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Review

Leveraging Unmanned Aerial Vehicle Technologies to Facilitate Precision Water Management in Smallholder Farms: A Scoping Review and Bibliometric Analysis

Ameera Yacoob [1,*], Shaeden Gokool [1], Alistair Clulow [1,2], Maqsooda Mahomed [1] and Tafadzwanashe Mabhaudhi [3,4]

[1] Centre for Water Resources Research, School of Agricultural, Earth and Environmental Science, University of KwaZulu-Natal, Pietermaritzburg 3209, South Africa; gokools@ukzn.ac.za (S.G.); clulowa@ukzn.ac.za (A.C.); mahomedm@ukzn.ac.za (M.M.)
[2] Discipline of Agrometeorology, School of Agricultural, Earth and Environmental Sciences, University of KwaZulu-Natal, Pietermaritzburg 3209, South Africa
[3] Centre for Transformative Agricultural and Food Systems, School of Agricultural, Earth & Environmental Sciences, University of KwaZulu-Natal, Pietermaritzburg 3209, South Africa; tafadzwanashe.mabhaudhi@lshtm.ac.uk
[4] Centre of Climate Change and Planetary Health, London School of Hygiene and Tropical Medicine, London WC1E 7HT, UK
* Correspondence: 218023873@stu.ukzn.ac.za; Tel.: +27-792913882

Abstract: While there is immense potential in using unmanned aerial vehicles (UAVs) to facilitate precision water management, there is currently no consensus on practical strategies to operationally implement these technologies to guide water resources management decisions, particularly within smallholder farming contexts. To address this gap, this study employs bibliometric techniques to assess the current state of UAV applications for evapotranspiration (ET) estimation in agricultural settings. The analysis of 49 peer-reviewed papers from Scopus was conducted using Biblioshiny and VOSviewer to enhance comprehension of this expanding research field. The study highlights a significant increase in scholarly research on utilising UAVs for precision water management over the past decade. The investigations indicate that UAVs in agriculture are gaining prominence and exhibit substantial potential for various precision agriculture (PA) applications. Significant cost reductions for UAV technology and remote sensing (RS) are anticipated soon, primarily driven by the availability of open-source platforms for processing tasks, such as Google Earth Engine. This research aims to inform smallholder farmers about the benefits of integrating UAVs into their farming practices, enhancing operational efficiency and productivity. Policymakers can use these findings to develop regulatory frameworks and incentive schemes that facilitate UAV adoption among smallholder farmers. Additionally, technology developers can leverage insights from this study to identify areas needing innovation and optimisation tailored to small-scale agriculture. Hence, this study seeks to bridge the gap between technological advancements and practical agricultural applications, promoting sustainable farming practices and enhancing the socioeconomic welfare of smallholder farmers.

Keywords: smallholder farming; precision agriculture; UAV; evapotranspiration; water stress; food security; Biblioshiny

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1. Introduction

In numerous developing nations globally, smallholder farms, defined as those encompassing less than two hectares, constitute significant contributors to agricultural output and stand as primary drivers of socioeconomic development [1]. Given their substantial yield output vis-à-vis land occupancy, these entities possess the capacity to serve as pivotal agents in addressing concerns regarding food security [1–3]. Despite their relative significance, the precarious circumstances prevailing among many such smallholder farmers often hinder the realisation of their agricultural productivity potential and render them ill-equipped to cope with climatic adversities [1,4].

From a South African perspective, many smallholder farmers, particularly those dependent on rain-fed agriculture, persistently encounter food and nutritional insecurity challenges attributable to water shortages, erratic weather patterns, and prolonged dry spells [5]. South Africa, on average, receives approximately half of the global mean annual precipitation (MAP), with pronounced precipitation variability and climatic extremities exacerbating these conditions; consequently, diminished water availability frequently compromises the optimal cultivation of crops, notably within dryland agricultural systems [6,7]. Given these circumstances and the distinctive challenges faced by these farmers, the implementation of innovative, evidence-based, and cost-effective interventions tailored to bolster productivity and fortify resilience against adversities holds promise for their improvement [4,8].

Precision Agriculture (PA) is pivotal in mitigating the global challenge of food security by implementing tailored strategies and management interventions. The PA process comprises data collection, analysis and communication technologies, decision making, and practice management [9]. Central to these endeavours is minimising the unnecessary depletion of critical resources, such as nutrients and water, while increasing crop yields and mitigating potential adverse environmental repercussions [10,11]. PA technologies serve as instrumental decision-support tools aimed at optimising agricultural operations, facilitating interventions in mitigating plant water stress, diagnosing plant diseases, assessing crop yields, and undertaking plant phenotyping, among other functions [9,12,13].

Accurate evapotranspiration (ET) spatiotemporal estimation and assessment of crop water status constitute fundamental aspects of precision water management, which in turn is a vital component of the PA paradigm [14,15]. Several methodologies have been devised for ET monitoring, with two primary categories prevalent in scientific inquiry: ground-based/in situ and remote sensing (RS) approaches. ET estimation through field-based methods typically entails the application of water balance principles. Moreover, micrometeorological techniques based on the principles of the shortened energy balance, such as the Bowen ratio [16,17], eddy covariance [18], scintillometry [19,20], and surface renewal [21] methods have garnered extensive utilisation in ET estimation endeavours.

Nonetheless, these measurements often exhibit limitations, being confined to specific points or weighted by area, posing challenges in extrapolating findings to broader scales owing to the intrinsic heterogeneity of land surfaces. Furthermore, there has been a notable surge in interest regarding the utilisation of RS and, more specifically, UAVs for PA applications in the past decade [15,22,23]. Given their distinctive attributes, UAVs offer advantages conducive to smallholder farms, enabling circumvention of limitations associated with in situ and satellite-based techniques.

Drone Applications in Precision Agriculture

UAVs are equipped with lightweight sensors capable of capturing high spatial-resolution images. This capability contrasts with many freely available satellite-based datasets, which often lack the spatial resolution required to accurately represent smallholder farms' spatial heterogeneity [24,25]. Moreover, satellite-based RS is more susceptible to cloud cover, whereas UAVs can be flown at lower altitudes, making them less prone to their impacts. UAVs can also be flown at user-defined intervals. In contrast, the satellite's flight path is fixed, and revisit and repeat cycles are restricted [26–28].

Despite their advantages, UAVs possess inherent limitations that warrant consideration. These include limited flight durations due to battery constraints, data processing and analysis challenges, and regulatory restrictions that may complicate operations. Moreover, the initial capital investment may create significant financial barriers for smallholder farmers, potentially hindering the widespread adoption of this technology [8,29,30].

Several essential factors emerge when comparing costs between UAVs and other RS platforms, such as satellites or manned aerial vehicles (MAVs). UAVs typically require a lower initial investment, being more affordable than high-resolution satellite data and devoid of recurring subscription fees for data access [8]. Although operational training for UAVs is necessary, it often proves more straightforward and accessible than the specialised qualifications required for traditional RS methods, making UAVs more user-friendly for smallholder farmers. Additionally, UAVs facilitate user-defined flight plans for immediate data acquisition, eliminating delays associated with satellite revisit times [4,5,28]. This combination of accessibility and cost-effectiveness positions UAVs as a viable option for smallholder farmers, allowing them to obtain timely, high-resolution data to enhance their agricultural practices without the financial constraints imposed by satellite-based RS services.

As research on UAV applications in agriculture has increased, it is necessary to synthesise the existing literature and explain the intellectual framework of this domain. Moreover, few reviews discuss UAV applications in the PA sector, focusing on ET estimation. For example, Rejeb et al. (2022) undertook a bibliometric analysis to summarise drone research in agriculture [13]. Similarly, Gokool et al. (2023) assessed using UAV technology in facilitating PA techniques, with a specific emphasis on small-scale farming operations [8].

Singh et al. (2022) conducted a scholarly investigation similar to Rejeb et al. (2022), focusing mainly on viticulture [31]. In contrast, Awais et al. (2022) detailed crop water status estimation using UAV-based methods [32]. Nhamo et al. (2020) examined the significance of UAVs in agricultural water management and crop health, highlighting their potential as an alternative approach to enhance productivity in smallholder farms [4]. In addition, Raparelli and Bajocco (2019) analysed the use of UAVs in agriculture and forestry research over the last twenty years. However, their investigation is limited to academic studies published only between 1995 and 2017, failing to capture the constantly evolving nature of this rapidly advancing field [33].

While the aforementioned studies offer a comprehensive analysis and generate novel and valuable insights, their primary focus has generally been on the capabilities of UAVs, particularly in the context of crop mapping and monitoring. Therefore, this study aims to fill the existing knowledge gap by conducting a comprehensive scoping review and bibliometric analysis of the literature on the practical use of UAVs for estimating ET or detecting crop water stress. The objective is to give current, concise insights that may guide and enhance PA practices.

Moreover, this research may serve as a vital resource for gaining a more profound understanding of using UAVs to enhance precision water management practices. With the increasing volume of scholarly output in scientific disciplines, it has become imperative for researchers to use quantitative review methodologies to comprehend the structure of knowledge [34]. Furthermore, as the complexity of research fields increases, it is essential to analyse the information created within these disciplines [35]. This analysis serves several purposes, including uncovering new contributions, documenting research traditions and trends, identifying the themes that have been investigated, and exploring prospective avenues for future research.

Consequently, the study endeavours to attain the objectives below:

1. Conduct a scoping literature review on UAV-based RS techniques to facilitate precision water management within smallholder farms.
2. Identify significant journals, publications, authors, and nations that have made notable contributions using UAVs in ET estimation and crop water stress detection.
3. Describe UAV-based approaches to monitor crop water use and aid PA.
4. Use co-citation analysis to group publications according to their semantic similarity, identify thematic areas, and map studies' main "intellectual structure."
5. Identify data analytic methods used to support the estimation of ET and detection of crop water stress and analyse these results within the context of smallholder farming.

2. Materials and Methods

2.1. Literature Search

An initial literature search was conducted using academic search engines, such as Elsevier, Scopus, and Science Direct, to identify prominent keywords in published papers from high-impact-factor journals that addressed three main areas of interest: precision water management (S1), unmanned aerial vehicles (S2), and crop water status (S3). An iterative procedure facilitated the identification of a definitive keyword string that most accurately described the objective of the investigation.

