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Review

Can Yield Prediction Be Fully Digitilized? A Systematic Review

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Abstract: Going beyond previous work, this paper presents a systematic literature review that explores the deployment of satellites, drones, and ground-based sensors for yield prediction in agriculture. It covers multiple aspects of the topic, including crop types, key sensor platforms, data analysis techniques, and performance in estimating yield. To this end, datasets from Scopus and Web of Science were analyzed, resulting in the full review of 269 out of 1429 retrieved publications. Our study revealed that China (93 articles, >1800 citations) and the USA (58 articles, >1600 citations) are prominent contributors in this field; while satellites were the primary remote sensing platform (62%), followed by airborne (30%) and proximal sensors (27%). Additionally, statistical methods were used in 157 articles, and model-based approaches were utilized in 60 articles, while machine learning and deep learning were employed in 142 articles and 62 articles, respectively. When comparing methods, machine learning and deep learning methods exhibited high accuracy in crop yield prediction, while other techniques also demonstrated success, contingent on the specific crop platform and method employed. The findings of this study serve as a comprehensive roadmap for researchers and farmers, enabling them to make data-driven decisions and optimize agricultural practices, paving the way towards a fully digitized yield prediction.

Keywords: remote sensing; vegetation index; platforms; sensors; satellite; proximal; airborne; digital agriculture 4.0

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1. Introduction

Estimating crop production is a crucial component in agriculture and has proven to be an effective approach for addressing food security concerns [1]. The World Health Organization [2] estimates that 820 million people worldwide still have insufficient access to food, while the Food and Agriculture Organization (FAO) projects a 70% increase in food demand required to support the global population of 9.1 billion by 2050 [3]. The droughts, floods, and heatwaves brought on by climate change are also putting added pressure on food production in many regions of the world [3]. In this context, yield prediction is an essential strategy that empowers farmers and the agricultural industry to manage resources efficiently, make informed decisions, and plan the harvesting, storage, processing, and logistics operations of the production, leading to increased productivity and cost savings. Moreover, timely forecasts enable farmers to plan for potential risks, such as severe weather events or pest outbreaks, allowing them to take prompt action and mitigate their impact [4]. Nevertheless, the estimation of crop production is a complex and intricate process that depends on a multitude of factors, such as the microclimate, weather, soil characteristics, fertilizer usage, and seed variety [5]. Therefore, numerous methods and techniques have been developed and used for optimizing yield prediction and improving the effectiveness of the developed models [6]. Precision agriculture could play a key role to yield estimation by utilizing various sensors including satellites, drones, and ground-based sensors, transforming the process of yield prediction by generating a plethora of data [7].

There have been a number of review papers focusing on the use of smart farming for yield prediction which offer insights into the challenges and opportunities of using remote sensing for crop management [8–10]. Several of these articles focus on the yield prediction of particular crops that are widely grown, such as maize, rice, sugarcane, sugar beet, and vines [11–15], while others include a more general overview of remote sensing technologies for specific application domains, such as crop management, crop monitoring, phenology, and other ecophysiological processes [16–19]. As reported [20], the relationship between vegetation indices obtained from remote sensing images (proximal, Unmanned Aerial Vehicles—UAVs, satellites) and crop yield is not static, but varies by vegetation stage. Towards this direction, a review of 69 studies by Benos et al. [21] highlighted a number of prediction levels at a specific vegetation stage or time before harvest. Schauberger et al. [22] performed a systematic review of crop yield forecasting methods in three often-used data domains: weather, remote sensing, and crop mask. By reviewing a large database (covering more than 350 articles), they reported that the most commonly-used models include statistical, process-based, and machine-learning models.

In relation to machine-learning models, the growing adoption of AI has allowed a noteworthy rise of studies focused on yield prediction [23–25]. Machine learning (ML) models treat the output, the crop yield, as an implicit function of the input variables, such as weather components and soil conditions, which can be very complex [26]. Many studies have used supervised and unsupervised learning, including various analytical models like Decision Trees, Random Forest, Support Vector Machines, Bayesian Networks, and Artificial Neural Networks [26–28]. Even though several review papers deliver a narrative overview of the topic [29–31], limited studies examine in depth all the necessary aspects for yield estimation. In this context, Van Klompenburg et al. [32] provided a systematic review of ML methods in yield prediction, including 567 relevant studies from six electronic databases. According to their findings, the algorithms that are most widely used were Neural Networks (NN) and Linear Regression algorithms, followed by Random Forest (RF) and Support Vector Machines (SVM). The most applied deep learning (DL) algorithm is Convolutional Neural Networks (CNN), and the other widely-used algorithms are Long-Short Term Memory (LSTM) and Deep Neural Networks (DNN). These findings are aligned with the systematic review of Oikonomidis et al. [33], who also reported the rapid increase of DL methods in crop yield prediction over the last five years. Similarly, the systematic review conducted by Muruganantham et al. [20] concluded that the performance and accuracy of the DL approach for crop yield prediction are better when compared to traditional ML approaches. Nevertheless, they are difficult to train and need recently developed hardware and optimization methodologies [34]. Large amounts of data are required to achieve good accuracy, and the complexity of DL approaches increases the algorithm's time complexity [35]. When assessing ML techniques for achieving high levels of prediction performance, special attention should be given to different scales. Although prediction models at the regional scale could exhibit good accuracy, their usefulness to inform the decision-making of individual farmers might be severely limited according to the systematic review of Leukel et al. [36]. The review also accentuated the greater effort required for collecting field-level yield data (e.g., in-field sampling) compared with accessing readily available yield data from governmental bodies and regional associations. Wang et al. [33] also evaluated the applicability of DL for yield prediction on multiple scales and listed some representative studies regarding the nature of application and performance.

Although research has made great strides and crop yield prediction models can estimate the actual yield reasonably, better model performance is still desirable [37]. In the pursuit of enhancing agricultural productivity and ensuring food security, there is a pressing need for further advancements in yield prediction techniques. To address this requirement, this study aims to conduct a comprehensive systematic literature review, focusing on the deployment and integration of cutting-edge technologies such as satellites, airborne, and ground-based sensors in the context of crop yield prediction. By synthesizing this knowledge, we aim to provide valuable guidance for researchers, policymakers, and practitioners in the agriculture sector to make informed decisions and develop improved crop management strategies. Specifically, our review goes beyond previous work by combining multiple aspects of the topic including crop types, key sensors and platforms, data analysis techniques, and their respective performance for estimating yields. To this end, the following research questions are developed to guide the study:

1. Which countries have been the key contributors to research related to the deployment of satellites, airborne, and ground-based sensors for crop yield prediction?
2. Which crop types have been predominantly used for yield estimation in the context of remote sensing technologies?
3. What are the most commonly employed remote sensing platforms and data analysis techniques for predicting crop yields in the existing literature?
4. Among the various methods and platforms utilized, which ones have demonstrated better performance and accuracy in predicting crop yields?

By answering the above questions, this paper aims at providing a comprehensive and objective framework of the topic. It also identifies gaps in the existing research, and highlights hotspots where further investigation is needed in this rapidly growing field.

2. Materials and Methods

2.1. Scientific Article Search

In this study, peer-reviewed articles related to the application of remote sensing technologies in yield prediction were extracted, aiming to identify relevant studies from the earliest instances to the present day. To this end, a systematic search procedure was developed by utilizing Scopus "www.scopus.com (accessed on 1 February 2023)" and Web of Science (WoS) "www.webofscience.com (accessed on 1 February 2023)" search engines following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework [38]. Specifically, the PRISMA Statement consists of a 27-item checklist and a four-phase flow diagram, aiming at helping authors improve the reporting of systematic reviews and meta-analyses [38]. To ensure a comprehensive selection of relevant research articles for the analysis, the study's approach was designed based on framed research questions and the aim of the review. It was acknowledged that using "yield prediction" alone as a search string would have generated a large number of published articles from various application fields that were not likely related to the aim of the review, leading to a complicated search. Therefore, the research words have been deliberately chosen, also considering relevant systematic reviews [22,32,39] to narrow down the focus from a main concept to a central idea. Specifically, the query used for encompassing all the works related to the topic without risking excluding any item is presented in Table 1.

Table 1. Search engines and queries that were used for the scope of this study.

Search Engine	Query
Scopus	TITLE-ABS-KEY ("yield forecasting" OR "yield prediction" OR "yield estimation" OR "crop modeling") AND TITLE-ABS-KEY ("satellite" OR "UAV" OR "proximal" OR "remote sensing" OR "proximal sensing" OR "aerial")
WoS	TS = ("yield forecasting" OR "yield prediction" OR "yield estimation" OR "crop modeling") AND TS = ("satellite" OR "UAV" OR "proximal" OR "remote sensing" OR "proximal sensing" OR "aerial")

Then, a filtering step was conducted by exploiting the exclusion criteria directly available in the Scopus and WoS search engine, that is, document type, language, and publication year. Open-access articles published in the English language were only selected, while review articles and conference papers were excluded. This was based on the fact that open-access publishing adheres to the principles of open science, fostering transparency and ensuring that research is readily accessible for thorough examination, and thereby upholding the fundamental tenets of scientific integrity. Furthermore, the time span of the investigation encompassed the entire body of literature from 2002 to 2022.

The search query generated 725 records through Scopus and 704 through WoS, with publication data containing information on the "Author, Title, Source", "Abstract, Keyword, Addresses", and "Cited, References and Use" categories, organized into fields. Moreover, by removing the repeated and review articles across the two selected databases, 864 articles were screened by title and abstract.

2.2. Article Selection Criteria

The initially retrieved articles were chosen based on specific criteria, including the type of remote sensing technology utilized in the study and the method employed for yield prediction. Analyzing the abstracts of these articles aided in identifying relevant keywords and assisting in the article selection process. To ensure the relevance and focus of the review, the following exclusion criteria were applied:

- Records not pertinent to the research objective (e.g., satellite RNA in plant pathology) were excluded;
- Articles falling within the agricultural sector but not directly related to crop yield prediction were also removed from consideration;
- Publications that did not incorporate the use of satellites, airborne, or ground-based sensors for crop yield prediction were excluded;
- Literature search for articles that are published between 1 January 2002 to 31 December 2022;
- Articles were included only if they forecasted crop yield, either in absolute or relative terms, and provided performance metrics for evaluation. In order to ensure consistency and comparability, particular attention was given to the presence of evaluation metrics such as R^2 (the coefficient of determination) and error metrics like the Root Mean Square Error (RMSE). Studies lacking these metrics were omitted from the dataset to standardize the evaluation process.

After applying all the exclusion criteria, a total of 456 full text articles were assessed for eligibility. Figure 1 presents the process for article selection and rejection from databases, based on the PRISMA framework.

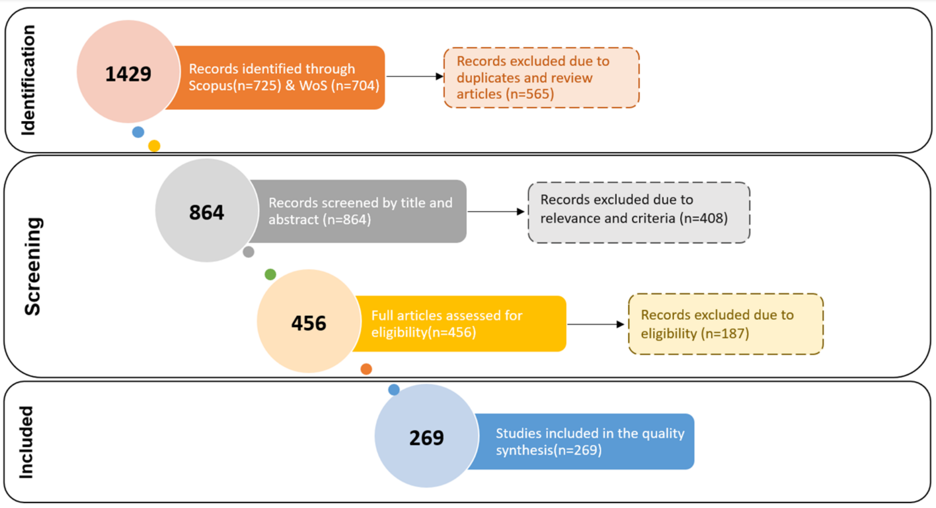

Figure 1. Systematic review procedure for article selection.

The eligibility process involved thoroughly analyzing the full articles to ensure that only the studies that met the necessary aforementioned criteria were included. As a result, a total of 269 studies were deemed suitable and incorporated into this comprehensive review.

2.3. Scientific Studies Classification & Statistical Analysis

The selected papers were tabulated and standardized to enable comparison and systematic evaluation by extracting the following variables from each study:

- Study data: lead author, year, title, citations;
- Experiment setup: study region, type of crop;
- Platform type: Satellite, Airborne Measurements (Unmanned Aerial Systems—UAS or Manned Flight), Ground based Measurements;
- Method type: machine learning, statistical analysis, model-based approach, Vegetation Indices (VIs);
- Evaluation: performance measures (e.g., R^2, RMSE, MAE).

Subsequently, the actual data collected from the papers were subjected to statistical analysis using XLSTAT software version 2016 from Addinsoft (www.xlstat.com, accessed on 1 April 2023). This analysis involved determining the number of research articles produced annually and by type. Additionally, further analyses were conducted based on crop type, platform type, sensor type, and the method's focus area for each year over the past two decades.

3. Results and Discussion

One of the principal findings of this study pertains to the number of publications per year from 2002 to 2022, which sheds light on the evolving trends and research activity in the field of yield prediction using remote sensing technologies. According to Figure 2, from 2002 to 2012, the publication rate was low, with an average of roughly one paper per year. However, between 2013 to 2017, the publication rate increased to an average of approximately six papers annually, indicating a growth stage. From 2018 onwards, a rapid increase in publications is evident, confirming the growing interest among researchers, which also reflects the yield prediction used in the literature. Specifically, the number of publications surged from 15 in 2018 to 42 in 2020 and reached its peak at 92 in 2022.

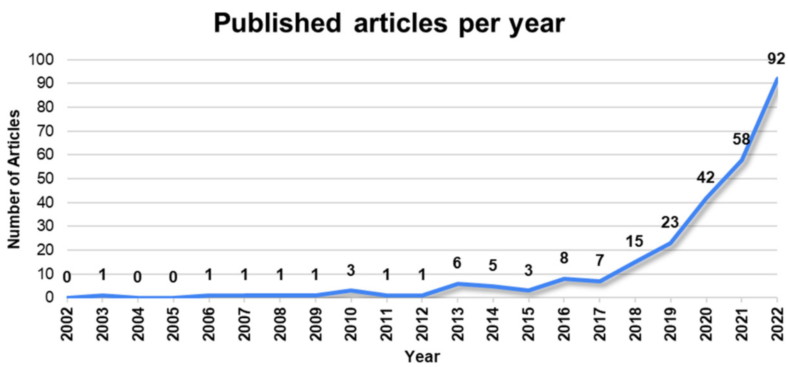

Figure 2. Number of publications per year throughout the period 2002 to 2022.

The higher number of articles in the last years can be explained by a confluence of factors, such as technological advancements in the Information and Communications Technology (ICT) area, augmented research funding, and an expanding understanding of remote sensing applications.

