

Review

Using Remote Sensing Vegetation Indices for the Discrimination and Monitoring of Agricultural Crops: A Critical Review

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Abstract: The agricultural sector is currently confronting multifaceted challenges such as an increased food demand, slow adoption of sustainable farming, a need for climate-resilient food systems, resource inequity, and the protection of small-scale farmers' practices. These issues are integral to food security and environmental health. Remote sensing technologies can assist precision agriculture in effectively addressing these complex problems by providing farmers with high-resolution lenses. The use of vegetation indices (VIs) is an essential component of remote sensing, which combines the variability of spectral reflectance value (derived from remote sensing data) with the growth stage of crops. A wide array of VIs can be used to classify the crops and evaluate their state and health. However, precisely this high number leads to difficulty in selecting the best VI and their combination for specific objectives. Without thorough documentation and analysis of appropriate VIs, users might find it difficult to use remote sensing data or obtain results with very low accuracy. Thus, the objective of this review is to conduct a critical analysis of the existing state of the art on the effective use of VIs for the discrimination and monitoring of several important agricultural crops (wheat, corn, sunflower, soybean, rape, potatoes, and forage crops), grasslands and meadows. This data could be highly useful for all the stakeholders involved in agricultural activities. The current review has shown that VIs appear to be suitable for mapping and monitoring agricultural crops, forage crops, meadows and pastures. Sentinel-1 and Sentinel-2 data were the most utilized sources, while some of the frequently used VIs were EVI, LAI, NDVI, GNDVI, PSRI, and SAVI. In most of the studies, an array of VIs needed to be employed to achieve a good discrimination of crops or prediction of yields. The main challenges in using VIs are related to the variation of the spectral characteristics during the vegetation period and to the similarities of the spectral signatures of various crops and semi-natural meadows. Thus, further studies are needed to establish appropriate models for the use of satellite data that would prove to have greater accuracy and provide more relevant information for the efficient monitoring of agricultural crops.

Keywords: precision agriculture; crop classification; satellite data; spatial analysis; spectral reflectance



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1. Introduction

Food security is of paramount importance as it not only ensures that individuals and communities have consistent access to sufficient, safe, and nutritious food but also is related to the well-being, stability, and progress of communities [1]. The agri-food sector

continues to be driven by climate change, increasingly unpredictable weather patterns, and global population growth [2]. In this context, the mapping and monitoring of agricultural crops by using precision agriculture and remote sensing serve as the “dynamic eyes and ears” of modern farming. They enable the acquisition and processing of data in real time and offer insights for optimizing the management of resources. This further contributes to the increase in yields and sustainability of farming practices in an ever-evolving agricultural landscape.

The heterogeneity of agricultural landscapes composed of croplands and meadows typically are the result of different land use practices and applications with regard to their ecosystem services [3]. These services include all the major sections provided in the Common International Classification of Ecosystem Services (CICES) [4]: (a) provisioning services (crop production, forage, and livestock grazing, pollination); (b) regulation and maintenance services (water regulation, carbon sequestration, soil fertility, and natural pest control); (c) supporting services (biodiversity); (d) cultural services (recreation and aesthetic, cultural, and traditional); and (e) economic services (particularly for farmers and rural communities). The provision of these ecosystem services is vital for the existence and well-being of communities, but it can be extremely variable across the various regions of the globe [3]. It is influenced by a series of factors such as weather conditions, soil quality, land management, biodiversity, water resources, and cultural, societal, policy and regulation factors. Thus, the current need is to provide an accurate classification and effective management of the agricultural areas. This is relevant because of the importance of the land covered by cropland and meadows and the complexity of the work involved in their conservation.

Mapping involves creating a static representation or inventory of the spatial distribution of various crops within a given area (typically done at the beginning of the growing season). Monitoring, on the other hand, is an ongoing process of tracking the dynamic changes in crop health and condition during the growing season. In the context of the current global population growth and climate change, Mercier et al. [5] showed that monitoring agricultural crops is an essential tool to effectively address these issues. In addition, other studies pointed out that the monitoring of agricultural crops contributes to the estimation of yields [6], prevention of disease and pest attacks [7], application of fertilizers [8], as well as water resource management [9]. Data on the types and yields of agricultural crops are often rare, especially in low- and middle-income countries. Thus, remote sensing by using satellite images can be utilized to fill these gaps, often in combination with artificial intelligence algorithms. As such, the mapping of agricultural land and monitoring of the state and well-being of crops using remote sensing is a key contribution to food security monitoring systems [10–12]. This technology holds an important advantage since most of the satellite image databases are freely available and have global coverage.

The data collected by remote sensing technologies typically includes information related to vegetation indices (VIs; all the abbreviations used in this manuscript can be found in Table S1), which provide valuable insights into the health, growth, and condition of crops and vegetation [13]. These indices can be calculated by using the data collected by remote sensing technologies, such as satellite and aerial imagery, drones, or ground-based sensors. VIs could be useful for both the classification of agricultural land use and the monitoring of agricultural crops. However, the high number of available VIs that can be computed hampers the process associated with their efficient selection and use [14]. Moreover, the spectral similarities of different crops might lead to misclassifications, which could deliver inaccuracies in assessing the health of crops. This could interfere with management decisions.

In this context, this review aims to assess the existing state of the art on the major VIs used to identify, discriminate, and monitor some of the most important agricultural crops in Europe (wheat, corn, sunflower, soybean, rape, potatoes, and forage crops) together with grasslands and meadows. Since these land use categories are of particular food and economic importance, a critical synthesis of the most relevant studies on the

identification and characterization of the VIs according to their advantages and constraints can be extremely useful for all the stakeholders involved in agricultural activities, from farmers and researchers up to the institutions addressing the centralization and monitoring of agricultural crops). A total of 113 scientific papers indexed in the major international databases (Web of Science Core Collection, Scopus, ScienceDirect, and Google Scholar) were selected based on the following keywords: satellite imaging, agriculture, and maize/corn/wheat/rapeseed/soy/potato/alfalfa/grassland. After an in-depth analysis of these scientific papers, the most relevant information required for an effective selection and use in studies concerning the seven selected agricultural crops, grasslands, and meadows was synthesized. Thus, the main objectives of the present study were: (1) synthesizing the information available in the scientific literature on the main VIs that can be used in studies aiming to map and monitor the selected seven agricultural crops, grasslands, and meadows; (2) highlighting the main characteristics of the VIs available through the use of satellite data, unmanned aerial vehicles (UAVs), and sensors; (3) highlighting the main advantages and limitations in the use of VIs for the crops studied; and (4) concluding remarks and discussion on future research directions that may lead to better accuracy of the results.

2. Insights into the Use of Remote Sensing Data for Crop Classification and Management

2.1. From Spectral Data to Crop Data

Remote sensing technology, with its wide-ranging applications, has transformed the agricultural landscape by providing valuable data for precise crop classification and management. An essential component of this technology is the use of VIs derived from remote sensing data (typically obtained from satellite or aerial imagery). The process of computing a certain VI for an agricultural crop involves collecting and processing spectral data from remote sensing imagery, which is tailored to the unique characteristics and growth stages of that crop. This process is based on measuring the reflectance of light at specific wavelengths to compute the index [15].

Remote sensing VIs are derived from a variety of sources, including (1) satellites (data from Earth-observing satellites); (2) aerial imagery (collected from aircraft, drones, or other platforms); (3) hyperspectral sensors (able to capture data at hundreds of narrow spectral bands); and (4) ground-based sensors (useful in crop monitoring). The major source of remote sensing data used in most agricultural studies is typically satellite imagery, especially from Earth-observing satellites [16]. As shown in Figure 1a, 64.62% of the total scientific papers analyzed in this review were based on satellite data. In comparison, only 22.12% were based on aerial data (mainly UAVs) and 13.27% from multiple sources. Figure 1b shows that all of the eight agricultural land use categories were studied using all three data sources, with a small percentage of scientific papers based on multiple source data (among all of the crops studied).

