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Review

Exploring the Potential of Remote Sensing to Facilitate Integrated Weed Management in Smallholder Farms: A Scoping Review

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Abstract: In light of a growing population and climate change compounding existing pressures on the agri-food system, there is a growing need to diversify agri-food systems and optimize the productivity and diversity of smallholder farming systems to enhance food and nutrition security under climate change. In this context, improving weed management takes on added significance, since weeds are among the primary factors contributing to crop yield losses for smallholder farmers. Adopting remote-sensing-based approaches to facilitate precision agricultural applications such as integrated weed management (IWM) has emerged as a potentially more effective alternative to conventional weed control approaches. However, given their unique socio-economic circumstances, there remains limited knowledge and understanding of how these technological advancements can be best utilized within smallholder farm settings. As such, this study used a systematic scoping review and attribute analysis to analyze 53 peer-reviewed articles from Scopus to gain further insight into remote-sensing-based IWM approaches and identify which are potentially best suited for smallholder farm applications. The findings of this review revealed that unmanned aerial vehicles (UAVs) are the most frequently utilized remote sensing platform for IWM applications and are also well suited for mapping and monitoring weeds within spatially heterogeneous areas such as smallholder farms. Despite the potential of these technologies for IWM, several obstacles to their operationalization within smallholder farm settings must be overcome, and careful consideration must be given on how best to maximize their potential before investing in these technologies.

Keywords: drones; food security; smart agriculture; UAVs

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1. Introduction

Globally, agri-food systems are under pressure to meet growing food demands. With this demand for food incessantly increasing due to the perpetually expanding population, there are growing concerns that food insecurity and malnutrition will be amplified, particularly under climate change [1]. Despite these concerns, only a select few crop species are grown worldwide for food production. This limited variety largely results from the green revolution paradigm that has dominated agricultural food production activities [2–4]. While the green revolution has undoubtedly contributed to an increase in food security, there is a growing consensus that declining agro-biodiversity has contributed to modern food production systems being more vulnerable to stressors, which will likely impact their ability to meet future food and nutrition targets due to their lower resilience [5]. Subsequently, there is a need to diversify agricultural food production systems by shifting away from the intensification and over-reliance of a select few crop species [2,6].

The increase in the cultivation of neglected and underutilized crops (NUCs) offers a great deal of promise to aid in addressing current and future food and nutrition security challenges. This is primarily attributed to the suitability of these crops for production in low-input agricultural systems, their relatively high nutrient density, and their tolerance to both biotic and abiotic stresses [2,6–8]. In regions such as sub-Saharan Africa, where the prevalence of food insecurity and malnutrition remains high, the promotion and prioritization of NUCs take on added significance. This is because local growing conditions are often unfavorable for major crops typically grown in commercial production systems [3]. Subsequently, NUCs can play an important role as supplementary or alternate sources of food and nutrition [2]. Considering that NUCs are less severely impacted by climatic variability and their larger-scale cultivation possesses immense potential in contributing to alleviating food insecurity, malnutrition, and poverty, particularly in resource-constrained and marginalized communities, there is a need to optimize and incentivize their production [4,8,9].

NUCs are typically characterized by lower yields than major crops; however, they can generally compensate for this by their ability to withstand adverse climatic and environmental conditions [10]. Nevertheless, it is critical to ensure that optimal yields of NUCs can be attained to realize the potential of these crops to alleviate the aforementioned socio-economic challenges. Furthermore, improving their yield potential may make their production more appealing, as improved profitability will be associated with their cultivation [10]. From a sub-Saharan African perspective, root and tuber crops are among the primary sources of food for the population. Therefore, achieving good, high-quality production levels of these crops takes on added significance in these regions [9]. With the cultivation of NUCs mainly being confined to smallholder farms (typically less than 2 ha in size), there exists an opportunity to improve food sovereignty by enabling smallholder farmers to exert a greater influence in food production systems [2,4,5]. This is particularly important as the potential of smallholder farmers remains underdeveloped despite being major contributors to global food production. For example, smallholder farmers produce approximately 80% of the food in sub-Saharan Africa and Asia [5,11,12]. Additionally, the promotion and prioritization of NUCs throughout all stages of the food system has the potential to improve the socio-economic circumstances of poverty-stricken and marginalized smallholder communities as their interest in cultivating these crops will grow once their value is better established [4].

While several factors may contribute to low yields and inferior product quality in many farmer's fields, poor weed management is often the primary contributing factor [9,13]. This can be attributed to the initial slow growth of these crops, which results in them being poor weed competitors, particularly during the early stages of crop development [9,13–17]. Weeds can compete with crops for primary resources such as water, sunlight, nutrients, and space. Moreover, weeds may contribute to allelopathic reactions that inhibit crop growth and development [14,16,18]. Since weeds are deleterious to crop production and their control or management can be resource-intensive, understanding and quantifying their impacts is essential to developing appropriate strategies that promote sustainable crop production whilst minimizing the wasteful use of critical resources [18,19].

Conventional weed control or management approaches typically involve uniformly spraying the entire field with herbicide and/or adopting manual weed control methods. However, weeds are usually unevenly distributed within these fields; therefore, this is inefficient from both a labor and economic perspective. Furthermore, applying herbicides can adversely impact the health of the surrounding environment [18,19], while manual weed control approaches may require additional laborers, which may also be challenging considering that many individuals shift to urban areas in search of employment, amongst other factors. Subsequently, weeds are not properly managed. Integrated weed management (IWM), also commonly referred to as precision weed management (PWM) or site-specific weed management (SSWM), has been advocated as an alternate approach to mitigating the harmful impacts of conventional methods by adopting a more efficient and sustainable approach [18,20]. It is centered on improving the understanding and quantifying crop–weed competition dynamics to develop customized weed management strategies [18,20]. Such an approach to weed management falls within the precision agriculture (PA) paradigm, which has begun to feature quite prominently within the agricultural arena over the past decade [21,22].