After this, Scopus was selected as the sole abstract and citation database for the bibliometric analysis due to its comprehensive and trustworthy standardised results. The meta-data of publications were retrieved using the following query string: "("precision agriculture" OR "precision farm*" OR "precision irrigation" OR "precision water management" OR "site-specific irrigation management" OR "site-specific management") AND ("unmanned aerial vehicle" OR "UAV" OR "unmanned aerial system" OR "UAS" OR "unmanned aerial systems imagery" OR "drone") AND ("evapotranspiration" OR "transpiration" OR "crop water use" OR "crop water requirement" OR "water requirement" OR "water stress" OR "stomatal conductance")" on 7 August 2023.

Despite recognising smallholder farms as a significant area of interest in this study, they were excluded from the search query due to the limited number of studies assessing the relevance of UAV applications in these settings. Consequently, the search query was broadened to enable a more comprehensive review of applicable techniques and to facilitate the contextualisation of the main findings. However, the ensuing discussion portion of this review will undertake a more comprehensive analysis of the findings to ascertain the cost-effectiveness of the platforms and methodologies used in the final selection of studies. The search was conducted without applying any constraints on the timespan; however, articles that were not published in accredited peer-reviewed journals and not written in English were excluded. The search results returned 69 references. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for scoping reviews (PRISMA-ScR) framework was used to avoid biased reporting by guiding decisions regarding selecting articles to be included or excluded from the review (see Figure 1).

The eligibility criteria for the review were established as follows:

1. The full-length article must be peer-reviewed, published in English, easily accessible, and readily available.
2. The study or review should specifically address the use of UAV technology for estimating ET or detecting crop water stress within the context of PA.

Two reviewers screened the title, abstract, and full-length article. Subsequently, a third-party independent reviewer resolved disputes to ascertain that all the papers included in the study adhered to the predetermined eligibility criteria. After screening these articles' titles and abstracts, 49 full-length articles were identified as eligible and were sought for downloading. No additional articles were sought following this process.

2.2. Data Analysis

Once the final database (n = 49) had been compiled, a citation analysis was executed using the Biblioshiny App version 4.3.0 (accessed using the R environment: Bibliometrix-R package) to explore the connection between authors and peer-reviewed articles, underlying citation patterns and the most influential authors and publications. Biblioshiny is a standard citation and co-citation analysis tool. This tool offers simple interaction with other software and significant data handling and analysis freedom. Moreover, a co-citation analysis was conducted using VOSviewer (version 1.6.19) software to visualise the findings and generate the bibliometric networks. VOSviewer offers a range of intuitive visualisations, particularly for analysing bibliometric maps [36]. Finally, the connections and linkages between countries, institutions, and journals were analysed to depict the collaboration network.

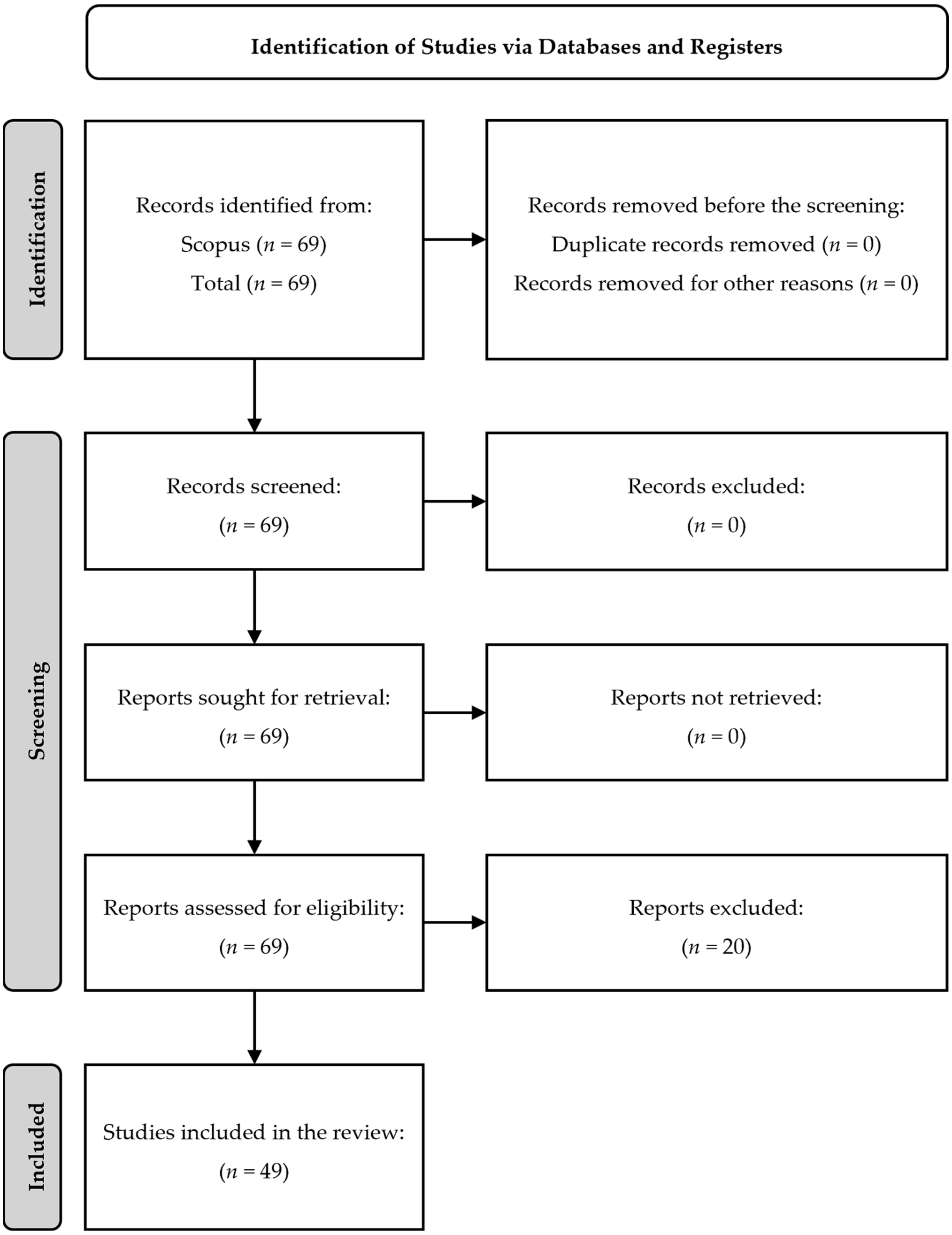

Figure 1. The flow diagram for article selection according to the PRISMA-ScR framework.

3. Results

The initial analysis focused on the temporal distribution of scholarly research on agricultural UAVs in precision water management, as shown in Figure 2. There has been a notable surge in publications since 2019, with six recorded publications. Hence, the period from 2013 to 2018 may be characterised as the first phase, during which an average of one article was published yearly. The surge in publications after 2019 indicates a notable rise in research activity, signifying the widespread use of UAVs in RS and PA [9]. Specifically, there was an increase in the number of publications from 6 in 2019 to 12 in 2022, reaching its highest point at 13 in 2021.

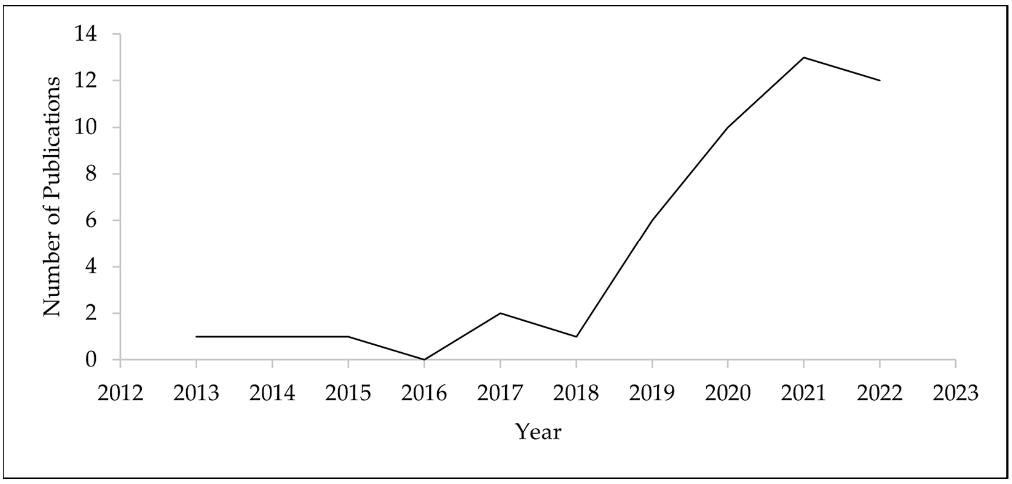

Figure 2. Annual publication distribution.

3.1. Fundamental Statistical Data

Table 1 presents a comprehensive overview of the essential statistical information on the overall literature dataset. Studies on using UAVs to enhance precision water management were first documented in 2013. Since then, this field of research has shown an upward trajectory, with a compound annual growth rate of about 7.18%. In 2015, there was a notable increase in the average total citations (TCs) per publication, reaching its highest point at 372, as shown in Figure 3. Similarly, it is worth noting that 2015 had the highest average total citations (TCs) per year, amounting to 41.33.

Table 1. Essential bibliographic details contained in the completed literature dataset.

Description	Result	Description	Result
Timespan	2013–2023	References	3040
Number of journals	21	Author's keywords (DE)	185
Number of publications	49	Authors	243
Annual growth rate %	7.18	Single-authored documents	0
Document average age	2.78	Co-authors per document	5.94
Average citations per document	41.29	International co-authorships %	36.73

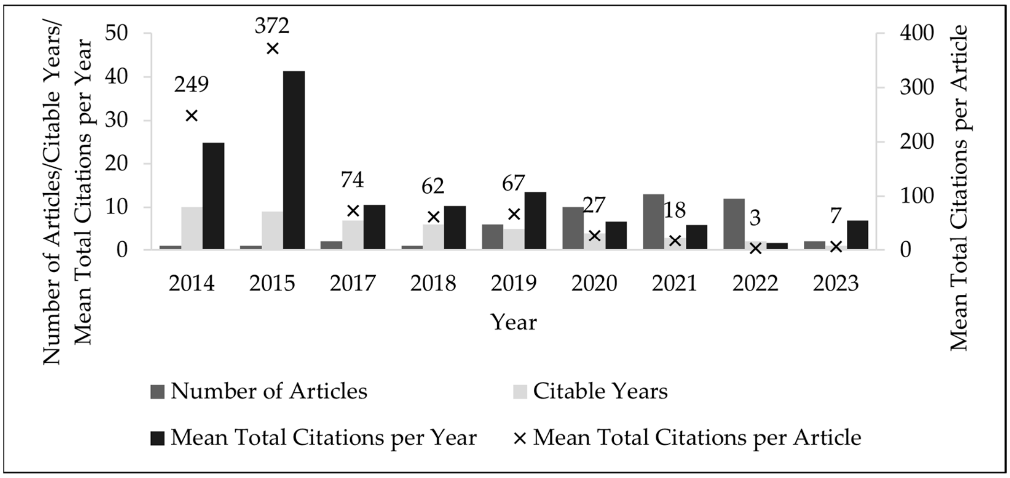

Figure 3. The dissemination of mean annual citations and publications.

