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REVIEW

A critical review on applications of hyperspectral remote sensing in crop monitoring

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Summary
Numerous technologies have contributed to the recent development of agriculture, especially the advancement in hyperspectral remote sensing (HRS) constituted a revolution in crop monitoring. The widespread use of HRS to obtain crop parameters suggests the need for a review of research advances in this area. HRS offers new theories and methods for studying crop parameters, but much work needs to be done both experimentally and theoretically before we can truly understand the physical and chemical processes that predict these crop parameters. The study focuses on the following elements: 1) The article provides a relatively comprehensive introduction to HRS and how it can be applied to crop monitoring; 2) Current state-of-the-art techniques are summarized and analyzed to inform further advances in crop monitoring; 3) Opportunities and challenges for crop monitoring applications using HRS are discussed, and future research is summarized. Finally, through a comprehensive discussion and analysis, the article proposes new directions for using HRS to study crop characteristics, such as new data mining techniques including deep learning provide opportunities for efficient processing of large amounts of HRS data; combining the temporal and dynamic characteristics of crop parameters and vegetation growth processes will greatly improve the accuracy of crop parameter detection and monitoring; multidata fusion and multiscale data assimilation will become HRS monitoring. Multidata fusion and multiscale data assimilation will become another research hotspot for HRS monitoring of crop parameters.

Keywords: Precision agriculture; Crop monitoring; Crop parameters; Hyperspectral remote sensing

Introduction

Precision farming or precision agriculture is based on using the inherent spatial and temporal variability in a field as a basis to manage farm operations (Goel *et al.*, 2003). It is a management practice made possible by the advent of suitable information technologies (Ryu *et al.*, 2009; Roslim *et al.*, 2021). Regarding time-effective methods, the practice of precision farming requires the development of accurate and reliable crop monitoring techniques to provide information on the spatial and temporal variations in key agronomic parameters (Steven, 2004). A comprehensive review on status of various components for precision farming and application of information technology was presented by Plant (2001). He clearly highlighted the importance of high-altitude remote sensing to obtain information on crop growth condition. Remote sensing is a useful tool for monitoring spatial and temporal variation in crop morphology and physiological conditions and for supporting precision agriculture practices (Lu *et al.*, 2020).

Traditional methods for detecting and monitoring essential parameters of crops need detailed sampling, time, and expensive laboratory chemical analyses, which is neither economically viable nor environmentally acceptable on a large scale (Mahajan *et al.*, 2017). Remote sensing can be used to collect information at vastly larger spatial extents more quickly and more cheaply per unit area than field sampling (Flynn *et al.*, 2020). It can also be combined with field data to more efficiently assess spatial and temporal distributions of crop parameters (Aneece *et al.*, 2017; Afrasiabian *et al.*, 2021). Over the past three decades, remote sensing techniques have been used as very useful tools to precisely monitor crops throughout their growing season to support decisions for good agricultural practices (Astor *et al.*, 2020).

Although the remote sensing technique is widely used for timely detection of variations in the spectral response of crops over large areas, the multispectral remote sensors exhibit serious limitations to accurately detect changes in crop because of coarse spectral resolutions that hide detailed information of signals from crop parameters (Hong and Abd El-Hamid, 2020). Early multispectral images are limited by spectral resolution, which affects the accuracy of retrieval variables and leads to the inability to detect early signals of crop stress in a timely and effective manner (Ang and Seng, 2021). Hyperspectral remote sensing (HRS), also known as imaging spectroscopy or hyperspectral imaging (HSI), involves hundreds of spectral narrow bands that are sensitive to distinct biophysical and biochemical characteristics masked by the broad bands of multispectral remote sensing (Goetz 2009; Slonecker *et al.*, 2018; Gao *et al.*, 2019; Meivel and Maheswari, 2021). Thus, advances in HRS provide opportunities for detailed mapping, modeling, and biophysical characterization of crops (Nidamanuri and Zbell, 2011). It is more capable of detecting subtle changes in ground cover and its variation over time.

HRS can be used to address the above challenges and facilitate more accurate and timely detection of crop physiological states. The main research is on field and laboratory hyperspectral measurements for monitoring agriculture and vegetation, retrieval of plant traits in leaf and canopy layers from hyperspectral measurements (Berger *et al.*, 2020; Dobrota *et al.*, 2021); hyperspectral sensor calibration and product validation for agriculture and vegetation monitoring, product quality validation (Fahey *et al.*, 2020; Jia *et al.*, 2022); statistical and computational methods for agricultural and vegetation monitoring (Murphy *et al.*, 2020; Ma *et al.*, 2021; Nansen *et al.*, 2021); studies for agricultural and vegetation living environments, microbial load, surrounding species, etc. (Santos-Rufo *et al.*, 2020).

HRS advances constitute a revolution in agriculture and in particular, crop monitoring. The widespread use of HRS for crop parameter acquisition suggests the necessity to review the progress of research in this field. The objectives of this paper are a) to discuss the different platforms and sensors of HRS, summarize the methods available for processing and analyzing hyperspectral information, and recent advances in HSI for agricultural applications; b) to discuss and summarize current developments in crop monitoring supported by HRS and to assess the performance of HRS under different applications; c) to further help agricultural researchers and practitioners better understand the advantages and limitations of HSI in agricultural applications and to promote the opportunities and challenges of using HRS for crop monitoring applications.

