remote sensing

Review

Combination of Remote Sensing and Artificial Intelligence in Fruit Growing: Progress, Challenges, and Potential Applications

Danielle Elis Garcia Furuya [1,*], Édson Luis Bolfe [1,2], Taya Cristo Parreiras [2], Jayme Garcia Arnal Barbedo [1], Thiago Teixeira Santos [1] and Luciano Gebler [3]

[1] Brazilian Agricultural Research Corporation, Embrapa Agricultura Digital, Campinas 13083-886, São Paulo, Brazil; edson.bolfe@embrapa.br (É.L.B.); jayme.barbedo@embrapa.br (J.G.A.B.); thiago.santos@embrapa.br (T.T.S.)
[2] Institute of Geosciences, State University of Campinas (Unicamp), Campinas 13083-970, São Paulo, Brazil; t234520@dac.unicamp.br
[3] Brazilian Agricultural Research Corporation, Embrapa Uva e Vinho, Vacaria 95200-970, Rio Grande do Sul, Brazil; luciano.gebler@embrapa.br
* Correspondence: danielle.furuya@colaborador.embrapa.br

Abstract: Fruit growing is important in the global agricultural economy, contributing significantly to food security, job creation, and rural development. With the advancement of technologies, mapping fruits using remote sensing and machine learning (ML) and deep learning (DL) techniques has become an essential tool to optimize production, monitor crop health, and predict harvests with greater accuracy. This study was developed in four main stages. In the first stage, a comprehensive review of the existing literature was made from July 2018 (first article found) to June 2024, totaling 117 articles. In the second stage, a general analysis of the data obtained was made, such as the identification of the most studied fruits with the techniques of interest. In the third stage, a more in-depth analysis was made focusing on apples and grapes, with 27 and 30 articles, respectively. The analysis included the use of remote sensing (orbital and proximal) imagery and ML/DL algorithms to map crop areas, detect diseases, and monitor crop development, among other analyses. The fourth stage shows the data's potential application in a Southern Brazilian region, known for apple and grape production. This study demonstrates how the integration of modern technologies can transform fruit farming, promoting more sustainable and efficient agriculture through remote sensing and artificial intelligence technologies.

Keywords: digital agriculture; deep learning; machine learning; orchard; apple; grape

check for updates

Citation: Furuya, D.E.G.; Bolfe, É.L.; Parreiras, T.C.; Barbedo, J.G.A.; Santos, T.T.; Gebler, L. Combination of Remote Sensing and Artificial Intelligence in Fruit Growing: Progress, Challenges, and Potential Applications. *Remote Sens.* **2024**, *16*, 4805. https://doi.org/10.3390/rs16244805

Academic Editor: Annamaria Castrignanò

Received: 20 September 2024
Revised: 18 December 2024
Accepted: 19 December 2024
Published: 23 December 2024

1. Introduction

Fruit cultivation plays a fundamental role in agriculture, combining efficient production with technological advancements. Several fruits are produced in significant quantities worldwide, directly impacting both the economy and society [1,2]. Apples are among the most economically important fruits globally [3], being widely cultivated in many countries [4]. Asia is the largest producer of apples, accounting for 64.10% of global production, followed by Europe with 20%, and the Americas with 11.6% [5]. Grapes are also one of the most consumed fruits worldwide, especially valued for wine production [6]. Citrus fruits are cultivated in over 140 countries, with approximately 70% of global production concentrated in Brazil, the United States, and Mediterranean countries [7]. Bananas are grown in more than 130 countries and rank as the second most important fruit crop in the world [8,9]. Jujube, a fruit cultivated for over 4000 years in China, has spread to other countries, where it plays a vital role in addressing economic, social, and ecological concerns [1]. Given the wide variety and high consumption of fruits, it is essential to carefully plan and manage all stages of cultivation.

Efficient monitoring and management of fruit crops are crucial to ensure quality and productivity. Every year, crops suffer losses due to several factors, including pests, adverse climatic conditions, socioeconomic constraints, and insufficient technical knowledge [10–12]. Detecting or accurately recognizing fruits in orchards is one of the key steps in predicting harvest logistics and ensuring efficiency [13].

Modern techniques such as precision agriculture enable farmers to monitor plant growth, detect pests and diseases, and optimize the use of natural resources like water and nutrients [14,15]. Advanced technologies such as drones and satellite imagery provide real-time data and detailed analysis for improved crop management. Remote sensing technology is increasingly being enhanced with higher spatial, temporal, and spectral resolutions [16]. Hyperspectral sensors, for instance, allow researchers and farmers to obtain detailed information about crop health, nutritional status, and water content [17].

The combination of remote sensing and artificial intelligence has gained prominence in fruit farming and crop monitoring. Machine learning and deep learning techniques enable the extraction of valuable, high-level information from data, and are particularly effective in high-precision classification and recognition tasks across many domains [18,19]. Machine learning requires predefining several parameters, which significantly impact recognition accuracy [20]. Deep learning aims to develop intelligent and robust mechanisms that can handle multiple learning patterns [21]. Despite some limitations, these techniques have yielded significant results in fruit farming research [22–25].

In the context of fruit production, Brazil ranks as the third-largest fruit producer globally, contributing 5.4% of global production (58 million metric tons) [26]. In 2023, Brazilian fruit exports increased by 6% in volume and 26.7% in value compared to the previous year, reaching a total of 1.085 million metric tons exported [27]. Brazil is particularly known for its apple and grape production, especially in the Southern region. The state of Rio Grande do Sul alone is responsible for more than 500,000 metric tons of apple production and over 80% of Brazil's grape production [28–31].

Although the combination of remote sensing techniques and artificial intelligence has shown promise, there is no comprehensive review specifically focused on apples and grapes that could support production in Brazil. Therefore, this study aims to (1) review studies that applied remote sensing and artificial intelligence for fruit analysis; (2) examine the techniques used for studying apples (*Malus domestica*) and grapes (*Vitis vinifera*), focusing on data types, algorithms, and research objectives, among other characteristics; and (3) analyze the case of the municipality of Vacaria, Rio Grande do Sul (Brazil), highlighting potential applications of these technologies in Brazil, which could also serve as a foundation for other apple- and grape-growing regions.

2. Materials and Methods

This study was conducted in four main stages: (i) review on fruit growing, (ii) analysis of general data, (iii) analysis of specific data, and (iv) potential applications for Brazil (Figure 1). The first stage involved a review of articles available on the Web of Science [32,33] using the following keywords: TS = ((fruit OR orchard OR apple OR grape) AND (machine learning OR deep learning OR artificial intelligence) AND (remote sensing)). The analysis was based on studies available from 2018 up until June 2024. Using the chosen keywords, the Web of Science filtered 177 studies, of which only 117 were analyzed. All articles that used the combination of remote sensing and artificial intelligence (machine learning or deep learning) to study some type of fruit were selected. The aim is to analyze the trends and types of fruits that are being studied.

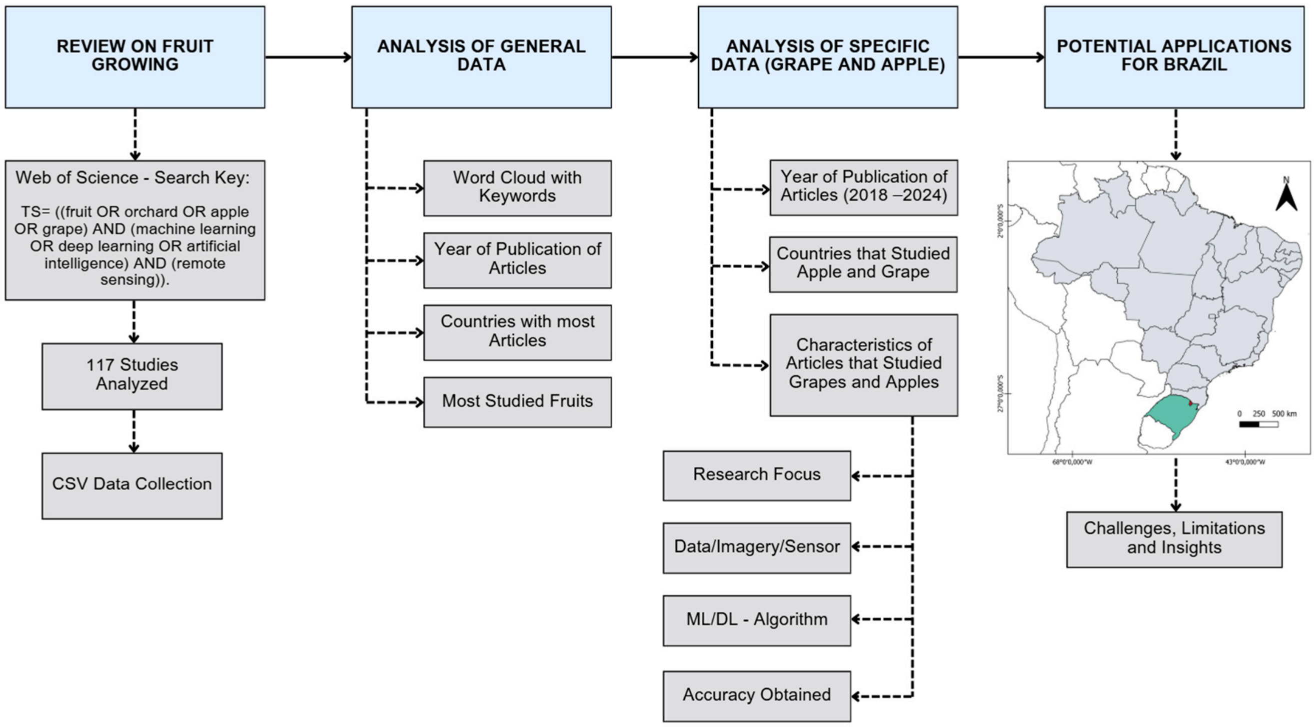

Figure 1. Flowchart showing the structure and steps taken in this study. Initially, data were collected from articles on the Web of Science. Subsequently, the information and data were distributed into three stages: analysis of general data, analysis of specific data (grape and apple), and potential applications for Brazil.

The second stage consisted of a more focused analysis of studies dealing with apples and grapes. The main sensors used, the machine learning and deep learning algorithms found, the most used evaluation metrics, and the focus of the research were identified. Subsequently, some of the studies found were analyzed in detail and the authors' suggestions for future research were presented.

The third stage focused on analyzing potential applications in the city of Vacaria, Brazil. As one of the ten Agrotechnological Districts (DATs) selected in the project "Center for Development in Digital Agriculture (CCD-SemeAr)" [34], led by the Brazilian Agricultural Research Corporation (Embrapa) and involving six other major research institutions, Vacaria was a natural choice, given its prominence in apple and grape production. Although this analysis was centered on Vacaria, the findings and methods discussed hold broader applicability, offering valuable insights for fruit production regions with similar agricultural profiles.

3. Results and Discussion

3.1. General Data

A word cloud was created with the keywords of all 117 articles (Figure 2). The objectives of the studies are varied, including subjects like orchard classification, fruit detection and segmentation, pest and disease identification and prediction, among others.

Figure 2. Word cloud with the keywords of the 117 articles analyzed in the Web of Science 2018/2024.

From 2021 onwards, the number of studies increased significantly due to advancements in techniques and data availability (Figure 3). Recently, there has been significant growth in the use of machine and deep learning algorithms, as well as in the different methods of obtaining remote sensing data, including new satellites, advanced sensors, and other emerging technologies that can enhance the mapping and monitoring of fruit cultivation. Furthermore, the journals with the most publications are "Remote Sensing" (with 28 articles) and "Computers and Electronics in Agriculture" (with 15 articles).

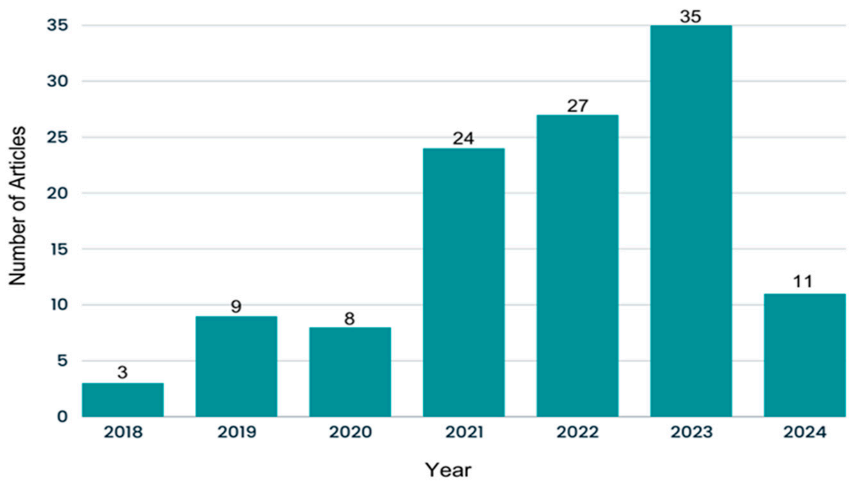

Figure 3. Distribution of the 117 articles selected on the Web of Science database per year of publication.

A total of twenty-six countries were identified, each with at least one article analyzing the cultivation of fruit in a specific area within the country. Six countries stand out with the highest number of studies and fruit species (Figure 4). China and the United States led with 34 and 10 articles, respectively, followed by Australia and Spain, with 7 articles, and Brazil and Italy, with 5 articles.

