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Yield prediction of root crops in field using remote sensing: A comprehensive review

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ABSTRACT

Yield information of root crops guides precision agriculture efforts and optimizes resource allocation. Predicting root crops prior to harvest is crucial to crop management and planning and requires obtaining root crop yield without damaging them. Non-destructive access to yield of root crops is challenging because of the edible portion of the crops being located underground, which impacts precision agriculture technology application. Remote sensing provides a possible way to solve this problem. There are no review reports on yield prediction for root crops using remote sensing, though root crops share the same growth characteristic of producing edible parts underground, which makes their yield prediction techniques similar. In this work, a total of 49 sources on the use of remote sensing techniques for yield prediction of root crops in field were collected, analyzed and discussed from the aspects of remote sensing platforms, input features and modelling methods. In terms of usage counts of remote sensing platforms, ground penetrating radars that are directly exposed to edible parts of root crops have the potential to be applied to root crop yield predictions, while spaceborne platforms are the current trend, accounting for 51 %. Feature combination from environment and crop itself is beneficial to crop yield prediction models, particularly the processed-based crop models. It is recommended to collect data time after ensuring specific root data types. Additionally, full-cycle data is suggested to be used to increase robustness of root crop yield prediction models. The result showed that plant-by-plant detection was only applied to radar-based platforms while spectral-based platforms are still in plot level, which further investigated that improving accuracy of root crop yield prediction through individual above ground phenotypic traits. The review is intended to summarize the development of root crop yield prediction using remote sensing and put forward further for further improvement.

1. Introduction

As the world population continues to grow, the importance of root crops, a non-grain food source, cannot be understated to food security (Raymundo et al., 2014). Root crops encompass a diverse range of plants that produce underground such as tubers (e.g., potato), tuberous roots (e.g., cassava and sweet potato), taproots (e.g., yam and carrot), and many other forms (Cai et al., 2024; Zhang et al., 2023). Despite belonging to different botanical families, these crops share a common characteristic of producing edible parts underground, leading to their grouping together as root crops (Chandrasekara and Kumar, 2016). Globally, root crops were grown in an area of 7.1×10^7 ha with a production of 9.1×10^8 tons in 2022 around the world (UN Food & Agriculture Organization, 2024). High-production characteristics of root crops make them potential crops for cultivation across the world, particularly in developing countries where they provide sustenance for millions of people (Skåra et al., 2022). Hence, there is a need to prioritize the production of root crops to meet the increasing demand for food supply (Zhang et al., 2024). Notably, root crop yield is an important indicator to their production management.

Yield information of root crops guides precision agriculture efforts

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Nomenclature

AGDB	Above-ground dry biomass
APAR	Absorbed Photosynthetically Active Radiation
ARIMA	Autoregressive Integrated Moving Average
AVHRR	Advanced Very High-Resolution Radiometer
EAT	Effective Accumulated Temperature
ET	Evapotranspiration
ETM+	Enhanced Thematic Mapper Plus
FAPAR	the Fraction of Absorbed Photosynthetically Active Radiation
GNDVI	Green Normalized Difference Vegetation Index
GPR	Ground Penetrating Radar
HCCACS-430	Holland Scientific Crop Circle™ ACS-430
HI	Harvest index
ISAVI	Integrated Soil Adjusted Vegetation Index
LAI	Leaf Area Index
LCI	Leaf Chlorophyll Index
LR	Linear Regression
LSTM	Long Short-Term Memory
LUE	Light Use Efficiency
MASVI2	Modified Soil Adjusted Vegetation Index 2
ML	Machine Learning
MLR	Multiple Linear Regression
MODIS	Moderate Resolution Imaging Spectroradiometer
MSI	Multispectral Instrument
MTR	Multi-target Regression
NDVI	Normalized Difference Vegetation Index
XNOAA	National Oceanic and Atmospheric Administration
NRCT	Normalized Relative Canopy Temperature
OLI	Operational Land Imager
OLSR	Ordinary Least Squares Regression
PLSR	Partial Least Squares Regression
PPI	Potato Productivity Index
REIP	Red Edge Inflection Point
RMSE	Root Mean Square Error
RF	Random Forest
SAVI	Soil Adjusted Vegetation Index
SLR	Simple Linear Regression
SVM	Support Vector Machine
SWIR	Short-wave Infrared
TCI	Temperature Condition Index
TDR	Time Domain Reflectometry
TIRS	Thermal Infrared Sensor
TM	Thematic Mapper
UAV	Unmanned Arial Vehicle
UWB Radar	UltraWideband Radar
VNIR	Visible and near-infrared
VCI	Vegetation Condition Index
VI	Vegetation Index
NRMSE	the mean of Normalized Root Mean Square Error

and offers valuable insights for the growth and planning of crops, spanning from plant level to global scale. The yield of root crops is expressed as edible part mass such as root and tuber mass. Obtaining yield information not only enables farmers to make necessary adjustments on fertilizers and water supply but plays an important role in farmers' negotiations of crop prices with buyers, as it helps to determine market values (Vannoppen and Gobin, 2022). Moreover, yield information is essential for policy and decisionmakers to make informed decisions on food and feedstocks, as well as for agricultural insurers to gain insights into the risk of negative weather impacts on cropping systems and yield anomalies (Khoshnevisan et al., 2014; Vannoppen and Gobin, 2022). In some studies, sensors placed on harvest machines provided the yield information of root crops (Thomas et al., 1999; Zhao et al., 2015). Nevertheless, this approach can only be employed by those who have access to harvesting equipment, and its ability to provide yield predictions is restricted to the harvest stage, thereby restricting its utility during the growing stage. Timely yield predictions of root crops prior to harvest at farm, regional and national scales is crucial.

Predicting yield of root crops is challenging due to their underground growth characteristic, limiting precision agriculture application. Unlike crops like maize or wheat, which are visually counted for yield without uprooting the entire plant, it is not possible to estimate the yield of root crops visually (Fernandez-Gallego et al., 2020; Li et al., 2022). Yield prediction of root crops can be done through samples collected from the field, or observing some phenotypes while the former is labor-intensive and destructive. Phenotypes of root crop can be observed using remote sensing technique, which is useful to predict root crop yield non-destructively (Rattanasopa et al., 2022; Tanabe et al., 2019).

Root crops share same growth characteristic that produces edible parts underground, which make their yield prediction techniques similar. Although there are many review articles on yield prediction, none of them have targeted root crops (Lin et al., 2023; Oikonomidis et al., 2022; Rashid et al., 2021; Tandzi and Mutengwa, 2020; van Klompenburg et al., 2020). Therefore, this review focuses on providing a general description of yield prediction for root crops in field conditions in terms of surveying the acquisition platforms and modelling methods, analyzing the problems associated with these methods, and proposing constructive solutions.