The list of selected papers for the review is summarized in Appendix A, Table A1, which includes relevant information such as the Title, Crop, Method, and Platform used in each study. This comprehensive summary allows readers to access and refer to the key details of the selected papers efficiently, aiding in the understanding and evaluation of the research conducted for the review.

3.1. Key Contributor Countries

This systematic review also provided insights into the geographical distribution of research and the key contributors in the field. Specifically, studies have been conducted in 55 countries (Figure 3), with China most frequently appearing, followed by the USA, India, Australia, and Brazil. There are also many experiments in developing countries, but often only with a single study on a single crop. Forecasting efforts in Europe are spread out geographically, largely following country size and production share, with a dearth of studies particularly in Eastern Europe. It is important to highlight that these findings are related to the study areas within the articles, not the countries of authorship.

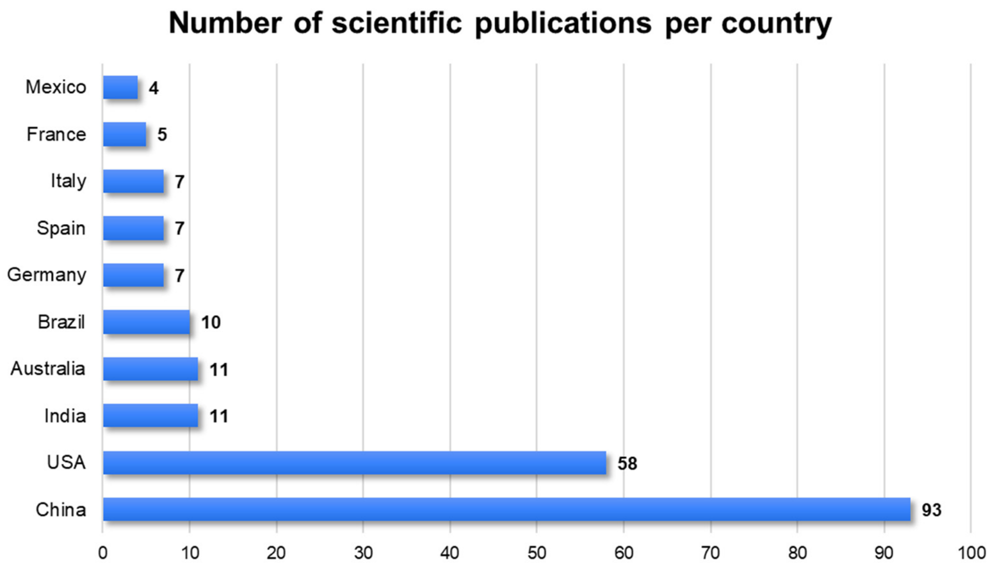

Figure 3. Top 10 countries in terms of publications 2002–2022.

The most active country in terms of experiments for the whole period encompassed by this study is, clearly, China with over 93 publications. Following closely, the USA ranks second with 58 publications. India and Australia occupy the third and fourth positions, respectively, with 11 research studies each, while Brazil closely trails with 10 studies. In a more detached group, the majority then consists of European countries (Germany, Spain, Italy, France) with <8 publications.

The number of citations received is often used as a proxy for research quality. However, it should be noted that this metric alone may not provide a completely accurate representation, as various factors, including the research institute, the researchers' country of origin, and the target audience, could influence citation counts [40]. Figure 4 illustrates the impact of research from different countries, and it becomes evident that China and the USA stand out, outperforming other countries in terms of citations. Notably, European countries, such as Germany and Spain, follow at a considerable distance with less than 370 citations, while Australia and Brazil are positioned further down the ranking. It is essential to highlight that these rankings are based on the currently available information and may be subject to updates as more recent citations become accessible, potentially influencing the relative positions of the countries in the future.

By examining publication patterns and citation metrics, it was possible to identify the countries that have made significant contributions to the topic of interest, helping researchers understand the global landscape of research and identify potential collaboration opportunities. It is evident that the USA and China have emerged as the most influential countries in the field of crop yield estimation using remote sensing technologies. These two (2) nations have demonstrated a significant presence with a substantial number of research articles focused on crop yield estimation, remote sensing applications, and related subjects. Moreover, their prominent position in terms of citations underscores their consistent production of high-quality research, substantial contributions to advancements in the field, and a profound understanding of effectively harnessing remote sensing data for accurate yield prediction. The notable impact of their research could be explained by the fact that they have the biggest economies and invest heavily in research and development. Consequently, they employ a large number of researchers who produce research publications [41].

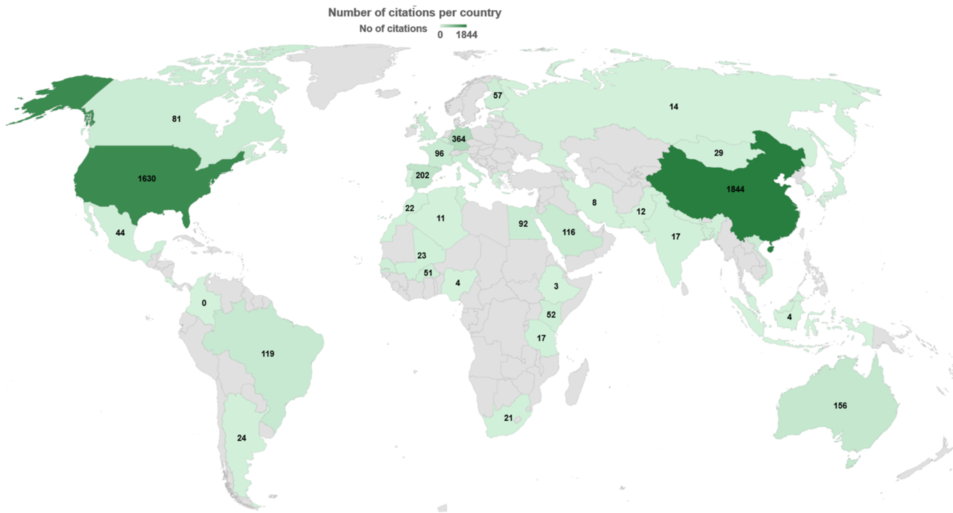

Figure 4. Geographical distribution of citations for all the selected articles (2002–2022).

3.2. Crops Used for Yield Estimation

The choice of crops for yield estimation is a pivotal aspect of research in the field of remote sensing-based agriculture. Through a thorough analysis of the literature, the study identified the most frequently studied crops used in yield estimation through remote sensing techniques. In total, the research encompassed a diverse array of crops, amounting to 48 different types, which were further classified into nine categories based on the Food and Agriculture Organization (FAO)'s classification [42]. Figure 5 illustrates the number of studies that included crops from each category and the prominent crops that have been extensively researched in the field of remote sensing-based yield estimations. Several studies addressed multiple crops, which means the total number of crops illustrated is greater than the number of studies analyzed.

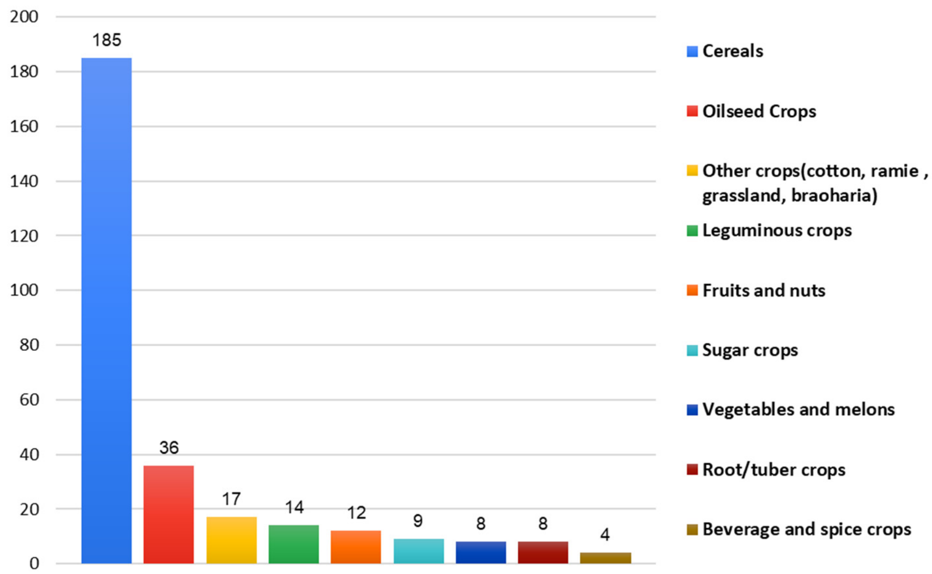

Figure 5. Categories of crops included in literature between 2002 and 2022.

Wheat (including durum wheat), maize, and rice emerge as highly studied crops, not only within the cereal category, but also overall. Additionally, oilseed crops, with soybeans leading the way, also receive significant attention in scientific publications. On the other hand, the fruits and nuts category along with vegetables and melons appeared to be the least researched category in terms of publications. It is noted that the category "Grass crops" comprises various crops, including Bachiaria pastures, Grassland, Miscanthus, perennial bioenergy grass, and ryegrass. Similarly, the category of "tomato" also includes research on processing tomato crops (Figure 6).

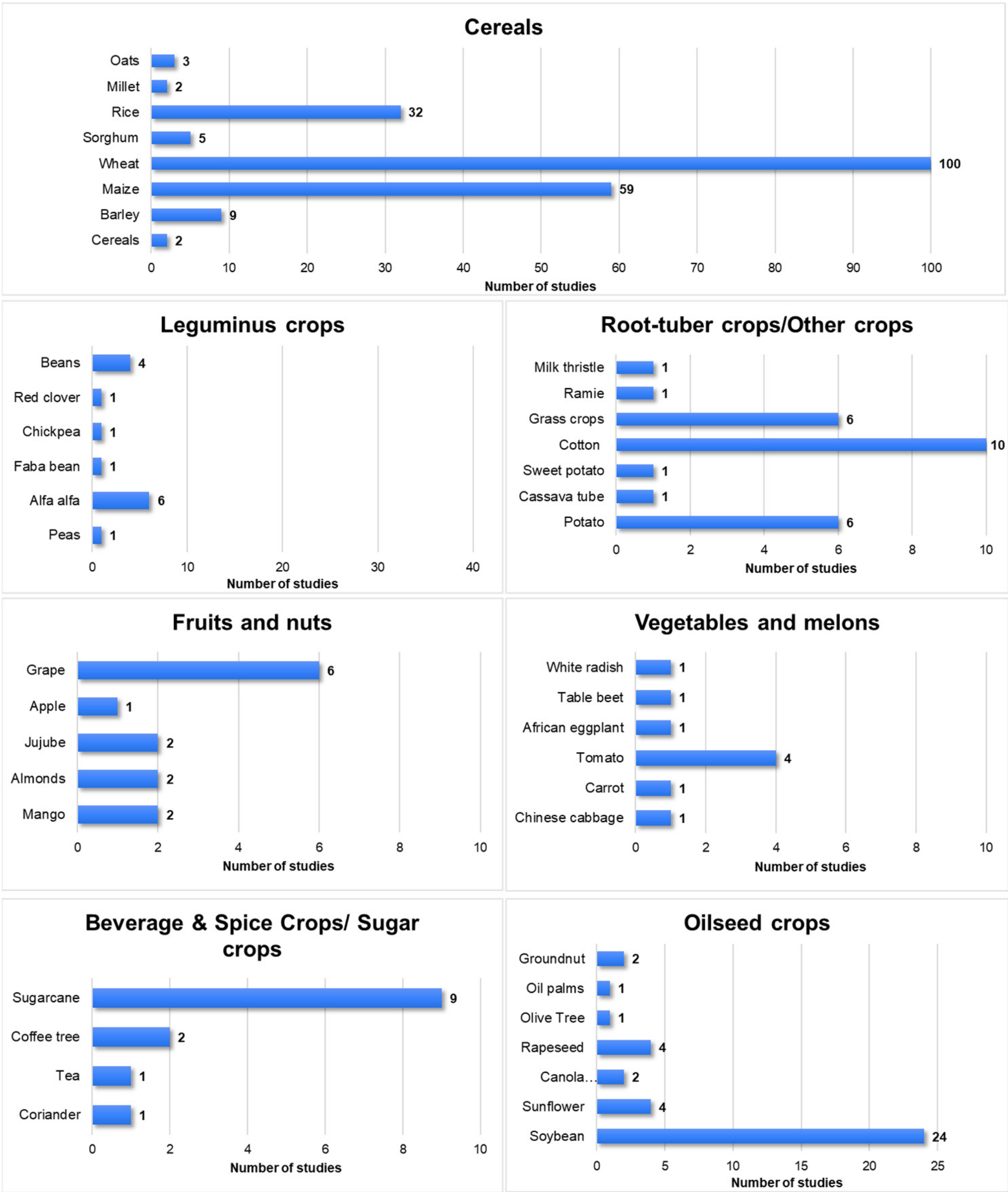

Figure 6. Number of studies per crop category and crop.

Overall, the prominent crops that were commonly utilized for yield prediction included cereals and oilseed crops. These crops were selected due to their nutritional value and, therefore, their economic significance, data availability, and relevance to global food security [43,44]. Another key factor influencing their widespread use could be the availability of extensive datasets, encompassing historical yield records, agronomic practices, and weather data. Such data availability facilitates researchers in conducting comprehensive yield prediction studies with greater ease. Moreover, these crops do not exhibit complex structure-like vineyards and orchards that may affect remote sensing results [45]. The frequent application of agricultural practices like irrigation and pruning that are conducted in other crops such as vineyards and orchards, could also affect the interpretation of the remote sensing results [46]. As a result, researchers may face additional technical challenges and data processing requirements for these crops. In contrast, cereals and oilseed crops generally experience less interference from such practices, leading to more reliable and consistent remote sensing outcomes.

3.3. Remote Sensing Platforms for Yield Forecasting Used in the Literature

The literature on remote sensing platforms for crop yield forecasting is vast and diverse. Different remote sensing platforms have different advantages and limitations in terms of spatial resolution, temporal resolution, spectral resolution, radiometric resolution, coverage area, revisit frequency, data availability, data cost, and data processing requirements. Therefore, selecting the most suitable remote sensing platform for a specific crop yield forecasting application depends on several factors, such as the type of crop, the scale of analysis, the purpose of forecasting, the available resources, and the user preferences.

The results indicate that various remote sensing platforms were widely utilized for crop yield estimation, with many studies employing multiple platforms simultaneously. Notably, the majority of the reviewed studies (62%) utilized satellite remotely-sensed data to generate yield forecasts throughout the growing season. However, for small-scale studies conducted on experimental plots, ground-based sensors (27%) or airborne sensors (30%) were more commonly employed (Figure 7). Nonetheless, even in cases where multiple platforms were used, satellites remained the primary choice for crop yield estimation. This diverse usage of remote sensing platforms underscores their versatility and the benefits they offer in gathering essential data for crop yield forecasting across different spatial scales and agricultural contexts.

