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Review

Remote Sensing Applications in Almond Orchards: A Comprehensive Systematic Review of Current Insights, Research Gaps, and Future Prospects

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Abstract: Almond cultivation is of great socio-economic importance worldwide. With the demand for almonds steadily increasing due to their nutritional value and versatility, optimizing the management of almond orchards becomes crucial to promote sustainable agriculture and ensure food security. The present systematic literature review, conducted according to the PRISMA protocol, is devoted to the applications of remote sensing technologies in almond orchards, a relatively new field of research. The study includes 82 articles published between 2010 and 2023 and provides insights into the predominant remote sensing applications, geographical distribution, and platforms and sensors used. The analysis shows that water management has a pivotal focus regarding the remote sensing application of almond crops, with 34 studies dedicated to this subject. This is followed by image classification, which was covered in 14 studies. Other applications studied include tree segmentation and parameter extraction, health monitoring and disease detection, and other types of applications. Geographically, the United States of America (USA), Australia and Spain, the top 3 world almond producers, are also the countries with the most contributions, spanning all the applications covered in the review. Other studies come from Portugal, Iran, Ecuador, Israel, Turkey, Romania, Greece, and Egypt. The USA and Spain lead water management studies, accounting for 23% and 13% of the total, respectively. As far as remote sensing platforms are concerned, satellites are the most widespread, accounting for 46% of the studies analyzed. Unmanned aerial vehicles follow as the second most used platform with 32% of studies, while manned aerial vehicle platforms are the least common with 22%. This up-to-date snapshot of remote sensing applications in almond orchards provides valuable insights for researchers and practitioners, identifying knowledge gaps that may guide future studies and contribute to the sustainability and optimization of almond crop management.

Keywords: *Prunus dulcis*; precision agriculture; satellite; manned aircraft; unmanned aerial vehicle; tree segmentation and parameters extraction; imagery classification; health monitoring and disease detection; water management; yield prediction

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1. Introduction

The global imperative to meet the rising demand for food, projected to increase by 70% by 2050 [1], underscores the need for efficient and sustainable agricultural practices. Among the diverse array of crops, almonds, renowned for their nutritional value and versatility, have become integral to providing protein-rich diets [2]. The almond tree (*Prunus dulcis* (Mill.) D.A. Webb) stands out as a profitable and nutritionally significant crop, with attributes including anti-inflammatory and hypocholesterolemic properties [3]. In addition, the by-products of the almond (skin, shell and hull) contain important bioactive compounds that have been shown to be effective in preventing degenerative diseases [4]. Notably, the almond industry has experienced substantial growth, with the United States of America (USA) and Spain emerging as leading producers [5]. These two countries are not only leading producers of almonds but are also top consumers [6]. A comprehensive overview of country-specific almond production and consumption is presented in Table 1 [5]. This table encapsulates key data, providing insights into the production and consumption dynamics of these globally significant almond-producing nations.

Table 1. Major almond producers and consumers: 2022 rankings.

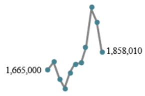
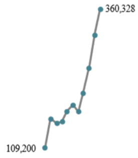
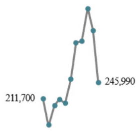
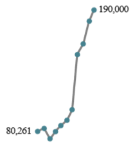
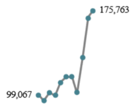
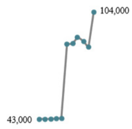
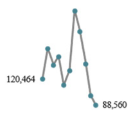
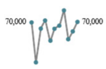
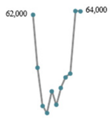
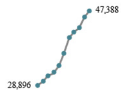
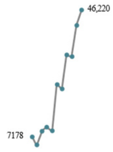
	Producers				Consumers	
	Producer	Production (Tons)	Evolution of Production (2012–2022)		Consumer	Consumption (Tons)
1	USA	1,858,010	+203,010 (12%)		USA	330,258
2	Australia	360,328	+251,128 (230%)		India	161,590
3	Spain	245,990	+34,290 (16%)		Spain	103,935
4	Turkey	190,000	+109,739 (137%)		China	94,947
5	Morocco	175,763	+76,696 (77%)		Germany	86,933
6	China	104,000	+61,000 (142%)		Italy	62,841
7	Iran	88,560	−31,904 (−27%)		Japan	49,047
8	Italy	74,590	−15,275 (−17%)		France	46,123
9	Tunisia	70,000	0		Morocco	39,945
10	Afghanistan	64,000	+2000 (3%)		Netherlands	38,793

Table 1. *Cont.*

Producers					Consumers	
	Producer	**Production (Tons)**	**Evolution of Production (2012–2022)**		**Consumer**	**Consumption (Tons)**
11	Algeria	62,988	−3499 (−5%)		South Korea	36,571
12	Chile	47,388	+18,492 (64%)		Australia	34,471
13	Portugal	46,220	+39,042 (544%)		Turkey	30,828

To address the escalating demand for almonds and ensure sustainable production, modern agricultural technologies and continuous crop monitoring are imperative [7]. The challenges posed by climate change, including water stress and disease outbreaks, further accentuate the need for advanced agricultural management strategies [8,9]. In response, Remote Sensing (RS) technologies have proven invaluable in monitoring and managing these challenges, offering a crucial tool for precision agriculture [10]. Over recent decades, RS has evolved into a prominent scientific field, using techniques to measure Earth's physical aspects through reflected or emitted radiation [11]. Advancements in data processing, geographical information systems (GIS), and global navigation satellite systems (GNSS) have expanded the applications of RS, making it an essential tool for monitoring agricultural landscapes [11]. This study focuses on a relatively new field within RS—the application of RS technologies in almond orchard monitoring and management.

The aim of this systematic review is to bridge existing gaps in almond cultivation research, particularly in the context of RS applications. This study spans the period from 2010 to 2023. The decision to limit this review to studies conducted between 2010 and 2023 is driven by the need to provide a current and comprehensive analysis of RS applications in almond orchards. This temporal restriction enables a more precise and pertinent evaluation of recent trends, technological progress and shifts in agricultural practices that impact the effectiveness of RS applications. This recent period allows for an in-depth exploration of current demands and innovations, ensuring a review that is aligned with the current state of scientific knowledge. Additionally, the past decade has seen remarkable advances in RS technologies and methods, making this period central to capturing the latest developments. During this period, significant improvements have been observed in sensor capabilities, data processing techniques and the broader integration of machine learning (ML) in RS applications.

The unique characteristics of almond trees, their response to water stress, susceptibility to disease, and distinctive planting and production methods demand a dedicated investigation into the applications of RS in this economically important crop. The specific objectives of this study include exploring RS applications associated with almond crops, identifying the most applied RS platforms and sensors, and understanding how RS techniques can be leveraged for effective tree segmentation and parameter extraction in almond orchards. Furthermore, it aims to examine the role of RS in crop classification, monitoring almond orchards, assessing crop health, managing water resources, and controlling diseases and pests. Additionally, RS-based approaches for estimating almond crop yield and gaining insights from phenological studies are also investigated.

Before delving into the specifics of RS applications in almond cultivation, a broader context for RS in agriculture needs to be established. RS serves as a valuable tool for monitoring various aspects of plants, offering insights into vegetation health, stress conditions, and growth dynamics [12]. This sets the stage for understanding its applicability to almond cultivation and justifying its role in addressing the unique challenges faced by almond producers. Previous review articles have explored the use of RS in horticulture [13], olive cultivation [14], and viticulture [15]. However, there is a lack of a comprehensive review specific to almond crops, with only one identified study conducted by Jafarbiglu and Pourreza [2]. Their review focused on RS platforms, sensors, and applications in nut crop management, providing a foundation that this study seeks to build upon and extend.

In the subsequent sections, the methodology employed in this systematic review is outlined, followed by an analysis and discussion of the results obtained, exploring research gaps and opportunities, and presenting key findings. This comprehensive review aims to provide valuable insights for researchers and practitioners in the fields of agriculture and RS, guiding future studies and applications to optimize almond crop management.

2. Materials and Methods

This systematic review was conducted based on the PRISMA protocol, an important framework that provides a standardized approach for conducting and presenting comprehensive analyzes. This protocol was developed to improve the transparency and quality of systematic reviews and meta-analyzes. It consists of a checklist that guides researchers through each stage of the review process.