PA practices involve the application of several customized management interventions and strategies that are guided and informed by state-of-the-art data collection, analysis, and communication technologies to enhance crop productivity, reduce unnecessary losses of critical resources such as water and nutrients, as well as mitigate potentially harmful impacts on the environment [21–23]. The use of remotely sensed data acquired from satellites and manned or unmanned aerial vehicles is often used to facilitate PA applications and has the potential to guide and inform integrated weed management. However, the spatial, spectral, and temporal resolution associated with various sensors may dictate how and for what purposes the data they capture can be used.

Considering the often fragmented and heterogeneous nature of smallholder farming systems coupled with their unique socio-economic circumstances, it is important to understand, in the context of IWM, which remote-sensing-based approaches are most relevant and can provide a pragmatic and feasible approach to facilitate improved weed management within these systems. To this end, a systematic scoping literature review and attribute analysis was conducted with the specific objectives of identifying (i) common remote sensing platforms, (ii) sensor characteristics, and (iii) data analysis procedures that are implemented to facilitate IWM and contextualizing these findings by considering the challenges and opportunities that exist from a smallholder agriculture perspective.

This review is divided into five sections. Section 1 provides the background to the review. An overview of the methods used to identify and evaluate the literature included in the review is presented in Section 2. Section 3 details the key findings of the attribute analysis inter alia*:* (i) influential publications, (ii) prominent authors, and (iii) impactful journals. Section 4 provides a concise discussion of the review's objectives, and the conclusions are presented in Section 5.

2. Materials and Methods

This systematic literature review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) approach. The literature database for the bibliometric analysis was compiled by first searching for articles within the Scopus abstract and citation database. The choice of keywords and variants used in the search string was informed by a subset of the literature identified through Google Scholar and the authors' experience in this subject area. A structured query string consisting of the following keywords and variants ("Remote sensing" OR "satellite" OR "UAV" OR "drone" OR "Unmanned aerial vehicle" AND "agriculture" OR "farm*" OR "crop" AND "Integrated weed management" OR "precision weed management" OR "site-specific weed management") was used to source the literature on 05 September 2023.

The search results were first filtered by selecting full-length articles written in English and published in accredited journals. Thereafter, the remaining articles were screened for eligibility based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) framework [24]. Only those articles that met the following eligibility criteria were retained in the final literature database: (i) the study must utilize at least one of the remote sensing platforms to implement IWM, (ii) the study applied remote-sensing-based techniques to guide and inform IWM decision making, and (iii) the study provided a methodological description of how the remotely sensed data were used to detect and map weeds.

The structured query search in Scopus yielded 111 potentially relevant studies. Twenty-one of these studies were excluded as they were not written in English or published in accredited peer-reviewed journals. The remaining 90 articles were then manually screened for eligibility by their titles and abstracts, and a further 19 articles were excluded. The authors then sought the remaining 71 articles, and a further 18 articles were removed after being assessed against the eligibility criteria defined for the study by examining the full text of each article. The final literature database containing 53 publications was then exported into the Biblioshiny and VOSviewer (version 1.6.20) software applications for further analysis [25,26]. An overview of the article selection process is provided in Figure 1. Additional attributes were added to the literature database to perform the attribute analysis by extracting specific information from each selected study. These include remote sensing platforms, sensor type, spatial resolution, classification method, classification algorithms, extracted bands and features, geographic location, and crop type.

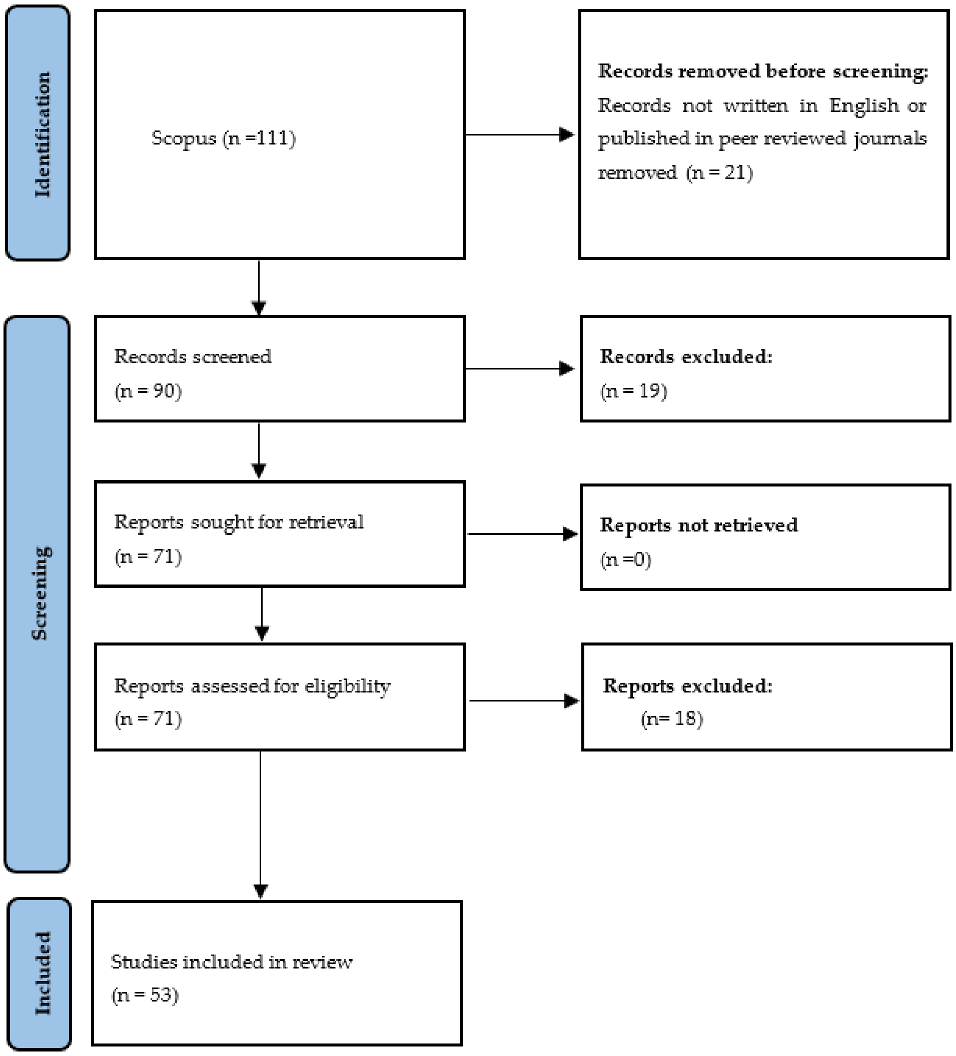

Figure 1. A conceptual flow diagram depicting how the final literature database was compiled using the PRISMA guidelines.