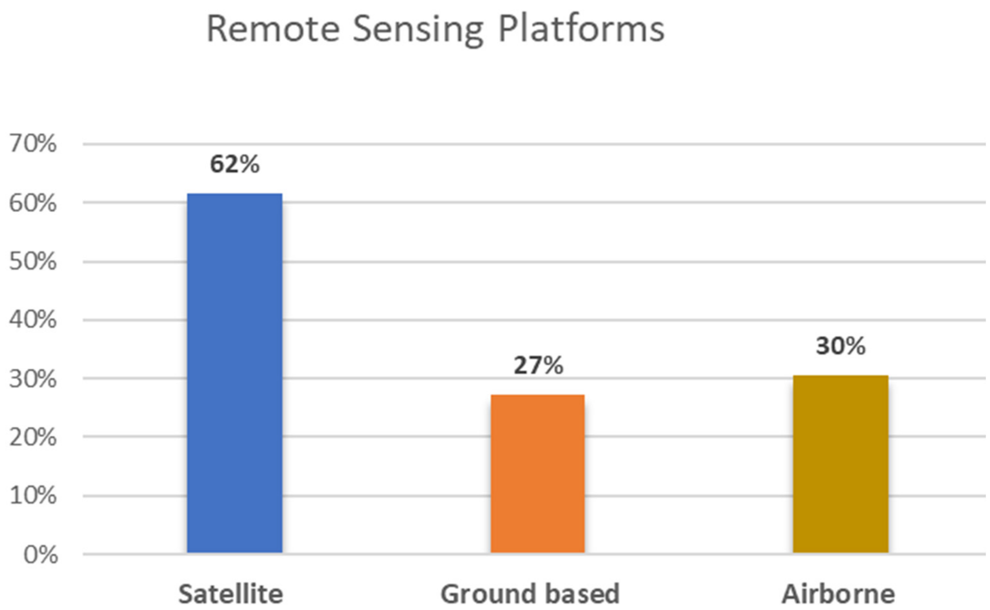

Figure 7. Remote sensing platforms for yield forecasting used in the literature.

Satellites play a crucial role in crop yield prediction by utilizing a diverse range of sensors to measure electromagnetic radiation reflected or emitted from the Earth's surface. Equipped with these sensors, satellites enable the spatial and multitemporal monitoring of soil and crop characteristics at different growth stages, providing valuable data for yield estimation. Figure 8 depicts the most common satellite systems used for yield prediction. Among the satellites commonly employed for this purpose, the Moderate Resolution Imaging Spectroradiometer (MODIS) emerges as the most frequently used, followed by Sentinel-2, Landsat, and Satellite pour l'Observation de la Terre (SPOT). Additionally, Synthetic Aperture Radar (SAR) sensors have also been utilized, with Sentinel-1 being the most prominent one.

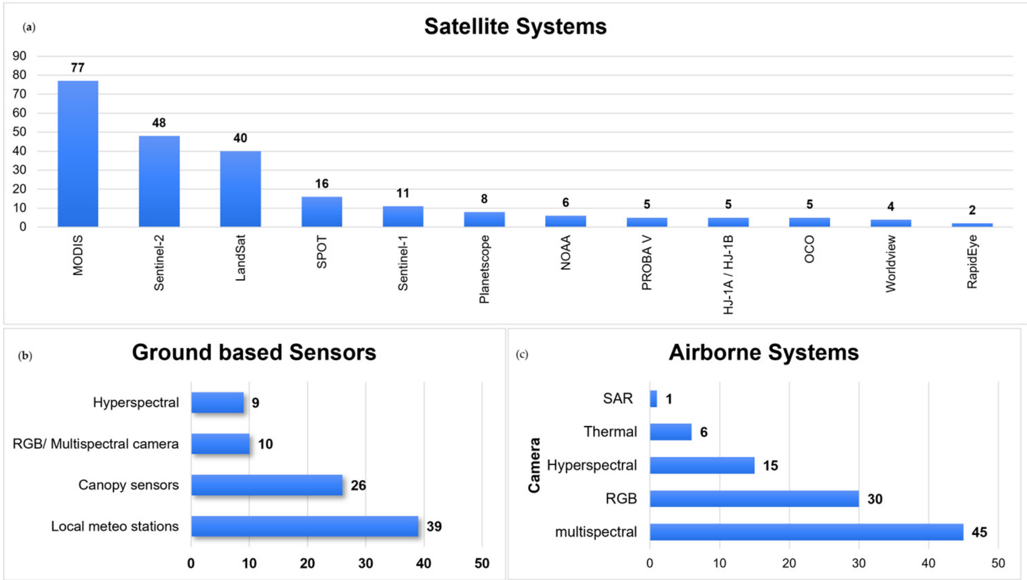

Figure 8. (**a**) Satellite platforms for yield forecasting used in the literature; (**b**) ground-based platforms for yield forecasting used in the literature; (**c**) airborne platforms for yield forecasting used in the literature.

Yield predictions could also be derived based on data recorded from airborne platforms. According to the findings of this study, out of the total 269 studies reviewed, 84 of them utilized airborne data for crop yield prediction, including four manned flights. Among these, 45 studies utilized multispectral cameras, 30 studies deployed RGB cameras, and 15 studies utilized hyperspectral data. The least commonly used sensors were the thermal and synthetic aperture radar (SAR). It is obvious that several studies deployed more than one sensor, indicating the integration of multiple data sources to improve the accuracy and comprehensiveness of crop yield prediction models. The diverse usage of these sensors underscores the significance of integrating different data types to capture various aspects of crop growth and health for more informed yield forecasting.

In the case of ground-based sensors, the instruments were grouped based on their functionalities and applications. Specifically, the canopy sensors and analyzers category encompassed instruments for Chlorophyll Measurement (SPAD), Crop Health, and Nutrient Management (e.g., GreenSeeker, NTech Industries, Ukiah, CA, USA and CropCircle, Holland Scientific Inc., Lincoln, NA, USA), as well as Spectral Analysis and Canopy Analysis sensors (e.g., Spectroradiometer, spectrometers, Li-Cor 2000 Plant Canopy Analyzer, Li-Cor, Lincoln, NE, USA). Local meteorological stations were extensively deployed, appearing in 39 studies, making them the most commonly used ground-based sensors. Following closely, canopy sensors were frequently employed in the research. However, thermal sensors and LiDAR/Laser scanner data were the least deployed among the ground-based sensor categories.

Summarizing the results, researchers primarily utilized satellite platforms to acquire the necessary data for their studies. Satellites, compared to the rest of the platforms, can cover large areas and provide high temporal resolution, while being cost effective [47]. Moreover, satellites can be used in multisource data integration, such as the integration of optical and SAR remote sensing [48]. These advantages can explain why the majority of the studies incorporated satellite remote sensing approaches.

Respectively, UAS encompasses high spatial ground resolution and the ability to provide flexible and timely surveillance. However, UAS surveys require the storage and management of large amounts of data and preprocessing, while the datasets generated are limited to those collected by the user [49]. Consequently, deploying UASs on a commercial scale involves significant expenses, encompassing equipment, data processing, and software costs, which can be a substantial investment for small-scale farmers [50,51].

On the other hand, proximal sensors present distinct advantages in terms of precision and cost-effectiveness in agriculture. Since most of these sensors are active, they are not as restricted by weather conditions. Due to the close proximity in which the data are collected, there is less atmospheric interference, leading to more accurate data as well as high spatial resolution [52]. Nevertheless, they also have limitations pertaining to coverage, data interpretation, maintenance demands, and initial expenses. Therefore, the evaluation of the specific needs and available resources is essential when contemplating the adoption of remote sensor technology.

3.4. Data Analysis Techniques for Yield Forecasting Used in the Literature

Analyzing remote sensing products for yield prediction involves a range of methodologies that encompass ML, DL, statistical, and model-based approaches. These methods leverage the power of remote sensing data to estimate and predict crop yields accurately.

Based on the findings of this study (Figure 9), a statistical analysis is the most prevalent method employed for crop yield prediction in the reviewed studies. Following the statistical analysis, machine learning (ML) and deep learning (DL) methods are also widely used for yield estimation. In contrast, model-based approaches are observed to be utilized less frequently. Statistical analysis techniques often provide straightforward and interpretable relationships between variables, making them a popular choice for analyzing and understanding the impact of different factors on crop yields. Machine learning and deep learning methods, on the other hand, excel at capturing complex patterns and relationships in large and high-dimensional datasets, which is particularly advantageous when dealing with remote sensing data.

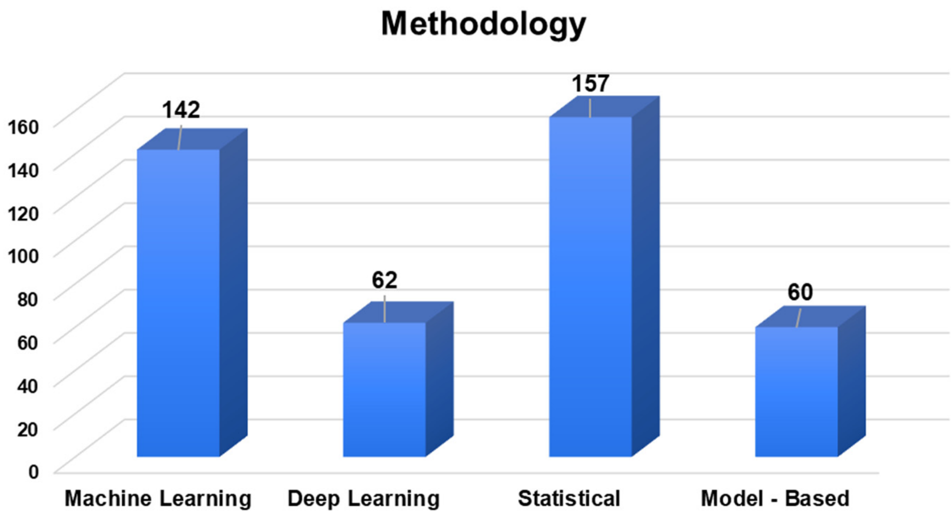

Figure 9. Overview of the methodological approach in the studies considered.

One of the significant discoveries of this study is the prominence of the Random Forest algorithm, which appeared in 89 studies, making it the most commonly used approach for crop yield prediction. This is aligned with the findings of another systematic review by van Klompenburg et al. [32], which reported that Random Forest is one of the most used models along with Linear Regression and the Gradient Boosting Tree. Following closely, Support Vector Machine (SVM) was featured in more than 52 studies, while Linear regressors were utilized in over 30 studies. Both XGBoost and Partial Least Square Regression (PLSR) are also frequently utilized, with more than 20 and 11 studies, respectively. It is worth noting that the Lasso Regression is another commonly used regularization technique (>14 studies), employing an L1 penalty to encourage sparsity in the model, resulting in the selection of relevant features. Similarly, the Ridge regression (>eight studies) is a variation of Linear Regression that incorporates a regularization term to prevent overfitting and enhance model performance when addressing multicollinearity. These methods have garnered significant attention in various research studies and applications, demonstrating their efficacy and versatility in yield prediction. Moving on to Neural Networks, Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN) take the lead as the top-ranked approaches, with 16 and 13 studies, respectively.

An intriguing observation from the study is that there were only three studies that employed ML and DL approaches between 2007 and 2010, whereas the vast majority of these studies were published from 2017 to 2022. This significant increase in the use of ML/DL techniques in recent years indicates a growing interest and recognition of the power and potential of these advanced methods for crop yield prediction using remote sensing data.

Model-based approaches, though less prevalent in this context, offer valuable insights and predictions by simulating the entire crop growth process and its intricate relationship with the environment from an ecological physiology perspective. These models integrate various factors such as crop characteristics, soil conditions, climate, and management practices to comprehensively simulate crucial physiological processes, including crop respiration, photosynthesis, phenology, biomass accumulation, crop distribution, and ultimately estimate crop yields. In this systematic review, several model-based approaches appeared for crop yield prediction using remote sensing data. It is essential to emphasize that model-based approaches typically necessitate a range of inputs, making remotely-sensed weather and biomass data particularly valuable for obtaining temporal and spatial information on a large scale.

Among model-based approaches, the Decision Support System for Agrotechnology Transfer (DSSAT) model [53] stood out with 13 featured studies, providing valuable insights into agricultural management practices and crop responses to environmental conditions. The Simple Algorithm For Yield model (SAFY) and WOrld FOod STudies (WOFOST) model [54–56] were each present in seven studies, offering simulations of crop growth under water-limited conditions and diverse environmental scenarios, respectively. AQUACROP [57–59], used in four studies, focused on crop water productivity, evaluating yield responses to water availability and irrigation management. The Agricultural Production Systems Simulator (APSIM) model [60–62] was investigated in three studies, encompassing various aspects of crop growth and management. Additionally, the PROSAIL (Prospect and Sail) model, deployed in seven studies, served as a radiative transfer model, enabling the assessment of crop health through light interactions in vegetation canopies. While it does not directly generate yield predictions, it was employed in conjunction with other models (APSIM, WOFROST) to extract Leaf Area Index (LAI) values, which were then used to estimate biomass.

It is important to note that different crop models operate based on distinct driving factors. For example, WOFOST focuses on carbon dioxide (CO_2), water, and temperature effects on yield, while AQUACROP emphasizes the impact of water stress on crop growth and yield, making it effective for simulating irrigation scenarios. APSIM, being a process-based model, considers a diverse range of soil processes, in addition to water balance and nutrient transformations [63]. Moreover, researchers have explored the benefits of coupled models, which combine two or more models with different principles and types. This approach aims to overcome the limitations of individual models, while capitalizing on their strengths, resulting in an improved simulation accuracy, modeling system stability, and reduced operational costs. These advances in model-based approaches contribute to a deeper understanding of crop–environment interactions and aid in making informed decisions for sustainable agricultural practices.

Each approach offered distinct advantages and addressed specific research objectives, enabling the extraction of meaningful information from remote sensing data for crop yield estimations. Specifically, the Statistical Analysis and Machine Learning methods are often used in crop yield estimation due to their ability to handle complex nonlinear relationships in high-dimensional datasets, as well as known parametric structures and unobserved cross-sectional heterogeneity [64]. Additionally, the performance of Deep Learning methods may be inadequate due to the fact that they heavily rely on the quality of the extracted features [65]. Finally, the low use of model-based methods on crop yield prediction could be explained by their high requirements for data and computational resources, and on their low flexibility compared to the other methods [66].

3.5. Spectral Vegetation Indices

Among the numerous vegetation indices developed, several have gained widespread adoption due to their effectiveness and versatility. As indicated by the results (Figure 10), the Normalized Difference Vegetation Index (NDVI) emerges as the most commonly used Vegetation Index. This can be explained by the high correlation this index presented, with key yield variables such as above ground biomass, crop height, and Leaf Area Index (LAI) [67,68]. The NDVI is also the most well-documented spectral vegetation index in the literature, resulting in reliable and accurate estimates of crop health and productivity, which are crucial for yield prediction [69]. Following closely is the Enhanced Vegetation Index (EVI), an improved vegetation index that addresses some of the limitations of the NDVI, particularly in areas with dense vegetation or atmospheric interference. Additionally, the LAI and Green Normalized Difference Vegetation Index (GNDVI) are widely employed in the studies. Each index offers unique advantages and applications, depending on specific research or monitoring objectives. Researchers, agronomists, and environmental scientists rely on these indices to analyze vegetation dynamics, assess crop health, monitor land cover changes, and make informed management decisions.

