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Exploring the utility of remote sensing technology in vegetation below ground biomass (BGB) estimation: a critical review of methods and challenges

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Understanding vegetation Below Ground Biomass (BGB) dynamics is essential to ensure long-term ecological functions such as carbon sequestration and optimizing critical tuber crops productivity. Whereas the utility of remote sensing in assessing vegetation Above Ground Biomass (AGB) is well documented in literature, studies using this technology to estimate BGB have become elusive due to technical challenges of direct underground sensing. Therefore, this study aims to critically review the methods and challenges in adopting remote sensing technology for estimating vegetation BGB, while proposing a consolidated approach for improving the accuracy of subsurface biomass assessment. The review indicates that although remote sensors do not directly measure underground, variations in BGB can be inferred through deriving canopy vegetation indices, where machine learning algorithms and empirical relationships play a crucial role in extrapolating these indices to predict subsurface biomass. While optical multispectral and hyperspectral sensors provide critical canopy biophysical information, offering invaluable insights about BGB status, these cameras are constrained by atmospheric interference and inability to penetrate dense vegetation. Active remote sensing cameras such as LiDAR do not provide biophysical information, however, they stand out for their ability to penetrate atmospheric conditions, dense vegetation, and provide topographic information, that can improve BGB estimation. Amongst the challenges highlighted, the review raises concerns about the reliability of using the remote sensing of vegetation AGB status and canopy spectral reflectance for estimating BGB, considering the influence of seasonality in crown cover fluctuations. Nevertheless, advances in Unmanned Aerial Vehicle (UAV) platforms coupled with smart optical and active sensors remain promising for accurately assessing vegetation BGB while overcoming various limitations such as low spatial resolution, long revisit cycles, and atmospheric influence. This review has consolidated methods for estimating vegetation and crop BGB, allowing researchers to evaluate their choice of technique based on the tradeoffs between sensors spectral characteristics, spatial coverages, and practicality.

KEYWORDS

remote sensing, below ground biomass, vegetation, tuber crops, methods, challenges

1 Introduction

Sources of vegetation biomass that include forests, shrubs, and grasslands play a crucial role in maintaining ecosystem health and resilience, serving as vital components for carbon sequestration, thereby mitigating climate change by prolonged storage of underground carbon stocks (Bai et al., 2022; Thompson et al., 2009). Vegetation biomass also provides critical ecosystems services such as regulating the water cycle, controlling floods, stabilizing the climate, and providing habitats that sustain fauna biodiversity (Abdullah et al., 2021). The accumulation of vegetation biomass is vital for the development of strong and abundant root systems, essential for supporting long-term adaptation to climate change and continuous provision of ecosystem services (Butnor et al., 2003). Similarly, crop biomass is a critical indicator of yield, reflecting the growth status, effectiveness of existing agricultural practices, and providing early warning systems for timely interventions to environmental stressors (Lecerf et al., 2019). Crops with well-developed biomass are more effective at capturing sunlight and absorbing nutrients and water from the soil, which contributes to higher productivity and yields (Servia et al., 2022). Therefore, monitoring vegetation biomass, including crops, is crucial for maintaining ecosystem health and resilience to ensure long-term ecological functions, and allowing timely interventions to optimize yields (Thiffault et al., 2011; Battude et al., 2016).

The characterization of vegetation biomass involves both Below-Ground Biomass (BGB) and Above-Ground Biomass (AGB), that includes the roots, leaves, stems, and vines (Singnar et al., 2021). Vegetation BGB is particularly essential because it stabilizes soils, reduces erosion, and optimizes water infiltrations, considerably supporting above ground biodiversity and productivity (Gregory, 2022). Due to practical challenges related to digging well-established roots and concerns regarding deforestation, ecosystem fragmentation, and crop yield losses associated with destructive sampling of field BGB data, most studies have extensively focused on assessing the AGB (Barbosa et al., 2014). However, this has significantly hindered understanding of subsurface biomass dynamics, resulting in an underestimation of the full potential of BGB; subsequently limiting the development of effective climate change mitigation strategies and accurate tuber and nut crop yield estimates (Streit et al., 2019). Therefore, adopting innovative approaches to monitor BGB across diverse vegetation and cropping systems is essential for achieving climate resilient ecosystems and sustainable food systems at a global scale (Fidelis et al., 2013).

Conventionally, vegetation BGB assessment involves destructive, laborious, and time-consuming approaches such as manual harvests, weighing, and extensive calculations (Næsset and Gobakken, 2008). Although studies like Næsset and Gobakken (2008), Sharma et al. (2022), Singh et al. (2022) have deemed this approach accurate, concerns regarding its practicality over large spatial extents and repeated observations remain (Tian et al., 2021). Furthermore, yield losses due to continuous destructive sampling for multitemporal biomass assessment is also regarded as its major limitation (Zhang and Zhang, 2022). Therefore, cost-effective and innovative approaches such as remote sensing technology have been proposed to address these challenges (Sharma et al., 2022; Geng et al., 2021). Remotely sensed data enables for the computation of optimal vegetation indices and metrics, based on AGB status and canopy spectral characteristics, ultimately allowing for BGB estimation (Bala and Islam, 2009).

Even though optical remote sensors do not directly measure underground (Tian et al., 2023), estimating vegetation BGB from these datasets typically relies on the assumption that subsurface biomass accumulation relies on canopy biochemical and physical characteristics such as photosynthetic rates (Gómez et al., 2019). The variations in these characteristics can be inferred through deriving canopy vegetation indices, where machine learning algorithms and empirical relationships play a crucial role in extrapolating these indices to predict BGB Suarez et al. (2020). Consequently, using vegetation canopy reflectance, remote sensing technology remains a promising solution for sustainably assessing BGB at large spatial extents and repeated observations, without compromising yields and ecosystem resilience (Abbas et al., 2020; Guerini Filho et al., 2020). Advancements in optical remote sensing over the past decades have led to the development of spaceborne multispectral and hyperspectral sensors such as PlanetScope, Sentinel-2, and Earth Observing-1 Hyperion (Bala and Islam, 2009; Suarez et al., 2020; Baloloy et al., 2018; Kattenborn et al., 2015; Jacon et al., 2021). These satellite sensors capture data across multiple spectral bands of the electromagnetic spectrum, enabling the computation of advanced vegetation indices that are optimized for estimating vegetation BGB from canopy reflectance with greater accuracy and precision (Xue and Su, 2017).

The relationship between canopy measured vegetation indices such as the Enhanced Vegetation Index (EVI), and agronomic characteristics such as BGB is well established in literature (Chapungu et al., 2020; Perry et al., 2022; Farias et al., 2023). For instance, Gómez et al. (2019) successfully estimated potato yield using spectral vegetation indices derived from the freely available 10-m-medium resolution Sentinel-2 dataset. The availability of these freely accessible satellite datasets offer a leverage for long term and large scale estimation of vegetation BGB at canopy reflectance level (Ghaderizadeh et al., 2021). Despite this success, technological limitations, such as surface information accuracy, mixed pixel issues, cloud contamination, vegetation index saturation, and low spatial resolution associated with satellite optical remote sensing remain disputed (Xia and Jia, 2022). Alternatively, space-borne laser and radar sensors, such as the Multi-Sensing Observation LiDAR and Imager (MOLI), Sentinel-1 Synthetic Aperture Radar (SAR), and BIOMASS P-band SAR, have been deployed to provide atmospheric interface-free and 3-Dimensional (3D) datasets, overcoming some of the limitations associated with optical satellite data (Rodríguez-Veiga et al., 2017).

LiDAR and SAR sensors, with their powerful laser and radar technology, respectively, penetrate the canopy and capture detailed structural information about both the ground and vegetation, enabling precise BGB estimations (Luo et al., 2017). For instance, the weather independent Sentinel-1 SAR data uses the 5.4 GH C-band to penetrate dense vegetation canopy, providing critical information such as topography, AGB structure, and moisture content, which convey subsurface biomass status through allometric equations, subsequently allowing for accurate BGB measurements (Suarez et al., 2024). Despite the potential of satellite LiDAR and Sentinel-1 SAR based measurements in accurately estimating vegetation BGB, these approaches remain limited by low spatial and temporal resolution. The emergence of Unmanned Aerial Vehicles (UAVs) featuring customizable data acquisition frequencies has presented an opportunity to integrate high spatial resolution sensors, ultimately bridging the gap between satellite remote sensing approaches and ground based measurements (Abiodun, 2020). Unmanned aerial vehicles are airborne platforms that can leverage advanced and high resolution sensors, ranging from LiDAR, multispectral, and hyperspectral cameras, allowing for close range vegetation and crop BGB monitoring (Liu et al., 2020).

The advancements in high-precision UAV platforms and satellite remote sensing have significantly enhanced the estimation of vegetation BGB by broadening the range of available data sources, offering varying spatial extents and spectral resolutions (Abdullah et al., 2021). Unmanned aerial vehicles can capture high resolution images over small spatial extents, while satellite constellations provide broader coverage with lower spatial resolution (Luo et al., 2017). Together, these remote sensing platforms enable more comprehensive and precise monitoring of vegetation BGB, supporting applications in various fields including agriculture, forestry, and grasslands. Despite the availability of various remote sensing datasets, few studies including Chen et al. (2023), have extensively assessed vegetation BGB compared to AGB (Næsset and Gobakken, 2008). This disparity has considerably restricted understanding of the value of vegetation BGB in climate change mitigation and the role of tuber crops in combating food insecurity (Fidelis et al., 2013; Servia et al., 2022). Whereas few studies, including Al-Gaadi et al. (2016), Bala and Islam (2009), Bolinder et al. (2015), have utilized remotely sensed data to estimate vegetation BGB, a comprehensive review of the methods and challenges of remote sensing for subsurface biomass estimation has remained elusive.