HRS monitoring platforms and sensors

Remote sensing platform is used to place various remote sensors to detect ground targets from a certain height or distance and to provide technical support and working conditions for the sensors (Zhong *et al.*, 2020). According to the height of the platform from the ground, it can be divided into three categories: ground platform, airborne platform, and spaceborne platform (Table 1). These remote sensing platforms with different technical performances and working modes form a multilayer and three-dimensional modern remote sensing information acquisition system, which provides a technical guarantee for the completion of thematic or integrated, regional or

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Table. 1. The synoptic scheme chart showing different hyperspectral remote sensing platforms with diverse features

Categories	Platform	Working height	Feature	Limit
Ground	Technology system based on vehicle, ship, handle, fixed or movable elevated platform, etc.	Working height is generally below 100 m.	Ground object spectrum accurate measurement.	Time-consuming, laborious, and unsuitable for large region.
Airborne	Balloon, plane, and other aircraft carriers in the air.	Working height is generally below 80 km.	Suitable for regional surface instant monitoring	Flight altitude and duration are limited and are greatly affected by weather and flight attitude.
Spacebome	Satellite, space shuttle, spacecraft, etc.	No national boundary and geography limitations	Suitable fbr large-scale surface periodical monitoring	Relatively low spatial resolution

global, and static or dynamic remote sensing activities. The working height of ground remote sensing platform is generally less than 100 m, which mainly includes vehicle, ship, handle, fixed or movable elevated platform, etc. Airborne remote sensing platform mainly includes balloon, plane, and other aircraft. Plane specially designed or modified as needed is the main platform of airborne remote sensing because of its flexibility, wide observation range, and high measurement accuracy. Spaceborne remote sensing platform mainly includes satellite, space shuttle, and spacecraft, etc. The prominent characteristics of spaceborne remote sensing are high altitude, large observation range, and fast monitoring speed (Wei *et al.*, 2021). Satellite is the widely used platform of spaceborne remote sensing, which is suitable for large-scale surface accurate monitoring. With the continuous improvement of sensor resolution, the status of satellite monitoring platform will become more important. Existing or planned satellite HRS platforms are summarized in Table 2. It can be seen that not many satellites are currently in running and are about to be launched, but the progress of research and development has been significantly accelerated in recent years. Furthermore, sensors with higher spatial resolution and wider spectral range have become a trend.

Application of HRS in monitoring diverse crop objects

A literature search was performed to examine if more research in using HSI for agricultural purposes had been published in recent years. It was found that there was an increasing number of publications in recent years that used HSI for agricultural applications (Table 3). During 2013–2019, we searched papers on the 'Web of Science' website using keywords containing 'HRS' and 'crop' to find that HRS has been widely used in monitoring of various crops which includes corn (Essayed and Darwish, 2017), wheat (Zhang *et al.*, 2018), rice (Krishna *et al.*, 2019), cotton (Marshall *et al.*, 2016), grapevine (Zovko *et al.*, 2019), *Crambe abyssinica* Hochst (Viana *et al.*, 2018), white bean, canola, peas (Pacheco *et al.*, 2008), sugarcane (Mokhele and Ahmed, 2010), soybean (Yuan *et al.*, 2017), sugar beet (Inoue *et al.*, 2016), mustard (Kumar *et al.*, 2013), barley (Lausch *et al.*, 2015), blackgram (Prabhakar *et al.*, 2013), and potato leave (Latorre-Carmona *et al.*, 2014). A chart showing the application domain of HRS in crop monitoring is provided for clear description. These monitoring work takes place in many different places such as North America, Asia, Europe, South America, and Africa, which means that specific crops are widely distributed in certain regions, or different regions have their own concerned crops. Corn, wheat, and rice are the three most widely distributed crops in the world. It also can be seen from these literatures that they are the three most common monitoring objects in the application of HRS technology. However, there are relatively few studies on many other crops, and even many crops which are important for regional economic development have not been studied, e.g., tobacco, tomato, pepper, cucumber,

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Table 2. Existing or planned satellite hyperspectral remote sensing platforms

Satellites	Sensors	Spatial Resolution	Spectral Resolution	Band Quantity	Spectral Range	Swath Breadth	Country	Launch Year
EO-1	Hyperion	30 m	10 nm	242	400–2500 nm	7.5 km	America	2000
PROBA	CHRIS	17/34 m	5/12 nm	153	400–1050 nm	14 km	Belgium	2001
AQUA	AIRS	13.5 km	1200 (lamdba/delta lambda)	2378	370–1540 nm	1650 km	America	2002
IMS	HySI	506 m	10 nm	64	400–950 nm	129 km	India	2008
HJ-1A	HSI	100 m	5 nm	128	450–950 nm	50 km	China	2008
ISS	HICO	100 m	5.7 nm	128	350–1080 nm	42 km	America	2009
FLORA	HSI	30 m	10 nm	200	380–960 nm	150 km	America and Brazil	2016
GF-5	AHSI	30 m	5/10 nm	330	400–2500 nm	60 km	China	2018
OVS-1A/B	OHS	10 m	2.5 nm	256	400–1000 nm	150 km/500 km	China	2018
PRISMA	PRISMA	30 m	10 nm	249	400–2500 nm	30 km	Italy	2019
ALOS-3	HISUI	30 m	10/12.5 nm	185	400–2500 nm	30 km	Japan	2019
EnMAP	EnMAP HSI	30 m	6.5/10 nm	244	420–2450 nm	30 km	Germany	2019
ISS	DESIS	30 m	–	235	400–1000 nm	–	Germany	2018
–	SHALOM	10 m	10 nm	275	400–2500 nm	30 km	Italy	2021
–	SBG	30 m	10 nm	214	380–2500 nm	150 km	America	2023