One of the key procedures involved a rigorous process to identify and select relevant records. The search, conducted on 12 December 2023, included two extensive bibliographic databases, Scopus, and Web of Science (WOS). For Scopus, the search query was formulated to capture relevant manuscripts:

TITLE-ABS-KEY ("remote sensing" OR "uav" OR "unmanned aerial vehicles" OR "satellite" OR "landsat" OR "sentinel" OR "MODIS" OR airborne OR aircraft OR drone OR multispectral OR hyperspectral OR "thermal infrared" OR "land surface temperature" OR "RADAR" OR "LIDAR") AND TITLE-ABS-KEY (almond OR "prunus dulcis").*

Simultaneously, WOS was queried using the following terms:

(TI = ("remote sensing" OR "uav" OR "unmanned aerial vehicles" OR "satellite" OR "landsat" OR "sentinel" OR "MODIS" OR airborne OR aircraft OR drone OR multispectral OR hyperspectral OR "thermal infrared" OR "land surface temperature" OR "RADAR" OR "LIDAR") AND TI = (almond OR "prunus dulcis")) OR (AB = ("remote sensing" OR "uav" OR "unmanned aerial vehicles" OR "satellite" OR "landsat" OR "sentinel" OR "MODIS" OR airborne OR aircraft OR drone OR multispectral OR hyperspectral OR "thermal infrared" OR "land surface temperature" OR "RADAR" OR "LIDAR") AND AB = (almond* OR "prunus dulcis")) OR (AK = ("remote sensing" OR "uav" OR "unmanned aerial vehicles" OR "satellite" OR "landsat" OR "sentinel" OR "MODIS" OR airborne OR aircraft OR drone OR multispectral OR hyperspectral OR "thermal infrared" OR "land surface temperature" OR "RADAR" OR "LIDAR") AND AK = (almond* OR "prunus dulcis")).*

The combination of both databases resulted in a total of 298 manuscripts: 154 from Scopus and 144 from WOS. Subsequent removal of duplicates identified within and between databases led to 187 unique manuscripts (111 duplicates). In this process, a title and abstract similarity analysis were applied due to small variations. Following this, a screening process excluded non-English-language manuscripts and research reviews, resulting in the consideration of 74 manuscripts (Figure 1). Additionally, a search in another database, Google Scholar, yielded eight studies deemed relevant. To systematically categorize and analyze the identified manuscripts, a second filter was applied, resulting in six distinct RS applications for almond crops. These applications, identified by specific keywords, are as follows (Figure 1):

1. Tree Segmentation and Parameter Extraction (TSPE): Studies focusing on segmenting almond trees and extracting key parameters, including keywords like tree segmentation, parameter extraction, number of trees, tree height, and canopy area.

2. Imagery Classification (IC): Research centered around the accurate classification of RS imagery related to almond orchards, incorporating keywords like cultivars, classification models, machine learning, and deep learning.
3. Health Monitoring and Disease Detection (HMDD): Studies concentrating on monitoring tree well-being and early disease detection using RS methods, with keywords related to health, pests, disease detection, and pesticides.
4. Water Management (WM): Research related to effective water management strategies for almond orchards employing RS techniques, incorporating keywords like water stress, crop water stress index (CWSI), evapotranspiration, and irrigation.
5. And Other (OTR). This category contains studies on several topics that were not included in the previous RS applications.

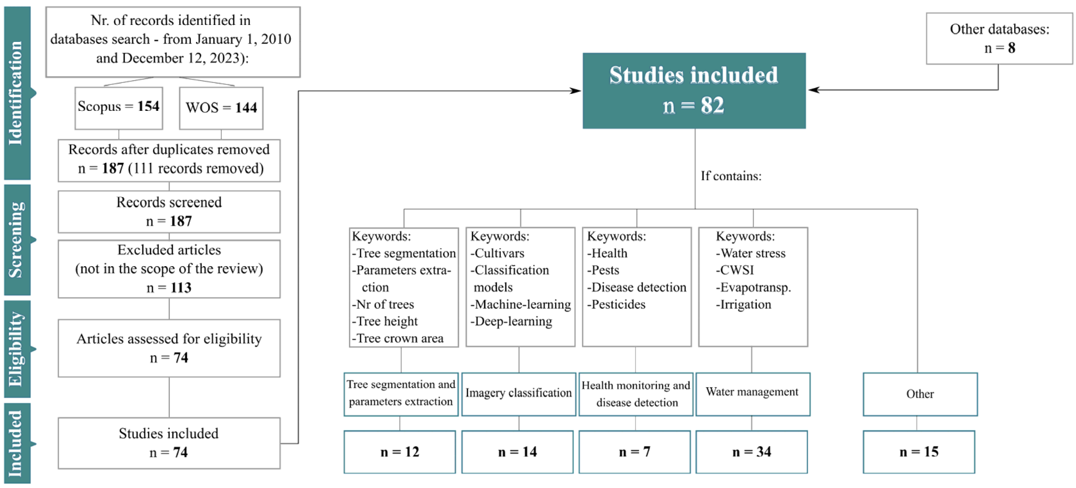


Figure 1. Flowchart depicting the implementation of the PRISMA protocol, and the systematic filtering of manuscripts based on remote sensing applications.

Upon the examination of the keywords extracted from the manuscript search, significant terms such as remote sensing, almond, Central Valley, evapotranspiration, and the Surface Energy Balance Algorithm for Land (SEBAL) (Figure 2). In addition, terms related to satellites (e.g., Sentinel-2) and sensors (LiDAR, Hyperspectral) were identified. Moreover, the spectral indices Normalized Difference Vegetation Index (NDVI) and CWSI deserve particular attention. The author keyword relationships were established using Python library NetworkX, version 3.2.1.

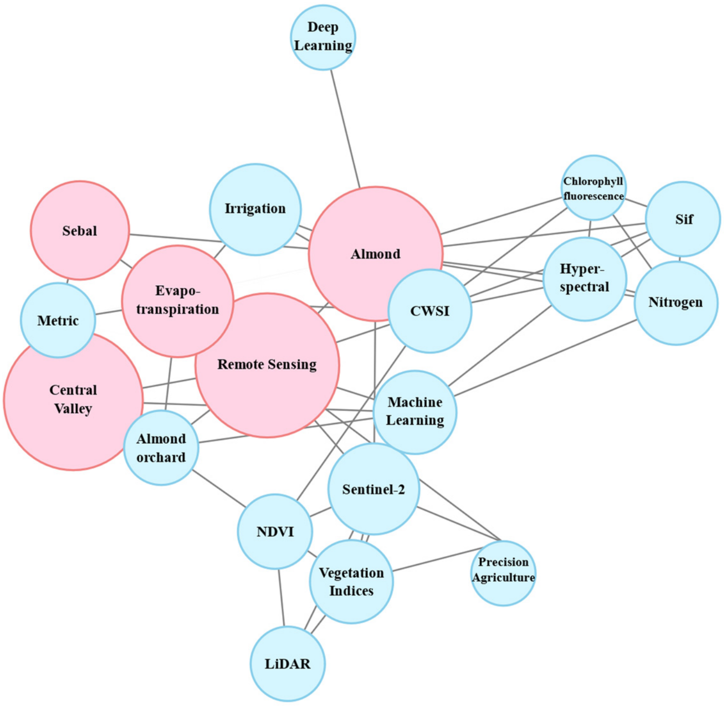


Figure 2. Primary author keywords identified in the reviewed manuscripts.

3. Results and Discussion

3.1. Overview of the Studies and Their Geographical Distribution

Between 2010 and 2023, the number of published studies exhibited a gradual increase (Figure 3a). There was a significant increase in the number of studies in the years 2017 (+8), 2019 (+12), 2021 (+16), and 2022 (+14). Conversely, no studies were identified in 2010, 2011, and 2015. In terms of the diverse applications of RS (Figure 3b), there is an irregular distribution concerning the number of publications and their respective publication dates. The application of WM predominates with 34 studies, followed by OTR with 15 studies, IC with 14 studies, TSPE with 12 studies and HMDD with 7 studies. Studies between 2012 and 2014 were related to the applications of TSPE, IC, WM and OTR. In contrast, studies for the HMDD application emerged later, starting in 2016.

In the analysis of studies conducted by different countries (Figure 4), the USA emerges as the predominant contributor, representing 51% of the identified studies. Spain also demonstrates significant representation with 26% of the studies, followed by Australia at 11%. In contrast, several other countries exhibit a smaller research footprint, including Portugal, which accounts for 4% of the studies, and Ecuador, Israel, Turkey, Romania, Greece, and Egypt, each contributing only 1% of the studies. Remarkably, some of these countries hold a pivotal role in almond production, with the USA, particularly the state of California, leading global production with an approximately 79% share. California, leveraging advanced technological methods, achieved an impressive average production of 2400 kg of almonds per hectare in the 2019–2020 season, emphasizing the cultivation of soft-shelled, non-self-fertile cultivars and using soil harvesting techniques. Australia secures the second position in global production with 360,328 tons in 2022. The European Union modestly contributes 6% to global almond production, led by Spain, which produces 245,990 tons of almonds. Portugal also plays an important role, as it is the country with the most incredible increase in production over the last decade (2012–2022: +544%). Additionally, notable production rates are observed in countries such as Tunisia, Iran, Chile, Turkey, and Morocco [5,16].