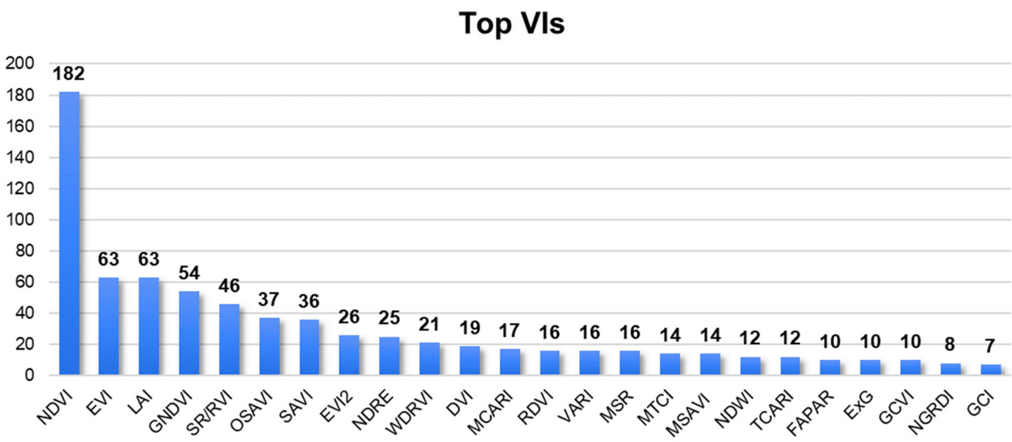

Figure 10. Most widely used vegetation indices (VIs) for crop yield prediction.

It is evident that various vegetation indices have gained popularity for their effectiveness, with the Normalized Difference Vegetation Index (NDVI) being the most widely used. The NDVI's strong correlation with key yield factors like biomass, crop height, and LAI contributes to its prevalence. The Enhanced Vegetation Index (EVI) is also popular, addressing the NDVI's limitations in dense vegetation or atmospheric conditions. The Leaf Area Index (LAI) and Green Normalized Difference Vegetation Index (GNDVI) are frequently employed too. These indices aid researchers, agronomists, and environmental scientists in analyzing vegetation, assessing crop health, monitoring land changes, and making informed decisions.

3.6. Accuracy Performance per Crop Category

Assessing accuracy performance per crop category is crucial for understanding the effectiveness of different methods and platforms in estimating yields for specific crops, aiding in informed decision-making and optimizing agricultural practices. Consequently, the highest performance measures (R^2) obtained for each study were extracted and organized into tables based on crop categories.

When comparing different methods in the case of sugar (Table 2), beverage, and spice crops, ML techniques exhibit high performance, as shown in the table (Table 2). Specifically, the Random Forest method stands out with a noteworthy RMSE of 1.51 t/ha and an R^2 value of 0.94. It surpasses other methods including the Classification and Regression Tree, Support Vector Regression, and K-Nearest Neighbor [70]. This finding is in line with the results obtained by Canata et al. [71], where RF regression outperformed Multiple Linear Regression (MLR) in predicting sugarcane yields. Similarly, Martello et al. found that the RF regression yielded superior results in predicting coffee tree yields [72].

Table 2. Reported method, platform, and R^2, for sugar, beverage, and spice crop category.

Crop	References	Method	Platform	R^2
Sugarcane	[73]	Statistical	Satellite × Proximal	0.53
	[74–77]	Statistical	Satellite	0.55 to 0.8
	[70,78]	ML, Statistical	Satellite	0.87 to 0.94
	[71]	ML	Satellite	0.70
	[79]	Model based	Satellite	0.86
Coriander	[80]	Statistical	Satellite	0.81 to 0.87
Tea	[81]	ML	Satellite	0.68 to 0.71
Coffee Tree	[82]	Statistical, Model based	Satellite	0.64 to 0.69
	[72]	ML, Statistical	Satellite	0.88 to 0.93

Furthermore, the most common platform used was satellite systems, indicating encouraging prediction accuracies (R^2 = 0.87) and RMSE = 11.33 (t·ha^{-1}) when compared to actual harvested yields [78]. Additionally, the utilization of SAR-based yield prediction models have also proved the potential to assist and support sugar mill technicians in refining yield estimates [75]. Nevertheless, a study by Duveiller et al. [77] highlights that the estimation of sugarcane yield is influenced by various aspects, namely: (1) the way time is regarded (thermal or calendar); (2) the purity of the signal; (3) how the information is extracted from the time series (i.e., the type of metrics); and (4) the timing of when the information is available. These factors can explain the different range of R^2 values retrieved from satellites for yield prediction (Table 2). Moral et al. [76] suggest that the empirical NDVI model is the most suitable approach for estimating sugarcane yield at the field level due to its simplicity and high accuracy throughout the entire crop cycle. In contrast to linear, logarithmic, power, and exponential models, a separate study [74] demonstrates that the polynomial model exhibits a significantly improved performance.

In the context of model-based yield prediction, the findings indicate a medium to high performance, with R^2 values ranging from 0.64 to 0.86. This can be explained by the selection of the model. A study conducted in the USA compared three statistical models that incorporated remote sensing and weather data. Among these models, the SiPAR model demonstrated a superior yield prediction compared to the cumulated DNVI (CNDVI) and Kumar and Monteith (K–M) models [79].

In the crop category of Vegetables and Melons (Table 3), ML techniques have demonstrated a high performance as well, achieving an R^2 value of 0.90. Apart from the deployed method, the selection of the VI plays a crucial role in achieving an optimal performance. According to the study conducted by Suarez et al. [83], the optimal results were produced when the Renormalized Vegetation Index (RDVI), Soil Adjusted Vegetation Index (SAVI), and Optimized Soil Adjusted Vegetation Index (OSAVI) were the predictor variables (R^2 = 0.77), with the lowest σ (10.75 t/ha) achieved with RDVI. EVI2 also performed better (R^2 = 0.55) than GNDVI (R^2 = 0.29). Another study [84] focusing on processing tomato crops identified plant height and VIs during the early to mid-fruit formation period as significant variables for predicting shoot masses. Notably, the NDVI and Weighted

Difference Vegetation Index (WDVI) were found to be significantly important for predicting tomato weight, while VIs one (1) month prior to harvest were significant in predicting fruit quantity.

Table 3. Reported method, platform, and R^2 for the Vegetables and Melons crop category.

Crop	Reference	Method	Platform	R^2
Chinese Cabbage White Radish	[85]	Statistical	Airborne	0.66 to 0.90
Carrot	[83]	Statistical	Satellite	0.29 to 0.78
African Eggplant	[86]	Statistical	Airborne × Proximal	0.54 to 0.87
Table Beet	[87]	Statistical	Airborne	0.89
Tomato	[88] *	Statistical	Satellite	0.69 to 0.81
	[84,89,90] *	ML, Statistical	Airborne	0.70 to 0.90

* Processing Tomato.

Moreover, recent findings [88] suggest a strong correlation between the development stages of the primary canopy in processing tomatoes and their final yield. This correlation may indicate a crucial stage during which the crops undergo discernible changes that can be detected using satellite-derived data. Additional research demonstrates the possibility of predicting average tomato biomass and yield up to 8 weeks before harvest, as well as at the individual plant level up to 4 weeks prior to harvest [89]. By employing time-series phenotypic features derived from UAVs, researchers observed a strong individual correlation between these features and the actual yield. Linear Regression models produced high values ($R^2 > 0.7$) in this regard [90].

In the context of oilseed crops (Table 4), the utilization of satellite NDVI series, captured fifty (50) days prior to harvest, has proven to be a reasonably accurate approach for estimating sunflower yields [91]. Furthermore, the effectiveness of Evolutionary Product-Unit Neural Network (EPUNN) models has been explored, revealing a superior accuracy compared to linear SMLR models, both in the training set and generalization set [92]. In the case of rapeseed yield estimation, plot-level VIs and leaf-related abundance showed a strong correlation, with an R^2 value above 0.75. Among the tested VIs, multiplying the NDVI, Chlorophyll Index Red Edge (CIred edge), Transformed Vegetation Index (TVI), and SAVI by short-stalk-leaf abundance yielded the most accurate results for yield estimation in rapeseed [93]. When it comes to model-based methods [63], the WOFOST model in comparison with the coupled CASA-WOFOST model demonstrated a faster running speed in yield simulations while maintaining a similar accuracy. This makes the proposed CASA-WOFOST model suitable for large-scale assessments using high-spatial-resolution images to obtain accurate yield simulations. An investigation was conducted to assess the potential of multisensor optical and multiorbital SAR data for monitoring winter rapeseed crops using the SAFY agrometeorological model. The results demonstrated that the assimilation of both SAR-derived dry matter (DM) and the optically derived Green Area Index (GAI) allowed for better control of the model compared to using SAR or optical data alone. This integration notably improved the optimization of parameters governing dry matter partitioning into leaves and effective light-use efficiency [94]. Another crucial aspect in satellite-based crop yield estimation is the spatial and temporal resolution of the deployed satellites. As highlighted by Chen et al. [95], sparse time series of satellite remote sensing, caused by low-temporal-frequency and/or cloud contamination, pose significant challenges for accurate crop yield estimation at regional to national scales. To address this limitation, the blending of high-spatial-resolution but low-temporal-frequency images with low-spatial-resolution but high-temporal-frequency images was proposed. This approach aims to increase the temporal resolution, while preserving essential spatial details, potentially enhancing the accuracy of crop yield estimations.

Table 4. Reported methods, platforms, and R^2 for the Oilseed Crop category.

Crop	References	Method	Platform	R^2
Groundnut	[96]	ML, Statistical	Satellite × Proximal	0.96
	[97]	ML/DL, Model based	Satellite × Proximal	0.68
Sunflower	[91]	ML	Satellite	0.90
	[80]	Statistical	Satellite	0.56
	[92]	ML/DL, Statistical	Airborne	0.43
	[98]	Statistical	Satellite	0.91
Olive Tree	[99]	Statistical	Airborne	0.97
Palm Oil	[100]	ML/DL	Satellite	0.82
Canola	[101]	Statistical	Airborne	0.82
	[95]	Statistical	Satellite	0.86
Rapeseed	[93]	Statistical	Airborne × Proximal	0.81
	[63]	Model based, Statistical	Satellite × Proximal	0.86
	[94]	Model based	Satellite × Proximal	0.82
	[98]	Statistical	Satellite	0.97
Soybean	[102–104]	ML/DL, Statistical	Satellite	0.87 to 0.90
	[98,105–111]	Statistical	Satellite	0.49 to 0.98
	[112,113]	ML/DL	Satellite	0.85
	[114]	ML	Satellite	0.61
	[115,116]	ML, Statistical	Satellite	0.86 to 0.90
	[117,118]	ML/DL	Airborne	0.72 to 0.66
	[119]	ML	Airborne	0.89
	[120]	Statistical	Airborne	0.74
	[121]	ML/DL	Satellite × Proximal	0.85
	[122]	ML, Statistical	Satellite × Proximal	0.82
	[123]	ML	Airborne × Proximal	0.97
	[124]	ML/DL, Statistical	Satellite × Proximal	0.67

It is not surprising to find numerous studies that involve soybeans in their research, as soybean is a widely cultivated and economically important crop. A study [111] comparing various spatial resolutions found compelling evidence in favor of higher resolution imagery over lower resolution options. The authors suggest selecting an NDVI resolution that matches or exceeds the current cropland mask resolution, taking into consideration factors such as computation cost. Notably, an interesting finding from another research study [122] is that county-scale models perform relatively poorly in field-scale validation (R^2 = 0.32), particularly in high-yielding fields. However, these county-scale models show a similar performance to field-scale models when evaluated at the county level (R^2 = 0.82).

In the Fruits and Nuts category (Table 5), orchard yield estimation has predominantly been conducted using proximal sensing and airborne sensing, or a combination of both along with satellite data. High-resolution satellite images have also been employed as a standalone method, achieving a satisfactory performance with an R^2-value of 0.87 [125,126]. The high efficiency of these methods could be attributed to their reliance on visual counting and the utilization of high-resolution data, which enable accurate and efficient orchard production estimations. Few studies used above-ground remote sensing to estimate tree production. The correlation between tree production and remotely-assessed features is not generic, and has to be calibrated for each orchard and each year to include climate and site effects [127].

Table 5. Reported methods, platforms, and R^2 for the Fruits and Nuts crop category.

Crop	References	Method	Platform	R^2
Vineyards	[125,128]	Statistical	Satellite × Proximal	0.42–0.87
	[129]	ML	Satellite × Proximal	0.79
	[130]	ML/DL	Proximal	0.91
	[131]	ML, Statistical	Proximal	0.86
Almond	[132]	Statistical	Airborne	0.84
	[133]	ML/DL, Statistical	Satellite × Airborne	0.71
Apple	[134]	ML/DL	Airborne	0.88
Jujube	[135,136]	Model based	Satellite	0.62 to 0.78
Mango	[126]	ML/DL, Statistical	Satellite	0.77
	[127]	ML, Statistical	Airborne	0.77

In relation to root tuber and other crops (Table 6), ML approaches are quite common, achieving a higher (>0.90) performance in terms of accuracy when compared to other methods. In cotton cultivation, developing efficient tools for precise yield estimation before harvest is crucial, and the UAV multispectral remote sensing system holds significant potential for rapidly, accurately, and economically assessing agricultural crop characteristics and yields. The connection between crop growth indicators like LAI and chlorophyll with canopy spectral reflectance allows spectral indices collected during the growing season to be utilized for crop yield estimation, given the correlation between yield and the amount of photosynthetic tissue. This enables wide-scale application, contrasting with traditional measurements of agronomic parameters such as LAI and chlorophyll [137]. Additionally, the feasibility of estimating cotton yield using low-altitude UAV imaging was verified in this study [138].

Table 6. Reported methods, platforms, and R^2 for the Root tuber and other crops category.

Crop	References	Method	Platform	R^2
Potato	[139]	Statistical	Satellite	0.65
	[140]	ML, Statistical	Satellite	0.89
	[141]	ML	Satellite × Proximal	0.86
	[67]	ML	Airborne	0.83
	[142]	ML, Statistical	Proximal	0.72
	[63]	Model based, Statistical	Satellite × Proximal	0.86
Cotton	[143,144]	Statistical	Airborne	0.52 to 0.94
	[145]	ML/DL	Airborne	0.85
	[146]	ML/DL, Statistical	Satellite	0.67
	[147]	Model based	Satellite × Proximal	0.96
	[137]	Statistical	Airborne × Proximal	0.84
	[148]	ML	Airborne × Proximal	0.93
	[138]	ML/DL, Statistical	Airborne	0.97
	[149,150]	ML, Statistical	Airborne	0.77 to 0.91

Table 6. *Cont.*

Crop	References	Method	Platform	R^2
Sweet Potato	[105]	Statistical	Satellite	0.68
Cassava Tuber	[151]	Statistical	Airborne	0.87
Ramie	[152]	Statistical	Airborne	0.66
Milk Thistle	[63]	Model based, Statistical	Satellite ×Proximal	0.86
Grassland *	[153]	ML	Airborne	0.87
	[154]	Statistical	Airborne	0.75
Perennial Ryegrass *	[155]	ML	Airborne	0.93
Perennial Bioenergy Grass *	[156]	Statistical	Satellite	0.88
Brachiaria Pastures *	[157]	ML	Satellite × Airborne	0.75
Miscanthus *	[158]	ML, Statistical, Model based	Airborne	0.79

* Grasses and other fodder crops.