3. Results

3.1. General Characteristics

Research on remote-sensing-based techniques to detect and map weeds to facilitate IWM has been ongoing for almost two decades. It has steadily increased annually by approximately 14% (Table 1). Of the 53 publications selected for further evaluation, more than 80% have been published in the last decade, of which approximately 53% have been published in the past three years (Figure 2). This may result from advancements in sensor capabilities, data accessibility, data processing, and computational power [27].

Table 1. A summary of the general characteristics of the selected studies included in the final literature database.

Description	Results	Description	Results
Time span	2006–2023	Keywords plus (ID)	410.00
Number of journals	24.00	Author keywords (DE)	192.00
Number of publications	53.00	Authors	186.00
Annual growth rate	13.80%	Single-authored articles	0.00
Document average age	4.91	Co-authors per article	4.94
Average citations per doc	50.11	International co-authorships	15.09%

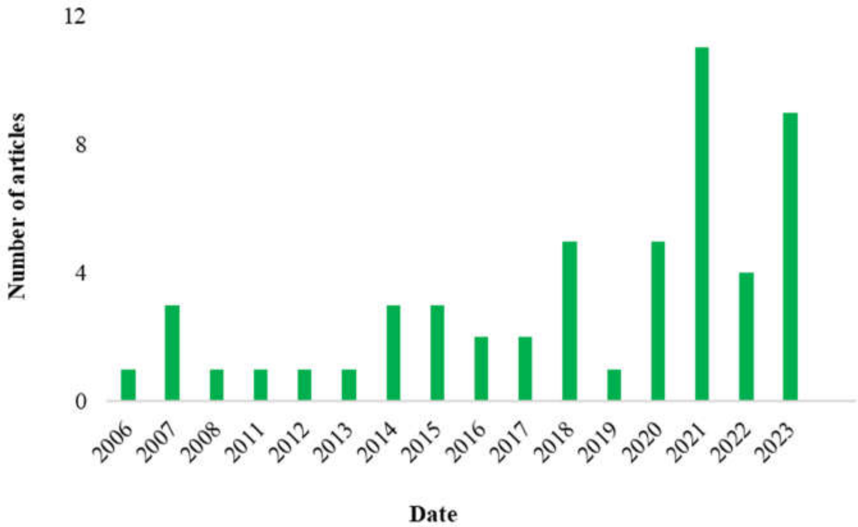

Figure 2. Annual distribution of published articles (years without published articles have been omitted).

The 53 publications contained within the final literature database were published across 24 journals, with *Computer and Electronics in Agriculture* (n = 8), *Remote Sensing* (n = 8), and *Precision Agriculture* (n = 7) accounting for approximately 43% of published articles. According to Bradford's law, articles published within these journals on remote sensing to facilitate IWM are among the most influential and of greatest interest (Figure 3). *Computer and Electronics in Agriculture* and *Precision Agriculture* also retain their position among the top 3 most influential journals when ranked according to the total number of citations and h-index values (Table 2).

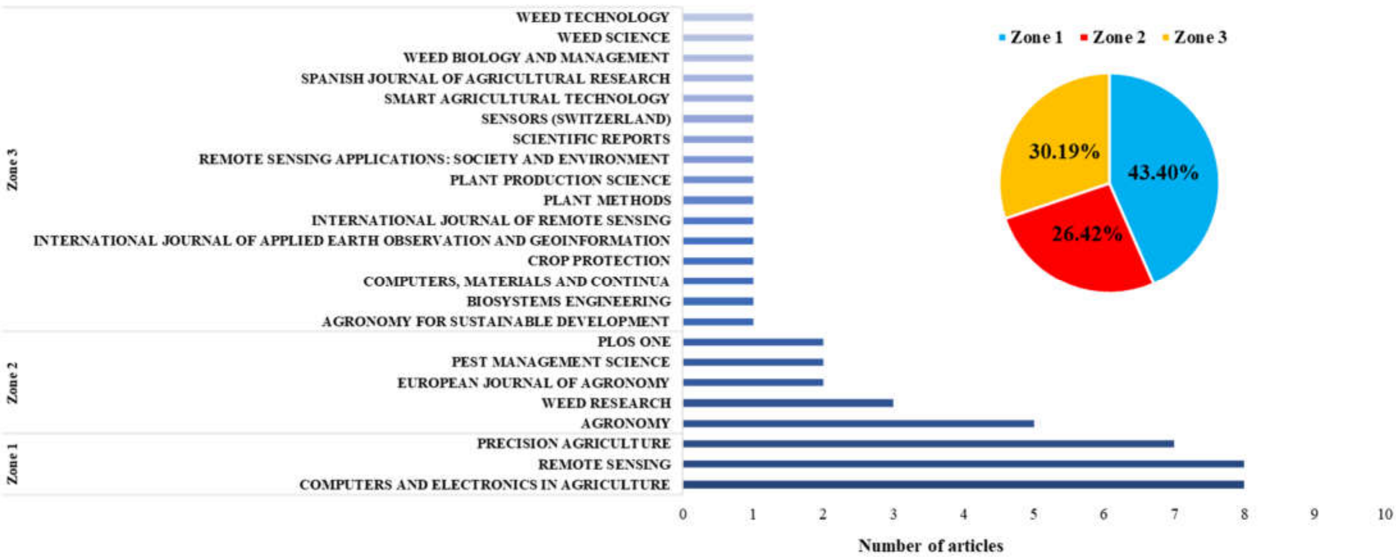

Figure 3. Number of publications per journal and journal ranking according to Bradford's law.