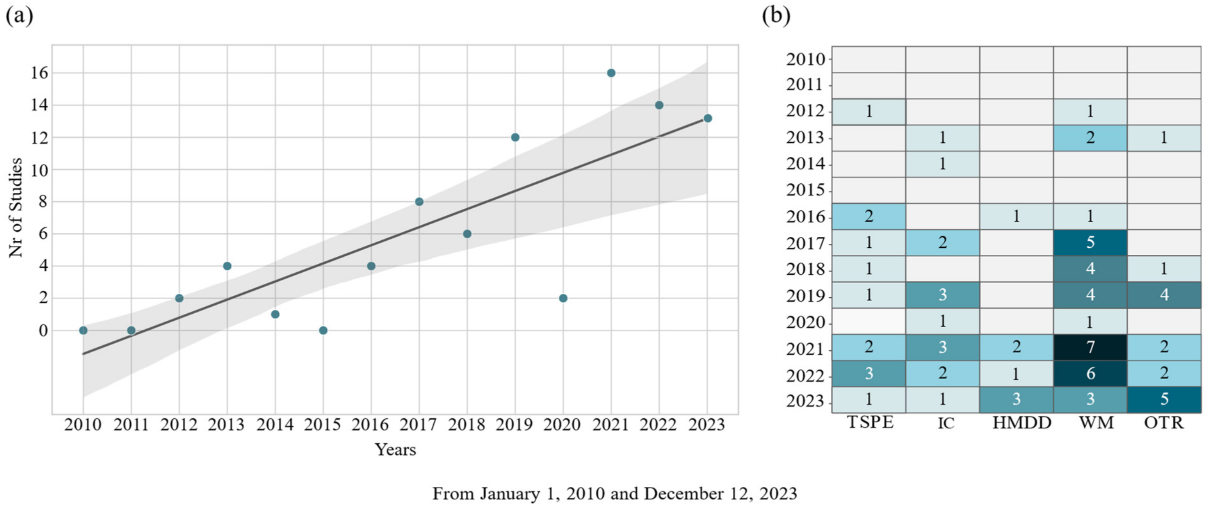


Figure 3. Overall count of publications spanning from 1 January 2010 and 12 December 2023 (**a**) and publications categorized by remote sensing application (**b**). TSPE: Tree Segmentation and Parameters Extraction; IC: Imagery Classification; HMDD: Health Monitoring and Disease Detection; WM: Water Management; and OTR: Other applications.

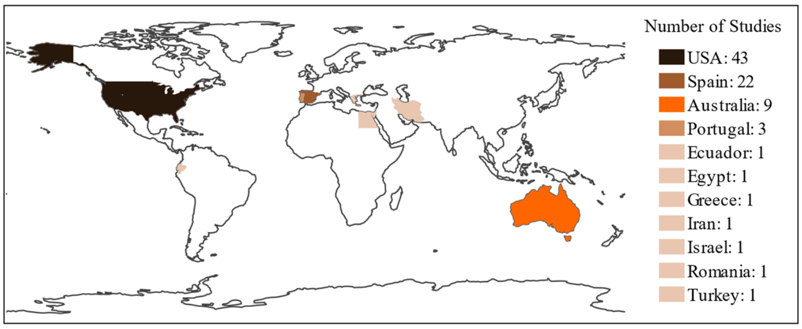


Figure 4. Aggregate number of studies categorized by country.

According to the studies analyzed, the correlation is obvious—the countries that invest heavily in almond production are also leaders in the research and implementation of RS technologies in almond cultivation. However, considering Australia's position as the fourth-largest almond producer globally, a gap exists in the importance of RS studies within the Australian context, warranting further exploration.

Examining the distribution of studies by country based on their RS applications (Figure 5), it is evident that in the USA (US), research spans across all applications, with an emphasis on WM constituting 23% of the studies. Spain (ES) showcases a diverse range of studies, with WM also being prominent at 13%. Particularly noteworthy in this country is the higher percentage of studies on the applications of TSPE (6%) and HMDD (5%) compared to the USA (TSPE—4% and HMDD—2%). In Australia (AU), 5% of the studies pertain to WM applications, another 5% to OTR applications, and only 1% to TSPE applications. Concerning Portugal (PT), of the 4% of studies identified, 2% belong to TSPE, 1% to IC, and 1% to HMDD. Ecuador (EC), Turkey (TR), Romania (RO), and Greece (GR) collectively account for only 1% of studies on IC applications. Conversely, Iran (IR) and Israel (IL) focus on TSPE applications, each representing 1% of the studies, while Egypt (EG) centers its research on OTR applications.

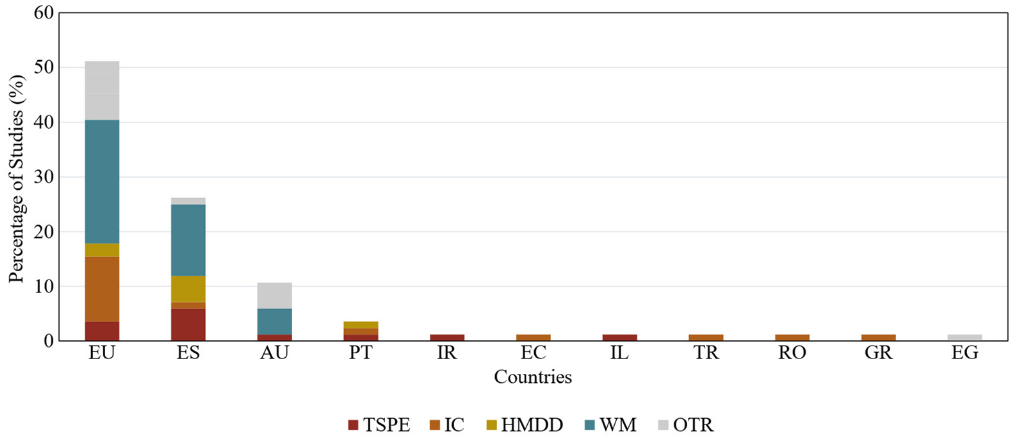


Figure 5. Percentage distribution of studies by country based on their respective remote sensing applications. TSPE: Tree Segmentation and Parameters Extraction; IC: Imagery Classification; HMDD: Health Monitoring and Disease Detection; WM: Water Management; and OTR: Other Applications.

3.2. Remote Sensing Platforms and Sensors

The distribution of RS platforms and sensors significantly influences the methodology of almond crop studies. Our analysis reveals discernible patterns in the utilization of RS platforms and sensors, providing insights into prevailing preferences within the research community.

Considering the most commonly used RS platforms, satellite was the most prevalent, being employed in 46% of the studies. The second most used platform was unmanned aerial vehicles (UAV) at 32%. Finally, the manned aerial vehicle (MAV) was the least used RS platform, representing 22% of the studies analyzed (Figure 6a). Among the sensors, the red-green-blue (RGB) sensor emerged as the most widely used, finding application in 40% of the studies analyzed. Multispectral (MSP) and thermal infrared (TIR) sensors were also widely embraced, featuring in 30% and 20% of the studies, respectively. In contrast, hyperspectral (HSP) and LiDAR (LDR) sensors were used less frequently, with only 7% and 3% of studies opting for these technologies, respectively (Figure 6b).

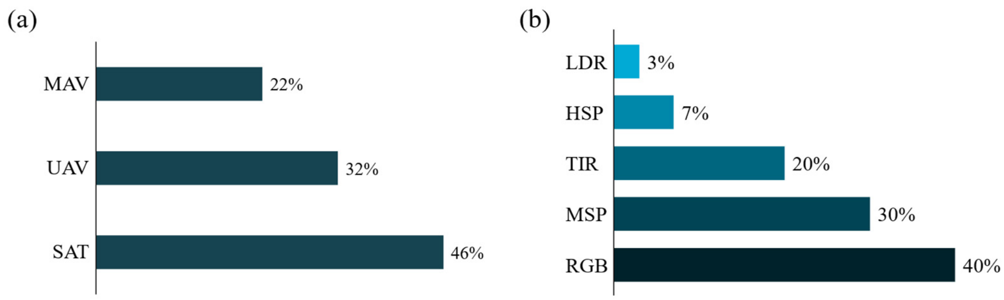


Figure 6. Remote Sensing platforms (**a**) and sensors (**b**) used in the reviewed studies. SAT: satellite; UAV: unmanned aerial vehicle; MAV: manned aerial vehicle; RGB: red, green, blue; MSP: multispectral; TIR: thermal infrared, HSP: hyperspectral; and LDR: LiDAR.

The predominant use of satellites and UAVs combined with RGB and MSP sensors in RS studies is justified by their clear advantages. Satellites offer global coverage, high revisit times and long operating times, making them suitable for monitoring large areas. UAVs offer flexibility in terms of flight altitude, spatial resolution, and revisit time to meet specific study requirements and enable targeted observations. RGB sensors capture true-color imagery for visual interpretation, while MSP sensors acquire data in several bands, which is particularly beneficial for applications that depend on VIs [17].

In examining the predominant platforms concerning the type of RS application, it is evident that studies using satellite data are predominantly associated with the WM application, constituting 26% of the studies using this platform. The IC application follows with a lower percentage, accounting for 9% of the studies. Conversely, studies focused on the TSPE and HMDD applications exhibit remarkably low utilization of satellites, representing 2% and 1% of the use of this platform, respectively. The TSPE application demands higher resolution images crucial for tree-level segmentation and parameter extraction, rendering the use of satellites less prevalent. Among studies using UAVs, those associated with TSPE application predominate at 11%, followed by IC and WM with 6% each. In contrast, applications with minimal UAV use include OTR applications, namely yield prediction (YP) with 2%. Studies related to YP application often rely on time-series data spanning a more extended period, posing challenges in obtaining such data through UAVs, which are more aptly acquired via satellite data. Among studies using MAV platforms, those related to WM applications stand out at 9%, followed by HMDD applications at 4% (Figure 7a).