2. Review protocol

Literature review has been conducted in three stages: search, select, and synthesize to provide a comprehensive overview of existing studies, following the guideline developed in the PRISMA 2020 statement (Page et al., 2021).

2.1. Search strategy

Three queries were conducted, as listed in Table 1. Nine varieties of root crops were chosen for the review based on their prevalence and status. The queries were searched with the "AND" logic in Engineering Village (EI) database (https://www.engineeringvillage.com/app/search/quick/) on January 8th, 2024. A total of 1122 studies were found, all of which had been published.

2.2. Selection process

The searched literature was verified and selected to meet the requirements of the review. To avoid missing potentially useful literature,

Table 1
Criteria overview used as components of query on EI database.

Criterion names	Formulas
Root crops	TS = potato* OR carrot* OR (sugar beet*) OR cassava* OR yam* OR peanut* OR (lotus root*)
Yield prediction	TS = yield OR production OR output OR number OR (root biomass) OR (tuber biomass)
Platforms	TS = (remote sensing) OR (unmanned aerial vehicle) OR UAV OR drone OR airborne OR aircraft OR satellite OR ground*

Note: TS: the topic fields, including title, abstract, and subject.' *' represent a word start with words.

the search for literature initially yielded a large number of search results, some of which were irrelevant and needed to be excluded. A manual selection process was employed to identify relevant literature for inclusion in the analysis. The process is performed by looking at the title and abstract to determine if the article meets manual exclusion criteria in Table 2. 49 sources were selected after manual selection.

2.3. Literature synthesis

The synthesis of the selected literature aimed to identify common patterns, recurring themes, and research gaps, with the goal of drawing evidence-based results. For synthesizing the current knowledge regarding root crop yield prediction, the selected sources were explored manually in terms of remote sensing platforms, modelling methods, and input features related with yield and analyzed in detail in Section 3.

3. Literature analysis

3.1. Overview

The pathway for root crop yield prediction is illustrated in Fig. 1, which comprises two main steps: data acquisition and yield modelling. Three types of remote sensing platforms based on their distance to the ground, i.e., spaceborne platforms, aerial platforms and ground-level platforms, are utilized to gather the necessary data. Subsequently, the acquired data is fed into yield modelling systems, which determines the selection of input features and the appropriate modelling methods.

3.2. Remote sensing platforms

Root crop data was collected from sensors installed on hosting platforms to predict root crop yield. These platforms were classified into three categories: spaceborne, aerial, and ground-level, as shown in Table 3.

3.2.1. Spaceborne platforms

Spaceborne platforms have been widely applied to crop yield prediction (Lin et al., 2023). Gómez et al. (2019) utilized data from Sentinel-2 satellite with Multi-Spectral Instrument (MSI) to predict potato yield, which showed R^2 of 0.93. Knudby (2004) explained 64 % of peanut yield variance using National Oceanic and Atmospheric Administration (NOAA) satellites with Advanced Very High-Resolution Radiometer (AVHRR) sensor. Results demonstrated that the spaceborne platforms can be used for yield prediction of root crops. Additionally, the satellite data are available online and continue providing earth observation with a large scale, which is suitable to agricultural yield statistics at the regional or country scale (Akhand et al., 2016; Vannoppen and Gobin, 2022).

The spaceborne platform usually carried multiple sensors with different spatial resolutions and bands, which makes them distinctive. Operational Land Imager (OLI) and Enhanced Thematic Mapper Plus (ETM+) that equip in Landsat contain spectral range from visible to short wave infrared (SWIR) with spatial resolution of 30 m while RapidEye provided spatial resolution of five meters but missed SWIR information (Hodrius et al., 2015).

In terms of root crop yield prediction, selection of satellite data was derived by vegetation index (VI) (Tedesco et al., 2021). VIs from NOAA satellite with AVHRR have been found to be useful for early drought and flood detection, which are suitable for use as a factor in yield prediction (Akhand et al., 2016). However, suitable VIs that were correlated with yield were verified after experiments. Moreover, weather condition like cloud cover limits the availability of the satellite data, thereby reducing the frequency of access to annual plants such as potatoes. Therefore, some research used multiple sensors based on spaceborne platforms to predict root crop yield, which meanwhile took into account varying availability of the satellite data in different years (Bouasria et al., 2021; Hodrius et al., 2015). Despite the recent emergence of satellite tending to high spatial and temporal resolution, such as PlanetScope (three-meter resolution and two-day period), their spatial, temporal and spectral flexibility, as well as their spatial resolution, are not comparable to aerial platforms and ground-level platforms (Abou Ali et al., 2020).

Table 2
Exclusion criteria for search result selection.

Numbers	Exclusion criteria
1	Documents do not focus on predicting yield
2	Yield prediction does not apply to root crops and their edible parts
3	Documents do not have any algorithm descriptions
4	Full text documents are not available

3.2.2. Aerial platforms

Aircrafts and UAVs are two kinds of aerial platforms, which have been applied to yield prediction of root crops. Currently UAVs are more popular for yield prediction of root crops, while early studies used aircrafts, as shown in Fig. 2a. Flying altitudes of aircrafts and UAVs were counted based on studies about root crop yield prediction. Results showed that the average altitude of aircrafts was 220 m for root crop yield prediction, while UAV's average altitude was 32.7 m and resulted in a better potential for root crop yield prediction, as shown in Fig. 2b. Unmanned operations of UAV are safer and flexible compared with human operation of aircrafts. In terms of UAV, ultra-low altitude UAV has the potential to predict yield of root crops (Balota and Oakes, 2016; Njane et al., 2023). For instance, Njane et al. (2023) applied DJI Phantom 4 multispectral UAV with a flight altitude of 6 m to obtain phenotype of potatoes for potato yield prediction, which reached a ground sampling distance of 0.3 cm / pixel.

Aerial platforms have less influence of clouds and have a higher spectral resolution and more suitable to field scale assessments compared with spaceborne platforms. Two band spectrophotometers hosted in an aircraft were used to obtain infrared and red reflected fluxes that were related to yield of sugar beet in early study (Steven et al., 1983). Subsequently, multispectral sensors and hyperspectral sensors were hosted in aircrafts or UAVs to predict yield of root crops. UAVs can be equipped with appropriate sensors for yield prediction of root crops, where hyperspectral sensors (three studies) and multispectral sensors (five studies) are used for yield prediction of root crops in recent 20 years. Commonly, hyperspectral sensors were applied to obtain spectral images of root crops and calculate VIs related with root crop yields (Liu et al., 2021; Sun et al., 2020). Li et al. (2020) obtained plant height and VIs for yield prediction of root crops combing multispectral and hyperspectral cameras, respectively. Multispectral cameras are capable to utilize algorithms to obtain spatial information of root crops such as plant height and canopy area, which are potential variables to predict yield of root crops (Rattanasopa et al., 2022).