3.2. Distribution Characteristics of Leading Research Countries

The distribution parameters of significant research nations indicate the respective countries' impact on the UAV applications for ET estimation within the PA domain. The dataset used in this scholarly research was disseminated throughout 22 distinct nations. The published papers have been circulated across different continents, including eight European countries (Spain, Italy, Greece, Denmark, France, Sweden, Portugal, Germany), seven Asian countries (China, Israel, South Korea, Pakistan, Saudi Arabia, Egypt, Iran), four American countries (USA, Brazil, Canada, Chile), two African countries (South Africa and Zimbabwe), and one Oceania country (Australia). As seen in Figure 4, most publications were published in the United States and China. The United States of America is first in terms of paper volume, with 15 articles. Nevertheless, the average number of article citations for the nation under review was comparatively lower than that of countries such as Spain and China.

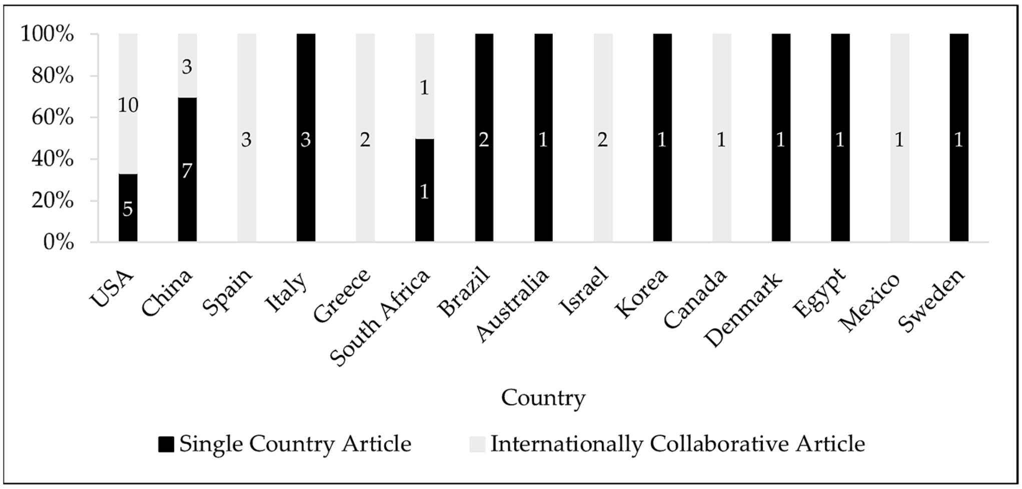

Figure 4. The nationalities of corresponding authors in the top 15 nations with the highest productivity in UAV applications in precision water management.

China emerged as the only developing nation in the top three regarding scholarly output, surpassing other countries significantly. China's research contributions constituted almost 22% of the overall production, demonstrating its substantial presence in the academic landscape. Furthermore, the average citation for each paper was 34.6, surpassing that of the United States (26.5). Additionally, its paper volume attained the second-highest position on a worldwide scale. Spain ranked second in total citations, with a cumulative count of 361; however, it achieved the highest average citations per article at 120.3. Furthermore, Spain positioned itself as the third highest publication volume, indicating its substantial impact on academic literature. Another significant contributor is South Africa, which is sixth in publication volume. This developing nation ranks fifth in total citations, with a total of 53. Additionally, South Africa had an average citation score of 26.5 per article.

3.3. Influential Authors and Citation Analysis

This section provides an overview of prominent authors and explores the use of author citation networks to represent and structure the existing body of literature visually. A collective of 243 authors contributed to the 49 articles on using UAVs to enhance precision water management. A total of 207 researchers contributed to the publication of a single paper, while 28 authors published two articles. Additionally, four authors had three articles published, and another four authors had four articles published. Figure 5 displays the author-level performance data for the 15 authors with the most publications (in chronological order). The authors showing the most activity in this study's emphasis area are Wenting Han, Lav Khot, Huihui Zhan, and Liyuan Zhang. Moreover, Wenting Han, and Liyuan Zhang, and have garnered the most citations.

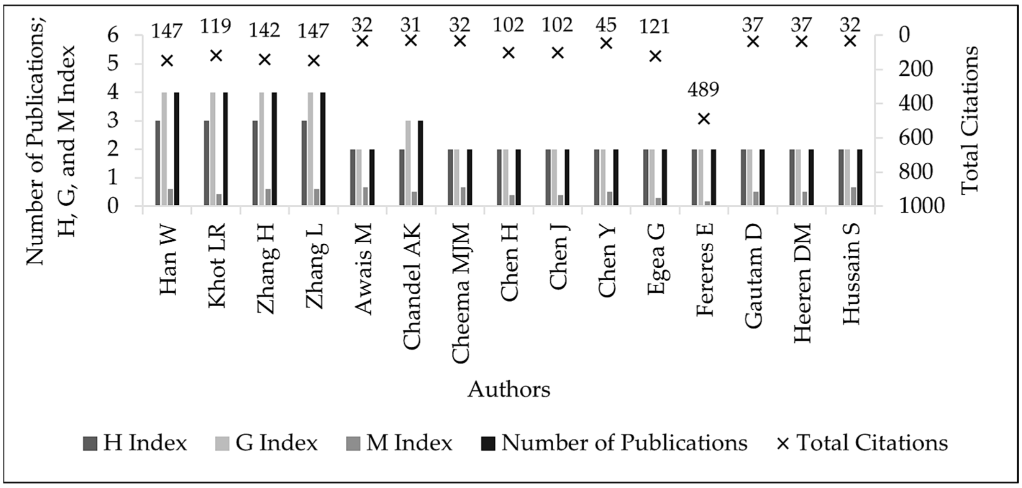

Figure 5. Key author-level citation metrics for authors with several publications.

The publications' global citation score (GCS), average TCs per year, and normalised citation score were all examined (Table 2). The GCS, which also contains citations from works in other fields, accurately represents the TCs a publication received in the abstract and citation database (Scopus) that was utilised. Gago et al. (2015) had the publication with the highest rank in terms of TCs and average TC per year [37]. The researchers comprehensively reviewed the capability of UAVs to analyse the water use of plants at a crop scale to enhance crop water stress management. This was accomplished by exploring the various RS-based indices obtained from UAV technology and their capacity to ascertain plant physiological properties.

Table 2. The Global Citation Score (GCS) of the ten highest-ranking publications.

Journal	TC	TC per Year	Normalised TC
Agricultural Water Management	372	41.33	1.00
Precision Agriculture	249	24.90	1.00
Precision Agriculture	240	21.82	1.00
Remote Sensing	146	29.20	2.17
Remote Sensing	108	27.00	4.03
Remote Sensing	97	19.40	1.44
Remote Sensing	88	12.57	1.20
Remote Sensing	82	16.40	1.22
Biosystems Engineering	62	10.33	1.00
Computers and Electronics in Agriculture	61	20.33	3.48

According to the normalised citation performance measure, the work authored by Messina et al. (2020) had the highest normalised TC score. This study comprehensively analyses the current advancements in UAV thermal RS in the agricultural sector. It provides a detailed description of the most recent applications and offers insights into potential areas for future research. The authors highlight that the crucial task of detecting water stress based on plant temperature data has significant value. In addition, Messina et al. (2020) explain that temperature-based indicators provide a rapid and efficient approach to evaluating and estimating the water status of crops. One widely used indicator for monitoring plant water status and managing irrigation resources is the crop water stress index (CWSI).

Another vital article in Table 2, which features a prominent author in the field, was the publication by Zhang et al. (2019). This study used high-resolution multispectral images obtained from a UAV to assess the suitability of the data for mapping the water stress condition of maize under different levels of deficit irrigation. Nine VIs associated explicitly with agricultural water stress were calculated from the multispectral imagery.

They were then used to develop inversion models for the CWSI. According to Zhang et al. (2019), "the ratio of Transformed Chlorophyll Absorption in Reflectance Index (TCARI) and Renormalized Difference Vegetation Index (RDVI), and the TCARI and Soil Adjusted Vegetation Index (SAVI) had the best correlations with the CWSI". The VI-CWSI regression models were compared to an empirical CWSI model developed using on-site canopy temperature, air temperature, and relative humidity measurements. In assessing crop and soil variability, the VI-CWSI regression models devised in this investigation were more effective than on-site measurements.

Furthermore, Sagan et al. (2019) ranked among the top five publications with the highest citation counts. The researchers assessed three commercially accessible thermal cameras for UAVs: the ICI 8640 P-series (Infrared Cameras Inc., Beaumont, TX, USA), FLIR Vue Pro R 640 (FLIR Systems, Wilsonville, OR, USA), and thermoMap (senseFly, Cheseaux-sur-Lausanne, Switzerland). The study's findings indicate that the three thermal cameras yielded valuable temperature data that may be effectively used in PA and plant phenotyping. The ICI 8640 P-series had the most favourable outcomes among the three systems [38]. However, the FLIR Vue Pro R 640 is a cost-effective alternative given its affordability and acceptable performance. Farmers and researchers may acquire crucial discernment on crop water conditions by using sophisticated analytics and integrating thermal data with other pertinent information, enabling them to implement prompt and precise irrigation management. This balance between cost and efficacy is essential for addressing agricultural challenges, particularly for smallholder farmers, by providing practical and affordable UAV-based thermal imaging solutions.

3.4. Influential Academic Journals

The completed literature database included 21 scholarly journals with a total of 49 papers that explore the use of UAVs for identifying crop water stress to facilitate PA. *Remote Sensing* and *Agricultural Water Management* exhibit the highest volume of papers, comprising around 53% of the overall publications. *Remote sensing* maintains its position at the forefront of the rankings for TCs, with a score of 660. Hence, this journal is prominent in the field of study focus. Figure 6 presents a visual representation of the critical journals categorised based on Bradford's law, a method used to determine the correlation between published articles and the journals in which they are published.