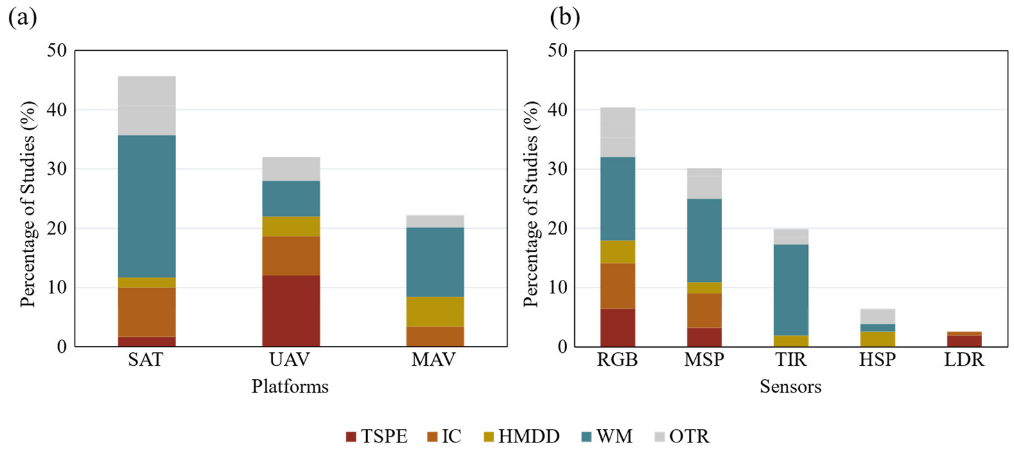


Figure 7. Remote sensing platforms (**a**) and sensors (**b**) employed in studies, categorized by remote sensing applications. TSPE: tree segmentation and parameters extraction; IC: imagery classification; HMDD: health monitoring and disease detection; WM: water management; OTR: other; SAT: satellite; UAV: unmanned aerial vehicle; MAV: manned aerial vehicle; RGB: red, green, blue; MSP: multispectral; TIR: thermal infrared; HSP: hyperspectral; LDR: LiDAR.

In terms of the most implemented sensors, several application types generally make use of RGB sensors. However, for more specific requirements, such as almond cultivar classification, water stress assessment, or disease detection, additional sensor types may be necessary. In the analyzed studies, the employment of TIR sensors in the WM application (15%) reveals a crucial role in estimating indices associated with water stress [18]. Additionally, MSP sensors were employed in the IC application (6%), acknowledging the necessity of multispectral data for calculating VIs, which play a vital role in the cultivar classification process [18]. Conversely, the HMDD application distinguished itself by employing HSP sensors (3%), as disease detection often benefits from the application of this sensor type [19]. The adoption of HSP sensors on UAVs for disease detection is driven by their ability to capture detailed spectral information across a wide range of wavelengths. This capability enables early and precise disease identification in plants, detecting spectral changes before visible symptoms manifest, thereby facilitating targeted and efficient disease management [20–22] (Figure 7b).

The effective synergy between platforms and sensors depends on a deep understanding of the intricacies of the targeted RS applications. This discerning selection process not only ensures the acquisition of relevant and high-fidelity data, but also increases the efficiency of RS methods in addressing the unique challenges of different applications.

3.3. Spectral Indices

Considering the most frequently used VIs (Figure 8), NDVI [23] was used most frequently in 46% of the studies. The Enhanced Vegetation Index (EVI) [24] was also frequently used in 16% of the studies, followed by the Soil Adjusted Vegetation Index (SAVI) [25] in 9%, the CWSI [26], and the Green Normalized Difference Vegetation Index (GNDVI) [27] in 8% each. When analyzing the RS applications, NDVI and EVI were used in all types of applications, especially in WM. On the other hand, CWSI was mainly used in WM as it is an efficient parameter to evaluate crop water use and water stress [28]. Green Leaf Index (GLI) [29], Plant Senescence Reflectance Index (PSRI) [30], and Red Edge Normalized Difference Vegetation Index (REN) [31] were only implemented in IC applications, while Canopy Chlorophyll Content Index (CCCI) [32] and Wide Dynamic Range Vegetation Index (WDRVI) [33] were specifically used for TSPE applications.

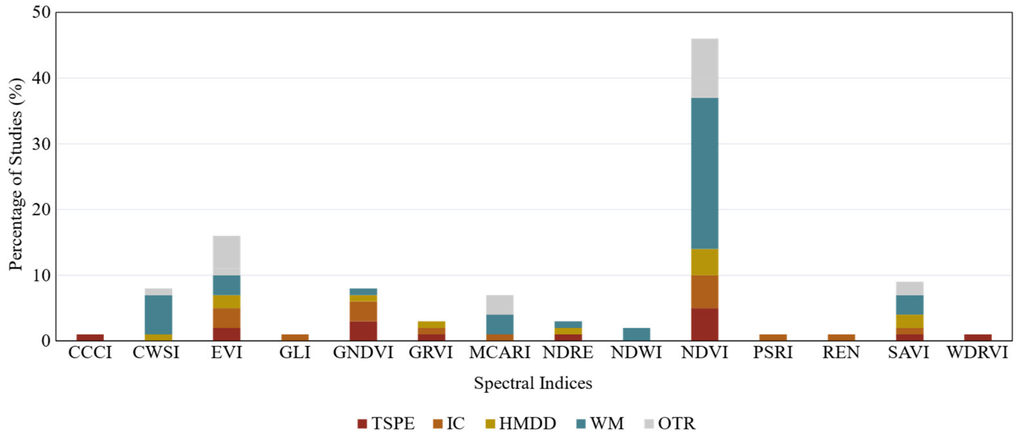


Figure 8. Spectral indices employed in studies according to remote sensing applications. TSPE: tree segmentation and parameters extraction; IC: imagery classification; HMDD: health monitoring and disease detection; WM: water management; OTR: other; CCCI: Canopy Chlorophyll Content Index; CWSI: Crop Water Stress Index; EVI: Enhanced Vegetation Index; GLI: Green Leaf Index; GNDVI: Green Normalized Difference Vegetation Index; GRVI: Green-Red Vegetation Index; MCARI: Modified Chlorophyll Absorption in Reflectance Index; NDRE: Normalized Difference Red Edge Index; NDWI: Normalized Difference Water Index; NDVI: Normalized Difference Vegetation Index; PSRI: Plant Senescence Reflectance Index; REN: Red Edge Normalized Difference Vegetation Index; SAVI: Soil Adjusted Vegetation Index; and WDRVI: Wide Dynamic Range Vegetation Index.

3.4. Remote Sensing Applications

3.4.1. Tree Segmentation and Parameters Extraction

Remote sensing techniques have become integral to agricultural monitoring, offering non-invasive and efficient means to gather essential information for optimizing cultivation practices. In this context, RS has proven particularly useful for segmenting individual almond trees and determining important parameters such as tree height, crown diameter, and biomass [34]. This subsection delves into a comprehensive review of studies centered on tree segmentation and parameter extraction in almond orchards.

The spatial resolution is a pivotal factor in TSPE, and, consequently, the choice of data platform is critical. Zarate-Valdez et al. [35] conducted a study exclusively employing satellite imagery. Their work focused on predicting the leaf area index (LAI) in almond orchards using VIs derived from Landsat imagery. For this purpose, the study uses ground measurements of LAI obtained with a mule lightbar (MLB) and compares them with VIs calculated from Landsat imagery. The results show that the EVI is the most accurate index for predicting LAI, with an R^2 of 0.78. Another study was recorded in connection with the use of satellite data in combination with UAV data. Sandonís-Pozo et al. [36] used satellite data to estimate geometric and structural parameters, bypassing the time-consuming procedures associated with LiDAR or UAV photogrammetry. They estimated critical orchard parameters using LiDAR data. They then interpolated these data using block kriging at different resolutions from PlanetScope (3 m) and Sentinel-2 (10 m). The results showed that NDVI and GNDVI had the strongest correlations with geometric and structural parameters.

Studies using MAV platforms and LiDAR data for vegetation characterization include the work by Fieber et al. [37], who developed methods employing small-footprint full-waveform LiDAR to estimate foliage-height profiles and gap probability. The results contribute to the calibration of full-waveform LiDAR data, enhancing applications in vegetation mapping, snow mass estimation, and soil moisture assessment.