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Table 3. Applications of hyperspectral remote sensing in crop monitoring during 2003–2019

Crops	Parameters	Sensors		Methods/Models	Literature
		Names	Platforms		
Corn	Water content	ASD	Ground	Photochemical reflectance index (PRI); nonphotochemical quenching (NPQ)	Chou *et al.*, 2017
		Tec5	Ground	Simple linear regressions (SLR); Linear models (LM)	Elsayed and Darwish, 2017
	Evapotranspiration	ASD	Spaceborne	LM	Marshall *et al.*, 2016
	Weed management	CASI	Airborne	General linear model (GLM)	Goel *et al.*, 2003
		ASD	Ground	Linear discriminant analysis (LDA); Maximum likelihood classification (MLC)	Huang *et al.*, 2016
	Yield estimation	Tec5	Ground	SLR; LM	Elsayed and Darwish, 2017
	Biomass assessment				
	Pigment content	CASI	Airborne	Leaf reflectance model (PROSPECT); Vegetation canopy model (SAIL); Marquet-Levenberg optimization method (MLO)	Li *et al.*, 2008
		Ocean Optics USB2000	Ground	Bayesian model averaging (BMA); Partial least-squares regression (PLSR); Stepwise multiple regression (SMR)	Zhao *et al.*, 2013
		CHRIS	Spaceborne	Bi-Lambertian model (BLM); PROSPECT	Latorre-Carmona *et al.*, 2014
		Ocean Optics USB2000	Ground	PLSR; Interval partial least-squares regression (iPLSR); Radiative transfer mode (PROSAIL)	Inoue *et al.*, 2016
	Nutrient concentration	CASI	Airborne	GLM	Goel *et al.*, 2003
		RDACS/H-3	Airborne	PLSR	Bajwa and Tian, 2005
		Ocean Optics USB2000	Ground	BMA; PLSR; SMR	Zhao *et al.*, 2013
	Bioenergy potential	HyMap	Airborne	PLSR	Udelhoven *et al.*, 2013
	Crop residue	Hyperion	Spaceborne	Spectral unmixing (SU); Manifold learning-based unmixing method (MLBUM); Linear unmixing (LU); Linear mixing model (LMM)	Chi and Crawford, 2014
	Stand density	Hyperspectral focal plane scanner; GER 1500	Airborne; Ground	Principal component regression analysis (PCRA)	Thorp *et al.*, 2008
		ESSI Probe-1	Airborne	Endmember selection (ES); SU; Linear regression model (LRM)	Pacheco *et al.*, 2008
	Gross photosynthesis	CASI; GER 1500	Airborne; Ground	Vegetation index- gross photosynthesis model (VI-GP)	Strachan *et al.*, 2008
Wheat	Nutrient concentration	Hyperion	Spaceborne	LRM; Correlation matrices (CMM)	Koppe *et al.*, 2010
		ASD	Ground	LRM	Mahajan *et al.*, 2014
		ASD	Ground	Angular insensitivity vegetation index model (AIVI)	He *et al.*, 2016a
		ASD	Ground	Multi-angular vegetation index (MAVISR); Regression models(REM)	He *et al.*, 2016b
		ASD	Ground	Savitaky-Golay smoothing method (SGSM); Line equations (LE)	Zhang *et al.*, 2018

(*Continued*)

Table 3. (*Continued*)

Crops	Parameters	Sensors		Methods/Models	Literature
		Names	Platforms		
	Pigment content	ASD	Ground	Duncan's multiple comparison (DMC); Integrated regression analysis (IRA); Correlation analyses (CA); LM; Inverted Gaussian model (ICM); Linear extrapolation method (LEM)	Feng *et al.*, 2008
		CASI	Airborne	PROSPECT; SAIL; MLO	Li *et al.*, 2008
		CASI	Airborne	PLSR; iPLSR; PROSAIL	Inoue *et al.*, 2016
		ASD	Ground	Univariate linear method (ULM); Multivariate linear model (MLM);	He *et al.*, 2018
	Evapotranspiration	ASD	Ground	Analysis of variance (ANOVA); Computation of correlation coefficients (CCC); Curve fitting (CF); Regression relations (RR)	Chattaraj *et al.*, 2013
	Biomass assessment	Hyperion	Spaceborne	LRM; CMM	Koppe *et al.*, 2010
		Hyperion	Spaceborne	LRM	Koppe *et al.*, 2012
	Weed management	GER 2600	Ground	Stepwise discriminant analysis (SDA)	Martin *et al.*, 2011
	Stand density	ESSI Probe-1	Airborne	ES; SU; LRM	Pacheco *et al.*, 2008
	Disease diagnosis	HyMap	Airborne	Support vector machines (SVM); Spectral angle mapper (SAM); Bhattacharyya distance (BD)	Mewes *et al.*, 2011
	Species identification	HyMap	Airborne	Object-oriented (OO); SVM; SAM	Nidamanuri and Zbell, 2011
	Gross photosynthesis	CASI; GER 1500	Airborne; Ground	VI-GP	Strachan *et al.*, 2008
Rice	Water content	Gaiasky-mini	Airborne	Global sensitivity analysis (GSA) method; Particle swarm optimization algorithm (PSO); PROSAIL	Yu *et al.*, 2017
		ASD	Ground	PLSR; Multiple linear regression (MLR); Artificial neural networks (ANN); Support vector machine regression (SVR); Random Forest models (RF)	Krishna *et al.*, 2019
	Yield estimation	ASD	Ground	MLR	Liu and Sun, 2016
		Gaiasky-mini	Airborne	GSA; PSO; PROSAIL	Yu *et al.*, 2017
	Evapotranspiration	HNBs	Spaceborne	LM	Marshall *et al.*, 2016
	Nutrient concentration	ASD	Ground	SMR	Tang *et al.*, 2007
		AISA	Airborne	PLSR; MLR; General-purpose prediction model (GPPM)	Ryu *et al.*, 2009
		AISA	Airborne	MLR; PLSR	Ryu *et al.*, 2011
		ASD	Ground	Linear correlation analysis (LCA); Regressive calibration models (RCM)	Mahajan *et al.*, 2017
	Heavy metal	UniSpec	Ground	PLSR; Correlation coefficient (CC)	Zhou *et al.*, 2019
	Disease diagnosis	ASD	Ground	LM; Curve models (CM); LRM	Tan *et al.*, 2019
		ASD	Ground	MLR	Prasannakumar *et al.*, 2013 Prasannakumar *et al.*, 2014