Researchers used mixed data sources, including airborne satellites and proximal sensors, to gather information and insights about leguminous crops (Table 7). Some studies may solely focus on using ML or DL algorithms, while others might combine both approaches or incorporate statistical methods for enhanced accuracy and interpretability. In the study conducted by Minch et al. [159], efficient flight parameters were investigated to create successful models for determining canopy heights, specifically for alfalfa yield estimation. The researchers strongly recommend using a flight parameter within the range of 50–75°, as it is likely to yield optimal data for accurate canopy height estimation in alfalfa fields.

Table 7. Reported methods, platforms, and R^2 for the Leguminous crop category.

Crop	References	Method	Platform	R^2
Alfa Alfa	[160,161]	Statistical	Satellite	0.72 to 0.94
	[162]	ML/DL	Airborne	0.87
	[159]	ML	Airborne	0.84
	[163]	Statistical	Airborne	0.64
	[164]	ML, Statistical	Satellite	0.93
Red Clover	[165]	ML/DL	Airborne	0.90
Chickpea	[166]	ML	Satellite × Proximal	0.92
Snap Bean *	[167]	ML/DL	Airborne	0.98
Peas	[160]	Statistical	Satellite	0.95
Beans *	[168]	Statistical	Airborne × Proximal	0.70
	[169]	ML	Satellite	0.54
	[170]	Statistical	Satellite × Proximal	0.84
Faba Bean	[171]	ML, Statistical	Airborne	0.72

* Included in beans.

The category of cereals encompasses a wide range of methods and platforms, prompting its separation into two tables: cereals (Table 8), and maize and wheat (Table 9).

Table 8. Reported methods, platforms, and R^2 for the cereal crop category.

Crop	Reference	Method	Platform	R^2
Cereal	[172,173]	Statistical	Satellite	0.71
Barley	[95,160,174]	Statistical	Satellite	0.86 to 0.93
	[175]	Statistical	Satellite × Airborne × Proximal	0.70
	[176,177]	Model based, Statistical	Satellite	0.6 to 0.77
	[178]	ML/DL	Airborne × Proximal	0.929
	[179]	ML × Statistical	Satellite × Proximal	0.88
	[180]	ML, Statistical, Model based	Satellite	0.47
Oats	[175]	Statistical	Satellite × Airborne × Proximal	0.79
	[178]	ML/DL	Airborne × Proximal	0.929
	[181]	Statistical	Proximal	0.90
Millet	[105]	Statistical	Satellite	0.68
	[169]	ML	Satellite	0.40
Sorghum	[105,161,182]	Statistical	Satellite	0.25 to 0.81
	[183]	ML/DL	Satellite × Proximal	0.35
	[169]	ML	Satellite	0.44
Rice	[105,184–188]	Statistical	Satellite	0.56 to 0.97
	[114,189–191]	ML	Satellite	0.43 to 0.95
	[192,193]	Model based	Satellite	0.89 to 0.96
	[194]	ML, Model based	Airborne × Proximal	0.75
	[195,196]	ML/DL, Statistical	Airborne × Proximal	0.22 0.51
	[197,198]	ML, Statistical	Airborne	0.76 to 0.8
	[97,199]	ML/DL, Model based	Satellite × Proximal	0.75 to 0.86
	[200]	Statistical, Model based	Satellite	0.80
	[201]	ML/DL	Satellite	0.81
	[202]	ML/DL	Airborne	0.84
	[203]	Statistical	Airborne × Proximal	0.64
	[204]	ML, Statistical	Airborne × Proximal	0.83
	[205]	ML, Statistical	Proximal	0.86
	[206]	Statistical, Model based	Airborne	0.94
	[207,208]	Statistical	Satellite × Proximal	0.66 to 0.90
	[209–212]	Statistical	Airborne	0.74 to 0.83

Table 9. Reported methods, platforms, and R^2 for wheat and maize.

Crop	References	Method	Platform	R^2
Maize	[213]	Statistical	Satellite × Proximal	0.87
	[214]	Statistical	Airborne × Proximal	0.83
	[215]	Statistical	Airborne	0.74
	[105,107,108,111,160,161,169,216–223]	Statistical	Satellite	0.46 to 0.99

Table 9. *Cont.*

Crop	References	Method	Platform	R^2
Maize	[224,225]	Model based, ML/DL	Satellite	0.85
	[226–229]	Model based	Satellite	0.68 to 0.83
	[230]	Model based	Airborne × Proximal	0.855
	[231]	Model based	Proximal	0.68
	[91,114,232–236]	ML	Satellite	0.43 to 0.92
	[237]	ML, Statistical, Model based	Satellite	0.59
	[115,238,239]	ML, Statistical	Satellite	0.48 to 0.91
	[121,240]	ML/DL	Satellite × Proximal	0.75 to 0.85
	[1,102–104,124,241,242]	ML/DL, Statistical	Satellite	0.70 to 0.92
	[243–246]	ML/DL	Airborne	0.57 to 0.93
	[247,248]	ML, Statistical	Satellite × Proximal	0.35 to 0.98
	[249]	ML	Proximal	0.7
	[250]	Model based, ML	Satellite × Proximal	0.58
	[251]	Statistical, Model based	Airborne	0.81
	[97]	ML/DL, Model based	Satellite × Proximal	0.75
	[252]	Statistical, Model based	Satellite	0.73
	[253]	ML, Model based	Satellite	0.76
	[254]	ML x Statistical	Airborne	0.80
Wheat	[80,95,107,111,160,161,174,219,255–263]	Statistical	Satellite	0.37 to 0.99
	[264]	ML/DL, Model based	Satellite	0.83
	[265]	ML/DL	Satellite	0.75
	[1,266]	ML/DL, Statistical	Satellite	0.72 to 0.78
	[176,267–270]	Model based, Statistical	Satellite	0.48 to 0.86
	[180,271,272]	ML, Model based	Satellite	0.55 to 0.75
	[115,273,274]	ML, Statistical	Satellite	0.72 to 0.89
	[25,114,234,275–277]	ML	Satellite	0.51 to 0.99
	[177,278–287]	Model based	Satellite	0.49 to 0.86
	[288–293]	ML/DL	Satellite	0.79 to 0.93
	[294,295]	Model based, Statistical	Proximal	0.698 to 0.77
	[296,297]	Statistical	Proximal	0.46 to 0.48
	[298,299]	ML/DL	Proximal	0.83 to 0.891
	[300]	Model based	Proximal	0.84
	[301]	ML, Statistical	Airborne	0.81
	[302–304]	ML/DL	Airborne	0.62 to 0.85
	[305]	Statistical	Airborne	0.70
	[306–310]	ML	Airborne	0.62 to 0.93
	[311–313]	ML/DL, Statistical	Airborne	0.59 to 0.84
	[314–316]	ML/DL, Statistical	Airborne × Proximal	0.83 to 0.93
	[178,317,318]	Statistical	Airborne × Proximal	0.73 to 0.929
	[319]	ML, Statistical	Airborne × Proximal	0.78

Table 9. *Cont.*

Crop	References	Method	Platform	R^2
Wheat	[179,320]	ML, Statistical	Satellite × Proximal	0.83 to 0.88
	[321,322]	ML/DL, Statistical Model based	Satellite × Proximal	0.68 to 0.91
	[323]	ML/DL, Statistical	Satellite × Proximal	0.50
	[63,324–327]	Statistical, Model based	Satellite × Proximal	0.61 to 0.93
	[328]	ML	Satellite × Proximal	0.89
	[329,330]	ML/DL	Satellite × Proximal	0.63 to 0.86
	[331]	ML/DL, Statistical, Model based	Satellite × Proximal	0.77
	[332]	Model based	Satellite × Proximal	0.49
	[333,334]	Statistical	Satellite × Proximal	0.55 to 0.76
	[175]	Statistical	Satellite × Airborne × Proximal	0.79

In the table focusing on wheat and maize (Table 9), it becomes evident that these crops have received special attention in the literature. The number of research papers dedicated to studying wheat and maize yield prediction is higher compared to other cereals, indicating their prominence in agricultural research. Moreover, the utilization of diverse approaches in predicting the yields of wheat and maize is also noteworthy. Researchers have explored a wide range of methods and platforms, including various machine learning algorithms, statistical models, and remote sensing technologies such as UAV multispectral imaging and satellite data.

Upon close examination of the provided table (Table 9), it becomes evident that a definitive and uniform trend in the methodologies employed for yield prediction is lacking. However, maize and, secondarily, wheat, rice, and soybean have emerged as extensively studied crops through the application of machine learning techniques. This observation is in accordance with the insights documented by Benos et al. [21]. The authors also reported that UAVs are constantly gaining ground against satellites mainly because of their flexibility and ability to provide images with high resolution under any weather conditions. Satellites, on the other hand, could supply time-series over large areas. At the same time, the range of approaches utilized aligns with a prior study [22] that has also observed a variety of methods used in predicting yields for staple crops, emphasizing that each new setting requires appropriate validation.

This information can be valuable for policymakers, farmers, and researchers to make informed decisions, optimize agricultural practices, and address food security challenges in an ever-changing climate and agricultural landscape.

Overall, the results emphasize the importance of assessing an accuracy performance for specific crop categories to enhance yield estimation methods. The highest performance measures (R^2) from various studies were compiled into tables based on crop categories. Machine Learning (ML) techniques, particularly Random Forest, excel in predicting sugar, beverage, and spice crops. Satellite systems, including the Synthetic Aperture Radar (SAR), prove effective for sugarcane yield prediction. In vegetables, ML methods give promising results, considering key vegetation indices. Orchards benefit from proximal and airborne sensing, while leguminous crops are studied using a mix of ML, DL, and statistical methods. Wheat and maize receive extensive attention, employing diverse methods including ML, DL, statistical, and model-based approaches.

Finally, it is necessary to pinpoint an important constraint of this study. Due to the extensive volume of articles analyzed and the diverse methodologies employed therein, specific details concerning the performance assessment were not documented. These details include whether cross-validation was utilized, whether the testing dataset was segregated, or if the same dataset was employed for both training and model validation.

4. Conclusions

By employing this systematic approach to data analysis, the study aims to provide valuable insights into the trends, patterns, and contributions of different methodologies and technologies in the field of crop yield prediction using remote sensing tools.

Understanding the geographical distribution of research efforts and the significant academic institution in this domain is crucial for comprehending the research landscape. Our research revealed that China (93 articles with over 1800 citations) and the USA (58 articles with over 1600 citations) are key contributors to the field of crop yield prediction using remote sensing techniques. Based on the results, cereal crops (185 papers) emerged as the most commonly studied for yield estimation with wheat being the most predominant crop. Among the remote sensing platforms, satellites (62%) were the most frequently employed platforms followed by airborne (30%) and proximal sensors (27%). The study extensively evaluated various algorithms and models for predicting crop yields based on remote sensing data. In terms of methodologies, machine learning was featured in 142 articles, while deep learning was employed in 62 articles for the purpose of yield prediction. Furthermore, statistical methods were utilized in 157 articles, and model-based approaches were featured in 60 articles as mechanisms for predicting crop yields. The performance of machine learning and deep learning methods has shown high accuracy in crop yield prediction, while other techniques have also demonstrated success depending on the crop and method. These insights offer a comprehensive understanding of the research domain and could guide future advancements in remote sensing-based crop yield estimations.

By consolidating and analyzing data from multiple studies, our research contributes to a comprehensive understanding of the current state of remote sensing-based crop yield estimation. This synthesis helps identify trends, gaps, and areas of progress in the research domain, providing valuable guidance for future studies in this area. The identified influential countries, methodologies, and successful algorithms can serve as a foundation for designing more effective and targeted research.

The findings of this study hold the potential to advance the accuracy and applicability of remote sensing-based crop yield estimation techniques. This, in turn, could contribute to improved agricultural management practices, increased food security, and sustainable agriculture. The comprehensive overview provided by this research empowers the scientific community to make informed decisions and develop innovative approaches to further enhance the accuracy and utility of remote sensing-based crop yield estimation methods in the future.

Author Contributions: N.D.: principal investigation, research supervision, data collection, data preprocessing, study design and methodology, statistical and formal analysis, and manuscript writing; E.A.: investigation, research supervision, study design and methodology, data curation, statistical and formal analysis, cross validation, and manuscript writing; E.L. and O.K.: data collection, data preprocessing, and manuscript review and editing; D.K. and S.F.: principal investigation, research supervision and manuscript revision and editing. All authors have read and agreed to the published version of the manuscript.

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Appendix A

Table A1 includes the list of studies that were analyzed in the context of the systematic review.

Table A1. List of studies included in the systematic review.