The preferences expressed in favor of satellite imagery could be explained, at least partially, by the advantages of this remote sensing data source in comparison with aerial and/or multi-source data. The advantages of satellite data are: (1) they are less expensive (in many cases free of charge), (2) they allow for the analysis of larger areas, (3) the analyses are easily replicable, and (4) the results are not influenced by local climate conditions (i.e., wind). Even so, satellite imagery is not perfect, as presented in detail in Section 3, for each of the eight agricultural crops analyzed in this review.

Some of the satellite imagery sources are available free of charge (MODIS—Moderate Resolution Imaging Spectroradiometer, provided by NASA; Landsat, provided by NASA and the U.S. Geological Survey; and Sentinel Satellites, provided by the European Space Agency—ESA), while others have restricted access, under a paywall (Maxar Technologies (formerly DigitalGlobe), Airbus, and Planet Labs). While both have their advantages and limitations, the choice of one over another should be relative to the specific objectives, available resources of agricultural users, and budget. Free satellite data are valuable for many applications and research use cases, while commercial satellites offer additional flexibility, high-resolution imagery, and tailored solutions.

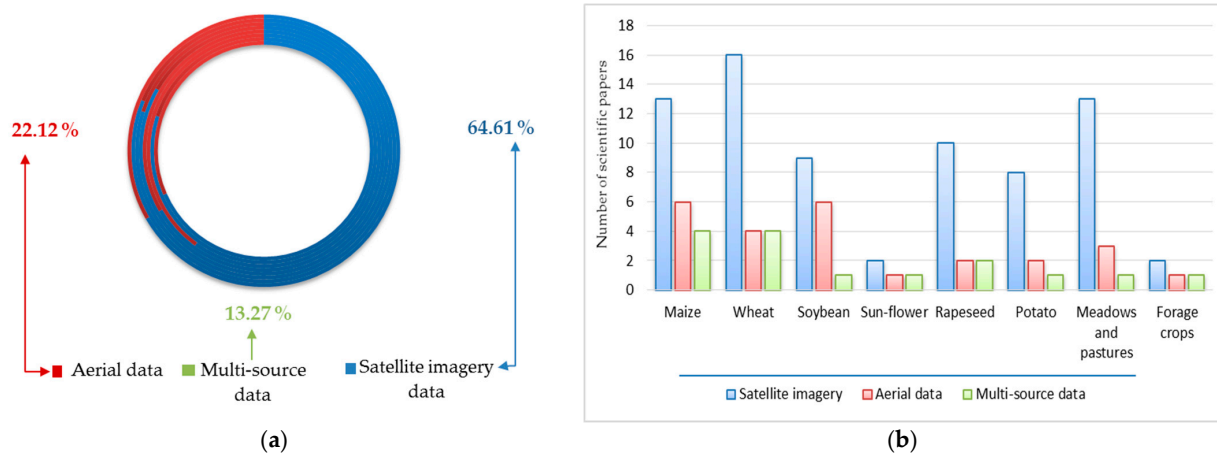


Figure 1. Major sources of remote sensing data used in agricultural studies: (a) Percent of aerial data versus multi-source and satellite imagery data from total publications; (b) Distribution of the remote sensing data sources among different agricultural land types.

As shown in Figure 2a, most of the remote sensing data sources used so far in scientific publications on the topic of agricultural crops were freely available data sources, while just 15.04% were under a paywall. Sentinel (69 publications) and Landsat (22 publications; Figure 2b) were among the most used satellite sources.

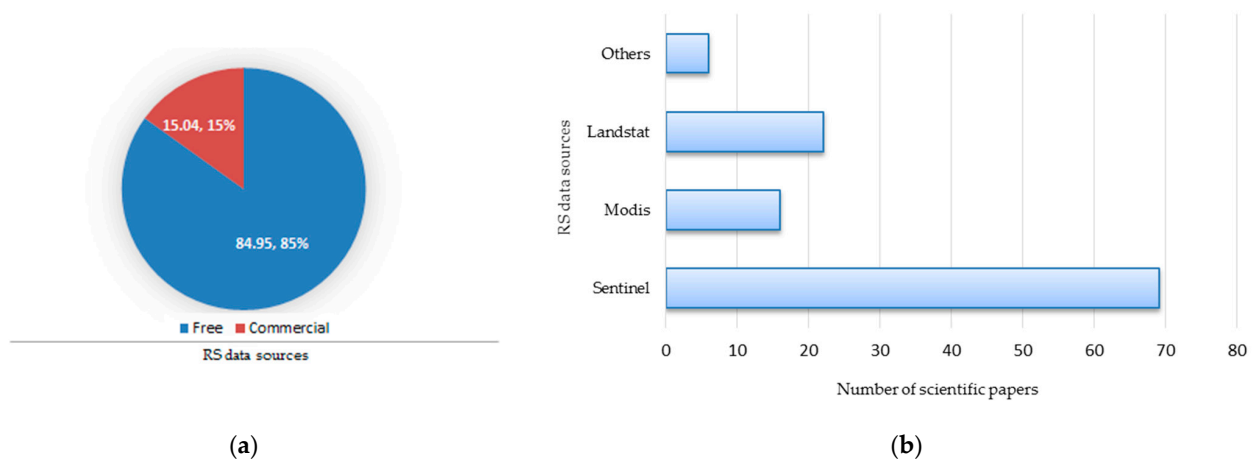


Figure 2. Major sources of remote sensing satellite data used in agricultural studies: (a) Percent of free versus commercial data sources from total publications; (b) The major remote sensing satellite data sources.

Researchers often combine data from multiple sources to deliver high-accuracy results and to create comprehensive datasets for agricultural studies [17,18]. Although the results presented in these studies showed high efficiency, the number of studies based on multiple-source data is very low (13.27%, as shown in Figure 1a,b). Some of these studies focused on the combined utilization of multitemporal synthetic-aperture radar (SAR) data with optical images, while others used multiple-source satellite data. For example, Skakun et al. [19] explored the feasibility and efficiency of integrating SAR data from Radarsat-2 in the C-band with optical images from Landsat-8/OLI for crop classification in Ukraine. Their findings highlighted that the synergistic use of both optical and SAR imagery enhanced the ability to discriminate various crops. Another study conducted by Villa et al. [20], aiming at delivering an in-season mapping of seven crops with optical and X-band SAR data, confirmed the efficiency of combining data from multiple sources, achieving an overall accuracy greater than 86%. Following a different approach, Sun et al. [21] delivered

a classification of crops based on multi-source satellite data (Sentinel-1, Sentinel-2, and Landsat-8) and multi-temporal data, achieving an overall accuracy of 93%.

The major steps followed by a specific VI in its transformation pathway from satellite data to crop data involves: (1) data acquisition (selection of the appropriate satellite imagery source and data acquisition); (2) preprocessing (atmospheric correction, radiometric calibration, and geometric correction); (3) band selection (which can vary depending on the satellite sensor, but the most commonly available and used are data with bands in the visible, near-infrared, and shortwave infrared ranges); (4) index computing (according to the formula specific to each VI); (5) temporal analysis (an important step for understanding crop development and detecting of anomalies); (6) validation (involves the validation of the VI results by comparing them with ground-truth measurements or field data to ensure accuracy and reliability); (7) interpretation of data (done according to the specific objectives); and (8) visualization (through images or maps aiming to visualize the spatial distribution of crop health and changes in vegetation over time). Each of these stages is critically important and requires careful attention. Any errors or misinterpretations during these stages can significantly impact the accuracy of the results [22].

2.2. Vegetation Indices Commonly Used for Crop Classification and Management

VIs were shown to be indispensable tools for agricultural research and management [23–25]. The classification and crucial insights into the health, growth, and conditions of crops can be enhanced by utilizing various VIs. Among the numerous VIs available, the studies conducted so far in agriculture relied mostly on 25 vegetation indices. Table 1 comprises a selection of VIs, including some of the most used and validated VIs and their respective equation and applications.

Table 1. The most utilized vegetation indices for agriculture research.

