameras, hyperspectral cameras, thermal infrared cameras and lidars, serve as the ‘eyes’ of UAVs for analysing farmland information. However, the application of UAVs may be hindered by their high cost and insufficient payload. Developing onboard cameras presents a positive direction towards a low-cost, lightweight and data-rich acquisition. The widespread utilization of UAV platforms has the potential to drive further advancements in research related to employing remote sensing technology for crop quality prediction. With the further development of remote sensing technology, UAVs need to serve as operational tools that integrate information acquisition, data processing, growth simulation and field management decision making.

7.2.2. Change from methodology to more physical models

An accurate excavation of the reflection, absorption, projection and emission characteristics of electromagnetic waves from different ground objects serves as the basis of target detection. Therefore, a thorough understanding of the radiation transfer mechanism and the soil-leaf-canopy process plays an important role in monitoring and predicting crop growth and quality. With the development of remote sensing technology, the renewal of remote sensing information acquisition tools and the enrichment of knowledge, humans can obtain more farmland information, which lays a foundation for the successful mathematical solution of physical processes. In order to adapt to the current and future development, the monitoring and prediction of crop growth, yield and quality need to become mechanistic, which requires a high processing efficiency of high spatial and temporal resolution data. Therefore, more physical models need to be constructed.

7.2.3. Change from crop quality monitoring to crop quality prediction

The existing remote sensing quality monitoring process is mostly a ‘reproduce’ of the crop historical growth process of the existing data, which is a post-event quality assessment. Therefore, future remote sensing quality research should have a predicting function. When using the data for the present growth period, quality prediction can be realised in advance by introducing future meteorological data. Some uncertainties are also present in the crop model itself, the input parameters and meteorological driving factors. If the simulation results are driven by different ensemble forecast data as ensemble members, then the ensemble of simulation results can represent their probability distribution. A single numerical simulation output can be transformed into a probability distribution to realise a probability prediction of crop yield.

Studies on quality remote sensing prediction should take climate change and other environmental problems into account and actively provide technical support and coping mechanisms for future planting conditions. In addition to crop growth and radiation transfer models, crop growth scenarios in the next 5, 10 or even 20 years should be created with the support of atmospheric models, climate models and hydrological models. On the basis of possible future crop growth scenarios, different varieties parameters and management measures should be combined to predict and analyse crop quality and yield so as to guide variety breeding and make reasonable response plans.

8. Conclusions

The use of remote sensing data often generates immediate and intermittent estimates of crop quality across regions, which are essential for ensuring food and nutritional safety. However, the existing models that predict grain quality using remote sensing data have unsatisfactory prediction accuracy and universal applicability due to environment and management differences. An important limitation is that reflectance is scanned preferentially from the upper canopy at the early stage of crop growth. Therefore, the composition of grain organs cannot be easily obtained by solely using remote sensing data. However, these problems can be addressed by an appropriate combination of growth rules, ecological factors, RTMs and remote sensing data from different platforms and with the help of some ancillary information, such as agricultural parameter measurements. Empirical, semi-empirical and mechanistic models make great efforts in determining the underlying mechanisms when using remote sensing data to monitor grain quality. Previous studies on grain quality have mostly focused on certain traits, such as GPC and starch content. Regardless of which quality monitoring method is used, more models of grain quality traits should be further explored. An in-depth understanding of the limitations of these methods not only helps us select the appropriate methods for grain quality monitoring but also fosters further research on grain quality.

CRediT authorship contribution statement

Zhenhai Li: Conceptualization, Writing – original draft, Writing – review & editing, Visualization, Project administration, Funding acquisition. **Chengzhi Fan:** Writing – original draft, Writing –

review & editing, Visualization. **Yu Zhao:** Formal analysis, Writing – original draft, Writing – review & editing, Visualization. **Xiuliang Jin:** Writing – original draft, Writing – review & editing. **Raffaele Casa:** Project administration, Writing – review & editing, Funding acquisition. **Wenjiang Huang:** Methodology, Writing – review & editing, Funding acquisition. **Xiaoyu Song:** Writing – original draft, Supervision. **Gerald Blasch:** Writing – original draft, Investigation. **Guijun Yang:** Funding acquisition, Supervision. **James Taylor:** Conceptualization, Writing – original draft, Writing – review & editing, Funding acquisition. **Zhenhong Li:** Conceptualization, Supervision, Writing – review & editing, Supervision, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This study was supported by the National Natural Science Foundation of China (42271396), the Natural Science Foundation of Shandong Province (ZR2022MD017), the Key R&D Project of Hebei Province (22326406D), and The European Space Agency (ESA) and Ministry of Science and Technology of China (MOST) Dragon (57457).

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