	Article	References	Crop	Method	Platform	Year
1	Comparison of earth observing-1 ALI and Landsat ETM+ for crop identification and yield prediction in Mexico	[219]	Maize, Wheat	Statistical	Satellite	2003
2	Early prediction of crop production using drought indices at different timescales and remote sensing data: application in the Ebro Valley (north-east Spain)	[174]	Wheat, Barley	Statistical	Satellite	2006
3	Estimating crop yield from multi-temporal satellite data using multivariate regression and neural network techniques	[102]	Maize, Soybean	ML/DL Statistical	Satellite	2007
4	Mapping sunflower yield as affected by Ridolfia segetum patches and elevation by applying evolutionary product unit neural networks to remote sensed data	[92]	Sunflower	ML/DL Statistical	Airborne	2008
5	Use of Vegetation Health Data for Estimation of Aus Rice Yield in Bangladesh	[184]	Rice	Statistical	Satellite	2009
6	Integrating Vegetation Indices Models and Phenological Classification with Composite SAR and Optical Data for Cereal Yield Estimation in Finland (Part I)	[175]	Summer Wheat, Barley, and Oats	Statistical	Satellite × Airborne × Proximal	2010
7	Cereal Yield Modeling in Finland Using Optical and Radar Remote Sensing	[172]	Cereal	Statistical	Satellite	2010
8	Application of vegetation indices for agricultural crop yield prediction using neural network techniques	[245]	Maize	ML/DL	Airborne	2010
9	Using SPOT data and leaf area index for rice yield estimation in Egyptian Nile delta	[185]	Rice	Statistical	Satellite	2011
10	Estimating regional wheat yield from the shape of decreasing curves of green area index temporal profiles retrieved from MODIS data	[255]	Wheat	Statistical	Satellite	2012
11	Forecasting regional sugarcane yield based on time integral and spatial aggregation of MODIS NDVI	[73]	Sugarcane	Statistical	Satellite × Proximal	2013
12	Estimating regional winter wheat yield by assimilation of time series of HJ-1 CCD NDVI into WOFOST-ACRM model with Ensemble Kalman Filter	[284]	Wheat	Model based	Satellite	2013
13	Enhanced processing of 1-km spatial resolution fAPAR time series for sugarcane yield forecasting and monitoring	[77]	Sugarcane	Statistical	Satellite	2013
14	Remote sensing based yield estimation in a stochastic framework—Case study of durum wheat in Tunisia	[256]	Wheat	Statistical	Satellite	2013
15	Rice yield forecasting models using satellite imagery in Egypt	[186]	Rice	Statistical	Satellite	2013
16	Remotely Sensed Rice Yield Prediction Using Multi-Temporal NDVI Data Derived from NOAA's-AVHRR	[187]	Rice	Statistical	Satellite	2013

Table A1. *Cont.*

	Article	References	Crop	Method	Platform	Year
17	Corn yield forecasting in northeast China using remotely sensed spectral indices and crop phenology metrics	[218]	Maize	Statistical	Satellite	2014
18	Estimation of the dynamics and yields of cereals in a semi-arid area using remote sensing and the SAFY growth model	[176]	Wheat and Barley	Model based Statistical	Satellite	2014
19	The use of ALOS/PALSAR data for estimating sugarcane productivity	[75]	Sugarcane	Statistical	Satellite	2014
20	Toward a satellite-based system of sugarcane yield estimation and forecasting in smallholder farming conditions: A case study on reunion island	[76]	Sugarcane	Statistical	Satellite	2014
21	Combined spectral and spatial modeling of corn yield based on aerial images and crop surface models acquired with an unmanned aircraft system	[215]	Maize	Statistical	Airborne	2014
22	Using a remote sensing-supported hydro-agroecological model for field-scale simulation of heterogeneous crop growth and yield: Application for wheat in central Europe	[326]	Wheat	Model based Statistical	Satellite × Proximal	2015
23	Improving winter wheat yield estimation by assimilation of the leaf area index from Landsat TM and MODIS data into the WOFOST model	[267]	Wheat	Model based Statistical	Satellite	2015
24	Assimilation of two variables derived from hyperspectral data into the DSSAT-CERES model for grain yield and quality estimation	[294]	Wheat	Model based Statistical	Proximal	2015
25	Assessment of multimodel ensemble seasonal hindcasts for satellite-based rice yield prediction	[208]	Rice	Statistical	Satellite × Proximal	2016
26	Early Maize Yield Forecasting from Remotely Sensed Temperature/Vegetation Index Measurements	[217]	Maize	Statistical	Satellite	2016
27	Correlation maps to assess soybean yield from EVI data in Paraná State, Brazil	[106]	Soybean	Statistical	Satellite	2016
28	Estimation of winter wheat biomass and yield by combining the aquacrop model and field hyperspectral data	[295]	Wheat	Model based Statistical	Proximal	2016
29	Improving spring maize yield estimation at field scale by assimilating time-series HJ-1 CCD data into the WOFOST model using a new method with fast algorithms	[229]	Maize	Model based	Satellite	2016
30	Prediction of potato crop yield using precision agriculture techniques	[139]	Potato	Statistical	Satellite	2016
31	Rice yield estimation using below cloud remote sensing images acquired by unmanned airborne vehicle system	[210]	Rice	Statistical	Airborne	2016
32	Cotton growth modeling and assessment using unmanned aircraft system visual-band imagery	[143]	Cotton	Statistical	Airborne	2016

Table A1. *Cont.*

	Article	References	Crop	Method	Platform	Year
33	Daily mapping of 30 m LAI and NDVI for grape yield prediction in California vineyards	[128]	Vineyards	Statistical	Satellite × Proximal	2017
34	Analysis of meteorological variations on wheat yield and its estimation using remotely sensed data. A case study of selected districts of Punjab Province, Pakistan (2001–14)	[257]	Wheat	Statistical	Satellite	2017
35	Forecasting winter wheat yields using MODIS NDVI data for the Central Free State region	[258]	Wheat	Statistical	Satellite	2017
36	Using MODIS Data to Predict Regional Corn Yields	[216]	Maize	Statistical	Satellite	2017
37	Improving Winter Wheat Yield Estimation from the CERES-Wheat Model to Assimilate Leaf Area Index with Different Assimilation Methods and Spatio-Temporal Scales	[327]	Wheat	Model based	Satellite × Proximal	2017
38	Estimation of winter wheat above-ground biomass using unmanned aerial vehicle-based snapshot hyperspectral sensor and crop height improved models	[319]	Wheat	ML Statistical	Airborne × Proximal	2017
39	Assimilation of temporal-spatial leaf area index into the CERES-Wheat model with ensemble Kalman filter and uncertainty assessment for improving winter wheat yield estimation	[300]	Wheat	Model based	Proximal	2017
40	Winter Wheat Production Estimation Based on Environmental Stress Factors from Satellite Observations	[268]	Wheat	Model based Statistical	Satellite	2018
41	Exploring the potential of high-resolution worldview-3 Imagery for estimating yield of mango	[126]	Mango	ML/DL Statistical	Satellite	2018
42	Utilizing Collocated Crop Growth Model Simulations to Train Agronomic Satellite Retrieval Algorithms	[224]	Maize	Model based ML/DL	Satellite	2018
43	Regional crop gross primary productivity and yield estimation using fused Landsat-MODIS data	[160]	Alfalfa, Barley, Maize, Wheat, Peas	Statistical	Satellite	2018
44	Assessing the variability of corn and soybean yields in central Iowa using high spatiotemporal resolution multi-satellite imagery	[108]	Maize and Soybean	Statistical	Satellite	2018
45	Remote estimation of rapeseed yield with unmanned aerial vehicle (UAV) imaging and spectral mixture analysis	[93]	Rapeseed	Statistical	Airborne × Proximal	2018
46	Spatiotemporal analysis of LANDSAT Data for crop yield prediction	[74]	Sugarcane	Statistical	Satellite	2018
47	Multi-year mapping of major crop yields in an irrigation district from high spatial and temporal resolution vegetation index	[91]	Maize, Sunflower	ML	Satellite	2018

Table A1. *Cont.*

	Article	References	Crop	Method	Platform	Year
48	Forecasting of cereal yields in a semi-arid area using the simple algorithm for yield estimation (Safy) agro-meteorological model combined with optical spot/hrv images	[177]	Wheat, Barley	Model based	Satellite	2018
49	Crop yield estimation using satellite images: Comparison of linear and non-linear model	[103]	Soybean, Maize	ML/DL Statistical	Satellite	2018
50	Estimation of Maize grain yield using multispectral satellite data sets (SPOT 5) and the random forest algorithm	[236]	Maize	ML	Satellite	2018
51	Estimating rice production in the Mekong Delta, Vietnam, utilizing time series of Sentinel-1 SAR data	[189]	Rice	ML	Satellite	2018
52	Modeling and Testing of Growth Status for Chinese Cabbage and White Radish with UAV-Based RGB Imagery	[85]	Chinese Cabbage, and White Radish	Statistical	Airborne	2018
53	Mango yield mapping at the orchard scale based on tree structure and land cover assessed by UAV	[127]	Mango	Statistical	Airborne	2018
54	Forecasting maize yield at field scale based on high-resolution satellite imagery	[220]	Maize	Statistical	Satellite	2018
55	Improving Site-Specific Maize Yield Estimation by Integrating Satellite Multispectral Data into a Crop Model	[226]	Maize	Model based	Satellite	2019
56	Determination of Appropriate Remote Sensing Indices for Spring Wheat Yield Estimation in Mongolia	[334]	Wheat	Statistical	Satellite × Proximal	2019
57	Maize yield estimation in West Africa from crop process-induced combinations of multi-domain remote sensing indices	[237]	Maize	ML Statistical Model based	Satellite	2019
58	A high-resolution, integrated system for rice yield forecasting at district level	[192]	Rice	Model based	Satellite	2019
59	Assimilating MODIS data-derived minimum input data set and water stress factors into CERES-Maize model improves regional corn yield predictions	[227]	Maize	Model based	Satellite	2019
60	County-level soybean yield prediction using deep CNN-LSTM model	[112]	Soybean	ML/DL	Satellite	2019
61	Synergistic integration of optical and microwave satellite data for crop yield estimation	[115]	Maize, Wheat, Soybean	ML Statistical	Satellite	2019
62	Using Solar-Induced Chlorophyll Fluorescence Observed by OCO-2 to Predict Autumn Crop Production in China	[105]	Rice, Maize, Sorghum, Millet, Sweet Potato, and Soybeans	Statistical	Satellite	2019
63	Crop yield estimation using time-series MODIS data and the effects of cropland masks in Ontario, Canada	[107]	Maize and Soybean	Statistical	Satellite	2019

Table A1. *Cont.*

	Article	References	Crop	Method	Platform	Year
64	California Almond Yield Prediction at the Orchard Level with a Machine Learning Approach	[133]	Almonds	ML/DL Statistical	Satellite × Airborne	2019
65	Joint assimilation of leaf area index and soil moisture from sentinel-1 and sentinel-2 data into the WOFOST model for winter wheat yield estimation	[285]	Wheat	Model based	Satellite	2019
66	High resolution wheat yield mapping using Sentinel-2	[274]	Wheat	ML Statistical	Satellite	2019
67	Evaluation of regional estimates of winter wheat yield by assimilating three remotely sensed reflectance datasets into the coupled WOFOST–PROSAIL model	[278]	Wheat	Model based	Satellite	2019
68	Assimilating Soil Moisture Retrieved from Sentinel-1 and Sentinel-2 Data into WOFOST Model to Improve Winter Wheat Yield Estimation	[286]	Wheat	Model based	Satellite	2019
69	Improving jujube fruit tree yield estimation at the field scale by assimilating a single Landsat remotely-sensed LAI into the WOFOST model	[135]	Jujube	Model based	Satellite	2019
70	Assimilation of remotely-sensed LAI into WOFOST model with the SUBPLEX algorithm for improving the field-scale jujube yield forecasts	[136]	Jujube	Model based	Satellite	2019
71	Potato yield prediction using machine learning techniques and Sentinel 2 data	[140]	Potato	ML Statistical	Satellite	2019
72	Assessing Multiple Years' Spatial Variability of Crop Yields Using Satellite Vegetation Indices	[80]	Wheat, Sunflower, and Coriander	Statistical	Satellite	2019
73	Field-scale rice yield estimation using sentinel-1A synthetic aperture radar (SAR) data in coastal saline region of Jiangsu Province, China	[188]	Rice	Statistical	Satellite	2019
74	Rice Yield Estimation Using Parcel-Level Relative Spectral Variables From UAV-Based Hyperspectral Imagery	[211]	Rice	Statistical	Airborne	2019
75	Establishment of Plot-Yield Prediction Models in Soybean Breeding Programs Using UAV-Based Hyperspectral Remote Sensing	[120]	Soybean	Statistical	Airborne	2019
76	Principal variable selection to explain grain yield variation in winter wheat from features extracted from UAV imagery	[301]	Wheat	ML Statistical	Airborne	2019
77	Biomass prediction of heterogeneous temperate grasslands using an SFM approach based on UAV imaging.	[154]	Grassland	Statistical	Airborne	2019
78	Accuracy of carrot yield forecasting using proximal hyperspectral and satellite multispectral data	[83]	Carrot	Statistical	Satellite	2020

Table A1. *Cont.*

	Article	References	Crop	Method	Platform	Year
79	Sight for Sorghums: Comparisons of Satellite- and Ground-Based Sorghum Yield Estimates in Mali	[182]	Sorghum	Statistical	Satellite	2020
80	Combining multi-source data and machine learning approaches to predict winter wheat yield in the conterminous United States	[329]	Wheat	ML/DL	Satellite × Proximal	2020
81	Multilevel Deep Learning Network for County-Level Corn Yield Estimation in the U.S. Corn Belt	[240]	Maize	ML/DL	Satellite × Proximal	2020
82	Assessing the benefit of satellite-based Solar-Induced Chlorophyll Fluorescence in crop yield prediction	[121]	Maize and Soybean	ML/DL	Satellite × Proximal	2020
83	Estimation of potato yield using satellite data at a municipal level: A machine learning approach	[141]	Potato	ML	Satellite × Proximal	2020
84	Rice Yield Estimation Based on an NPP Model With a Changing Harvest Index	[193]	Rice	Model based	Satellite	2020
85	To blend or not to blend? A framework for nationwide landsat-MODIS data selection for crop yield prediction	[95]	Canola, Wheat, and Barley	Statistical	Satellite	2020
86	Combining Optical, Fluorescence, Thermal Satellite, and Environmental Data to Predict County-Level Maize Yield in China Using Machine Learning Approaches	[241]	Maize	ML/DL	Satellite	2020
87	Prediction of winter wheat yield based on multi-source data and machine learning in China	[265]	Wheat	ML/DL	Satellite	2020
88	The ability of sun-induced chlorophyll fluorescence from OCO-2 and MODIS-EVI to monitor spatial variations of soybean and maize yields in the midwestern USA	[104]	Maize and Soybean	ML/DL Statistical	Satellite	2020
89	Reconstruction of time series leaf area index for improving wheat yield estimates at field scales by fusion of Sentinel-2, -3 and MODIS imagery	[263]	Wheat	Statistical	Satellite	2020
90	Using HJ-CCD image and PLS algorithm to estimate the yield of field-grown winter wheat	[259]	Wheat	Statistical	Satellite	2020
91	Predicting soybean yield at the regional scale using remote sensing and climatic data	[109]	Soybean	Statistical	Satellite	2020
92	High-Resolution Soybean Yield Mapping Across the US Midwest Using Subfield Harvester Data	[122]	Soybean	ML Statistical	Satellite × Proximal	2020
93	Estimating Wheat Grain Yield Using Sentinel-2 Imagery and Exploring Topographic Features and Rainfall Effects on Wheat Performance in Navarre, Spain	[320]	Wheat	ML Statistical	Satellite × Proximal	2020
94	Predicting wheat yield at the field scale by combining high-resolution Sentinel-2 satellite imagery and crop modelling	[333]	Wheat	Statistical	Satellite × Proximal	2020

