agriculture

MDPI

Review

Applying Remote Sensing, Sensors, and Computational Techniques to Sustainable Agriculture: From Grain Production to Post-Harvest

Dágila Melo Rodrigues [1], Paulo Carteri Coradi [1,2,*], Newiton da Silva Timm [1], Michele Fornari [1], Paulo Grellmann [2], Telmo Jorge Carneiro Amado [1], Paulo Eduardo Teodoro [3], Larissa Pereira Ribeiro Teodoro [3], Fábio Henrique Rojo Baio [3] and José Luís Trevizan Chiomento [4]

[1] Department Agricultural Engineering, Rural Sciences Center, Federal University of Santa Maria, Avenue Roraima, 1000, Camobi, Santa Maria 97105-900, Brazil; dagilarodrigues2012@gmail.com (D.M.R.); newiton.silva.timm@hotmail.com (N.d.S.T.); michelefornari@gmail.com (M.F.); proftelmoamado@gmail.com (T.J.C.A.)

[2] Laboratory of Post-Harvest (LAPOS), Campus Cachoeira do Sul, Federal University of Santa Maria, Highway Taufik Germano, 3013, Passo D'Areia, Cachoeira do Sul 96506-322, Brazil; paulogrellmann@outlook.com

[3] Campus de Chapadão do Sul, Federal University of Mato Grosso do Sul, Chapadão do Sul 79560-000, Brazil; eduteodoro@hotmail.com (P.E.T.); larissa.uems@gmail.com (L.P.R.T.); fabio.baio@ufms.br (F.H.R.B.)

[4] Department of Agronomy, University of Passo Fundo, Avenue Brasil Leste, 285, São José Passo Fundo 99052-900, Brazil; jltrevizan@upf.br

* Correspondence: paulocoradi@yahoo.com.br

Abstract: In recent years, agricultural remote sensing technology has made great progress. The availability of sensors capable of detecting electromagnetic energy and/or heat emitted by targets improves the pre-harvest process and therefore becomes an indispensable tool in the post-harvest phase. Therefore, we outline how remote sensing tools can support a range of agricultural processes from field to storage through crop yield estimation, grain quality monitoring, storage unit identification and characterization, and production process planning. The use of sensors in the field and post-harvest processes allows for accurate real-time monitoring of operations and grain quality, enabling decision-making supported by computer tools such as the Internet of Things (IoT) and artificial intelligence algorithms. This way, grain producers can get ahead, track and reduce losses, and maintain grain quality from field to consumer.

Keywords: grain production; grain post-harvest; agricultural monitoring; prediction of agricultural results

check for updates

Citation: Rodrigues, D.M.; Coradi, P.C.; Timm, N.d.S.; Fornari, M.; Grellmann, P.; Amado, T.J.C.; Teodoro, P.E.; Teodoro, L.P.R.; Baio, F.H.R.; Chiomento, J.L.T. Applying Remote Sensing, Sensors, and Computational Techniques to Sustainable Agriculture: From Grain Production to Post-Harvest. *Agriculture* **2024**, *14*, 161. https://doi.org/10.3390/agriculture14010161

Academic Editors: Ziliang Liu, Jun Wang and Lizhen Deng

Received: 13 December 2023
Revised: 10 January 2024
Accepted: 16 January 2024
Published: 22 January 2024

1. Introduction

As the world's population increases, there is a need to increase food production, which poses a challenge to society [1]. Increased food production must be achieved through sustainable management of the entire production system [2]. Agricultural intensification is necessary due to limited production areas. To achieve this, new technologies and management practices must be introduced in agriculture to reduce the side effects of increased use of fertilizers, pesticides, and other inputs.

Advances in data collection and processing technologies have been successfully used around the world to support decision-making in various agricultural processes. These advancements include harvest sensors, which are capable of estimating grain yields before harvest [3–5], weed occurrence, weed nutritional status [6], plants [7], top-dressing nitrogen [8], water stress [9], and grain protein content [10,11]. Such applications help improve grain yield, quality and input use efficiency as well as reduce nutrient losses and negative environmental impacts [12,13].

After harvest, storage capacity must be 20% higher than yield to avoid product losses and improve logistics and quality [14]. However, in some countries, in addition to poor quality control of grains stored in structures, there is also the problem of insufficient storage capacity, especially in terms of crucial factors such as grain moisture content and the temperature and relative humidity of intergranular air, which are necessary for food preservation.

Using sensors and Internet of Things (IoT) applications, grain quality can be monitored and predicted throughout the grain storage period. Therefore, precision agriculture tools such as remote sensing can help monitor pre- and post-harvest processes by leveraging a range of advanced information, communication, analysis, and data processing technologies such as big data analytics, digital platforms, processing clouds, and artificial intelligence. These technologies allow for the extraction of a wealth of information about data collected during decision-making [15,16].

2. Review Methodology

2.1. Search Strategy

For this review, precise examination and evaluation standards were established. The most significant research question that directed our review was as follows: How do far-flung sensing, PC vision, and their integration contribute to tracking grain properties at the manufacturing and post-harvest stages? We evaluated manuscripts addressing advances in far-flung sensing and relevant equipment used for tracking the complete grain production chain, from the field to the post-harvest process. To this end, we conducted a scientific literature search of the "CAPES Journal Portal" as well as the Science Direct, Scopus, and Web of Science databases. We selected articles published in journals from 2002 to 2023 that provided primary studies associated with the following topics: sensors in agriculture; agricultural yield forecasting techniques; equipment for far-flung tracking of post-harvest grains; and artificial intelligence in agriculture. The database search used a mixture of the following terms: (ALL = ((remote sensor OR tracking)) AND production AND post-harvest)). No restrictions on language or type of publication were applied at this stage (Figure 1A,B).

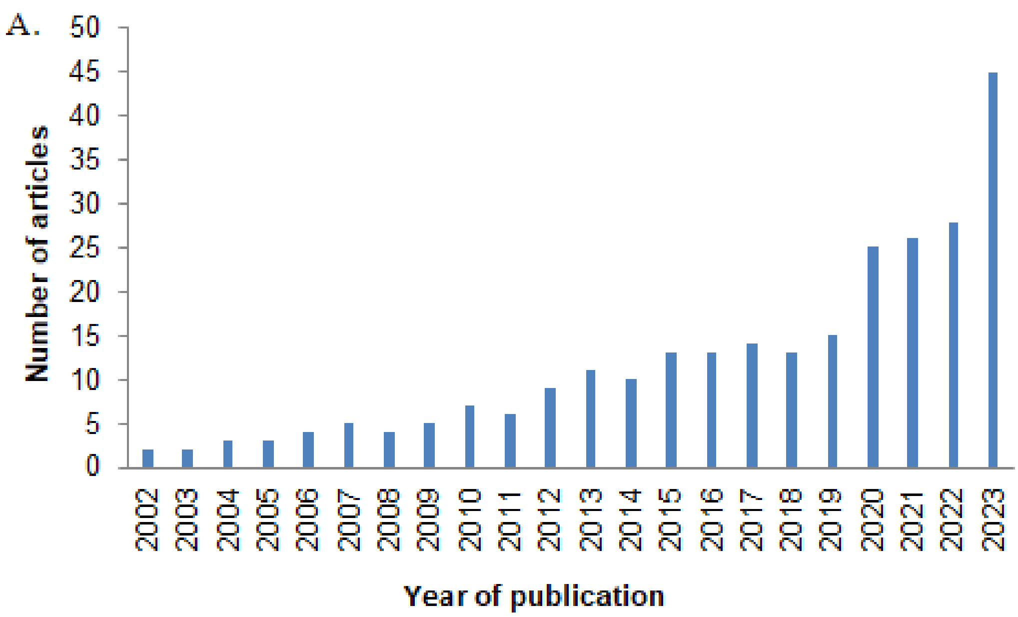

Figure 1. *Cont.*

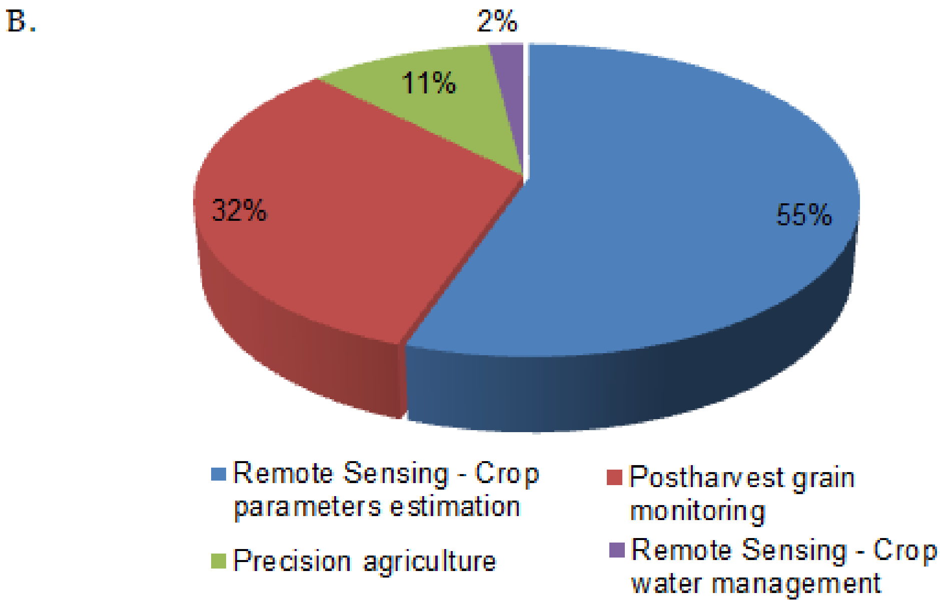

Figure 1. Index of publication per year (**A**) and area (**B**).

2.2. Eligibility Criteria and Selection Process

References were selected independently and in parallel by two co-authors regarding inclusion/exclusion criteria. Manuscripts that did not meet the inclusion criteria were excluded from the posterior analysis. Additionally, manuscripts were selected if they met all of the following criteria: a) the abstract described a study related to any remote sensing or monitoring (grain, production, and post-harvest); b) at least one of the remote sensing or monitoring techniques were related to any production or post-harvest stage. After the screening process, data were extracted from papers tables or text.

2.3. Studies Evaluation Synthesis and Results

The selected manuscripts were categorized according to publication year, author's geographic region, and publication journal to provide information on the development of research on a particular topic. Furthermore, the remote sensing or monitoring technologies featured in each analyzed manuscript were identified in conjunction with production management or control of post-harvest grain operations. To identify the techniques, technologies, and applications of remote sensing and computational technologies in the grain production and post-harvest stages, we extracted the data and organized it in a spreadsheet with the following fields: spatiotemporal resolutions of satellite sensors (satellite, sensor, temporal resolution, precision agriculture application, references); vegetation indices and sensors (vegetation indices, equation, types of sensors, applications, references); remote sensing techniques used for monitoring grains in the post-harvest stages (sensing method, post-harvest stage, references); prediction of results based on easy-to-measure parameters, such as soil and weather attributes sensing and monitoring techniques, combined with predictive algorithms (applied technique, the objective of the application, references).

The references were chosen openly and in parallel by two co-authors concurring to the inclusion/exclusion criteria. Unique duplicates that did not meet the consolidation criteria were denied from empower examination. Unique duplicates were chosen that met all of the taking after criteria: (a) the hypothetical delineated a think approximately related to any more distant identifying or watching (grain, era and post-harvest); (b) at smallest one of the more distant recognizing or watching methodologies was related to many arrange of era or post-harvest. After the screening handle, the data was removed from the tables or works of the articles.

3. Remote Sensing Applied on the Agriculture

3.1. Remote Sensing Techniques, Applications, and Sensors

Figure 2 and Table 1 presents a summary of remote sensing techniques available, their characteristics, applications, and sensor types.