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Table 3. (*Continued*)

Crops	Parameters	Sensors		Methods/Models	Literature
		Names	Platforms		
	Pigment content	ASD	Ground	PLSR; iPLSR; PROSAIL	Inoue *et al.*, 2016
		Gaiasky-mini	Airborne	GSA; PSO; PROSAIL	Yu *et al.*, 2017
	Crop residue	DAIS 7915; ROSIS	Airborne	Semi-empirical regression model (SERM)	Boschetti *et al.*, 2006
Cotton	Evapotranspiration	HNBs	Spaceborne	LM	Marshall *et al.*, 2016
	Weed management	ASD	Ground	LDA; MLC	Huang *et al.*, 2016
	Yield estimation	AVNIR	Airborne	K-means clustering method (KMCM); Minimum distance method (MDM)	Zarco-Tejada *et al.*, 2005
	Disease diagnosis	ASD	Ground	Pearson correlation coefficient (PCC); LRM	Prabhakar *et al.*, 2011
Grapevine	Water content	VNIR-1600; SWIR-384	Ground	Partial least squares-discriminant analysis (PLS-DA); PLS-Single vector machines (PLS-SVM)	Zovko *et al.*, 2019
	Pigment content	Ocean Optics USB2000	Ground	Markov-chain canopy reflectance model (MCRM); PROSPECT; Crop reflectance operational models (CROM)	Martin *et al.*, 2007
	Nutrient concentration	CASI	Airborne	CMM; Factorial analysis (FA); Cluster analysis (CLA)	Gil-Perez *et al.*, 2010
Crambe abyssinica Hochst	Yield estimation	FieldSpec 4 Hi-Res sensor (FS4); Greenseeker 505 Handheld sensor (GS)	Ground	LRM; Spearman rank correlation coefficient (SRCC); ANOVA	Viana *et al.*, 2018
White bean Canola Peas	Stand density	ESSI Probe-1	Airborne	ES; SU; LRM	Pacheco *et al.*, 2008
Sugarcane	Species identification	Hyperion	Spaceborne	Maximum likelihood (ML); Minimum distance (MID); Mahalanobis distance (MD); Parallelepiped methods (PM)	Govender *et al.*, 2008
	Disease diagnosis Pigment content	Ocean Optics SD-2000	Ground	Reverse transcriptase-polymerase chain reaction analysis (RT-PCR); Resubstitution method (RM); Cross-validation technique (CVT); SAS Proc Mixed	Grisham *et al.*, 2010
	Nutrient concentration	ASD	Ground	Pearson moment product (PMP); LRM; CMM	Mokhele and Ahmed, 2010
Soybean	Weed management	ASD	Ground	Discriminant model (DM); LMM; LDA	Koger *et al.*, 2004a
		ASD	Ground	LDA; MLC	Huang *et al.*, 2016
	Yield estimation Gross photosynthesis	Cubert GmbH	Airborne	RF; ANN; SVM	Yuan *et al.*, 2017
	Pigment content	CASI	Airborne	PROSPECT; SAIL; MLO	Li *et al.*, 2008
		Ocean Optics USB2000	Ground	PLSR; iPLSR; PROSAIL	Inoue *et al.*, 2016
	Nutrient concentration	RDACS/H-3	Airborne	PLSR	Bajwa and Tian, 2005
		ASD	Ground	LRM	Guo *et al.*, 2017

(*Continued*)

Table 3. (*Continued*)

Crops	Parameters	Sensors		Methods/Models	Literature
		Names	Platforms		
	Species identification	Hyperion	Spaceborne	Extreme learning machines (ELM); Optimally pruned ELM (OP-ELM)	Moreno *et al.*, 2014
	Crop residue	ASD	Ground	Linear discriminant models (LDM); DM	Koger *et al.*, 2004b
		Hyperion	Spaceborne	SU; MLBUM; LU; LMM	Chi and Crawford, 2014
Sugar beet	Pigment content	CHRIS	Spaceborne	BLM; PROSPECT	Latorre-Carmona *et al.*, 2014
		Ocean Optics USB2000	Ground	PLSR; iPLSR; PROSAIL	Inoue *et al.*, 2016
	Water content	ASD	Ground	Non-linear classification and regression trees technique (CART); PCA; Correlation dimension estimator (CorrDim); Nearest neighbor dimension estimator (NNDim); Maximum likelihood estimator (MaxLike); Packing number estimator (PackNum); Geodesic minimum spanning tree estimator (GMST); Univariate linear regression (ULR); MLR	Borzuchowski and Schulz, 2010
Mustard	Disease diagnosis	ASD	Ground	Standard statistical methods (SSM)	Kumar *et al.*, 2013
Barley	Phenology derivation	AISA	Airborne	LibSVM; Recursive conditional correlation weighting selection algorithm (RCCW)	Lausch *et al.*, 2015
	Weed management	GER 2600	Ground	SDA	Martin *et al.*, 2011
	Water content	ASD	Ground	CART; PCA; CorrDim; NNDim; MaxLike; PackNum; GMST; ULR; MLR	Borzuchowski and Schulz, 2010
	Species identification	HyMap	Airborne	OO; SVM; SAM	Nidamanuri and Zbell, 2011
Blackgram	Disease diagnosis	ASD	Ground	Multinomial logistic regression models (MLRM)	Prabhakar *et al.*, 2013
Potato leave	Pigment content	CHRIS	Spaceborne	BLM; PROSPECT	Latorre-Carmona *et al.*, 2014