In studies involving UAVs, structural parameters were efficiently collected on a large scale, with tree height being a commonly reported parameter in six studies. Tree crown area and volume, reported in four studies each, along with the number of trees, reported in three studies, underscore the versatility of UAVs in acquiring critical orchard data. Zhao et al. [38] explored tree classification using unsupervised and supervised methods, combining the Hue, Saturation, and Value (HSV) and Gray Level Concurrence Matrix (GLCM) approaches to achieve optimal results. Torres-Sánchez et al. [39] used object-based image analysis (OBIA) on photogrammetric point clouds to effectively identify almond trees and characterize their geometric features. Their tree height extraction algorithm achieved an R^2 of 0.94. López-Granados et al. [3] focused on monitoring flower density and flowering times for different almond tree cultivars using color photogrammetric point clouds. Guimarães et al. [40] proposed a method for analyzing the vegetative state of almond crops based on multitemporal data acquired using a MSP sensor, extracting individual tree parameters, and calculating NDVI for orchard monitoring. Their results revealed significant temporal variation in the vegetative state of almond trees. Martínez-Casasnovas et al. [41] used LiDAR data and UAV images to gather structural and geometric parameters, as well as VIs, establishing management zones (MZs) in hedgerow almond orchards. The study showcased the potential of LiDAR and UAV data in defining MZs for precision agriculture. Rojo et al. [42] correlated ground-based canopy light absorption data with UAV-captured RGB images to predict crop production variability. Chenari et al. [43] employed UAV-acquired data and object-oriented classification for high-resolution forest mapping in an Iranian shrub forest, outperforming pixel-based classification in overall accuracy (OA). Llorens et al. [44] conducted work involving several MSP VIs and extracted geometric and structural parameters using 3D LiDAR point clouds. Correlations revealed robust relationships between NDVI and both maximum width and cross-sectional area. Lastly, Caras et al. [45] used RS techniques to study the impact of weed management on almond tree growth, employing UAVs with MSP cameras for data collection. Their research evaluated practices such as ground covers, mulches, and herbicides, identifying the most effective approach as combining pre-emergent herbicides and ground cover, resulting in higher almond yields and improved quality parameters. As presented in Figure 9a, the UAV was the most adopted platform in 77% of the studies, followed by satellite in 15%, while MAV accounted for only 8%.

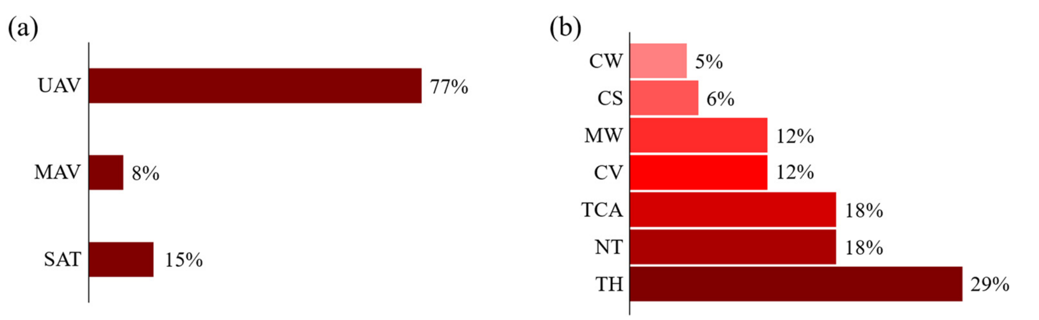


Figure 9. Remote sensing platforms implemented in tree segmentation and parameters extraction studies (**a**) and the extracted parameters (**b**). TH: tree height; NT: number of trees; TCA: tree crown area; CV: crown volume; MW: max width; CS: canopy size; CW: crown width.

Several structural parameters were extracted from the studies mentioned above. As can be seen in Figure 9b, the most frequently collected parameter was tree height (TH). A total of 29% of the studies extracted this type of information. This was followed by the number of trees (NT) and tree crown area (TCA), both of which were collected in 18% of the cases. Among the parameters that were extracted less frequently, canopy size (CS) was included in only 6% of the studies and crown width (CW) in 5% of the studies.

3.4.2. Imagery Classification

Remote sensing imagery classification is a crucial process for extracting meaningful insights from remotely sensed data. This involves categorizing pixels or regions within an image based on their spectral, spatial, and temporal characteristics. Advanced techniques, including maximum likelihood classification (MLC) and support vector machine (SVM), are commonly applied for supervised classification. Unsupervised methods like K-means clustering identify natural clusters in the absence of class labels. DL, particularly convolutional neural networks (CNN) and recurrent neural networks (RNN), have transformed the field, with CNN focusing on spatial pattern recognition and RNN addressing temporal dependencies in time-series images. Integration of data from various sensors and time points, along with robust evaluation metrics like OA and receiver operating characteristics curve (ROC), further enhances classification accuracy. This evolving field continues to benefit from technological advancements, promising increasingly refined and efficient classification processes in the future [46,47]. In this subsection, several studies on the classification of RS imagery in almond orchards are analyzed.

In the studies using only the satellite platform, it was found that machine learning (ML) models were implemented in two studies. Ikiel et al. [48] used satellite images to study land cover changes. They found that almond orchards expanded in maquis areas due to increased demand, and terraces were developed on sloping lands. On the other hand, Li et al. [49] studied the use of fully polarimetric UAVSAR data for crop classification in California's Central Valley. They applied Cloude-Pottier (CP) and Freeman-Durden (FD) decompositions, finding that polarimetric features and ML achieved accurate classification (random forest (RF) = 96% for almond). Regarding studies using only the satellite platform and DL models, three studies were identified. Sheoran and Haack [50] investigated the effectiveness of radar texturing and sensor fusion approaches using the maximum likelihood decision rule (MLD). The fusion of Landsat and radar textures resulted in an OA of 97%, illustrating the advantages of sensor integration. On the other hand, Yan e Ryu [51] efficiently mapped crops in U.S. farming regions using Google Street View (GSV) images and a CNN. Their approach demonstrated high reliability, achieving accurate crop image classification (92–97% OA, 95% for almond crops). Madaan e Kaur [52], in turn, attempted to classify five different crop types in Fresno county, California, using RapidEye satellite images and the USDA/NASS reference data. The authors employed NNs, CNNs and RNNs to train the multitemporal satellite images and achieve high classification accuracy (NN: 89%, CNN: 94%, RNN: 91%). Considering studies using only the satellite platform and both ML and DL models, only one study was identified. Peña et al. [53] used RS to identify nine summer crops from ASTER satellite imagery, combining OBIA with advanced ML. Woody crops (Almond, Walnut, Vineyard) and herbaceous crops were considered. Evaluating decision tree (DT), logistic regression (LR), SVM, and multilayer perceptron (MLP) methods, MLP and SVM stood out, achieving a high overall accuracy of 88%, surpassing LR (86%) and outperforming DT (79%).

Regarding the studies combining the use of satellite and MAV platforms, only one study using DL models was reported. Li et al. [54] presented the iterative deep learning (IDL) framework for precise crop classification in high-resolution agricultural RS. Combining a region proposal network (RPN) and CNN, IDL categorizes low-level crop (LLC) and high-level crop (HLC). Experimental results showcase IDL effectiveness, achieving an average OA of 92% for the almond crop. On the other hand, when analyzing studies that integrate satellite and UAV platforms, only one was reported, including ML and DL models.

Zhong et al. [55] developed a DL-based classification system for summer crops. Two DL models, long short-term memory (LSTM) and Conv1D, were compared with ML classifiers: Extreme Gradient Boosting (XGBoost), RF, SVM. LSTM had the lowest performance (82.41% OA), while XGBoost outperformed others (OA = 84.17%). The Conv1D-based model showed the best results, achieving an OA of 85.54%.

Among the studies using only the MAV platform, only one study employing ML and DL models was considered. Li et al. [56] explored crop monitoring using UAVSAR data, emphasizing polarimetric signatures for crops like almonds, walnuts, alfalfa, winter wheat, corn, sunflowers, and tomatoes. They found that polarimetric decomposition parameters provided superior classification accuracy (up to 97.48% with SVM) compared to linear polarizations. The study underscores L-band SAR's efficacy in precise plant monitoring and classification.

In studies employing UAV platforms, a study focused on the modification of the RF model was identified. Cánovas-García et al. [57] classified tree species, including almond orchards, to map agricultural land cover. They adjusted the RF classifier in out-of-bag cross-validation using patch-based splits. The modified RF algorithm yielded accurate results without overestimation, offering a less biased accuracy estimate compared to images with a different approach. Regarding other studies using UAV and ML models, three studies were identified. In a study performed by Zhang et al. [58], the authors classified almond orchards using MSP UAV imagery and VIs. They considered 11 VIs and analyzed 593 data points. Among six ML algorithms, SVM, k-nearest neighbor (kNN), and linear discriminant analysis (LDA) were chosen. Results indicated that increasing the number of VIs initially improved accuracy, with SVM showing the best performance overall (96%). On the other hand, Guimarães et al. [19] applied ML for almond cultivar classification. SVM and RF stood out with 76% and 74% OAs using VIs and spectral bands. Adding the canopy height model (CHM) improved results, yielding 88% and 84% OAs for RF and XGBoost. The best performance, a 99% OA, was achieved by RF and XGBoost using VIs, CHM, and tree crown area (TCA). This study emphasizes the importance of feature selection and the efficacy of ML classifiers with RS data for precise almond cultivar classification. McPeek et al. [59], in turn, developed a method for automated phenotyping of permanent crops, in order to increase the number of progeny that can be evaluated. The study used data normalization to reduce variance in a dataset, and a subset of the data was tested for classification accuracy using principal component analysis (PCA) and LDA (OA: 92%). The results showed that the method was effective in classifying almond varieties based on their reflectance spectra. Finally, among the studies using a UAV platform and DL models, the study by Șandric et al. [60] was identified. The authors proposed a methodological framework for detecting individual tree's properties using CNN and visible indices. The Mask R-CNN model was used for detecting and mapping each individual tree morphometrical properties, such as height and crown width. The results showed that the proposed methodology is stable and scalable across several zones around the globe.