Reviewing the methods and challenges in the adoption of remote sensing to estimate subsurface biomass is essential to provide valuable insights and guidelines for future studies, allowing researchers to identify suitable approaches that can overcome challenges of using this technology for vegetation BGB estimation. Hence, this study aims to conduct a critical review of the utility of remote sensing technology in assessing vegetation and crops BGB. This review evaluates the efficacy and limitations of existing remote sensing methodologies, focusing on their application to BGB estimation in various vegetation and crop types. The review critically examines the progress accomplished in remote sensing techniques, including advancements in sensor technology, data acquisition, and analytical approaches. The study further explores emerging trends and provides insights to guide the development of innovative and scalable approaches for vegetation and crops BGB estimation, contributing to both ecological research and precision agriculture applications.

2 Literature search and inclusion

Relevant publications were retrieved from Google Scholar to identify potential key terms for formulating the search string, as suggested by Aromataris and Riitano (2014). Thereafter, the following string was formulated: "Remote sensing" OR "Geographic information system" OR "Earth Observation" OR "Satellite" AND "Below Ground Biomass" OR "Tuber Biomass" OR "Root Biomass" OR "Subsurface Biomass" OR "Underground Biomass" OR "Subsoil Biomass". A comprehensive literature database was then conducted using the search string on the Web of Science (WOS), Scopus, and Science Direct scientific databases on 19 August 2024 (Table 1). These scientific databases were chosen based on pervious literature reviews conducted on similar topics (Ndlovu et al., 2024; Sibiya et al., 2025). The literature search was limited to the tittles, abstracts, and keywords of the publications without restricting the year of publication and geographic location. Furthermore, literature reviews were excluded in the literature search, and only publications written in English were considered for practicality and to avoid language discrepancies.

2.1 Data extraction and analysis

A total of 785 publications were initially retrieved from the WOS, Scopus, and Science Direct databases (Figure 1). After removing 326 duplicates and 67 non-full text articles, the abstracts of the remaining publications were critically evaluated to identify those focused on the remote sensing of vegetation BGB. Subsequently, 43 publications were identified as suitable for inclusion in the review. Thereafter, by examining the reference lists of these 43 publications, 7 relevant articles were added, resulting in a final total of 50 publications included.

The final 50 publications included in this review were critically read from abstract through the results, discussion, and conclusion, and data extracted and recorded in Microsoft Excel. The extracted data included various aspects such as vegetation types, remote sensing platforms and sensors, methodologies employed, key findings, limitations, and recommendations. Therefore, the results of this review reflect the in-depth analysis of the content of these publications.

3 Progress in the application of remote sensing in estimating vegetation BGB

3.1 Vegetation types identified in literature

The inception of remote sensing technology, offering a wide variety of sensors including spaceborne, airborne, and proximal remote sensing, has successfully enabled the assessment of vegetation and crops BGB across various ecosystems. Amongst others, this review noted extensive use of X-ray imaging, magnetic resonance, electrical and seismic methods, multispectral, hyperspectral sensors, and Red-Green-Blue (RGB) sensors. Furthermore, as shown in Figure 2, remote sensing technology has been used to estimate BGB across various vegetation types, including tuber crops, vegetables, forests, grasslands, orchards, and shrubs. This review further indicates that remote sensing technology has been predominantly applied in tuber crops, followed by forests and sand trees compared to other vegetation.

The recent response to climate action has drawn more attention to forest research to comprehensively optimize techniques on

TABLE 1 Topical terms used in the literature search.

Search platform	Search criterion	Articles retrieved
Scopus	(TITLE-ABS-KEY (remote AND sensing) OR TITLE-ABS-KEY (earth AND observation) OR TITLE-ABS-KEY (satellite) OR TITLE-ABS-KEY (geographic AND information AND system) AND TITLE-ABS-KEY (below AND ground AND biomass) OR TITLE-ABS-KEY (root AND biomass) OR TITLE-ABS-KEY (subsurface AND biomass) OR TITLE-ABS-KEY (subsoil AND biomass))	138
Science direct	"Remote sensing OR Geographic information system OR Earth Observation OR Satellite AND Below Ground Biomass OR Tuber Biomass OR Root Biomass OR Subsurface Biomass OR underground Biomass OR Subsoil Biomass"	178
Web of science	Remote sensing (Abstract) OR Earth observation (Abstract) OR Geographic information system (Abstract) OR Satellite (Abstract) AND below ground biomass (Abstract) OR Root biomass (Abstract) OR subsurface biomass (Abstract) OR tuber biomass (Abstract) OR Underground biomass (Abstract) OR subsoil biomass (Abstract) and Open Access and Article (Document Types) and Open Access and Article (Document Types) and All Open Access (Open Access) and REMOTE SENSING (Publication Titles) and English (Languages) and Remote Sensing or Imaging Science Photographic Technology or Environmental Sciences Ecology (Research Areas)	469

carbon sequestration (Dainelli et al., 2021). In addition, forests ecosystems are characterized by high economic value in revenue as trees are predominantly used for various applications such as timber (Fassnacht et al., 2024). Likewise, agricultural crops such as the Neglected and Underutilized Crops (NUCs) have recently gained popularity due to their high nutritive value and potential to enhance food security (Mudau et al., 2022). Furthermore, the recent population growth and high demand for food has brought attention to agricultural crops research, aiming to optimize production and meet the growing demand (Mabhaudhi et al., 2022). For instance, studies like Jewan et al. (2022) assessed the utility of commercial UAV platforms and low cost cameras in estimating Bambara groundnut yield to optimize its production. Despite grasslands and shrubs forming an essential source of grazing and browsing in large ecosystems such as rangelands and protected areas as noted by Masenyama et al. (2022), very few publications were recorded in this regard (Figure 2). Nevertheless, grasslands and rangelands provide essential ecosystem and socioeconomic services as reported by Chapungu et al. (2020), hence further research is needed to fully assess and maintain their stability.

3.2 The evolution of remote sensing technology in estimating vegetation BGB

The temporal distribution and frequency of sensors used in literature for estimating vegetation BGB is shown in Figure 3. The use of remote sensing technology in estimating vegetation BGB was established over 2 decades ago, noting its durability and long-term adoption. Notably, proximal remote sensing devices such as Analytical Spectral Devices (ASD), Electrical Resistivity Tomography (ERT), and Ground Penetrating Radar (GPR) recorded the most publications for various reasons, including their long-term existence since 1999, marking the beginning of remote sensing adoption in vegetation BGB estimation. Proximal remote sensing devices (Table 2) offer superior accuracy in comparison to other remote sensing techniques because they are employed close to the target vegetation, providing site-specific measurements that are less affected by external factors such as cloud cover, low spatial resolution, and temporal delays (Zhu et al., 2014; Streit et al., 2019; Rossi et al., 2011). Despite this prosperity, proximal remote sensing is considerably restricted by long term and frequent observations particularly in large spatial extents due to manpower required to carry these devices (Suarez et al., 2020; Wang et al., 2023a). To address these, a decade later in 2009, spaceborne remote sensing platforms were adopted to assess vegetation BGB at relatively lower spatial resolution and prolonged revisit cycles. Despite satellite remote sensing having relatively lower spatial and temporal resolution, many studies including Liao et al. (2022), Bala and Islam (2009), Carbajal-Carrasco et al. (2024) have successfully leveraged this dataset for more than a dozen years to assess vegetation BGB. However, it is essential to note that majority of optical satellite remote sensing datasets such as the Sentinel series, have been accessible for over a decade at no cost, which has also contributed to their increasing and widespread adoption for estimating vegetation BGB (Bala and Islam, 2009; Middleton et al., 2013).

Despite the wide and long term adoption of satellite remote sensing, literature has proven this approach to be prone to atmospheric interference, particularly in summer under limited cloud free scenes (Chapungu et al., 2020). This approach is further limited by prolonged revisit cycles and low spatial resolution, considerably restricting its application in small spatial extents, such as small-scale farming systems (Tedesco et al., 2021; Bouasria et al., 2021). To address these challenges, remote sensing cameras have been revolutionised and miniaturised to fit into aerial vehicles such as drones, allowing hovering under cloud cover and enabling acquisition of high spatial resolution datasets (Jewan et al., 2022). This adaptation accounts for relatively larger spatial extents while maintaining high spatial resolution datasets and user defined frequency of observations (Saif et al., 2023). However, whereas manned aircrafts systems were adopted from 2008 to 2015, only two publications were retrieved during this period (Kristensen et al., 2015; Næsset and Gobakken, 2008). This is because the operation of manned aircraft systems demands extensive training and significantly costly, thus raising concerns about their cost-effectiveness and overall worthiness (Jang et al., 2020). Therefore, in 2017, publications adopting cost effective UAV systems emerged, signalling the revolution of vegetation BGB remote sensing (Luo et al., 2017). This approach enabled the mounting of very small and high-resolution sensors on UAV platforms such as LIDAR, multispectral, and hyperspectral cameras, facilitating a cost-effective, efficient data acquisition, subsequently bridging the gap between satellite, proximal, and manned aircraft systems (ten Harkel

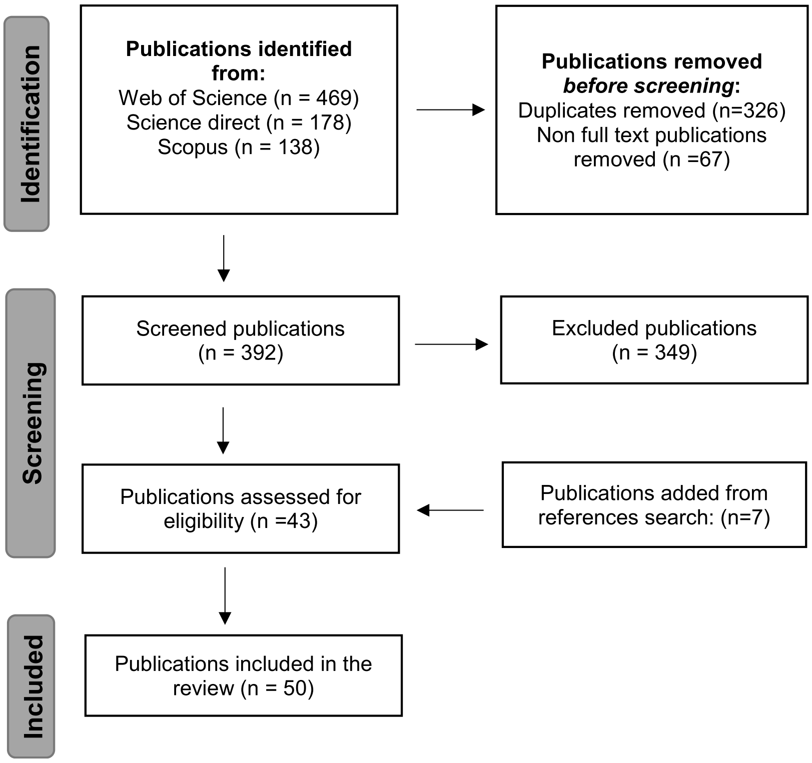

FIGURE 1
Literature search, exclusion, and inclusion flow diagram.

