Remote Sensing Applications in Almond Orchards

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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.

Prunus dulcis | precision agriculture | satellite | manned aircraft | unmanned aerial vehicle | tree segmentation and parameters extraction | imagery classification

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].

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].

2. 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 [12]. 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. [13] 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. [14] 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. [15], 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. [16] 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. [17] 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. [18] 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. [19] 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. [20] correlated ground-based canopy light absorption data with UAV-captured RGB images to predict crop production variability. Chenari et al. [21] 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. [22] 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. [23] 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.

3. 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 [24][25]. 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. [26] 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. [27] 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 [28] 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 [29] 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 [30], 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. [31] 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. [32] 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. [33] 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. [34] 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. [35] 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. [36], 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. [37] 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 emphasizes the importance of feature selection and the efficacy of ML classifiers with RS data for precise almond cultivar classification. McPeek et al. [38], 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. [39] 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.

4. 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 [40][41]. 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. [42] 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. [43] 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 underscores the effectiveness of an integrated approach in mapping plant diseases, particularly Xf infections in almond orchards. Another study conducted by Camino et al. [44] 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. [45] 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. [46] 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. [47] 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. [48] 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%).

5. 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 [49]. 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 [50].

Considering studies using the satellite platform, 12 studies associated with estimates of evapotranspiration (ET) were identified. Gaur et al. [51] 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. [52] 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 [53] 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. [54] 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. [55] 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. [56] 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. [57] developed a RS model for almond orchards, accurately estimating actual ET and water stress using multispectral and thermal imagery. He et al. [58] employed high-resolution satellite data and the METRIC model for precise almond tree crop ET estimation. Knipper et al. [59] investigated methods for separating transpiration (T) and evaporation (E) in almond orchards using the ALEXI modeling framework. Mokhtari et al. [60] 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 [61] 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. [62] 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. [63], 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. [64] 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. [65], 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. [66] 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. [67] 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. [68] 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. [69] 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 [70] enhanced crop models and evaluated agricultural drought effects, revealing correlations between soil moisture, precipitation, and almond crop yields. Paul et al. [71] 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. [72] used a thermal infrared sensor on an aircraft, demonstrating a strong correlation between mean canopy temperature, stomatal conductance, and SWP. Camino et al. [73] 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. [74] examined intra-tree structural variation and its correlation with CWSI and stomatal conductance. Peddinti and Kisekka [75] assessed turbulent fluxes over an almond orchard using three RS-based models, with SEBAL demonstrating the highest overall performance. Suarez et al. [76] used the SCOPE model to measure the maximum carboxylation rate (Vcmax) as an indicator of photosynthetic rate reductions under stress. Cheng et al. [77] 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. [78] 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. [79] 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. [80] 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. [81] 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. [82] assessed irrigation effects on almond tree transpiration, revealing variations in transpiration rates among different irrigation treatments.

6. Other Applications

In studies exploring diverse applications, Abdel Rahman et al. [83] 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 [84][85][86][87]. The first study examined the feasibility of using DESIS imagery from the International Space Station to estimate leaf nitrogen content in almond orchards [84]. 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 [85]. 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 [86]. 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 [87]. 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 [88] 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 [89] 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. [90] 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. [91], 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. [92] 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. [93] 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. [94] 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. [95] 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. [96] 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. [97] 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.

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