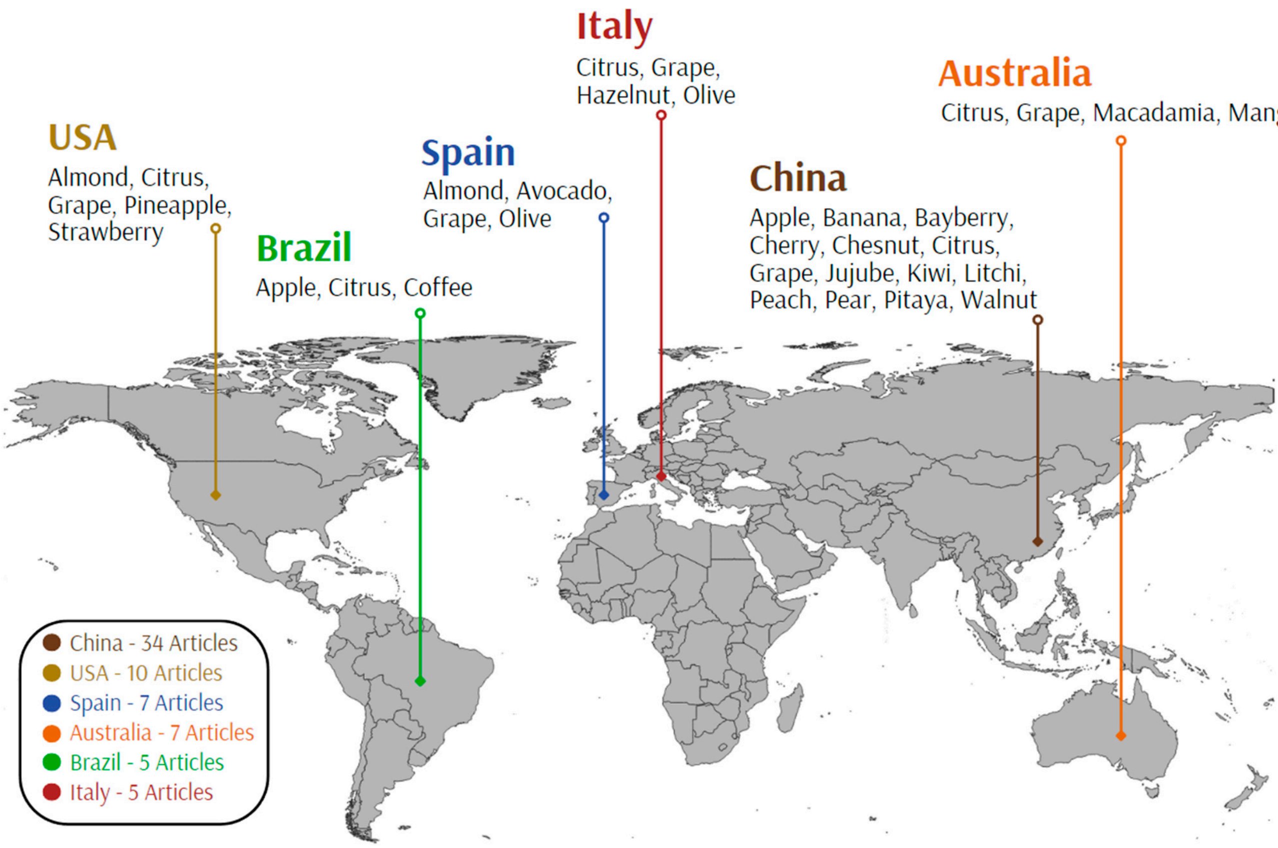

Figure 4. Countries that appear in the highest number of articles. The fruit crops studied in each major country are also shown.

The articles selected for this review collectively investigated 38 fruit crops (Figure 5). Apples and grapes have the largest number of studies, followed by citrus.

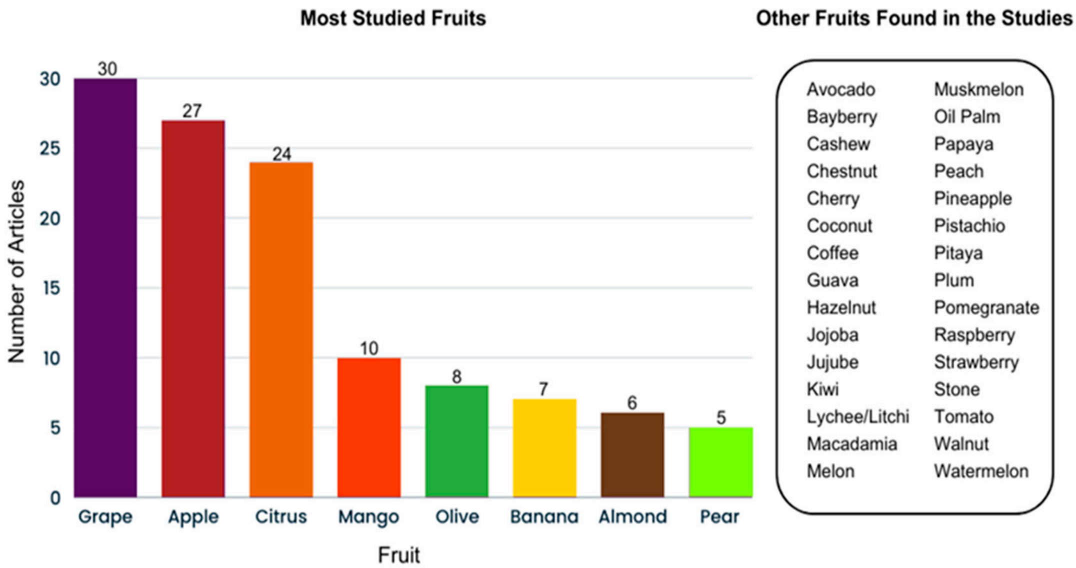

Figure 5. Distribution of the eight most studied fruits (number of articles) based on the review. On the right is a list of other fruit crops that were studied in at least one article.

3.2. Specific Data (Apple and Grape)

In this step, information related to the articles dealing with apples and grapes was analyzed. The distribution of articles by year of publication is shown in Figure 6.

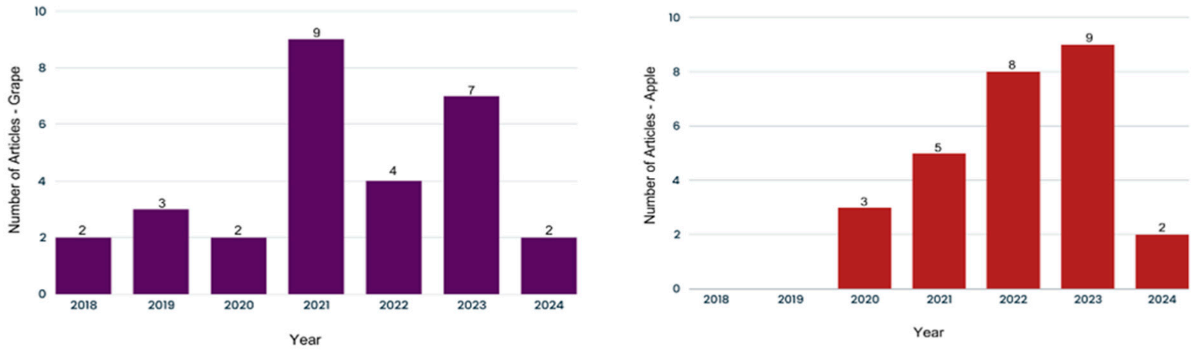

Figure 6. Distribution of the number of articles per year for grapes (**left**) and apples (**right**).

Although most of the studies in the review focused on grapes and apples, the studied areas were concentrated in only thirteen and five countries, respectively (Figure 7). Although the two fruits have been studied in few countries, these are geographically widespread, which shows the importance of apple and grape cultivation in different regions.

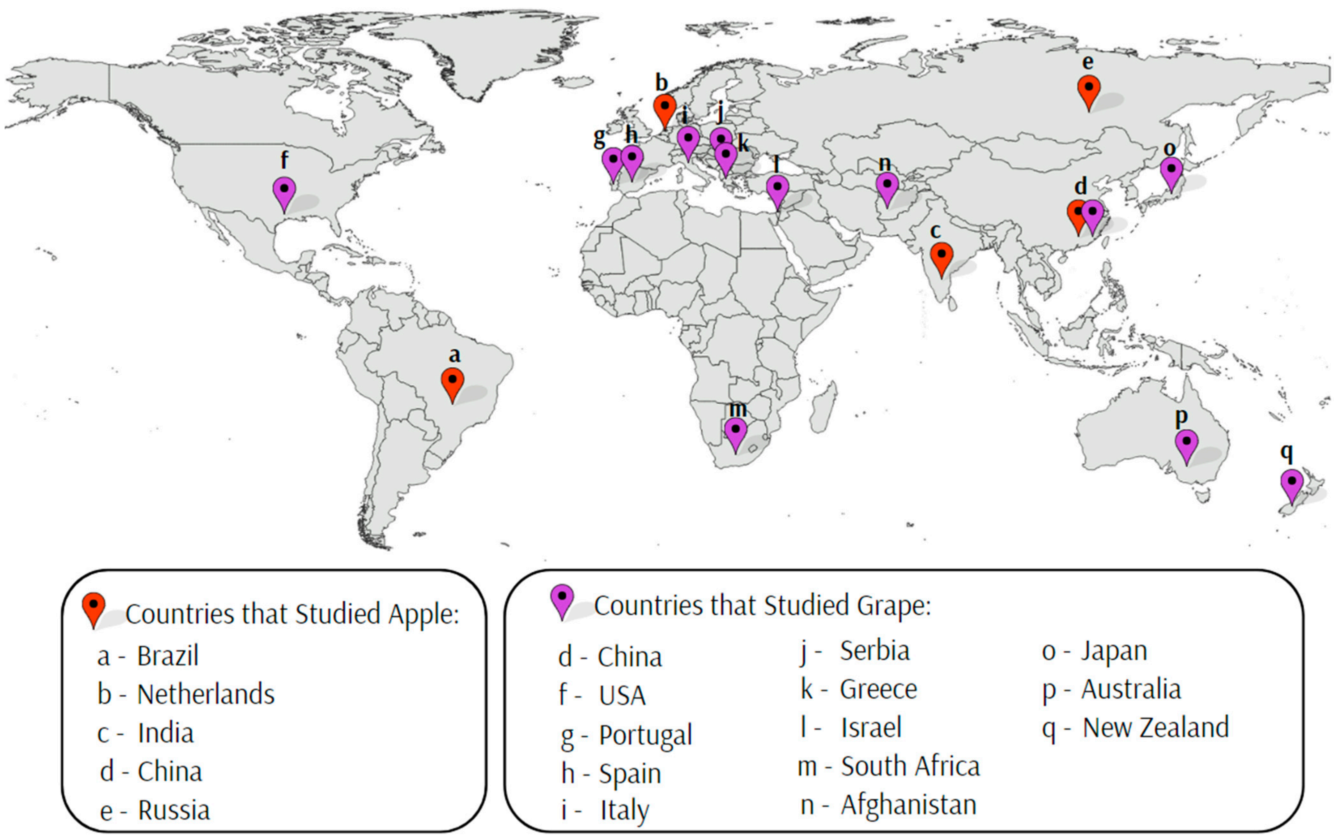

Figure 7. Countries found as study areas for apple and grape cultivation in at least one article in the review.

The information from the Web of Science review is summarized in Table 1 (grapes) and Table 2 (apple) to provide a clearer understanding about the techniques used to study these fruits. It is important to highlight that in studies dedicated to grapes, the terms may appear as ”Grape”, “Grapevine”, “Vineyard”, or “Viticulture”.

Of the total number of studies found on grapes and apples, some correspond to review articles, which explains why Table 1 contains fewer articles than Figure 5. The key strategies and findings reported in the articles are summarized in the following section. Gutiérrez et al., 2018 [35] proposed a new non-destructive tool useful for plant phenotyping under field conditions. The authors used SVM and MLP with hyperspectral images to classify a large number of grapevine varieties (*Vitis vinifera* L.) in Spain. For the analyses, 1200 spectral samples were acquired at two different leaf phenological stages from the canopy of 30 different varieties in a vineyard. Recall and F1 values reached 0.99 in tests employing a 5-fold cross validation, while prediction accuracy for individual varieties ranged from 0.94 to 0.99 and from 0.83 to 0.97 using MLP and SVM, respectively. The best activation function for MLP was the hyperbolic tangent function and the best SVM kernel was linear.

Table 1. Characteristics of studies on grapes found in this review.

Reference	Fruit(s)-Research Focus	Data/Imagery/Sensor (Origin)	ML/DL-Algorithm	Accuracy
Gutiérrez et al., 2018 [35]	Grape; Classification of grapevines	A Resonon Pika L VNIR hyperspectral imaging camera (Resonon, Inc., Bozeman, MA, USA) mounted on the front part of an all-terrain vehicle (ATV) (Trail Boss 330, Polaris Industries, MN, USA).	SVM, MLP	Both classifiers: recall F1 scores up to 0.99 for 5-fold cross validation. Prediction performance for individual varieties of MLP ranged from 0.94 to 0.99 while SVM ranged from 0.83 to 0.97.
Loggenberg et al., 2018 [36]	Grape; Water stress in Vineyards	SIMERA HX MkII hyperspectral sensor (SIMERA Technology Group, Somerset West, South Africa).	RF, XGBoost	Using all wavebands (p = 176), RF produced a test accuracy of 83.3% (KHAT (kappa analysis) = 0.67), and XGBoost reached an accuracy of 80.0% (KHAT = 0.6). Using a subset of wavebands (p = 18) resulted in slight increases in accuracy ranging from 1.7% to 5.5% for both RF and XGBoost.
Fuentes et al., 2019 [37]	Grape; Predict smoke taint in grapes	Thermal images with an infrared thermal camera FLIR® T-series (Model B360) (FLIR Systems, Portland, OR, USA). Full berries scanned with a spectrophotometer (ASD FieldSpec®3, Analytical Spectral Devices, Boulder, CO, USA).	A regression model	Accuracy of 96%.
Maimaitiyiming et al., 2019 [38]	Grape; Estimating grapevine berry yield and quality	Hyperspectral reflectance—spectroradiometer PSR-3500 (Spectral Revolution, Inc., Lawrence, MA, USA).	MLR, PLSR, RFR, WRELM, WRELM-TanhRe (proposed model)	WRELM-TanhRe: highest prediction accuracy for all berry yields and quality parameters (R^2 of 0.522–0.682 and RMSE of 2–15%).
Ohana-Levi et al., 2019 [39]	Grape; Determination of irrigation management zones	UAV—A FLIR SC2000 thermal camera (FLIR® Systems, Inc., Bilerica, MA, USA) and a multispectral camera MicaSense RedEdge (MicaSense® Inc., Seattle, WA, USA).	BRT, K-means	BRT: cross-validation score of 0.84 with measured values of the predictors vs. yield. A cross-validation score of 0.97.