Fusion of data from spaceborne and aerial platforms provide comprehensive and accurate information to predict yield of root crops. Strengths of spaceborne and aerial platforms are complementary. The aerial platforms offer superior high spatial resolution and flexible data acquisition while spaceborne platforms covers large areas and readily available historical data, as shown in Table 4. A hybrid image analysis method was proposed based on both spaceborne and aerial platforms to predict yield of potatoes, which achieved R^2 of 0.88 (Sivarajan, 2011).

3.2.3. Ground-level platforms

Typically, ground-level platforms are able to carry heavy sensors and capture high-resolution data with more viewing angles for predicting yield of root crops while aerial and spaceborne systems can provide higher efficiency and larger area coverage, as shown in Table 4. Ground-level platforms used in the studies except for two instances where the platform wasn't specified were accounted. Results found that the platforms identified include tractors (one study), pushcarts (four studies),

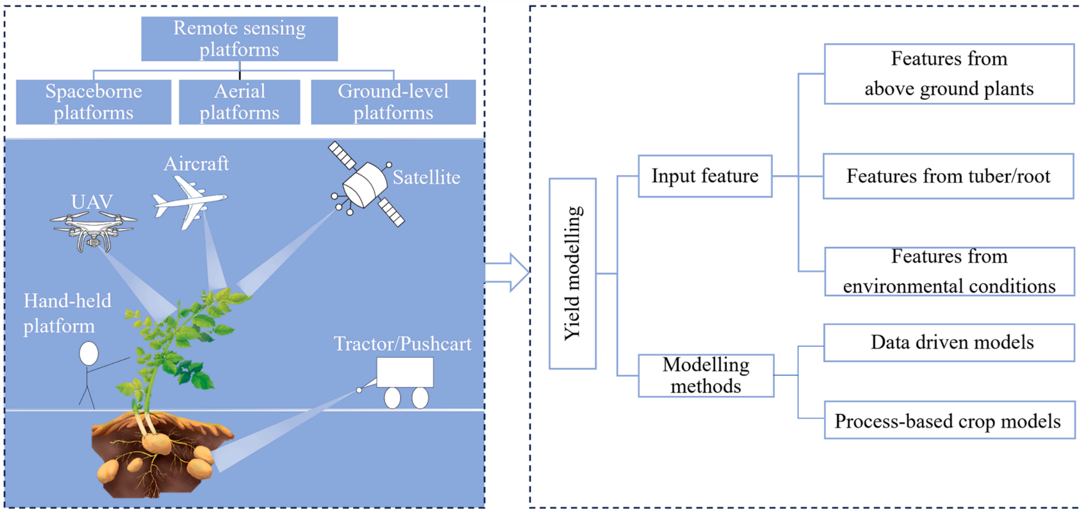

Fig. 1. A diagram of the pathway of root crop yield prediction.

and handheld operations (four studies). Pushcarts are a relatively low-cost alternative to tractors while the handheld operations are based on sensor design. Handheld devices often work vertically downward from the top of canopy of root crops with a distance shown in Table 5. All of them require manual labor of varying intensity, which has the potential risk for damaging crops.

The types of ground-level platforms have been related to the sensor type used. Spectral-based (five studies) and radar-based (six studies) are two main kinds of sensors for yield prediction of root crops. Spectral-based sensors were handheld while radar-based sensors were equipped in tractors and pushcarts. For specific varieties of root crops, handheld spectral-based sensors were used to estimate yield of potatoes while radar-based sensors were used for other varieties such as sugar beet, peanut, and cassava.

Although particular crop types are different, their common characteristic produced underground make prediction instrument and methods in agreement. Potatoes and sugar beets were analysed using similar instruments to obtain NDVI for yield prediction (Bu et al., 2016; Sharma et al., 2017). GPR, especially IDS Georadar, was mainly used for cassava, with some studies investigating peanuts (Agbona et al., 2021; Dobreva et al., 2021; Teare, 2021). The consistency in instrument use across root crops stems from their similar characteristics and highlights untapped potential of these technologies for advancing subterranean crop analysis.

3.3. Yield modelling of root crops

Existing studies all extracted features from acquired data and then built a relation with actual yield of root crops. Consequently, this study investigates input features and corresponding methods for yield prediction of root crops, as shown in Table 6.

3.3.1. Input feature

Features were extracted from acquired data and input to prediction models of root crop yield. Identifying features that correlate with the yield of root crops is crucial for accurately predicting their yield. The features primarily originate from environmental conditions and the plants themselves. The features from plant itself was divided into features of above ground plants and tuber/root, as shown in Fig. 3a.

Soil and weather are two environmental features, which influence crop growth and final yield, as shown in Fig. 3b. SAVI and soil moisture status are common input features from soil. SAVI has been frequently used to correct for the influence of soil brightness when vegetative cover was low (Abou Ali et al., 2020; Jayanthi, 2003). Soil moisture status such as soil water depletion, soil moisture and soil water content is another indicator of soil features and has been used to predict the root crop yield (Razzaghi et al., 2017; Vannoppen and Gobin, 2022). Weather features including temperature, cloud cover as well as precipitation is a common input from environment (Chiang et al., 2000; Ghorbanpour et al., 2022). Despite the count of soil and weather features being used equally, they have been used individually slightly more often than jointly (Fig. 3b).

The plant features are related to the root crop yield indirectly or relatively directly including the features of above ground plants and tuber/root, respectively. Above ground plants root crop are usually measured to gain spectral and spatial features such as VIs, green leaf aera, canopy cover and plant height (Bu et al., 2016; Tanabe et al., 2019). Spatial features from above ground plants are indirect related to root crop yield and easy to get if obtaining phenotype of root crop plants. Tuber/root features are relatively direct to the root crop yield since they are from tuber and root but difficult to interpret visually, such as backscattered energy and variance of signal amplitude (Agbona et al., 2023; Konstantinovic et al., 2008; Larson et al., 2018).

A combination of plant and environmental features provides rich information for yield prediction of root crops. Akhand et al. (2016) and Abou Ali et al. (2020) combined plant index and environmental index to predict the root crop yield, which achieved prediction error less than 10 % and a R^2 of 0.44 ~ 0.57, respectively. Due to many environmental indicators influencing root crop yield, the number of environmental features are more than that from plants in some researches (Razzaghi et al., 2017). In terms of frequency of usage, out of a total of 10 references that used both plant and environmental traits, NDVI was used five times while VCI was used two times, as shown in Fig. 3c.