Vegetation Indices	Equation	Definition	References
Vegetation Indices Considering Atmospheric Effects	$ARVI = (R_{NIR} - R_{RB}) / (R_{NIR} + R_{RB})$	Used to measure and monitor the health and condition of vegetation while minimizing the impact of atmospheric influences on satellite imagery	[26]
Canopy Chlorophyll Content Index	$CCC(I) = [(R_{NIR} - R_{REDEGE}) / (R_{NIR} + R_{REDEGE})] / [(R_{NIR} - R_{RED}) / (R_{NIR} + R_{RED})]$	An indication of stresses related to plant diseases, nutritional deficiencies, and environmental factors	[27]
Enhanced Vegetation Index	$EVI = 2.5(R_{NIR} - R_{RED}) / (R_{NIR} + 6R_{RED} - 7.5R_{BLUE} + 1)$	Used to evaluate the vitality and health of plants It refines NDVI by accounting for atmospheric conditions and soil background, offering a more precise depiction of plant growth.	[28]
Green Normalized Difference Vegetation Index	$GNDVI = (R_{NIR} - R_{GREEN}) / (R_{NIR} + R_{GREEN})$	An index of photosynthetic activity, particularly effective in crops with dense canopies or in more advanced developmental stages	[29]
Leaf Area Vegetation Index	$LAI = \text{leaf area (m}^2\text{)} / \text{ground area (m}^2\text{)}$	Holds significance in monitoring the health of crops and forests, as well as assessing environmental and climatic conditions	[30]
Modified Chlorophyll and Reflectance Index	$MCARI = [(R_{700} - R_{670}) - 0.2 \times (R_{700} - R_{550})] \times (R_{700} / R_{670})$	Useful in assessing the chlorophyll content of plants, offering insights into their physiological status and health	[31]
NDVI (Normalized Difference Vegetation Index)	$NDVI = (R_{NIR} - R_{RED}) / (R_{NIR} + R_{RED})$	Quantifies photosynthetically active biomass in plants. Although it is one of the most suitable and used VI for crop monitoring, this index is notably sensitive to variations in soil brightness and atmospheric conditions.	[32]
Normalized Difference Water Content	$NDWI = (R_{800} - R_{680}) / (R_{800} + R_{680})$	Quantifies and assesses the water content in vegetation, providing insights into the hydration status of plants	[33]

Table 1. Cont.

Vegetation Indices	Equation	Definition	References
Normalized Difference Phenology Index	$NDPI = (\rho_{NIR} - \rho_{RED}^{SWIR}) / (\rho_{NIR} + \rho_{RED}^{SWIR})$	Enables more precise monitoring of spring phenology in regions with snow cover thanks to its robustness against snowmelt	[34]
Optimized Soil Adjusted Vegetation Index	$OSAVI = (1 + 0.16) (R_{NIR} - R_{RED}) / (R_{NIR} + R_{RED} + 0.16)$	It is employed for monitoring regions characterized by sparse vegetation and bare soil areas within the canopy	[35]
Plant Senescence Reflectance Index	$PSRI = (R_{680} - R_{500}) / R_{750}$	Assesses and quantifies the process of plant senescence, providing insights into the aging and declining health of plants	[36]
Red Edge Chlorophyll Index	$RECI = (R_{NIR} - R_{REDEGE}) - 1$	Indicates the photosynthetic activity of the canopy cover, being very useful in identifying areas with yellow or shed foliage	[37,38]
Renormalized difference vegetation index	$RDVI = (R_{NIR} - R_{RED}) / \sqrt{(R_{NIR} + R_{RED})}$	Makes use of the variance between near-infrared (NIR) and red wavelengths in conjunction with NDVI, being able to accentuate thriving vegetation while remaining unaffected by soil and sun viewing geometry influences	[39]
Soil Adjusted Vegetation Index	$SAVI = [(R_{NIR} - R_{RED}) / (R_{NIR} + R_{RED} + L)] \times \frac{1}{1 + L}$	Integrates a soil adjustment factor into its calculation, being very useful in regions with sparse vegetation or significant soil influences that may complicate vegetation monitoring	[40]
Simple Ratio Index	$SR = R_{NIR} / R_{RED}$	Easily comprehensible and effective across diverse conditions It may saturate in areas of dense vegetation, particularly when LAI reaches very high levels.	[41]
Transformed chlorophyll absorption ratio	$TCARI = 3 \times [(R_{REDEGE} - R_{RED}) - 0.2 \times (R_{REDEGE} - R_{GREEN})] \times (R_{REDEGE} / R_{RED})$	Offers enhanced precision in estimating chlorophyll content	[31]

An important aspect that should be considered when selecting a certain VI is that they are versatile tools in agriculture, serving various purposes, from agricultural land use classification to crop monitoring. While some VIs could be used for the analysis of multiple objectives (NDVI, MCARI, PSRI etc.), others are more specific for a particular application (for example, CCC and LCC for crop classification). Still, various VIs exhibit distinct sensitivities and are best suited for different stages of the crop growth cycle.

As such, while some VIs are best suited for application during the early stages of plant development when leaf cover is limited (for example, MSAVI), others perform better during the period of rapid growth (NDVI). These sensitivities will be detailed in the later sections when the specificities for each land use analyzed in this review (crops plus pastures and meadows) will be discussed.

3. The Current Status and Limitations of the Use of VIs for Crop Classification and Monitoring

3.1. General Remarks

As highlighted in the previous sections, VIs derived from remote sensing technologies offer immense potential for precision agriculture, resource optimization, and global food security in an ever-changing environment. Still, the misunderstanding of their specific functions and use cases could lead to inaccurate results. The research conducted so far has demonstrated the potential for using VIs to map and monitor a significant number of agricultural crops. While the results are satisfactory (achieving up to 90% accuracy for some crops using specific indices), further studies are still required to develop more accurate satellite data models and to address key aspects essential for effective agricultural crop classification and monitoring.

Much of the available research on this topic is aimed at mapping crop types during a growing season, which can be technically difficult [42]. Some of the challenges identified are (1) variations in crop growth (variability in growth rates, canopy development, and

flowering times can complicate mapping); (2) overlapping plant canopies (this usually happens when multiple crops are grown in close proximity); (3) inter- and intra-field variability (due to differences in soil types, irrigation, or management practices. Within a single field, this could be expressed by variations in crop health or stress levels); (4) cloud covering (one of the most common issues for satellite imagery, since clouds affect the availability of cloud-free satellite images, leading to gaps in monitoring during the growing season); and (5) spectral confusion (some crops are difficult to be discriminated from others, because of their similar spectral responses in certain growth stages). There are also other factors that could impact the quality of crop mapping, such as atmospheric interference (atmospheric conditions such as aerosols, haze, and water vapor) that can affect the quality of satellite imagery and VIs values.

In order to effectively address these issues, recent studies employed a different approach—a combination of the variability of spectral reflectance value and the stage of crop growth during the growing season [43]. This approach required monitoring changes in the area under investigation during the growing season and VIs. Such an approach showed the potential to eliminate some of the challenges described previously, but it did not manage to fill all the existing gaps. This will be detailed in the next sections for each of the eight agricultural land use categories considered in this review.

The challenges mentioned before were partly eliminated for some crops (which now can be assessed with high and sometimes very high accuracy), while other crops are still difficult to discriminate and/or monitor effectively. This could also be due to the attention researchers have shown to certain crops and their reduced interest in others. This review showed that most of the available studies conducted on this topic were focused on mainly three crops (wheat, maize, and soybean) and meadows and pastures. These preferences could be further explained by the global importance of these crops and agricultural lands, as all are listed among the first 6 most important crops and produce in the world [44]. This does not mean that the difficulties encountered in the discrimination and monitoring of some agricultural crops are not also generated by other factors (as listed and described previously).

3.2. Crop-Specific Analysis

3.2.1. Maize Crop

The first studies focusing on the application of VIs for maize research date back to 1997, which ranks maize among the first agricultural crops subject to research using remote sensing technologies (Table 2). Almost half of these studies were conducted in the USA (approx. 45%), followed by Asia (approx. 30%) and Europe (approx. 25%). This categorization closely mirrors the classification of crops based on their recorded maize production. According to FAOSTAT data for 2021 [44], the Americas emerged as the leading maize-producing regions, with the USA and Brazil collectively contributing to 39% of global production. China held the second position as the largest producer, with a substantial share of nearly 23%.