Table 2. Journal publication metrics listed in chronological order.

Journal	Number of Publications	TCs	h-Index	Publication Year Start
Weed Science	1	70	1	2006
Weed Research	3	81	3	2007
Weed Biology and Management	1	21	1	2007
Weed Technology	1	12	1	2007

Computers and Electronics in Agriculture	8	705	6	2008
Crop Protection	1	13	1	2011
Precision Agriculture	7	506	7	2012
Plos One	2	363	2	2013
European Journal of Agronomy	2	67	2	2014
Biosystems Engineering	1	26	1	2015
Sensors (Switzerland)	1	133	1	2015
Agronomy for Sustainable Development	1	68	1	2016
Remote Sensing	8	349	7	2018
International Journal of Applied Earth Observation and Geoinformation	1	85	1	2018
International Journal of Remote Sensing	1	44	1	2018
Pest Management Science	2	42	1	2020
Spanish Journal of Agricultural Research	1	4	1	2020
Agronomy	5	44	3	2021
Plant Production Science	1	18	1	2021
Scientific Reports	1	2	1	2022
Remote Sensing Applications: Society and Environment	1	2	1	2023
Smart Agricultural Technology	1	1	1	2023

A total of 186 authors contributed to the 53 publications on using remote sensing to facilitate IWM. Of these 186 authors, 14 published 3 or more articles (Table 3). Francisca López-Granados can be considered the most influential author in this research focus area, ranking highest for 4 out of the 5 author performance metrics (listed in Table 3). Torres-Sánchez et al. [28] received the highest number of citations and average citations per year. In their study, the authors investigated using an unmanned aerial vehicle (UAV) equipped with a low-cost commercial-grade camera for vegetation fraction (VF) mapping to facilitate early-season IWM in wheat fields. Several visible spectral indices were derived to quantify VF, and the influence of flight altitude and image acquisition dates on classification accuracy was also evaluated. Overall, the study's results demonstrated that using visible spectral indices derived from a low-cost commercial-grade camera onboard a UAV flying at low altitudes can satisfactorily distinguish VF in wheat fields and thus has potential for early IWM applications. The most highly cited article based on the normalized TC metric was by Gallo et al. [29]. These authors employed the latest version of the You Only Look Once (YOLOv7) deep learning algorithm to detect weeds among chicory using red, green, and blue (RGB) imagery acquired from a UAV. The study's results demonstrated that the YOLOv7 algorithm performed satisfactorily for weed detection and outperformed previous versions. However, the need for large-scale datasets to develop and test the model may limit its suitability for operational applications.

Table 3. Author-level citation metrics for authors with 3 or more publications.

Author	h-Index	g-Index	m-Index	TCs	Number of Articles	Publication Start Year
LÓPEZ-GRANADOS F	14.00	18.00	0.78	1833.00	18.00	2006
DE CASTRO AI	10.00	11.00	0.83	1397.00	11.00	2012
TORRES-SÁNCHEZ J	9.00	12.00	0.82	1393.00	12.00	2013
JURADO-EXPÓSITO M	7.00	7.00	0.39	282.00	7.00	2006
PEÑA JM	7.00	7.00	0.70	1114.00	7.00	2014
JIMÉNEZ-BRENES FM	5.00	5.00	0.83	244.00	5.00	2018
PEÑA-BARRAGÁN JM	5.00	5.00	0.29	444.00	5.00	2007
MESAS-CARRASCOSA FJ	4.00	5.00	0.40	265.00	5.00	2014
RASMUSSEN J	3.00	4.00	0.33	48.00	4.00	2015
SERRANO-PÉREZ A	3.00	3.00	0.33	326.00	3.00	2015

The top 10 keywords and words that frequently appear in the titles of references but not in the titles or keywords of articles (Keywords plus) are shown in Table 4, whereas the co-occurrence of keywords that appear 3 times or more are shown in Figure 4. The results suggest that UAVs feature quite prominently in IWM practices. Furthermore, UAV-acquired or -derived (vegetation indices) data are often used with machine and deep learning techniques to aid with image analysis and classification to detect and map weeds, which can serve as a precursor to implementing weed control interventions. It should be noted that some of the keywords and keywords plus also formed part of the search query string used to identify the pool of literature that was reviewed and analyzed. Subsequently, there is an element of bias that may exist in the aforementioned finding.