Table 1. *Cont.*

Reference	Fruit(s)-Research Focus	Data/Imagery/Sensor (Origin)	ML/DL-Algorithm	Accuracy
Ballesteros et al., 2020 [40]	Grape; Vineyard yield estimation	A quadcopter md4-1000 (Microdrones, Inc., Kreuztal, Germany) with a mounted multispectral Sequoia camera (Parrot, Paris, France).	MLP	Combination of VIs and Fc: RMSE = 0.9 kg vine^{-1}, and RE = 21.8%. Simple use of VIs: RMSE = 1.2 kg vine^{-1}, and RE = 28.7%. Machine learning techniques resulted in much more accurate results: RMSE = 0.5 kg vine^{-1}, and RE = 12.1%.
Summerson et al., 2020 [41]	Grape; Detection of smoke-derived compounds from bushfires in Cabernet-Sauvignon grapes, must, and wine	MicroPHAZIRTM RX Analyzer (Thermo Fisher Scientific, Waltham, MA, USA).	Levenberg Marquardt, Bayesian regularization, ANN (Five models)	R above 0.95 for all models.
Arab et al., 2021 [42]	Grape; Develop yield prediction models	Landsat 8 OLI.	ANN	NDVI in 2017 (R = 0.94); 2018 (R = 0.95); 2019 (R = 0.92).
Gautam, Ostendorf, and Pagay, 2021 [43]	Grape; Estimation of grapevine crop coefficient	A hexacopter multirotor (DJI Matrice 600 Pro, Dà-Jiāng Innovations Science and Technology Co., Ltd., Shenzhen, China). The UAV carried trifecta cameras including a multispectral sensor placed in a Gimbal (DJI Ronin, Dà-Jiāng Innovations Science and Technology Co., Ltd., Shenzhen, China).	CNN, RF	RF: highest accuracy—R^2 = 0.675; RMSE = 0.062; and MAE = 0.047.
Gomes., Mendes-Ferreira, and Melo-Pinto, 2021 [44]	Grape; Prediction of sugar and pH levels	Hyperspectral camera: JAI Pulnix (JAI, Yokohama, Japan). Specim Imspector V10E spectrograph (Specim, Oulu, Finland).	1D CNN	RMSEP values of 1.118 °Brix and 1.085 °Brix for sugar content and 0.199 and 0.183 for pH.
Kasimati et al., 2021 [45]	Grape; Prediction of total soluble solids among wine grapes	UAV and Sentinel-2	Ordinary least square, Theil–Sen estimator, Huber regression, DT, AdaBoost, RF, Extremely randomized trees	Best-fitted regressions with R^2 value of 0.61.

Table 1. *Cont.*

Reference	Fruit(s)-Research Focus	Data/Imagery/Sensor (Origin)	ML/DL-Algorithm	Accuracy
Khan et al., 2021 [46]	Apple, banana, citrus, pear, grape; Fruit growth prediction	Publicly available dataset from the Food and Agriculture Organization (FAO) of the United Nations.	AdaBoost, MLP, SVR, LR Agricultural Deep Learning (AGR-DL)—Proposed model	Precision of LR—87.65% SVR—88.96% AdaBoost—90.37% MLP—91.23% AGR-DL—94.12% (capable of achieving up to 95.56%).
Navarro et al., 2021 [47]	Grape; Image classification of seedless table grape varieties	Dark chamber, an illumination subsystem, a multispectral image capturing subsystem, and a processing subsystem. Two multispectral cameras of mosaic type from Photonfocus: MV1-D2048x1088-HS03-96-G2 and MV1-D2048x1088-HS02-96-G2.	AlexNet, ResNet, 3DeepM architecture	Optimization procedures to determine the size and sequence of the kernels for the 3D convolutions have made it possible to obtain 100% accuracy in the classification of multispectral images of five table grape varieties.
Barriguinha et al., 2022 [48]	Grape; Estimating wine grape yield	Sentinel-2A and 2B.	LSTM Neural Network	The best prediction was made for 2020 at the VER (veraison) phenological stage, with the model overestimating the yield per hectare by 8%, with the average absolute error for the entire period being 17%.
Kasimati et al., 2022 [49]	Grape; Grape sugar content prediction	Active proximal canopy sensor (ACS-470, Holland Scientific Inc., Lincoln, NE, USA); Spectrosense+ passive GPS sensor (Skye Instruments Ltd., Landrindod Wells, UK); Garmin GPS16X HVS (Garmin, Olathe, Kansas, USA); Phantom 4 Pro drone (Dà-Jing Innovations, Shenzhen, Guangdong, China) equipped with a multispectral Parrot Sequoia+ camera (Parrot SA, Paris, France); Sentinel-2 satellite images (ESA portal).	OLS, Theil-Sen, Huber Regression, DT, AdaBoost, RF, Extra Trees, SVM, ARD	Regression models with both manually fine-tuned ML (R^2 = 0.61) and AutoML (R^2 = 0.65). Average of R^2 = 0.66 combining multiple sensors and growth stages per year.

Table 1. *Cont.*

Reference	Fruit(s)-Research Focus	Data/Imagery/Sensor (Origin)	ML/DL-Algorithm	Accuracy
Noguera, Millan, and Andújar, 2022 [50]	Red-grape; New device for in-field fruit-ripening assessment	The multispectral sensor device is composed of different elements that are assembled inside a 3D-printed enclosure: AMS AS7265x development board (AMS AG, Premstätten, Austria)—Arduino MKRZero Board (Arduino LLC, Monza, Italy)—LED PCB (OSLON P1616 SFH 4737, OSRAM, Germany)—OLED Screen. Spectral data—captures of a surface of known reflectance (Labsphere, Inc, North Sutton, NH, USA).	MLP with back propagation	R^2 = 0.70 and RMSE = 1.21 for SSC (soluble solid content); R^2 = 0.67 and RMSE = 0.91 for TA (titratable acidity).
Peng et al., 2022 [51]	Grape; Predict nutrient content	UAV—A six-rotor M600 UAV (Dajiang Innovation Technology Co., Ltd., Shenzhen, China) to carry a six-channel multispectral Micro-MCA camera (Tetracam Inc., Chatsworth, CA, USA).	RF, SVM, ELM	Best model: ELM. Obtained R^2—0.853; RRMSE—0.113; WIA—0.955.
Dutta et al., 2023 [52]	Raspberry, coconut, papaya, orange, apple, muskmelon, watermelon, grapes, mango, banana, and pomegranate; Pomological recommendation system	Dataset from the Kaggle source.	Light GBM	The accuracy of the model is 99%, the macro average is 0.99, and the weighted average is 0.9.
Imran et al., 2023 [53]	Grape; Detecting Flavescence Dorée (a highly epidemic and incurable disease) in Vineyards	Two portable hyperspectral micro-spectrometers (Hamamatsu C12880MA series and DLP NIRScan Nano Evaluation Module (EVM), Texas Instruments, Dallas, TX, USA).	LR, SVM, XGBoost, RF, Cubist	LR—accuracy of 96%; SVM—accuracy of 85%.

Table 1. *Cont.*

Reference	Fruit(s)-Research Focus	Data/Imagery/Sensor (Origin)	ML/DL-Algorithm	Accuracy
Lyu et al., 2023 [54]	Grape; Non-destructive and rapid prediction of grape quality	Global navigation satellite system (GNSS) with real-time kinematic (RTK) correction (model: GPS1200+, Leica Geosystems AG., Heerbrugg, Switzerland). Portable digital refractometer (PAL-ALPHA Digital Refractometer, ATAGO CO., LTD, Tokyo, Japan). Multispectral imagery acquired by DJI P4 Multispectral (Da-Jiang Innovations, Shenzhen, China).	Ridge regression, lasso regression, KNN, SVR, RFR, XGBoost, ANN	RFR and XGBoost outperform other regression models with an average of RMSE of 1.19 and 1.2 °Brix and R^2 of 0.52 and 0.52, respectively.
Swe, Takai, and Noguchi, 2023 [55]	Grape; Brix prediction model in Rondo wine grapes	Hyper Suprime-Cam (HSC) camera.	EBM, SVR, Ridge regressor	Accuracy from 0.72 to 0.75 for the EBM followed by the SVR model and from 0.74 to 0.77 for the ridge regression model.
Tao et al., 2023 [56]	Grape; Retrieving soil moisture from grape growing areas	NASA Terra satellite's MODIS.	RF, GBDT, CatBoost	Integrating multiple features and using the stacking ensemble learning algorithm, the average R^2 and RMSE of 25-period soil moisture retrieval models were 0.7504 and 0.0245 m^3/m^3.
Wu et al., 2023 [57]	Grape, peach, apple, cherry; Mapping—classification and identification of orchards	UAV—DJI Phantom 4 four-rotor.	FCN, SegNet, U-Net and ISDU-Net model (proposed model)	ISDU-Net obtained pixel accuracy, mean IoU, frequency weight IoU, and Kappa coefficient of 87.73%, 70.68%, 78.69%, and 0.84, respectively.
Gavrilović et al., 2024 [24]	Grape; Precision viticulture: vine detection and vineyard zoning	UAV—DJI Phantom P4 v2.0 drone (DJI Sky City, Shenzhen, China). Multispectral camera, MicaSense RedEdge-M (MicaSense, Inc., Seattle, WA, USA).	YOLOv5s, K-means	Accuracy, precision, recall, and F1-Score above 0.85, reaching 0.98.
Peanusaha et al., 2024 [58]	Grape; Nitrogen retrieval in grapevine	LI-COR leaf area meter (LI-3100, LI-COR Bioscience, NE, USA). Field spectrometer, SVC HR-1024i (Spectra Vista Corp, NY, USA).	RFR, GPR	A hybrid model with machine learning and a radiative transfer model can reduce 50% of the spectral bands required and maintain an acceptable level of accuracy (R^2 = 0.54).

Gavrilović et al., 2024 [24] used YOLOv5 and transfer learning with UAV images for vine detection and vineyard zoning. YOLOv5 achieved 90% accuracy using images and several spectral bands of various phenological stages. In addition, the authors employed K-means with NDVI for the evaluation of nitrogen, phosphorus, and potassium content in leaf blades and petioles. According to the authors, the model studied leads to fast results and has minimum data requirements, making it ideal for precision viticulture. Gomes et al., 2021 [44] proposed a new model based on the one-dimensional convolutional neural network (1D CNN) architecture for predicting sugar content and pH, using hyperspectral reflectance data from grape vintages. The results for the generalization capacity of the model were a RMSEP (root-mean-square error of predictions) of 1.118 °Brix and 1.085 °Brix for sugar content and 0.199 and 0.183 for pH. The model proved to be capable of non-destructively and rapidly assessing wine grape ripeness.

Peng et al., 2022 [51] combined vegetation indices with machine learning algorithms to analyze leaf nitrogen content (LNC), leaf potassium content (LKC), and leaf phosphorus content (LPC) in grape leaves using UAV-acquired images. Three irrigation levels and four fertilization levels were established. The authors showed that UAV multispectral images are an effective option for predicting nutrient content in grape leaves, and the combination of spectral variables with algorithms such as RF, SVM, ELM can result in better nutrient predictions (with R^2 above 0.65 during the new-shoot growth period and above 0.75 during other growth periods). In addition, the authors found that phosphorus was the main nutrient absorbed during the veraison and ripening periods, and potassium was the main nutrient absorbed during the fruit expansion period. Finally, it was also observed that during the periods of new-shoot growth and flowering, there were high nitrogen demands.

Arab et al., 2021 [42] developed a grape yield prediction model with ANN and Landsat 8 OLI satellite-based time-series images. In this study, the normalized difference vegetation index (NDVI), leaf area index (LAI), and normalized difference water index (NDWI) were drawn from data captured in 2017, 2018, and 2019. According to the authors, machine learning based on artificial neural networks using satellite time-series images can achieve reliable yield prediction models of table grapes. NDVI had the highest accuracy (R = 0.92 to 0.94) compared to the other indices. Kasimati et al., 2021 [45] proposed a method to predict wine grape quality using UAV and Sentinel-2 imagery, linear and nonlinear regression models (machine learning), and NDVI. The authors found that proximal sensors performed best in predicting early-season grape quality parameters, while remote sensors performed better in later growth stages.

Navarro et al., 2021 [47] developed the 3DeepM architecture for classifying a sample of 12,210 multispectral images of seedless table grape varieties. 3DeepM was superior to other techniques in terms of number of parameters, number of classes, accuracy, and training time. Also, a computer vision system was designed for the acquisition of multispectral images in the range of 400 nm to 1000 nm. According to the authors, the fact that 3DeepM has relatively few parameters makes it suitable for real-time applications.