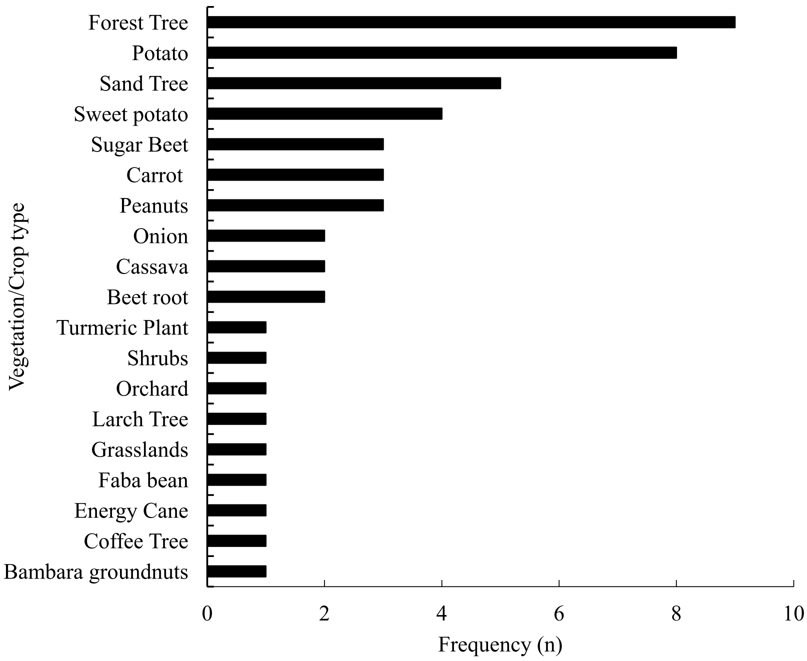

FIGURE 2
The frequency of vegetation types used in below ground biomass estimation.

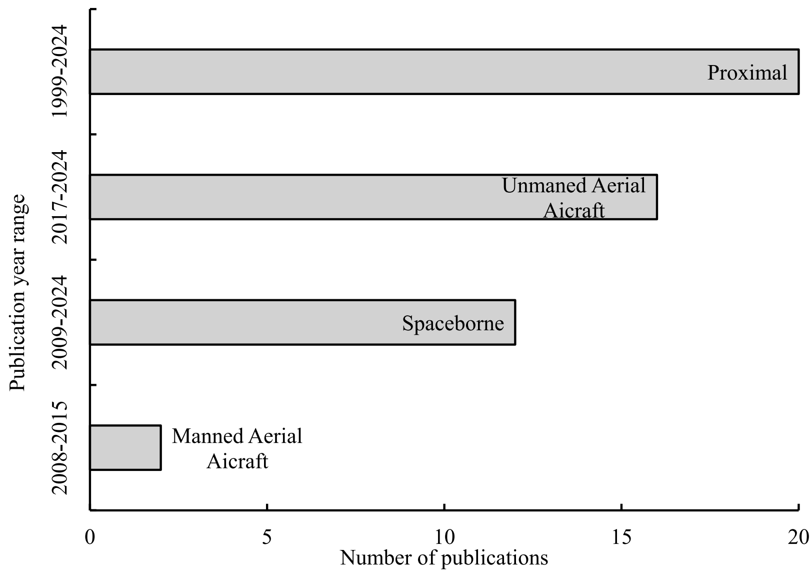

FIGURE 3
The temporal distribution of different sensor platforms used to estimate vegetation BGB.

et al., 2020). Since then, most publications on vegetation BGB estimations have been acquired using UAV remote sensing, noting the efficiency and practicality of this approach.

3.3 Remote sensing platforms, sensors, and spectral features used to assess vegetation BGB

Table 1 presents information on remote sensing platforms and their associated sensor characteristics, including spatial resolutions and spectral bands used to assess vegetation BGB. The results highlight the growing adoption of proximal, spaceborne, and airborne remote sensing over the recent decades for assessing vegetation BGB (Table 2). These results further indicate consolidated information that demonstrates the effectiveness of various sensor spectral characteristics such as the spatial resolution, spectral bands, and bandwidth in modelling vegetation BGB, providing valuable insights and guidance on suitable approaches for future research (Zhu et al., 2014; Streit et al., 2019; Bala and Islam, 2009). The findings in table 1 only show the spectral characteristics of sensors that have proven proficient in accurately estimating vegetation BGB, rather than focusing solely on the overall spectral characteristics of the sensors themselves (Cui et al., 2012; Næsset and Gobakken, 2008). For example, while sensors like MODIS feature Shortwave Infrared (SWIR) and thermal bands, these were not included in this study due to lack of evidence in literature for their utility in assessing vegetation BGB (Bala and Islam, 2009). In this regard, a significant dominance of the visible, NIR, and red edge bands in estimating vegetation BGB was noted for prominence in enabling the computation of optimal vegetation indices for BGB estimation such as the Normalised Difference Vegetation Index (NDVI) (Bouasria et al., 2021; Pugh et al., 2024; Li et al., 2021).

The visible portion of the electromagnetic spectrum ranges from 440 to 700 nm, consisting of the Red, Blue, and Green spectral bands, is essential for reflecting light and subsequently contributing to the detection of vegetation physical and colour characteristics (Teng et al., 2019). The NIR portion ranging from 700 nm to 1,100 nm section of the electromagnetic spectrum, plays an immense role in estimating vegetation biomass and health (Sun et al., 2020). For instance, vegetation chlorophyll primarily absorbs in the blue and red portions of the visible spectrum, and reflects green light, contributing to the green colour perceived by human eyes and remote sensing cameras (Selvaraj et al., 2020). In addition to this, Vegetation strongly reflects light in the NIR region, enabling the quantification of biochemical and biophysical characteristics (Shahi et al., 2023). Typically, the variations in chlorophyll reflectance, particularly in the Red and NIR band allows for the computation of vegetation indices that can infer BGB such as NDVI (Praseartkul et al., 2023). These indices are essential for assessing vegetation health and, by extension, indicate the presence of a well-developed BGB capable of absorbing adequate nutrients and water, supporting the formation of healthy canopy and AGB (Bu et al., 2016).

The Red-Edge portion ranges from 690 nm to 750 nm in the electromagnetic bands, marking the transition from the Red to NIR section (Tahir et al., 2020). The Red-Edge portion is sensitive to photosynthetic activity and is essential for computing advanced vegetation indices such as the Normalized Difference Red Edge (NDRE) Index for quantifying AGB productivity (Abdullah et al., 2021). The quantification of AGB productivity is closely linked to the development of BGB, as there is a strong relationship between the two variables (Jewan et al., 2022). This relationship arises from the fact that both AGB and BGB are influenced by similar edaphic factors such as soil nutrients, soil moisture availability, and overall plant health (Bala and Islam, 2009). A well-developed BGB typically supports robust AGB growth by enhancing the ability of vegetation to absorb water and nutrients, which in turn promotes higher biomass production above ground (Al-Gaadi et al., 2016).

TABLE 2 Specification of remote sensing technology used in assessing vegetation below ground biomass.

Platform	Sensor	Category	Spectral bands used	Spatial resolution	Vegetation/crop type	References
Airborne	(OEM) 20-Megapixel RGB camera	RGB	Red, Green, Blue	1.37 cm	Peanuts	Pugh et al. (2024)
	GEMS Multispectral camera	Multispectral	Red, Green, Blue, NIR	2 cm	Potatoes	Li et al. (2021)
	Headwall Nano-Hyperspec	Hyperspectral	273 bands (400–1,000 nm)	3 cm	Potatoes	Saif et al. (2023)
	Compact Airborne Spectrographic Imager	Hyperspectral	350–1,050 nm	1 m	Forests	Luo et al. (2017)
	Leica Airborne Laser	LiDAR	Red, Blue, Green, 120 Hz	Acc- 0.14 m, Prec- 1 cm	Forests	Luo et al. (2017)
	LTM 3100C LiDAR	LiDAR	Red, Blue, Green, 100 KHz	4.5 m	Forests	Kristensen et al. (2015)
	MicaSense Altum	Multispectral	Red, Blue, Green, NIR, Red Edge, Thermal	3–50 cm	Sweet Potatoes	Ramírez et al. (2023)
	MicaSense Red Edge	Multispectral	Red, Blue, Green, NIR, Red Edge	2 cm	Beet Roots, Cassava, and Potatoes	Wright et al. (2004)
	Tetracam μ-MCA06	Multispectral	Red, Blue, Green, NIR (1and2), Red Edge	1.5 cm	Onions	Messina et al. (2021)
	Optech ALTM1210	LiDAR	Red, Blue, Green, 21 Hz	21–48 cm	Beet Roots	Næsset and Gobakken (2008)
	Parrot Sequoia	Multispectral	Green, Red, Red Edge, NIR	11.3 cm	Groundnuts and Shrubs	Abdullah et al. (2021)
	Canon S100 modified by MaxMax	Multispectral	Green, Red, NIR	0.4 cm	Bambara groundnuts	Jewan et al. (2022)
	Single-lens reflex camera	RGB	Red, Green, Blue	1.4 cm	Sweet Potatoes	Teng et al. (2019)
	VUX-SYS Laser Scanner	LiDAR	Red, Blue, Green, 5,500 KHz	Acc-1 cm, Prec-0.5 cm	Sweet Potatoes and Sugar Beets	ten Harkel et al. (2020)
Proximal	ACS-470 Sensor	Multispectral	Red, Green, Red Edge, NIR	-	Sugar Beets	Bu et al. (2016)
	FieldSpec Handheld spectrometer	Hyperspectral	350–1,100 nm	<1.5 nm	Onions and Potatoes	Marino and Alvino (2015)
	FTIR spectroscopy	Hyperspectral	400–4,500 cm	4 cm	Faba Beans	Streit et al. (2019)
	Electrical Resistivity Tomography	—	—	—	Coffee Trees, Orchards, Sand Trees, and Forests	Paglis (2013)
	Ground Penetrating Radar	—	10 MHz - 2.6 GHz	—	Cassava, Energy Cane, Forests, Larch Trees, and Sand Trees	Zenone et al. (2008)
Spaceborne	Landsat-8	Multispectral	Red, Green, Blue, NIR	30 m	Grasslands, Sugar Beets, Potatoes, and Sweet Potatoes	Carbajal-Carrasco et al. (2024)
	RGB-RedEdgeM Sensor	Multispectral	Red, Blue, Green, Yellow, Red edge, NIR	4.6 cm	Turmeric Plant	Praseartkul et al. (2023)
	Sentinel-2	Multispectral	Red, Blue, Green, Red Edge, NIR	10–20 m	Sugar Beets, Carrots, Potatoes, and Sweet Potatoes	Tedesco et al. (2021)
	MODIS	Multispectral	Red, Green, Blue, NIR	500 m	Potatoes	Bala and Islam (2009)
	WorldView-2	Multispectral	Blue, Green, Yellow, Red, Red Edge, NIR	3 m	Carrots	Suarez et al. (2020)
	Advanced Very High-Resolution Radiometer	Multispectral	Red, Green, Blue, NIR	1.1 km	Potatoes	Kawsar et al. (2016)