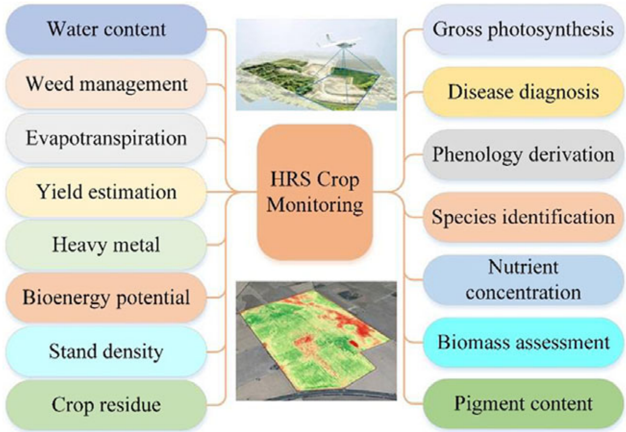

Figure 1. Applications of HRS in retrieving crop parameters (HRS: hyperspectral remote sensing).

and carrot. There are many types of hyperspectral sensors at present, and similar studies still need to be further conducted in other areas for different crop species.

Application of HRS in retrieving key crop parameters

HRS provides an effective means for the extraction of plant parameters (Millan and Azofeifa, 2018; Yu *et al.*, 2018). It also has been widely used in retrieving crop parameters including water content (Chou *et al.*, 2017), weed management (Huang *et al.*, 2016), evapotranspiration (Marshall *et al.*, 2016), yield estimation (Elsayed and Darwish, 2017), heavy metal (Zhou *et al.*, 2019), bioenergy potential (Udelhoven *et al.*, 2013), stand density (Pacheco *et al.*, 2008), crop residue (Chi and Crawford, 2014), gross photosynthesis (Yuan *et al.*, 2017), disease diagnosis (Prasannakumar *et al.*, 2014), phenology derivation (Lausch *et al.*, 2015), species identification (Moreno *et al.*, 2014), nutrient concentration (Mahajan *et al.*, 2017), biomass assessment, and pigment content (Inoue *et al.*, 2016). In order to show the application of HRS in retrieving these parameters more clearly, a chronological diagram was drawn (Figure 1). In summary, pigment content and nutrient concentration were the most common theme in HRS for crop monitoring over decades (Table 3). Over time, the applications of HRS in crop monitoring have been growing and the contents have become more diversified and quantitative. Especially in recent years, the applications of HRS focus on emerging agricultural research domains, such as the heavy metal detecting and water content retrieving. However, most of the study cases were based on ground remote sensing platforms, and there were almost no airborne or spaceborne remote sensing platforms.

Diversified extraction models and methods

It can be seen from the study cases in the past 20 years that various methods or models were used to extract crop parameters (Table 3). In order to clearly show the applications of methods or models, the network diagrams reveal the relationships between applied methods or models with monitoring objects, crop parameters, and monitoring platforms that were explored, respectively. As the three most widely distributed crops, corn, wheat, and rice had received extensive attention; therefore, many methods or models were involved (Xu *et al.*, 2021) (Figure 2). A large number of methods or models had been applied to extract nutrient concentration, pigment content, and water content, which also showed that these parameters were concerned by researchers (Figure 3). Because most of the study cases were based on the ground monitoring platform, there were few