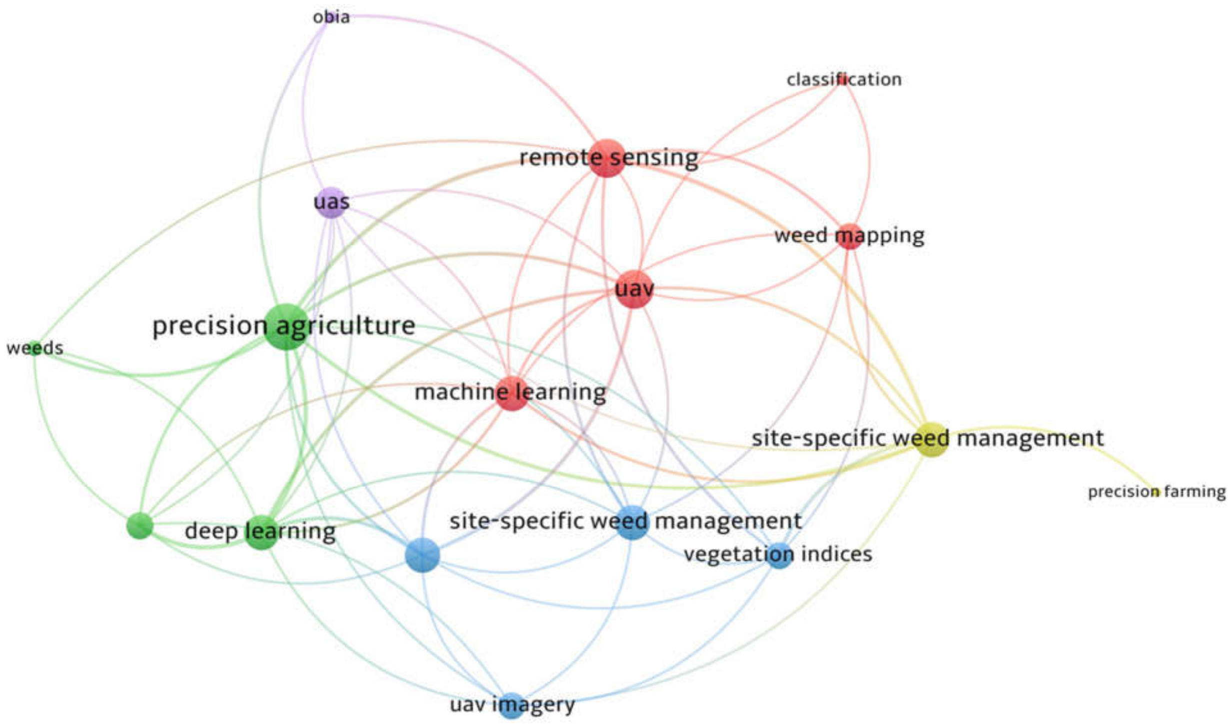

Figure 4. Co-occurrence network of author keywords.

Table 4. Top 10 author keywords and keywords plus.

Keywords	Frequency	Keywords Plus	Frequency
Site-specific weed management	16	Weed control	31
Precision agriculture	15	Precision agriculture	24
Remote sensing	12	Crops	17
Unmanned aerial vehicles (UAV)	9	Remote sensing	17
Deep learning	8	UAV	17
Machine learning	7	Weed	17
Vegetation indices	5	Deep learning	15
Weed detection	5	Image analysis	14
Weed mapping	5	Unmanned vehicle	14
OBIA	4	Antennas	11

3.2. Key Attributes

Remote Sensing Technologies

Satellites, manned aerial vehicles (MAVs), and UAVs have all been utilized to collect data to aid in weed detection for IWM applications. The earliest reported study by López-

Granados et al. [30] involved the acquisition of aerial imagery in southern Spain over a winter wheat crop with natural weed infestations using an MAV. MAVs featured almost exclusively during the formative years of this particular research focus area (Figure 5). However, as UAV technologies began to emerge, they quickly dominated this research space and have remained the preferred platform for weed detection to facilitate IWM.

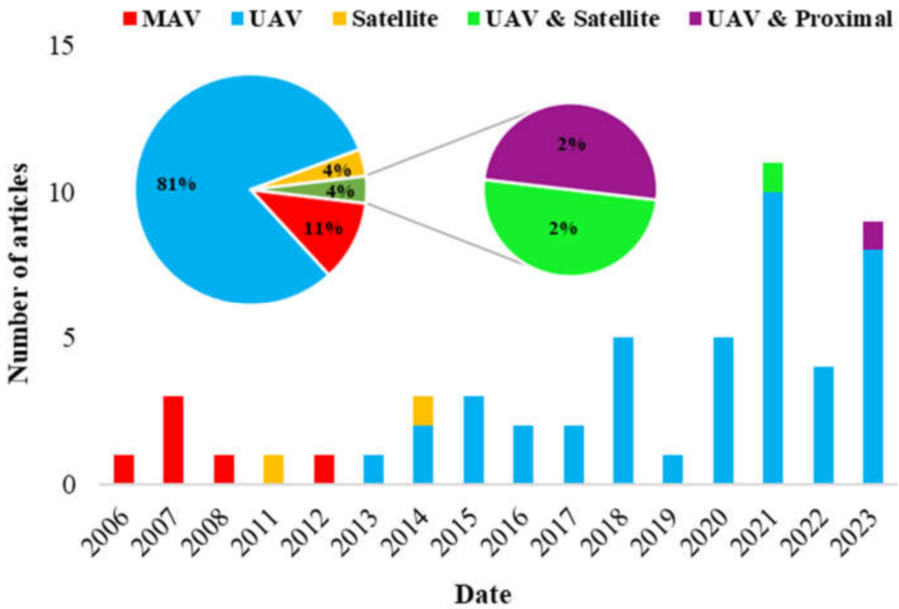

Figure 5. Historical evolution and percentage contribution of articles per sensing platform.

This may be due to the unique characteristics of UAVs and their associated sensors that enable them to acquire very-high-spatial-resolution data at user-defined intervals in near-real time for most weather [18,31]. UAVs further possess fewer limitations imposed by weather conditions, with the ability to fly even on cloudy days; greater flexibility in acquisition scheduling and payload options; reduced costs of vehicles and sensors; and access to difficult-to-reach areas; amongst others [28,32]. The spatial resolution of the satellite sensors (Quickbird and Sentinel-2) used in various studies ranged from 2.4 to 10 m, whereas the spatial resolution of the sensors onboard MAVs ranged from 0.12 to 0.30 m. Although acceptable-to-good accuracies were attained at these spatial resolutions, detecting and differentiating weeds from crops necessitates very-high-spatial-resolution imagery [20,31]. UAVs are typically equipped with sensors that can provide images with centimeter-to-sub-centimeter spatial resolution. Furthermore, the added flexibility of easily flying at various altitudes allows for optimizing flight planning and data capturing at the most appropriate spatial resolution [20,31].