(Continued on following page)

TABLE 2 (*Continued*) Specification of remote sensing technology used in assessing vegetation below ground biomass.

Platform	Sensor	Category	Spectral bands used	Spatial resolution	Vegetation/crop type	References
	Landsat –7	Multispectral	Red, Green, Blue, Red Edge	30 m	Sweet Potatoes	Carbajal-Carrasco et al. (2024)
	Landsat - 5	Multispectral	Red, Green, Blue, Red Edge, NIR	60 m	Sweet Potatoes	Carbajal-Carrasco et al. (2024)

Abbreviations: Prec, Precision; Acc, Accuracy; KHz, Kilohertz; Hz, Hertz, GHz, Gigahertz.

Therefore, assessing AGB using the aforementioned spectral characteristics hold a great promise to provide invaluable insights into the status of BGB development and *vice versa*. For example, Streit et al. (2019) successfully assessed the contribution of the root system to yielding potential of faba bean using a hyperspectral FTIR spectroscopy. While the visible, NIR, and red-edge bands have proven effective in estimating BGB, it is vital to note that their sensitivity can vary across different vegetation types, growth stages, and environmental conditions. For instance, in agricultural tuber crops, these bands may strongly correlate with the BGB, however, the same bands can be less effective in estimating forests and shrubs subsurface biomass due to variability in leaf structures and canopy densities (Dainelli et al., 2021; Deliry and Avdan, 2021).

Information on spatial resolution indicates how each sensor can be adopted based on the spatial extent and vegetation types monitored. For instance, small-scale farming systems, characterized by limited plot sizes, require high spatial resolutions to ensure sufficient pixels for adequate sampling and accurate BGB estimation. High resolution imagery allows for a better representation of field heterogeneity, enabling efficient differentiation of vegetation indicators that are directly linked to BGB, such as vegetation health and canopy structure. Conversely, larger ecosystems, such as commercial farming and forest systems, can be effectively monitored using low spatial resolution sensors like Landsat-8, which offer advantage of broader spatial coverage and minimal pixel contamination. For instance, Al-Gaadi et al. (2016) used the freely available Landsat-8 dataset to predict potato yield during the maturity stage in a 30 ha field, achieving the lowest prediction error of 13.5% at most. Despite the noted characteristics variations amongst the cameras, the choice of each sensor depends on the trade-offs between sensors spectral characteristics, spatial coverages, and practicality.

3.4 The utility of machine learning and statistical approaches for vegetation BGB estimation

A wide range of machine learning and traditional statistical models have been used to estimate vegetation and crop BGB, resulting in distinct prediction accuracies. A noticeable predominant use of linear regression models (Paglis, 2013; Butnor et al., 2003), including multiple linear regression (Suarez et al., 2024; Chancia et al., 2021), Ordinary Least Squares (OLS) (Liu et al., 2018; Sun et al., 2020), and stepwise regression (Kristensen et al., 2015) have been widely adopted, with reported R^2 values ranging from as low as 0.052 to 0.97. While some studies like Næsset and Gobakken (2008) achieved high prediction accuracies (R^2 = 0.85) estimating BGB in boreal forest zones, others using basic linear, multiple and OLS regression have shown low prediction accuracies. For instance, Suarez et al. (2020) used a linear regression model to estimate carrot yield using proximal and satellite remote sensing data and achieved prediction accuracies ranging from R^2 = 0.10–0.57. Liu et al. (2018) used a Ground Penetrating Radar with OLS regression to detect fine roots in agricultural crops and achieved prediction accuracies ranging from R^2 = 0.052 to 0.56. These aforementioned studies, amongst others such as Teng et al. (2019), Ramírez et al. (2023) and Wright et al. (2004), indicate the inconsistency of these models in capturing the complexity of vegetation and crop BGB.

In contrast, comparatively fewer studies used advanced and potent machine learning algorithms such as Random Forest (Fan et al., 2024; Madugundu et al., 2024), Support Vector Machine (SVM) (Sun et al., 2020; Li et al., 2021), Artificial Neural Networks (ANN) (Akhand et al., 2016; Carbajal-Carrasco et al., 2024), and eXtreme Gradient Boosting (XGBoost). Studies that have used these models typically demonstrated strong performance, with Random Forest achieving R^2 values up to 0.93 (Pugh et al., 2024) and ANN models reporting prediction errors under 10% (Akhand et al., 2016). Hybrid and ensemble models such as regression quantile lasso with Random Forest (Gómez et al., 2019) also yielded high accuracies (R^2 = 0.88–0.89), yet remained relatively underexplored across the literature. The use of empirical equations, including in a study by Al-Gaadi et al. (2016) to estimate potato crop BGB also noted a dearth in literature. In addition, the limited use of non-linear and automated modeling approaches, including AutoML tools (Tedesco et al., 2021) indicated a methodological gap in current vegetation and crop BGB prediction literature. Therefore, despite the nature of linear models in offering ease of interpretation, their widespread use may oversimplify the inherently complex nature of BGB systems, which indicates the need for broader adoption of data-driven and non-linear modeling strategies such as deep learning in future studies.

3.5 Remote sensing methods and challenges for estimating vegetation BGB

3.5.1 Ground penetrating radar (GPR)

Ground Penetrating Radar (GPR) system is the second most frequently used remote sensing technology for estimating vegetation and crop BGB after multispectral sensors (Figure 4). The GPR system is a proximal remote sensing approach used for detecting and localization of vegetation BGB up to 30 m belowground (Liu et al., 2018). The 30-m coverage of the GPR system allows for the detection of most vegetation BGB, as the majority of plants typically

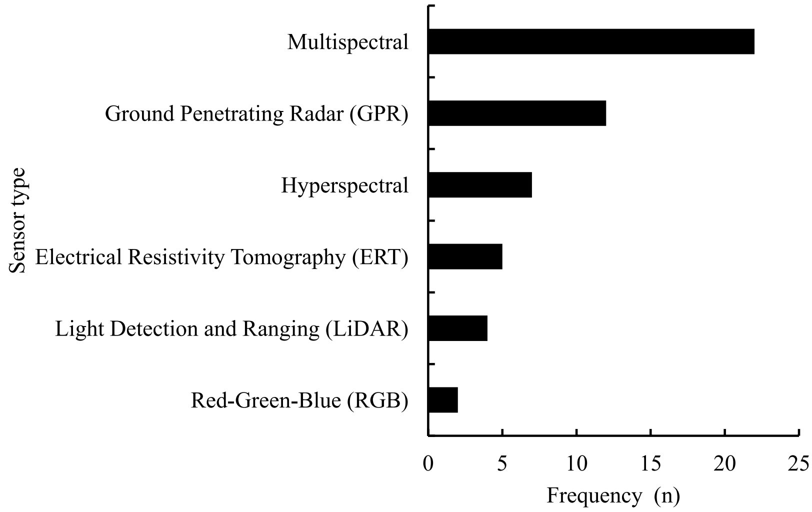

FIGURE 4
The frequency of remote sensing technology sensors used for assessing vegetation BGB.

do not extend deeper than 30 m belowground (Agbona et al., 2021). Ground penetrating radar systems provide a 3-Dimesional (3D) full resolution subsurface architecture using bow-tie antennas emitting a frequency ranging from 10 MHz to 2.6 GHz (Agbona et al., 2021). The GPR system can be integrated with the antenna, allowing easy deploy and use in confined spaces such as small-scale farming systems and dense forests (Barton and Montagu, 2004). The antenna emits and receives radar waves and works closely with the GPR unit that processes the signals and displays the data (Butnor et al., 2003). Alternatively, the GPR unit can be mounted on an aerial vehicle or alternatively operated on the ground while the antenna is positioned separately (Cui et al., 2011). This separation provides more flexibility, especially for large-scale surveys and challenging terrains such as dense natural forests (Cui et al., 2012). However, Guo et al. (2013) emphasized the importance of ensuring correct positioning of the antenna to the GPR system to effectively send and receive electromagnetic waves from the soil. The GPR systems heavily depends on soil permittivity such as conductivity and dielectric constants, which is determined by calculating the Time Domain Reflectometry (TDR) as explained by Hruska et al. (1999). The TDR verifies the quality of signal paths, essential for determining soil permittivity in allowing the GPR frequency to directly detect subsurface biomass (Isaac and Anglaaere, 2013).