Barriguinha et al., 2022 [48] developed a vineyard yield estimation model based on remote sensing (Sentinel-2) and climate data coupled with machine learning (Long Short-Term Memory (LSTM) neural networks). The model was tested from 2016 to 2021 using yield data from 169 administrative areas covering 250,000 ha, of which 43,000 ha are vineyards in production in Portugal. The authors considered three main phenological stages: (1) budbreak (BUD); (2) flowering (FLO); and (3) veraison (VER). Stages 2 and 3 were explored to estimate wine grape yield in advance. The best prediction was achieved in 2020 during VER, with a yield per hectare overestimation of 8% and with an average absolute error for the entire period of 17%. The optimal combination of input features, which led to a Mean Absolute Error (MAE) of 672.55 kg/hectare and a Mean Squared Error (MSE) of 81.30 kg/hectare, included NDVI, temperature, relative humidity, precipitation, and wind intensity.

Tao et al., 2023 [56] analyzed soil moisture during key grape growth stages from 2009 to 2018. Seven features based on evapotranspiration (ET), land surface temperature

(LST), and spectral reflectance (SR) were derived from Moderate Resolution Imaging Spectroradiometer (MODIS) data and then integrated with topographic features. Twenty-five-period models covering April–October and having an 8-day temporal resolution were constructed. The authors also compared three individual machine learning models (random forest, gradient boosting decision tree, and category boosting) with the ensemble model using the stacking algorithm. The authors observed that the stacking-based ensemble model could retrieve soil moisture more accurately (R^2 = 0.7504 and RMSE = 0.0245 m^3/m^3). It was also reported that, during the main grape growth stages, spring and summer droughts were more severe than autumn droughts in the study area.

Santos et al. 2020 [59] proposed a methodology with the development of a new algorithm, based on image collection via SLAM and a convolutional network for detecting grapes in an espalier training system, that reached scores superior to 0.9 for detection in wine grapes, a challenging crop that presents enormous variability in shape, size, color, and compactness, which can be used in other crops that adopt the same training system, such as apples, peaches, and berries.

As indicated in Table 1, several sensors, algorithms, and metrics have already been used to analyze different aspects related to grapes, such as water stress [36]; classification, prediction and estimation of grapes and grapevine variables [24,35,38,40,42,43,47,48,54,57]; smoke taint prediction [37,41]; irrigation management [39]; fruit growth prediction [46]; sugar prediction [44,49,55]; prediction of total soluble solids [45]; nutrient content prediction [51,58]; in-field fruit-ripening measurement [50]; soil moisture retrieval [56]; disease detection [53]; and pomological recommendations [52].

The articles analyzed in this review included many suggestions for future work, including the following: apply hybrid machine vision techniques and deep learning models to develop precision agriculture systems [60]; explore high-resolution images such as those delivered by Sentinel-2 and PlanetScope images [24,56]; use different deep learning models with an increased number of convolution layers and using hyperspectral data to predict sugar and pH levels [44]; implement different deep learning algorithms using datasets collected in different countries and comparing fruit production in developed and developing countries [46]; combine spectral variables to predict nitrogen, phosphorus, and potassium [51]; improve resource use across agricultural production systems to address problems like climate change, rising costs, and excessive waste [61]; use seasonal calibration for grapevine quality prediction [45]; explore a model that identifies high- and low-productivity fruit orchards [57]; expand the number of grape samples and varieties, and extend the use of multispectral images to other fruits, vegetables, leaves, and flowers [41,47,50,52,54]; integrate vegetation indices such as LAI, SAR, and LIDAR [48]; scale up UAV-based models and utilize deep learning to explore their potential superiority over traditional methods [38]; understand the relationship between equivalent water thickness and nitrogen [58]; develop cheaper multispectral devices [35]; collect more spectral data from healthy and infected leaf samples and study different biotic and abiotic stressors for disease diagnosis [53]; and combine evapotranspiration and plant-based sensors to maximize water use efficiency [43].

Table 2 summarizes the studies that used remote sensing and ML/DL algorithms to study apples.

Table 2. Characteristics of the studies dedicated to apples.

Reference	Fruit(s)-Research Focus	Data/Imagery/Sensor (Origin)	ML/DL-Algorithm	Accuracy
Chen et al., 2020 [62]	Apple; Estimation of leaf nitrogen content in apple-trees	An ASD FieldSpec 3 portable spectroradiometer (Analytical Spectral Devices, Inc., St, Boulder, CO, USA)	PLSR, SVM, BPANN, ELM, and RF	The model by Rfrog-ELM achieved the best results (R^2P = 0.843, RMSEP = 2.461 g·kg^{-1}, and RPD = 2.508).
Wu et al., 2020 [23]	Apple; Extracting apple tree crown information	UAV (Phantom 4 Pro, DJI Company, Guangdong, China) equipped with a spatial resolution vision spectrum (RGB) camera	Proposed model is based on the Faster R-CNN detector and U-Net	Precision and recall of 91.1% and 94.1%, respectively, branch segmentation with an overall accuracy of 97.1%, and crown parameter estimation with an overall accuracy exceeding 92%.
Bai et al., 2021 [63]	Apple; Predicting apple fruit yields	Qianxun positioning SR2 satellite-based RTK receiver mobile device (Qianxun Spatial Intelligence Inc., Hangzhou, China); Satellite—PlanetScope	RF∑NDVI and CASASR model	∑NDVI was the optimal predictor to construct an RF model for apple fruit yield, and the R^2, RMSE, and RPD values of the RF∑NDVI model reached 0.71, 16.40 kg/tree, and 1.83, respectively.
Biffi et al., 2021 [64]	Apple; Detect apple fruits	Canon EOS—T6 camera (Tokyo, Japan, CMOS sensor of 5184 × 3456 pixel (17.9 Mp) and pixel size of 4.3 µm)	ATSS, RetinaNet, Libra-RCNN, Cascade R-CNN, Faster R-CNN, FSAF, and HRNet	The ATSS-based approach outperformed the other methods with a maximum average precision of 0.946.
Fan et al., 2021 [22]	Apple; A method for segmenting apples	Canon PowerShot G16 camera and Intel Realsense Depth camera D435	Mask R-CNN Patch-based segmentation algorithm that is a generalization of the K-means clustering algorithm	Average accuracy rate of 99.26%, recall rate of 98.69%, false positive rate of 0.06%, and false negative rate of 1.44%.
Khan et al., 2021 [46]	Apple, banana, citrus, pear, grape; Fruit growth prediction	Publicly available dataset from the Food and Agriculture Organization (FAO) of the United Nations	AdaBoost, MLP, SVR, and LR Agricultural Deep Learning (AGR-DL)—Proposed model	Precision of LR—87.65%; SVR—88.96%; AdaBoost—90.37%; MLP—91.23%; AGR-DL—94.12% (capable of achieving up to 95.56%).
Ta, Chang & Zhang., 2021 [65]	Apple; Estimation of apple tree leaf chlorophyll content	Spectroradiometer SVC HR1024i (Spectra Vista Crop., Poughkeepsie, NY, USA); Hand-held chlorophyll meter (SPAD-502, Minolta Osaka Company Ltd., Tokyo, Japan)	RF, SVR, ULR, and MLR	RF—best model: R^2 value was greater than 0.94, and RMSE was less than 1.37 at different growth stages. The prediction accuracy for the 1st growth stage (R^2 = 0.96; RMSE = 0.95) was best with the RF.

Table 2. *Cont.*

Reference	Fruit(s)-Research Focus	Data/Imagery/Sensor (Origin)	ML/DL-Algorithm	Accuracy
Chen et al., 2022 [66]	Apple; Yield prediction of individual apple trees	LiDAR data were acquired using the Riegl VUX-1 (RIEGL Co., Austria) laser sensor on a DJI M600 (SZ DJI Technology Co., Shenzhen, China) flight platform. Multispectral images were acquired using a Parrot Sequoia multispectral camera (MicaSense Inc., USA) on a DJ PHANTOM 4 PRO (SZ DJI Technology Co., China)	SVM, KNN, EL, and SVM-RFE	SVM performs best, followed by KNN. The performance of the SVM model fluctuates around 0.80. The accuracy of all models is satisfactory, with the validation R^2 exceeding 0.740 and the test R^2 exceeding 0.650.
Li et al., 2022 [67]	Apple; Retrieval of nitrogen content in apple canopy	UAV—an eight-rotor UAV M600 Pro with a UHD185 imager (produced by Cubert, Ulm, Germany)	MLR, PLS, SVM, BPNN, and RF	SVM—best model: training set with an R^2 of 0.733, an RMSE of 6.00%, an nRMSE of 12.76%, and a MAE of 4.49%. Good performance in validation with an R^2 of 0.671, an RMSE of 4.73%, an nRMSE of 14.83%, and a MAE of 3.98%.
Liu et al., 2022 [68]	Apple; Prediction of apple first flowering date	MOD11A1 LST (V006) from the Terre satellite and elevation data from ASTER GDEM V1	STR and RF	LST using STR: MAE from 0.51 to 0.68 °C and RMSE from 1.07 to 1.21 °C.
Uryasheva et al., 2022 [69]	Apple; Apple leaf segmentation under field conditions (assessment of plant health and identification of stressed plants)	Three cameras to acquire close-range multispectral images: Seek Thermal CompactPro, Logitech Brio 4 K, and the multispectral sensor camera MicaSense RedEdge-MX	CNN-based segmentation	CNN algorithm: IoU = 0.72.
Zhang et al., 2022 [70]	Apple; Estimation of flowering intensity in an apple orchard	Aerial vehicle: DJI™ Phantom 3 PRO, Shenzhen, China (quad-rotor); Camera: FC300X, Shenzhen, China (RGB); Ground vehicle: Tractor (generic); camera type: Intel® RealSense™ Depth Camera D435 (RGB-Depth)	K-Means clustering and hierarchical clustering	Both models with $R^2 > 0.65$, RRMSE < 20%, and p-stat < 0.005.
Zhou et al., 2022 [71]	Apple, peach, pear; Classification of fruit trees	Sentinel-2	DT	The accuracy of DT constructed using the vegetation index under the three treatments (SVIs, ∑VIs, and ΔVIs) were 0.8936, 0.9153, and 0.8887 on the training set and 0.8355, 0.7611, and 0.7940 on the test set.

Table 2. *Cont.*

Reference	Fruit(s)-Research Focus	Data/Imagery/Sensor (Origin)	ML/DL-Algorithm	Accuracy
Dutta et al., 2023 [52]	Raspberry, coconut, papaya, orange, apple, muskmelon, watermelon, grapes, mango, banana, and pomegranate; Pomological recommendation system	Dataset from the Kaggle source	Light GBM	The accuracy of the model is 99%, the macro average is 0.99, and the weighted average is 0.9.
Jiang et al., 2023 [72]	Apple; Monitoring the severity of mosaic disease in apple leaves	A portable plant leaf measuring instrument (Dualex Scientific+, Force-a, Orsay Cedex, France); A SOC-710 portable hyperspectral spectrometer (Surface Optics Corp, San Diego, CA, USA); ENVI 5.3 (Exelis, McLean, VA, USA)	PLSR, RF, ANN, and XGB	The VPs-XGBoost estimation model based on multiple parameters (R^2v = 0.849; RPD = 2.572) was more accurate.
Singha et al., 2023 [73]	Apple; Apple yield prediction mapping	Various satellite multisensor data	RF, SVM, XGBoost, KNN, and Cubist	The Cubist model performed best, with R^2 of 0.83, RMSE of 0.56 t/ha, and MAE of 0.2 t/ha.
Wu et al., 2023 [57]	Grape, peach, apple, cherry; Classification and identification of orchards	UAV—DJI Phantom 4 four-rotor	FCN, SegNet, U-Net, and ISDU-Net model (proposed model)	ISDU-Net obtained pixel accuracy, mean IoU, frequency weight IoU, and Kappa coefficient of 87.73%, 70.68%, 78.69%, and 0.84, respectively.
Yang et al., 2023 [74]	Apple; Assess spatiotemporally varied ecohydrological effects of apple orchards	Landsat 5/7/8	RF, SVM, and ANN	RF, ANN, and SVM had overall accuracy of 0.95, 0.84, and 0.94, Kappa coefficients of 0.93, 0.76, and 0.91, and elapsed time of 19, 40, and 55 min, respectively.
Zhang et al., 2023 [75]	Apple; Canopy nitrogen content inversion in apple orchards	Analytical Spectra Devices Field spec 4 (ASD FieldSpec 4); DJI DJ M600 Pro UAV, equipped with a Parrot Sequoia multispectral camera	RBF-NN, ELM, RFR, XGBoost, and SVR	The XGBoost model was the optimal model for the canopy nitrogen content inversion (R^2 = 0.759, RMSE = 0.098, and RPD = 1.855).

Table 2. *Cont.*

Reference	Fruit(s)-Research Focus	Data/Imagery/Sensor (Origin)	ML/DL-Algorithm	Accuracy
Zhao et al., 2023 [76]	Walnut, apple, pear, jujube; Extraction method of fruit planting distribution	SRTM, Sentinel-1 SAR, and Sentinel-2	RF, SVM, OO, and RF + OO	RF + OO had the highest accuracy (OA = 0.94; Kappa = 0.92), and SVM had the lowest accuracy (OA = 0.52; Kappa = 0.31).
Chen et al., 2024 [77]	Apple; Assess apple leaf nitrogen content	ASD FieldSpec spectral radiometer [FieldSpec® Pro FR and FieldSpec 4, ASD Inc. Boulder, CO, USA]	Boruta-Iteration-DNN	Boruta-iteration-DNN—without DAA (Day After Anthesis): validation R^2 improved from 0.69 to 0.75; NRMSE reduced from 11.92% to 9.97%; with DAA: validation R^2 improved from 0.72 to 0.79; NRMSE reduced from 11.09% to 9.06%.
Zhao et al., 2024 [78]	Apple; Estimation of the leaf nitrogen content of apple tree canopies	UAV—A DJI M600 UAV equipped with a Micro-MCA Snap multispectral imager (Tetracam Inc., Chatsworth, CA, USA)	PLSR, RR, and RFR	RF best accuracy: the validation set of the four periods of apple trees ranged from 0.670 to 0.797 for R^2, 0.838 mg L^{-1} to 4.403 mg L^{-1} for RMSE, and 1.74 to 2.222 for RPD.