In terms of the data sources for remote sensing, it must be pointed out that the majority of research on the use of VIs for maize relied on satellite imagery (approx. 60%), either independently or in conjunction with UAVs and remote sensors (Table 2). The most frequently accessed satellite data sources were Sentinel 1 and 2 (comprising 58.33% of the data sources), followed by MODIS.

As highlighted in Table 2, most of the studies related to the use of VIs in maize research focused on NDVI index alone or in combination with other VIs. Generally, researchers used NDVI to discriminate maize crops [45–47], to predict yields [6,48–52], to detect stress [53], and to make decisions related to fertilization [49]. While NDVI is a prominent choice, other VIs such as EVI and GNDVI were also employed in maize research, depending on the specific objectives and data available. Generally, the combined use of two or more VIs delivered a higher accuracy of the results compared to the use of just one VI. Sonobe [45] demonstrated the importance of using multiple VIs in identifying specific crop types,

highlighting that the best-performing VIs for maize discrimination were REIP (Red edge inflection point), CRI550 (Carotenoid Reflectance Index 550 nm), CRI700 (Carotenoid Reflectance Index 700) and MSBI (Modified Soil-Adjusted Vegetation Index).

The efficiency in using VIs for accurate identification and monitoring of crops is highly influenced by the phenological stages of the crop. Different crops have distinct phenological patterns, with key stages such as emergence, leaf expansion, flowering, and senescence [54]. Understanding these stages and their impact on VIs is vital for precise crop monitoring and management. An important contribution to this research topic was delivered by Wei et al. [47], who managed to provide the earliest stages of discriminating maize and soybeans. Based on several VIs acquired from Sentinel-2, the authors concluded that the earliest stage when maize can be effectively discriminated from soybean was in early July, corresponding to the seven-leaf (for maize) and flowering stages (for soybean). This period corresponded to robust growth in both crops, with soybeans having higher cover density and chlorophyll water content compared to corn.

Promising results could be achieved also by using UAV data, as long as the operator of the equipment is highly trained and performs the requested adjustments according to each crop specificity.

Table 2. An extensive review of VIs used in maize crop research.

Country/Region	Satellite Data Used	Remote Sensors Used (If Applicable)	Time Span of the Study	Computed Indices	References
Syria	-	FieldSPEX (Analytical Spectral Devices™, Lake Grove, NY, USA)	1997	NDVI	[55]
Mexico	NOAA-AVHRR	-	May–October 1997	NDVI, LAI	[51]
USA	-	AccuPAR Ceptometer (Decagon Devices, Pullman, Washington, USA) ASD FieldSpec Pro FR (Analytical Spectral Devices, Boulder, CO, USA)	1999	TGI, MCARI, CVI, NDVI, TCARI	[56]
USA, Illinois	MODIS MCD43A4	-	2002–2017	NDVI	[57]
USA	-	ASD FieldSpec Pro FR spectrometer (Analytical Spectral Devices, Inc., Boulder, CO, USA), LI-COR (Lincoln, NE, USA) LI 1800-12 light integrating sphere	2003	CVI, MCARI, GNDVI	[53]
Spain, Germany, France	Sentinel-2	LI-COR LAI-2000 SPAD-502 (Seedburo Equipment Company, Des Plaines, IL, USA)	2003–2007	LAI, Chlorophyll Content	[58]
China	HJ-1A/1B satellite chinezesc		2009–2015	NDVI	[59]
China	Sentinel-2	-	2012–2013	LAI, S-WI I, S-WI II, S-NDII, S-TBWI, EVI, TCARI, S-OSAVI, S-TCARI/OSAVI, S-MTCI, S-CI, S-NDVI, S-DCNI I, S-OSAVI × Clred edge	[6]
France	Sentinel-1	LI-COR 3100 planimeter (LI-COR Biosciences, Lincoln Inc., Lincoln, NE, USA)	2014	NDVI	[60]
Japan	Sentinel-2A	-	2016	82 indices, among which: ARVI, CARI, CCCI, CRI 550, NDVI, GDVI, GNDVI, GVM, REIP, SLAVI	[45]
Czech Republic	-	eBee UAV, with multispectral and thermal sensors (senseFly, Cheseaux-sur-Lausanne, Switzerland)	2016–2017	NDVI, GNDVI, NDRE	[61]

Table 2. *Cont.*

Country/Region	Satellite Data Used	Remote Sensors Used (If Applicable)	Time Span of the Study	Computed Indices	References
Italy	Sentinel-2	Grain yield monitor (model and manufacturer are not specified)	2016–2018	NDVI, NDRE1, NDRE2, GNDVI, GARVI, EVI, WDRVI, WDRVI, GCVI	[50]
USA, Mississippi	-	MicaSense RedEdge™ multispectral band sensor (MicaSense, Inc., Seattle, WA, USA) mounted on a UAS (manufacturer not specified)	2017–2019	DVI, DVI, RDVI, TDVI, NDVI, GNDVI, NDRE, SCCC, EVI, TVI, VARIgreen, GARI, GCI, GLI, TGI, NLI, MNLI, SAVI, GSAVI, GSAVI, GOSAVI, MSAVI2, MSR, GRVI, WDRVI, SR	[49]
Belgium	Sentinel-1 Sentinel-2	-	March–August 2017	NDVI	[46]
Saudi Arabia	CubeSat, Landsat 8, MODIS	-	April–October 2017	NIR, LAI, REGFLEC-based LAI	[62]
Brazil	-	DJI Matrice 200 RPA (DJI, Shenzhen, China) with an embedded multispectral camera (Micasense, model RedEdge-M)	2018–2019	NDVI, NDRE	[48]
Brazil	Sentinel-2	-	2019–2020	NDVI	[63]
USA	PlanetScope	Minolta SPAD-502 meter (Konika Minolta Business Solutions, Osaka, Japan), LI-COR LAI-2000 (LI-COR Biosciences, Lincoln Inc., Lincoln, NE, USA)	2018	EVI, EVI2, GCI, NDVI, MSAVI2, SAVI	[64]
Mexico	-	Parrot Sequoia camera attached to a 3 DR SOLO quadcopter (3D Robotics, Berkeley, CA, USA), DJI RGB sensor integrated into a DJI Phantom 4 quadcopter (DJI, Shenzhen, China)	2018	TGI, VARI, NDVI, NDRE, WDRVI	[52]
China	Sentinel-2	-	2019–2020	NDVI GBDT and RF B12, NDTI, LSWI, NDSV B12, B11, B8, LSWI, NRED2	[47]

Hoss et al. [48] assessed the NDVI of a maize crop by employing a DJI Matrice 200 RPA drone fitted with a multispectral camera. Their findings revealed that flying at higher altitudes during data collection (90 m and 120 m) yielded more accurate results compared to low altitudes (30 m and 60 m).

3.2.2. Wheat Crop

The studies related to the use of VIs for wheat identification and management began in 2004, with over half of the research papers presenting results from the last 5 years (Table 3). More than half of these studies were developed in Europe (57.14%), followed by Asia (19.04%) and the USA (14.28%). Among the European countries, this literature review shows that France is the leading country in remote sensing wheat research, with 41.66% of the total scientific articles analyzed. This could be partially explained by the position of France as the biggest wheat producer in the EU, with an output of 34.6 million tons in 2022 [65] and extensive cultivation in regions like the Paris Basin.

It seems that most of the research papers related to the use of VIs in wheat were based on data originating from satellite imagery (41.55%) alone or in combination with remote sensors (Table 3). The most accessed satellite data sources were Sentinel 1 and 2 (93.75%), followed by MODIS.

These studies provide important findings related to the use of VIs in wheat identification and management, including their potential applications and future recommendations (based on the major constraints identified).

Most of the analyzed studies were focused on identifying the most suitable VIs and multiple-source data for crop management assessments. According to the results presented in these scientific papers, the best performing VIs (mostly derived from satellite imagery) were fAPAR (quantifies the fraction of the solar radiation absorbed by live

leaves for the photosynthesis activity), fCover (fraction of vegetation cover), freshAGB (above-ground fresh biomass), EVI, PSRI, and NDVI for crop management, while ARI2 (Anthocyanin Reflectance Index 2), EVI, gNDVI, MCARI, NDVI, NDWI, PSRI, and SR3 for wheat discrimination.