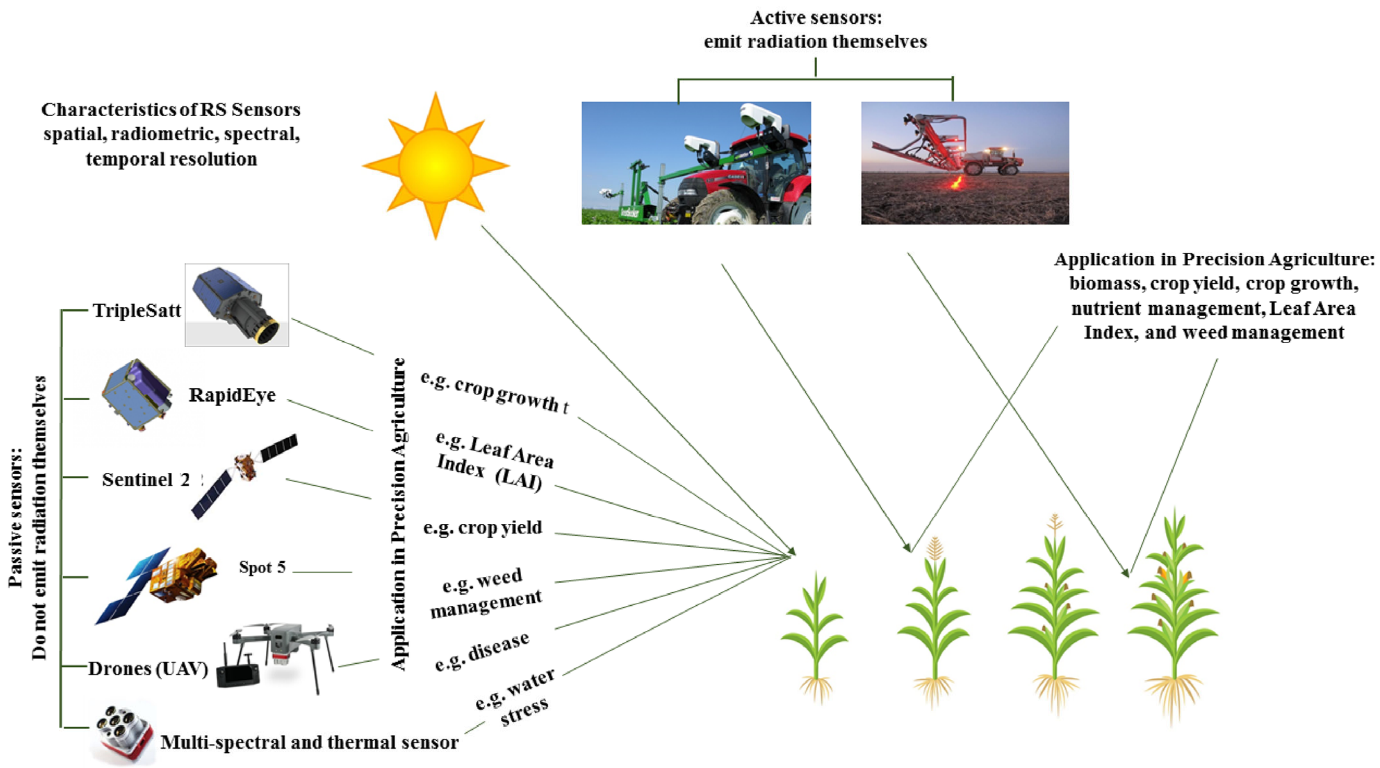

Figure 2. Remote sensing techniques, their characteristics, applications, and sensors.

Table 1. Spatiotemporal resolutions of satellite sensors with high resolution (<30 m) and temporal sensors used for precision agriculture.

Satellite (Active Years)	Sensor (Spatial Resolution)	Temporal Resolution (Days)	Precision Agriculture Application	References
Kompsat-3A (2015–current)	MS V NIR (2.2 m); SWIR (5.5 m)	1.4	Disease detection and phenotyping	Bajwa et al. [17] and Zhang et al. [18]
Wordview-3 (2014–current)	SS (1.24 m)	<1	Weed management and crop residues mapping	Caturegli et al. [19] and Hively et al. [20]
RapidEye (2008–current)	MS (6.5 m)	1–5.5	Weed control, estimation of leaf area index, estimation of forest area, and biomass	Dong et al. [3], Halperin et al. [21], and Coffer et al. [22]
GeoEye-1 (2008–current)	MS (1.65 m)	2.1–8.3	Management of nutrients and canopy mortality caused by insects	Dennison et al. [19] and Caturegli et al. [23]
Lidar (1995)	VIS (10 cm)	N/A	Mapping of leaf mass variation	Chlus et al. [24]
Spot-1 (1986–1990)—Spot-2 (1990–2009)—Spot-5 (2002)	MS (20 m); MS (2.5–10 m)	1–2.6	Mapping of environmental indicators, Mapping of weeds, and Monitoring of agricultural practices	Pasqualini et al. [25], Hajj at al. [26], and Johansen et al. [27]
Sentinel-1 (2014–current)—Sentinel-2 (2015–current)	SAR (5–40 m)—MS (10 m); NIR (20 m); SWIR (60 m)	1–3	Phenology, Effect of lodging on wheat, Detection of abiotic and biotic stress, and Estimated productivity	Segarra et al. [5], Gómez el al. [28], Chauhan et al. [29], and Meroni et al. [30]

Crop biomass and grain yield forecast usually require higher spatial resolution (1–3 m) compared, for example, with the application for variable fertilizer and seed rate technology [31]. Besides, weed mapping and variable herbicide rate technology require higher spatial resolution than identifying only the ridges (for example, 5–50 cm) [32]. Aerial platforms, such as UAVs (Unmanned Aerial Vehicles), provide images with a higher spatial resolution (<3 m) compared to satellites. Thus, UAVs offer better flexibility in providing images with higher spatial and temporal resolution according to the target to be sensed. Xie et al. [33] assessed the classification and crop monitoring over an agricultural area with corn, soybean, and winter wheat from multi-year polarimetric observables from RADARSAT-2 using machine learning. The authors found that multitemporal polarimetric synthetic aperture radar (PolSAR) can estimate plant growth with a root mean squared error (RMSE) around 40–50 cm over the cycle. Random Forest (RF) approach proved to be more accurate in crop classification. Cheng et al. [34], when assessing multispectral information to predict winter wheat yield, found contrasts between the multi and hiperspectral approaches. On the other hand, the predictions achieved using hyperspectral information was more accurate. These findings highlight the potential of the shortwave infrared groups to supplant the unmistakable and close infrared groups in yield predictions.

3.2. Vegetation Sensors in Agriculture and Applications

Figure 3 and Table 2 present a summary of the application of crop sensors.

Table 2. Vegetation indices and sensors currently used in agriculture.

Vegetation Indices	Equation	Types of Sensors	Applications	References
Normalized difference vegetation index (NDVI)	$\frac{\rho_{NIR}-\rho_{red}}{\rho_{NIR}+\rho_{red}}$	Passive: multispectral (MCA-6 Tetracam, Mapir); Active: Greenseeker crop circle	Estimation of grain yield, biomass, phenotyping, nutrient management, diseases, and pest identification	Raun et al. [35], Genc et al. [36], Maimaitijiang et al. [37], Schaefer and Lambd [38], Calera et al. [39], and Peng et al. [40]
Normalized difference red edge (NDRE)	$\frac{\rho_{NIR}-\rho_{rededge}}{\rho_{NIR}+\rho_{rededge}}$	Passive: multispectral (Micansense RedEdge Mx); Active: Nsensor (RapidSCAN)	Biomass, productivity, N status, grain yield, diseases, water stress, and leaf area index estimation	Aranguren et al. [10], and Zhou et al. [11], Amaral et al. [41], Jorge et al. [42], Pourazar et al. [43]
Green NDVI (GNDVI)	$\frac{\rho_{NIR}-\rho_{green}}{\rho_{NIR}+\rho_{green}}$	Passive: multispectral; (MCA-6 Tetracam, Parrot Sequoia)	Diseases, invasive plants, and water stress	Zhou et al. (2018) [44], and Baron et al. [45]
Red edge normalized difference vegetation index (RENDVI)	$\frac{\rho_{NIR}-\rho_{rededge}}{\rho_{NIR}+\rho_{rededge}}$	Passive: multispectral (Micansense RedEdge Mx); Active: Nsensor (RapidSCAN)	Yield, diseases, and N status	Shaver et al. [46], Martínez et al. [47], and Pourazar et al. [43]
Red edge DVI (REDVI)	$NIR - REDEDGE$	Passive: multispectral (Micansense RedEdge Mx); Active: Nsensor (RapidSCAN)	Rice yield	Kanke et al. [48]
Shortwave Infrared Water Stress Index (SIWSI)	$\frac{858.5\text{ nm}-1640\text{ nm}}{858.5\text{ nm}+1640\text{ nm}}$	Passive: thermal (Micansense Altum), hyperspectral (Cubert GmbH)	Leaf moisture content	Fensholt and Sandholt [49]

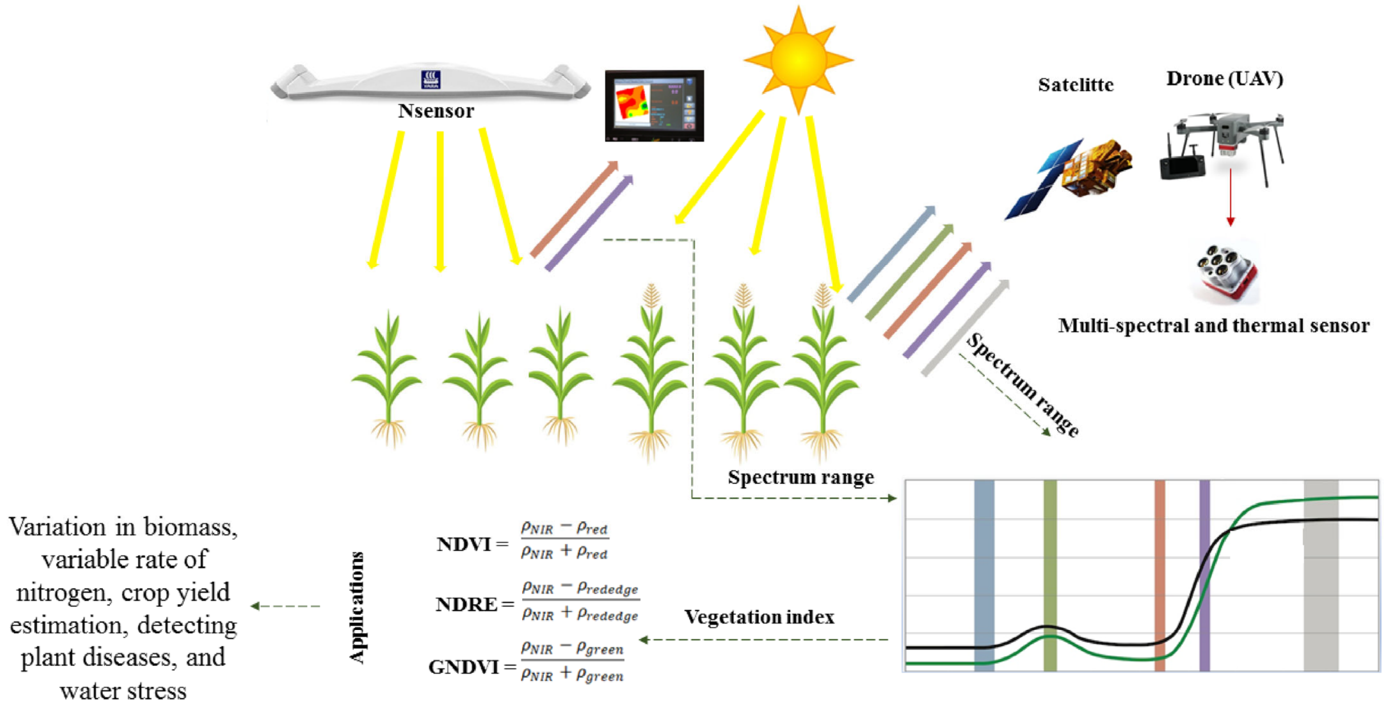

Figure 3. Application of vegetation sensors in agriculture.

The most advantage of red edge vegetation indices is that they are less affected by plant canopy structures. Hence, they are more promising for the development of models for assessing leaf range record and grain efficiency. Eitel et al. [50] found that the use of the red edge improved the ability to estimate changes in chlorophyll content ($r^2 > 0.73$, RMSE < 1.69) compared to devices that did not use ($r^2 = 0.57$, RMSE = 2.11). Vegetation indices based on the red edge such as Red Edge Normalized Difference Vegetation Index (RENDVI), Normalized Difference Vegetation Index (NDRE), and Red Edge Difference Vegetation Index (REDVI) frequently have a better relationship with plant nutrients uptake and biomass production under dense canopy conditions than NDVI, such as those present during the advance corn growth stages [51].

The measurement of reflectance or emissivity in the near and medium infrared bands is particularly useful in the development of indices that help to understand intrinsic characteristics of the plant, such as water, pigments, sugar, carbohydrates, and protein content. The radiation reflected or emitted in thermal infrared bands is related to the temperature of the plant and this with the rate of transpiration of the plant. Thus, the indices obtained from these thermal reflectance data can be used to understand the level of the plant's water stress and other biotic stresses, such as diseases [52,53]. In this context, vegetation indices based on infrared reflectance, and thermal emissions, such as crop water stress index (CWSI) and short-wave infrared water stress index (SIWSI) are particularly useful. These indices have been successfully used for a broad range of objectives in agriculture including plant stress due to excess or water deficit, soil moisture, plant diseases, and crop yield forecast [54].

The early season assessment of crop yield at regional, State, and National scales is key information for agricultural planning and public policy. The applications of this information in post-harvest are growing allowing redesign of the whole organization strategy for the flow of the production, from the crops to the food processing and production industries decreasing loss and keeping the quality. However, the crop yield forecast in many countries is based on conventional data collection procedures through plot scale or human perception [53–56]. These techniques are often subjective, expensive, time-consuming, and are subject to bias due to incomplete or wrong observations, leading to an inaccurate assessment of crop yield [57].