Looking at Figure 10a, satellite is the most used platform in 50% of the studies, followed by UAV in 37% and MAV in 13%. Figure 10b demonstrates consistently high OA results, regardless of whether ML or DL classification models were employed. Some studies even show cases where ML models performed equally well or even better than DL models [53,56]. This observation is noteworthy given the resource-intensive nature of DL models, coupled with their often-complex operational mechanisms (black box models). In contrast, ML models, such as decision trees (DT) and RF, offer a high level of interpretability, allowing for a clear understanding of the decision-making process [61].

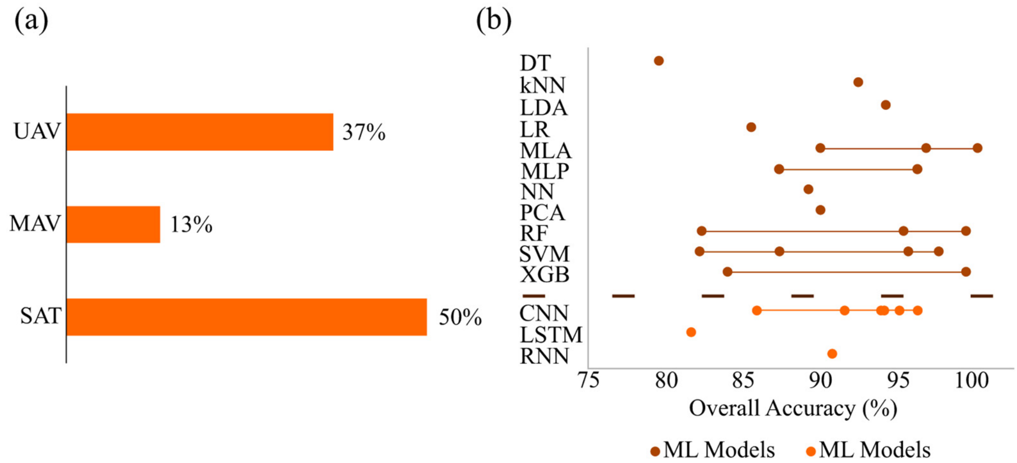


Figure 10. Remote sensing platforms in imagery classification studies (**a**) and performance evaluation of machine learning (ML) and deep-learning (DL) models (**b**). DT: decision trees; kNN: k-nearest neighbor, LDA: linear discriminant analysis; LR: logistic regression; MLA: maximum likelihood algorithm; MLP: multilayer perceptron; NN: neural network; PCA: principal component analysis; RF: random forest; SVM: support vector machine; XGB: extreme gradient boosting; CNN: convolutional neural networks; LSTM: long short-term memory; RNN: recurrent neural networks.

3.4.3. Health Monitoring and Disease Detection

Recent advancements in high-resolution RS data have empowered the mapping of crop areas affected by pests and diseases, facilitating the identification of vulnerable regions across extensive agricultural landscapes. Using satellites, UAVs, and other platforms, this technology collects unprecedented-scale data. Combined with advanced ML and data analysis, it enables precise differentiation between healthy and infested vegetation, supporting targeted control efforts. Field data further refines algorithms and enhances accuracy, contributing to the more precise mapping of pests and diseases. This innovation equips agricultural and environmental stakeholders with informed decision-making tools to foster sustainable and resilient agricultural systems [62,63]. In this subsection, various studies on almond crop monitoring and disease detection are presented.

When considering studies that combine the use of satellite and MAV platforms, one study focused on the identification of Xylella Fastidiosa (Xf) was conducted. Poblete et al. [22] successfully employed ML to detect Xf symptoms in vascular plants, achieving a high accuracy of 93.67% in identifying symptomatic trees. ML models, incorporating spectral data and LiDAR metrics, demonstrated accurate identification of symptomatic trees (84.0% to 96.0%). Thermal sensors exhibited 81.7% accuracy in early detection.

Among the studies related to the use of an MAV platform, three were conducted, two of which addressed the identification of Xf and one focused on the identification of ochre spot. Camino et al. [21] used RS technology to predict Xf infections by combining a dispersal model with an RS-driven SVM, improving accuracy to 80%. The RS-spread model outperformed RS-only and visual inspections, achieving 71% accuracy and a kappa of 0.33 in qPCR analysis, compared to 64–65% and a kappa of 0.26–31, respectively. This study underscores the effectiveness of an integrated approach in mapping plant diseases, particularly Xf infections in almond orchards. Another study conducted by Camino et al. [64] aimed to detect Xf infection, employing both laboratory and field data to build and validate an ML model. The methods included the use of SCOPE and PROSAIL-PRO models, leaf measurement, and hyperspectral imagery. The results demonstrated that the developed model could identify Xf infection with high accuracy, sensitivity, and specificity rates, along with an AUC of 0.96 in the validation set. On the other hand, López-López et al. [20] investigated red leaf spot disease in almond orchards using high-resolution aerial images. They analyzed crown temperatures and VIs for early disease detection, with chlorophyll and fluorescence effectively identifying early-stage red leaf spots. Nonlinear models distinguished asymptomatic and early-stage plants, while linear models excelled at identifying asymptomatic plants in advanced disease stages. However, parameters like stomatal conductance and chlorophyll content showed no significant differences between healthy and symptomatic leaves.

Regarding studies using UAV platforms, Li et al. [65] tested a hexacopter for almond pest control in California, comparing it to a compressed air sprayer. Despite similar residue levels, the hexacopter exhibited lower canopy penetration and is viewed as a rapid complement rather than a replacement for traditional spraying. Martínez-Heredia et al. [66] used a UAV with an RGB sensor to efficiently detect ochre spot disease in almond trees. They captured low-altitude images of leaves, processed them with MATLAB for contour identification and irrelevant object removal, and analyzed leaf color for symptoms. Ochre spot hue values ranged from 6 to 62, while healthy leaves fell between 64 and 128. The system provided disease progression percentage and GPS coordinates, triggering alerts when thresholds were exceeded. Finally, Guimarães et al. [67] conducted a study in a rain-fed almond orchard in Portugal, using UAV data and ML models to identify aphids. Data processing included photogrammetry, canopy delineation, feature extraction, labeling, and ML model implementation. The results showed that SVM performed the best with 77% overall accuracy, followed by kNN (74%), XGBoost (71%), and RF (69%).

Regarding Figure 11a, MAV was the most used platform in 50% of the studies, followed by UAV in 37% and satellite in 13%.

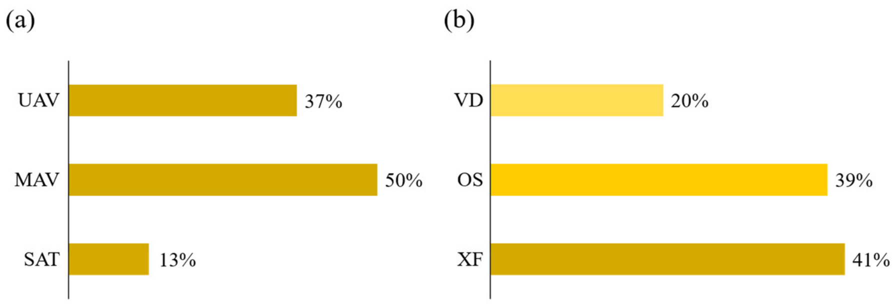


Figure 11. Remote sensing platforms (**a**) implemented in studies health monitoring and disease detection studies along with the diseases identified (**b**). XF: Xylella Fastidiosa, OS: Ochre Spot, VD: Verticillium Dahlia.

Considering the diseases identified (Figure 11b), it was found that 41% of the studies focused on the disease Xylella fastidiosa, another 39% dealt with ochre spot, and only 20% addressed Verticillium dahlia (Figure 9). Xylella fastidiosa is a plant pathogenic bacterium that causes severe diseases in several crops. It blocks the movement of water and nutrients in the plant, eventually causing withering and death. Therefore, it is essential to adopt best management practices to control its spread, such as using tolerant or resistant cultivars, insect vector control, and early detection, which can be provided using RS platforms and sensors [68]. On the other hand, ochre spot disease causes yellow-red spots on the leaves, which can eventually lead to a high presence of ochre spots caused by the pathogen. The disease can have negative consequences for the yield and quality of almonds, and infected trees should be treated promptly to prevent the spread of the disease [66].

3.4.4. Water Management

Water resource management is a critical global concern. Water plays a pivotal role in the production of food, energy, and sustaining health, while also being vital for providing potable water and ensuring sanitation [69]. Remote sensing platforms are progressively becoming integral to in situ monitoring networks due to their equipped sensors capable of conducting both direct and indirect measurements of various components within the hydrological cycle. Furthermore, these sensors offer crucial information for water management and enable the monitoring of the impact of hazards [70]. In this section, several studies demonstrating the importance of RS platforms and sensors in water monitoring and management will be presented.