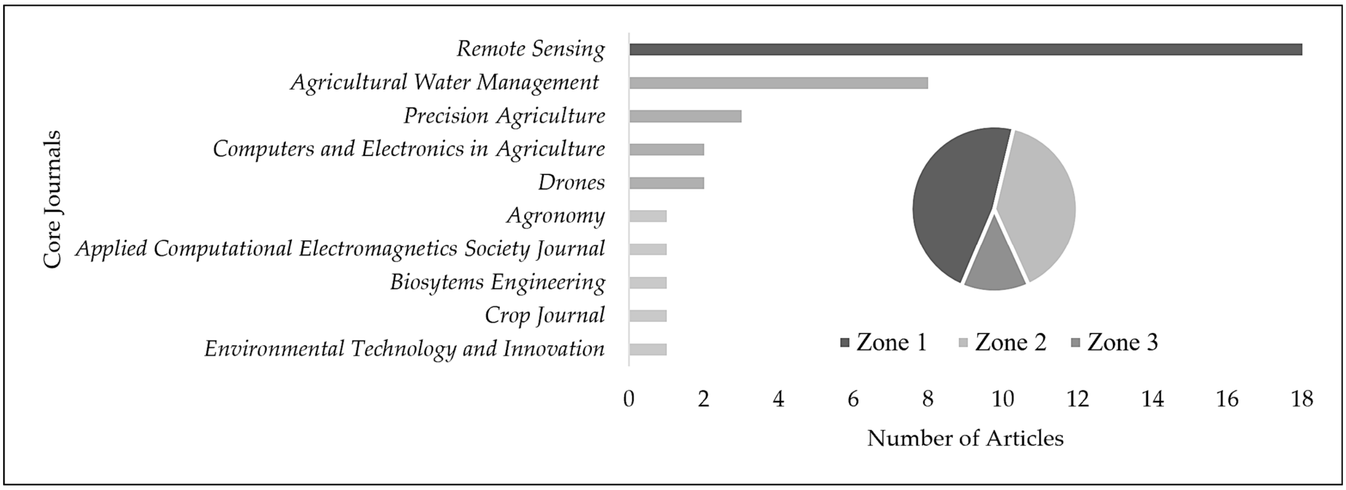

Figure 6. The categorisation of academic journals based on Bradford's law, fostering the dissemination of scholarly investigations.

Bradford's law proposes separating the pool of journal citations for a particular study emphasis area into three distinct zones based on their frequency. Zone 1 signifies the journals of utmost significance since they obtain the highest frequency of citations within their respective topic areas and hence receive the most scholarly attention. Zones 2 and

3 correspond to the journals with the average and least number of citations, respectively. According to Bradford's law, eighteen papers were published in a single journal under Zone 1. Additionally, fifteen articles were published across four journals under Zone 2, while five were published across five journals under Zone 3. According to the findings shown in Table 3, *Remote Sensing* emerges as one of the most influential journals, as it attains a high ranking in terms of output, TCs, and citation.

Table 3. Evaluation of publishing sources based on the number of articles published.

Journal	Publication Start Year	Number of Publications	h-Index	TCs
Remote Sensing	2017	18	11	660
Agricultural Water Management	2015	8	6	504
Precision Agriculture	2013	3	3	548
Computers and Electronics in Agriculture	2021	2	2	65
Drones	2020	2	2	26
International Journal of Environmental Science and Technology	2023	1	1	14
Crop Journal	2022	1	1	2
Journal of Intelligent and Robotic Systems: Theory and Applications	2022	1	1	2
Journal of ASABE	2022	1	1	2
Journal of Universal Computer Science	2022	1	1	4
Remote Sensing Applications: Society and Environment	2022	1	1	1
Environmental Technology and Innovation	2021	1	1	18
Hydrology	2021	1	1	12
Information Sciences Letters	2021	1	1	13
International Journal of Applied Earth Observation and Geoinformation	2021	1	1	11
Journal of Sensors	2021	1	1	6
Agronomy	2020	1	1	27
Applied Computational Electromagnetics Society Journal	2020	1	1	11
Sensors (Switzerland)	2020	1	1	25
Water (Switzerland)	2020	1	1	10
Biosystems Engineering	2018	1	1	62

3.5. The Frequency, Growth, and Co-Occurrence of Keywords

The selection of keywords by authors for a publication has a pivotal role in shaping the communication of the article within scientific communities [39]. Keyword analysis is a method to uncover overarching research patterns by aggregating the terms found in relevant papers within a particular field [40]. The Bibliometrix and Biblioshiny installation packages in R Studio were used to quantify the top twenty authors and supplementary keywords inside this domain (Tables 4 and 5). To ensure consistency, semantically equivalent terms were merged, such as the consolidation of "drone" and "drones", as well as "crop water stress index" and "CWSI". According to Table 4, it is evident from the respective frequencies of 14% and 4% that authors prefer the term UAVs over the colloquial phrase "drones". Additionally, "evapotranspiration" and "precision agriculture" are highly ranked. Despite being ranked sixth, the CWSI is the first term that offers valuable information concerning an index used to quantify crop water stress. As a result, it is considered one of the most widely utilised indices whose values range from 0 to 1 and is positively correlated with the water stress level of many plant species. The CWSI integrates canopy temperature and environmental variables such as humidity and solar radiation to comprehensively measure plant water stress. Awais et al. (2023) revealed that the CWSI obtained via thermal sensors on UAVs might be deemed suitable for real-time irrigation management. Additionally, this index has been used in the detection of ET, as shown by previous studies conducted by Bellvert et al. (2014), Santesteban et al. (2017), and Awais et al. (2023) [25,32,41].

Table 4. Frequency of the top 20 author's keywords.

Author Keyword	Frequency (%)	Author Keyword	Frequency (%)
remote sensing	14.00	canopy temperature	3.00
unmanned aerial vehicles	14.00	land surface temperature	3.00
evapotranspiration	10.00	thermal imagery	3.00
precision agriculture	9.00	deep learning	3.00
CWSI	7.00	irrigation	3.00
water stress	6.00	grapevines	2.00
precision irrigation	4.00	image processing	2.00
stomatal conductance	4.00	irrigation scheduling	2.00
vegetation index	4.00	Landsat 8	2.00
drone	4.00	machine learning	2.00

Table 5. Frequency of the top 20 keywords plus.

Keyword Plus	Frequency (%)	Keyword Plus	Frequency (%)
remote sensing	13.00	water stress	3.00
unmanned aerial vehicle	11.00	infrared-imaging	3.00
antennas	8.00	crop water stress indices	3.00
crops	8.00	vegetation index	3.00
evapotranspiration	8.00	agricultural robots	2.00
irrigation	7.00	energy balance	2.00
precision agriculture	7.00	satellite imagery	2.00
water management	4.00	land surface temperature	2.00
soil moisture	4.00	plants (botany)	2.00
vegetation	3.00	water supply	2.00

Stomatal conductance (4%) and canopy temperature (3%) are also valuable indicators of water stress [5,42]. However, in terms of their frequency of occurrence, stomatal conductance was shown to be more prevalent. The widespread use of "deep learning" and "machine learning" suggests that much of the literature has been dedicated to exploring Artificial Intelligence (AI) techniques for UAV-based agriculture. Machine Learning (ML) methods are well suited for analysing data supplied by UAVs and other remote-sensing and ground-based systems due to their adaptability and capacity to process large quantities of nonlinear data [43,44]. Another notable term that garnered attention was thermal imaging, accounting for 3% of the data. Thermal imaging serves to detect variations in the temperature of the leaf surface caused by physiological changes resulting from water stress. Moreover, leaf stomata closure decreases transpiration and evaporative cooling, resulting in a noticeable elevation in leaf temperature detected by thermal sensors [9].

Antennas (8%) transmit high-frequency radio signals between a smart controller and a UAV (refer to Table 5). Several studies have referenced the use of antennas in the context of georeferencing, namely, the Global Navigation Satellite System (GNSS) [45,46] and telemetry antennas [47,48]. Furthermore, soil moisture (4%) is crucial to crop water management, affecting ET and crop growth [49]. InfraRed-imaging (3%) has emerged as a valuable technique for identifying and measuring crop water stress [50]. Moreover, methodologies for estimating ET with the use of UAVs mostly employ VI-based modelling (3%) [51] or energy balance (2%) techniques [52]. Another crucial term is land surface temperature (2%). This variable is often included as a principal input in energy balance models like the Surface Energy Balance Algorithm for Land (SEBAL) for estimating ET [53].

3.6. Visualising Thematic Clusters in Keyword Co-Occurrence Networks

Keyword co-occurrence networks allow researchers to identify fundamental themes within a particular domain of study [13]. Furthermore, these networks serve as a powerful scientometric instrument that enables the visualisation and demonstration of shared characteristics among co-occurring phrases or themes in scholarly literature. Using this methodology, researchers can comprehensively understand a publication's content and crucial details on the procedures, theoretical frameworks, and perspectives. Thirty nodes are distributed between three distinct clusters. In addition, nodes in Figure 7 represent keywords that appeared at least six times in the literature.

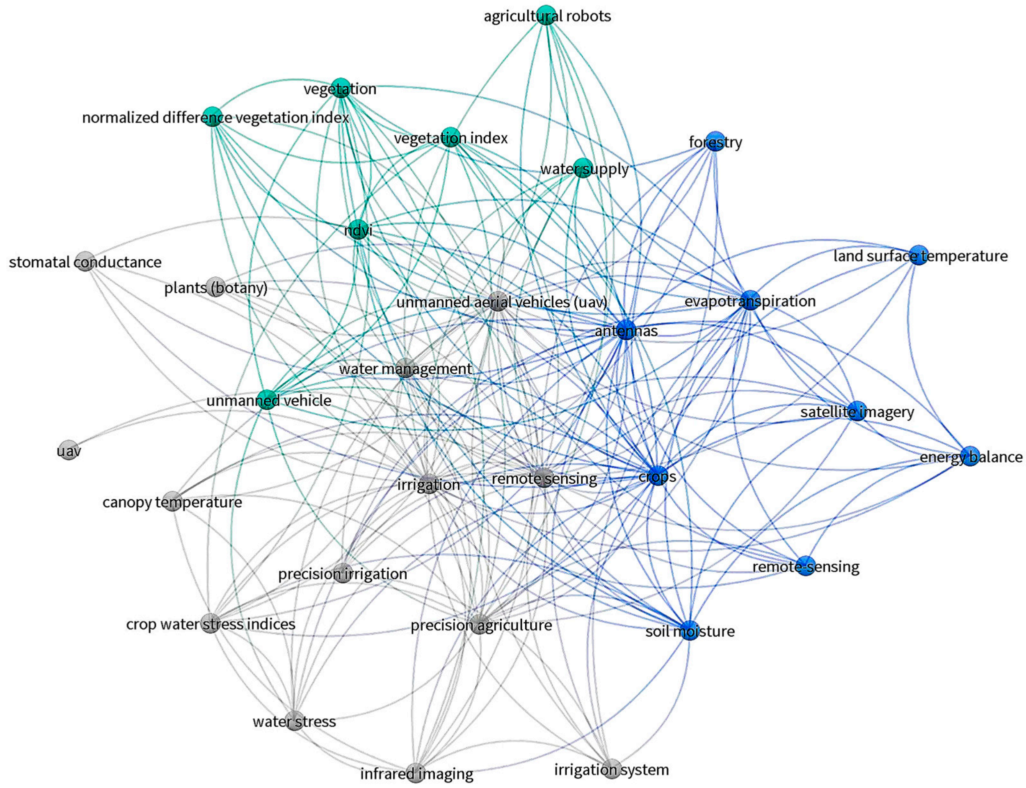

Figure 7. Co-occurrence network of keywords that appeared at least six times in the literature database. The various colours represent distinct thematic clusters, indicating groups of related keywords.