The GPR system includes two approaches: (1) Directly estimating subsurface biomass using GPR indices such as the pixels within threshold range, high amplitude area, and time intervals between zeros (Hardiman et al., 2017). This approach is suitable for agricultural crops and grasses due to their shallow and well defined roots systems, enabling easy detection by the GPR system (Teng et al., 2019). (2) Using prior information of root density and indirectly sensing the root diameter using the GPR (Barton and Montagu, 2004). The second approach is suitable for trees and shrubs due to the challenges in detecting their roots by the GPR system, while information about their root orientation is often available through their taxonomic classification and nomenclature (Barton and Montagu, 2004). The second approach is only limited to cylindrical shaped roots, and based on the idea that root diameter is directly proportional to the subsurface biomass (Barton and Montagu, 2004). For example, using the second approach, a study by Barton and Montagu (2004) demonstrated the potential of a GPR system by burying nine tree roots at various depths in a prepared soil medium, and discovered that using 800 MHz and 1 GHz antennas, all the roots were detected except for the smallest (1 cm). Regardless of the approach used to sense subsurface biomass, the GRP dataset preprocessing procedure remains the same, and includes regularization, zero-time correlation, background removal, band pass filtering, attenuation compensation, 3D migration, and Hilbert transform, in that order (Cui et al., 2012).

The capability of RadExplorer v1.42 software to accurately preprocess GPR radiograms is well documented in literature (Zhu et al., 2014; Liu et al., 2018; Hruska et al., 1999). The first stage is regularization, which involves the use of nearest neighbor interpolation algorithm to interpolate the GPR acquired traces into regular grids of data (Zhu et al., 2014). Thereafter, the second stage where the arrival time of the reflection from ground surface is set to zero, strong wave and coupling are removed as background noise from the grids of data (Butnor et al., 2003). High frequency noise and current offset are removed and suppressed respectively by setting the low and high frequency (f_L and f_H) of the GPR data through band-pass filtering approach in the third stage (Leucci, 2010). In instances where energy and signal strength are lost in less permitting soils like clay and compacted mediums, attenuation compensation is performed to rectify possible spectral distortions (Zhu et al., 2014). Thereafter, in the fourth stage, the data is transformed into a clear 3D subsurface architecture using Frequency-Wavenumber (F-K) migration (Agbona et al., 2021). The F-K migration approach adjusts coarse datasets to make it sharp and clear for analysis (Agbona et al., 2021). The final preprocessing steps involves generating magnitude information rather than amplitude, to detect roots and extract GPR indices from the profile as explained in detail by Zhu et al. (2014). After collecting and preprocessing the data, GPR indices can be generated and combined with validation data to develop a subsurface biomass prediction model using machine learning and statistical methods (Liu et al., 2018).

Despite the potential approach presented by the GPR system, its challenges are well documented in literature (Zhu et al., 2014; Hruska et al., 1999; Agbona et al., 2021). The GPR system is often site-specific due to its requirements of connection to the antenna, which limits long range and global earth observation (Agbona et al., 2021). In addition, the GPR system faces challenges when used in densely vegetated areas, as the radar waves can be absorbed and scattered, reducing their ability to penetrate deeper into the soil (Liu et al., 2018). To rectify this, studies like Zhu et al. (2014), Guo et al. (2013), Liu et al. (2018) suggested methods like clearing vegetation canopy to minimize interference, using lower frequency antennas to enhance penetration, and applying advanced preprocessing techniques to filter out scattering noise. Furthermore, Cui et al. (2012) recommended cutting vegetation above the stump to allow radar signals to penetrate more effectively to the underground biomass and reduce soil interference. However, clearing vegetation remains a challenge, as it can be time-consuming and labour intensive, particularly at large spatial extents. In addition, clearing vegetation is destructive, which may limit future sampling on the same study site, and raise concerns regarding deforestation and yield losses. Moreover, the GPR system is generally effective only for detecting coarse roots that are considerably separate from each other as reported by Zhu et al. (2014). Liu et al. (2018) also reported that in cases where fine roots overlap coarse roots, the GPR system may fail to detect the latter. Despite these challenges, advancements in remote sensing, such as aerial vehicles equipped with modern GPR units, provide promising solutions for assessing BGB in vegetated areas and croplands (Leucci, 2010). For instance, leveraging the advances in GPR systems, Liu et al. (2018) successfully used this approach to detect fine roots in agricultural crops, which highlights improvements from the findings reported by Butnor et al. (2003), deeming the method only applicable to coarse roots. In addition, Wang et al. (2023b) introduced the upgraded MAVIN GPR system that allows integration with drone platforms, providing efficiency and access to hard-to-reach sites. Reich (2023) further proved that the upgraded GPR systems are less prone to vegetation interference, and can ultimately enhance vegetation subsurface biomass.

3.5.2 Electrical resistivity tomography (ERT)

The fourth frequently used remote sensing concept for estimating vegetation and crop BGB is Electrical Resistivity Tomography (ERT) (Figure 4). The ERT is a proximal remote sensing technique that involves the application of electrical current in the soil through electrodes and measuring the resulting potential difference in the selected positions (Paglis, 2013). Typically, electrical resistivity is the ability of any medium to restrict the flow of electrical current (Rossi et al., 2011). The ability of vegetation roots to significantly influence potential difference in the soil is well documented in literature (Balwant et al., 2022). Therefore, the use of ERT holds a great potential to estimate vegetation and crop subsurface dynamics, thereby allowing researchers to study variability in root size, distribution, and density subsurface (Zenone et al., 2008). Similar to the GPR, the ERT is based on the same approach and notion that roots are cylindrically shaped. A complementary study by Zenone et al. (2008) combined ERT and GPR to estimate pine tree root biomass and discovered that both 3D ERT and GPR variation soil map models can be related to the shape and size of the roots, consequently allowing BGB estimations.

Prior to using ERT to sense vegetation subsurface biomass, a bare soil medium is used as a control to calibrate the electrodes (Paglis, 2013). The calibration of sensors in the remote sensing as a field is well documented in literature, essential for keeping measurements within the accepted margin of error (Balwant et al., 2022; Paglis, 2013; Rossi et al., 2011). Thereafter, two electrodes defined as cathode and anode are inserted in a square unit soil medium and electrical current applied (Messina et al., 2021). The resulting potential difference in various sampling points provide an estimate of vegetation subsurface biomass variability across the experimental plot (Zenone et al., 2008). The potential difference from the root systems indicates different sizes, density, and water content. To validate ERT results, vegetation subsurface biomass is destructively sampled, and oven dried to a constant mass to eliminate water, and correlating ERT derived parameters (Balwant et al., 2022). In addition, soil samples are oven dried to get soil Dry Mass (DM), and subsequently, Root Mass Density (RMD) is calculated (Paglis, 2013). Thereafter, the RMD is used to create spatial variability maps of subsurface biomass across the study area using relevant software such as the surfer.V.10.

This review indicates that ERT has only been used four times based on the assessed literature to quantify vegetation and crop BGB as illustrated in Figure 4. The spatial coverage of the ERT approach is similar to the GPR system, hence it shares most of downsides such as labour intensity, since inserting and removing the electrodes in different locations across an experimental site can be challenging (Paglis, 2013). Rossi et al. (2011) noted that calibrating the electrodes across different soil types can be challenging as an experimental plot may exhibit different soil types, including porosity, moisture content, available elements, and nutrients. Zenone et al. (2008) further pointed out that the availability of foreign material in soil may cause significant distinctions in the flow of electrical current, and potentially be sensed as vegetation roots, thereby resulting in measurement errors. Furthermore, Zenone et al. (2008) argued that in forests and shrublands, various root systems of different vegetation types may exist below surface and potentially interfere with the targeted root systems. These limitations may raise serious concerns regarding the universal applicability of this approach; hence few publications are available in literature. However, its potential can significantly contribute to crop BGB estimations, particularly in small-holder and commercial farming systems, where soil is cultivated and there is limited foreign root interference. In addition, small holder systems are usually characterized by small farming plots, usually less than 1.5 ha, and operating the ERT systems may be logistically and practically feasible (Amede et al., 2023). Despite these concerns, technological improvements such as root architecture calibration on the ERT systems can potentially enhance the estimation of vegetation and crop BGB, thereby facilitating the detection of diverse roots detection and distinction from foreign materials.

3.5.3 Proximal hyperspectral remote sensing

Hyperspectral sensors feature various narrow bands, enabling acquisition of detailed and more nuanced vegetation and crop characteristics of the canopy such as health and pest infestation (Saif et al., 2023). This study noted 20 publications that utilized proximal hyperspectral remote sensing devices such as the Analytical Spectral Devices (ASD) to assess vegetation and crop BGB (Luo et al., 2017; Marino and Alvino, 2015; Sun et al., 2020; Suarez et al., 2020) (Figure 4). For instance, Streit et al. (2019) used the Fourier Transform Infrared (FTIR) spectrometer to determine how winter faba bean genotype roots systems can influence its AGB. The findings of the study indicated the significant value of vegetation BGB estimation in predicting AGB, providing insights into the strong positive relationship between the two variables. Furthermore, given the well-established relationship between vegetation health and its BGB in literature, spectral characteristics including optimized vegetation indices of the canopy can potentially accurately map subsurface biomass as reported by Wright et al. (2004), Sun et al. (2020), Middleton et al. (2013).

Despite the wide range of the electromagnetic portion spectrometers cover, it has been noted that only specific bands are selected for certain applications (Suarez et al., 2020). For instance, Suarez et al. (2020) combined proximal hyperspectral remote sensing with spaceborne multispectral data to estimate carrot yield, and only used a spectrum portion corresponding with the multispectral imagery. Following preprocessing, the collected data is averaged to a mean value, and vegetation indices computed by assigning the spectral reflectance to corresponding band reflectance such as the RGB, NIR, and Red edge (Streit et al., 2019). Machine learning techniques have proven prosperity in processing dense and complex datasets such as hyperspectral data over traditional statistical approaches (Li et al., 2021; Carbajal-Carrasco et al., 2024). Therefore, machine learning algorithms are then employed to analyze the data (Sun et al., 2020), and subsequently map vegetation BGB using field collected and converted validation data as explained by Dogra et al. (2025).