Similar to grapes, apples have also been studied for various purposes using remote sensing and ML/DL algorithms (Table 2). Studies increasingly highlight the efficiency of artificial intelligence in fruit cultivation, particularly in the case of apples. Zhao et al., 2024 [78] conducted a study to estimate the nitrogen content in apple canopy leaves using UAV images and three machine learning methods, partial least squares regression (PLSR), ridge regression (RR), and random forest regression (RFR). The authors studied nitrogen estimation of apple trees at the flowering and fruiting stage, pre-fruit expansion stage, and post-fruit expansion stage in Xinjiang, China. They reported that the use of machine learning can considerably improve the accuracy of nitrogen estimation in apple trees and that the best method for this task is RF, with R^2 values ranging from 0.670 to 0.797, RMSE from 0.838 mg L^{-1} to 4.403 mg L^{-1}, and RPD from 1.740 to 2.222.

Zhang et al., 2023 [75] proposed a method to estimate nitrogen content in apple orchard canopies using ground hyper-spectral data, UAV multispectral data, and apple leaf samples. The authors extracted the canopy information and fused the hyperspectral and UAV multispectral data using the Convolution Calculation of the Spectral Response Function (SRF-CC). Five machine learning algorithms were investigated: radial basis function neural network (RBF-NN), extreme learning machine (ELM), random forest regression (RFR), extreme gradient boosting (XGBoost), and support vector regression (SVR). The authors found that SRF-CC was an effective method ($R^2 > 0.70$). In addition, the XGBoost model was the most accurate for estimating canopy nitrogen content ($R^2 = 0.759$, RMSE = 0.098, and RPD = 1.855).

The study by Ta, Chang, and Zhang., 2021 [65] evaluated four approaches (univariate linear regression—ULR; multivariate linear regression—MLR; support vector regression—SVR; and random forest regression—RF) to estimate leaf chlorophyll content (LCC) in apple trees at five different growth stages. Samples were collected from 2016 to 2018 in 10–20-year-old orchards. The MLR, SVR, and RF models achieved R^2 values of 0.79, 0.82, and 0.94 and RMSEs of 2.27, 2.02, and 1.37, respectively. Considering only the first growth stage, RF was also the best model, with $R^2 = 0.96$, and RMSE = 0.95.

Fan et al., 2021 [22] proposed an apple segmentation method based on gray-centered RGB color space. The method proposed by the authors is a patch-based segmentation algorithm that is a generalization of the K-means clustering algorithm. The algorithm explores illumination and shadow patterns in apple images to distinguish the fruits from other objects. According to the authors, the proposed method was tested on 180 apple images and showed an average precision of 99.26%, recall rate of 98.69%, false positive rate of 0.06%, and false negative rate of 1.44%. Wu et al., 2020 [23] described a technique for orchard data acquisition and analysis that uses UAV images and neural networks. The goal was to automatically detect and segment individual trees and measure the width, perimeter, and canopy projection area of apple trees. The model is based on the Faster R-CNN and U-Net detector, achieving a precision and recall of 91.1% and 94.1%, respectively. Branches were segmented with an overall accuracy of 97.1%, and canopy parameters were estimated with an overall accuracy of over 92%. The authors emphasized that the technique allows growers to monitor tree growth and saves labor by avoiding field measurements.

Uryasheva et al., 2022 [69] developed a plant health detection system using 360,000 images of healthy and infected apple trees. The CNN algorithm was used for leaf segmentation, and VIs were also calculated for a single pixel. In addition, the authors developed an application for post-processing and data visualization that allows assessing the health of large agricultural areas and analyzing each tree individually. The model achieved an IoU of 0.72.

Yang et al., 2023 [74] proposed a method to estimate the age of apple trees and quantify the impacts of apple orchards on soil water balance. The authors used Landsat 5, 7, and 8 images and tested three algorithms (RF, SVM, and ANN). RF had the best performance in terms of accuracy and running time, and thus, it was selected for further experiments. The area and age of apple orchard trees were identified with R^2 values of 0.94 and 0.68, respectively. Also, in the study, the authors found that the cumulative regional-scale soil water consumption by apple orchards and old trees reached 129 GL (gigalitres) in 2020, and the ratio of actual evapotranspiration to precipitation was 109% when the apple tree was 22 years old. This is another example of a study that contributes to agricultural production and sustainable water resource management.

Zhang et al., 2023 [79] built and made available a database containing data collected by a UAV during the full flowering period of an apple orchard for the years 2018, 2019, and 2020. According to the authors, the data aim to support research on machine vision, remote sensing, image classification, and deep learning. As shown in Table 2, the combination of remote sensing and artificial intelligence has also been extensively explored for apple applications.

This study identified many techniques for the prediction of nutrient content [62,65,67,75,77,78]; the extraction of apple tree crown information [23]; the prediction of apple yields [63,66,73]; apple detection, classification, mapping, and segmentation [22,57,64,69,71,76]; fruit growth prediction [46]; the prediction or estimation of apple flowering [68,70]; pomological recommendations [52]; disease recognition [72]; and the assessment of the ecohydrological impacts of apple orchards [74].

The suggestions for future work in the articles analyzed include the following: improve the quality of input data, change image acquisition, test different altitudes and flight speeds (in the case of UAV), diversify training data, increase samples and acquire more accurate information from fruit trees [23,70,78,80]; test with other fruit varieties and add color, weight, and shape attributes [22,52,64]; use multiple independent base learners [66]; apply hybrid machine vision techniques and deep learning models to develop automated systems [60]; improve the model algorithm, integrating multidimensional features utilizing bands, spectral features, and texture [71,72,75]; adopt larger-scale applications for spatial distribution and pattern analysis [68]; implement algorithms for data collected in other countries [46]; generate a new remote sensing index for fruit tree detection using radar [76]; develop deep learning methods [62,65]; explore a model that identifies high- and low-productivity orchards [57]; and employ advanced data preprocessing techniques and hyperspectral images, and improve the hyperspectral data already being used [67,77].

According to Tables 1 and 2, the most commonly used algorithms in grape and apple studies are random forest and support vector machine, with neural networks also featured in several analyses. In fruit growing, neural networks can be particularly effective for large sample sizes, while RF and SVM may be more suitable for smaller datasets with lower computational demands. No minimum limit per model/algorithm is established for ML and DL algorithms and models. Depending on the study's focus, different values can be considered. In the studies analyzed, most presented metrics above 80%, which can serve as a parameter for new tests. Regarding sensors, satellite data from Sentinel-2, Landsat, and MODIS, among others, are frequently utilized. However, hyperspectral and UAV-derived data still predominate in fruit growing studies due to their higher level of detail. Proximal data are also notable for providing enhanced precision, which is crucial for in-depth analysis.

3.3. Challenges, Limitations, and Potential Applications for Brazil

Fruit growing plays an important role in the economy and society [1,2]. Grape and apple production stands out in many countries around the world, including the USA, Brazil, Spain, Italy, China, and Australia (Figures 4 and 7). The geographic distribution of grapes and apples shows that these can be successfully cultivated under different climatic and soil conditions.

The city of Vacaria (Figure 8), in the state of Rio Grande do Sul, Brazil (latitude of 28°30′44″S and longitude of 50°56′02″W), has 2124.5 km^2 of territorial area and 23.59 km^2 of urbanized area [81]. Vacaria is among the most important fruit producing areas in Brazil [82], being responsible for 25% of the national apple production with 254 thousand metric tons harvested in 2020 [30,83]. In 2022, its area covered with apple orchards reached 6672 hectares, with an average yield of 29,250 kg/hectare. Vacaria also produced 873 tons of grapes in 2022, with 117 hectares of harvested area and an average yield of 7462 kg/hectare [84]. In 2023, Vacaria was the largest producer of apples in the state of Rio Grande do Sul. The state produced 553,768 metric tons of apples [85] and 904,794 metric tons of grapes in 2023 [86].

The research using remote sensing in viticulture mainly focuses on estimating and predicting yield and fruit quality, managing water resources and irrigation, detecting diseases and assessing fruit ripeness, monitoring nutrient levels, and detecting grapevines and grape types. When conducting studies in viticulture, most researchers have used proximal hyperspectral sensors for close-range measurements. These sensors are often mounted on ground-based platforms or handheld devices. The next most favored choice are multispectral sensors mounted on multirotor UAVs (drones) for suborbital-level measurements. Additionally, medium-resolution multispectral sensors on satellites are also useful for regional tasks like estimating soil moisture and modeling fruit productivity and growth. These satellite images provide larger-scale and cost-effective solutions. Locally, remote sensing is losing its prominence as demands require greater image detail in order to obtain meaningful results that are of interest to producers, such as pest and disease mapping, production mapping, both for productivity and quality, and organization of management and production zones. In these cases, very high-resolution satellite-based or proximal sensing images become important for the production process.

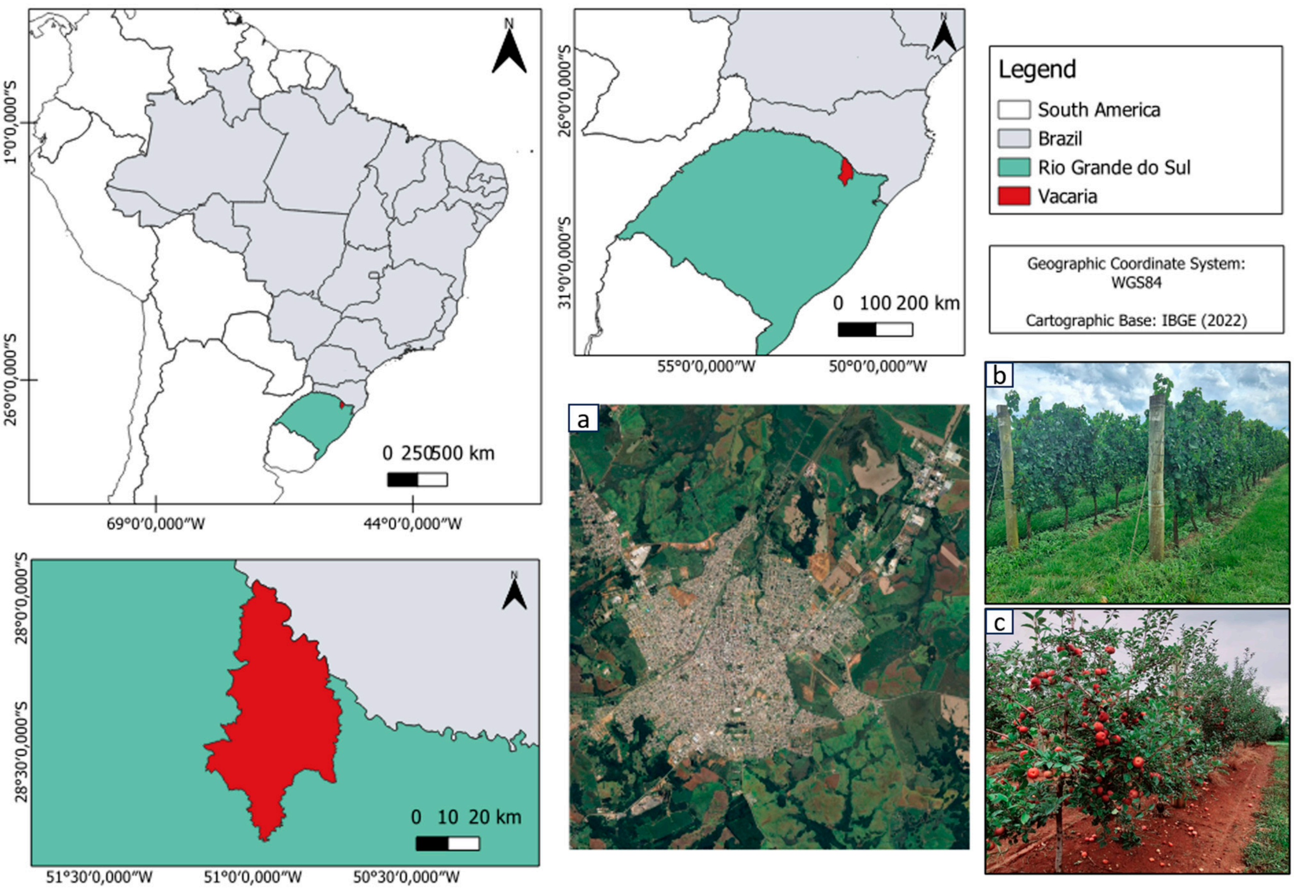

Figure 8. Location of the city of Vacaria, in the state of Rio Grande do Sul, Brazil. On the right, there is an image from Google Earth Satellite (**a**), and there are examples of images collected in the study area, showcasing grape (**b**) and apple (**c**) cultivation in 2024.

3.3.1. Enological Parameters for Fruit Quality Assessment

Estimating enological parameters such as sugar content (Brix), pH, anthocyanin, and maturity level using non-destructive methods is an essential task directly related to determining the best time for harvest, evaluating production yield, and assessing wine quality and consistency. Studies of this nature have been conducted exclusively on a local scale, in commercial farms or experimental areas, employing linear and non-linear regression techniques based on machine learning, primarily using high-spatial-resolution data obtained from multispectral sensors at a suborbital level (mounted on UAVs) and hyperspectral sensors at a proximal level (handheld or on-terrain devices) [38,44,45,49,54,55]. The complexity of the task has led researchers to test various algorithms with different structures (based on decision trees, linear regression and regularization, support vector machines, boosting, nearest neighbors, and neural networks), achieving better results when used with data from different phenological stages, from flowering through veraison and harvest, and using variable selection steps for dimensionality reduction [44,45,49,54,55]. High spatial resolution in these cases limits the spectral range of applications to around 1100 nm, but vegetation indices based mainly on near-infrared and red-edge reflectance have produced models with good predictive power (R^2 between 0.52 and 0.87). However, the best estimates were obtained by Gomes et al., 2021 [44] with proximal and hyperspectral imaging, analyzed using convolutional neural networks for sugar content and pH. Although not directly comparable, significantly inferior results were obtained with vegetation indices associated with multispectral images at suborbital levels and decision tree-based algorithms (RF and XGBoost) for estimation [54].