Although this review provides a classification of the best-performing VIs, it is important to mention that their performance could be influenced by crop development stages. As such, a certain VI could perform better in some phenological stages and yet deliver low-accuracy results for other stages. The solution to achieve high-accuracy results could be the combined use of two or more VIs, which could complement each other throughout all the phenological stages involved in wheat production. This conclusion is consistent with the findings of Kamenova and Dimitrov [66], who conducted a study aiming at testing the utility of a set of 40 VIs in retrieving LAI, fAPAR, and fCover of winter wheat using Sentinel-2 data. Their results showed that only some of the VIs studied effectively delivered high-accuracy results, pointing out that each of these top-performing indices was supported by several other VIs with similar modeling accuracy. Moreover, it was observed that during the tillering stage, CIre7 (Chlorophyll Index—Red-Edge) proved most effective for LAI, while NDRE (normalized difference red edge index) performed well for fAPAR and fCover. In the stem elongation stage, DVI (Difference Vegetation Index) excelled for LAI, while MCARI/OSAVI were top performers for fAPAR and fCover. Wang et al. [67] introduced a calibrated relative threshold method in their study, leveraging historical ground-based phenology observations to extract winter wheat phenology. This approach effectively reduces bias and uncertainty in threshold settings, yielding significant and precise insights into wheat phenological dates and the vegetative growth period. The study's success in utilizing the NDVI time series enhances the reliability of their findings.

Although the combined use of two or more VIs is more promising and documented, some studies focused on and demonstrated that, in some cases, high-accuracy results can also be delivered through the use of just one VI. A relevant study was conducted by Naser et al. [68], who demonstrated that utilizing NDVI measurements could be promising for distinguishing between winter wheat genotypes based on their productivity. The authors showed that the most suitable period for such differentiation and classification of wheat genotypes spans from the anthesis growth stage to the mid-grain filling stage, as shown by the overall accuracy in NDVI and grain yield classes.

In terms of accuracy, the best results were recorded when two or more satellite data sources were used in combination. In many situations, the results obtained from both satellites were combined to eliminate errors and enhance the overall accuracy of the outcome. An example in this sense is the research conducted by Mercier et al. [42], who sought to forecast wheat phenological stages by using VIs derived separately from Sentinel-1 and Sentinel-2 data, as well as their combined application. Their findings indicated that the combination of both satellite datasets improved the accuracy of identifying the start and end of tillering in wheat. Moreover, the authors concluded that Sentinel-1 data performed better in recognizing the tillering stage, while Sentinel-2 data outperformed in identifying the flowering, fruit development, and ripening stages.

While it might be tempting to extend this pattern and utilize combined data from 2 or more different sources (such as integrating sensors with satellite imagery), this approach may not always deliver highly accurate results. Gozdowski et al. [69] aimed to establish a connection between NDVI values acquired from satellites and values obtained using portable ground-based sensors (OptTx sensor). The conclusion of their study was that there seems to be a disparity between satellite-derived NDVI values and those gathered from terrestrial sensors, mainly due to differences in their calculation. As such, despite the generally accepted practice of combining multiple sources of data to improve the accuracy of the results, special attention should be given to the compatibility of these sources, particularly when it comes to combining sensors with satellite or UAV data.

Table 3. An extensive review of VIs used in wheat crop research.

Wheat Variety	Country/Region	Satellite Data Used	Remote Sensors Used (If Applicable)	Time Span of the Study	Computed Indices	References
Autumn wheat	Japan	Sentinel-2A	-	2016	82 VIs, among which, ARVI, CARI, CCCI, CRI 550, NDVI, GDVI, GNDVI, GVMi, SLAVI, etc.	[45]
Wheat	Bulgaria	Sentinel-2	-	2016–2018	36 VIs, among which, REP, MTCl, NDRE, CCCI, NDVI, SR, VAR1, WDRVI, VI, NDI, GBM, TCARI, MCARI, gNDVI, etc.	[70]
Autumn wheat	Bulgaria	Sentinel-2	-	2016–2018	40 VIs, among which, CCCI, Clg7, Clg8, DVI, EVI, GIPVI, gNDVI, MCARI, MTCl, NDI, NDRE, NPCI, OSAVI, NDVI, REP, TCI, SR, SR1, SR2, SR3, SR4, TCARI, TSAVI, VARI, WDRVI, NPCI, SAVI2, etc.	[66]
Wheat	France	Sentinel-1 and 2	-	January–July 2017	NDVI, S2REP, MCARI, WdVI and LAI	[43]
Wheat	France	Sentinel-1 and 2	-	January–July 2017	ID DOY LAI VV GNDVI IRECI, NDI, NDVI, GNDVI, PSSRa, REIP, SAVI etc.	[5]
Spring wheat	Finland	Sentinel-2	-	April 2016–October 2017	NDVI	[71]
Wheat	Spain, Germany, France	Sentinel-2	LI-COR LAI-2000 SPAD-502 (Seedburo Equipment Company, Des Plaines, IL, USA)	2003–2004, 2006, 2007	LAI, Chlorophyll Content	[58]
Cereals, including wheat	Norway	Sentinel-2	-	May–October 2019	SAVI	[72]
Cereals, including wheat	Austria, Germany	Sentinel-2	-	2015	Spectral signatures and classification margins	[73]
Cereals, including wheat	UE	Sentinel-1	-	2018	Crop type mapping	[74]

Table 3. Cont.

Wheat Variety	Country/Region	Satellite Data Used	Remote Sensors Used (If Applicable)	Time Span of the Study	Computed Indices	References
Wheat	Belgium	Sentinel-1 Sentinel-2	-	2018	NDVI	[46]
Autumn wheat	China	Sentinel-2	-	2016	LAI, LCC, CCC	[75]
Wheat	France	Sentinel-1	LI-COR 3100 planimeter (LI-COR Biosciences, Lincoln Inc., Lincoln, NE, USA)	2014	NDVI	[60]
Wheat	Australia	-	FieldSpec spectrometer (Analytical Spectral Devices, Boulder, CO, USA)	2004–2006	nitrogen nutrition index/canopy chlorophyll content index (CCCI)	[76]
Wheat	USA	-	-	2004	CVI, Mcari, gNDVI	[53]
Wheat	India	Sentinel-2A and 2B	-	2019	NDVI, SAVI, SR, CI	[77]
Wheat	China	MODIS	-	2014–2017	NDVI	[78]
Wheat	China	Sentinel-2A and 2B	-	September 2017–June 2018	NDPI	[79]
Wheat	Poland	-	-	2013–2014	NDVI	[63]
Wheat	USA	-	Green Seeker Model 505 (Trimble Navigation Limited, Sunnyvale, CA, USA)		NDVI	[68]

3.2.3. Sunflower Crop

The first studies focusing on the application of VIs for sunflowers were conducted in 1997. Thus, sunflower is among the first agricultural crops subject to research using remote sensing technologies, next to maize (Table 4). More than half of the studies analyzed in this review were conducted in Europe (63.63%), with the rest originating from Asia. The same pattern of categorization described for wheat and maize was observed for sunflower, as well. Most of the studies conducted in Europe on this topic were developed in Ukraine, a country that stands out as the world's largest producer of sunflower (more than 30% of global production) [65].

Table 4. An extensive review of VIs used in sunflower crop research.