Methods of features extraction are various according to their types. For some environmental features such as temperature and precipitation, they have been collected from public database without processing. For index from above ground plants and environments such as NDVI and TCI, they are calculated using particular spectral region. For tuber and root features, they followed signal processing including noise filter, migration and background correction. For spatial features of above ground plants, different algorithms need to be used depending on the specific spatial features. For instance, crop height was calculated using DSM while canopy area was obtained counting canopy pixels after removing background (Rattanasopa et al., 2022).

3.3.2. Modelling methods

Modelling methods are meant to find and explain relationship between the extracted features and root crop yield. Obtaining their correct

Table 3
Platforms and devices for root crop data acquisition.

Platforms	Root crops	Sensors / Data sources	References
Spaceborne platforms	Sugar beet and potato	MSI	Vannoppen and Gobin (2022)
	Peanut	AVHRR	Knudby (2004)
	Potato	MSI	Al-Gaadi et al. (2016)
	Potato	MODIS	Bala and Islam (2009)
	Potato	SMOS, ADAM	Ozalp (2020)
	Potato and sugar beet	DGPS, RapidEye, meteorological sensors, CMD MiniExplorer	Brogi et al. (2020)
	Potato	TM, ETM+, OLI	Mahdi et al. (2020)
	Potato	ETM+, OLI	Awad and Al-Aawar (2018)
	Potato	MSI	Gómez et al. (2021)
	Sugar beet	ETM+, TIRS, ERA-5, SRTM	Ghorbanpour et al. (2022)
	Potato	PlanetScope	Abou Ali et al. (2020)
	Potato	MSI	Gómez et al. (2019)
	Potato	MODIS, OLI, LISS3, MSI	Kumar et al. (2019)
	Sweet potato	MODIS	Moussa Kourouma et al. (2021)
	Potato	MSI	Singha and Swain (2022)
	Potato	AVHRR	Akhand et al. (2016)
	Sugar beet	ETM+, OLI, RapidEye, publicly available databases	Hodrius et al. (2015)
	Cassava	MSI	Ayu Purnamasari et al. (2019)
	Sweet potato	MSI	Tedesco et al. (2021)
	Sugar beet	MSI, OLI	Bouasria et al. (2021)
	Potato	MODIS, PRISM, US SoilGrids100m soil maps, C-band SAR, MSI	Ebrahimy et al. (2023)
	Potato	ISCCP	Chiang et al. (2000)
	Sugar beet	HRG-X	Hongo and Niwa (2012)
	Carrot	MSI, OLI, TIRS	Al-Gaadi et al. (2022)
	Potato	OLI, ETM+	Jaafar and Mourad (2021)
	Potato	TM	Sivarajan (2011)
Aerial platforms	Potato	VNIR-1800, SWIR-384	Liu et al. (2021)
	Sugar beet	Two-band spectrophotometer	Steven et al. (1983)
	Sugar beet	CAESAR scanner	Clevers (1997)
	Peanut	Headwall Nano-Hyperspec	Bagherian et al. (2022)
	Potato	Headwall Nano-Hyperspec	Li et al. (2020)
	Cassava	RedEdge	Rattanasopa et al. (2022)
	Potato	Multispectral camera	Li et al. (2021)
	Potato	Multispectral camera	Njane et al. (2023)
	Potato	Multispectral camera	Tanabe et al. (2019)
	Potato	Kodak Megaplus 4.2i camera	Sivarajan (2011)
	Peanut	Sony Alpha 6000 digital camera	Balota and Oakes (2016)
	Potato and sugar beet	Kodak Megaplus 4.2i camera	Jayanthi (2003)
	Potato	Headwall Nano-Hyperspec	Sun et al. (2020)
Ground-level platforms	Potato	GreenSeeker, Crop Circle ACS-430	Sharma et al. (2017)
	Potato	Nikon D60, TDR	Razzaghi et al. (2017)
	Sugar beet	M−Sequence UWB radar	Konstantinovic et al., (2008)
	Peanut	GPR	Dobreva et al. (2021)
	Potato	Kodak D5100 reflex, Fluke Ti-32	Elsayed et al. (2021)
	Potato	USB 2000 spectrometer, SUNSCAN Canopy Analysis	Luo et al. (2020)
	Cassava	GPR	Agbona et al. (2023)
	Cassava	GPR	Teare (2021)
	Sugar beet	GreenSeeker, Crop Circle ACS-470	Bu et al. (2016)
	Cassava	GPR	Larson et al. (2018)
	Cassava	GPR	Agbona et al. (2021)

relation is important using remote sensing non-destructively since edible parts of root crops were produced underground. Modelling for yield prediction of root crops starts with processed-based crop models or data driven models. Processed-based crop models simulate and analyze the energy conversion of root crops based on a large body of theories from the fields of crop ecology, crop physiology, meteorology, and soil science while data driven models rely on number of data to establish their potential relation (Maestrini et al., 2022). The proportion of results on the models showed data driven models (83.67 %) are used more than process-based crop models (16.33 %). The applicable scenarios, advantages, limitations, and application of the modelling methods are shown in Table 7. Compared to the data driven models, the process-based crop models describe physiological processes of root crops more accurately, which is more transferrable (Liu et al., 2021). However, when faced with changing conditions, process-based crop models demonstrate less flexibility compared to data-driven models. The rigid nature of process-based models, which rely on predefined physiological processes, limits their ability to adjust to dynamic environmental factors. In contrast, data-driven models more readily adapt, leveraging real-time data to refine predictions and improve accuracy in rapidly shifting conditions.

Various processed-based crop models have been proposed with promising results of yield prediction of root crops. Simple processed-based crop models have been described using mathematical equation for sugar beet (Clevers, 1997; Steven et al., 1983) and potato (Jaafar and Mourad, 2021), which achieved minimum RMSE of 3.74 t/ha for potato and the lowest error of 6 % for sugar beet. Monteith's light use efficiency model was employed for yield prediction of potato and sugar beet on the basis of light use efficiency, which obtained prediction accuracy of 95 ~ 97 % for potatoes (Awad and Al-Aawar, 2018; Ghorbanpour et al., 2022). Razzaghi et al. (2017) applied the AquaCrop model to simulate potato yield, reporting minimum NRMSE of 0.035. Hodrius et al. (2015) utilized PROMET for sugar beet yield prediction, which showed maximum R^2 of 0.90. Brogi et al. (2020) predicted yield of sugar beet and potatoes using the AgroC model, obtaining a minimum error of 0.1 t/ha for sugar beet in 2016.