3.3.2. Grapevine Yield Estimation

One of the main applications of RS and AI in viticulture is the generation of multivariate regression models for yield estimation, a task of high complexity due to spatial variability, and this is also related to monitoring fruit quality, given that plants may offer a high yield but produce poor-quality fruit [38,40]. To achieve this objective, the authors usually develop models at larger scales of operation, from local to regional, mainly using multispectral images acquired at orbital [42,48] and suborbital [40] levels; although, proximal hyperspectral data have also been employed [38]. The accuracy of the models varies depending on sensor resolution and application scale, with less accurate results at lower scales [38]. The combination of orbital sensor data (such as Sentinel-2) and suborbital data can provide broader and more detailed coverage, improving estimates. Integrating climatic data with vegetation indices can provide a more comprehensive understanding of grapevine productivity. ML models like ELM and RF prove effective, but neural networks and modeling with DL techniques, such as LSTM, can improve results due to DL's ability to capture more complex relationships in the data. The applicability may vary by region due to differences in climate, soil type, and cultivation practices, so adjusting models to local conditions may be essential.

3.3.3. Grape Type Classification and Vineyard Detection

The integration of artificial intelligence and remote sensing in viticulture has led to significant advancements in grape type classification [35,47] and vineyard detection [24,57]. Hyperspectral proximal imaging has produced classifications of more than 30 grape varieties, including both white and red types, such as Cabernet Sauvignon, Pinot Noir, Chardonnay, and Tempranillo, with remarkable accuracies (>99%), using both machine and deep learning algorithms. Proximal sensing and hyperspectral data, specifically analyzing up to 300 bands within the 488–953 nm range, have enabled models to capture detailed spectral information crucial for identifying subtle differences in grapevine characteristics, particularly in Spain [35,47]. Single- and multi-year deep-learning-based classifications using sub-orbital multispectral (400–850 nm) images have been performed in Serbia [24] and China [57], with outstanding results. Although not directly comparable, the YOLO and ISDU-Net networks yielded models with accuracies up to 96% in a one-year analysis and 85% in a three-year test. Accurate detection of vineyards is essential for characterizing the spatial variability of production and establishing management zones combining vegetation indices and interpolated nutritional content data [24].

3.3.4. Nitrogen and Chlorophyll Estimation

Nitrogen is essential for apple trees' growth, development, quality, and yield. Effective nitrogen management ensures optimal fruit production and quality while reducing environmental impact. Overapplication of nitrogen-based fertilizers can lead to nutrient imbalances and pollution. Studies conducted in apple production areas, particularly in China, focused on modeling the relationship between spectral variables and biochemical parameters of leaves and canopies, specifically N and chlorophyll content, which is often related to N status [62,65,67,75,77,78].

These studies sought to estimate leaf or canopy nitrogen content using hyperspectral and multispectral data acquired from proximal sensors or at suborbital levels. Ground-level hyperspectral sensors yield the most accurate models, with R^2 values > 0.80, but this approach is highly localized and requires extensive preprocessing and a higher number of samples [62,65,77]. On the other hand, suborbital-level analysis utilizing multitemporal images and multispectral sensors, based on vegetation indices and machine learning (particularly the random forest algorithm), also resulted in accurate estimates, with R^2 values up to 0.75 [78]. In comparing analysis methods, it was found that nonlinear regression approaches based on machine learning algorithms outperformed multivariate linear regression methods in all cases. Ensembles of decision trees, especially the random forest algorithm, were shown to produce the most accurate estimates, with XGBoost outperforming RF in one case [75].

Regarding spectral variables, to accurately estimate the N levels in apple trees, it is important to analyze various spectral bands and transformations. Nevertheless, the most valuable ones are often located within the VNIR range (400–700 nm and 900–1200 nm) [62,67,75]. These bands are essential as they are closely linked to leaf nitrogen levels due to their sensitivity to chlorophyll content and leaf structure. Spectral transformations and vegetation indices such as the Soil-Adjusted Vegetation Index (SAVI), the Modified Normalized Leaf Index (MNLI), and the Green Normalized Difference Vegetation Index, for example, are useful tools [75,78]. In addition to these primary bands and indices, the mid-infrared range (1880–1891 nm) can also offer supplementary information [62].

Particularly in studies involving ground-based sensing using hyperspectral sensors, variable selection or screening methods, especially those based on ensemble models, are crucial for eliminating irrelevant or redundant spectral bands [65,77]. This simplifies the data and focuses the analysis on the most informative features, leading to the creation of models that generalize better and are less prone to overfitting. Screening variables based on correlation was related to less accurate predictions [67,75,77].

The studies have shown a positive relationship between the number of days of data collection (multiple phenology stages) and model performances, as measured by R^2 values. Regardless of the data level of acquisition (proximal or suborbital), assessments over multiple periods tend to yield better estimates, with R^2 values up to 0.94, compared to those with fewer periods, which show lower R^2 values around 0.67 [67,75]. This suggests that the ideal time for estimating N varies throughout the season. Phenology affects the distribution of nutrients in plants throughout the seasons and can influence leaf composition, including nitrogen content. Studies by Chen et al. 2020 [62] and Chen et al. 2024 [77] demonstrate that incorporating phenology as a variable could improve the estimates. Additionally, the accuracy of N content assessment appears to enhance as fruit development progresses, with the pre-fruit expansion stage demonstrating the best validation metrics compared to flowering, fruiting, and other stages [78].

Therefore, in the analyzed studies, remote sensing techniques offered non-destructive, rapid, and more precise assessments of N content. These methods are more efficient than traditional lab tests and help in timely management decisions. Using proximal or suborbital spectral data acquired at different growth stages, analyzed by variable screening techniques and machine learning algorithms to monitor canopy or leaf N levels, enables precise and accurate fertilization strategies, leading to better crop management and environmental sustainability.

3.3.5. Assessment of Apple Yield and Fruit Detection

Remote sensing is commonly used to estimate crop yield through statistical or mechanistic modeling for fruit detection [87]. Statistical models examine the connection between spectral features (such as vegetation indices and spectral bands) and crop yield using linear or non-linear regression based on machine learning, while mechanistic approaches use remotely sensed data on crop health, soil moisture, temperature, and other environmental factors to simulate crop growth. These methods can be applied at various scales, from on-farm use to national yield predictions [63,66,73]. However, for fruit production, particularly in apple growing, machine vision techniques like image segmentation and object detection based on deep learning are becoming local strategies for detecting and counting fruits, as well as assessing fruit quality. These techniques support the monitoring of crop dynamics and aid decision-making in precision agriculture and intelligent orchard management [22,64,76].

The authors of the analyzed studies used these techniques, seeking to estimate production directly (in kg/tree or t/ha), as was the case of Bai et al., 2021 [63], Chen et al., 2022 [66], and Singha et al., 2023 [73], or to detect and count fruits in an automated way [22,64,76]. Regarding the direct estimation of yield, whether at the individual tree or orchard level, studies reveal that multisensor approaches, with the integration of spectral variables linked to vegetation status (VIs or spectral bands) and complementary remote sensing data, such as climate parameters, terrain characteristics, soil factors, and morphological features related to canopy structure, can significantly improve the estimates, whether at the suborbital level [66] or with time series of satellite images [63,73].

For the analysis of multivariate data sets, algorithms based on ensemble learning, whether individual, such as random forest [63] and Cubist [73], or based on the integration of algorithms with different structures, such as SVM and KNN [66], are the main choices. EL algorithms are effective in capturing complex relationships between multiple variables and building multiple models to combine predictions. Thus, they work to reduce overfitting and offer flexibility to deal with high-dimensional datasets. In addition, they are widely used in selecting the most appropriate variables.

Remote sensing sensors and computer vision frameworks based on deep learning (DL) are increasingly gaining traction in detecting and counting apple fruits, which is crucial for accurate yield estimation, presenting outstanding results. This is particularly useful for small farms with limited resources, where this task is traditionally carried out through manual fruit counting and orchard extrapolation. However, these methods face challenges related to occlusion caused by high-density orchards, anti-haze systems, and variations in illumination, all of which affect fruit visibility. To address these challenges, proximal-level images using the visible spectrum (RGB images) were employed, as they provide very high-resolution data with reduced operational costs. Simple transformations for lightness normalization can improve fruit identification in unbalanced lighting conditions, and data impaired by fog or compression issues can still yield good results. However, it is important to note that model scalability may be limited, and bounding box sizes must be carefully evaluated to achieve more precise segmentation in different environments [22,64].

4. Final Considerations

Based on studies integrating remote sensing (RS) and AI to improve grape and apple production, several factors merit attention, especially operational costs, pre- and post-processing methods, and spatial dependency. Studies in viticulture using RS and AI have been conducted in more than 10 countries across six continents. However, over 80% of apple production research (17 of 20 studies) has been conducted in China, primarily on the Fuji variety in the Shandong and Shaanxi provinces. These results may not fully represent other regions due to environmental and strategic production differences.

The operational costs of predictive models for estimating grape yield and quality vary by technology, method, phenological stage, and variety. While non-destructive methods, like hyperspectral imaging and UAV sensors, enhance accuracy and scalability, they can be costly. More accessible methods, such as NIR spectroscopy, offer lower costs but may have limitations in resolution and coverage.

Models often require field data for calibration and validation, especially in areas with high spatial variability. While effective locally, field-based models may struggle with scalability due to regional variability, spatial dependency, and technological limitations. Reproducibility can also be affected by data availability and environmental diversity.

Orbital data provide a broad, continuous, and often free view of crops but may lack the spatial resolution needed for detailed analyses. Although the SWIR band, related to water content and lignin, in satellite imagery has been useful for estimating grape yield on a large scale, it is less accessible in proximal and suborbital sensors due to cost and technology constraints.

Dimensionality reduction, widely used in grape and apple RS and AI studies, simplifies data, reduces processing time, and improves interpretation without compromising accuracy. Variable selection techniques, such as Variable Importance in Ensemble Models, Recursive Feature Elimination (RFE), and Genetic Algorithms (GA), are frequently used.

Modeling approaches increasingly include stacking, which combines multiple models to improve prediction accuracy. Ensemble algorithms, primarily random forest (RF) and support vector machines (SVMs), remain prominent, though deep learning algorithms show promise, especially in classification and segmentation tasks.

Vacaria, one of Brazil's leading apple producers, presents a promising environment for implementing RS and AI technologies. By employing high-resolution satellite imagery, multispectral UAV data, and proximal hyperspectral sensors, Vacaria could optimize resource use, enhance productivity, and improve fruit quality through more efficient planning. These technologies would allow local farmers to monitor fruit quality, predict yields, and manage resources like water and fertilizers more effectively. Precision agriculture in Vacaria could support practices such as managing nitrogen levels in apple orchards and identifying grapevine diseases, aligning with sustainable agriculture trends. Future studies will further analyze the performance of satellite and UAV imagery, along with machine learning and deep learning algorithms in Vacaria. Regarding literature reviews, future studies will use the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines.

In conclusion, integrating RS and AI in Vacaria has the potential to transform fruit cultivation, boosting sustainability, productivity, and profitability in the region. This supports the objectives of the Center for Development in Digital Agriculture (CCD-SemeAr) project, in which Vacaria is one of ten Agrotechnological Districts. The project aims to support small- and medium-sized producers, promote rural connectivity, and advance digital technologies in agriculture, including AI, RS, and precision agriculture. Integrating advanced technology with traditional farming practices is essential for sustaining Vacaria's competitive edge in the global fruit market.

Author Contributions: Conceptualization, É.L.B. and D.E.G.F.; methodology, D.E.G.F. and É.L.B.; formal analysis, D.E.G.F., T.C.P. and É.L.B.; investigation, D.E.G.F. and T.C.P.; resources, É.L.B.; writing—original draft preparation, D.E.G.F.; writing—review and editing, D.E.G.F., T.C.P., É.L.B., J.G.A.B., T.T.S. and L.G.; visualization, D.E.G.F.; supervision, É.L.B.; project administration, É.L.B.; funding acquisition, É.L.B., D.E.G.F. and T.C.P. All authors have read and agreed to the published version of the manuscript.