Considering studies using the satellite platform, 12 studies associated with estimates of evapotranspiration (ET) were identified. Gaur et al. [71] applied the Simplified-Surface Energy Balance Index Algorithm (S-SEBI) to estimate ET in almond orchards, demonstrating reliable results with a low average root mean square error (RMSE) of 0.12 mm/h. He et al. [72] used the Mapping ET at high resolution with the Internal Calibration (METRIC) technique for accurate daily and monthly ET estimates in a Californian almond orchard. Schauer and Senay [73] studied crop water dynamics in the California Central Valley using Landsat-derived annual actual ET with the SSEBop model, revealing a substantial rise in almond cultivation area and water consumption. Xue et al. [74] compared three RS ET models (pySEBAL, SEBS, and METRIC) for daily actual ET in almond orchards, showing generally acceptable agreement with in situ measurements. Sánchez et al. [75] used the simplified Two-Source Energy Balance (STSEB) model to assess crop ET and related coefficients, aiding in predicting water needs based on orchard age and biophysical parameters. Bellvert et al. [76] estimated actual ET and crop coefficients for almonds, revealing varying water stress coefficients (Ks) through regressions between CWSI and stem water potential (SWP). Another study by Bellvert et al. [77] developed a RS model for almond orchards, accurately estimating actual ET and water stress using multispectral and thermal imagery. He et al. [78] employed high-resolution satellite data and the METRIC model for precise almond tree crop ET estimation. Knipper et al. [79] investigated methods for separating transpiration (T) and evaporation (E) in almond orchards using the ALEXI modeling framework. Mokhtari et al. [80] assessed Multi-Sensor Data Fusion-Evapotranspiration (MSDF-ET) for estimating ETa from Landsat 8 data, displaying reliable results compared to eddy covariance measurements. Peddinti and Kisekka [81] used the TSEB model to study land use effects on ET in a California almond orchard, emphasizing the importance of high-resolution thermal imagery for precise estimates. Wong et al. [82] analyzed agricultural water use in the California Central Valley using Landsat data, providing insights for sustainable groundwater management.

Regarding studies using the satellite platform, six studies related to irrigation monitoring were identified. In Bretreger et al. [83], Landsat 8 data is employed to monitor paddock-scale irrigation. Strong relationships (R^2 between 0.72 and 0.85) between NDVI/EVI and ground-based crop water measurements show the effectiveness of RS for irrigation monitoring. On the other hand, González-Gómez et al. [84] studied the impact of soil management (conventional and vegetation cover) and irrigation levels on almond orchards from 2018 to 2020. They found that combining vegetation cover with optimal irrigation improves orchard performance, leading to increased biomass and yield. Beverly et al. [85], in turn, sought to improve irrigated agricultural productivity in northern Victoria by using a bio-economic modeling framework. Their study revealed that optimizing water efficiency, achieved through genetic improvement and precision water management, along with accessing 50% of available groundwater, had the greatest potential to maximize irrigated agricultural gross margins. Bretreger et al. [86] compared tabulated crop coefficients to RS equivalents for monitoring irrigation water use. Localized tabulated coefficients, particularly for Australia, outperformed crop-specific RS equivalents, which struggled to match North American relationships. The study suggests that, overall, using localized tabulated crop coefficients is more effective in monitoring irrigation water use. Bretreger et al. [87] used RS to quantify irrigation water use in remote areas, employing FAO56-based soil water deficit modeling. Their results revealed close agreement between metered irrigation time series and modeling, with only minor variations. Monte Carlo uncertainty analysis on RAW showed substantial improvements, ranging from 3% to 15% monthly and 56% to 68% annually, compared to studies neglecting soil water deficits. Jofre-Čekalović et al. [88] developed a study on almond crop water use under diverse irrigation treatments and surface energy balance algorithms. Data from a central California almond orchard was used, showing TSEB2 + S3 provided the most accurate evapotranspiration estimates. The results show that deficit irrigation strategies could save up to 37% of water without significantly reducing crop yield.

In relation to other types of studies concerning different topics, four studies were conducted using a satellite platform. Wen et al. [89] employed RS to analyze how water and salt stresses affect diverse crops in real agricultural conditions. Using the Sentinel-2 satellite system, the study revealed varied crop responses to salt and drought stress, considering factors such as crop type, growing season, and stress timing. Alam et al. [10] studied the water-energy-food nexus in the California Central Valley, providing insights into regional precipitation and actual ET. Boken [90] enhanced crop models and evaluated agricultural drought effects, revealing correlations between soil moisture, precipitation, and almond crop yields. Paul et al. [91] proposed a new methodology for agricultural water management, demonstrating reduced water use and increased crop yield compared to traditional approaches.

Two studies using MAV platforms focused on intra-crown temperature in almond trees and its correlation with water status. Gonzalez-Dugo et al. [92] used a thermal infrared sensor on an aircraft, demonstrating a strong correlation between mean canopy temperature, stomatal conductance, and SWP. Camino et al. [93] studied solar-induced chlorophyll fluorescence (SIF) and CWSI variability in tree crowns under different water stress levels, providing insights into leaf physiological measures.

Four studies using MAV platforms addressed various topics. Camino et al. [18] examined intra-tree structural variation and its correlation with CWSI and stomatal conductance. Peddinti and Kisekka [94] assessed turbulent fluxes over an almond orchard using three RS-based models, with SEBAL demonstrating the highest overall performance. Suarez et al. [95] used the SCOPE model to measure the maximum carboxylation rate (Vcmax) as an indicator of photosynthetic rate reductions under stress. Cheng et al. [96] detected diurnal variations in fruit orchard canopy water content using a MSP and TIR MAV sensor.

Five studies using UAVs focused on water stress monitoring in almond orchards. Zhao et al. [97] presented a framework for processing high-resolution MSP imagery based on PCA for quantifying crop stress, showing a significant correlation between the first principal component and SWP. Gutiérrez-Gordillo et al. [7] evaluated UAV-based indicators for early water stress detection in four almond cultivars, emphasizing the sensitivity of CWSI compared to NDVI. Ballester et al. [98] assessed spectral indices for detecting water stress in fruit trees, revealing the effectiveness of UAV-based imagery in capturing water stress conditions. Zhao et al. [99] studied water status in a large almond farm in California using high-resolution multispectral imagery from a small UAV, predicting SWP through NDVI. Gonzalez-Dugo et al. [100] measured SWP and CWSI, assessing water status and providing guidance for irrigation management based on crop development and economic factors.

Another UAV study focused on a different topic, where Quintanilla-Albornoz et al. [101] assessed irrigation effects on almond tree transpiration, revealing variations in transpiration rates among different irrigation treatments.

Figure 12a shows that satellites were the most frequently used platform in 63% of the studies, followed by UAVs in 20% and MAVs in 17%. Different methods have been employed in WM studies (Figure 12b), with an emphasis on VIs such as NDVI (used in 38% of studies), CWSI (employed in 28% of studies), and the combined application of both (found in 5% of studies). The TSEB method also stands out, being employed in 14% of the studies. The METRIC and S-SEBI methods, applied for evapotranspiration estimations, were also extensively used in 10% and 5% of studies, respectively.

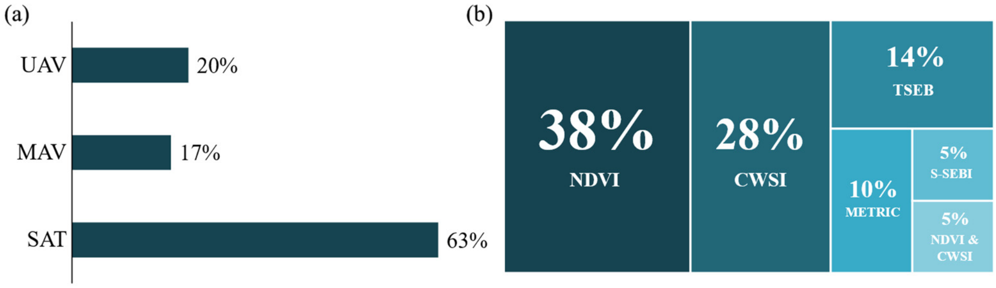


Figure 12. Remote sensing platforms (**a**) implemented in water management studies and methods primary employed (**b**) NDVI: Normalized Difference Vegetation Index; CWSI: Crop Water Stress Index; METRIC: Mapping Evapotranspiration at High Resolution with Internal Calibration; S-SEBI: Simplified-Surface Energy Balance Index Algorithm; and TSEB: Two-Source Energy Balance.

3.4.5. Other Applications

In studies exploring diverse applications, Abdel Rahman et al. [102] adeptly gathered geospatial data for agriculture, mapping promising and degraded areas, and economic planning. The outcomes revealed areas suitable for almond production (10.4%).

In investigations related to nitrogen assessment, Wang et al. conducted several studies [103–106]. The first study examined the feasibility of using DESIS imagery from the International Space Station to estimate leaf nitrogen content in almond orchards [103]. Using a radiative transfer model and solar-induced fluorescence data, the study demonstrated that coupled Cab and SIF predicted 90% of leaf nitrogen variability, showcasing the potential for large-scale leaf nitrogen quantification crucial for precision agriculture. In a second study, the use of solar-induced fluorescence (SIF) was explored as a non-destructive indicator for monitoring crop nitrogen status [104]. Employing MAV imaging spectroscopy and modeling methods, the study found a significant relationship between SIF and leaf nitrogen concentration, suggesting SIF's potential as a cost-effective and timely tool for assessing plant health and nitrogen status over large areas. In a third study, the use of MAV RS data to estimate leaf nitrogen in almond orchards is evaluated, employing ML algorithms with input parameters like plant traits, MAV-quantified solar-induced SIF, and CWSI [105]. The study identified MAV-quantified Cab and SIF as the most influential spectral plant traits for predicting leaf nitrogen, emphasizing the significance of using multiple plant traits to enhance prediction model accuracy. In the fourth study, the authors examined the role of leaf Cx in quantifying leaf nitrogen using Fluspect and MAV imaging spectroscopy in almond orchards for optimized fertilizer applications [106]. By employing SIF and chlorophyll a + b content (Cab), the authors demonstrated the superiority of this method over standard VIs, with leaf Cx ranking third after Cab and SIF consistently over two growing seasons.