While very-high-spatial-resolution imagery is paramount to accurately detect weeds, the spectral resolution of the imaging sensor is equally important, as it influences the ability to differentiate between weeds and crops based on their unique spectral properties [20]. There are several types of sensors that can be used for remote-sensing-based IWM applications, of which RGB and multi-spectral sensors feature most prominently. RGB sensors are among the most popular and widely utilized sensors as they provide high-quality images, can be used for several applications, are relatively inexpensive, possess minimal operational requirements, and do not require radiometric and atmospheric corrections [20,31]. While multi-spectral sensors are accompanied by, inter alia, higher costs and additional image processing requirements, their use remains quite popular due to their ability to acquire information across more than three bands (RGB), allowing for a wider range of potential applications beyond crop and weed mapping [20,33].

Algorithms and Methodologies

Machine-learning-based approaches have been widely used to detect and differentiate weeds from crops. These approaches typically involve the use of nonparametric methods to identify and learn complex relationships between target (e.g., weeds) and predictor (e.g., spectral bands, indices, or physical characteristics) variables [27]. In most instances, all spectral bands captured by a sensor will be used as predictor variables when training and applying a classification algorithm. However, the sensor type and classification approach influences the choice of spectrally derived indices or physical characteristics that may be used. For RGB sensors, simple ratios between the RGB bands, excess green (ExG), excess red (ExR), excess green–red (ExGR), color index of vegetation (CIVE), shape, texture, and canopy height are often used. While many of the aforementioned predictor variables are also used for multi-spectral sensors, some of the commonly used multi-spectral-specific indices include the normalized difference vegetation index (NDVI), ratio vegetation index (RVI), normalized green–red difference index (NGRDI), soil adjusted vegetation index (SAVI), and near-infra-red–green ratio (NIRG).

Several machine-learning-based algorithms have been used to detect and map weeds [20], with the random forest algorithm being the most extensively applied. According to Bahrami et al. [27], this may potentially be due to (i) the robust nature of the algorithm, (ii) its ability to perform efficiently even on large volumes of data, (iii) it uses relatively few hyper-parameters, and iv) is less sensitive to noise and overfitting. In addition to the choice of predictor variables and classification algorithms, another important factor to consider when detecting and differentiating weeds from crops is the classification approach, i.e., pixel- or object-based.

Pixel-based approaches have traditionally been the go-to method for land cover classification studies and involve using the attributes of individual pixels to perform a classification [34,35]. This approach is appropriate when the spatial resolution of the pixel is similar in size to the object that is being classified. However, with very-high-resolution imagery such as that used for crop and weed mapping, the size of the pixels can be significantly smaller than the object being classified. It may lead to greater classification inaccuracies [36]. Object-based methods overcome this limitation by performing a pre-classification, whereby a segmentation algorithm is used to generate objects by grouping pixels based on their spectral properties, shape, size, or texture. The attributes of these objects are then used to perform a classification [34,35]. Although object-based methods overcome some of the limitations associated with pixel-based approaches, they do possess limitations of their own, such as the impact of the choice of segmentation algorithm, over- or under-segmentation, and computational effort that is required [35,37]. Subsequently, the strengths and limitations of each of these approaches will need to be considered before deciding which method to adopt. However, pixel- and object-based approaches have been shown to perform well for crop and weed mapping [38–40].

Deep learning is a subset of machine learning (ML) that has also featured quite prominently in weed mapping studies and has often produced superior results to traditional machine-learning-based approaches [33]. Deep learning is centered on a far more complex image analysis process whereby meaningful features are automatically extracted from the raw input data, requiring relatively limited user input to develop, train, and evaluate the model to perform classifications. Deep learning models for weed mapping are usually based on some form of convolutional neural network (CNN), with the most popular example among the reviewed studies being the YOLO model [29,41–43]. Despite their ability to produce highly accurate results and requiring relatively minimal user intervention, these models are complex, computationally demanding, and data-intensive, which may limit their feasibility for widespread crop and weed mapping applications.

Studies on Crops Association with Weeds

The geographic distribution and frequency of studies by region are shown in Figure 6. Research on the use of remote sensing data to aid in detecting and mapping weeds for IWM applications has been conducted in 18 countries, with Spain being the leading nation in this research focus area. Most of this research has been conducted in European nations, accounting for approximately 70% of the studies undertaken globally. Contrastingly, limited studies have been conducted within nations that form part of the Global South. Regarding the detection and mapping of weeds among crops, crops that have featured most frequently (Figure 7) in the reviewed studies were wheat (n = 13), sunflower (n = 8), and maize (n = 7). This is potentially due to their status as major grain and oilseed crops. Consequently, these crops generally attract greater interest as the impacts of weeds can significantly affect global grain and oilseed supplies, which in turn threatens food security.

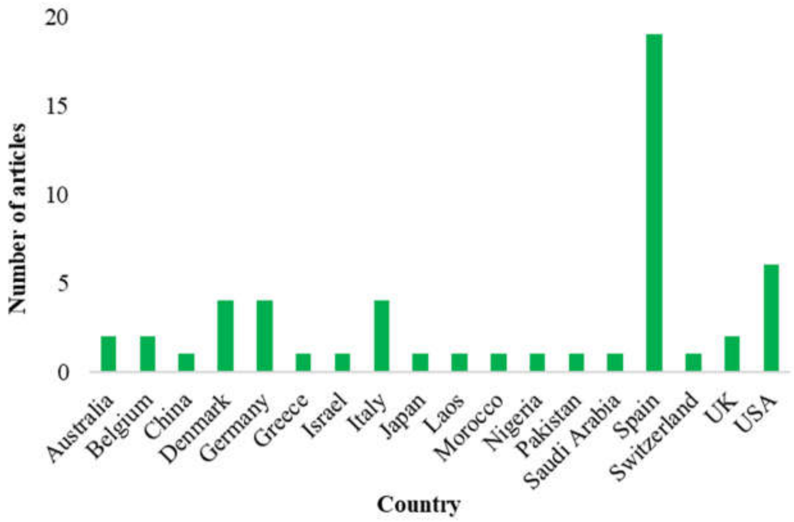

Figure 6. Frequency of studies by region.