One cluster involves precision irrigation, which relates to water management. Other keywords within this cluster include crop water stress indices such as 'stomatal conductance' and 'canopy temperature'. Information on these indicators can aid in providing insight into the water status of crops, thereby optimising water use concerning irrigation management. The second cluster relates to ET. 'Crops' and 'soil moisture' are integral to the ET process since they influence the amount of water lost from the land surface to the atmosphere. Moreover, RS-based approaches are widespread in ET estimation. The two leading RS platforms include 'UAVs' and 'satellite imagery'.

RS-based ET estimation often employs the 'energy balance' method, which considers the energy exchanges at the land surface. 'Land surface temperature' (LST) is a vital component of this method and is measured using thermal infrared sensors on RS platforms (e.g., satellites or drones). The third cluster relates to 'vegetation' involving 'VIs'. The Normalised Difference Vegetation Index (NDVI) has been widely used in vegetation monitoring, specifically in ET estimation and crop water-stress detection. Moreover, vegetation, including trees, shrubs, crops, and grasses, plays a central role in transpiration. Nevertheless, the transpiration rate depends on factors such as the type of vegetation, its growth stage, and environmental conditions.

4. Discussion

Currently, there is no established method for selecting a practical UAV-based approach to determine crop water status and subsequently guide irrigation management decisions for small-scale agriculture. This is crucial since these farmers' challenges and limitations are primarily due to the prevalent resource constraints in their environments. Therefore, in this study, clustering techniques were employed to facilitate the identification of overarching themes on case study applications involving UAVs to estimate ET or detect crop water stress in PA. The results section consolidates data from 49 publications across various journals. Hence, these themes were examined and will be further discussed concerning the smallholder farmer context.

4.1. Advances in Thermal Remote Sensing

Thermal RS has gained prominence in the literature due to advancements in sensor technology and a subsequent reduction in costs. This technology utilises thermal and near-infrared (NIR) imagery to compute the crop coefficient (Kc) and ET, as the transpiration rate is closely related to canopy temperature. Kc has been shown to correlate with canopy reflectance; however, the accuracy of these measurements can be influenced by various factors, including the properties of the thermal camera, prevailing weather conditions, and the multiple sources of emitted and reflected thermal radiation. Consequently, meticulous calibration of ground data collection and reference panels for temperature measurement and data processing are essential to ensure accurate temperature retrieval [9,54].

In water stress conditions, the closure of leaf stomata leads to reduced transpiration and evaporative cooling, resulting in a significant increase in leaf temperature, which thermal sensors can detect. Using thermal images obtained from UAVs and establishing correlations between foliar temperature and stomatal conductance, valuable insights can be gained into how plants respond to water stress [5,24,42,55,56]. Monitoring these variables during crop growth enables small-scale farmers to implement effective strategies to minimise losses and maximise crop production.

It is noteworthy, however, that leaf or canopy temperature alone does not comprehensively characterise crop water status; an equally stressed canopy can exhibit temperatures of 25 °C or 35 °C, depending on the ambient temperature (Ta). To address this limitation, the canopy-to-air temperature difference (Tc − Ta) has been proposed as a more informative metric, demonstrating a strong correlation with stem water potential, leaf water potential, and stomatal conductance in horticultural crops [46]. While these in situ measurements provide a viable means for detecting crop water stress, relying solely on UAV-based measurements can present challenges.

4.2. Practical UAV Solutions for Small-Scale Farmers

Using an RGB sensor on a cost-effective UAV may be the most practical option for small-scale farmers concerned with irrigation applications. For example, Messina and Modica (2022) suggest enhancing RGB sensors to capture images in spectral bands such as Red Edge and NIR, thereby circumventing the need to invest in a more expensive multispectral camera [57]. Furthermore, Gautam et al. (2021) used an RGB camera mounted on an autonomous UAV to compute the canopy area as a proxy of Kc [46]. Thus, with the enhanced autonomy of UAVs and the improved efficiency of data processing techniques, it may be feasible for farmers to estimate irrigation needs at various stages throughout the season by using a UAV-based RGB camera. Furthermore, images captured by these sensors require less processing, eliminating the need for additional processing software. As a result, operational expenses are reduced [58].

4.3. Energy Balance Models for ET Estimation

Two primary models that facilitated ET estimation emerged in the database: thermal band-based energy-balance techniques and empirical VI models [59]. UAV-based energy balance methods are generally modified versions of satellite-based energy balance models, such as SEBAL, Surface Energy Balance System (SEBS), Mapping Evapotranspiration at High Resolution with Internalized Calibration (METRIC), One Source Energy Balance (OSEB), Two Source Energy Balance (TSEB), Dual-Temperature Difference (DTD), and High-Resolution Mapping of Evapotranspiration (HRMET), leveraging UAV datasets for accurate ET estimation [30,60]. Moreover, energy balance approaches are subdivided into various approaches, whereby UAV inputs are used directly, or a coarser satellite resolution image is downscaled.

Adopting RS-based ET estimation models in smallholder settings is often hindered by their complexity and data requirements. Smallholder farmers frequently lack access to comprehensive in situ datasets, such as meteorological data, land surface temperature, and canopy structure data, which are essential for many ET models. The acquisition of these datasets is often costly and necessitates specialised equipment, placing an additional burden on limited resources. Furthermore, the technical expertise required to operate these models frequently exceeds the capabilities of smallholder farmers. Moreover, utilising these models necessitates a thorough understanding of the underlying principles and advanced data processing and analysis skills, which are typically unavailable within this demographic.

The data requirements inherent in many energy balance models, such as SEBS and SEBAL, pose significant challenges for their application in smallholder farming contexts. Models like SEBS, demanding extensive data inputs including thermal infrared imagery, meteorological data, and land cover information, often prove too intricate and data-intensive for resource-constrained smallholder settings [61]. Furthermore, these models frequently lack direct measurement validation and are best suited for larger spatial scales, limiting their practical applicability for smaller, more fragmented farmlands. Models like SEBAL require calibration against ground-based measurements or other independent ET data sources [53,62,63], which may be scarce in smallholder settings. Additionally, the specialised expertise in remote sensing, meteorology, and data analysis needed to implement these models may not be readily available to farmers in these contexts.

Addressing the limitations of complex ET models in smallholder settings requires a shift toward simplified approaches and tailored solutions. OSEB and HRMET, with their minimal input data requirements, offer alternative approaches worth further investigation [30]. Developing adapted methods designed to align with the resource constraints and expertise levels of smallholder farmers is crucial. Collaborative efforts involving researchers, extension services, and farmers are essential to develop and implement practical ET estimation methods that are locally relevant and sustainable. Additionally, models like METRIC-EEFLUX and the QWaterModel, known for their low data requirements, free accessibility, and user-friendliness [64–66], provide promising alternatives. However, further testing of these models in diverse smallholder farming environments is necessary to validate their accuracy and reliability.

The versatility and practicality of UAVs, coupled with using less data-intensive energy balance models, make them particularly well suited for smallholder agriculture. Future research should prioritise the development of user-friendly ET estimation methods tailored for smallholder settings, focusing on accessible data collection methods and straightforward analysis techniques. Empowering farmers through training programs that foster an understanding of ET, utilise readily available sensors, and interpret data for informed decision making is crucial. By prioritising accessibility and practicality, researchers can better support smallholder farmers in adopting sustainable water management practices and enhancing agricultural productivity.

4.4. VI Methods for ET Estimation

To this end, the use of VI-based ET estimation methods may prove to be most appropriate. Methods utilising VIs to estimate ET often involve establishing a relationship between a VI and Kc [67]. Past studies have employed diverse spectral and thermal indicators like NDVI and CWSI to predict Kc [46]. The association between NDVI and Kc can be ascertained through basic linear regression or advanced approaches involving ML techniques. Subsequently, by using NDVI as a proxy for Kc, the computation of ET becomes more accessible. NDVI is often the preferred indicator of choice as it is versatile and can be easily computed using the data acquired from most multispectral sensors onboard various remote sensing platforms. Subsequently, it has frequently been used as a primary indicator for vegetation assessment in agricultural studies [68].

4.5. The Role of CWSI in Water Management

Tang et al. (2019) confirmed that the CWSI may be a more effective indicator when included in maize ET calculations under rain-fed conditions. The researchers used the index to ascertain the stress coefficient (Ks = 1 − CWSI). Their findings indicated that ET calculated using the Ks-CWSI approach had a stronger association with the modified FAO-56 Kc technique, as shown by a coefficient of determination (R^2) value of 0.81. Notably, numerous small-scale farms in sub-Saharan Africa rely on rainfall for irrigation, leading to significant water scarcity issues. As a result, most agricultural development in these settings occurs under water-stress conditions [4].

4.6. Utilisation of the Water Deficit Index (WDI) for Crop Stress Assessment

The WDI is another valuable indicator for assessing crop water stress by depicting the relationship between actual (ETa) and potential evapotranspiration (ETp), defined as WDI = 1 − (ETa/ETp) [69]. In a study by Antoniuk et al. (2021), the authors utilised a UAS equipped with multispectral and thermal sensors to detect and quantify drought stress in winter wheat using the Water Deficit Index (WDI). The results concluded that the significant correlation of the WDI to stomatal conductance and leaf water potential indicates the possibility of detecting early drought signals [70].