Country/Region	Satellite Data Used	Remote Sensors Used (If Applicable)	Time Span of the Study	Computed Indices	References
Syria	-	FieldSPEC (Analytical Spectral Devices TM , Lake Grove, NY, USA)	1997	NDVI	[55]
Spain, Germany, France	Sentinel-2	LI-COR LAI-2000 SPAD-502 (Seedburo Equipment Company, Des Plaines, IL, USA)	2003–2004, 2006, 2007	LAI, Chlorophyll Content	[58]
China	HJ-1A/1B (Chinese satellite)	-	2009–2015	NDVI	[59]
Ukraine	MODIS	-	2012–2019	NDVI	[80]
Ukraine	MODIS	-	2016–2020	EVI, FAPAR, LAI, LSWI, NDVI	[81]
Ukraine	Sentinel-1 and 2	-	2016–2021	NDVI	[80]
France	Sentinel-1	LI-COR 3100 planimeter (LI-COR Biosciences, Lincoln Inc., Lincoln, NE, USA)	2014	NDVI	[60]
India	Sentinel-2A and 2B	-	2019	NDVI, SAVI, SR, CI	[77]
China	Sentinel-2	-	2019–2020	NDVI	[82]

In terms of the data sources for remote sensing, it was pointed out that the majority of research on the use of VIs for sunflower relied on satellite imagery (approximately 81%), either independently or in conjunction with instruments with laser scanners (LI-COR 3100C; LI-COR LAI-2000; and SPAD-502). One study only relied on data acquired through the spectroradiometers FieldSpec alone (Table 4). The most frequently used satellite data sources were Sentinel-1 and 2 (comprising over 63% of the data sources), followed by MODIS.

Most of the research conducted on the application of VIs in sunflower studies primarily centered on the sole use of the NDVI index (constituting 45% of all the papers analyzed) or in conjunction with other VIs. Generally, researchers used VIs to evaluate crop rotation [80], predict yields [81], and assess crop health and growth [82].

Lykhovyd [81] performed a study in Ukraine focusing on predicting the yields of the major oil-producing crops, including sunflower. They managed to achieve accurate predictions using only NDVI, showing that the best forecasts can be obtained with NDVI values acquired in July. Despite these results, it is still generally believed that the combined use of two or more VIs would deliver higher accuracy of the outcomes.

The studies conducted so far regarding the use of VIs in sunflower research demonstrated the efficiency of remote sensing technologies in providing low-cost, low-timing, and accurate results, which could assist farmers and other stakeholders in applying the most sustainable agricultural practices according to the principles of precision agriculture. In this sense, it is worth mentioning the study developed by Kussul et al. [80], who made important contributions to the sunflower rotation pattern. Based on the combined use of 5 VIs acquired from the MODIS satellite, the authors showed that a 3-year or longer interval

between sunflower plantings optimally supported the sustainability of soil fertility. These results are of particular importance since the present crop rotation rules applied in Ukraine assume that sunflowers can be planted on the same field only once every 7 years [80].

3.2.4. Soybean Crop

The studies on the application of VIs in soybean research analyzed in this review were conducted between 1997 and 2020, with half of them having a lifespan during the last 5 years (Table 5). Most of them were conducted in the USA (approx. 44%) and China (approx. 44%).

It is noteworthy that the majority of research (approx. 90%) utilized satellite imagery, either independently or in conjunction with instruments featuring laser scanning capabilities (e.g., LI-COR 3100). Additionally, one study exclusively employed data obtained from spectroradiometers such as FieldSpec (Table 5). Among the satellite data sources, Sentinel-1 and 2 were the most frequently utilized, constituting approximately 80% of the remote sensing data sources, while one study utilized MODIS satellite imagery.

Most of the studies focusing on the use of VIs in soybean research predominantly revolved around the exclusive application of the NDVI index, accounting for 44% of the total papers analyzed or in combination with other VIs.

Generally, researchers used VIs to discriminate soybeans from other crops [47] and to assess crop health and growth [57,60,83].

When it comes to identifying soybean plants during their early growth stages, Wei et al. [47] employed algorithms with accuracies ranging from 35% to 71%. During the mid-development phases, the accuracy improved significantly, ranging from 69% to 100%. In the final stage of development, the accuracy reached impressive levels between 92% and 100%. The flowering stage in early July emerged as the most suitable for soybean identification, offering identification accuracy of up to 87%.

Shen et al. [84] further noted that the soybean growing seasons exhibited variations influenced by regional and climatic conditions, particularly during the early growth stages, with deviations becoming less prominent towards the end of the crop cycle.

In 2017, Veloso et al. [60] conducted an analysis of SAR (synthetic aperture radar) and NDVI time profiles in fields exhibiting diverse management practices and environmental conditions. Their study placed a particular emphasis on SAR data, specifically the VH/VV ratio, which had limited documentation in prior research. They examined time series data related to optical and NDVI (including VH, VV, and VH/VV) and interpreted these data in a physical context, considering factors such as precipitation, temperature, and on-site measurements (GAI (green area index) and fresh biomass). Their research demonstrated that utilizing comprehensive time series data enables the capture of brief phenological stages and facilitates an accurate description of various crop developments.

Table 5. An extensive review of VIs used in soybean crop research.

Country/Region	Satellite Data Used	Remote Sensors Used (If Applicable)	Time Span of the Study	Computed Indices	References
Syria	-	FieldSPEC (Analytical Spectral Devices TM , Lake Grove, NY, USA)	1997	NDVI	[55]
USA, Illinois	MODIS MCD43A4	-	2002–2017	NDVI	[57]
France	Sentinel-1	LI-COR 3100 planimeter (LI-COR Biosciences, Lincoln Inc., Lincoln, NE, USA)	2014	NDVI, SAR	[60]
China	Sentinel-2A/B	-	2015–2020	OSAVI, SIWSI, TCARI	[83]
China	Sentinel-2	-	2017–2018	NDVI, EVI, GCVI, NDWI, EVI, LSWI	[85]
Northeast China, Missouri, Illinois, Indiana, Ohio	Sentinel-2A/B	-	2017–2021	OSAVI, SIWSI, TCARI	[83]
Brazil	Sentinel-2	-	2019–2020	BNDVI, EVI, EVI 2, GNDVI, NDVI, NDRE, NDII, NDII 2	[86]
China	Sentinel-2	-	2019–2020	B8, B11, B12, GBDT, LSWI, NDVI, NDTI, NDSV, NRED2 RF	[47]
Brazil	Sentinel-2	-	2020	NDVI	[63]

3.2.5. Rapeseed Crop

The research related to the utilization of VIs in rapeseed studies, as reviewed here, spans from 2003 to 2021 (Table 6). Notably, more than 70% of the studies were conducted within the last 6 years in Europe. These observations could be partially explained by the fact that the EU is positioned among the leading producers of rapeseed worldwide, with a share of 19.5% of the total global production in 2022/2023. Furthermore, within the EU, France is the leading producer of rapeseed, which can also be seen in the research related to this crop [66]. Therefore, as illustrated in Table 6, over 40% of the scientific papers included in this review originated from France.

It can be highlighted that the majority of research concerning the use of VIs on rapeseed relied on satellite imagery (approx. 88%), either independently or in conjunction with remote sensors (Table 6). The most frequently accessed satellite data sources were Sentinel 1 and 2 (58.33%). As highlighted previously for the other crops, a combination of two or more satellite imagery sources could significantly improve the accuracy of the results. Mercier et al. [42] showed in a research based on remote sensing data from Sentinel-1 and 2 (alone and combined) that the best accuracy was achieved when both satellites were considered. The authors highlighted that a better identification of rapeseed can be made at the beginning and the end of ripening.

Furthermore, the most performing VIs for the identification of vegetation phenophases were NDVI and S2REP (Sentinel-2 Red Edge Position), and the least important was MCARI (Table 6). Zamani-Noor et al. [87] utilized NDVI and NDYI (Normalized Difference Yellowness Index) values to estimate rapeseed growth timing, observing NDVI fluctuations throughout the growth stages of the crop, with variations observed in plots with different seed densities and nitrogen rates. Han et al. [88] found comparable results for rapeseed, with NDVI values exceeding 0.7 during stem elongation and subsequently dropping to around 0.6 during the flowering stage.

3.2.6. Potato Crop

The research concerning the use of VIs in potato studies, as summarized in Table 7, covers the period from 1997 to 2020. Notably, over 54% of the studies were carried out in the past 6 years, with the majority originating from Europe.

The majority of the studies exclusively utilized satellite imagery (72%; Table 7), while two studies used FieldSPEC and Fieldscout equipment, respectively. As shown in Table 7, only one study relied on data acquired using UAV (combined with HandySpec Field spectrometer). The satellite-based studies primarily made use of Sentinel-1 and 2 data. Unlike the approaches used for other crops examined in this review, most potato studies relied on a single VI, typically NDVI or NDYI. In general, VIs have been employed by researchers to differentiate potatoes from other crops [44,54], to predict yields [89,90] and to evaluate crop health and growth [90–93].