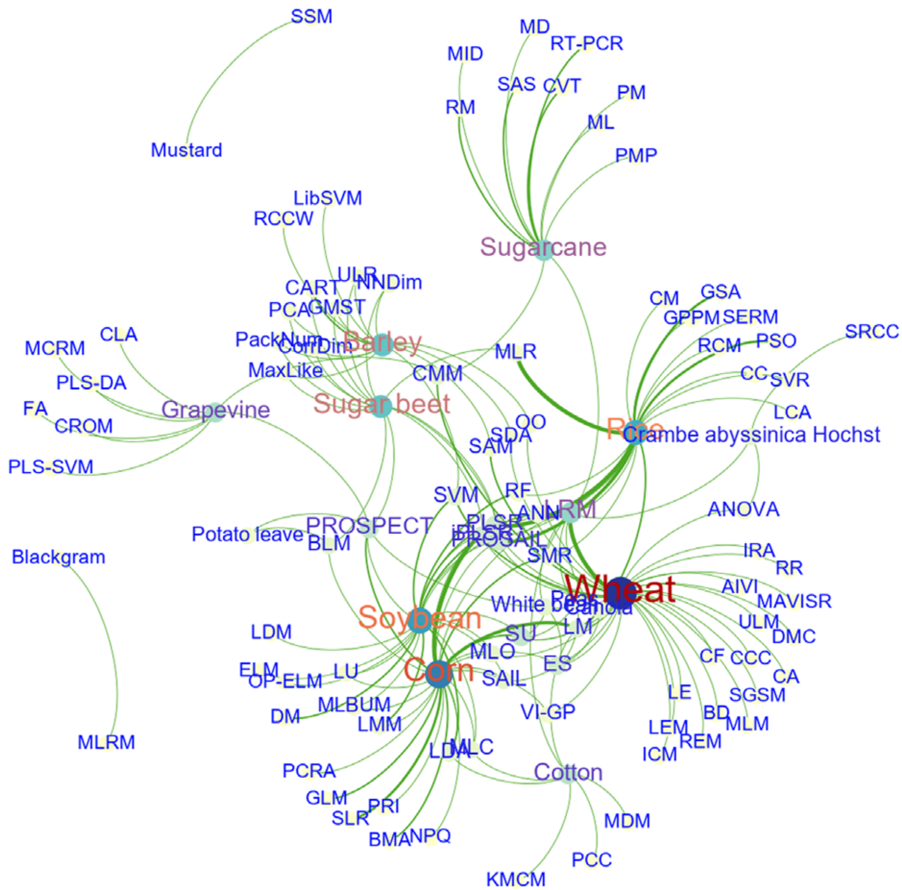

Figure 2. The relationships between objects and applied methods or models.

methods applied to the airborne platform, especially to the spaceborne platform (Figure 4). These methods or models can be summarized into four main categories: linear analysis, non-linear analysis, image classification, and physical model. Linear analysis was the most commonly used method, but physical models were rarely used. A large number of methods reveal that the use of HRS technology for crop monitoring has received widespread attention (Figure 5). However, so many options confuse people in choosing models or methods, which indicates that there is still a need to explore universal quantitative models or methods and extensively apply them to practical work to test the actual effect.

Opportunities and challenges

Although HRS provides new insights of its theory and methodology for studying the crop parameters, there is much work that has to be done both experimentally and theoretically before we can really understand the physical and chemical processes predicting these crop parameters. For example, in terms of data acquisition, the limitations are sensor calibration required; changes in ambient light conditions influence signal and need frequent white reference calibration; and canopy structure and camera geometries or sun angle influence signal. How to effectively achieve HRS data mining, information extraction, high-efficiency data compression and high-speed data transmission is one of the important issues to be solved in the future.

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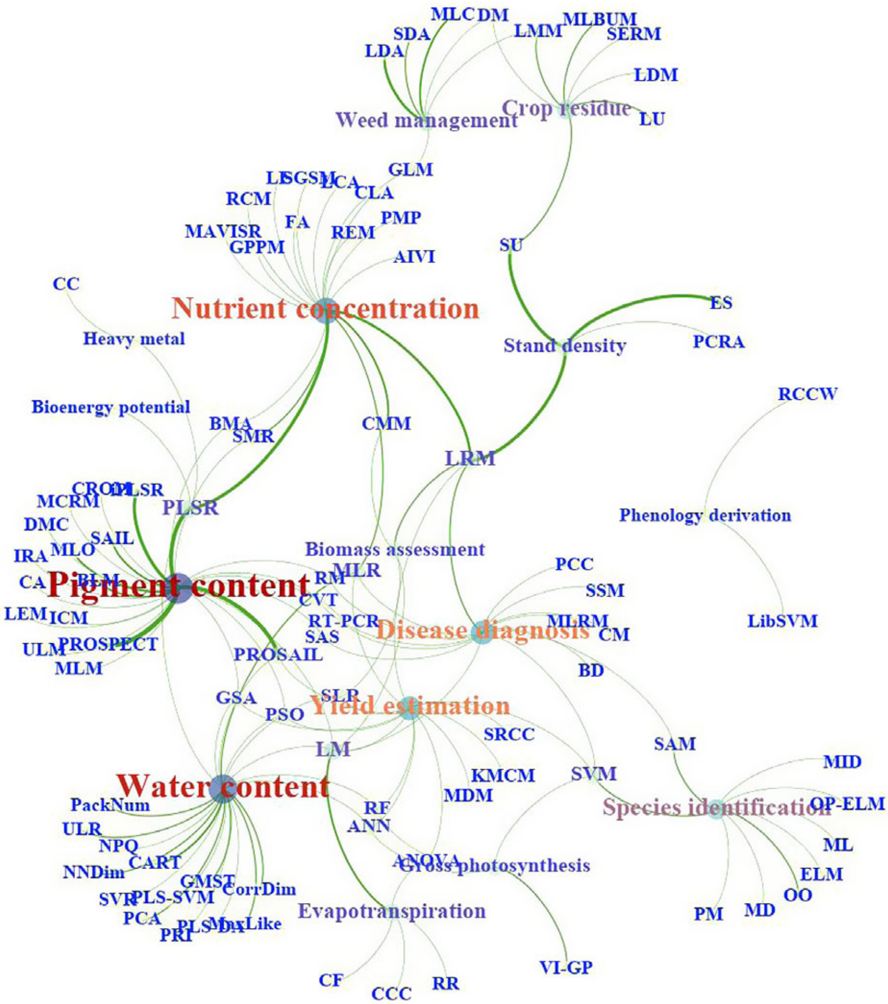

Figure 3. The relationships between parameters and applied methods or models.