Compared with the processed-based crop models, data driven models approximate complex relationship between input and root crop yield relying on number of data instead of human experience. Regression models are commonly used in data-driven modelling, which have been successfully deployed to predict root crop yield, such as MLR (Dobreva et al., 2021; Sivarajan, 2011), SLR (Bouasria et al., 2021; Rattanasopa et al., 2022), Ridge regression (Sun et al., 2020), RF regression (Ebrahimy et al., 2023) and PLSR (Liu et al., 2021). Some researchers have found correlation between the input and root crop yield, which can be potentially seen as SLR (Al-Gaadi et al., 2016; Konstantinovic et al., 2008). LR has been used commonly in regression models (Ayu

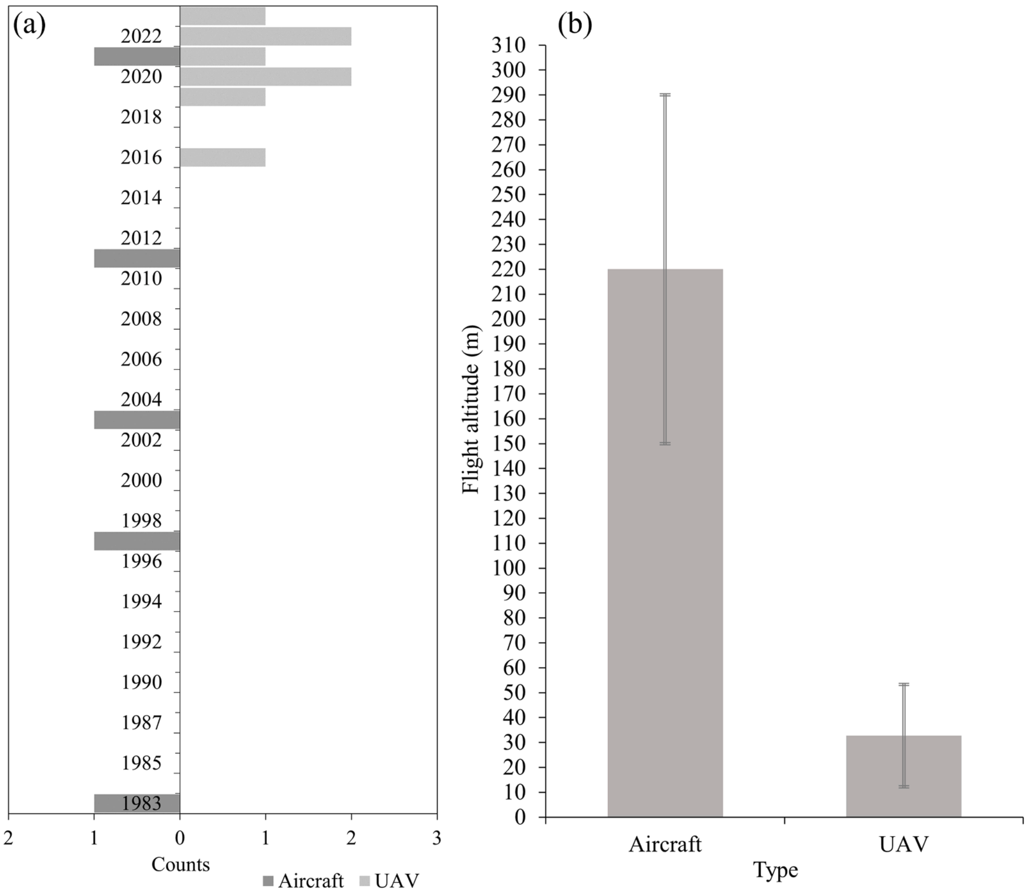

Fig. 2. Aerial platform counts in 1983–2023 (a) and their flying altitudes (b) for yield prediction of root crops. Vertical bar represents standard error.

Table 4
Analysis of remote sensing platform types in terms of advantages, limitations, and applicable scenarios.

Remote sensing platform types	Advantages	Limitations	Applicable scenarios
Spaceborne platforms	Large area coverage, readily available	Limited temporal and spatial resolution in comparison	Field level, county level and above
Aerial platforms	High spatial resolution, flexibility in mission planning	Limited operational range, weather-dependent operations	Plot level
Ground-level platforms	No atmospheric distortion, immediate access to data	Limited area range	Plot level and plant level

Table 5
Shooting distances for ground-level based handheld device.

References	Bu et al. (2016)	Sharma et al. (2017)	Razzaghi et al. (2017)	Elsayed et al. (2021)
Shooting distance (cm)	50	60 ~ 120	100	100

Purnamasari et al., 2019; Knudby, 2004; Luo et al., 2020; Moussa Kourouma et al., 2021; Njane et al., 2023). Some studies have used multiple data driven models to predict root crop yield and found that the models were superior under different conditions (Kumar et al., 2019; Li et al., 2021; Ozalp, 2020; Sharma et al., 2017). Moreover, the choice of predictive model is related to inputs with specific characteristics. Agbona et al. (2023) employed autoregressive models for processing time series data while Larson et al. (2018) obtained GPR lines of cassava for volumetric modelling. Singha and Swain (2022) utilized ordinary kriging based on the geometry feature to generate yield maps of potatoes. The rest of models, such as, the deep Gaussian process and ANFIS-GA model, are mature but not much applied for yield prediction of root crops (Elsayed et al., 2021; Mahdi et al., 2020).

4. Current trends and future perspectives

4.1. Chance of remote sensing platforms for yield prediction of root crops

The majority of root crop yield predictions rely on high-resolution images from Sentinel-2′s MSI sensor, using NDVI and other VIs for accurate root crop yield prediction. Most studies (51 %) utilized spaceborne platforms for yield prediction of root crops, as shown in Fig. 4a. The most commonly used sensor for predicting root crops yield has been the MSI, hosted on Sentinel-2, as shown in Fig. 4b. A further investigation of the data sources using MSI found 10 m spatial resolution satellite images to be the mostly used, which demonstrated the relative high resolution of satellite images to be beneficial to predict root crop yield. In addition, the NDVI has been the most commonly calculated vegetation index from the MSI data and multiple VIs combination is prevalent to yield prediction of root crops.

Despite the popularity of using data from spaceborne platforms, the data is incomplete due to cloud occlusion or availability, especially for optical imagery. On the one hand, clouds scatter visible light reflected from objects, causing optical sensor on satellites to not receive enough light to see objects on the ground. On the other hand, spaceborne platforms operate on fixed observation intervals, which often fail to fully

Table 6
Yield modelling of root crops in terms of input feature, results and specific methods.