Funding: This study was financed, in part, by the São Paulo Research Foundation (FAPESP), Brazil. Process Number #2022/09319-9, #2024/05205-4, and #2024/13150-5, São Paulo Research Foundation (FAPESP); and Coordination for the Improvement of Higher Education Personnel (CAPES), Brazil, Financial Code 001.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

∑VIs	Accumulated monthly vegetation indices
ΔVIs	Difference in vegetation indices between adjacent months
ANN	Artificial neural network
ARD	Automatic relevance determination
ATSS	Adaptive training sample selection
BPANN	Back-propagation artificial neural network
BPNN	Back propagation neural network
BRT	Gradient boosted regression tree
CASASR	Carnegie–Ames–Stanford approach ratio vegetation index
CatBoost	Category boosting
CNN	Convolutional neural network
Cubist	Cubist regression
DL	Deep learning
DNN	Deep neural network
DT	Decision tree

EBM	Explainable boosting machine
ELM	Extreme learning machine
ESA	European Space Agency
EWT	Equivalent water thickness
Extra Trees	Extremely randomized trees
FAO	Food and Agriculture Organization
Fc	Fraction cover
FCN	Fully convolutional networks
FSAF	Feature selective anchor-free
GBDT	Gradient boosting decision tree
GL	Gigalitres
GPR	Gaussian process regression
HRNet	High-resolution network
IoU	Intersection over Union
ISDU-Net	Improved U-Net model
KNN	k-Nearest neighbor
LAI	Leaf area index
Libra-RCNN	Libra regions with convolutional neural network
LIDAR	Light detection and ranging
Light GBM	Light gradient boosting machine
LR	Logistic regression
LST	Land surface temperature
LSTM	Long short-term memory
ML	Machine learning
MLP	Multilayer perceptron
MLR	Multiple linear regression
NDVI	Normalized difference vegetation index
NDWI	Normalized difference water index
NRMSE	Normalized root mean square error
OLI	Operational land imager
OLS	Ordinary least squares
OO	Object-oriented
pH	Potential of hydrogen
PLSR	Partial least squares regression
R2	Coefficient of determination
RBF-NN	Radial basis function neural network
RE	Relative error
RF	Random forest
RF∑NDVI	Random forest with accumulated values of the normalized difference vegetation index
RGB	Red–green–blue
RPD	Relative prediction deviation
RR	Ridge regression
RFR	Random forest regression
RMSEP	Root-mean-square error of predictions
RRMSE	Relative root mean square error
SAR	Synthetic aperture radar
SRTM	Shuttle radar topography mission
STR	Spatio-temporal reconstruction
SVIs	Single month vegetation indices

SVM	Support vector machine
SVM-RFE	Support vector machine–recursive feature elimination
SVR	Support vector regression
SWIR	Short-wave infrared
UAV	Unmanned aerial vehicle
ULR	Univariate linear regression
VIs	Vegetation indices
VPs	Multiple parameters
WIA	Willmott consistency index
WRELM	Weighted regularized extreme learning machine
XGBoost	Extreme gradient boosting
YOLO	You only look once

References

1. Dou, J.-F.; Kou, X.H.; Wu, C.E.; Fan, G.J.; Li, T.T.; Li, X.J.; Zhou, D.D.; Yan, Z.C.; Zhu, J.P. Recent advances and development of postharvest management research for fresh jujube fruit: A review. *Sci. Hortic.* **2023**, *310*, 111769. [CrossRef]
2. Noor, A.; Moyle, P.M.; Malik, A.; Ziora, Z.M.; Pant, K.K. Transformative upcycling of fruit-vegetable waste for nutraceutical and pharmaceutical breakthroughs and circular economy evolution. *Process Saf. Environ. Prot.* **2024**, *187*, 1022–1036. [CrossRef]
3. Mousavi, S.M.; Jafari, A.; ShirmardiI, M. The effect of seaweed foliar application on yield and quality of apple cv.'Golden Delicious'. *Sci. Hortic.* **2024**, *323*, 112529. [CrossRef]
4. Li, Y.; Feng, X.; Liu, Y.; Han, X. Apple quality identification and classification by image processing based on convolutional neural networks. *Sci. Rep.* **2021**, *11*, 16618. [CrossRef] [PubMed]
5. Asma, U.; Morozova, K.; Ferrentino, G.; Scampicchio, M. Apples and apple by-products: Antioxidant properties and food applications. *Antioxidants* **2023**, *12*, 1456. [CrossRef] [PubMed]
6. Dos Santos Silva, M.E.; Grisi, C.V.B.; da Silva, S.P.; Madruga, M.S.; da Silva, F.A.P. The technological potential of agro-industrial residue from grape pulping (*Vitis* spp.) for application in meat products: A review. *Food Biosci.* **2022**, *49*, 101877.
7. Kumari, S.; Bhowal, R.; Suprasanna, P. Sustainable approaches for biodiversity and bioprospecting of Citrus. *Sustainability* **2023**, *15*, 7731. [CrossRef]
8. Al-Dairi, M.; Pathare, P.B.; Al-Yahyai, R.; Jayasuriya, H.; Al-Attabi, Z. Postharvest quality, technologies, and strategies to reduce losses along the supply chain of banana: A review. *Trends Food Sci. Technol.* **2023**, *134*, 177–191. [CrossRef]
9. Li, X.; Xiong, T.; Zhu, Q.; Zhou, Y.; Lei, Q.; Lu, H.; Chen, W.; Li, X.; Zhu, X. Combination of 1-MCP and modified atmosphere packaging (MAP) maintains banana fruit quality under high temperature storage by improving antioxidant system and cell wall structure. *Postharvest Biol. Technol.* **2023**, *198*, 112265. [CrossRef]
10. Shah, Z.A.; Dar, M.A.; Dar, E.A.; Obianefo, C.A.; Bhat, A.H.; Ali, M.T.; El-Sharnouby, M.; Shukry, M.; Kesba, H.; Sayed, S. Sustainable fruit growing: An analysis of differences in apple productivity in the Indian state of Jammu and Kashmir. *Sustainability* **2022**, *14*, 14544. [CrossRef]
11. Gonzalez Nieto, L.; Huber, A.; Gao, R.; Biasuz, E.C.; Cheng, L.; Stroock, A.D.; Lakso, A.; Robinson, T.L. Trunk Water Potential Measured with Microtensiometers for Managing Water Stress in "Gala" Apple Trees. *Plants* **2023**, *12*, 1912. [CrossRef] [PubMed]
12. Chandio, A.A.; Gokmenoglu, K.K.; Joyo, M.A.; Jiang, Y. Modeling the climate change impacts on major fruits production: Recent evidence from Pakistan. *Sci. Hortic.* **2024**, *324*, 112618. [CrossRef]
13. Lu, S.; Chen, W.; Zhang, X.; Karkee, M. Canopy-attention-YOLOv4-based immature/mature apple fruit detection on dense-foliage tree architectures for early crop load estimation. *Comput. Electron. Agric.* **2022**, *193*, 106696. [CrossRef]
14. Karunathilake, E.M.B.M.; Le, A.T.; Heo, S.; Chung, Y.S.; Mansoor, S. The path to smart farming: Innovations and opportunities in precision agriculture. *Agriculture* **2023**, *13*, 1593. [CrossRef]
15. Alahmad, T.; Neményi, M.; Nyéki, A. Applying IoT sensors and big data to improve precision crop production: A review. *Agronomy* **2023**, *13*, 2603. [CrossRef]
16. Bolfe, É.L.; Jorge, L.A.D.C.; Sanches, I.D.A.; Luchiari Júnior, A.; da Costa, C.C.; Victoria, D.D.C.; Inamasu, R.Y.; Grego, C.R.; Ferreira, V.R.; Ramirez, A.R. Precision and digital agriculture: Adoption of technologies and perception of Brazilian farmers. *Agriculture* **2020**, *10*, 653. [CrossRef]
17. Avola, G.; Matese, A.; Riggi, E. An Overview of the Special Issue on "Precision Agriculture Using Hyperspectral Images". *Remote Sens.* **2023**, *15*, 1917. [CrossRef]
18. Zheng, C.; Abd-Elrahman, A.; Whitaker, V. Remote sensing and machine learning in crop phenotyping and management, with an emphasis on applications in strawberry farming. *Remote Sens.* **2021**, *13*, 531. [CrossRef]
19. Han, W.; Zhang, X.; Wang, Y.; Wang, L.; Huang, X.; Li, J.; Wang, S.; Chen, W.; Li, X.; Feng, R.; et al. A survey of machine learning and deep learning in remote sensing of geological environment: Challenges, advances, and opportunities. *ISPRS J. Photogramm. Remote Sens.* **2023**, *202*, 87–113. [CrossRef]
20. Xiao, F.; Wang, H.; Li, Y.; Cao, Y.; Lv, X.; Xu, G. Object detection and recognition techniques based on digital image processing and traditional machine learning for fruit and vegetable harvesting robots: An overview and review. *Agronomy* **2023**, *13*, 639. [CrossRef]

21. Sarker, I.H. Deep learning: A comprehensive overview on techniques, taxonomy, applications and research directions. *SN Comput. Sci.* **2021**, *2*, 420. [CrossRef] [PubMed]
22. Fan, P.; Lang, G.; Yan, B.; Lei, X.; Guo, P.; Liu, Z.; Yang, F. A method of segmenting apples based on gray-centered RGB color space. *Remote Sens.* **2021**, *13*, 1211. [CrossRef]
23. Wu, J.; Yang, G.; Yang, H.; Zhu, Y.; Li, Z.; Lei, L.; Zhao, C. Extracting apple tree crown information from remote imagery using deep learning. *Comput. Electron. Agric.* **2020**, *174*, 105504. [CrossRef]
24. Gavrilović, M.; Jovanović, D.; Božović, P.; Benka, P.; Govedarica, M. Vineyard Zoning and Vine Detection Using Machine Learning in Unmanned Aerial Vehicle Imagery. *Remote Sens.* **2024**, *16*, 584. [CrossRef]
25. Tian, H.; Fang, X.; Lan, Y.; Ma, C.; Huang, H.; Lu, X.; Zhao, D.; Liu, H.; Zhang, Y. Extraction of citrus trees from UAV remote sensing imagery using YOLOv5s and coordinate transformation. *Remote Sens.* **2022**, *14*, 4208. [CrossRef]
26. EMBRAPA. Ciência e Tecnologia Tornaram o Brasil um dos Maiores Produtores Mundiais de Alimentos. 2022. Available online: https://www.embrapa.br/busca-de-noticias/-/noticia/75085849/ciencia-e-tecnologia-tornaram-o-brasil-um-dos-maiores-produtores-mundiais-de-alimentos (accessed on 18 July 2024).
27. ABRAFRUTAS. Brasil Exportou Mais de um Milhão de Toneladas de Frutas em 2023; Entenda. 2024. Available online: https://abrafrutas.org/2024/03/brasil-produziu-mais-de-um-milhao-de-toneladas-de-frutas-em-2023-entenda/ (accessed on 18 July 2024).
28. Bueno, M.P.; Silva, A.C.; Nunes, A.L.D.P.F.; Sardinha, A.C.; dos Santos Lima, P.T.; Silva, J.F. Análise da comercialização da cadeia produtiva da maçã brasileira: Produção, importação e exportação no período 2015 a 2019. *Braz. J. Dev.* **2021**, *7*, 34061–34078. [CrossRef]
29. Susin, E.; Silvestre, W.P.; Cocco, C. Effect of the application of abscisic acid and ethephon on the quality of Merlot grapes grown in Serra Gaúcha, South Brazil. *Res. Soc. Dev.* **2022**, *11*, e370111638513. [CrossRef]
30. ABRAFRUTAS—Associação Brasileira dos Produtores Exportadores de Frutas e Derivados. Colheita da maçã avança e irá Superar Volume de 2020. 2021. Available online: https://abrafrutas.org/2021!04/colheita-da-maca-avanca-e-ira-superar-volume-de-2020/ (accessed on 18 July 2024).
31. Echeverrigaray, S.; Scariot, F.J.; Fontanella, G.; Favaron, F.; Sella, L.; Santos, M.C.; Schwambach, J.; Pedrotti, C.; Delamare, A.P.L. Colletotrichum species causing grape ripe rot disease in Vitis labrusca and V. vinifera varieties in the highlands of southern Brazil. *Plant Pathol.* **2020**, *69*, 1504–1512. [CrossRef]
32. Shi, Y.; Wang, Z.; Zhang, G.; Wei, X.; Ma, W.; Yu, H. Evaluating the Research Status of the Remote Sensing-Mediated Monitoring of Forest Biomass: A Bibliometric Analysis of WOS. *Forests* **2024**, *15*, 524. [CrossRef]
33. Wang, J.; Wang, S.; Zou, D.; Chen, H.; Zhong, R.; Li, H.; Zhou, W.; Yan, K. Social network and bibliometric analysis of unmanned aerial vehicle remote sensing applications from 2010 to 2021. *Remote Sens.* **2021**, *13*, 2912. [CrossRef]
34. FAPESP. Fundação de Amparo à Pesquisa do Estado de São Paulo. Center of Science for Development in Digital Agriculture. 2022—CCD-AD/SemeAr. Available online: https://bv.fapesp.br/en/auxilios/111242/center-of-science-for-development-in-digital-agriculture-ccd-adsemear/ (accessed on 14 July 2024).
35. Gutiérrez, S.; Fernández-Novales, J.; Diago, M.P.; Tardaguila, J. On-the-go hyperspectral imaging under field conditions and machine learning for the classification of grapevine varieties. *Front. Plant Sci.* **2018**, *9*, 1102. [CrossRef] [PubMed]
36. Loggenberg, K.; Strever, A.; Greyling, B.; Poona, N. Modelling water stress in a Shiraz vineyard using hyperspectral imaging and machine learning. *Remote Sens.* **2018**, *10*, 202. [CrossRef]
37. Fuentes, S.; Tongson, E.J.; De Bei, R.; Gonzalez Viejo, C.; Ristic, R.; Tyerman, S.; Wilkinson, K. Non-invasive tools to detect smoke contamination in grapevine canopies, berries and wine: A remote sensing and machine learning modeling approach. *Sensors* **2019**, *19*, 3335. [CrossRef]
38. Maimaitiyiming, M.; Sagan, V.; Sidike, P.; Kwasniewski, M.T. Dual activation function-based Extreme Learning Machine (ELM) for estimating grapevine berry yield and quality. *Remote Sens.* **2019**, *11*, 740. [CrossRef]
39. Ohana-Levi, N.; Bahat, I.; Peeters, A.; Shtein, A.; Netzer, Y.; Cohen, Y.; Ben-Gal, A. A weighted multivariate spatial clustering model to determine irrigation management zones. *Comput. Electron. Agric.* **2019**, *162*, 719–731. [CrossRef]
40. Ballesteros, R.; Intrigliolo, D.S.; Ortega, J.F.; Ramírez-Cuesta, J.M.; Buesa, I.; Moreno, M.A. Vineyard yield estimation by combining remote sensing, computer vision and artificial neural network techniques. *Precis. Agric.* **2020**, *21*, 1242–1262. [CrossRef]
41. Summerson, V.; Viejo, C.G.; Torrico, D.D.; Pang, A.; Fuentes, S. Detection of smoke-derived compounds from bushfires in Cabernet-Sauvignon grapes, must, and wine using Near-Infrared spectroscopy and machine learning algorithms. *OENO One* **2020**, *54*, 1105–1119. [CrossRef]
42. Arab, S.T.; Noguchi, R.; Matsushita, S.; Ahamed, T. Prediction of grape yields from time-series vegetation indices using satellite remote sensing and a machine-learning approach. *Remote Sens. Appl. Soc. Environ.* **2021**, *22*, 100485. [CrossRef]
43. Gautam, D.; Ostendorf, B.; Pagay, V. Estimation of grapevine crop coefficient using a multispectral camera on an unmanned aerial vehicle. *Remote Sens.* **2021**, *13*, 2639. [CrossRef]
44. Gomes, V.; Mendes-Ferreira, A.; Melo-Pinto, P. Application of hyperspectral imaging and deep learning for robust prediction of sugar and pH levels in wine grape berries. *Sensors* **2021**, *21*, 3459. [CrossRef]
45. Kasimati, A.; Espejo-Garcia, B.; Vali, E.; Malounas, I.; Fountas, S. Investigating a selection of methods for the prediction of total soluble solids among wine grape quality characteristics using normalized difference vegetation index data from proximal and remote sensing. *Front. Plant Sci.* **2021**, *12*, 683078. [CrossRef]