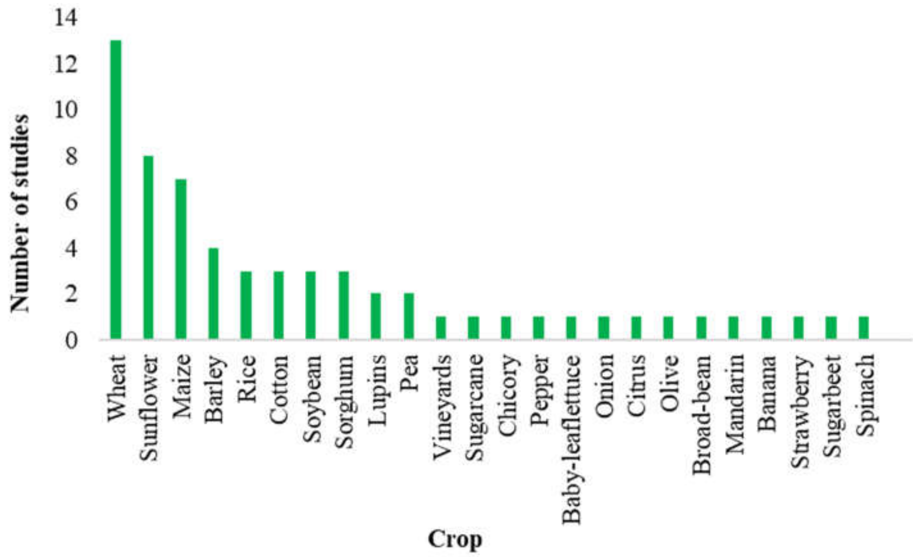

Figure 7. Number of articles per crop type.

4. Discussion

To our knowledge, there has been no standard approach for systematically identifying a remote sensing platform and considering sensor characteristics and data analysis procedures to facilitate IWM for smallholder agriculture. The information presented in the results section is extracted and synthesized from 53 studies published in various journals. This review highlights remote sensing approaches as the focus of most of the studies discriminating weeds from cultivated systems, which are also considered one of the most important technologies for PA [30]. In past decades, MAVs and satellites were used to capture images for PA applications [23]. However, satellites and MAVs may be less attractive for widespread IWM applications [20,23], particularly in smallholder farm settings.

Considering the often fragmented and heterogeneous nature of smallholder farming systems, freely available satellite earth observation datasets are generally unsuitable for these environments due to the spatial, spectral, and temporal trade-offs that are characteristic of these datasets [44]. In addition, the large cost implications of more advanced satellite and manned aerial systems render these options unfeasible for many of these farmers [20,23]. The unique characteristics offered by UAVs, such as their ability to provide cost-effective spatially representative data at user-defined intervals, have seen this technology emerge as an important tool to facilitate PA applications such as IWM and are promising for smallholder farm applications [18–20,23,28,31,32,45–47].

As previously indicated in Section 3.2, very-high-spatial-resolution imagery is preferential to accurately detect and map weeds [18,20], which restricts the types of sensors and remote sensing platforms suitable for this task [48]. While several sensors exist, of which RGB and multi-spectral sensors feature more prominently than others, UAV-mounted RGB sensors remain the most widely used sensor for IWM [18,20]. Although the purchasing of UAVs and associated ancillary resources requires a substantial upfront investment, it provides higher-resolution images compared to other remote sensing systems. Furthermore, this initial investment is compensated by the repeatability of flights, which increases the frequency of derived datasets, thus minimizing the costs of labor and critical resources. Additionally, UAVs equipped with a relatively cheap RGB sensor may represent the most feasible option for smallholder farmers concerned with IWM applications, since images from these sensors require less additional processing, which reduces the need for purchasing additional processing software, thereby reducing overall operational costs [33].

A variety of classification methods can be implemented to detect and map weeds using UAV imagery and can be performed using proprietary or open-source software. Recently, ML algorithms implemented within cloud computing environments are being implemented more frequently as they offer many advantages over traditional methods, particularly for processing and analyzing large complex datasets [27]. Furthermore, with cloud-based platforms such as Google Earth Engine (GEE) being freely available and easily accessible, many of the barriers that have restricted users (particularly those in developing countries) from exploiting technological advancements to guide agricultural operations have now been removed [40]. While the availability and accessibility of such a powerful data processing platform have opened up many new and exciting avenues to a wide range of users interested in utilizing remote sensing to guide and inform PA applications, users will require good internet connectivity. They may also be restricted with regards to (i) the amount of data that can be stored and processed, as well as by (ii) the choice of techniques that are available to them [49]. For example, users can only choose from selected ML algorithms when performing image classifications within the platform.

Similarly, while deep learning has shown a great deal of promise for producing very accurate maps, these techniques are not directly available within GEE. Furthermore, when considering other major limitations of these techniques for weed detection, such as computational resources and large datasets for training that are expensive and time-consuming to acquire, as well as the specialized skills required to implement them, these requirements typically limit their application for smallholder farmers [23,29,33,50,51]. Subsequently, users interested in adopting these approaches will require high-powered computational resources and a large volume of data to successfully implement these techniques; neither are readily available nor easily accessible in resource-constrained regions.

According to the geographic distribution and frequency of studies (Figure 6), using remote sensing for weed management is mainly concentrated in the Global North [52]. Considering that the demand for agricultural products will increase globally, owing to the rapidly growing population and rising incomes, and since a majority of food is also produced within sub-Saharan Africa, research to determine cost-effective ways of maximizing the use of technologies like UAVs for use in the Global South is equally crucial and required.