Root crop types	Input features	Specific methods	Results	References
Potato	Cloud cover, water vapor, index of El Nino variability	LR	Linear correlation value = -0.6	Chiang et al. (2000)
	NDVI, plant height	Multiple regression	R^2 = 0.5835 ~ 0.9998	Tanabe et al. (2019)
	AGDB, HI, crop moisture	Yield = AGDB × HI/ (1-%moisture)	RMSE = 3.74 ~ 4.25 t/ha	Jaafar and Mourad (2021)
	VCI, TCI	Artificial neural network	Error < 10 %	Akhand et al. (2016)
	NDVI	Ordinary kriging	R^2 = 0.692	Singha and Swain (2022)
	NDVI, GNDVI, SAVI, MASVI2	OLSR	R^2 = 0.44 ~ 0.57	Abou Ali et al. (2020)
	Red, red-edge and infrared bands of the spectrum	SVM	R^2 = 0.93	Gómez et al. (2019)
	PPI	RF regression	R^2 = 0.77	Gómez et al. (2021)
	ET	Monteith's light use efficiency model	Accuracy = 95 % ~ 97 %	Awad and Al-Aawar (2018)
	NDVI, LAI, FPAR	Regression model	Error = 15 %	Bala and Islam (2009)
	Soil moisture, precipitations, temperature, NDVI	ARIMA, SVM	MSE = 0.0199 ~ 0.0954	Ozalp (2020)
	Satellite images	Deep Gaussian process	RMSE = 5.58 ~ 8.18 t/ha	Mahdi et al. (2020)
	NDVI, weather data, soil water, depletion	RF regression	R^2 = 0.56	Vannoppen and Gobin (2022)
	VCI, weather data	Agro-meteorological stepwise regression model, VCI based empirical model	NRMSE = 0.098 ~ 0.218	Kumar et al. (2019)
	VIs, soil data	RF regression	NRMSE = 0.0523 ~ 0.1225	Ebrahimy et al. (2023)
	NDVI	ML	R^2 = 0.34 ~ 0.66	Sharma et al. (2017)
	Total dry matter yield, canopy cover, dry matter, soil water content	AquaCrop	NRMSE = 0.035 ~ 0.059	Razzaghi et al. (2017)
	VIs, LAI	LR	R^2 = 0.83	Luo et al. (2020)
	NRCT, RGB indices	Adaptive neuro-fuzzy inference system with a genetic algorithm (ANFIS-GA)	R^2 = 0.8	Elsayed et al. (2021)
	Full-spectrum, VNIR-only, SWIR-only	PLSR	R^2 = 0.68 ~ 0.82	Liu et al. (2021)
	SAVI	LR	Error = 3.8 % ~ 10.2 %	Al-Gaadi et al. (2016)
	Mean spectrum	Ridge regression	R^2 = 0.63	Sun et al. (2020)
	Full wavelength	PLSR	R^2 = 0.81	Li et al. (2020)
	VIs, cultivar	ML	R^2 = 0.75 ~ 0.79	Li et al. (2021)
	Volume, LCI	LR	R^2 = 0.96 ~ 0.99	Njane et al. (2023)
	ET, ISAVI	MLR	R^2 = 0.88	Sivarajan (2011)
	SAVI	Regression model	R^2 = 0.92	Jayanthi (2003)
	Weather data, soil data, land use data	AgroC	Error = 0.1 ~ 0.4t/ha	Brogi et al. (2020)
Carrot	VIs	LR	R^2 = 0.77	Al-Gaadi et al. (2022)
Cassava	Averaged energy density	LR	R^2 = 0.91	Teare (2021)
	GPR lines	Volumetric modelling	/	Larson et al. (2018)
	GPR feature	Bayesian Ridge Regression	R^2 = 0.41	Agbona et al. (2021)
	VIs, FAPAR, LAI	LR	R^2 = 0.77	Ayu Purnamasari et al. (2019)
	Variance of signal amplitude	Autoregressive model	Standard error = 9.57	Agbona et al. (2023)
	VIs, plant height, canopy area	LR	R^2 = 0.50 ~ 0.87	Rattanasopa et al. (2022)
Peanut	Color indices	LR	R^2 = 0.39	Balota and Oakes (2016)
	Integrated NDVI	LR	RMSE = 176 kg/ha	Knudby (2004)
	GPR feature	Multiple linear regression	RMSE = 279 g	Dobreva et al. (2021)
	Mean and standard deviation of spectral reflectance	CNN, MLP regressor	R^2 = 0.45 ~ 0.73	Bagherian et al. (2022)
Sweet potato	VIs	MTR	MAE = 2.66 ~ 3.55 t/ha	Tedesco et al. (2021)
	NDVI, VCI	LR	R^2 = 0.127	Moussa Kourouma et al. (2021)
Sugar beet	NDVI , Meteorological data	LR	Error = 3.8 t/ha	Hongo and Niwa (2012)
	VIs, canopy height	Regression model	R^2 = 0.615	Bu et al. (2016)
	VIs	SLR	RMSE = 9.93 t/ha	Bouasria et al. (2021)
	Green leaf aera	PROMET	R^2 = 0.44 ~ 0.90	Hodrius et al. (2015)
	NDVI, Meteorological data	Monteith's light use efficiency model	/	Ghorbanpour et al. (2022)
	Backscattered energy	Regression model	Accuracy > 0.8	Konstantinovic et al. (2008)
	fraction of photosynthetically active radiation	SUCROS	R^2 = 0.98	Clevers (1997)
	Red band, infrared band	Mathematical model	Error < 6 %	Steven et al. (1983)
	SAVI	Regression model	R^2 = 0.84	Jayanthi (2003)
	Weather data, soil data, land use data	AgroC	Error = 0.1 ~ 0.4 t/ha	Brogi et al. (2020)
	NDVI, weather data, soil water, depletion	RF regression	R^2 = 0.84	Vannoppen and Gobin (2022)

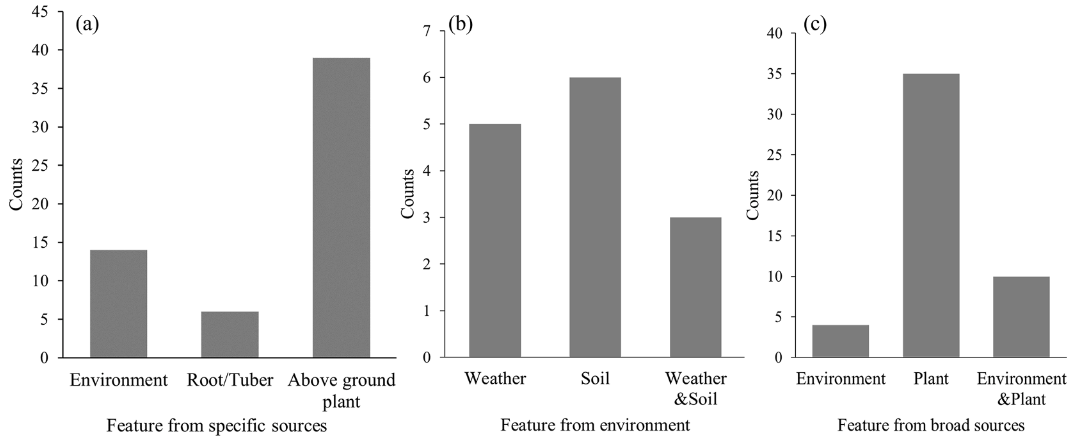

Fig. 3. Number of studies based on different feature classification. Classification of input features from three specifc sources (a); classifcation in terms of environmental features (b); and classifciation of input features from environment, plant and both application (c).