Among the concerns of potato cultivation are disease susceptibility, nutrient depletion, water stress, and the broader implications of climate variability, which, within the context of climate change, exert stress on all crops. The research conducted so far has already demonstrated the utility of remote sensing technologies in dealing with these critical issues.

Nebiker et al. [90] made a significant contribution to this research area by focusing on key aspects related to the detection of blight disease within a potato field in one of their studies. Aiming to explore the potential of Light-Weight Multispectral UAV Sensors and their ability to detect potato diseases, the researchers demonstrated that potato blight can be successfully detected at an early stage of infestation by using NDVI. A reference study was also conducted by Singha et al. [93], who harnessed satellite data from Sentinel 1 and 2 to track the potato crop's growth cycle. Their NDVI analysis indicated the utility of satellite-based monitoring in offering valuable insights for both farmers and researchers, facilitating informed decision-making throughout the development of the potato crop.

Table 6. An extensive review of VIs used in rapeseed crop research.

Country/Region	Satellite Data Used	Remote Sensors Used (If Applicable)	Time Span of the Study	Computed Indices	References
Spain, Germany, France	Sentinel-2	LI-COR LAI-2000 SPAD-502 (Seedburo Equipment Company, Des Plaines, IL, USA)	2003–2004; 2006; 2007	LAI, Chlorophyll Content	[58]
France	Sentinel-1	LI-COR 3100 planimeter (LI-COR Biosciences, Lincoln Inc., Lincoln, NE, USA)	2014	NDVI	[60]
Finland	Sentinel-2	-	April–October 2016–2017	NDVI	[71]
France	Sentinel-1 and 2	-	January–July 2017	LAI, MCARI, NDVI, S2REP, WDVl	[42]
France	Sentinel-1 and 2	-	January–July 2017	DOY, ID, IRECI, GNDVI, LAI, VV NDI, NDVI, PSSRa, REIP, SAVI etc.	[5]
Germany	Sentinel-1 and 2 LUCAS	-	21 April–19 May 2018	NDYI	[74]
Germany	Landsat 8, OLI and Sentinel	-	2018	NDVI, NDYI	[88]
Belgium	Sentinel-1 Sentinel-2	-	2018	NDVI	[46]
Germany	-	UAV-octocopter (CiS GmbH, Rostock, Germany)	2019–2021	NDVI, NDYI	[87]

Table 7. An extensive review of VIs used in potato crop research.

Country/Region	Satellite Data Used	Remote Sensors Used (If Applicable)	Time Span of the Study	Computed Indices	References
Syria	-	FieldSPEC (manufactured by Analytical Spectral Devices TM , Lake Grove, NY, USA)	1997	NDVI	[55]
Romania	-	SPAD-502 (Seedburo Equipment Company, Des Plaines, IL, USA), CropScan multispectral radiometer (CROPSCAN, Inc., Rochester, NY, USA)	2011	NDVI	[92]
Switzerland	-	eBee UAV (senseFly, Cheseaux-sur-Lausanne, Switzerland), HandySpec Field (tec5, Steinbach, Germany)	2015	NDVI	[90]
Japan	Sentinel-2A	-	2016	82 indices: ARVI, CARI, CCCI, CRI 550, GDVI, GNDVI, GVMI, NDVI, SLAVI, etc.	[45]
The Netherlands	Sentinel-2	-	2016	CCC, LAI, LCC, WDV	[91]
Finland	Sentinel-2	-	April to October 2016–2017	NDVI	[71]
Belgium	Sentinel-2	-	2016–2018	NDVI	[89]
UE	Sentinel-1	-	2018	NDVI	[72]
Belgium	Sentinel-1 Sentinel-2	-	2018	NDVI	[46]
India	Sentinel-1 and 2	-	2019–2020	NDVI	[93]

3.2.7. Forage Crop

Based on the data extracted from the international databases examined in this research, it appears that there is a scarcity of studies related to the utilization of VIs in forage crops. As pointed out in Table 8, the literature research performed for this review (as described in the first section of this manuscript) generated only four scientific articles published so far on this topic. Much more attention was given to grasslands and pastures, as we will detail in the next subsection. The time span of the studies comprised the period between 2003 and 2021. Half of the research papers were developed by Saudi Arabia, followed by some EU countries (France, Germany, Italy, and Spain).

All the studies exclusively utilized satellite imagery alone or in combination with specialized spectrometers. The satellite-based studies were based on the use of Sentinel-2 data (two papers), Landsat-8, CubeSat and MODIS (two papers). The efficiency of several VIs was investigated, including EVI, LAI and NDVI.

Considering the crucial role of sown grasslands as a significant source of animal forage and their numerous ecosystem services [94], there is a pressing need for research aimed at validating the effectiveness of such crops. The key aspects that should be addressed in forage crop studies include selecting high-performance forage plant mixtures suited to specific field conditions, optimizing fertilization and water needs for the introduced species, and identifying and adhering to the optimal harvest timing for the crop.

Table 8. An extensive review of VIs used in forage crop research.

Type of Meadows and Pastures, as Reported	Country/Region	Satellite Data Used	Remote Sensors Used (If Applicable)	Time Span of the Study	Computed Indices	References
Alfalfa	Spain, Germany, France	Sentinel-2	LI-COR LAI-2000 SPAD-502 (Seedburo Equipment Company, Des Plaines, IL, USA)	2003–2004, 2006, 2007	LAI, Chlorophyll Content	[58]
Alfalfa	Saudi Arabia	Landsat-8	Large rectangular baler—CLAAS model Quadrant 3200 (CLAAS, Harzewinkel, Germany), equipped with a Hay yield monitor data (model 500 of Harvest Tec, Hudson, NY, USA)	October 2013–May 2014	EVI, GRVI, GNDVI, LSWI, NDVI, SAVI, SR	[95]
Alfalfa	Saudi Arabia	CubeSat, Landsat-8, MODIS	-	2017	LAI, NIR, REGFLEC-based LAI	[63]
Forage crops	Italy	Sentinel-2	-	28 February–30 June 2021	NDVI	[96]

The primary goals of the previous research in this field have typically revolved around assessing the productivity of cultivated grasslands and tracking this metric in response to specific stress factors. While relatively limited in number, the existing studies on cultivated meadows have underscored the potential of remote sensing in effectively addressing the most vital elements related to forage crop management.

Kayad et al. [50] made a significant contribution to this research field, highlighting the potential of SAVI and NDVI to assess alfalfa yield variability (using Landsat-8 imagery and hay yield monitor data). Furthermore, the authors managed to explore the potential of predicting alfalfa yield through VIs.

3.2.8. Meadows and Pastures

As emphasized in the preceding section, this literature review revealed a greater volume of studies on the use of VIs in meadows and pastures compared to forage crops. As indicated in Table 9, the studies spanned from 2010 to 2021, highlighting the relatively recent nature of this research, primarily within the past decade. It's noteworthy that over 90% of these studies were carried out in European countries, encompassing various biogeographical regions across the continent.

In the context of research on meadows and pastures, all of the remote sensing data sources exclusively consisted of satellite imagery. The primary satellite of choice was Sentinel-2, accounting for approximately 56% of the data, followed closely by Landsat at approximately 31%.

Grasslands are natural habitats that host a very high biodiversity of plant and animal species and perform a number of essential ecosystem functions. In this respect, grassland ecosystems are a source of food for domestic animals, a habitat, and a food source for wild animals, a means of preventing and combating soil erosion and a means of improving soil structure and fertility [94]. In the current context, defined by the major concern of human society in combating climate change, these large areas covered by vegetation can contribute significantly to reducing the intensification of global warming by sequestration of carbon in the soil. Recent studies in Poland have shown that a 700 ha regenerative grassland can capture more than 4500 t CO₂e per year from the atmosphere and store it in the soil, equivalent to emissions from the manufacture of 2400 t steel [97]. Taking into account the multiple functions of grasslands, studies aiming to monitor these ecosystems to ensure a favorable conservation status are imperative. Classical studies of monitoring the conservation status of the meadows involve a series of activities that consume energy, time and material resources, as they are based on the field study of relevant plots through their floral inventory. The results of such studies will, therefore, largely depend on the availability of these resources and the knowledge of the specialists who perform the plant species investigations. A viable alternative to classical grassland inventory techniques is the use of satellite images, a method that could provide better accuracy of the results obtained in a shorter time frame and without special material costs.