The accurate evaluation of the crop performance on large scale has been becoming a reality after the progress in remote sensing technology by modern satellites and UAV-coupled sensors. The approaches based on remote sensing by satellite or UAV provide repeated measurements at different spatial, temporal, and spectral scales that allow estimating various canopy parameters, such as vegetation cover, leaf area index, and absorbed fraction of photo-synthetically active radiation, which can be used in crop yield models [58].

According to Peng et al. [40], the remote sensing crop yield forecast is carried out in two ways. The first approach uses biophysical parameters of vegetation as a leaf area index (LAI) obtained by remote detection and the data is used in specific models to estimate crop yield. The second process uses statistical relationships such as regression or empirical relationships between parameters and harvest indices derived from remote sensors (such as NDVI and NDRE vegetation index), in addition to the harvest yield observed in a cultivated area. Maresma et al. [59] presented a regression-based approach to assess the relationship between corn yield, biomass, and spectral indices measured at corn crop stage V12. Related to other studies, they also found that red NDVI-based indices and the wide dynamic range vegetation index (WDRVI) had a higher correlation with grain yields obtained in a range of fertilizer rate input. Kumar et al. [60] correlated the NDVI values of different satellites to estimate the crop yield in wheat and found coefficients of determination above 0.90. Rao et al. [61] evaluated the Normalized Difference Vegetation Index (NDVI) to estimate sugarcane yield and reported a strong relationship between yield and NDVI (R = 0.84). Alongside, Rahman and Robson, Rahman and Robson [62] reported that the green normalized difference vegetation index (GNDVI) derived from the Landsat 30 m resolution had a significant correlation (R^2 = 0.69) with crop yield. Ali and Imran [62] used the red edge extracted from hyperspectral images to predict the leaf area index (R^2 = 0.93) and the chlorophyll content (R^2 = 0.90) to estimate yield (R^2 = 0.91) of Kinnow tangerines.

Reliable estimate of crop yield based on the canopy reflectance throughout the different growth stages can be a challenging task, especially during the initial stages of crop growth due to the interference of the bare soil surface [63]. To overcome this limitation, Zhen et al. [64] used other vegetation indices modified to minimize the soil interference in the estimative of leaf area index (LAI) and, consequently, crop yield. Recently, vegetation indices based on red-edge have shown satisfactory efficiency for estimating the yield of different crops.

3.3. Advantages and Disadvantages of the Remote Sensing

The advantage of remote sensing as a whole, compared to other conventional data collection methodologies, is the fast and non-destructive sample collection. For example, it is possible to have information on several variables, such as nitrogen content, plant mass, disease severity, among others. At the satellite orbital level, the advantages are even greater, as it makes it possible to sample large and larger areas with repeatability depending on the time span in which the satellite is visited, that is, every so often the satellite images the area, enabling a high sampling rate at a lower cost and time when compared to traditional sampling in the field, even in conditions where there is a need to pay for the satellite.

The disadvantages of sampling via an orbital satellite sensor are that it is collected when clouds are present at certain periods of the year, depending on the region, making sampling and sample quality unfeasible. Another disadvantage is obtaining images via free satellites, for example Landsat and Sentinel. It is worth noting that the aim is always to collect images with the highest spatial resolution, with the greatest possible number of pixels, to achieve the desirable detail of the target for analysis. This is especially important for smaller areas and objects, such as fruit plots or cities. However, it makes no difference for larger areas where target detailing is not the main objective. Image collection via drone is an alternative to the disadvantages mentioned above, as it is possible to fly below the clouds without their interference in image collection. On the other hand, the main disadvantage of using a drone is the high initial cost and the need for training to operate the drone and process images. Even so, drones make it possible to collect samples with the possibility of repeating them daily or on different days.

Among the main advantages of using vegetation indices are the future diagnosis of elements that do not yet have scientific support, for example, a plant attacked by insect pests that ends up changing its physiology, which could probably be detected by some spectral response, mainly by hyperspectral sensors, being an area still new and very little studied. There is still a large scope for development in the application of sensors.

4. Using Remote Sensing on the Post-Harvest Grain Monitoring

4.1. Post-Harvest Grain Monitoring

Although the feasibility of using remote sensing techniques in agriculture has been demonstrated since the 1980s, the operational use of remote sensing data has recently been intensified and used operationally for a variety of agricultural applications [65], among them post-harvest of grains. The use of sensors can assist in monitoring quality and reducing losses [66]. Temperature sensors can be used next to the grains as an indirect indicator of the quality of the product during transport, drying, and storage. Obtaining real-time information about the conditions of the grains helps in making decisions on the post-harvest stages. Table 3 presents studies that used remote sensing techniques applied to the monitoring post-harvest grain quality.

Table 3. Studies on the remote sensing techniques used for monitoring grains in the post-harvest stages.

Sensing Method	Post-Harvest Stage	Reference
Sensor package—CO_2 sensor, temperature sensor, and relative humidity sensor	Grain transport	Danao et al. [67]
Multispectral vision sensor	Grain cleanness	Wallays et al. [68]
Microwave moisture sensor	Grain drying	Lewis et al. [69]
Moisture content sensor	Grain drying	Li et al. [70]
Online Moisture Detector Based on V/F Conversion	Grain drying	Liu et al. [71]
CO_2 sensor	Grain storage	Neethirajan et al. [72]
CO_2 sensor	Grain storage	Ubhi and Sadaka [73]
The wireless network of the temperature sensor, humidity sensor, and light sensor	Grain storage	Onibonoje et al. [74]
Internet of Thighs (IoT)—microcontroller and various sensors	Grain storage	Kodali et al. [75]
Internet of Thighs (IoT)—temperature sensor, humidity sensor, and CO_2 sensor	Grain storage	Sindwani et al. [76]
Cyber-Physical System (CPS)—temperature and humidity sensor	Grain storage	Parvin et al. [77]
Compact microwave device—insect activity sensor	Grain storage	Lewis et al. [69]
Wireless Phosphine Sensors	Grain storage	Brabec et al. [78]
Temperature sensor, humidity sensor, and CO_2 sensor	Grain storage	Kumar et al. [79]
Electromagnetic imaging	Grain storage	Asefi et al. [80], Gilmore et al. [81], Asefi et al. [82], Gilmore et al. [83]

4.2. Grain Monitoring in Transport

For monitoring grains during transport from the field to the storage units and from the storage units to the industry, Danao et al. [67] studied the development of a probe to monitor temperature, relative humidity, carbon dioxide (CO_2) levels, and logistical information during the transportation of soybeans. According to Nunes et al. [84], taking into consideration that grain transportation can be carried out over long separations which the grain mass amid transportation frequently features a tall dampness substance, there may be dangers of warm and dampness exchange, causing the grain mass to warm up and driving to quantitative and subjective misfortunes. Nunes et al. [84] approved a method with a test framework for real-time observing of temperature, relative stickiness and carbon dioxide within the mass of corn grains amid transportation and capacity, in arrange to identify early misfortunes of dry matter and anticipate conceivable changes within the physical quality of the grains. The hardware comprised of a microcontroller, system hardware, advanced sensors for identifying temperature and relative mugginess and a non-destructive infrared sensor for measuring CO_2 concentration. Real-time checking frameworks decided changes within the physical quality of the grains early and palatably, as affirmed by the physical investigations of electrical conductivity and germination. Real-time observing gear and the application of Machine Learning were viable in foreseeing dry matter misfortune, due to the tall balance dampness substance and breath of the grain mass inside 2 h. All the machine learning models, but the back vector machine, gotten palatable comes about, in a comparative way to the different straight relapse investigation. Figure 4 appears an outline of a test for checking these parameters amid grain transportation.

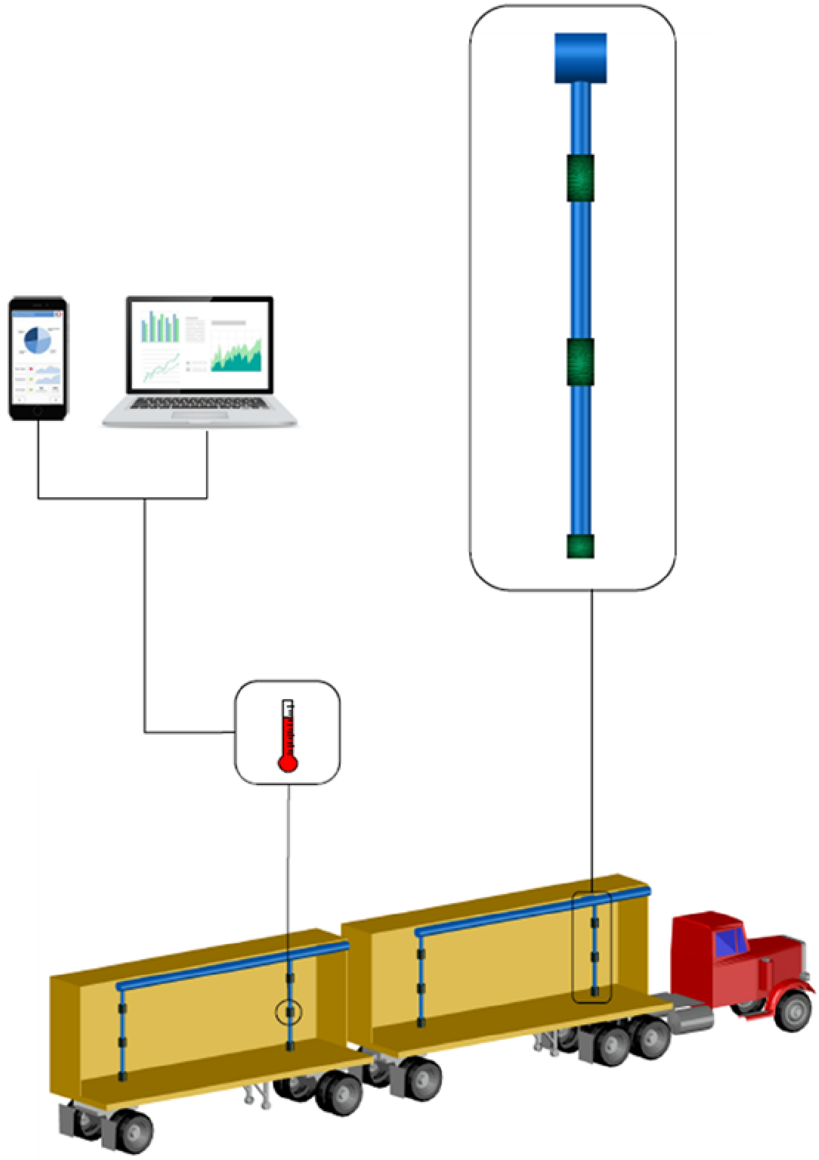

Figure 4. Illustration of a probe for monitoring temperature, relative humidity, carbon dioxide levels, and logistical information during the grain transportation.

The grain monitoring probe was designed to be placed inside vehicles responsible for transporting grain, allowing parameters to be monitored during product movement. The probes were constructed with four vertically spaced chambers in the grain mass and an optional fifth chamber for the overhead space above the grain mass within the loading portion of the transport vehicle. These probes are useful for better understanding conditions during soybean transportation, which can lead to better management of grain handling and transportation operations to minimize soybean quality loss in the post-harvest period [67,82]. In addition to monitoring temperature and other parameters during transport, this type of grain mass sensing contributes to decision-making in the storage unit. When the product arrives at the destination, the operators know in advance its main characteristics, making the industrialization processes more efficient.

When batches of grain are unloaded in the storage units, the grains are submitted to cleaning. For this, Wallays et al. [68] used a hyperspectral waveband selection for the online verification of grain cleaning. Seeking online monitoring of the percentage of impurities next to the grains, these authors developed a multispectral vision sensor able to create a virtual image with maximum contrast between the grains and the impurities, allowing each pixel to be classified individually. The selected bands were 465–475 nm, 522–532 nm, 676–705 nm, 849–858 nm, and 906–945 nm, which allowed discriminating between clean and impure grains.

4.3. Advantages and Disadvantages of the Grain Monitoring in the Transport

Thus, it can be stated that monitoring intergranular variables, such as temperature, relative humidity and CO_2 concentration in real time in the grain mass during transport, especially over long distances, has as its main advantage the possibility of monitoring possible changes that occur due to the increase in the metabolic activity of the grains and consequently the respiratory intensity of the grain mass, avoiding possible losses of dry matter and nutritional quality of the grains. Furthermore, monitoring the transport of grains from crops to storage units or from units to industry helps to segregate batches and their destinations in the following processes for better grain conservation, consequently increasing the value of the product. Often the qualitative changes that occur in the later stages of post-harvest are due to errors and lack of control that occurred in the previous stages. Thus, monitoring grain mass contributes to the batch traceability process, consequently bringing greater control over post-harvest grain losses. Disadvantages include the initial costs of equipment and sensors, as well as training and operational adaptations for installing and handling monitoring technologies.