As the resolution of HSI remote sensing sensors increases, more and more dimensions of information are obtained and the volume of data shows significant growth. The limit of employing HRS is the large volume of data that can be generated from spectral images. The large amount of data can make data management particularly important. While acquiring large amounts of hyperspectral image data, one is faced with the problem of how to maximize the use of these massive data. Although some progress has been made in the technology of hyperspectral data classification and information extraction, it still lags behind the development of sensors in general. Therefore, there is still a long way for research on hyperspectral data classification and information extraction.

The current HRS processing methods are particularly rich. On the one hand, new data mining technologies such as deep learning provide opportunities for efficient processing of large amounts of HRS data. Deep learning proposes a method for computer to automatically learn pattern features and incorporates feature learning into the process of model building, thus reducing the incompleteness caused by artificial design features. The findings show that machine learning applications using deep learning as the core method have achieved excellent recognition or classification performance beyond existing algorithms. On the other hand, in view of the huge amount

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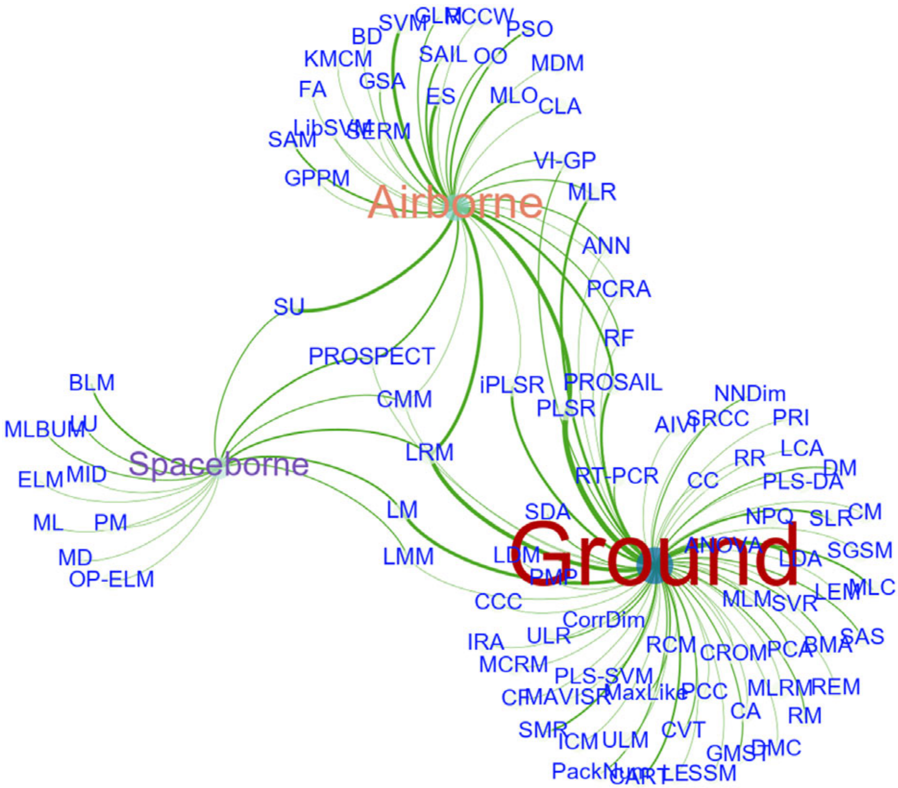

Figure 4. The relationships between platforms and applied methods or models.

of HRS data, we must extract more effective feature parameters for crop monitoring from the original measurement data. There are two ways to realize this process: band selection and feature extraction. We all know that we should choose those bands with more information, less data correlation, large spectral difference of crop parameters and good separability as the best working bands, and develop feature extraction indexes or methods that are easy to implement with higher extraction accuracy. However, due to the different research objects and regions, the best spectral parameters or characteristic indices of the same crop attribute are also different. Most of the existing spectral indices are based on limited data sets, which makes the monitoring model still lack universality in the selection and application of characteristic parameters.

Specific methods are widely used in building models, including principal component regression analysis, multiple linear regression, partial least-squares regression, stepwise multiple regression, univariate linear method, multivariate linear model, linear correlation analysis, etc. Some studies have explored the methods of nonlinear mathematical analysis, such as support vector machines, nonlinear classification and regression trees technique and artificial neural networks technology. These nonlinear methods can compensate for the shortcomings of linear methods to some extent and improve the prediction accuracy of the model. On the basis of these studies, we should try new artificial intelligence modeling methods such as linear and nonlinear coupling, machine learning and explore their application in crop monitoring. Furthermore, the development from empirical model to physical model will improve the universality and robustness of the model. In addition, in the application of HRS for acquiring crop parameters, more attention should be paid to the application of multivariate models involving multiple parameters, rather than to the single-factor model.