While past studies mainly focused on three major food staples, namely sunflower, wheat, and maize, a need exists to diversify our agri-food systems with more climate-resilient and nutrient-rich crops. In this regard, NUCs can complement the cultivation of staple crops, along with the potential to improve the sustainability and resilience of food systems, which in turn can enhance food and nutrition security [3,4]. Furthermore, with the cultivation of NUCs mainly being confined to smallholder farms, there exists an opportunity to improve the socio-economic circumstances of poverty-stricken and marginalized smallholder communities and improve food sovereignty by enabling smallholder farmers to exert a greater influence in food production systems [2–4]. Subsequently, research on IWM using UAVs for NUC and weed combinations is required, with techniques and findings from studies conducted on major crops used as guides. Considering the limited literature on the use of UAVs for weed detection within smallholder farms and on NUCs, a review of such caliber was both necessary and important to undertake.

Studies conducted on crop–weed competition using UAVs were mainly limited to assessing crop yield losses, overlooking the significant uptake of soil water by weeds, which also threatens crop productivity and exceeds the global water constraints [53]. Since farming is not solely driven by yield and considering the global threats of climate change, environmental degradation, and an ever-growing population exerting pressure on over-constrained water resources, the water use of weeds also represents a critical component of assessing and managing weeds in the agricultural sector ([53]. For example, several smallholder farms in sub-Saharan Africa are reliant on rainfed irrigation and challenged by water scarcity concerns. Therefore, if weeds are not properly managed, or their water use is not adequately accounted for, weeds may deprive crops of an already limited water supply, which can eventually result in lower crop productivity [54]. Furthermore, insufficient rainfall during crop production periods and periods of dry spells could lead to food insecurity issues. Hence, in addition to crop yield and crop status monitoring, research on the use of UAV technologies for water use estimation is required, given that these technologies possess the capabilities for several applications, including water use applications.

With the development of UAVs, monitoring both early- and late-season weeds provides unprecedented opportunities for cost-effective near-real-time mapping with high spatial, spectral, and temporal resolutions [55]. Early-season weed monitoring is generally found to be more suitable and preferred for weed identification as it is critical for safeguarding the productivity of the growing crop, as weeds compete with the crop for a longer period and can cause higher yield losses if allowed to produce seed [56,57]. This is particularly true for an NUC crop such as taro, which can take up to 49 days to emerge [58]. Furthermore, taro is relatively slow growing, taking up to 300 days to reach physiological maturity. Hence, it is important to keep the site weed-free. Furthermore, performing early discrimination of the types of weeds growing in the crop field provides the added advantage of selecting the correct type of herbicide treatment to be applied, thus avoiding using a wide-spectrum herbicide [40]. For smallholder farmers, this could result in reduced costs, and given that manual weed removal is often practiced, it presents the best time to manage weeds, as they are easier to control [51].

Compared to early-season weeds, late-season weeds do not directly affect crop yield as they do not compete for resources during the crop's critical growth [59]. However, weeds that survive early weed management methods due to herbicide resistance or incorrect herbicide selection or application can persist, thus resulting in a higher weed seedbank that affects subsequent growing seasons [55,56,59–61]. Therefore, mapping of late-season weeds can provide information for developing long-term weed management strategies and for farmers to evaluate the efficiency of their previous weed control methods [59,60]. For smallholder farmers, these late-season weed maps can be useful in reducing herbicide use and crop management costs. Considering the merits of mapping both early- and late-season weeds for smallholder farmers, the two approaches can complement each other, with a useful application being to combine them to determine the effectiveness of the management decisions made in such farm settings.

Despite the economic and environmental advantages that PA techniques can potentially bring, adopting geospatial information technologies is lagging in the developing world, with the biggest gap in PA adoption for smallholder farms [62]. The hesitancy of these farmers is due to feasibility considerations, being less high-tech-oriented and the high initial investment costs, and still preferring traditional practices that are no longer practical [62]. Consequently, it is very important to develop cost-effective tools and utilize open-source software where possible to address the specific issues faced in such countries, and thus its adoption worldwide, especially in weed management, to control and increase yield production, leading to a better economy for the country and farmers. While UAV technology may remain unaffordable for many small-scale farmers, specialists can leverage innovative UAV-based business enterprises to offer a more affordable option where the investment cost is shared across multiple farms by a UAV service provider [12].

Other key barriers that have not been identified through the bibliometric and attribute analysis but will significantly influence the adoption of UAV technologies by smallholder farmers include a lack of awareness and digital skills among farmers, requiring co-learning and participatory approaches among the public and private sectors, civil society, and academia [12,49]. The public and private sectors can partner with non-governmental organizations and leverage their on-ground presence (e.g., agricultural extension workers) for delivering hands-on training, building digital capacities of farmers [12], and creating decision support systems that offer advisory services to the farmers. Further addressing these barriers requires creating solutions within a user-centered framework accounting for local contexts, such as language and societal barriers, and enabling policies to support the digitalization of the sector. For example, with supportive policy frameworks and subsidies for purchasing UAV models, China has become one of the most UAV-friendly countries, possessing over 50,000 agricultural drones in operation [12]. Considering these favorable policies and technological support mechanisms, it is envisaged that at least 80% of the future UAV market will be in the PA segment [12].

5. Conclusions

NUCs have the potential to address food and nutrition insecurity, given their adaptability to low-input agricultural systems, high nutrient density, and tolerance to biotic and abiotic stresses. Given that approximately 80% of the food produced in Asia and sub-Saharan Africa comes from smallholder farms and that NUCs are the main sources of food consumed by the latter population, there is a need to support smallholder farmers in achieving good, high-quality production levels of these crops. Poor weed management primarily contributes to low yields and inferior product quality. Since conventional weed management techniques are unfavorable for several reasons, IWM represents an alternate approach to mitigating the harmful impacts of conventional methods and is also well suited for smallholder farm applications. While the findings presented herein should be contextualized within the confines and context of this study, this review has demonstrated and detailed how UAVs stand out as a promising technology for weed identification and management within small- to medium-scale farms due to their unique characteristics. However, the adoption of PA facilitated by UAVs for smallholder farmers is still nascent. It is limited by several obstacles to their operational application within smallholder farm settings, which must be overcome. Thus, careful consideration is first required on how best to optimize the potential of UAVs before investing in these technologies for smallholder applications.

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