4.7. The Role of Machine Learning in ET and Water Stress Assessment

The literature database has extensively employed ML techniques to estimate ET and water stress. These approaches offer several advantages in dealing with complex and high-dimensional data and capturing nonlinear relationships, making them well suited for modelling and forecasting hydrological variables. Moreover, numerous studies have demonstrated that ML can accurately capture complex relationships between VIs, environmental factors, and ET, enabling more precise mapping of ET across different land covers and weather conditions [71–74].

In addition, ML algorithms, such as random forest, support vector machines, and multiple linear regression, have proven effective in analysing crop characteristics such as water and health status [75–77]. However, among these algorithms, the random forest ensemble has consistently outperformed the other two mentioned algorithms. This was demonstrated in various studies [51,78]. In addition, deep learning, a branch of ML, has been extensively used in agricultural water status research and has consistently achieved better outcomes than conventional ML methods [58]. Although these models may provide accurate results that require little user involvement, their complexity, demanding computational and data-intensive requirements may restrict their practicality for broad usage in facilitating precision water management in smallholder farms. For example, Niu et al. (2022) [47] compared a stochastic configuration networks (SCN) model to a linear regression model. The authors established a relationship between NDVI and Kc for estimating the ET of pomegranate trees. The findings showed that the SCN model achieved an R^2 value of 0.995, while the linear regression model achieved 0.975. While the SCN model achieved superior performance, the linear regression model demonstrated exemplary performance and may be the preferred method of choice in many instances due to its simplicity, interpretability, and computing efficiency.

4.8. Future Directions and Research Gaps

In addition to the various approaches that have been identified from the literature database for the estimation of ET and crop water stress, most research has been focused on orchards, including pistachio [53], olive [57], almond [24,79], pomegranate [47], pecan [80], and vineyards, including grapevine [46,81,82] and pinot noir [41,83]. There have been fewer studies conducted on staple crops like maize [9,59,84] or winter wheat [50,70] and no studies on neglected and underutilised crops. Therefore, it would be advantageous to prioritise research on these and other climate-resilient and nutrient-rich crops since many smallholder farmers grow these staple crops. Improving the productivity of these farms can not only aid in enhancing food and nutrition security but also improve the socioeconomic conditions of these often-marginalised smallholder communities.

4.9. Challenges and Opportunities

The previous discussion emphasised the many themes of using UAVs to facilitate precision water management in smallholder farms. Nevertheless, despite the global recognition and demonstration of the immense potential of these advanced technologies, their adoption in resource-constrained nations has significantly lagged. The innovation gap in the context of smallholder farms within these regions might be ascribed to many factors.

- Cost and affordability: the price of UAV technology might be a considerable obstacle, particularly for small-scale farms or enterprises, due to the initial outlay costs and infrastructure requirements involved in obtaining and maintaining the equipment. Fortunately, as UAV technology advances, new camera designs are being introduced, costs are decreasing, image processing techniques are improving, and more experiments are being conducted on UAV-based RS for agricultural purposes. In addition, the initial outlay is also offset by the potential for repeat flights, resulting in more frequent datasets and reduced labour and resource expenses.
- Technical literacy and information accessibility: insufficient technical literacy among smallholder farmers may hinder their comprehension, operation, and maintenance of drone technology. Moreover, inequities in accessing information and extension services might lead to unequal dissemination of knowledge on the advantages and uses of UAV technology. Therefore, smallholder farmers may exhibit risk aversion and be reluctant to invest in new technology without compelling information about their benefits, hindering the pace at which it is adopted. Nevertheless, collaboration between the public and private sectors can be established through partnerships with non-governmental organisations with a local presence, such as agricultural extension workers. These partnerships can provide practical training to farmers and enhance their technological skills.
- Limited infrastructure: inadequate infrastructure might impede the implementation and use of UAVs in rural regions where many smallholder farms are situated. These factors include substandard road networks, insufficient electrical supply, and no charging facilities. Subsequently, governmental organisations should ensure capacity development by equipping the relevant farmers with the necessary tools to operate these technologies.
- Data-intensive methods: in small-scale farming, it is anticipated that the UAV will collect most of the data. Nevertheless, several techniques outlined in the literature rely on high-quality in situ measurements to develop and verify the models for predicting crucial variables. Hence, more research is necessary regarding UAV-based methodologies, including all the required data acquisition to provide the desired outcome.
- Research into practical alternatives: the most frequently used VIs rely on multispectral cameras to detect crop water stress. Furthermore, the thermal sensor attachment is widespread in several investigations. However, as previously stated, an RGB sensor on an affordable UAV might be the most feasible choice for small-scale farmers interested in irrigation applications. Nevertheless, a few investigations have shown the sensor's capacity in this aspect. Hence, further research using the RBG sensor and cutting-edge methodologies is necessary to decrease operating expenses.
- Computational resources: processing, disseminating, and displaying UAV data require considerable computational capacity. Potential users may need supplementary resources or new skills to manage the substantial amounts of data associated with UAVs effectively. However, geospatial cloud computing platforms, such as GEE, have significantly transformed how geospatial data are handled and processed. These systems offer several advantages over conventional approaches by integrating ML techniques. Furthermore, this platform provides access to sophisticated computational capabilities for handling large volumes of geographical data and warrants further investigation.

5. Conclusions

Smallholder farmers primarily rely on indigenous knowledge for their agricultural practices; however, these practices can be enhanced by integrating modern farming techniques to improve productivity and resilience in the face of climate change. Consequently, further efforts are needed to improve accessibility to and utilisation of technological advancements for small-scale and developing farmers. The agricultural industry is increasingly recognising the significance of this research area and is supporting the development of practical approaches that benefit all agrarian stakeholders. UAVs are gaining traction for various precision agriculture applications, with anticipated cost reductions due to open-source processing platforms, such as Google Earth Engine. This review highlights various methods, challenges, and opportunities for using UAV technologies to estimate crop water use, identify water stress, and understand the contextual conditions in which smallholder farmers operate. UAVs equipped with multispectral or hyperspectral cameras can effectively map crop water stress, enabling precise irrigation and reducing water waste. High-resolution UAV imagery provides insights into crop health indicators, such as chlorophyll levels and vegetation indices, facilitating early interventions and improved yields. Furthermore, deploying RGB sensors on cost-effective UAVs offers a practical solution for small-scale farmers focused on irrigation, especially as these sensors can be adapted to capture images in spectral bands such as Red Edge and NIR, thereby eliminating the need for more expensive equipment. A multi-pronged approach is essential for implementing drone technology in small-scale agriculture; this approach should include user-friendly UAV applications, farmer training programs, and collaborative efforts among researchers, extension services, and farmers. Such initiatives will bridge the gap between cutting-edge technology and the practical needs of smallholders, promoting sustainable and productive agricultural practices. While this review contributes to the growing body of knowledge in the field, it acknowledges limitations stemming from the subjective selection of studies included. Nonetheless, the findings offer a foundation for developing effective precision water management practices by applying UAV technologies in agriculture.

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References

1. Kamara, A.; Conteh, A.R.; Rhodes, E.; Cooke, R. The relevance of smallholder farming to African agricultural growth and development. *Afr. J. Food Agric. Nutr. Dev.* **2019**, *19*, 14043–14065. [CrossRef]
2. Lowder, S.; Skoet, J.; Singh, S. What do we Really Know about the Number and Distribution of Farms and Family Farms in the World? Background Paper for the State of Food and Agriculture 2014. ESA Working Paper No. 14-02. Available online: https://ageconsearch.umn.edu/record/288983/?v=pdf (accessed on 10 August 2023).