Table 7
Analysis of modelling methods in terms of advantages, limitations, and applicable scenarios.

Modelling methods	Advantages	Limitations	Applicable scenarios
Process-based crop models	Accurate representation of physiological processes	Parameter extensiveness, less adaptability to changing conditions	Detailed understanding of crop physiology, simulation of growth stages
Data driven models	Flexibility to adapt to various datasets, can handle complex and non-linear relationships	Interpretability deficit, sensitivity to data quality	Large and high-quality datasets

align with the critical growth stages of plants. This temporal mismatch results in incomplete data, limiting the ability to capture the full dynamics of crop development and potentially compromising the accuracy of yield predictions. For cloud occlusion, deep learning-based methods were proposed for cloud-free image reconstruction and showed promising results on satellite image dataset (Ivanchuk et al., 2023; Oehmcke et al., 2020). Generation of synthetic satellite images using deep learning-based methods is a possible solution to increase availability of satellite data (Abady et al., 2022, 2020).

GPRs should be mentioned particularly since its signal is exposed to root crop tuber directly, which has the potential for root crop yield prediction. GPRs explore the subsurface of the earth to depths ranging from s a few centimeters to several kilometers under ideal conditions, which is sufficient to detect tuber or root underground. GPRs measure both the amplitude and the travel time of the reflected energy from tuber or root while the measured data do not need to analyze the plant growth using the processed-based crop models, as shown in Fig. 5b.

However, there are some problems needed to be solved. GPR data are in the time domain and do not represent spatial relations, as shown in Fig. 5a, which makes it difficult to interpret visually and relate it to the root crop yield, especially the root crop weight. Larson et al. (2018) utilized Voxler software to visualize cassava root underground with three dimensional (3D) models, as shown in Fig. 5c. A significant bulk of cassava roots were in the unmeasured area marked “Area Not Imaged” as the above ground cassava stalks obstructed the imaging areas. Dobreva et al. (2021) attempted to mitigate this limitation by tilting the GPR towards the peanut plants to reduce interference from the above-ground portions, as shown in Fig. 5d. While this tilting method mitigated interference, it caused vertical misalignment of the GPR data between channels. To address this, the surface return on each B-scan was visually identified, and the data were time-shifted to align with a common temporal reference (Dobreva et al., 2021).

4.2. Input features related to root crop yield

Feature combination from environment and crop itself is beneficial to crop yield prediction models simulating crop growth, particularly the processed-based crop models. The processed-based crop models aim to quantitatively explain the physiological processes of root crops, relying on energy conversion, with key conversion efficiencies including radiation interception efficiency, conversion efficiency, and partitioning

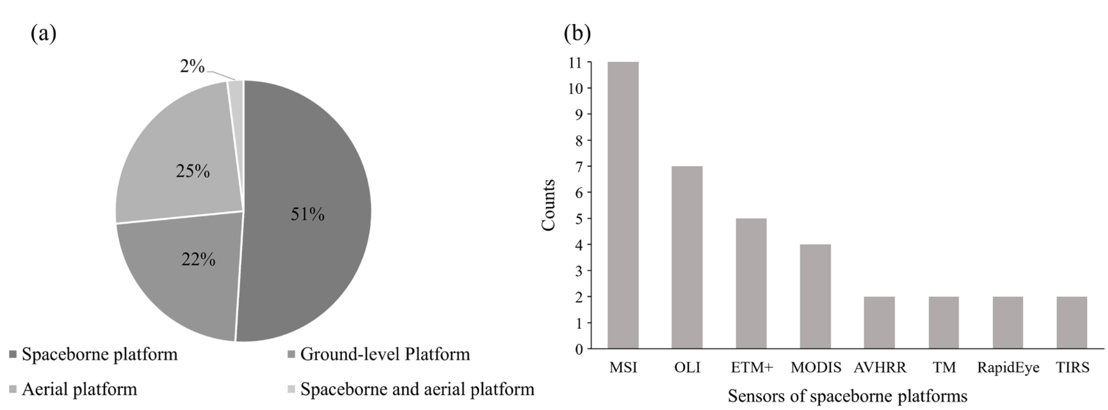

Fig. 4. Main platform and sensor statistic of for yield prediction of root crops. (a) The proportion of platforms for yield prediction of root crops; (b) Sensors from spaceborne platforms (usage more than once).

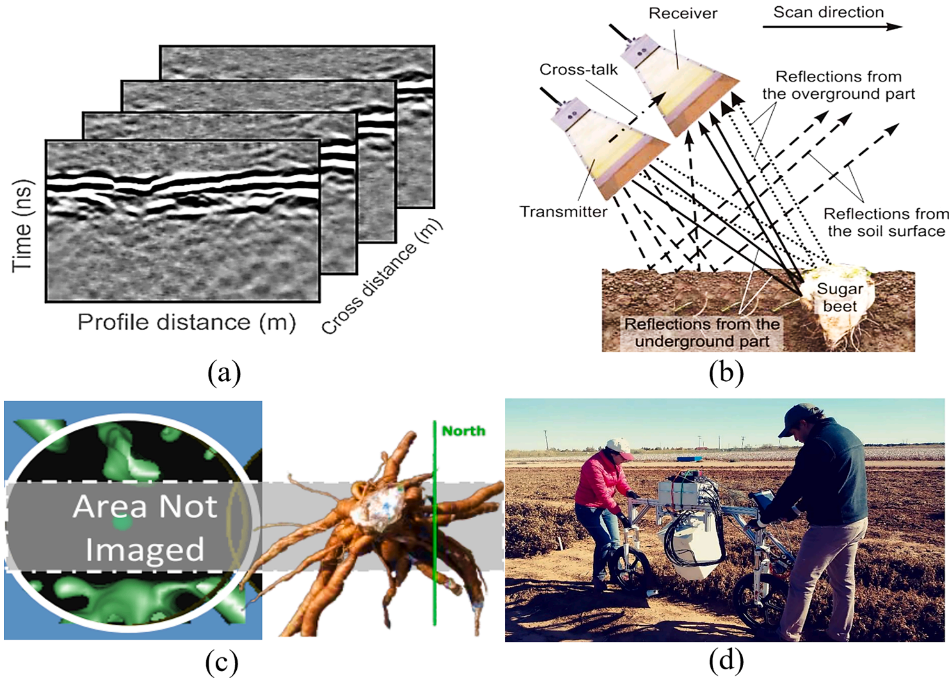

Fig. 5. Some examples of GPR. (a) GPR data cube of GPR, refer to Dobreva et al. (2021); (b) Principle of GPR, refer to Konstantinovic et al. (2008); (c) A 3D model of cassava root and its ground truth, refer to Larson et al. (2018); (d) Tilted GPR, refer to Dobreva et al. (2021).