Despite the potential of hyperspectral remote sensing in assessing vegetation BGB, some studies have reported a poor prediction performance of this approach over other existing methods like multispectral. For instance, Suarez et al. (2020) used multispectral remote sensing (Sentinel-2 and WorldView-3), and a handheld spectrometer to assess carrot yield. The study indicated that satellite multispectral remote sensing reported a significantly higher prediction accuracy (R^2 = 0.57) than the proximal hyperspectral spectrometer (R^2 = 0.29). The study further identified a poor relationship between the measured AGB and carrot yield and reported that without destructively sampling the canopy and subsequently performing chemical analysis, validating the exact spectral variations can be challenging. Consequently, vegetation and crop BGB estimations cannot be based solely on the correlation with AGB, it is essential to include canopy spectral characteristics such as optimized vegetation indices and validation subsurface measurements.

Proximal remote sensing data collections can be challenging, as they involve a series of requirements, including a specific time frame and weather conditions (Crocombe, 2008). Field spectrometers are explicitly operated on clear sky conditions between 08:00–14:00 GMT, and repeated readings on the same sampling point (Burkart et al., 2013). The user should wear dark colored clothing to prevent light reflection, and possibly attaining wrong spectral reflectance values (Marino and Alvino, 2015). Field spectrometers, in particular require frequent calibrations across various lighting conditions, and can be heavy to carry, particularly in larger spatial extents (Streit et al., 2019). The battery life of some spectrometers may not last the entire duration of measurements, and given the restricted operating window, serious concerns regarding the practicality of this approach for prolonged observation and large spatial extents persist. Furthermore, field spectrometers are generally only suitable for low-growing vegetation such as shrubs, crops, grass, and orchards due to several practical limitations, including their requirement for close proximity to the target surface to capture accurate spectral measurements, making them ideal for vegetation that is easily accessible at ground level.

Similarly, lab spectrometers require samples to be destructively sampled from the field and transported to a dark laboratory room for spectral measurements (Marino and Alvino, 2015). However, delays between field data collection and laboratory analysis can lead to sample degradation, potentially resulting in spectral measurements that do not accurately reflect the true properties of the measured vegetation. Furthermore, background measurements for Carbon Dioxide (CO_2) compensations are required in every 20 min to account for the absorption of light by CO_2, which can interfere with the accuracy of reflectance (Suarez et al., 2020). Carbon dioxide can absorb specific wavelengths of light, leading to biased reflectance results (Wang et al., 2020). Nevertheless, given that field spectrometers are operated by humans, their application of forest and other tall vegetation can be challenging. In addition, spectrometer data is usually dense and complex, potentially requiring extensive preprocessing and high computational power. Considering that vegetation BGB can be accurately estimated from detailed canopy reflectance information, hyperspectral spectrometers can provide invaluable spectral resolution datasets, enabling precise subsurface biomass assessment, despite these challenges (Suarez et al., 2020).

3.5.4 Satellite multispectral remote sensing

Satellite multispectral remote sensing offers a broad-scale approach to indirectly estimate vegetation BGB by analysing spectral canopy indicators, reflecting subsurface conditions across large spatial extents (Al-Gaadi et al., 2016). The use of satellite multispectral remote sensing to characterize vegetation BGB has gained popularity over the last decade (Figure 3). Satellite mounted sensors cover a broad array of the electromagnetic bands, ranging from the visible, NIR, Red edge, SWI, thermal, and microwave sections (Suarez et al., 2020). This wide range allows computation of optimal vegetation indices for various applications including assessing vegetation and crop BGB (Bala and Islam, 2009). This study indicates that satellite mounted sensors are the third mostly used cameras to characterize vegetation BGB, noting their significant contribution towards assessing vegetation subsurface biomass (Figure 3). This popularity is attributed to the critical characteristics offered by satellite remote sensing such as wide spatial coverage, free availability of the data, reasonable revisits cycles, and critical spectral bands for estimating vegetation and crop BGB (Chapungu et al., 2020). For example, the NIR band available in the majority of satellite remote sensing cameras, has demonstrated effectiveness in calculating vegetation indices such as the NDVI, which literature has proven to strongly correlate to BGB (Baloloy et al., 2018; Suarez et al., 2024; Carbajal-Carrasco et al., 2024).

The principle of satellite remote sensing for estimating vegetation BGB is based on the idea that canopy reflectance fluctuations and AGB provide valuable insights into underground conditions (Madugundu et al., 2024). For instance, healthy and developed canopy indicates well-established root systems, reflecting the capability of the vegetation to absorb water and essential nutrients from the soil for productivity (Pugh et al., 2024). The variations in reflectance between well and poorly developed vegetation canopy offer invaluable insights into the differences of the BGB (Kawsar et al., 2016). Various vegetation indices such as NDVI, have been developed to indicate variations in canopy metrics, aiming to estimate the diversity of biophysical characteristics, which in turn, indicate the status of the root systems (Bala and Islam, 2009). Therefore, leveraging satellite remote sensing capabilities has proven efficiency in characterizing variations in vegetation AGB and canopy reflectance, subsequently enabling researchers to estimate the status of BGB (Tedesco et al., 2021; Bouasria et al., 2021). However, various debates prevail around the complexities involved in accurately estimating vegetation BGB using satellite remote sensing techniques. For instance, studies like Madugundu et al. (2024), Carbajal-Carrasco et al. (2024) argued that ecological factors such as different vegetation species exhibiting diverse roots systems and biomass allocation strategies, have led to serious debates regarding the appropriateness of applying a one size fits all approach for estimating BGB from canopy reflectance across various ecosystems.

Nonetheless, studies like Gómez et al. (2019), Sassu et al. (2021), Huylenbroeck et al. (2020) argued that remote sensing is a versatile tool capable of incorporating various ecological dynamics, proving its effectiveness when applied in well-established frameworks. For instance, Chapungu et al. (2020) used the freely available LANDSAT-8 dataset to estimate grasslands BGB in a Savannah biome based on the assumption that grass roots typically do not extend over 40 cm below the surface, achieving R^2 = 0.352. In addition, the complexities related to manually digging vegetation root systems as validation data, has led to serious concerns regarding the accuracy and practicality of using satellite remote sensing to assess BGB (Huynh et al., 2021). Abdulmanov et al. (2021) argued that remote sensing coupled with Geographic Information Systems (GIS) capabilities provide the luxury for minimal destructive sampling, requiring only few samples for validation, while sophisticated modelling techniques allow for estimates of the vegetation BGB. Furthermore, vegetation AGB and canopy experiences significant annual seasonal fluctuations, while the BGB tends to remain relatively stable (Liao et al., 2022). This raises concerns about the capability of satellite remote sensing capacity to accurately account for these temporal changes, which could result in potential underestimation of BGB over time. Despite the advancements in satellite remote sensing technology, there are still concerns over limitations in temporal and spatial resolutions, which significantly disregard quick changes in vegetation and spatial coverage for small spatial extents, respectively (Baloloy et al., 2018). Furthermore, concerns persist regarding satellite remote sensing being prone to atmospheric interference, particularly in summer where there are limited cloud free scenes (Bala and Islam, 2009).

3.5.5 UAV optical and active remote sensing

The concept behind UAV-remote sensing is the same as spaceborne multispectral and hyperspectral remote sensing, however, UAV systems feature more advanced technological improvements systems, facilitating a more precise and accurate vegetation and crop BGB estimation, by overcoming limitations associated with satellite remote sensing (Jewan et al., 2022; Saif et al., 2023). The recent revolution of remote sensing technology such as miniaturization of cameras has allowed leveraging of the new drone technology to overcome limitations such as low spatial resolution, long revisit cycles, and atmospheric interference (Sassu et al., 2021). Unmanned aerial vehicle-remote sensing attributed to the recent miniaturization of sensors has allowed affixation of various sensors including RGB, multispectral, hyperspectral and LiDAR sensors (Wallace et al., 2012; Adão et al., 2017; Gang et al., 2018; Diez et al., 2021). Chancia et al. (2021) leveraged the DJI Matrice M600 coupled with a multispectral sensor to predict table beetroot yield, achieving a high prediction accuracy (R^2 = 0.70) and a 24% estimation error. This recent development of new cutting-edge UAV-technology has allowed a swift response to climate change adaptation, such as provision of real time data, facilitation of precision agriculture for sustainable resource management, and high resolution datasets to enhance the precision of vegetation and crop BGB estimation (ten Harkel et al., 2020). This review indicates that UAV systems are the second most used platforms, with crops being the predominant type of vegetation assessed for BGB (Figures 2, 3). These results indicate a greater adoption of UAV-acquired datasets for crop BGB assessment compared to other vegetation types. For example, Tahir et al. (2020) derived NDVI using the NIR and Red band from the DJI Phantom 4 Pro UAV system to estimate groundnuts yield at the maturity stage and achieved a high prediction accuracy (R^2 = 0.92).

The advent UAV remote sensing has gained various technological advancements facilitating more comprehensive and improved vegetation BGB estimation (Praseartkul et al., 2023). For instance, the development of dual gimbal connectors, allowing the operation of two different sensors simultaneously, thereby reducing time taken for field surveying (Shen et al., 2020). High resolution datasets obtained from UAV remotely sensed data also allow for advanced image preprocessing such as soil background removal to improve vegetation BGB estimation. For instance, Wright et al. (2004) used Green Ratio Vegetation Index (GRVI) from a UAV-remotely sensed image to eliminate background interference, where values lower than 0.12 were classified as soil background and were subsequently removed to enhance the prediction accuracy of peanuts. In addition, UAV acquired datasets along with preprocessing software allow for derivation of a high-resolution Digital Elevation Model (DEM), facilitating comprehensive topographic analysis such as aspect, slope, Topographic Roughness Index (TRI), elevation, and Topographic Wetness Index (TWI) (Uysal et al., 2015). For example, the MicaSense Altum multispectral and DJI Zenmuse L1 LiDAR cameras offer resolutions of at least 33 cm per pixel and 5 cm per pixel for DEMs, respectively. The DEM derived variables analyses allow for more comprehensive insights of the topographic influence in roots dynamics, facilitating valuable insights on vegetation and crop BGB.