3. Kpienbaareh, D.; Sun, X.; Wang, J.; Luginaah, I.; Bezner Kerr, R.; Lupafya, E.; Dakishoni, L. Crop type and land cover mapping in northern Malawi using the integration of Sentinel-1, Sentinel-2, and PlanetScope satellite data. *Remote Sens.* **2021**, *13*, 700. [CrossRef]
4. Nhamo, L.; Magidi, J.; Nyamugama, A.; Clulow, A.D.; Sibanda, M.; Chimonyo, V.G.P.; Mabhaudhi, T. Prospects of improving agricultural and water productivity through unmanned aerial vehicles. *Agriculture* **2020**, *10*, 256. [CrossRef]
5. Brewer, K.; Clulow, A.; Sibanda, M.; Gokool, S.; Odindi, J.; Mutanga, O.; Naiken, V.; Chimonyo, V.G.P.; Mabhaudhi, T. Estimation of maize foliar temperature and stomatal conductance as indicators of water stress based on optical and thermal imagery acquired using an unmanned aerial vehicle (UAV) platform. *Drones* **2022**, *6*, 169. [CrossRef]
6. Pitman, W. Overview of water resource assessment in South Africa: Current state and future challenges. *Water SA* **2011**, *37*, 659–664. [CrossRef]
7. Haarhoff, S.J.; Kotzé, T.; Swanepoel, P. A prospectus for sustainability of rainfed maize production systems in South Africa. *Crop Sci.* **2020**, *60*, 14–28. [CrossRef]
8. Gokool, S.; Mahomed, M.; Kunz, R.; Clulow, A.; Sibanda, M.; Naiken, V.; Chetty, K.; Mabhaudhi, T. Crop monitoring in smallholder farms using unmanned aerial vehicles to facilitate precision agriculture practices: A scoping review and bibliometric analysis. *Sustainability* **2023**, *15*, 3557. [CrossRef]
9. Messina, G.; Modica, G. Applications of UAV thermal imagery in precision agriculture: State of the art and future research outlook. *Remote Sens.* **2020**, *12*, 1491. [CrossRef]
10. Sishodia, R.P.; Ray, R.L.; Singh, S.K. Applications of remote sensing in precision agriculture: A review. *Remote Sens.* **2020**, *12*, 3136. [CrossRef]
11. Boursianis, A.D.; Papadopoulou, M.S.; Diamantoulakis, P.; Liopa-Tsakalidi, A.; Barouchas, P.; Salahas, G.; Karagiannidis, G.; Wan, S.; Goudos, S.K. Internet of Things (IoT) and agricultural Unmanned Aerial Vehicles (UAVs) in smart farming: A comprehensive review. *Internet Things* **2022**, *18*, 100187. [CrossRef]
12. Bukowiecki, J.; Rose, T.; Kage, H. Sentinel-2 data for precision agriculture?—A UAV-based assessment. *Sensors* **2021**, *21*, 2861. [CrossRef] [PubMed]
13. Rejeb, A.; Abdollahi, A.; Rejeb, K.; Treiblmaier, H. Drones in agriculture: A review and bibliometric analysis. *Comput. Electron. Agric.* **2022**, *198*, 107017. [CrossRef]
14. Verstraeten, W.W.; Veroustraete, F.; Feyen, J. Assessment of evapotranspiration and soil moisture content across different scales of observation. *Sensors* **2008**, *8*, 70–117. [CrossRef]
15. Niu, H.; Wang, D.; Chen, Y. Estimating actual crop evapotranspiration using deep stochastic configuration networks model and UAV-based crop coefficients in a pomegranate orchard. *J. Intell. Robot. Syst.* **2020**, *104*, 76–82. [CrossRef]
16. Fritschen, L.J. Accuracy of evapotranspiration determinations by the Bowen ratio method. *Hydrol. Sci. J.* **1965**, *10*, 38–48. [CrossRef]
17. Angus, D.E.; Watts, P.J. Evapotranspiration—How Good is the Bowen Ratio Method? In *Developments in Agricultural and Managed Forest Ecology*; Sharma, M.L., Ed.; Elsevier: Amsterdam, The Netherlands, 1984; Volume 13, pp. 133–150.
18. Nagler, P.L.; Scott, R.L.; Westenburg, C.; Cleverly, J.R.; Glenn, E.P.; Huete, A.R. Evapotranspiration on western U.S. rivers estimated using the Enhanced Vegetation Index from MODIS and data from eddy covariance and Bowen ratio flux towers. *Remote Sens. Environ.* **2005**, *97*, 337–351. [CrossRef]
19. De Bruin, H.; Meijninger, W.; Smedman, A.-S.; Magnusson, M. Displaced-Beam Small Aperture Scintillometer Test. Part I: The Wintex Data-Set. *Bound. Layer Meteorol.* **2002**, *105*, 129–148. [CrossRef]
20. Beyrich, F.; Bange, J.; Hartogensis, O.K.; Raasch, S.; Braam, M.; van Dinther, D.; Gräf, D.; van Kesteren, B.; van den Kroonenberg, A.C.; Maronga, B.; et al. Towards a Validation of Scintillometer Measurements: The LITFASS-2009 Experiment. *Bound. Layer Meteorol.* **2012**, *144*, 83–112. [CrossRef]
21. Paw, U.K.T.; Qiu, J.; Su, H.-B.; Watanabe, T.; Brunet, Y. Surface renewal analysis: A new method to obtain scalar fluxes. *Agric. For. Meteorol.* **1995**, *74*, 119–137. [CrossRef]
22. Díaz-Varela, R.A.; De la Rosa, R.; León, L.; Zarco-Tejada, P.J. High-resolution airborne UAV imagery to assess olive tree crown parameters using 3D photo reconstruction: Application in breeding trials. *Remote Sens.* **2015**, *7*, 4213–4232. [CrossRef]
23. Abbasi, N.; Nouri, H.; Didan, K.; Barreto-Muñoz, A.; Chavoshi Borujeni, S.; Opp, C.; Nagler, P.; Thenkabail, P.S.; Siebert, S. Mapping vegetation index-derived actual evapotranspiration across croplands using the Google Earth Engine platform. *Remote Sens.* **2023**, *15*, 1017. [CrossRef]
24. Gonzalez-Dugoa, V.; Zarco-Tejadaa, P.; Fereres, E. Applicability and limitations of using the crop water stress index as an indicator of water deficits in citrus orchards. *Agric. For. Meteorol.* **2014**, *198*, 94–104. [CrossRef]
25. Santesteban, L.G.; Di Gennaro, S.F.; Herrero-Langreo, A.; Miranda, C.; Royo, J.B.; Matese, A. High-resolution UAV-based thermal imaging to estimate the instantaneous and seasonal variability of plant water status within a vineyard. *Agric. Water Manag.* **2017**, *183*, 49–59. [CrossRef]
26. Torres-Sánchez, J.; Peña, J.M.; de Castro, A.I.; López-Granados, F. Multi-temporal mapping of the vegetation fraction in early-season wheat fields using images from UAV. *Comput. Electron. Agric.* **2014**, *103*, 104–113. [CrossRef]
27. Bennett, M.K.; Younes, N.; Joyce, K. Automating Drone Image Processing to Map Coral Reef Substrates Using Google Earth Engine. *Drones* **2020**, *4*, 50. [CrossRef]

28. Cucho-Padin, G.; Loayza, H.; Palacios, S.; Balcazar, M.; Carbajal, M.; Roberto, Q. Development of low-cost remote sensing tools and methods for supporting smallholder agriculture. *Appl. Geomat.* **2019**, *12*, 247–263. [CrossRef]
29. Zhang, C.; Kovacs, J.M. The application of small unmanned aerial systems for precision agriculture: A review. *Precis. Agric.* **2012**, *13*, 693–712. [CrossRef]
30. Niu, H.; Hollenbeck, D.; Zhao, T.; Wang, D.; Chen, Y. Evapotranspiration estimation with small UAVs in precision agriculture. *Sensors* **2020**, *20*, 6427. [CrossRef]
31. Singh, A.P.; Yerudkar, A.; Mariani, V.; Iannelli, L.; Glielmo, L. A bibliometric review of the use of unmanned aerial vehicles in precision agriculture and precision viticulture for sensing applications. *Remote Sens.* **2022**, *14*, 1604. [CrossRef]
32. Awais, M.; Li, W.; Cheema, M.; Zaman, Q.; Shaheen, A.; Aslam, B.; Zhu, W.; Ajmal, M.; Faheem, M. UAV-based remote sensing in plant stress imagine using high-resolution thermal sensor for digital agriculture practices: A meta-review. *Int. J. Environ. Sci. Technol.* **2023**, *20*, 1135–1152. [CrossRef]
33. Raparelli, E.; Bajocco, S. A bibliometric analysis on the use of unmanned aerial vehicles in agricultural and forestry studies. *Int. J. Remote Sens.* **2019**, *40*, 9070–9083. [CrossRef]
34. Rivera, M.; Pizam, A. Advances in hospitality research: "From Rodney Dangerfield to Aretha Franklin". *Int. J. Contemp. Hosp. Manag.* **2015**, *27*, 362–378. [CrossRef]
35. Ferreira, M.A.; Pinto, C.; Serra, F. The transaction costs theory in international business research: A bibliometric study over three decades. *Scientometrics* **2014**, *98*, 1899–1922. [CrossRef]
36. Geng, D.; Feng, Y.; Zhu, Q. Sustainable design for users: A literature review and bibliometric analysis. *Environ. Sci. Pollut. Res.* **2020**, *27*, 29824–29836. [CrossRef] [PubMed]
37. Gago, J.; Douthe, C.; Coopman, R.E.; Gallego, P.P.; Ribas-Carbo, M.; Flexas, J.; Escalona, J.; Medrano, H. UAVs challenge to assess water stress for sustainable agriculture. *Agric. Water Manag.* **2015**, *153*, 9–19. [CrossRef]
38. Sagan, V.; Maimaitijiang, M.; Sidike, P.; Eblimit, K.; Peterson, K.; Hartling, S.; Esposito, F.; Khanal, K.; Newcomb, M.; Pauli, D.; et al. UAV-based high resolution thermal imaging for vegetation monitoring and plant phenotyping using ICI 8640 P, FLIR Vue Pro R 640, and thermoMap cameras. *Remote Sens.* **2019**, *11*, 330. [CrossRef]
39. Kim, W.; Khan, G.; Wood, J.; Mahmood, M. Employee engagement for sustainable organizations: Keyword analysis using social network analysis and burst detection approach. *Sustainability* **2016**, *8*, 631. [CrossRef]
40. Dixit, A.; Jakhar, S. Airport capacity management: A review and bibliometric analysis. *J. Air Transp. Manag.* **2021**, *91*, 102010. [CrossRef]
41. Bellvert, J.; Zarco-Tejada, P.; Girona, J.; Fereres, E. Mapping crop water stress index in a 'Pinot-noir' vineyard: Comparing ground measurements with thermal remote sensing imagery from an unmanned aerial vehicle. *Precis. Agric.* **2014**, *15*, 361–376. [CrossRef]
42. Han, Y.; Tarakey, B.A.; Hong, S.-J.; Kim, S.-Y.; Kim, E.; Lee, C.-H.; Kim, G. Calibration and image processing of aerial thermal image for UAV application in crop water stress estimation. *J. Sens.* **2021**, *2021*, 5537795. [CrossRef]
43. Inoue, Y. Satellite- and drone-based remote sensing of crops and soils for smart farming—A review. *Soil Sci. Plant Nutr.* **2020**, *66*, 798–810. [CrossRef]
44. Ali, I.; Greifeneder, F.; Stamenkovic, J.; Neumann, M.; Notarnicola, C. Review of machine learning approaches for biomass and soil moisture retrievals from remote sensing data. *Remote Sens.* **2015**, *7*, 16398–16421. [CrossRef]
45. Gautam, D.; Pagay, V. A Review of Current and Potential Applications of Remote Sensing to Study the Water Status of Horticultural Crops. *Agronomy* **2020**, *10*, 140. [CrossRef]
46. Gautam, D.; Ostendorf, B.; Pagay, V. Estimation of grapevine crop coefficient using a multispectral camera on an unmanned aerial vehicle. *Remote Sens.* **2021**, *13*, 2639. [CrossRef]
47. Niu, H.; Zhao, T.; Wang, D.; Chen, Y. Estimating evapotranspiration of pomegranate trees using stochastic configuration networks (SCN) and UAV multispectral imagery. *J. Intell. Robot. Syst.* **2022**, *104*, 66. [CrossRef]
48. Chávez, R.; Grönwall, J.; Kwast, J.; Danert, K.; Foppen, J. Estimating domestic self-supply groundwater use in urban continental Africa. *Environ. Res. Lett.* **2020**, *15*, 1040b2. [CrossRef]
49. Said Mohamed, E.; Belal, A.A.; Kotb Abd-Elmabod, S.; El-Shirbeny, M.A.; Gad, A.; Zahran, M.B. Smart farming for improving agricultural management. *Egypt. J. Remote Sens. Space Sci.* **2021**, *24*, 971–981. [CrossRef]
50. Zhou, Z.; Majeed, Y.; Naranjo, G.; Gambacorta, E. Assessment for crop water stress with infrared thermal imagery in precision agriculture: A review and future prospects for deep learning applications. *Comput. Electron. Agric.* **2021**, *182*, 106019. [CrossRef]
51. Shao, G.; Han, W.; Zhang, H.; Wang, Y.; Zhang, L.; Niu, Y.; Zhang, Y.; Cao, P. Estimation of transpiration coefficient and aboveground biomass in maize using time-series UAV multispectral imagery. *Crop J.* **2022**, *10*, 1376–1385. [CrossRef]
52. Ortega-Farías, S.; Ortega-Salazar, S.; Poblete, T.; Kilic, A.; Allen, R.; Poblete-Echeverría, C.; Ahumada-Orellana, L.; Zuñiga, M.; Sepúlveda, D. Estimation of Energy Balance Components over a Drip-Irrigated Olive Orchard Using Thermal and Multispectral Cameras Placed on a Helicopter-Based Unmanned Aerial Vehicle (UAV). *Remote Sens.* **2016**, *8*, 638. [CrossRef]
53. Aliabad, F.A.; Shojaei, S.; Mortaz, M.; Ferreira, C.S.S.; Kalantari, Z. Use of Landsat 8 and UAV images to assess changes in temperature and evapotranspiration by economic trees following foliar spraying with light-reflecting compounds. *Remote Sens.* **2022**, *14*, 6153. [CrossRef]
54. Masina, M.; Lambertini, A.; Daprà, I.; Mandanici, E.; Lamberti, A. Remote sensing analysis of surface temperature from heterogeneous data in a maize field and related water stress. *Remote Sens.* **2020**, *12*, 2506. [CrossRef]