efficiency (Silva-Díaz et al., 2020). Except for partitioning efficiency, interception efficiency is affected by above ground plant structure while conversion efficiency is formalized as radiation use efficiency and influenced by environment (Sadras et al., 2016; Silva-Díaz et al., 2020). Therefore, diverse features from environment and the crop itself enhance providing insights to explain this energy conversion. When it comes to many various features and not all predictor variables are equally important to yield prediction model, it is important to select features to reduce data collection cost (He et al., 2022). Relief-based algorithms are mostly used for canopy features selection of root crops, which eliminates features based on their relevance to the categories (Li et al., 2020; Sun et al., 2023).

Convolutional neural networks (CNN) learn features without manual feature extraction, making them highly suitable for building flexible relationships between input and root crop yield. Existing features or their combinations do not fully explain root crop yield, which make feature selection difficult. Mahdi et al. (2020) employed the deep Gaussian process that combines Gaussian Process and CNN to predict potato yield from satellite imagery, which achieved a RMSE of 5.58 ~ 8.18 t/ha. There are no studies employing CNN for yield prediction of root crops on plot scale. One study predicted rice yield from UAV imagery utilizing ConvNeXt, achieving an R^2 value of 0.98 (Yang et al., 2023). While manual feature extraction is not necessary for CNN, the model is lacking of interpretability and requires a large and high-quality dataset, as shown in Table 7. Therefore, further consideration should be given to data type and collection time that is related to root crop yield prediction models.

4.3. Collection time and frequency of root crop data for yield prediction

The optimal timing for collecting multispectral and hyperspectral data is crucial for accurately predicting root crop yields, as the time domain can significantly influence the data's correlation with yield outcomes. Multispectral and hyperspectral data are mostly used in yield prediction of root crops. Li et al. (2021) showed multispectral data from early growing season were more correlated with potato yield than later growing season while Li et al. (2020) found the potato yield prediction model based on data collected 90 days after planting (DAP) was better than the model from 60 DAP using hyperspectral imaging. Influence of crop growth stages on spectral characteristics and varying sensitivity of multispectral and hyperspectral data to yield-related features at different stages make multispectral data more advantageous in early stages and hyperspectral data more effective in later stages, highlighting the importance of determining specific types of root crop data required before deciding on the timing of data collection.

Yield response of root crops depends on their growth status, which is related to cultivar, climate, and management (Ierna and Mauromicale, 2018; Li et al., 2021; Zemba et al., 2013). Developing date-specific yield prediction models would not be generalizable outside of a given date despite their performance being well (Liu et al., 2021). Meanwhile, it is unrealistic to capture all dimensions of variation affecting a crop. It is suggested that full-cycle data be used to increase robustness of root crop yield prediction models. Given the high cost of full-cycle data collection, data is gathered once or twice a month to improve data availability, ensuring alignment with the entire growth period of root crops (Ayu Purnamasari et al., 2019; Rattanasopa et al., 2022). Particularly, data are collected at least once during each specific growth stage (Liu et al., 2021).

4.4. Scale of yield prediction of root crops

The scale of yield prediction of root crops ranges from plant level to global scale, depending on the specific objectives of each study. Root crop yields obtained from less-than-field-level studies were predicted for their agronomy management while the other larger-than-field-level studies were mostly for national statistics. The scale of root crop yield predictions largely determines applicable scenarios of remote sensing platforms, as shown in Table 4. The highest resolution of spaceborne platforms reaches meter level, which is used for yield prediction on field level or larger (Ebrahimy et al., 2023). Both aerial and ground-based platforms support yield prediction on plot level while ground-based platforms detect plants by plants.

Plant-by-plant detection was only applied to radar-based platforms while spectral-based platforms still are in plot level since above-ground plant environment is more complex than underground environment (Larson et al., 2018). Measuring above ground crop phenotypes at plant level has been shown to be superior to obtaining them from plot scale (Shen et al., 2024). Individual above ground phenotypic traits serve as predictive factors, and their accuracy directly influences the yield of root crops, which presents a potential direction for improving the yield prediction of such crops. While there are no studies on plant-by-plant yield prediction based on above-ground parts, some initial research has been conducted on leaf and stem segmentation of root crops in the field (Barreto et al., 2023; Jiang et al., 2024).

4.5. Conclusions

A comprehensive review was presented for yield prediction of root crops including remote sensing platforms, input features and modelling methods. Root crops share a common characteristic of producing edible parts underground, which requires predicting their yields. Spaceborne platforms have been widely used to access aboveground-based factors and establish relationships with root and tuber crop yields, which rely heavily on data quality, model robustness and applicability. GPRs, on the other hand, provide direct access to root and tuber signals from which root crop yield can be obtained, with initial applications in sugar beet, peanut and cassava. Feature combination from environment and crop itself is beneficial to crop yield prediction models simulating crop growth, particularly the processed-based crop models. It is recommended to collect data time after ensuring specific root data types. To increase adaptability and accuracy of yield prediction models, full-cycle data monitoring and individual above ground phenotypic traits are suggested. An inherent challenge lies in differential discernibility of growth stages; specifically, later growth stage of development exhibits a greater complexity in delineation compared to the initial growth stage. Data fusion from different phases is a possible solution. As root crop yield prediction involves multiple disciplines such as agriculture, remote sensing, data science, their convergence is poised to offer unprecedented insights into root crop yield predictions through the synergy of multidisciplinary expertise in the future.

CRediT authorship contribution statement

Hanhui Jiang: Writing – original draft, Formal analysis, Data curation, Conceptualization. **Liguo Jiang:** Data curation, Formal analysis, Writing – review & editing. **Leilei He:** Writing – review & editing, Formal analysis. **Bryan Gilbert Murengami:** Writing – review & editing, Data curation. **Xudong Jing:** Writing – review & editing, Data curation, Conceptualization. **Paula A. Misiewicz:** Writing – review & editing, Investigation. **Fernando Auat Cheein:** Writing – review & editing, Investigation. **Longsheng Fu:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization.

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.

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Data availability

No data was used for the research described in the article.

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