Table A1. *Cont.*

	Article	References	Crop	Method	Platform	Year
95	Vineyard yield estimation using 2-D proximal sensing: A multitemporal approach	[129]	Vineyards	ML	Satellite × Proximal	2020
96	Yield prediction by machine learning from UAS-based multi-sensor data fusion in soybean	[123]	Soybean	ML	Airborne × Proximal	2020
97	Remote sensing techniques and stable isotopes as phenotyping tools to assess wheat yield performance: Effects of growing temperature and vernalization	[317]	Wheat	Statistical	Airborne × Proximal	2020
98	Crop yield prediction using multitemporal UAV data and spatio-temporal deep learning models	[178]	Wheat, Barley, and Oats	ML/DL	Airborne × Proximal	2020
99	Validation of white oat yield estimation models using vegetation indices	[181]	White Oat	Statistical	Proximal	2020
100	The role of topography, soil, and remotely sensed vegetation condition towards predicting crop yield	[124]	Maize and Soybean	ML/DL Statistical	Satellite × Proximal	2020
101	Deep phenotyping of yield-related traits in wheat	[296]	Wheat	Statistical	Proximal	2020
102	High-Throughput Field Phenotyping Traits of Grain Yield Formation and Nitrogen Use Efficiency: Optimizing the Selection of Vegetation Indices and Growth Stages	[297]	Wheat	Statistical	Proximal	2020
103	A study on trade-offs between spatial resolution and temporal sampling density for wheat yield estimation using both thermal and calendar time	[260]	Wheat	Statistical	Satellite	2020
104	Estimating yields of household fields in rural subsistence farming systems to study food security in Burkina Faso	[169]	Beans, Maize, Sorghum, and Millet	ML	Satellite	2020
105	Ensemble Machine Learning Methods to Estimate the Sugarcane Yield Based on Remote Sensing Information	[70]	Sugarcane	ML Statistical	Satellite	2020
106	Integrating Landsat-8 and Sentinel-2 Time Series Data for Yield Prediction of Sugarcane Crops at the Block Level	[78]	Sugarcane	ML Statistical	Satellite	2020
107	Alfalfa yield prediction using UAV-based hyperspectral imagery and ensemble learning	[162]	Alfa Alfa	ML/DL	Airborne	2020
108	Estimation of the yield and plant height of winter wheat using UAV-based hyperspectral images	[312]	Wheat	ML/DL	Airborne	2020
109	Aerial hyperspectral imagery and deep neural networks for high-throughput yield phenotyping in wheat	[313]	Wheat	ML/DL	Airborne	2020
110	Modified Red Blue Vegetation Index for Chlorophyll Estimation and Yield Prediction of Maize from Visible Images Captured by UAV	[243]	Maize	ML/DL	Airborne	2020

Table A1. *Cont.*

	Article	References	Crop	Method	Platform	Year
111	A Canopy Information Measurement Method for Modern Standardized Apple Orchards Based on UAV Multimodal Information	[134]	Apple	ML/DL	Airborne	2020
112	Soybean yield prediction from UAV using multimodal data fusion and deep learning	[117]	Soybean	ML/DL	Airborne	2020
113	Nondestructive estimation of potato yield using relative variables derived from multi-period LAI and hyperspectral data based on weighted growth stage	[67]	Potato	ML	Airborne	2020
114	Use of UAS Multispectral Imagery at Different Physiological Stages for Yield Prediction and Input Resource Optimization in Corn	[246]	Maize	ML/DL Statistical	Airborne	2020
115	Predicting Biomass and Yield in a Tomato Phenotyping Experiment Using UAV Imagery and Random Forest	[89]	Tomato	ML	Airborne	2020
116	Correlating the Plant Height of Wheat with Above-Ground Biomass and Crop Yield Using Drone Imagery and Crop Surface Model, A Case Study from Nepal	[305]	Wheat	Statistical	Airborne	2020
117	Yield estimation in cotton using UAV-based multi-sensor imagery	[144]	Cotton	Statistical	Airborne	2020
118	Bayesian Calibration of the Aquacrop-OS Model for Durum Wheat by Assimilation of Canopy Cover Retrieved from VENµS Satellite Data	[280]	Wheat	Model based		2020
119	Crop yield prediction through proximal sensing and machine learning algorithms	[142]	Potato	ML Statistical		2020
120	Seasonal bean yield forecast for non-irrigated croplands through climate and vegetation index data: Geospatial effects	[170]	Beans	Statistical	Satellite × Proximal	2021
121	A deep learning framework under attention mechanism for wheat yield estimation using remotely sensed indices in the Guanzhong Plain, PR China	[330]	Wheat	ML/DL	Satellite × Proximal	2021
122	Geographically and temporally weighted neural network for winter wheat yield prediction	[331]	Wheat	ML/DL Model based Statistical	Satellite × Proximal	2021
123	Improving Wheat Yield Estimates by Integrating a Remotely Sensed Drought Monitoring Index Into the Simple Algorithm for Yield Estimate Model	[332]	Wheat	Model based	Satellite × Proximal	2021
124	Integration of a crop growth model and deep learning methods to improve satellite-based yield estimation of winter wheat in henan province, china	[322]	Wheat	ML/DL Model based	Satellite × Proximal	2021
125	Cereal yield forecasting with satellite drought-based indices, weather data and regional climate indices using machine learning in morocco	[179]	Wheat, Barley	ML Statistical	Satellite × Proximal	0.88

Table A1. *Cont.*

	Article	References	Crop	Method	Platform	Year
126	A million kernels of truth: Insights into scalable satellite maize yield mapping and yield gap analysis from an extensive ground dataset in the US Corn Belt	[228]	Maize	Model based	Satellite	2021
127	Yield forecasting with machine learning and small data: What gains for grains?	[180]	Wheat, Barley	ML Statistical Model based	Satellite	2021
128	The ARYA crop yield forecasting algorithm: Application to the main wheat exporting countries	[287]	Wheat	Model based	Satellite	2021
129	Corn Biomass Estimation by Integrating Remote Sensing and Long-Term Observation Data Based on Machine Learning Techniques	[242]	Maize	ML/DL	Satellite	2021
130	Exploiting Hierarchical Features for Crop Yield Prediction Based on 3-D Convolutional Neural Networks and Multikernel Gaussian Process	[293]	Wheat	ML/DL	Satellite	2021
131	Crop yield prediction from multi-spectral, multi-temporal remotely sensed imagery using recurrent 3D convolutional neural networks	[1]	Wheat, Maize	ML/DL Statistical	Satellite	2021
132	Prediction of Crop Yield Using Phenological Information Extracted from Remote Sensing Vegetation Index	[232]	Maize	ML	Satellite	2021
133	NDVI Variation and Yield Prediction in Growing Season: A Case Study with Tea in Tanuyen Vietnam	[81]	Tea	ML	Satellite	2021
134	Forecasting Oil Crops Yields on the Regional Scale Using Normalized Difference Vegetation Index	[98]	Sunflower, Winter Rape, and Soybean	Statistical	Satellite	2021
135	Relationship between MODIS Derived NDVI and Yield of Cereals for Selected European Countries	[173]	Cereal	Statistical	Satellite	2021
136	Remote and proximal sensing-derived spectral indices and biophysical variables for spatial variation determination in vineyards	[125]	Vineyards	Statistical	Satellite × Proximal	2021
137	Machine learning models based on remote and proximal sensing as potential methods for in-season biomass yields prediction in commercial sorghum fields	[183]	Sorghum	ML/DL	Satellite × Proximal	2021
138	Machine learning models based on remote and proximal sensing as potential methods for in-season biomass yields prediction in commercial sorghum fields	[247]	Maize	ML Statistical	Satellite × Proximal	2021
139	Long-Term Hindcasts of Wheat Yield in Fields Using Remotely Sensed Phenology, Climate Data and Machine Learning	[321]	Wheat	ML/DL Statistical Model based	Satellite × Proximal	2021

Table A1. *Cont.*

	Article	References	Crop	Method	Platform	Year
140	Predicting Maize Yield at the Plot Scale of Different Fertilizer Systems by Multi-Source Data and Machine Learning Methods	[248]	Maize	ML Statistical	Satellite × Proximal	2021
141	Forecasting Rainfed Agricultural Production in Arid and Semi-Arid Lands Using Learning Machine Methods: A Case Study	[166]	Chickpea	ML	Satellite × Proximal	2021
142	Wheat yield prediction based on unmanned aerial vehicles-collected red–green–blue imagery	[316]	Wheat	ML/DL Statistical	Airborne × Proximal	2021
143	Entropy Weight Ensemble Framework for Yield Prediction of Winter Wheat Under Different Water Stress Treatments Using Unmanned Aerial Vehicle-Based Multispectral and Thermal Data	[318]	Wheat	Statistical	Airborne × Proximal	2021
144	Assimilation of LAI Derived from UAV Multispectral Data into the SAFY Model to Estimate Maize Yield	[230]	Maize	Model based	Airborne × Proximal	2021
145	Grain Yield Estimation in Rice Breeding Using Phenological Data and Vegetation Indices Derived from UAV Images	[194]	Rice	ML Model based	Airborne × Proximal	2021
146	The feasibility of hand-held thermal and UAV-based multispectral imaging for canopy water status assessment and yield prediction of irrigated African eggplant (*Solanum aethopicum* L.)	[86]	African Eggplant	Statistical	Airborne × Proximal	2021
147	Improving Biomass and Grain Yield Prediction of Wheat Genotypes on Sodic Soil Using Integrated High-Resolution Multispectral, Hyperspectral, 3D Point Cloud, and Machine Learning Techniques	[314]	Wheat	ML/DL Statistical	Airborne × Proximal	2021
148	Assimilation of coupled microwave/thermal infrared soil moisture profiles into a crop model for robust maize yield estimates over Southeast United States	[231]	Maize	Model based	Proximal	2021
149	An LSTM neural network for improving wheat yield estimates by integrating remote sensing data and meteorological data in the Guanzhong Plain, PR China	[298]	Wheat	ML/DL	Proximal	2021
150	Crop yield prediction based on agrometeorological indexes and remote sensing data	[249]	Maize	ML	Proximal	2021
151	A satellite-based method for national winter wheat yield estimating in china	[279]	Wheat	Model based	Satellite	2021
152	Estimation of Winter Wheat Yield in Arid and Semiarid Regions Based on Assimilated Multi-Source Sentinel Data and the CERES-Wheat Model	[281]	Wheat	Model based	Satellite	2021
153	Winter wheat yield estimation based on assimilated Sentinel-2 images with the CERES-Wheat model	[270]	Wheat	Model based Statistical	Satellite	2021

Table A1. *Cont.*

	Article	References	Crop	Method	Platform	Year
154	Sugarcane Yield Mapping Using High-Resolution Imagery Data and Machine Learning Technique	[71]	Sugarcane	ML	Satellite	2021
155	Estimation of Crop Yield From Combined Optical and SAR Imagery Using Gaussian Kernel Regression	[190]	Rice	ML	Satellite	2021
156	Integrated method for rice cultivation monitoring using Sentinel-2 data and Leaf Area Index	[191]	Rice	ML	Satellite	2021
157	Remote Sensing-Based Estimation of Advanced Perennial Grass Biomass Yields for Bioenergy	[156]	Perennial Bioenergy Grass	Statistical	Satellite	2021
158	Prediction of Crop Yield for New Mexico Based on Climate and Remote Sensing Data for the 1920–2019 Period	[161]	Alfalfa, Wheat, Maize, and Sorghum	Statistical	Satellite	2021
159	Broadacre Crop Yield Estimation Using Imaging Spectroscopy from Unmanned Aerial Systems (UAS): A Field-Based Case Study with Snap Bean	[167]	Snap Bean	ML/DL	Airborne	2021
160	Combining spectral and textural information in UAV hyperspectral images to estimate rice grain yield	[197]	Rice	ML Statistical	Airborne	2021
161	Temporal Vegetation Indices and Plant Height from Remotely Sensed Imagery Can Predict Grain Yield and Flowering Time Breeding Value in Maize via Machine Learning Regression	[254]	Maize	ML Statistical	Airborne	2021
162	Rice Yield Estimation Based on Vegetation Index and Florescence Spectral Information from UAV Hyperspectral Remote Sensing	[212]	Rice	Statistical	Airborne	2021
163	Creating a Field-Wide Forage Canopy Model Using UAVs and Photogrammetry Processing	[159]	Alfa Alfa	ML	Airborne	2021
164	Maize yield prediction at an early developmental stage using multispectral images and genotype data for preliminary hybrid selection	[244]	Maize	ML/DL	Airborne	2021
165	The Application of an Unmanned Aerial System and Machine Learning Techniques for Red Clover-Grass Mixture Yield Estimation under Variety Performance Trials.	[165]	Red Clover	ML/DL	Airborne	2021
166	Predicting within-field variability in grain yield and protein content of winter wheat using UAV-based multispectral imagery and machine learning approaches	[302]	Winter Wheat	ML/DL	Airborne	2021
167	Cotton yield estimation model based on machine learning using time series UAV remote sensing data	[145]	Cotton	ML/DL	Airborne	2021

Table A1. *Cont.*

	Article	References	Crop	Method	Platform	Year
168	Assessment of Ensemble Learning to Predict Wheat Grain Yield Based on UAV-Multispectral Reflectance	[307]	Wheat	ML	Airborne	2021
169	Prediction of plant-level tomato biomass and yield using machine learning with unmanned aerial vehicle imagery	[84]	Processing Tomato	ML Statistical	Airborne	2021
170	Improving Accuracy of Herbage Yield Predictions in Perennial Ryegrass with UAV-Based Structural and Spectral Data Fusion and Machine Learning	[155]	Perennial Ryegrass	ML	Airborne	2021
171	Unmanned Aircraft System- (UAS-) Based High-Throughput Phenotyping (HTP) for Tomato Yield Estimation	[90]	Tomato	ML	Airborne	2021
172	Estimation of Fractional Photosynthetically Active Radiation From a Canopy 3D Model; Case Study: Almond Yield Prediction	[132]	Almonds	Statistical	Airborne	2021
173	Combining Spectral and Texture Features of UAV Images for the Remote Estimation of Rice LAI throughout the Entire Growing Season	[209]	Rice	Statistical	Airborne	2021
174	Predicting Table Beet Root Yield with Multispectral UAS Imagery	[87]	Table Beet	Statistical	Airborne	2021
175	Alfalfa (*Medicago sativa* L.) crop vigor and yield characterization using high-resolution aerial multispectral and thermal infrared imaging technique	[163]	Alfa Alfa	Statistical	Airborne	2021
176	Ramie Yield Estimation Based on UAV RGB Images	[152]	Ramie	Statistical	Airborne	2021
177	Early Estimation of Olive Production from Light Drone Orthophoto, through Canopy Radius	[99]	Olive Tree	Statistical	Airborne	2021
178	Predicting rice yield at pixel scale through synthetic use of crop and deep learning models with satellite data in South and North Korea	[199]	Rice	ML/DL Model based	Satellite × Proximal	2022
179	Improving wheat yield estimates using data augmentation models and remotely sensed biophysical indices within deep neural networks in the Guanzhong Plain, PR China	[323]	Wheat	ML/DL Statistical	Satellite × Proximal	2022
180	Coupling remote sensing and crop growth model to estimate national wheat yield in Ethiopia	[324]	Wheat	Statistical Model based	Satellite × Proximal	2022
181	Assessing the impacts of natural disasters on rice production in Jiangxi, China	[207]	Rice	Statistical	Satellite × Proximal	2022
182	Estimating Groundnut Yield in Smallholder Agriculture Systems Using PlanetScope Data	[96]	Groundnut	ML Statistical	Satellite × Proximal	2022
183	A dataset of winter wheat aboveground biomass in China during 2007–2015 based on data assimilation	[282]	Wheat	Model based	Satellite	2022