UAV technology features three varieties, including the rotary wings, fixed wing, and hybrid drone (Wong et al., 2021). The rotary wing is characterized by rotating blades that allows advanced features, such as Vertical Takeoff And Landing (VTOL), facilitating efficient operation in confined spaces, making them versatile and capable of hovering in small spatial extents (Kocamer et al., 2023). The rotary wing UAV systems are conventionally utilized for aerial photography, inspections, and more precise maneuvers such as precision agricultural applications (Ucgun et al., 2021). This review indicates that the fixed wing UAV system is particularly predominant in assessing vegetation BGB at smaller spatial extents, such as agricultural farms (Ye et al., 2020). Rotary-wing UAV systems are characterized by their adjustable flight speed and rapid maneuverability, enabling the acquisition of high spatial resolution images (Wang et al., 2021b). High resolution sensors have proven to perform optimally at lower UAV flight speeds, as this reduces the likelihood of motion blur, allowing for more detailed image capture, and subsequently enhancing the overall resolution of the data (Awais et al., 2021). In addition, lower speeds lead to more stable UAV flight conditions by reducing the impact of extreme winds, thereby facilitating high resolution imagery acquisition (Døssing et al., 2021). However, literature has proven that slower speeds are at an expense of longer flights durations (Raj and Murray, 2020; Tamke and Buscher, 2023; Chin et al., 2020).

Conversely, the fixed wing UAV system features a rigid wing structure, relying on forward motion with runway or launch system to takeoff, making it efficient for long-range flights and large area coverage (Shi et al., 2023). Fixed wing UAV systems are powered by high speed, durability, and adaptability for relatively larger spatial extents, such as forests to facilitate quick vegetation monitoring (Zhang et al., 2022). Abdullah et al. (2021) leveraged the Parrot Disco Pro fixed wing UAV with a multispectral sensor to assess BGB and carbon stock in a large commercial forest. However, the fixed wing faces challenges for monitoring small spatial extents such as farms, and can considerably hinder high spatial resolution dataset acquisition due its high speed (Song and Park, 2020). Nevertheless, the hybrid UAV system integrates features of both rotary-wing and fixed-wing drones, enabling VTOL capabilities similar to a helicopter while also allowing for transition to fixed-wing flight (Muslimov and Munasypov, 2021). This versatility makes hybrid UAV systems the most adaptable, as they can operate across a wide range of spatial extents including short and long range flights, thereby balancing efficiency and flexibility (Dündar et al., 2020).

3.5.6 Satellite and UAV-radar and laser remote sensing

The BIOMASS P-band Synthetic Aperture Radar (SAR) was deployed to address limitations associated with multispectral 2D optical satellite data (Rodríguez-Veiga et al., 2017). This approach uses SAR technology, which allows for capture of images regardless of weather conditions, including cloud cover and darkness (Wallace et al., 2012). Unlike optical imaging systems that rely on visible light, SAR uses microwave signals to penetrate clouds and rain, subsequently sensing surface roughness, moisture content, and vegetation structure, which can provide indirect insights into BGB (Mandal et al., 2020). In addition, Sentinel-1 SAR offers higher spatial resolution (5 m), which significantly improves the estimation of vegetation BGB compared to Sentinel-2 (10 m) optical sensors (Villarroya-Carpio et al., 2022; Guerini Filho et al., 2020; dos Santos et al., 2022). However, despite these capabilities, radar sensors such as SAR are significantly affected by noise and require extensive preprocessing, including spatial speckle filtering and the aggregation of data to coarser resolutions (Zou et al., 2022; Deng et al., 2024). This limitation further implicates poor estimation of vegetation and crop BGB, particularly in small spatial extents due to low spatial resolution (Koley and Chockalingam, 2022).

LiDAR remote sensing has emerged as one of the most promising technology to characterize vegetation and crop AGB, surpassing the existing optical reflectance methods (Wallace et al., 2012). LiDAR is an active sensor that utilizes pulse ranging instruments to emit laser pulses, record multiple returns of the laser beams, and digitize the full amplitude of the backscattered energy (Kristensen et al., 2015). Typically, LiDAR emits rapid laser beams directly to the vegetation canopy and analyses the time taken for the light to return, and subsequently create highly accurate 3D representations of the terrain and vegetation structure (Luo et al., 2017). The captured detailed 3D LiDAR data representing the full vegetation canopy is used to analyse the structure and density, which correlates with AGB status, subsequently allowing for an indirect estimation of BGB (Luo et al., 2017). LiDAR-derived point clouds typically provide data on canopy height, tree volume, and density, which are used to extract AGB information, including the Canopy Height Model (CHM), vegetation density, structure, and tree metrics (Kristensen et al., 2015). Thereafter, the AGB information is then applied to known allometric equations, such as those detailed by Kuyah et al. (2012) and Dogra et al. (2025) which are calibrated to estimate BGB from AGB and other LiDAR-derived metrics. However, LiDAR data alone does not account for essential factors like soil type, moisture, root distribution, and biophysical variables essential for accurate BGB estimation (Luo et al., 2017). Therefore, empirical models, including machine learning approaches, can be used to combine LiDAR-data with other datasets, such as field measured biophysical and topographic variables, as well as other remote sensing dataset, to effectively model vegetation and crop BGB (Salas, 2021; ten Harkel et al., 2020).

Typically, LiDAR units calculate the azimuth and zenith angles between the sensor and vegetation to determine their relative x, y, and z coordinates (Eitel et al., 2014). This process occurs at a rapid rate of over 280,000 points per second, facilitating more detailed and noise-free point clouds for accurate BGB estimation (Raj et al., 2020). The utility of LiDAR point clouds to estimate vegetation BGB is also motivated by the idea that denser canopies often indicate healthier and developed root systems (Wang et al., 2020). Although LiDAR sensors such as spaceborne Multi-Sensing Observation LiDAR and Imager (MOLI) are invaluable for capturing detailed vegetation above ground structural information, they do not provide direct biophysical data such as vegetation health, which are typically assessed through its integration with multispectral or hyperspectral sensors (Salas, 2021).The recent miniaturization of LiDAR sensors including low weights and dimensions, has allowed compatibility with UAV technology, enhancing the spatial and temporal resolution of the dataset (ten Harkel et al., 2020).

The emergence of advanced UAV equipped with high-resolution LiDAR sensors represents a significant leap forward in remote sensing technology, effectively bridging the gap between conventional vegetation BGB estimation approaches and the inferior satellite optical remote sensing (Olson and Anderson, 2021; Wang et al., 2021a). For instance, DJI developed the UAV-mountable Zenmuse L1 LiDAR camera, capable of covering up to 2 km^2 in a single flight and achieving vertical and horizontal accuracies of 5 cm and 10 cm, respectively (Gaffey and Bhardwaj, 2020). The DJI Zenmuse L1 is an active sensor that features both LiDAR and RGB camera, enabling up to three returns of data at 240,000 points per second (Butters et al., 2021). Therefore, DJI Zenmuse L1 and similar LiDAR remote sensing capabilities can effectively provide accurate and critical datasets for the estimation of vegetation BGB (Butters et al., 2021). Despite these capabilities, UAV-LiDAR remote sensing capabilities can be limited by their costs, including external expensive components like the Real-Time Kinematic (RTK) base station required for Global Navigation Satellite System (GNSS) data, which enables the highest level of accuracy (Wen and Hsu, 2021). In addition, LiDAR dataset can effectively estimate vegetation and crop BGB when integrated with other datasets such as multispectral, hyperspectral, topographic, and *in-situ* biophysical variables (Salas, 2021).

3.5.7 The integration of multivariate datasets, and use of surface from motion (SfM) approach

Remote sensing technology has been identified as the versatile tool, and proven efficiency when applied in well-established phenomenon (Praseartkul et al., 2023). In circumstances where two distinct datasets have a potential to provide a valuable and comprehensive assessment, the integration of both dataset can be performed (Wagner and Egerer, 2022). Combining various datasets such as derived vegetation indices, topographic information, and biophysical characteristics has proven invaluable in providing a more comprehensive BGB estimation (Furlan et al., 2023). For example, Zenone et al. (2008) integrated GPR and ERT dataset to understand pine tree forests roots, and Luo et al. (2017) fused hyperspectral imagery with LiDAR data to map forest BGB. Briefly, Saif et al. (2023) also combined spectral vegetation and textural indices from a UAV-hyperspectral image to provide a more comprehensive table beet root yield prediction. The hyperspectral data was preprocessed with headwall hyper spec III spectral view V3.1 software (Zhi et al., 2022). Subsequently, the hyperspectral radiance was converted to reflectance due to radiance being susceptible to illumination conditions (Li et al., 2020). Texture indices involved the calculation of Gray-Level Co-occurrence Matrix (GLCM) followed by the extraction of its descriptive stats (Wang et al., 2023a). The textural indices can be calculated over the 240 narrow hyperspectral derived spectral bands (Saif et al., 2023). For textural analysis, a smaller kernel is preferred because a larger kernel tends to cause over smoothing (Xu et al., 2022). Quantization levels are employed to evaluate the GLCM means of each kernel, after which the average of GLCM means is regarded the texture for each sample plot (Fu et al., 2021). The study by Saif et al. (2023) reported that hyperspectral data is prone to thermal, quantization, and shot noise. However, principal component can be used to de-noise the data, and this approach lies on the idea that most noise is contained in the principal component with lower eigen values (Greenacre et al., 2022).