Prior research in grassland ecosystems has primarily focused on evaluating the productivity and growth rates of plant species, with relatively limited emphasis on assessing the floral biodiversity present within these environments [98].

The main VIs followed in semi-natural grassland studies were NDVI [99–103], EVI [3,104], and PSRI ([99,104]; Table 7). It is notable that while some studies focused on the combined use of several VIs, the majority of the analyzed scientific papers utilized only one index, as indicated in Table 9.

Meshesha et al. [105] conducted a study with the objective of predicting feed production using satellite imagery from Sentinel-2. The research focused on tracking two VIs, NDVI and EVI, and found that when combined with ground data from a semi-permanent grassland in Ethiopia, satellite data could effectively generate models for predicting biomass in meadows with high accuracy.

In a related study, Ara et al. [100] monitored spatio-temporal phenological variations within a semi-natural meadow in Australia, using the NDVI derived from Sentinel-2 satellite imagery captured from red spectral bands (B4) and near-infrared (B8). The authors successfully assessed changes occurring in the floral composition throughout the calendar year, achieving an accuracy rate of 75–81%.

Similar findings were corroborated by other researchers, such as Ren et al. [102], who evaluated the performance of NDVI and PSRI in a study conducted in China. Their results indicated that PSRI is a robust VI with utility in monitoring grassland phenology in addition to the traditional NDVI index.

Table 9. An extensive review of VIs used in meadows and pastures research.

Type of Agricultural Land: Meadows or Pastures, as Reported	Country/Region	Satellite Data Used	Remote Sensors Used (If Applicable)	Time Span of the Study	Computed Indices	References
Pastures and arable land	France	SPOT-5, Landsat and RADARSAT-2	-	2010	NDVI, LAI, fCOVER	[106]
Pastures	Czech Republic	MODIS	-	2010–2011	NDVI, PSRI	[104]
Meadows	France	MODIS	-	2012–2014	NDVI	[103]
Pastures and arable land	Czech Republic	Landsat-8, Land Parcel Identification System (LPIS)	-	2013–2016	NDVI, SR, SGI	[102]
Pastures	China	Landsat-7 ETM + , Landsat-8 OLI, Sentinel-2A MSI, MODIS	-	2014–2015 June–August	LAI	[107]
Pastures	Australia	Sentinel-2	-	2019–2020	NDVI	[100]
Pastures	Belgium	Sentinel-1 A and B	-	April–July 2019	SAR	[108]
Meadows	Czech Republic	Sentinel-2	-	2015–2019	FAPAR, FCOVER, LAI, CAB, CWC, NDVI	[101]
Meadows	Belgium	Sentinel-1 and 2	-	2018	NDVI	[46]
Meadows	Italy	Sentinel-2	-	28 February– 30 June 2021	NDVI	[96]
Meadows	Norway	Sentinel-2	-	May–October 2019	SAVI	[72]
Meadows	Germany	Sentinel-2, Landsat-8, PlanetScope	-	2017–2020	EVI	[109]
Meadows	Switzerland	Sentinel-2	-	2017–2019	NDVI, EVI	[3]
Pastures	Ethiopia	Sentinel-2	-	2018	NDVI, EVI	[106]
Meadows	Italy	Landsat-8, Sentinel-2, PlanetScope	-	2021	EVI, GNDVI, GVMI, MSAVI, NBR, NDGI, NDMI, NDII, NDREI, NDVI, PSRI, RECI, RENDVI, RESI, RVI, SAVI, VARI, WDRVI	[99]

4. Road Mapping Future Research Perspectives

The application of vegetation indices for crop classification and discrimination has experienced significant progress. Yet, there are notable gaps in the current research that warrant further exploration. As discussed in earlier sections, previous studies have primarily concentrated on employing traditional vegetation indices, such as NDVI, LAI and EVI, derived from satellite data. While this approach provides valuable insights into overall vegetation health, it may lack the precision needed to capture subtle variations in crop conditions. Recent research has emphasized that individual wavelengths, whether measured at ground level or remotely, offer a more detailed and nuanced perspective on the spectral characteristics of crops, such as early disease detection, optimizing irrigation strategies, and assessing overall crop performance [55,110].

Ground-level measurements, typically obtained through handheld devices or field spectrometers, offer detailed data at specific locations. In contrast, remote sensing technologies, equipped with sensors that capture individual wavelengths, improve spatial resolution, enabling a comprehensive assessment of crop variability over larger geographical extents. In a study by Yue et al. [111], the estimation of above-ground biomass of winter wheat based on images obtained with a snapshot hyperspectral sensor mounted on a UAV showed promising results. The new UAV-based snapshot hyperspectral sensor improved crop height determination, leading to enhanced above-ground biomass estimation. The authors recommended this approach for crop mapping applications [111]. Additionally, Thenkabail et al. [55] conducted research aimed at evaluating the performance of various types of hyperspectral vegetation indices in characterizing agricultural crop biophysical variables for five irrigated summer crops (cotton, potato, soybeans, corn, and sunflower). The researchers endorsed the use of a specific set of 12 narrow bands as optimal for accurately estimating biophysical information related to agricultural crops within the 350 nm to 1050 nm range.

Overall, the existing studies on this topic demonstrate that the dual approach, integrating ground-level precision with the extensive coverage of remote sensing technologies, holds potential as a comprehensive and accessible solution for precise crop monitoring and management. Therefore, future research efforts should aim to further investigate and enhance the reliability and versatility of narrow-band sensors and individual wavelengths.

5. Conclusions

The research conducted on the use of VIs in agricultural crops, forage crops, meadows and pastures has shown that they are suitable for mapping and monitoring several agricultural crops. Over 50% of the scientific papers examined in the current study relied on satellite data, with Sentinel-1 and Sentinel-2 being the most frequently utilized sources. Most of the studies employed several VIs to achieve good discrimination of crops or prediction of yields; however, that is not always the case for certain crops (i.e., sunflower). To date, some of the frequently employed VIs include EVI, LAI, NDVI, GNDVI, PSRI, and SAVI. Although the results achieved by these studies are satisfactory (in some crops, using certain indices, an accuracy of up to 90% was recorded), further studies are needed to establish models for using satellite data with greater accuracy and to provide information for the efficient monitoring of agricultural crops.

Moreover, although substantial research has been carried out aimed at differentiating the areas occupied by semi-natural meadows from agricultural and forage crops, there are still many aspects related to this topic that should be clarified or improved. This objective can be difficult to achieve only by utilizing information obtained by the acquisition of spectral images, mainly because the spectral characteristics vary significantly during the vegetation period. At the same time, the spectral signatures of various types of crops and semi-natural meadows are quite similar during the year, depending on their individual state of growth, which in turn are determined by the phenology and the culture system.

Therefore, the identification of the most appropriate VIs based on the developmental stage of crops (and their combined use during the different phenological periods) appears to be a crucial factor contributing to the accuracy of the results. Furthermore, the studies analyzed in this review demonstrated that the combined use of two or more satellite sources or the incorporation of a UAV (for example) could contribute to higher accuracy in the results. Another challenge observed in the studies aimed at discriminating areas occupied by semi-natural meadows against those occupied by agricultural and forage crops was the identification of optimal methods of classifying land use in areas that are mostly covered by clouds, which restrict access to satellite data. The identification of the optimal models for the classification of land use categories for such areas is therefore still undergoing and a topic of further research efforts. In addition, the integration of individual wavelengths in future research presents a promising avenue for advancing precision agriculture, offering a more detailed and accessible perspective on crop biophysical variables.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/agronomy13123040/s1>, Table S1: List of abbreviations.

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