4.4. Grain Monitoring during Drying

The cleaned grains are then taken to the drying stage. This step also requires constant monitoring. Figure 5 illustrates a system for monitoring the grains during drying. Lewis et al. [69] developed a grain drying system with monitoring of the moisture content reduction using a microwave sensor operating at 5.8 GHz. Lewis et al. [69] reported that it was possible to determine the moisture content in real-time and with a calibration standard error lower than 0.54% when compared to the reference method conducted in the oven. In the same way, Li et al. [70] developed an online device for measuring the moisture content of the grains during the drying process. The sensor developed by Li et al. [69] determines the moisture content of a single grain at a time, through the application of a direct current. The generated electrical circuit measures the electrical resistance of the grain, which employing mathematical equations designed for each species allows reaching the moisture content of the product. The results presented by Li et al. [85] showed that the device has an excellent performance in grains with varied moisture content (10–35% w.b) and temperature (−20–50 °C), with an absolute measurement error within 0.5%. The data obtained with the device are adequate to characterize the uniformity of the drying process of the grains. The drying monitoring sensor based on the electrical resistance of the grains improves the accuracy and reliability of the measurement and can be useful in other intelligent equipment for drying the grains.

Liu et al. [71] developed an online detector of the moisture content of the grains during the drying process that acts based on the voltage-frequency conversion. The sensor also consists of detecting the electrical resistance values of the grain, which is based on the voltage-frequency conversion, followed by moisture content and frequency conversion, and the non-linear correction as a function of temperature. The operating mechanism of this detector is remarkably like that described by Li et al. [85] and presented satisfactory results for application in monitoring grain drying. The industry needs good precision when reducing the moisture content in the drying process. Grains with high moisture content tend to deteriorate more quickly during storage, while excessively dried grains result in lower economic yield due to the reduction in total mass.

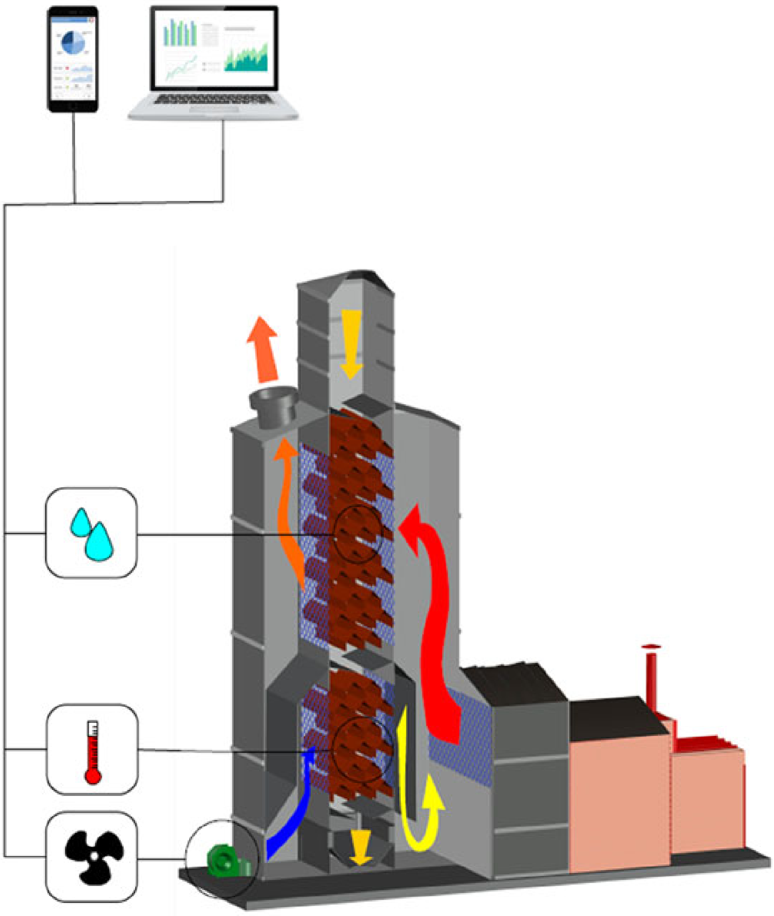

Figure 5. Illustration of a grain monitoring system during drying.

4.5. Advantages and Disadvantages of Monitoring Grains during Drying

Thus, monitoring the temperature and relative humidity of the dryer's inlet air, drying and exhaust air in real time, allow for the evaluation of the dryers' performance, for better drying efficiency with lower energy costs. Meanwhile, monitoring grain mass is a response to drying for the effects of moisture removal. Drying at high temperatures has the advantage of high drying speed and flow of batches of grains. On the other hand, it causes greater stress to the grains due to the high temperature, which can cause physical damage and consequently nutritional changes. Therefore, real-time monitoring of the of grain mass temperature can be a parameter for determining the intensity of drying in the stages of water removal from the grains. For drying at low temperatures, the monitoring of temperature and relative humidity variables is associated with the equilibrium moisture conditions of the grains. In this case, drying occurs in fixed layers from bottom to top inside the dryers, with a drying front in the grain mass, which at the same time remains stored in the same space. In this system, the drying air will need to be sufficiently heated at ambient conditions and dehydrated to remove moisture from the grains through the hygroscopic process (difference in vapor pressure between the grain and the drying air) and at the same time, the moisture from the grains at the end of the drying process must stabilize within a safe range for storage (between 12 and 14% w.b.), depending on the region. Real-time monitoring will provide greater control of the process and grain quality. The disadvantages are the costs of dryer instrumentation and the need for more qualified personnel to handle the equipment, as well as sensitivity and knowledge about the differences between the types of grains during drying.

4.6. Grain Monitoring in the Storage

As most grains are delivered at given times of the year and are still required by businesses all through the year, an expansive portion of the dried grains are put away. Figure 6 shows a framework for observing grain amid capacity and its advance over a long time. To protect put away grain, it is fundamental to keep the mass with a secure water substance of between 11 and 14% and an intergranular temperature underneath 22 °C (depending on the locale). This requires that air circulation and thermometry are working appropriately, checking the conditions of the discuss entering the capacity storehouse and the intergranular discuss. As well as observing the temperature, measuring the intergranular relative stickiness is vital for deciding the harmony dampness substance of the put away item and foreseeing respiratory issues. Given that grains are great warm insulin which the temperature of the grain mass is measured by sensors interior the silos, the thermometry framework frequently falls flat to distinguish item warming problems. Therefore, observing the whole CO_2 concentration interior the capacity storehouse could be a great pointer of item breath and air circulation control. At levels above 600 ppm CO_2, there is a chance of the item disintegrating. The combination of these factors indirectly characterizes the quality of the grain and makes it possible to anticipate conceivable dangers of the item weakening (Figure 6).

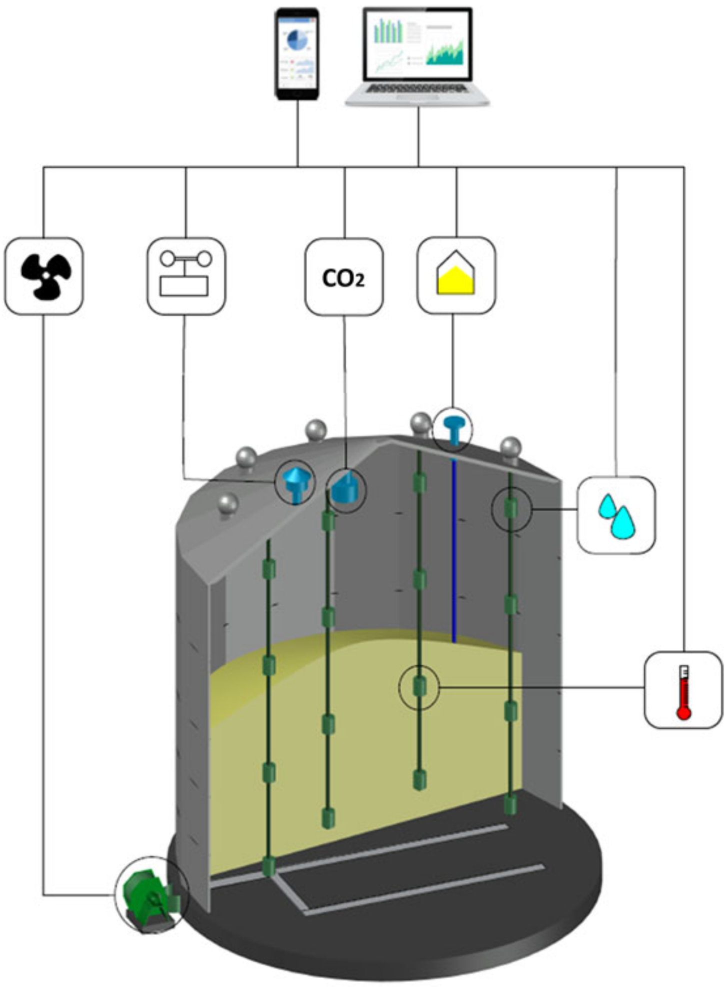

Figure 6. Illustration of a grain monitoring system during storage.

The warming of put away grain favors the advancement of creepy crawly bothers. Agreeing to Badgujar et al. [86] the checking of creepy crawly bothers in put away items could be a common hone for the post-harvest administration of put away cereals and cereal-based items, which makes a difference to ensure the quality of the item from gather to the conclusion customer. Be that as it may, current inspecting and observing strategies can be time-consuming, labor-intensive, costly and require encounter in recognizing creepy crawlies. Hence, Badgujar et al. [86] created a computerized image-based distinguishing proof framework for common creepy crawly species put away on create utilizing profound learning strategies. Top-down pictures of common grown-up creepy crawly species of *Rhyzopertha dominica*, *Cryptolestes ferrugineus*, *Tribolium castaneum*, *Sitophilus oryzae* and *Oryzaephilus surinamensis* were obtained and analyzed. State-of-the-art convolutional neural organize (CNN) models based on profound learning (ResNet-50, MobileNet-v2, DarkNet-53 and EfficientNet-b0) were prepared with an exchange learning approach to classify the creepy crawly species. All the models were able to accurately recognize the creepy crawly species with at slightest 96% precision and with few classification mistakes. One issue with prepared CNNs was that they didn't clarify the thinking behind the classification and were alluded to as "dark boxes". Subsequently, visualization strategies called Gradient-weighted Course Actuation Mapping (Grad-CAM) were executed to misuse the dark box network. Grad-CAM employments warm maps to highlight the most image highlights on which the organize has centered in order to create creepy crawly species expectations. Grad-CAM confirms the network's expectation conjointly makes a difference to make strides the network's execution. This think about contributed to the in general objective of creating a camera-based framework to screen creepy crawlies in put away grain. The framework created would engage distribution centers and other food offices as an apparatus to rapidly and precisely recognize creepy crawly species in put away item situations and may well be actualized as part of a real-time checking framework.

Neethirajan et al. [72] created a CO_2 sensor to remotely screen the quality of stored grain. The sensor was created employing a conductive polyaniline boronic acid polymer as the electrically conductive region of the sensor. The created sensor measured CO_2 levels within the 380–2400 ppm, recognized at diverse temperatures (between 25 and 55 °C), which needs water from the air to operate, permitting CO_2 to be recognized between 20 and 70% relative stickiness. Amid grain capacity, variables such as temperature and relative stickiness, grain dampness substance, CO_2 and creepy crawly concentration must be observed and controlled, continuously looking for the leading conditions for grain preservation.

Respiration rate over the time was analyzed by Ubhi and Sadaka [73] using CO_2 concentration sensors. The authors reported that the farther detecting method employing a weight sensor was found to be solid and touchy for measuring the respiration rate of grains within the parameters tried. As of late, Onibonoje et al. [74] considered a remote sensor organize framework to screen natural components (temperature, relative humidity and light) that influence grain capacity. The sensors were conveyed in settled areas flawlessly disseminated in a grain capacity storehouse. Onibonoje et al. [74] detailed that the remote sensor organize framework created makes a difference to guarantee nourishment security. As said prior, programmed capacity procedures are broadly utilized in capacity units to distinguish grain weakening by checking the temperature and relative stickiness of the discuss, the dampness substance of the grain and the CO_2 concentration. Depending on the measure of the storehouse, one or more cables containing an arrangement of sensors are hung vertically. On each cable, the sensors are as a rule 1.2 m separated. The number of cables in a storehouse depends on variables such as the estimate of the storehouse (primarily its breadth), the climatic conditions of the locale and the species of grain to be put away. One of the most points of interest of this framework is the real-time observing of capacity parameters [80,86]. The commonplace dividing between sensors (1.2 m) within the cable comes about in moo spatial determination.