Despite the proven capabilities of UAV remote sensing in providing high resolution and comprehensive datasets for vegetation BGB estimation, this approach only captures 2D datasets from the canopy (Deliry and Avdan, 2021). To overcome this limitation, Surface from Motion (SfM) techniques combine vertical and horizontal 2D images to create a 3D dataset, facilitating a more detail information about the vegetation above ground structure, and subsequently improving BGB estimation (Prior et al., 2021). For example, Teng et al. (2019) leveraged SfM image processing to construct 3D point clouds using multiple 2D images from a UAV-digital single-lens reflex camera system to assess sweet potatoes yield. Using relevant software such as Agisoft Photo scan, these 2D images can be transformed into a 3D SfM dataset, with Bundle-Adjustment approaches minimizing errors in point cloud generation (Al Khalil, 2020). Thereafter, these point clouds are used to generate Digital Surface Models (DSM), which use terrain information for estimating vegetation and crop BGB (Iheaturu et al., 2020). Despite the effectiveness of this approach, concerns remain about the potential for vegetation in the middle of the experimental plot to go undetected by the ground moving platform. In addition, this approach does not consider landscape variations within the plot, where certain vegetation may be taller due to their positioning, resulting in higher elevation compared to others. Therefore, it is essential to incorporate topographic variables such as aspect, slope, and elevation to account for these variations and subsequently improve vegetation and crop BGB estimation.

3.6 Overall progress and future research opportunities

Remote sensing has proven effective in assessing vegetation BGB across various ecosystems, including forests, grasslands, and agricultural landscapes (Wright et al., 2004; Chapungu et al., 2020). The utility of vegetation canopy spectral information and metrics acquired from multispectral, RGB, hyperspectral, and LiDAR has proven invaluable to provide insights into the status of BGB biomass, subsequently allowing its assessment (Abdullah et al., 2021; Bala and Islam, 2009). However, several challenges have been presented in literature. One of the major challenges in assessing vegetation and crop BGB is the difficulty associated with digging up roots for validating remote sensing datasets, hence fewer studies have been published in this topic (Marino and Alvino, 2015). This challenge has led to insufficient validation data, significantly raising questions about the reliability and validity of assessing vegetation BGB estimation using remote sensing (Al-Gaadi et al., 2016). The current reliance on destructive sampling for ground-truth validation presents practical and ecological limitations, which are labor-intensive, time-consuming, disturb the soil structure, and ecosystem processes, thereby limiting their scalability across large spatial and temporal scales. In practice, this restricts the size and diversity of training datasets available for model development, which affects robustness of remote sensing models for vegetation and crop BGB estimation.

To address this limitation, future research should explore possible and promising non-invasive and minimal invasive ground-truthing techniques, which may include minirhizotron imaging systems that enable repeated *in-situ* root observations without excavation, and stable isotope tracing, which provides insights into root dynamics and carbon allocation patterns over time. These technologies can offer continuous, spatially representative datasets that complement remote sensing observations and reduce dependence on destructive methods. Integrating such non-invasive techniques into the model-building workflow presents the potential to enhance validation, improve model accuracy, and expand the applicability of vegetation and crop BGB estimation across broader ecological and agricultural contexts. Furthermoe, the advent of cloud computing techniques like deep transfer learning models such as Long Short-Term Memory-based Recurrent Neural Networks (LSTM-based RNN), AlexNet, Visual Geometry Group (VGG), and Residual Network (ResNet) facilitating models' calibrations to build models for accurately predicting vegetation and crop BGB using less field validation data (Wang et al., 2023c; Wang et al., 2018; Yang et al., 2021; Alom et al., 2018).

Seasonal changes in vegetation canopy like forests have a potential to misrepresent the true state of BGB, thereby raising questions about the reliability of using the remote sensing AGB as an indicator for assessing BGB (Carbajal-Carrasco et al., 2024). During the winter season, vegetation sheds its green leaves, exposing a significant area of soil background, hence this seasonal change of the canopy raises concerns about the effectiveness of optical remote sensing to detect these variations, especially for perennial vegetation, such as forests, that persist across seasons (Wright et al., 2004). The integration of active remote sensing, such as LiDAR technology and field measured variables, is strongly recommended, as this approach can accurately assess vegetation structure and other critical information without depending on the green canopy, thereby enhancing prediction accuracy of BGB (Luo et al., 2017). In addition, future studies should also consider the application of advanced SAR sensors such as Phased Array L-Band SAR-2 (PALSAR-2), PALSAR-4, and NASA-ISRO SAR (NISAR), which use the L and S bands for improved canopy penetration and structural insights (Yu and Saatchi, 2016; Hayashi et al., 2019). Furthermore, the application of representative spaceborne LiDAR missions, such as Ice, Cloud, and Elevation Satellite-2 (ICESat-2), and Global Ecosystem Dynamics Investigation (GEDI) (Urbazaev et al., 2022), which have been widely used for AGB estimation remains elusive in literature for vegetation and crop BGB predictions. These missions provide critical structural metrics such as canopy height and vertical foliage profiles that can serve as indirect indicators of BGB when integrated with other remote sensing datasets.

Despite the success of site specific handheld hyperspectral spectrometers, ERT, and GPR in assessing vegetation BGB, these devices often require significant fieldwork to gather data, which can be labor-intensive, time consuming, and logistically challenging (Butnor et al., 2003; Leucci, 2010). Regardless the proven potential of integrating various datasets such as SfM to enhance understanding of vegetation biomass dynamics, few studies have successfully adopted this approach (Teng et al., 2019). Furthermore, the incorporation of landscape variables remains underexplored, indicating a gap that must be addressed to advance the accuracy and applicability of remote sensing techniques in vegetation BGB assessments, considering the significant topographic variations (Teng et al., 2019).

The integration of new UAV cutting-edge technology in assessing vegetation BGB across various diverse ecosystems ranging from forestry to agriculture has proven efficiency by subduing limitations associated with the inferior satellite remote sensing (Wright et al., 2004). This new innovation allows sensor miniaturization, facilitating the acquisition of high spatial resolution data, with user defined revisit cycles and cloud free datasets (ten Harkel et al., 2020). The integration of new UAV technology has been deemed the future of remote sensing, facilitating precision agriculture, particularly in assessing neglected and underutilized crops such as sweet potatoes, taro, and cassava (Shahi et al., 2023; Madugundu et al., 2024). In addition, this approach has provided invaluable insights into forest management, facilitating climate change related mitigation strategies, such as the impact of root systems in carbon sequestration (Abdullah et al., 2021). However, issues related to high costs associated with the purchase, maintenance, and specialized training and operational expertise for advanced UAV systems can be prohibitive for many regions, such as the global south (Pugh et al., 2024). The global south is currently characterized by low investments and funding opportunities, significantly restricting the adoption of this innovation (Jewan et al., 2022). Considering the high population density in the global south compared to other regions, increased adoption of UAV technology is required to optimize crop production and mitigate climate change risks. Despite this potential, only 50 studies have been published on the utility of remote sensing technology to evaluate vegetation BGB over the past 25 years, noting a considerable need for further exploration of this technology. The limited number of publications indicates that researchers are yet to fully explore the potential of this approach for estimating vegetation BGB.

3.7 Limitations of the study

This study reviewed the applications, methods, and challenges of remote sensing technology for vegetation and crop BGB estimation; however, several limitations including methodological, evidence based, and intrinsic to emerging technologies, have been encountered during the study. The method of this study was limited by the availability of publications specifically focusing on vegetation and crop BGB estimation using remote sensing technology, with only 50 relevant papers identified from the initial pool of 785. This low number of publications indicates the relatively underexplored nature of vegetation and crop BGB research compared to AGB studies, which constrained the analysis depth of the findings. Furthermore, evidence-based limitation encountered was that the few reviewed publications exhibited substantial heterogeneity in terms of vegetation types, geographic location, remote sensing platforms, and analytical approaches, which limited the ability to draw deep understanding of the existing methodologies and challenges. Finally, limitations intrinsic to emerging approaches were that most advanced remote sensing technologies such as PALSAR-4, NISAR, and newer UAV-based active sensors are either newly launched and some still in early phases of application, which as a result, empirical evidence of their effectiveness for vegetation and crop BGB estimation remains scarce, and current discussions about their potential are largely speculative.

4 Conclusion

This review indicates a significant leap forward in using remote sensing technology to assess vegetation and crop BGB, providing valuable insights on the methodologies, various platforms, and sensor spectral characteristics. While approaches like GPR and ERT provide valuable and accurate direct insights to BGB, their limited spatial coverage restricts their application to large spatial extents. Advances in remote sensing have resulted in the development of sophisticated optical sensors that, although unable to directly measure subsurface biomass, leverage canopy spectral reflectance to estimate BGB. Among these advancements, active LiDAR sensors stand out for their ability to capture the full vegetation volume using point clouds, subsequently improving BGB estimations by subduing atmospheric interference, pixel contamination, and saturation. Meanwhile, satellite multispectral and hyperspectral sensors, despite facing certain limitations such as atmospheric interference, low spatial and temporal resolution, provide critical vegetation biophysical information, which offers valuable insights to canopy health and biomass, subsequently allowing for BGB estimation. The advent of UAV platforms presents an advanced and unique opportunity to attach miniaturized smart and high spatial resolution sensors, such as LiDAR for accurately estimating vegetation and crop BGB, while combatting satellite remote sensing challenges. Despite the potential of this innovation, very few studies have adopted it, necessitating a need for future studies to explore its full potential in assessing vegetation and crop BGB in this ever-changing climate, coupled by high food demands. Nonetheless, the assessment of vegetation BGB has been steadily improving with advancements in remote sensing technologies. Collectively, these advancements have provided a wide range of remote sensing approaches to monitor vegetation BGB, allowing researchers to evaluate their choices based on tradeoffs between spatial coverages and spectral sensors characteristics. Furthermore, these advancements offer a more comprehensive and reliable approach to understanding vegetation BGB, paving the way for reliable assessments of ecosystem health and tuber crops productivity.

Author contributions

CD: Writing – review and editing, Methodology, Writing – original draft, Formal Analysis, Data curation, Investigation, Validation, Conceptualization, Visualization. JO: Resources, Project administration, Conceptualization, Methodology, Writing – review and editing, Supervision. TM: Project administration, Resources, Supervision, Writing – review and editing, Conceptualization, Methodology. OM: Resources, Writing – review and editing, Funding acquisition, Methodology, Project administration, Conceptualization, Supervision.

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Conflict of interest

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