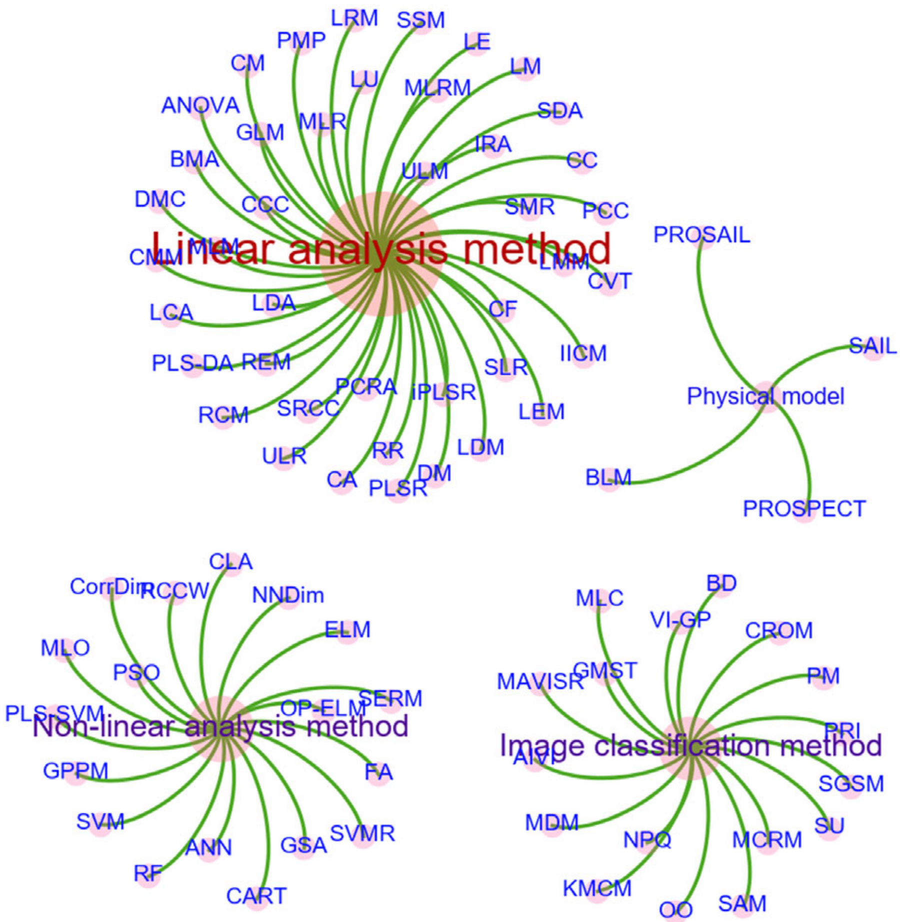

Figure 5. Classification of methods or models by features.

Crop spectra have not only high similarity and spatial variability, but also strong temporal dynamics. The spectral variation of crop parameters with time will be more distinct due to the influence of seasonal characteristics of vegetation. Specifically reflected in the vegetative growth and reproductive growth stages, as well as the staggered stage of vegetative and reproductive growth will cause changes in physical and chemical components and their contribution to spectral reflectance differences. Therefore, by making full use of the advantages of HRS in distinguishing subtle differences of the surface and combining with the temporal and dynamic characteristics of crop parameters, the accuracy of detecting and monitoring of crop parameters will be greatly improved. Further data accumulation and methodological exploration are, however, required to achieve monitoring of crop parameters considering the dynamic process of vegetation growth due to the redundancy of the spectral resolution and the limitation of the temporal resolution of the HRS data, as well as the complexity of the associated models.

With the successful development and launch of ground-based, airborne and spaceborne hyperspectral sensors worldwide, it is easier to obtain reliable and time-sensitive hyperspectral data of the land surface. Moreover, the new features of high spatial resolution, high spectral resolution, and high temporal resolution of HRS technology have become more and more obvious. However, optical HRS means may be affected by many factors such as dust, rust, plowing, particle size distribution, and vegetation coverage, which makes single type of optical HRS data is rather limited and problematic when striving for quantitatively accurate information. Sensors with different working modes and wavelength ranges can provide a variety of detecting means and methods, which can form complementary information to improve monitoring accuracy. For this reason, multidata fusion and multiscale data assimilation will become another research hotspot in HRS monitoring of crop parameters. Fusing hyperspectral data with other types of sensor data, such as Li DAR, SAR, and high spatial resolution images, will have wide application prospects if it can expand the monitoring range or improve the detection accuracy. In addition, with the continuous improvement of temporal and spatial resolution of HRS data and the diversity of data acquisition ways (e.g., ground-based, air borne, and spaceborne), HRS data assimilation has great potential for application. Multiscale data assimilation will improve the monitoring accuracy of land surface process and promote the comprehensive application of multiresolution (temporal, spatial, and spectral) HRS data in agricultural science.

Spaceborne hyperspectral sensors are clearly less used than airborne hyperspectral sensors. Since remote sensing satellite hyperspectral data provide simultaneous views and repeat coverage, two important advantages over ground-based observations and airborne hyperspectral data, research into the potential of satellite hyperspectral data for crop monitoring has become an important issue. Furthermore, the estimation of crop parameters using airborne and satellite hyperspectral sensors is currently limited mainly to small agricultural areas and is still in the testing phase, mainly because the relatively high cost of HSI cameras does not allow for widespread use, which is one of the important issues to be addressed by HRS applications. In addition, the modeling technique used for crop monitoring in most of the previous studies was the simple statistical method, which has several drawbacks related to the physical interpretation of the results and the complexity of transferring the models from one sensor to another (Gomez *et al.*, 2008; Peón *et al.*, 2017). Laboratory and airborne imaging spectroscopy of crop have shown to have considerable potential for the estimation of crop parameters with promising results. However, only a few studies exist that determine crop parameters directly from satellite hyperspectral imagery. Although this approach holds great potential for digital crop mapping with satellite hyperspectral imagery, crop parameter assessment from image data acquired by spaceborne systems is a more difficult issue, mainly due to atmospheric distortions and lower spatial and spectral resolution of the sensors (Mulder *et al.*, 2011). In order to be able to fully exploit data from forthcoming hyperspectral satellites, information on several issues related to sensor spatial and spectral resolution and range, as well as on calibration and validation issues, is still required. The development of more physically based models in this context would offer a real step forward towards the generalization of the estimation approaches, but at present still seems an elusive objective (Casa *et al.*, 2013).

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