Asefi et al. [80] evaluated a recent substitute for this monitoring technique [80]. These authors used electromagnetic imaging to monitor grain kept in silos. Global sensitivity, the utilization of inexpensive electromagnetic radiation, the capacity to produce images with high spatial resolution and without disturbing or interacting with grain are just a few benefits of using electromagnetic images [80]. Similar to this, but on a larger scale, Asefi et al. [80] and Gilmore et al. [81] also investigated the monitoring of grain storage conditions. Gilmore et al. [81] reported that the electromagnetic imaging system demonstrated the ability to identify a 25% moisture-containing deteriorating region in the grain mass in addition to a 15% moisture-containing grain mass. Therefore, it is economically feasible to monitor stored grain using systems based on electromagnetic imaging [81]. The temperature rise in the grain mass caused by insects near the grain can also be detected using this sensing technique. Using photos, this technology can keep an eye on even the smallest changes to the storage environment [82]. An inexpensive, low-power single board computer called the Jetson Nano, a manual focus camera, and a trained deep learning model made up the fundamental insect detection system created by Mendoza et al. [87]. Using a real-time visual feed, the model was validated. The authors claim that effective insect control depends on the timely detection, classification, and monitoring of insect pests in grain warehouses and food facilities. The insect's image is taken by the camera and sent to a Jetson Nano for processing. A deep learning model that has been trained to identify the types and abundance of insects is used by the Jetson Nano. The detection results are shown on a monitor under three different lighting conditions: white LED light, yellow LED light, and no lighting condition. The system was tested with various stored grain insect pests and was able to detect and classify adult warehouse insects with an acceptable level of accuracy by comparing accuracy based on light sources and F1 scores. The outcomes show that the system is an automated insect detection solution that is both efficient and reasonably priced.

Gilmore et al. [81] demonstrated a breakthrough in the application of electromagnetic imaging technology. A three-dimensional electromagnetic imaging system for measuring grain moisture content during storage was developed by these authors. Data from the three-point sensors built into the compartment was compared with the outcomes of the 3D image. The electromagnetic imaging system can track the loss of moisture during drying and storage, according to Gilmore et al. [83]. They also mentioned that the method could indicate when the grains had reached safe storage temperatures.

External factors such as the presence of insects, in addition to climate factors, such as temperature and relative humidity, and intrinsic grain characteristics such as moisture content and respiration rate, can lower grain quality standards [88,89]. In order to prevent, control, and monitor the presence of insects near grain, it is necessary. Consequently, a small gadget was developed by Reimer et al. [90] to track insect activity in grain samples. The sensor's foundation is an active microwave cavity, as the authors have shown. Since the presence of insects is a drawback for industries looking for optimal grain storage conditions, the sensor created by Reimer et al. [90] may be used to track the population density of insects in stored grain. The presence of insects must be detected using these sensors.

Fumigation, or the process of applying phosphine to the grain, is one of the primary methods used for this. Upon observing the use of this method, Brabec et al. [78] assessed wireless phosphine sensors to track the gas used to fumigate grain that was kept in storage. The automated fumigation data, according to the authors, gave a thorough picture of the procedure. Those in charge of fumigation can use this information to more effectively assess the process and guarantee effective insect control. Wireless phosphine sensors, according to Brabec et al. [78], offer a practical way to keep an eye on fumigation treatments, giving more information on variations in phosphine concentration during treatments. Internet-based systems facilitate easy access to data for both active fumigation and treatment outcome summaries [78]. As a result, sensor-assisted hermetic vacuum storage has become a viable substitute for traditional methods [79]. Kumar et al. [79] used hermetic storage, eliminating the oxygen in the storage cell and detecting the grains using temperature, relative humidity, pressure, and CO_2 sensors in place of chemical agents to control insects in stored grains. According to Kumar et al. [79], the CO_2 sensor can show whether the grains are free of insects. Thus, to indicate the quality of grain stored in an airtight system, a decision support system based on multiple sensors—such as temperature and relative humidity—in addition to the CO_2 sensor can be helpful. Furthermore, the authors noted that the management of phosphine fumigation may benefit from hermetic storage if the aforementioned factors are detected.

4.7. Advantages and Disadvantages of Grain Monitoring in Storage

Storage is considered the last stage within the post-harvest processes, and its main objective is to preserve the grain mass for as long as possible, up to a year, for example. At this stage, losses occur due to storage conditions, but also due to the effects that the grains suffered in previous stages. Thus, at this stage it is very important to maintain the grains with favorable intergranular temperature and relative humidity conditions to reduce metabolic activity and respiration of the grain mass. Therefore, monitoring the ambient and intergranular air automatically is a great advantage for applying the aeration operation to the grain mass, mainly to prevent the stored product from breathing. Traditionally, grains stored in silos are monitored by measuring temperature (thermometry) through thermocouple sensors installed equidistant (for example, 3 in 3 m) in the grain mass and more recently by digital sensors.

Although measuring the intergranular temperature is an acceptable method for evaluating the heating and consequently the indirect deterioration of the grains, it is not very efficient, because the sensor installed in the grain mass makes the punctual measurement of the temperature, i.e., The changes that occur between the sensors are not easily detectable, especially since the grains are good thermal insulators, and it may be too late to control deterioration. Recently, there have been some advances with the addition of monitoring intergranular relative humidity together with temperature, bringing the advantage of enabling the real-time determination of the hygroscopic equilibrium humidity of the grains, through mathematical models. With this, it is possible to predict the appropriate air conditions to carry out aeration or cooling of the grain mass without increasing changes in the safe storage water content, avoiding both quantitative and qualitative losses. Currently, research has been evolving towards real-time monitoring and measurement of CO_2 in stored grain mass. Determining the concentration of CO_2 inside the silo makes it possible to measure the real intensity of the total respiration of the grain mass, unlike measuring the temperature. Scientifically proven, in the atmosphere under normal conditions we have a concentration of approximately 420 ppm of CO_2. Inside the silo, an acceptable atmosphere of up to 600 ppm of CO_2 is considered, without changes to the product's respiration. Between 600 and 1000 ppm initial conditions for grain deterioration. Above 1000 ppm alert conditions and above 5000 ppm the product is already highly deteriorated. In this context, the great advantage is that monitoring intergranular temperature and relative humidity will determine the hygroscopic equilibrium humidity of the air with the stored grains to verify whether aeration is being carried out well, without changing the water content of the grain mass. However, the CO_2 measurement will guide whether or not to activate aeration.

5. Artificial Intelligence Applied on the Grain Production

Table 4 presents studies on the prediction of results based on easy-to-measure parameters using agricultural sensing and monitoring techniques combined with predictive algorithms. Tan et al. [91] evaluated the prediction of the protein content in wheat grains using satellite images and partial least-square algorithm. Tan et al. [91] reported that the NDVI, SIPI, PSRI, and EVI parameters were sensitive to predicting the protein content of the grains based on the partial least square algorithm and broadband sensor images (HJ-CCD). Also, the authors reported that the prediction accuracy was over 90%.A forecast of corn grain yield and nitrogen (N) loss in the soil was studied by Shahhosseini et al. [92], through learning algorithms. These authors evaluated the potential of four machine learning algorithms (LASSO Regression, Ridge Regression, random forests, Extreme Gradient Boosting, and their ensembles) as meta-models for a cultivation systems simulator to inform the development of decision support tools projected with the information available at the time of planting. The simulated data set included more than three million data, including genotype, environment, and management scenarios. The XGBoost was the most accurate model for forecasting corn yields and the random forests predicted the loss of N at the time of planting with higher precision.

Silva et al. [93] identified which vegetation indices can be used to predict soybean grain yield using UAV and remote multispectral sensors. The processing of the vegetation index models was conducted based on the image reflectance factor data performed in the field. A decision tree algorithm was generated considering soybean grain yield as a dependent variable. Silva et al. [93] reported that the SAVI and NDVI indices stood out for their productivity forecast, where the regions with the highest values of these indices can indicate the highest yield observed in the field, providing an advantage in management at the property level.

Table 4. Studies on prediction of results based on easy-to-measure parameters using agricultural sensing and monitoring techniques combined with predictive algorithms.

Applied Technique	Application	Reference
Satellite images and partial least square algorithm	Predicting grain protein content	Tan et al. [91]
Machine learning algorithms	Maize yield and nitrate loss prediction	Shahhosseini et al. [92]
UAV-multispectral and vegetation indices	Soybean grain yield prediction	Silva et al. [93]
Multi-Source Data and Machine Learning	Prediction of Winter Wheat Yield	Han et al. [94]
Multi-temporal UAV-based RGB and multispectral images	Grain yield prediction of rice	Wan et al. [95]
Active mounted sensor	Predicting Rice Grain Yield	Zhang et al. [96]
Simple regression or a crop model and Landsat images	Predicting wheat grain yield	Gaso et al. [97]
Sequential assimilation	Predicting wheat productivity	Guo et al. [98]
Multiple classifications and prediction models	Grain loss prediction	Li and Mao [85]
Predictive algorithms	Evaluating maize and soybean grain dry-down in the field	Martinez-Feria et al. [99]
Neural-network-based model predictive	Grain drying	Li and Chen [100]
GA-SVM-IMPC controller	Grain drying	Dai et al. [101]
Decision Tree Algorithm	Analysis of Grain Storage Loss	Liu et al. [102]
Predicting insect populations	Grain Storage	Nyabako et al. [103]

The prediction of wheat yield based on data from multiple sources and machine learning was studied by Han et al. [94]. The authors developed a modeling framework to integrate climate data, remote sensing data, and soil data to predict wheat production based on the Google Earth Engine (GEE) platform. The findings revelead that the models can accurately predict grain yield up to 1 to 2 months before harvest dates, with an error lower than 10%. Support vector machine (SVM), Gaussian process regression (GPR), and random forests (RF) represent the three best methods for predicting yields among the eight typical machine learning models evaluated in this study [94].

Wan et al. [95] presented a method of forecasting the yield of rice grains using UAV-based multi-temporal RGB and multispectral images and model transfer. A UAV platform with RGB and multispectral cameras was used to collect high spatial resolution images of the rice crop under different nitrogen treatments over two years. The vegetation indices, canopy height, and canopy cover were extracted from UAV-based images, which were then used to develop random forest forecasting models for grain production.

Wan et al. [95] reported that the normalized difference yellowing index (NDYI) was the most useful index for monitoring changes in the leaf's chlorophyll content, as well as the leaf's green throughout the growth period. The vegetation indices provided a comparable forecast of grain yield to above-ground biomass measured in the field and to the chlorophyll content in the leaves. The fusion of the multi-temporal normalized difference vegetation index (NDVI), NDYI, canopy height, and canopy cover achieved the best grain yield prediction with a relative mean square error between 2.75 and 3.56%. Also, the authors reported that the initial growth stage of the plant is ideal for predicting grain yield.

Zhang et al. [96] also studied the initial stages of plant growth intermediates. These authors studied the forecast of rice grain yield based on the dynamic changes in vegetation indices. Spectral reflectance data were collected several times during the initial stages of growth intermediates using a mounted active sensor. Data were then used to calculate the ideal vegetation indices (normalized difference red edge index, NDRE; normalized difference vegetation index, NDVI; ratio vegetation index, RVI; red edge ratio vegetation index, RERVI), which were used to develop a dynamic change model and a grain yield forecasting model at the station. Zhang et al. [96] reported that the NDRE index was more stable than other indexes (NDVI, RVI, RERVI), with a lower standard deviation. Besides, this index was used to create a high-precision model.

The grain yield prediction is the main response to the farmer at the field level. However, prediction models are also used and applied in the post-harvest stages. Li and Mao [85] evaluated a method for predicting grain loss based on the integration of several models. Losses can occur at different stages, such as harvest time, degree of pests, mode of harvest, degree of mold in the harvest, mode of drying, mode of transport, technical level, whether to plant crops in the next season, threshing mode, level of education, economic income, the climate in the harvest, quality of the equipment, the abundance of human resources, awareness of grain savings, way of packaging, the situation of the land, way of cleaning grains, time of planting, operating attitude, the average distance between harvest and drying area, the average distance between drying area and storage area, harvest maturity, and intercropping with other crops. Li and Mao [85] studied the k-nearest neighbor's algorithm (kNN), soft max regression, decision tree, and XG Boost algorithms models. The method of transport in the field had the greatest impact on loss, followed by the degree of pests and the mode of harvest. Therefore, transportation, pest control, and changing harvesting methods must be improved to reduce grain loss in the early post-harvest stages [85].

The correct time to harvest is a crucial factor to avoid the loss of grains still in the field. Thus, Martinez-Feria et al. [99] studied corn and soybean drying in the field using predictive algorithms and genotype and environment analysis. The algorithms used were guided by changes in the moisture content of grain balance (function of relative humidity and air temperature) and require three input parameters: moisture content at physiological maturity, a drying coefficient, and a power constant.

Martinez-Feria et al. [99] reported that the evaluation of the variance components and treatment effects revealed that genotypes, climatic years, and planting dates had little influence on the post-maturation drying coefficient, but significantly influenced the moisture content of the grains in the physiological maturity. Thus, the precise implementation of the algorithms in all environments would require estimating the moisture content of the initial grain, through modeling approaches or field measurements.