46. Khan, T.; Sherazi, H.H.R.; Ali, M.; Letchmunan, S.; Butt, U.M. Deep learning-based growth prediction system: A use case of China agriculture. *Agronomy* **2021**, *11*, 1551. [CrossRef]
47. Navarro, P.J.; Miller, L.; Gila-Navarro, A.; Díaz-Galián, M.V.; Aguila, D.J.; Egea-Cortines, M. 3DeepM: An ad hoc architecture based on deep learning methods for multispectral image classification. *Remote Sens.* **2021**, *13*, 729. [CrossRef]
48. Barriguinha, A.; Jardim, B.; de Castro Neto, M.; Gil, A. Using NDVI, climate data and machine learning to estimate yield in the Douro wine region. *Int. J. Appl. Earth Obs. Geoinf.* **2022**, *114*, 103069. [CrossRef]
49. Kasimati, A.; Espejo-García, B.; Darra, N.; Fountas, S. Predicting grape sugar content under quality attributes using normalized difference vegetation index data and automated machine learning. *Sensors* **2022**, *22*, 3249. [CrossRef] [PubMed]
50. Noguera, M.; Millan, B.; Andújar, J.M. New, low-cost, hand-held multispectral device for in-field fruit-ripening assessment. *Agriculture* **2022**, *13*, 4. [CrossRef]
51. Peng, X.; Chen, D.; Zhou, Z.; Zhang, Z.; Xu, C.; Zha, Q.; Wang, F.; Hu, X. Prediction of the nitrogen, phosphorus and potassium contents in grape leaves at different growth stages based on UAV multispectral remote sensing. *Remote Sens.* **2022**, *14*, 2659. [CrossRef]
52. Dutta, M.; Gupta, D.; Juneja, S.; Shah, A.; Shaikh, A.; Shukla, V.; Kumar, M. Boosting of fruit choices using machine learning-based pomological recommendation system. *SN Appl. Sci.* **2023**, *5*, 241. [CrossRef]
53. Imran, H.A.; Zeggada, A.; Ianniello, I.; Melgani, F.; Polverari, A.; Baroni, A.; Danzi, D.; Goller, R. Low-Cost Handheld Spectrometry for Detecting Flavescence Dorée in Vineyards. *Appl. Sci.* **2023**, *13*, 2388. [CrossRef]
54. Lyu, H.; Grafton, M.; Ramilan, T.; Irwin, M.; Wei, H.E.; Sandoval, E. Using Remote and Proximal Sensing Data and Vine Vigor Parameters for Non-Destructive and Rapid Prediction of Grape Quality. *Remote Sens.* **2023**, *15*, 5412. [CrossRef]
55. Swe, K.N.; Takai, S.; Noguchi, N. Novel approaches for a brix prediction model in Rondo wine grapes using a hyperspectral Camera: Comparison between destructive and Non-destructive sensing methods. *Comput. Electron. Agric.* **2023**, *211*, 108037. [CrossRef]
56. Tao, S.; Zhang, X.; Feng, R.; Qi, W.; Wang, Y.; Shrestha, B. Retrieving soil moisture from grape growing areas using multi-feature and stacking-based ensemble learning modeling. *Comput. Electron. Agric.* **2023**, *204*, 107537. [CrossRef]
57. Wu, C.; Jia, W.; Yang, J.; Zhang, T.; Dai, A.; Zhou, H. Economic fruit forest classification based on improved U-net model in UAV multispectral imagery. *Remote Sens.* **2023**, *15*, 2500. [CrossRef]
58. Peanusaha, S.; Pourreza, A.; Kamiya, Y.; Fidelibus, M.W.; Chakraborty, M. Nitrogen retrieval in grapevine (*Vitis vinifera* L.) leaves by hyperspectral sensing. *Remote Sens. Environ.* **2024**, *302*, 113966. [CrossRef]
59. Santos, T.T.; De Souza, L.L.; dos Santos, A.A.; Avila, S. Grape detection, segmentation, and tracking using deep neural networks and three-dimensional association. *Comput. Electron. Agric.* **2020**, *170*, 105247. [CrossRef]
60. Darwin, B.; Dharmaraj, P.; Prince, S.; Popescu, D.E.; Hemanth, D.J. Recognition of bloom/yield in crop images using deep learning models for smart agriculture: A review. *Agronomy* **2021**, *11*, 646. [CrossRef]
61. Tardaguila, J.; Stoll, M.; Gutiérrez, S.; Proffitt, T.; Diago, M.P. Smart applications and digital technologies in viticulture: A review. *Smart Agric. Technol.* **2021**, *1*, 100005. [CrossRef]
62. Chen, S.; Hu, T.; Luo, L.; He, Q.; Zhang, S.; Li, M.; Cui, X.; Li, H. Rapid estimation of leaf nitrogen content in apple-trees based on canopy hyperspectral reflectance using multivariate methods. *Infrared Phys. Technol.* **2020**, *111*, 103542. [CrossRef]
63. Bai, X.; Li, Z.; Li, W.; Zhao, Y.; Li, M.; Chen, H.; Wei, S.; Jiang, Y.; Yang, G.; Zhu, X. Comparison of machine-learning and casa models for predicting apple fruit yields from time-series planet imageries. *Remote Sens.* **2021**, *13*, 3073. [CrossRef]
64. Biffi, L.J.; Mitishita, E.; Liesenberg, V.; Santos, A.A.D.; Goncalves, D.N.; Estrabis, N.V.; Silva, J.A.; Osco, L.P.; Ramos, A.P.M.; Centeno, J.A.S.; et al. ATSS deep learning-based approach to detect apple fruits. *Remote Sens.* **2020**, *13*, 54. [CrossRef]
65. Ta, N.; Chang, Q.; Zhang, Y. Estimation of apple tree leaf chlorophyll content based on machine learning methods. *Remote Sens.* **2021**, *13*, 3902. [CrossRef]
66. Chen, R.; Zhang, C.; Xu, B.; Zhu, Y.; Zhao, F.; Han, S.; Yang, G.; Yang, H. Predicting individual apple tree yield using UAV multi-source remote sensing data and ensemble learning. *Comput. Electron. Agric.* **2022**, *201*, 107275. [CrossRef]
67. Li, M.; Zhu, X.; Li, W.; Tang, X.; Yu, X.; Jiang, Y. Retrieval of nitrogen content in apple canopy based on unmanned aerial vehicle hyperspectral images using a modified correlation coefficient method. *Sustainability* **2022**, *14*, 1992. [CrossRef]
68. Liu, M.; Zhu, Y.; Yang, H.; Pu, R.; Qiu, C.; Zhao, F.; Han, S.; Xu, W.; Meng, Y.; Long, H.; et al. Prediction of apple first flowering date using daily land surface temperature spatio-temporal reconstruction and machine learning. *Comput. Electron. Agric.* **2022**, *202*, 107366. [CrossRef]
69. Uryasheva, A.; Kalashnikova, A.; Shadrin, D.; Evteeva, K.; Moskovtsev, E.; Rodichenko, N. Computer vision-based platform for apple leaves segmentation in field conditions to support digital phenotyping. *Comput. Electron. Agric.* **2022**, *201*, 107269. [CrossRef]
70. Zhang, C.; Mouton, C.; Valente, J.; Kooistra, L.; van Ooteghem, R.; de Hoog, D.; van Dalfsen, P.; de Jong, P.F. Automatic flower cluster estimation in apple orchards using aerial and ground based point clouds. *Biosyst. Eng.* **2022**, *221*, 164–180. [CrossRef]
71. Zhou, X.X.; Li, Y.Y.; Luo, Y.K.; Sun, Y.W.; Su, Y.J.; Tan, C.W.; Liu, Y.J. Research on remote sensing classification of fruit trees based on Sentinel-2 multi-temporal imageries. *Sci. Rep.* **2022**, *12*, 11549. [CrossRef]
72. Jiang, D.; Chang, Q.; Zhang, Z.; Liu, Y.; Zhang, Y.; Zheng, Z. Monitoring the Degree of Mosaic Disease in Apple Leaves Using Hyperspectral Images. *Remote Sens.* **2023**, *15*, 2504. [CrossRef]

73. Singha, C.; Gulzar, S.; Swain, K.C.; Pradhan, D. Apple yield prediction mapping using machine learning techniques through the Google Earth Engine cloud in Kashmir Valley, India. *J. Appl. Remote Sens.* **2023**, *17*, 014505. [CrossRef]
74. Yang, Y.; Li, B.; Shi, P.; Li, Z. Assessing spatiotemporally varied ecohydrological effects of apple orchards based on regional-scale estimation of tree distribution and ages. *Agric. Water Manag.* **2023**, *287*, 108456. [CrossRef]
75. Zhang, C.; Zhu, X.; Li, M.; Xue, Y.; Qin, A.; Gao, G.; Wang, M.; Jiang, Y. Utilization of the Fusion of Ground-Space Remote Sensing Data for Canopy Nitrogen Content Inversion in Apple Orchards. *Horticulturae* **2023**, *9*, 1085. [CrossRef]
76. Zhao, G.; Wang, L.; Zheng, J.; Tuerxun, N.; Han, W.; Liu, L. Optimized Extraction Method of Fruit Planting Distribution Based on Spectral and Radar Data Fusion of Key Time Phase. *Remote Sens.* **2023**, *15*, 4140. [CrossRef]
77. Chen, R.; Liu, W.; Yang, H.; Jin, X.; Yang, G.; Zhou, Y.; Zhang, C.; Han, S.; Meng, Y.; Zhai, C.; et al. A novel framework to assess apple leaf nitrogen content: Fusion of hyperspectral reflectance and phenology information through deep learning. *Comput. Electron. Agric.* **2024**, *219*, 108816. [CrossRef]
78. Zhao, X.; Zhao, Z.; Zhao, F.; Liu, J.; Li, Z.; Wang, X.; Gao, Y. An Estimation of the Leaf Nitrogen Content of Apple Tree Canopies Based on Multispectral Unmanned Aerial Vehicle Imagery and Machine Learning Methods. *Agronomy* **2024**, *14*, 552. [CrossRef]
79. Zhang, C.; Valente, J.; Wang, W.; van Dalfsen, P.; de Jong, P.F.; Rijk, B.; Kooistra, L. Data on three-year flowering intensity monitoring in an apple orchard: A collection of RGB images acquired from unmanned aerial vehicles. *Data Brief* **2023**, *49*, 109356. [CrossRef]
80. Ozdarici-Ok, A.; Ok, A.O. Using remote sensing to identify individual tree species in orchards: A review. *Sci. Hortic.* **2023**, *321*, 112333. [CrossRef]
81. IBGE. Instituto Brasileiro de Geografia e Estatística. 2022. Brasil, Rio Grande do Sul, Vacaria. Available online: https://cidades.ibge.gov.br/brasil/rs/vacaria/panorama (accessed on 18 July 2024).
82. Agapomi, 2024, n. 359, p. 8-9. Available online: http://www.infoteca.cnptia.embrapa.br/infoteca/handle/doc/1163933 (accessed on 18 July 2024).
83. Stedile, N.L.R.; Faria, N.M.X.; Claus, S.M.; Brandão, D.S. Caracterização das unidades de produção agrícola que usam agrotóxicos em Vacaria (RS). *Rev. Econ. Sociol. Rural.* **2021**, *60*, e234912. [CrossRef]
84. IBGE. Instituto Brasileiro de Geografia e Estatística. 2022. Brasil, Rio Grande do Sul, Vacaria, Produção Agrícola—Lavoura Permanente. Available online: https://cidades.ibge.gov.br/brasil/rs/vacaria/pesquisa/15/11863?ano=2022 (accessed on 18 July 2024).
85. IBGE. Instituto Brasileiro de Geografia e Estatística. 2023. Produção de Maçã. Available online: https://www.ibge.gov.br/explica/producao-agropecuaria/maca/rs (accessed on 13 September 2024).
86. IBGE. Instituto Brasileiro de Geografia e Estatística. 2023. Produção de Uva. Available online: https://www.ibge.gov.br/explica/producao-agropecuaria/uva/rs (accessed on 13 September 2024).
87. Jiayi Zhao, J.; Lipani, A.; Schillaci, C. Fallen apple detection as an auxiliary task: Boosting robotic apple detection performance through multi-task learning. *Smart Agric. Technol.* **2024**, *8*, 100436.