Table A1. *Cont.*

	Article	References	Crop	Method	Platform	Year
184	Accurately mapping global wheat production system using deep learning algorithms	[288]	Wheat	ML/DL	Satellite	2022
185	Improving the Forecasting of Winter Wheat Yields in Northern China with Machine Learning–Dynamical Hybrid Subseasonal-to-Seasonal Ensemble Prediction	[275]	Wheat	ML	Satellite	2022
186	Integrating climate and satellite remote sensing data for predicting county-level wheat yield in China using machine learning methods	[25]	Wheat	ML	Satellite	2022
187	A Geographically Weighted Random Forest Approach to Predict Corn Yield in the US Corn Belt	[233]	Maize	ML	Satellite	2022
188	Spatial Rice Yield Estimation Using Multiple Linear Regression Analysis, Semi-Physical Approach and Assimilating SAR Satellite Derived Products with DSSAT Crop Simulation Model	[200]	Rice	Statistical Model based	Satellite	2022
189	Regional Yield Estimation for Sugarcane Using MODIS and Weather Data: A Case Study in Florida and Louisiana, United States of America	[79]	Sugarcane	Model based	Satellite	2022
190	Rice Yield Prediction and Model Interpretation Based on Satellite and Climatic Indicators Using a Transformer Method	[201]	Rice	ML/DL	Satellite	2022
191	Extreme Gradient Boosting for yield estimation compared with Deep Learning approaches	[113]	Soybean	ML/DL	Satellite	2022
192	Developing a Dual-Stream Deep-Learning Neural Network Model for Improving County-Level Winter Wheat Yield Estimates in China	[289]	Wheat	ML/DL	Satellite	2022
193	A New Framework for Winter Wheat Yield Prediction Integrating Deep Learning and Bayesian Optimization	[290]	Wheat	ML/DL	Satellite	2022
194	Improving Winter Wheat Yield Forecasting Based on Multi-Source Data and Machine Learning	[277]	Wheat	ML Statistical	Satellite	2022
195	Remote Sensing—Based Assessment of the Water-Use Efficiency of Maize over a Large, Arid, Regional Irrigation District	[221]	Maize	Statistical	Satellite	2022
196	In-Season Wheat Yield Forecasting at High Resolution Using Regional Climate Model and Crop Model	[283]	Wheat	Model based	Satellite	2022
197	Winter Wheat Yield Prediction Using an LSTM Model from MODIS LAI Products	[291]	Wheat	ML/DL	Satellite	2022

Table A1. *Cont.*

	Article	References	Crop	Method	Platform	Year
198	Downscaling solar-induced chlorophyll fluorescence for field-scale cotton yield estimation by a two-step convolutional neural network	[146]	Cotton	ML/DL Statistical	Satellite	2022
199	High-resolution crop yield and water productivity dataset generated using random forest and remote sensing	[234]	Maize, Wheat	ML	Satellite	2022
200	Soybean yield prediction using remote sensing in Southwestern Piauí State, Brazil.	[110]	Soybean	Statistical	Satellite	2022
201	A generalized model to predict large-scale crop yields integrating satellite-based vegetation index time series and phenology metrics	[222]	Maize	Statistical	Satellite	2022
202	Improving crop yield estimation by applying higher resolution satellite NDVI imagery and high-resolution cropland masks	[111]	Maize, Soybeans, Spring Wheat, and Winter Wheat	Statistical	Satellite	2022
203	Wheat growth monitoring and yield estimation based on remote sensing data assimilation into the SAFY crop growth model	[325]	Wheat	Statistical Model based	Satellite × Proximal	2022
204	Simulation of Spatiotemporal Variations in Cotton Lint Yield in the Texas High Plains	[147]	Cotton	Model based	Satellite × Proximal	2022
205	Crop Yield Estimation at Field Scales by Assimilating Time Series of Sentinel-2 Data Into a Modified CASA-WOFOST Coupled Model	[63]	Wheat, Rape, Milk Thistle, and Potato	Model based Statistical	Satellite × Proximal	2022
206	Estimating Maize Yield in the Black Soil Region of Northeast China Using Land Surface Data Assimilation: Integrating a Crop Model and Remote Sensing	[250]	Maize	Model based ML	Satellite × Proximal	2022
207	Assimilation of Remote Sensing Data into Crop Growth Model for Yield Estimation: A Case Study from India	[97]	Rice, Groundnut, Maize	ML/DL Model based	Satellite × Proximal	2022
208	Evaluation of Random Forests (RF) for Regional and Local-Scale Wheat Yield Prediction in Southeast Australia	[328]	Wheat	ML	Satellite × Proximal	2022
209	Assimilation of Multisensor Optical and Multiorbital SAR Satellite Data in a Simplified Agrometeorological Model for Rapeseed Crops Monitoring	[94]	Winter Rapeseed	Model based	Satellite × Proximal	2022
210	Maize yield prediction using NDVI derived from Sentinal 2 data in Siddipet district of Telangana state	[213]	Maize	Statistical	Satellite Proximal	2022
211	Maize Yield Estimation in Intercropped Smallholder Fields Using Satellite Data in Southern Malawi	[223]	Maize	Statistical	Satellite × Proximal	2022
212	Multispectral remote sensing for accurate acquisition of rice phenotypes: Impacts of radiometric calibration and unmanned aerial vehicle flying altitudes	[196]	Rice	ML/DL	Airborne × Proximal	2022

Table A1. *Cont.*

	Article	References	Crop	Method	Platform	Year
213	Predicting In-Season Corn Grain Yield Using Optical Sensors	[214]	Maize	Statistical	Airborne × Proximal	2022
214	Cotton yield prediction using drone derived LAI and chlorophyll content	[137]	Cotton	Statistical	Airborne × Proximal	2022
215	Remotely Sensed Prediction of Rice Yield at Different Growth Durations Using UAV Multispectral Imagery	[203]	Rice	Statistical	Airborne × Proximal	2022
216	Correlation between Ground Measurements and UAV Sensed Vegetation Indices for Yield Prediction of Common Bean Grown under Different Irrigation Treatments and Sowing Periods	[168]	Beans	Statistical	Airborne × Proximal	2022
217	Detecting Intra-Field Variation in Rice Yield With Unmanned Aerial Vehicle Imagery and Deep Learning	[195]	Rice	ML/DL Statistical	Airborne × Proximal	2022
218	Comparison of Winter Wheat Yield Estimation Based on Near-Surface Hyperspectral and UAV Hyperspectral Remote Sensing Data	[315]	Wheat	ML/DL Statistical	Airborne × Proximal	2022
219	Estimating Yield-Related Traits Using UAV-Derived Multispectral Images to Improve Rice Grain Yield Prediction	[204]	Rice	ML Statistical	Airborne × Proximal	2022
220	Cotton Yield Estimation From Aerial Imagery Using Machine Learning Approaches	[148]	Cotton	ML	Airborne × Proximal	2022
221	Rice Yield Estimation Based on Continuous Wavelet Transform With Multiple Growth Period	[205]	Rice	ML Statistical	Proximal	2022
222	Deciphering the contributions of spectral and structural data to wheat yield estimation from proximal sensing	[299]	Wheat	ML/DL	Proximal	2022
223	End-to-end deep learning for directly estimating grape yield from ground-based imagery	[130]	Vineyards	ML/DL	Proximal	2022
224	Comparing a New Non-Invasive Vineyard Yield Estimation Approach Based on Image Analysis with Manual Sample-Based Methods	[131]	Vineyards	ML Statistical	Proximal	2022
225	Predictive Modeling of Above-Ground Biomass in Brachiaria Pastures from Satellite and UAV Imagery Using Machine Learning Approaches	[157]	Brachiaria Pastures	ML	Satellite × Airborne	2022
226	Transfer-Learning-Based Approach for Yield Prediction of Winter Wheat from Planet Data and SAFY Model	[264]	Wheat	ML/DL Model based	Satellite	2022
227	Evaluation of Different Modelling Techniques with Fusion of Satellite, Soil and Agro-Meteorological Data for the Assessment of Durum Wheat Yield under a Large Scale Application	[271]	Wheat	ML Model based	Satellite	2022

Table A1. *Cont.*

	Article	References	Crop	Method	Platform	Year
228	Kernel Ridge Regression Hybrid Method for Wheat Yield Prediction with Satellite-Derived Predictors	[276]	Wheat	ML Statistical	Satellite	2022
229	Early season prediction of within-field crop yield variability by assimilating CubeSat data into a crop model	[252]	Maize	Statistical Model based	Satellite	2022
230	Assessing the Yield of Wheat Using Satellite Remote Sensing-Based Machine Learning Algorithms and Simulation Modeling	[272]	Wheat	ML Model based	Satellite	2022
231	Linking Remote Sensing with APSIM through Emulation and Bayesian Optimization to Improve Yield Prediction	[225]	Maize	ML/DL Model based	Satellite	2022
232	Subfield maize yield prediction improves when in-season crop water deficit is included in remote sensing imagery-based models	[253]	Maize	ML Model based	Satellite	2022
233	Wheat Crop Yield Estimation using Geomatics Tools in Saharanpur District	[262]	Wheat	Statistical	Satellite	2022
234	Early Prediction of Coffee Yield in the Central Highlands of Vietnam Using a Statistical Approach and Satellite Remote Sensing Vegetation Biophysical Variables	[82]	Coffee Tree	Statistical Model based	Satellite	2022
235	A deep learning multi-layer perceptron and remote sensing approach for soil health based crop yield estimation	[266]	Wheat	ML/DL Statistical	Satellite	2022
236	Field-level crop yield estimation with PRISMA and Sentinel-2	[114]	Maize, Rice, Soybean, Wheat	ML	Satellite	2022
237	Wheat yield estimation using remote sensing data based on machine learning approaches	[292]	Wheat	ML/DL	Satellite	2022
238	Winter Wheat Yield Estimation Based on Optimal Weighted Vegetation Index and BHT-ARIMA Model	[269]	Wheat	Statistical Model based	Satellite	2022
239	Oil Palm Yield Estimation Based on Vegetation and Humidity Indices Generated from Satellite Images and Machine Learning Techniques	[100]	Palm Oil	ML/DL	Satellite	2022
240	Soya Yield Prediction on a Within-Field Scale Using Machine Learning Models Trained on Sentinel-2 and Soil Data	[116]	Soybean	ML	Satellite	2022
241	Coffee-Yield Estimation Using High-Resolution Time-Series Satellite Images and Machine Learning	[72]	Coffee Tree	ML Statistical	Satellite	2022
242	Alfalfa yield estimation based on time series of Landsat 8 and PROBA-V images: An investigation of machine learning techniques and spectral-temporal features	[164]	Alfa Alfa	ML Statistical	Satellite	2022

Table A1. *Cont.*

	Article	References	Crop	Method	Platform	Year
243	A Comprehensive Comparison of Machine Learning and Feature Selection Methods for Maize Biomass Estimation Using Sentinel-1 SAR, Sentinel-2 Vegetation Indices, and Biophysical Variables	[235]	Maize	ML	Satellite	2022
244	In-Season Prediction of Corn Grain Yield through PlanetScope and Sentinel-2 Images	[238]	Maize	ML Statistical	Satellite	2022
245	Wheat Yield Estimation Using Remote Sensing Indices Derived from Sentinel-2 Time Series and Google Earth Engine in a Highly Fragmented and Heterogeneous Agricultural Region	[273]	Wheat	ML Statistical	Satellite	2022
246	Field Data Collection Methods Strongly Affect Satellite-Based Crop Yield Estimation	[239]	Maize	ML Statistical	Satellite	2022
247	Development of a Multi-Scale Tomato Yield Prediction Model in Azerbaijan Using Spectral Indices from Sentinel-2 Imagery	[88]	Processing Tomato	Statistical	Satellite	2022
248	The Potential of Using Radarsat-2 Satellite Image for Modeling and Mapping Wheat Yield in a Semiarid Environment	[261]	Wheat	Statistical	Satellite	2022
249	Radiative transfer model inversion using high-resolution hyperspectral airborne imagery—Retrieving maize LAI to access biomass and grain yield	[251]	Maize	Statistical Model based	Airborne	2022
250	UAV-Based Hyperspectral and Ensemble Machine Learning for Predicting Yield in Winter Wheat	[306]	Wheat	ML	Airborne	2022
251	Multisite and Multitemporal Grassland Yield Estimation Using UAV-Borne Hyperspectral Data	[153]	Grassland	ML	Airborne	2022
252	Transferability of Models for Predicting Rice Grain Yield from Unmanned Aerial Vehicle (UAV) Multispectral Imagery across Years, Cultivars and Sensors	[198]	Rice	ML Statistical	Airborne	2022
253	Field-scale rice yield estimation based on UAV-based MiniSAR data with Ku band and modified water-cloud model of panicle layer at panicle stage	[206]	Rice	Statistical Model based	Airborne	2022
254	UAV Remote Sensing for High-Throughput Phenotyping and for Yield Prediction of Miscanthus by Machine Learning Techniques	[158]	Miscanthus	ML Statistical Model based	Airborne	2022
255	UAV Remote Sensing Prediction Method of Winter Wheat Yield Based on the Fused Features of Crop and Soil	[303]	Wheat	ML/DL	Airborne	2022
256	Deep Convolutional Neural Network for Rice Density Prescription Map at Ripening Stage Using Unmanned Aerial Vehicle-Based Remotely Sensed Images	[202]	Rice	ML/DL	Airborne	2022

Table A1. *Cont.*

	Article	References	Crop	Method	Platform	Year
257	Estimation of soybean yield parameters under lodging conditions using RGB information from unmanned aerial vehicles	[118]	Soybean	ML/DL	Airborne	2022
258	Improving Wheat Yield Prediction Accuracy Using LSTM-RF Framework Based on UAV Thermal Infrared and Multispectral Imagery	[304]	Wheat	ML/DL	Airborne	2022
259	Yield estimation of high-density cotton fields using low-altitude UAV imaging and deep learning	[138]	Cotton	ML/DL Statistical	Airborne	2022
260	Preharvest phenotypic prediction of grain quality and yield of durum wheat using multispectral imaging	[311]	Wheat	ML/DL Statistical	Airborne	2022
261	Estimation of soybean grain yield from multispectral high-resolution UAV data with machine learning models in West Africa	[119]	Soybean	ML	Airborne	2022
262	Cotton Yield Estimation Using the Remotely Sensed Cotton Boll Index from UAV Images	[149]	Cotton	ML Statistical	Airborne	2022
263	UAV-based multi-sensor data fusion and machine learning algorithm for yield prediction in wheat	[308]	Wheat	ML	Airborne	2022
264	Prediction of Field-Scale Wheat Yield Using Machine Learning Method and Multi-Spectral UAV Data	[309]	Wheat	ML.	Airborne	2022
265	Cotton Yield Estimation Based on Vegetation Indices and Texture Features Derived From RGB Image	[150]	Cotton	ML Statistical	Airborne	2022
266	Estimation of plant height and yield based on UAV imagery in faba bean (*Vicia faba* L.)	[171]	Faba Bean	ML Statistical	Airborne	2022
267	The Optimal Phenological Phase of Maize for Yield Prediction with High-Frequency UAV Remote Sensing	[310]	Maize	ML	Airborne	2022
268	High-Resolution Flowering Index for Canola Yield Modelling	[101]	Canola Seed	Statistical	Airborne	2022
269	UAV-Based Multispectral Imagery for Estimating Cassava Tuber Yields	[151]	Cassava Tuber	Statistical	Airborne	2022

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