6. Internet of Things (IoT) and Artificial Intelligence Applied on the Grain Post-Harvest

Still regarding grain conservation during the post-harvest stages, the Internet of Things (IoT) can help improve methods for monitoring and traceability of food products. Kodali et al. [75] described a system that consists of a microcontroller and several sensors that can collect information such as temperature, humidity, CO_2, and food quality and send that information to the operator in charge while responding appropriately to ensure that products are kept in optimal storage conditions. The monitoring device also moderates the temperature levels and moisture content of the beans using fans and cooling units controlled by the IoT system. Any mold and/or insect infestation, for example, is notified to the manager so that arrangements can be made [75]. Sindwani et al. [76] also indicated the use of a real-time monitoring system based on the IoT system, observing storage parameters such as air temperature, relative humidity, and CO_2 concentration. These authors used a hardware device that contains two sensors and a battery for the power supply. The sensors are utilized to detect the parameters of temperature, relative humidity, and CO_2. The online portal was created to analyze and collect data in real-time from the sensors. This portal can be easily integrated with the digital portal already present in most storage units.

Besides, Parvin et al. [77] studied an intelligent system based on a sensor optimized for the efficient monitoring of stored grains. These authors used a cyber-physical system (CPSs), which is like the Internet of Things (IoT) but provides intelligent mechanisms with greater coordination and control between physical communication and computational elements. A typical CPS application would be to monitor a particular aspect using many wireless sensor networks and communicate the processed information to a central node. According to Parvin et al. [77], the monitoring function can be performed through continuous detection of various parameters, such as temperature and humidity of the interstitial air within the grain storage environment by a wireless sensor network and by the efficient collection, processing, and display of data.

Once the data is collected, the management and control unit are used to predict the distribution of the temperature and moisture content of the grains, as well as the temperature and humidity of the interstitial air in storage. This will help to effectively reduce the temperature and moisture content of the beans to ensure their quality. When the temperature and relative humidity in the storage compartment are higher than the predefined limit values, the coordinating sensor node sends the command to the control sensor node via the serial port. The control node then performs the necessary actions, such as turning on the cooling or aeration fan to reduce the temperature and relative humidity and thus maintain the quality and safety of the stored grains [77].

In a full-scale silo, Duan et al. [104] assessed temperature sensors to measure grain mass temperature data over a 423-day period in addition to meteorological data. The study used machine learning algorithms, support vector regression (SVR) and adaptive boosting (AdaBoost) to evaluate meteorological data and predict the average grain mass temperature. The SVR model would use different kernel functions, and the AdaBoost model would select the right base estimator and number of estimators. Pearson's correlation coefficient was used to examine the relationship between a sizable body of historical grain mass temperature data and the corresponding weather forecast data. Strong correlations between a few meteorological factors were discovered. Principal component analysis (PCA) was used to reduce the dimensionality of the data in order to remove unnecessary information. The forecast models were then compared both before and after PCA dimensionality reduction. The outcomes demonstrated that the suggested strategies are capable of achieving high accuracy, with the Adboost method achieving the best performance following PCA dimensionality reduction.

An adaptive neighborhood clustering algorithm (ANCA)-based three-dimensional (3D) temperature visualization technique was assessed by Li et al. [105]. There are four calculation modules in the ANCA-based visualization method. In order to model the temperature field, discrete grain temperature data from sensors is first gathered and interpolated using backpropagation (BP) neural networks. After that, a fresh ANCA is used to combine spatiotemporal information and categorize the interpolation data. Next, the boundary points of each cluster are determined using the Quickhull algorithm. Ultimately, the polyhedra ascertained from the boundary points are constructed into a three-dimensional model of the grain mass temperature and rendered in various colors. According to the experimental results, ANCA performs significantly better in terms of compactness (about 95.7% of the cases tested) and separation (about 91.3% of the cases tested) than the DBSCAN and MeanShift algorithms. Furthermore, the temperature visualization method in the grain mass using the ANCA-based approach exhibits improved visual effects and reduced rendering times. In order to help grain warehouse managers maintain grain quality during storage, this research developed an effective 3D visualization technique that enabled them to get real-time information about the field temperature of bulk grain.

In order to address these issues, this study suggested a multi-output spatiotemporal model that combines Transformer and Graph Convolution Neural Networks (GCN). GCN records the topological data of the sensor network in the silo as well as the spatial correlations between the sensors. Transformer describes temporal dependencies and records both short- and long-term temporal resources. The suggested model was constructed using a dataset and its performance was assessed and contrasted with that of the four other models. The suggested model performs better than the others in terms of MAE and RMSE, according to the findings. Furthermore, a three-dimensional interpolation based on the forecast results allowed for a continuous temperature field of the entire silo, making the temperature conditions accessible at all locations, as well as the discrete areas detected [106].

Evaluation of the primary factors leading to the control of insects in stored grain was conducted by Abdelsamea et al. [107]. In order to assess the significance of the parameters and predict how well the solution would work to heat insect pests to death, several machine learning models were used. Through 10-fold cross-validation, the effectiveness of the machine learning models was confirmed. Random Forest model achieved an F1 score of 99.5%, recall of 99.01%, precision of 100%, and accuracy of 99.5%. The optimal environmental factors and parameters that significantly impact rice weevil disinfestation were found by a machine learning approach using SHAP values as an explainable post-hoc model. A flexible model for determining the optimal lethal temperature to eradicate insects from grains kept in clear plastic bags was identified by machine learning. The model can predict whether specific set of parameters will work well for using thermal control to treat insects.

Sitophilus oryzae and *Sitophilus zeamais* are the two primary insect pests that infest stored grain globally, according to Yang et al. [108]. Because of their similar appearances, it can be difficult to identify the two pests quickly and accurately. In visible light, adult *S. zeamais* are both brighter and darker than adult *S. oryzae*. The high efficiency of the convolutional neural network (CNN) in object recognition makes it suitable for effective differentiation. A multilayer convolutional structure (MCS) feature extractor was suggested by the authors to extract insect features from each layer of the CNN architecture. In the context of wheat, a regional proposal network is used to pinpoint the location of a possible pest. Combining softmax and soft L1 loss functions, as well as adding deeper layer variables to the classification and bounding box regression subnetworks, increases both the robustness of bounding box regression and the accuracy of classification. With an average detection speed of 0.182 ± 0.005 s per test, the proposed multilayer convolutional structure network (MCSNet) achieves an average accuracy of $87.89 \pm 2.36\%$ in laboratory test. After field testing, the accuracy of the model was determined to be $90.35 \pm 3.12\%$. *S. oryzae* had an average accuracy higher than *S. zeamais* under all test conditions. In tests performed in the lab and field, the proposed MCSNet model proved to be a quick and precise technique for identifying sibling groups from visible light images.

The stages of grain drying and storage also involve predictive outcomes (Table 4). Li and Chen [97] investigated a predictive control scheme based on a neural network for grain dryers in an effort to increase the precision of the moisture content of grains discharged from grain dryers as well as the level of automation and intelligence in the grain drying process. For a real grain dryer system, a mathematical model based on the theory of grain drying is constructed. This model allows for the quick simulation of an adequate number of input and output time series of the grain dryer under various conditions. Instead of using the mathematical model as a predictive model, a non-linear autoregressive neural network is trained using the data series as a training set.

Instantaneous input-output feedback is introduced by a nonlinear neural network autoregressive model with exogenous input (NARX), which is based on the static neural network, in a study by Li and Chen [100]. The dynamic input-output characteristic of the grain dryer is suggested to be represented instead of the mathematical model based on equations. A model predictive control (MPC) controller with a particle swarm optimization (PSO) algorithm was created to achieve accurate closed-loop control using this NARX neural network as the predictive model. Li and Chen [100] tested sufficient simulations under various conditions to the PSO-MPC control scheme's performance and found that the error in grain moisture content is less than 1% (w.b).

Using a machine learning technique, Nyabako et al. [103] recently predicted the insect population and the resulting damage to grain mass. Information from storage units was gathered, and it was then correlated with the local weather at each site to analyze the data. Using parameter selection algorithms and decision tree learning algorithms, models were created from this input data to forecast insect infestation and the potential harm to grain that is stored. More than 96% of the variation in germination rates was explained by the mathematical models proposed by Jian et al. [109] to predict the germination rates of stored canola. The temperature distribution and moisture content of soybeans stored in bag silos were predicted by Barreto et al. [110] as a result of seasonal climate variation. The authors found a temperature differential between the lower, middle, and upper layers and suggested a limit of 3% for the reference CO_2 concentration in grains that were stored. Although Taher et al.'s model [111] sought to forecast soybean loss during storage by tracking CO_2 concentration over the course of the storage period and achieved a 73% correlation.

In order to predict the physical and physiological quality of stored soybean seeds, André et al. [112] examined the performance of machine learning algorithms based on variables monitored during seed conditioning (temperature and packaging) and storage time. Artificial Neural Network (ANN), Random Forest (RF), Multiple Linear Regression, and the REPTree and M5P decision tree algorithms were used to analyze the data. The combination of the input variables temperature and storage time for the RF and REPTree algorithms performed better than linear regression in predicting the quality of seeds, providing higher accuracy rates. Among the most significant findings, the authors verified that T + P + ST, T + ST, P + ST, and ST had the highest mean r and the lowest mean MAE for predicting apparent specific mass. However, Person's correlations for these inputs were 0.63 and the MAE varied from 9.59 to 10.47. The inputs T + P + ST and T + ST performed better for germination prediction (r = 0.65 and r = 0.67, respectively) using the ANN, REPTree, M5P, and RF models. For this reason, the use of computational intelligence algorithms is an excellent resource for predicting soybean seed quality using data from easy-to-measure variables.

In order to classify commercial rice samples based on dimensionless morphometric parameters and color parameters extracted using CV algorithms from digital images obtained from a smartphone camera, Aznan et al. [113] studied the application of computer vision (CV) and machine learning (ML). Nine morphocolorimetric parameters were used to create an ANN model that classified rice samples into 15 commercial rice varieties. To further simulate the real-world application models in various scenarios, they were also implemented and assessed on an alternative imaging system. The findings demonstrated that, with an overall accuracy of 90.7% (Model 2), the best classification accuracy was achieved using the Bayesian Regularization (BR) neural network with ten hidden neurons, which provided 91.6% (MSE $\leq$ 0.01) and 88.5% (MSE = 0.01) for the training and testing steps, respectively. Additionally, the implementation classified rice samples with high accuracy (93.9%).

The adoption by the industry of fast, reliable and precise techniques, such as those described here, can make it possible to include various morpho-colorimetric properties of rice in consumer perception studies. Physical classification is the method used by rice unloading, delivery, storage, and processing units to commercially characterize the quality of the grains, according to Carneiro et al. [114]. Traditional method is often used for this stage, which is time-consuming and labor-intensive and produces subjective results because the evaluation is visual. Grain quality can be characterized using non-destructive technologies and computer intelligence, which can speed up, improve accuracy, and reduce reliance on the process. Thus, the purpose of this study was to categorize any flaws and to describe and forecast the quality of processed brown rice grains. To do this, samples were taken from the top and bottom of four drying silos, each of which could hold up to 40,000 bags.

The grain samples were subjected to dry aeration until their moisture content (w.b.) reached 12%, which had previous moisture contents of 16%, 17%, 18%, and 19%. For this, machine learning algorithm models (multilayer perceptron ANN, M5P, REPTree and Random Tree decision tree algorithms, and Random Forest) and near-infrared spectroscopy technology were employed. A strong negative correlation (r = 0.98) was verified between observed and predicted values of moisture content and whole grain yield. Conversely, a robust positive correlation (r = 0.97) was noted between the moisture content and the physical defects categorized within the different physicochemical components analyzed. These findings demonstrate how useful near-infrared spectroscopy technology is. With a mean absolute error of 0.017, a coefficient of determination of 0.92, and a Pearson's correlation coefficient of 0.96, the Random Tree model is the recommended due to its successful prediction of the grain quality results. The findings demonstrate that a great non-destructive substitute for physical sorting of whole and defective rice grains in terms of assessing their physical and chemical qualities is the combination of near-infrared spectroscopy technology and machine learning models. Because of this, it is advised to use NIR for monitoring. Additionally, the Internet of Things (IoT) and artificial intelligence can be used to apply predictive algorithms that enable the prediction of deterioration, which helps to maintain grain quality.

7. Conclusions and Proposal for Monitoring from Production Grain to Post-Harvest

The information gathered in this review contributes positively to the entire grain production chain, from the application of remote sensing in the field to the post-harvest stages (Figure 7). The remote sensing associated with the techniques of monitoring and prediction of results helps in a precise way the management of agricultural properties, increasing the chances of hits at the time of taking decisions [107,108]. The present work reviewed grain storage strategies focusing on different environmental factors and measurable variables, and how current sensor and computational technologies improve the indirect predictive monitoring of grain quality. Several scientific studies showed how preventative monitoring techniques helped reduce losses on the post-harvest stages of grain production.