55. Gerhards, M.; Schlerf, M.; Mallick, K.; Udelhoven, T. Challenges and future perspectives of multi-/hyperspectral thermal infrared remote sensing for crop water-stress detection: A review. *Remote Sens.* **2019**, *11*, 1240. [CrossRef]
56. Messina, G.; Modica, G. Twenty years of remote sensing applications targeting landscape analysis and environmental issues in olive growing: A review. *Remote Sens.* **2022**, *14*, 5430. [CrossRef]
57. Jackson, R.D. Canopy Temperature and Crop Water Stress. In *Advances in Irrigation*; Hillel, D., Ed.; Elsevier: Amsterdam, The Netherlands, 1982; Volume 1, pp. 43–85.
58. Rosle, R.; Che'Ya, N.N.; Ang, Y.; Rahmat, F.; Wayayok, A.; Berahim, Z.; Fazlil Ilahi, W.F.; Ismail, M.R.; Omar, M.H. Weed detection in rice fields using remote sensing technique: A review. *Appl. Sci.* **2021**, *11*, 701. [CrossRef]
59. Tang, J.; Han, W.; Zhang, L. UAV multispectral imagery combined with the FAO-56 dual approach for maize evapotranspiration mapping in the North China Plain. *Remote Sens.* **2019**, *11*, 2519. [CrossRef]
60. Molaei, B.; Chandel, A.K.; Peters, R.T.; Khot, L.R.; Khan, A.; Maureira, F.; Stockle, C. Investigating the application of artificial hot and cold reference surfaces for improved ETc estimation using the UAS-METRIC energy balance model. *Agric. Water Manag.* **2023**, *284*, 108346. [CrossRef]
61. Gibson, L.A.; Münch, Z.; Engelbrecht, J. Particular uncertainties encountered in using a pre-packaged SEBS model to derive evapotranspiration in a heterogeneous study area in South Africa. *Hydrol. Earth Syst. Sci.* **2011**, *15*, 295–310. [CrossRef]
62. Bastiaanssen, W.G.M.; Cheema, M.J.M.; Immerzeel, W.W.; Miltenburg, I.J.; Pelgrum, H. Surface energy balance and actual evapotranspiration of the transboundary Indus Basin estimated from satellite measurements and the ETLook model. *Water Resour. Res.* **2012**, *48*, W11512. [CrossRef]
63. Guzinski, R.; Nieto, H.; Jensen, R.; Mendiguren, G. Remotely sensed land-surface energy fluxes at sub-field scale in heterogeneous agricultural landscape and coniferous plantation. *Biogeosciences* **2014**, *11*, 5021–5046. [CrossRef]
64. Timmermans, W.; Kustas, W.; Andreu, A. Utility of an automated thermal-based approach for monitoring evapotranspiration. *Acta Geophys.* **2015**, *63*, 1571–1608. [CrossRef]
65. Filgueiras, R.; Mantovani, E.; Althoff, D.; Balieiro Ribeiro, R.; Venancio, L.; Argolo dos Santos, R. Dynamics of actual crop evapotranspiration based in the comparative analysis of SEBAL and METRIC-EEFLUX. *IRRIGA* **2019**, *1*, 72–80. [CrossRef]
66. Ellsäßer, F.; Röll, A.; Stiegler, C.; Hendrayanto; Hölscher, D. Introducing QWaterModel, a QGIS plugin for predicting evapotranspiration from land surface temperatures. *Environ. Model. Softw.* **2020**, *130*, 104739. [CrossRef]
67. Ihuoma, S.O.; Madramootoo, C.A.; Kalacska, M. Integration of satellite imagery and in situ soil moisture data for estimating irrigation water requirements. *Int. J. Appl. Earth Obs. Geoinf.* **2021**, *102*, 102396. [CrossRef]
68. Venancio, L.P.; Eugenio, F.C.; Filgueiras, R.; França da Cunha, F.; Argolo dos Santos, R.; Ribeiro, W.R.; Mantovani, E.C. Mapping within-field variability of soybean evapotranspiration and crop coefficient using the Earth Engine Evaporation Flux (EEFlux) application. *PLoS ONE* **2020**, *15*, e0235620. [CrossRef]
69. Moran, M.S.; Clarke, T.R.; Inoue, Y.; Vidal, A. Estimating crop water deficit using the relation between surface-air temperature and spectral vegetation index. *Remote Sens. Environ.* **1994**, *49*, 246–263. [CrossRef]
70. Antoniuk, V.; Manevski, K.; Kørup, K.; Larsen, R.; Sandholt, I.; Zhang, X.; Andersen, M.N. Diurnal and seasonal mapping of water deficit index and evapotranspiration by an unmanned aerial system: A case study for winter wheat in Denmark. *Remote Sens.* **2021**, *13*, 2998. [CrossRef]
71. Tabari, H.; Martinez, C.; Ezani, A.; Hosseinzadeh Talaee, P. Applicability of support vector machines and adaptive neurofuzzy inference system for modeling potato crop evapotranspiration. *Irrig. Sci.* **2013**, *31*, 575–588. [CrossRef]
72. Gocic, M.; Petković, D.; Shamshirband, S.; Kamsin, A. Comparative analysis of reference evapotranspiration equations modelling by extreme learning machine. *Comput. Electron. Agric.* **2016**, *127*, 56–63. [CrossRef]
73. Kisi, O.; Sanikhani, H.; Zounemat-Kermani, M.; Niazi, F. Long-term monthly evapotranspiration modeling by several data-driven methods without climatic data. *Comput. Electron. Agric.* **2015**, *115*, 66–77. [CrossRef]
74. Petković, D.; Gocic, M.; Shamshirband, S.; Qasem, S.N.; Trajkovic, S. Particle swarm optimization-based radial basis function network for estimation of reference evapotranspiration. *Theor. Appl. Climatol.* **2016**, *125*, 555–563. [CrossRef]
75. Han, L.; Yang, G.; Dai, H.; Xu, B.; Yang, H.; Feng, H.; Li, Z.; Yang, X. Modeling maize above-ground biomass based on machine learning approaches using UAV remote-sensing data. *Plant Methods* **2019**, *15*, 10. [CrossRef] [PubMed]
76. Hassanijalilian, O.; Igathinathane, C.; Doetkott, C.; Bajwa, S.G.; Bajwa, S.G.; Nowatzki, J.; Esmaeili, S.A.H.; Esmaeili, S.A.H. Chlorophyll estimation in soybean leaves infield with smartphone digital imaging and machine learning. *Comput. Electron. Agric.* **2020**, *174*, 105433. [CrossRef]
77. Guo, Y.; Yin, G.; Sun, H.; Wang, H.; Chen, S.; Senthilnath, J.; Wang, J.; Fu, Y. Scaling effects on chlorophyll content estimations with RGB camera mounted on a UAV platform using machine-learning methods. *Sensors* **2020**, *20*, 5130. [CrossRef]
78. Marques Ramos, A.P.; Osco, L.P.; Garcia Furuya, D.E.; Nunes Gonçalves, W.; Cordeiro Santana, D.; Ribeiro Teodoro, L.P.; da Silva Junior, C.A.; Capristo-Silva, G.F.; Li, J.; Rojo Baio, F.H.; et al. A random forest ranking approach to predict yield in maize with uav-based vegetation spectral indices. *Comput. Electron. Agric.* **2020**, *178*, 105791. [CrossRef]
79. Peddinti, S.R.; Kisekka, I. Estimation of turbulent fluxes over almond orchards using high-resolution aerial imagery with one and two-source energy balance models. *Agric. Water Manag.* **2022**, *269*, 107671. [CrossRef]
80. Mokari, E.; Samani, Z.; Heerema, R.; Dehghan-Niri, E.; DuBois, D.; Ward, F.; Pierce, C. Development of a new UAV-thermal imaging based model for estimating pecan evapotranspiration. *Comput. Electron. Agric.* **2022**, *194*, 106752. [CrossRef]

81. Chandel, A.K.; Molaei, B.; Khot, L.R.; Peters, R.T.; Stöckle, C.O. High resolution geospatial evapotranspiration mapping of irrigated field crops using multispectral and thermal infrared imagery with METRIC energy balance model. *Drones* **2020**, *4*, 52. [CrossRef]
82. Espinoza, C.Z.; Khot, L.R.; Sankaran, S.; Jacoby, P.W. High resolution multispectral and thermal remote sensing-based water stress assessment in subsurface irrigated grapevines. *Remote Sens.* **2017**, *9*, 961. [CrossRef]
83. Lu, S.; Xuan, J.; Zhang, T.; Bai, X.; Tian, F.; Ortega-Farias, S. Effect of the shadow pixels on evapotranspiration inversion of vineyard: A high-resolution UAV-based and ground-based remote sensing measurements. *Remote Sens.* **2022**, *14*, 2259. [CrossRef]
84. Zhang, L.; Niu, Y.; Zhang, H.; Han, W.; Li, G.; Tang, J.; Peng, X. Maize canopy temperature extracted from UAV thermal and RGB imagery and its application in water stress monitoring. *Front. Plant Sci.* **2019**, *10*, 1270. [CrossRef] [PubMed]