Baticados and Capareda [107] assessed dust-reducing strategies using aerial-based sensors, specifically the Drone-Based Particulate Matter Sensor (DPMS). Their findings revealed that employing low-dust harvesters and optimizing fan speed significantly reduced PM10 emissions, while water application to the orchard floor showed no significant effect. The study also underscores the effectiveness of the DPMS in evaluating and informing strategies for mitigating particulate matter emissions during almond harvesting.

Jafarbiglu and Pourreza [108] aimed to quantify directional effects of solar radiation on canopy spectral reflectance, presenting results that highlighted the impact of sun-view geometry on reflectance across different spectral bands. The study outcomes, including significant variations in reflectance and RMSD values, are anticipated to enhance the reliability and repeatability of UAS-based RS analysis.

Regarding studies related to phenology, Shuai et al. [109] applied satellite data to monitor phenological changes across three diverse locations—an almond orchard in California, a winter wheat area in China, and a northern hardwood forest in New Hampshire. The authors used the MODIS 500 m reflectance anisotropy product bidirectional reflectance (BR) factor to assess the performance of the MODIS BRDF daily product in estimating key phenological parameters at these sites. The results demonstrated a robust correlation between DB phenology parameters and ground-based observations, underscoring the effectiveness of the MODIS DB BRDF product for monitoring and modeling ecosystem phenology. In De Castro et al. [110], a methodology was developed to map crop calendar events and phenology-related metrics using RS data in the Castilla-La Mancha region, Spain. OBIA techniques are employed. The approach involved three key steps: (1) generation of crop masks, (2) extraction of crop calendar events, and (3) calculation of phenology-related metrics. Validation using real data confirmed the method's reliability in providing accurate estimates of harvest calendar events and phenology-related metrics at the regional scale, showcasing its potential for crop monitoring and yield estimation. Finally, Chen et al. [111] integrated both satellite and UAV data, addressing the challenges associated with quantifying floral phenology using traditional methods. The authors explored two primary categories of RS methods: classification-based and index-based. The results revealed that the enhanced bloom index (EBI) outperformed other indices in terms of accuracy and sensitivity. The study concluded that EBI represents a valuable tool for monitoring and quantifying spatio-temporal variations in flowering status.

Among the studies related to yield prediction using satellite platforms, two employed ML models. Zhang et al. [112] used various models, including stochastic gradient boosting (SGB), to forecast almond orchard yields in the California Central Valley. RS data served as crucial features for model performance, revealing a robust correlation between estimated and actual yields at the orchard level, with an average R^2 of 0.71 for predictions in March and June. Factors influencing yields included higher temperatures from April to June benefiting southern orchards and increased March rainfall reducing yields, especially in northern orchards. Chen et al. [113] focused on improving agricultural management and economic analysis by studying the age distribution of tree crops. Using high-resolution satellite imagery and a RF model, they achieved an 87% OA in mapping tree crop planting years in the California Central Valley. This information proved vital for decision-making in agricultural management, water resource planning, and predicting agricultural product supply and demand.

In the realm of satellite-based studies for yield prediction, one employed DL models. Chakraborty et al. [114] used a data-driven approach with computer vision to predict early almond yield and promote sustainable agriculture. Over three years, they mapped bloom density in almond orchards using digital images. Model accuracy evaluation (precision of 0.76 and recall of 0.71) revealed a significant correlation with manually determined bloom density, offering insights for sustainable agriculture, cost reduction, and optimization of almond yield and quality by minimizing soil and water contamination.

In studies leveraging MAV platforms for yield prediction, two approaches were identified—one based on the Linear Regression (LR) model and the other on a combination of ML and DL models. Gonzalez-Dugo et al. [115] investigated the effectiveness of CWSI in monitoring almond tree transpiration and water status. They established a method to estimate crop yield based on the correlation between canopy temperature and transpiration. The study demonstrated a strong seasonal correlation between CWSI and final yield (R^2 = 0.80) using a non-water stress baseline (NWSB) established over three years. Tang et al. [116] explored RS technologies for yield estimation in almond tree crops at the field scale. Traditional and ML methods, including Random Forest Regression (RFR), Gradient Boosting Trees for Regression (GBTR), and XGBoost models, were developed, incorporating Landsat VIs and weather data. The study also introduced sophisticated DL models (DNN, CNN, and RNN) to enhance yield estimation with extensive RS datasets. Texture features, when added to the RF and XGBoost models, improved their ability to explain variations in almond yield.

4. Exploring Research Gaps and Opportunities for Remote Sensing Applications in Almond Crop Studies

A comprehensive review of RS applications in almond crops has enabled the identification of research gaps and promising opportunities for future research in this domain. This systematic review, covering the period from 2010 to 2023, not only provides an overview of the current landscape but also highlights unexplored areas that deserve attention in the field of RS for almond crops. By synthesizing a wide array of literature, an up-to-date overview of the current landscape is presented, but areas that remain largely unexplored are also highlighted, thereby delineating paths for further exploration in the realm of RS for almond crops. The analysis reveals a concentration of research efforts in studies emphasizing WM, representing a critical area of interest in almond cultivation [2]. However, a significant research gap exists in other crucial applications, such as HMDD, YP, and P. It is imperative for future research endeavors to address these gaps, providing a more holistic understanding of almond orchard dynamics. An examination of the geographical distribution of RS studies highlights a concentration in leading almond-producing regions, such as the United States and Spain. However, major producers like Australia receive comparatively less attention in the current research landscape. Future investigations should prioritize broadening the geographical focus to include emerging almond-growing regions and adapting methodologies to regional specificities. This approach holds the potential to yield valuable insights for sustainable almond cultivation on a global scale.

An area that is ripe for exploration is the incorporation of innovative data collection and analysis methods that have yet to be thoroughly investigated. Future research endeavors are poised to derive significant advantages from the integration of various sensors, including RGB, MSP, TIR, HSP, and LiDAR, harnessing the strengths inherent in each sensor type [17]. This advanced integration has the potential to improve the precision, efficiency, and depth of almond crop monitoring. Moreover, conducting studies based on time series data from different RS platforms emerges as a critical strategy to enable more accurate predictions and a deeper understanding of almond growth dynamics [117]. This temporal dimension can provide valuable insights into how almond crops evolve over time, allowing for more informed and nuanced decision-making in agricultural practices. Given the escalating impact of climate change on agricultural productivity [8], this review suggests that future research should explore the interplay between RS applications and changing environmental conditions affecting almond crops. Understanding how RS technologies can contribute to adaptation strategies in the face of evolving climate patterns presents a fruitful subject for exploration.

5. Conclusions

In this review article spanning the timeframe from 2010 to 2023, the examination of RS applications in almond crops has illuminated critical facets shaping the current landscape and charted pathways for future research endeavors. The primary focus on WM management, constituting 41% of the scrutinized studies, underscores the pivotal role of judicious water use in almond cultivation. However, this emphasis reveals a relative oversight of other vital aspects, including disease detection, yield prediction, and phenological studies, thereby signifying untapped opportunities for research diversification within the almond cultivation domain. A second salient observation pertains to the geographical distribution of studies, revealing a substantial concentration in major almond-producing regions, particularly the USA and Spain. This concentration accentuates the need for more comprehensive geographical investigations, extending research into regions experiencing burgeoning almond production, such as Portugal, Turkey, Chile, and Australia. Tailoring RS applications to address regional specificities is imperative, fostering a globally inclusive research agenda that transcends current limitations. A third noteworthy conclusion is the prevalence of RS platforms, with satellites playing a dominant role in 46% of the studies analyzed, followed by UAVs at 32%. Aerial systems, in contrast, featured in only 22% of the studies, showcasing the dynamic landscape of RS technologies. This insight underscores the need for continual adaptation to technological advancements, with satellites and UAVs taking center stage in advancing our understanding of almond crop dynamics. Indeed, the continuous improvement in the resolution of satellite images and the flexibility associated with UAVs have been prioritized. Lastly, the prominence of specific sensors constitutes the fourth conclusion, where RGB sensors dominate 40% of the analyzed studies. MSP and TIR sensors also found frequent application, featuring in 30% and 20% of the studies, respectively. In contrast, HSP and LiDAR sensors were less commonly used, appearing in only 7% and 3% of the studies, respectively. This sensor utilization pattern emphasizes the need for a nuanced selection of sensors based on the specific requirements of almond crop studies, paving the way for precision agriculture tailored to the unique characteristics of almond orchards.

This comprehensive review not only offers an overview of the current state of RS applications in almond crops but also reveals opportunities for future research exploration. Addressing the identified research gaps, expanding geographical coverage, and embracing technological innovations are pivotal steps for the scientific community to advance the field. Through such endeavors, it is possible to contribute to sustainable and efficient almond cultivation practices on a global scale, ensuring resilience in the face of evolving agricultural challenges and climatic uncertainties.

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