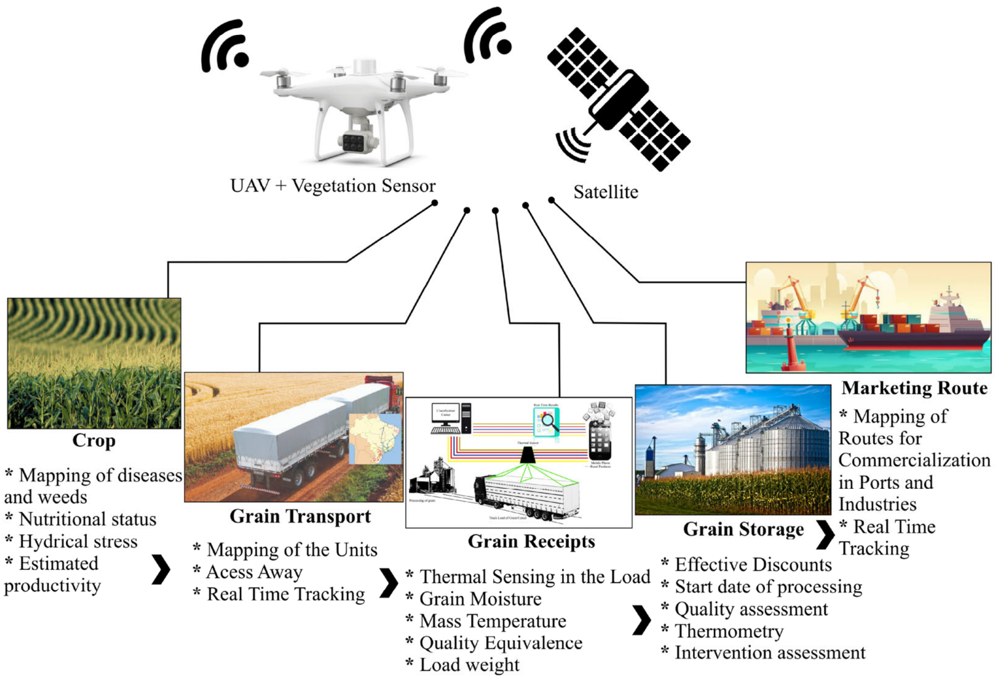

Figure 7. Summary of the monitoring the grain production chain: production to post-harvest.

New paths for the technological advancement of grain quality monitoring in storage and transportation are being opened up by the growth of the IoT paradigm and the increasing application of AI approaches in the widest range of agricultural sectors. These advances support post-harvest grain deterioration prevention strategies. Using the most recent advances in remote sensing, monitoring, IoT, and AI technologies, a scheme has been developed to monitor and predict grain quality from production to post-harvest (Figure 8). This scheme is based on the systematic review and focuses on various environmental factors and measurable variables. Based on novel studies [107,108,115–130], Figure 8 was created in order to calculate the equilibrium moisture content and dry matter loss of the grain mass during transportation, drying, and storage as well as to predict the physical and physicochemical changes in the grains, we suggested that technology and devices be developed to obtain intergranular temperature, relative humidity, and CO_2 concentration in real time (Figure 8).

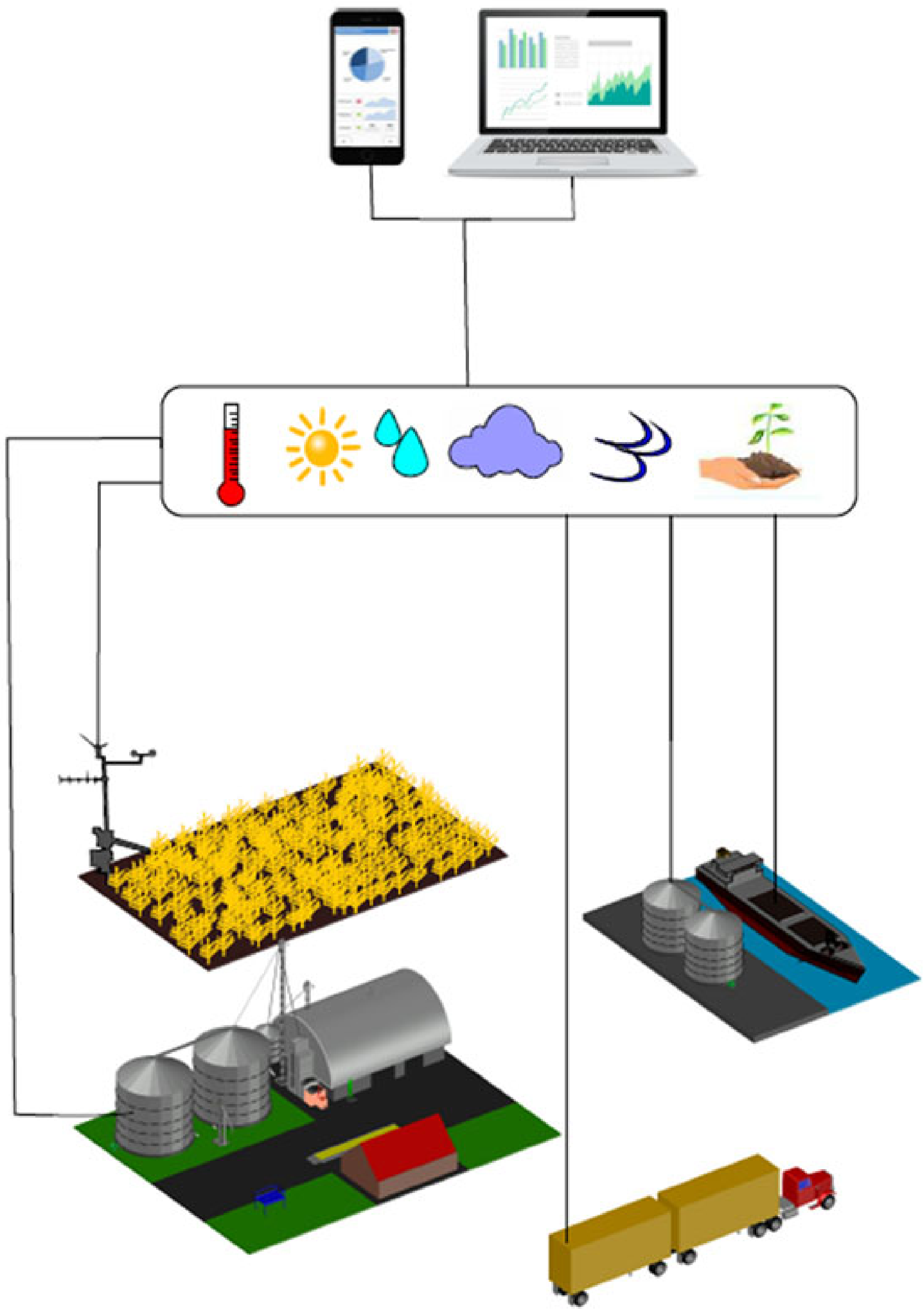

Figure 8. Illustration of the whole grain production system managed by the producer through the latest technologies of remote sensing, monitoring, internet of things, and artificial intelligence.

Author Contributions: Writing (Original draft), D.M.R.; Conceptualization, writing (Review and Editing), and supervision, P.C.C.; Writing (Original draft), N.d.S.T.; Writing (Original draft), M.F.; Visualization, P.G.; Writing (Review and Editing), T.J.C.A.; Visualization, P.E.T.; Visualization, L.P.R.T.; Writing (Original draft), F.H.R.B.; Writing (Review and Editing), J.L.T.C. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by CAPES (Coordination for the Improvement of Higher Education Personnel)—Financial Code 001, CNPq (National Council for Scientific Technological Development)—Financial Code 001, and FAPERGS-RS (Research Support Foundation of the State of Rio Grande do Sul)—Financial Code 001 for funding in the research projects, laboratories for carrying out the experiments.

Data Availability Statement: Not applicable.

Acknowledgments: The authors would like to thank UFSM (Federal University of Santa Maria)-Laboratory of Post-harvest (LAPOS)-Research Group at Post-harvest Innovation: Technology, Quality and Sustainability for their contributions in the research project.

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

References

1. FAO. *The Future of Food and Agriculture—Trends and Challenges*; Food and Agriculture Organization of the United Nations: Rome, Italy, 2019.
2. Gomiero, T.; Pimentel, D.; Paoletti, M.G. Environmental impact of different agricultural management practices: Conventional vs. Organic agriculture. *Crit. Rev. Plant Sci.* **2011**, *30*, 95–124. [CrossRef]
3. Dong, T.; Liu, J.; Shang, J.; Qian, B.; Ma, B.; Kovacs, J.M.; Walters, D.; Jiao, X.; Geng, X.; Shi, Y. Assessment of red edge vegetation indices for crop leaf area index estimation. *Remote Sens. Environ.* **2019**, *222*, 133–143. [CrossRef]
4. Schwalbert, R.A.; Amado, T.; Corassa, G.; Pott, L.P.; Prasad, P.V.V.; Ciampitti, I.A. Satellite-based soybean yield forecast: Integrating machine learning and weather data for improving crop yield prediction in southern Brazil. *Agric. For. Meteorol.* **2020**, *284*, 107886. [CrossRef]
5. Segarra, J.; Buchaillot, M.L.; Araus, J.L.; Kefauver, S.C. Sensor remoto para agricultura de precisão: Recursos e aplicativos aprimorados do Sentinel-2. *Agron. J.* **2020**, *10*, 641. [CrossRef]
6. Pott, L.P.; Amado, T.J.C.; Schwalbert, R.A.; Sebem, E.; Jugulam, M.; Ciampitti, I.A. Pre-planting weed detection based on ground field spectral data. *Pest. Manag. Sci.* **2019**, *76*, 1173–1182. [CrossRef]
7. Hunt, E.R.; Daughtry, C.S.T. What good are unmanned aircraft systems for agricultural remote sensing and precision agriculture? *Intern. J. Remote Sens.* **2018**, *39*, 5345–5376. [CrossRef]
8. Schwalbert, R.A.; Amado, T.; Reimche, G.B.; Gebert, F. Fine-tuning of wheat (*Triticum aestivum* L.) variable nitrogen rate by combining crop sensing and management zones approaches in southern Brazil. *Prec. Agric.* **2019**, *20*, 56–77. [CrossRef]
9. Vanino, S.; Nino, P.; De Michele, C.; Falanga Bolognesi, S.; D'Urso, G.; Di Bene, C.; Pennelli, B.; Vuolo, F.; Farina, R.; Pulighe, G. Capability of Sentinel-2 data for estimating maximum evapotranspiration and irrigation requirements for tomato crop in Central Italy. *Remote Sens. Environ.* **2018**, *215*, 452–470. [CrossRef]
10. Aranguren, M.; Castellón, A.; Aizpurua, A. Crop Sensor Based Non-destructive Estimation of Nitrogen Nutritional Status, Yield, and Grain Protein Content in Wheat. *Agriculture* **2020**, *10*, 148. [CrossRef]
11. Zhou, X.; Kono, Y.; Win, A.; Matsui, T.; Tanaka, S.T.T. Predicting within-field variability in grain yield and protein content of winter wheat using UAV-based multispectral imagery and machine learning approaches. *Plant Prod. Sci.* **2020**, *24*, 137–151. [CrossRef]
12. Bongiovanni, R.; Lowenberg-DeBoer, J. Precision agriculture and sustainability. *Precis. Agric.* **2004**, *5*, 359–387. [CrossRef]
13. Aubert, B.A.; Schroeder, A.; Grimaudo, J. IT as enabler of sustainable farming: An empirical analysis of farmers adoption decision of precision agriculture technology. *Decis. Support. Syst.* **2012**, *54*, 510–520. [CrossRef]
14. Duysak, H.; Yigit, E. Machine learning based quantity measurement method for grain silos. *Measurement* **2020**, *152*, 107279. [CrossRef]
15. Berry, J.K.; Delgado, J.A.; Khosla, R.; Pierce, F.J. Precision conservation for environmental sustainability. *J. Soil. Water Conserv.* **2013**, *58*, 332–339. Available online: https://www.jswconline.org/content/58/6/332 (accessed on 1 January 2024).
16. Delgado, J.; Short, N.M.; Roberts, D.P.; Vandenberg, B. Big data analysis for sustainable agriculture. *Front. Sustain. Food Syst.* **2019**, *3*, 54. [CrossRef]
17. Bajwa, S.G.; Rupe, J.C.; Mason, J. Soybean disease monitoring with leaf reflectance. *Remote Sens.* **2017**, *9*, 127. [CrossRef]
18. Zhang, C.; Marzougui, A.; Sankaran, S. High-resolution satellite imagery applications in crop phenotyping: An overview. *Comput. Electron. Agric.* **2020**, *175*, 105584. [CrossRef]
19. Caturegli, L.; Casucci, M.; Lulli, F.; Grossi, N.; Gaetani, M.; Magni, S.; Bonari, E.; Volterrani, M. GeoEye-1 satellite versus ground-based multispectral data for estimating nitrogen status of turf grasses. *Intern. J. Remote Sens.* **2015**, *36*, 2238–2251. [CrossRef]
20. Hively, W.D.; Lamb, B.T.; Daughtry, C.S.T.; Shermeyer, J.; McCarty, G.W.; Quemada, M. Mapping crop residue and tillage intensity using world view—3 satellite shortwave infrared residue indices. *Remote Sens.* **2018**, *10*, 1657. [CrossRef]
21. Halperin, J.; LeMay, V.; Coops, N.; Verchot, L.; Marshall, P.; Lochhead, K. Canopy cover estimation in miombo woodlands of Zambia: Comparison of Landsat 8 OLI versus Rapid Eye imagery using parametric, nonparametric, and semi parametric methods. *Remote Sens. Environ.* **2016**, *179*, 170–182. [CrossRef]

22. Mahlein, A.K. Plant disease detection by imaging sensors–parallels and specific demands for precision agriculture and plant phenotyping. *Plant Dis. J.* **2016**, *100*, 241–251. [CrossRef] [PubMed]
23. Coffer, M.M.; Schaeffer, A.B.; Zimmerman, C.R.; Hill, V.; Li, J.; Islam, K.A.; Whitman, J.P. Performance across WorldView-2 and Rapid Eye for reproducible sea grass mapping. *Remote Sens. Environ.* **2020**, *250*, 112036. [CrossRef] [PubMed]
24. Dennison, P.E.; Brunelle, A.R.; Carter, V.A. Assessing canopy mortality during a mountain pine beetle outbreak using GeoEye-1 high spatial resolution satellite data. *Remote Sens. Environ.* **2010**, *114*, 2431–2435. [CrossRef]
25. Chlus, A.; Kruger, E.L.; Townsend, P.A. Mapping three-dimensional variation in leaf mass per area with imaging spectroscopy and lidar in a temperate broadleaf forest. *Remote Sens. Environ.* **2020**, *250*, 112043. [CrossRef]
26. Pasqualini, V.; Pergent-Martini, C.; Pergent, G.; Agreil, M.; Skoufas, G.; Sourbes, L.; Tsirika, A. Use of SPOT 5 for mapping seagrasses: An application to Posidonia oceanica. *Remote Sens. Environ.* **2005**, *94*, 39–45. [CrossRef]
27. Hajj, M.E.; Bégué, A.; Guillaume, S.; Martiné, J.F. Integrating SPOT-5 time series, crop growth modeling and expert knowledge for monitoring agricultural practices—The case of sugarcane harvest on Reunion Island. *Remote Sens. Environ.* **2019**, *10*, 2052–2061. [CrossRef]
28. Johansen, K.; Phinn, S.; Witte, C. Mapping of riparian zone attributes using discrete return LiDAR, quick bird and SPOT-5 imagery: Assessing accuracy and costs. *Remote Sens. Environ.* **2010**, *114*, 2679–2691. [CrossRef]
29. Gómez, D.; Salvador, P.; Sanz, J.; Casanova, J.L. Potato yield prediction using Machine Learning Techniques and sentinel 2 data. *Remote Sens.* **2019**, *11*, 1745. [CrossRef]
30. Chauhan, S.; Darvishzadeh, R.; Lu, Y.; Boschetti, M.; Nelson, A. Understanding wheat lodging using multi-temporal Sentinel-1 and Sentinel-2 data. *Remote Sens. Environ.* **2020**, *243*, 111804. [CrossRef]
31. Meroni, M.; D'Andrimont, R.; Vrieling, A.; Fasbender, D.; Lemoine, G.; Rembold, F.; Seguini, L.; Verhegghen, A. Comparing land surface phenology of major European crops as derived from SAR and multispectral data of Sentinel-1 and -2. *Remote Sens. Environ.* **2021**, *253*, 112232. [CrossRef]
32. Mulla, D.J. Twenty-five years of remote sensing in precision agriculture: Key advances and remaining knowledge gaps. *Biosyst. Eng.* **2013**, *114*, 358–371. [CrossRef]
33. Castaldi, F.F.; Pelosi, F.; Pascucci, S.; Casa, R. Assessing the potential of images from unmanned aerial vehicles (UAV) to support herbicide patch spraying in maize. *Precision Agric.* **2017**, *18*, 76–94. [CrossRef]
34. Xie, Q.; Lai, K.; Wang, J.; Lopez-Sanchez, J.M.; Shang, J.; Liao, C.; Peng, X. Crop monitoring and classification using polarimetric RADARSAT-2 time-series data across growing season: A case study in southwestern Ontario, Canada. *Remote Sens.* **2021**, *13*, 1394. [CrossRef]
35. Cheng, E.; Zhang, B.; Peng, D.; Zhong, L.; Yu, L.; Liu, Y.; Yang, S. Wheat yield estimation using remote sensing data based on machine learning approaches. *Front. Plant Sci.* **2022**, *13*, 1090970. [CrossRef] [PubMed]
36. Raun, W.R.; Solie, J.B.; Stone, M.L.; Martin, K.L.; Freeman, K.W.; Mullen, R.W.; Zhang, H.; Schepers, J.S.; Johnson, G.V. Optical sensor-based algorithm for crop nitrogen fertilization. *Commun. Soil Sci. Plant Anal.* **2005**, *36*, 2759–2781. [CrossRef]
37. Genc, H.; Genc, L.; Turhan, H.; Smith, S.; Nation, J. Vegetation indices as indicators of damage by the sunn pest (*Hemiptera: Scutelleridae*) to field grown wheat. *Afr. J. Biotechnol.* **2018**, *7*, 173–180. Available online: https://www.ajol.info/index.php/ajb/article/view/58347 (accessed on 1 December 2023).
38. Maimaitijiang, M.; Ghulam, A.; Sandoval, J.S.O.; Maimaitiyiming, M. Drivers of land cover and land use changes in St. Louis metropolitan area over the past 40 years characterized by remote sensing and census population data. *Intern. J. Appl. Earth Obs. Geoinf.* **2015**, *35*, 161–174. [CrossRef]
39. Schaefer, M.T.; Lamb, D.W. A combination of plant NDVI and LiDAR measurements improve the estimation of p of pasture biomass in tall fescue (*Festucaarundinacea* var. Fletcher). *Remote Sens.* **2016**, *8*, 109. [CrossRef]
40. Calera, A.; Campos, I.; Osann, A.; D'Urso, G.; Menenti, M. Remote sensing for crop water management: From ET modelling to services for the end users. *Sensors* **2017**, *17*, 1104. [CrossRef]
41. Peng, Y.; Li, Y.; Dai, C.; Fang, S.; Gong, Y.; Wu, X.; Zhu, R.; Liu, K. Remote prediction of yield based on LAI estimation in oilseed rape under different planting methods and nitrogen fertilizer applications. *Agric. For. Meteorol.* **2019**, *271*, 116–125. [CrossRef]
42. Amaral, L.R.; Molin, J.P.; Portz, G.; Finazzi, F.B.; Cortinov, L. Comparison of crop canopy reflectance sensors used to identify sugarcane biomass and nitrogen status. *Precis. Agric.* **2015**, *16*, 15–22. [CrossRef]
43. Jorge, J.; Vallbé, M.; Soler, J.A. Detection of irrigation in homogeneities in an olive grove using the NDRE vegetation index obtained from UAV images. *Eur. J. Remote Sens.* **2019**, *52*, 169–177. [CrossRef]
44. Pourazar, H.; Samadzadegan, F.; Javan, F.D. Aerial multispectral imagery for plant disease detection: Radiometric calibration necessity assessment. *Eur. J. Remote Sens.* **2019**, *52*, 17–31. [CrossRef]
45. Zhou, J.; Khot, L.R.; Boydston, R.A.; Miklas, P.N.; Porter, L. Low altitude remote sensing technologies for crop stress monitoring: A case study on spatial and temporal monitoring of irrigated pinto bean. *Precis. Agric.* **2018**, *19*, 555–569. [CrossRef]
46. Baron, J.; Hill, D.J. Monitoring grassland invasion by spotted knapweed (*Centaurea maculosa*) with RPAS-acquired multispectral imagery. *Remote Sens. Environ.* **2020**, *249*, 112008. [CrossRef]
47. Shaver, T.M.; Kruger, G.R.; Rudnick, D.R. Crop canopy sensor orientation for late season nitrogen determination in corn. *J. Plant Nutr.* **2017**, *40*, 2217–2223. [CrossRef]
48. Martínez-Casasnovas, J.A.; Uribeetxebarría, A.; Escolà, A.; Arnó, J. Sentinel-2 vegetation indices and apparent electrical conductivity to predict barley (*Hordeum vulgare* L.) yield. *Precis. Agric.* **2019**, *4*, 15–421. [CrossRef]

49. Kanke, Y.; Tubana, B.; Dalen, M.; Harrell, D. Evaluation of red and red edge reflectance-based vegetation índices for rice biomass and grain yield prediction models in paddy fields. *Precis. Agric.* **2016**, *17*, 507–530. [CrossRef]
50. Fensholt, A.; Sandholt, I. Derivation of a shortwave infrared water stress index from MODIS near- and shortwave infrared data in a semiarid environment. *Remote Sens. Environ.* **2003**, *87*, 111–121. [CrossRef]
51. Eitel, J.U.; Keefe, R.F.; Long, D.S.; Davis, A.S.; Vierling, L.A. Active ground optical remote sensing for improved monitoring of seedling stress in nurseries. *Sensors* **2010**, *10*, 2843–2850. [CrossRef] [PubMed]
52. Li, F.; Miao, Y.; Feng, G.; Yuan, F.; Yue, S.; Gao, X.; Liu, Y.; Liu, B.; Ustin, S.L.; Chen, X. Improving estimation of summer maize nitrogen status with red edge-based spectral vegetation indices. *Fields Crops Res.* **2014**, *157*, 111–123. [CrossRef]
53. Prashar, A.; Jones, H.G. Assessing Drought Responses Using Thermal Infrared Imaging. In *Environmental Responses in Plants*; Duque, P., Ed.; Methods in Molecular Biology; Humana Press: New York, NY, USA, 2016. [CrossRef]
54. Khanal, S.; Fulton, J.; Shearer, S. An overview of current and potential applications of thermal remote sensing in precision agriculture. *Comput. Electron. Agric.* **2017**, *139*, 22–32. [CrossRef]
55. Filippi, P.; Jones, E.J.; Wimalathunge, N.S.; Somarathna, P.D.S.N.; Pozza, L.E.; Ugbaje, S.U.; Jephcott, T.G.; Paterson, S.E.; Whelan, B.M.; Bishop, T.F.A. An approach to forecast grain crop yield using multi-layered, multi-farm data sets and machine learning. *Precis. Agric.* **2019**, *20*, 1015–1029. [CrossRef]
56. Kogan, F. Vegetation health for insuring drought-related yield losses and food security enhancement. In *Remote Sensing for Food Security*; Kogan, F., Ed.; Springer International Publishing: Cham, Switzerland, 2019; pp. 163–173. [CrossRef]
57. Kogan, F.; Guo, W.; Yang, W. Drought and food security prediction from NOAA new generation of operational satellites. *Geomat. Nat. Hazards* **2019**, *10*, 651–666. [CrossRef]
58. Lobell, D.B. The use of satellite data for crop yield gap analysis. *Fields Crops Res.* **2013**, *143*, 56–64. [CrossRef]
59. Dubey, S.K.; Gavli, A.S.; Yadav, S.K.; Sehgal, S.; Ray, S.S. Remote Sensing-Based Yield Forecasting for Sugarcane (*Saccharum officinarum* L.) crop in India. *J. Indian. Soc. Remote Sens.* **2018**, *46*, 1823–1833. [CrossRef]
60. Maresma, Á.; Ariza, M.; Martínez, E.; Lloveras, J.; Martínez-Casasnovas, J.A. Analysis of vegetation índices to determine nitrogen application and yield prediction in maize (*Zea mays* L.) from a standard UAV service. *Remote Sens.* **2016**, *8*, 973. [CrossRef]
61. Kumar, S.; Saxena, S.; Dubey, S.K.; Chaudhary, K.; Sehgal, S.; Ray, S.S. Analysis of wheat crop forecasts, in India, generated using remote sensing data, under fasal project. *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.* **2019**, *42*, 223–228. [CrossRef]
62. Rao, P.V.K.; Rao, V.V.; Venkataratnam, L. Remote sensing: A technology for assessment of sugarcane crop acreage and yield. *Sugar Tech.* **2022**, *4*, 97–101. [CrossRef]
63. Rahman, M.M.; Robson, A. A novel approach for sugarcane yield prediction using Landsat time series imagery: A case study on Bundaberg region. *Adv. Remote Sens.* **2016**, *5*, 93–102. [CrossRef]
64. Ali, A.; Imran, M.M. Evaluating the potential of red edge position (REP) of hyperspectral remote sensing data for real time estimation of LAI & chlorophyll content of kinnow mandarin (*Citrus reticulata*) fruit orchards. *Sci. Hortic.* **2020**, *267*, 109326. [CrossRef]
65. Zhen, Z.; Chen, S.; Qin, W.; Yan, G.; Gastellu-Etchegorry, J.P.; Cao, L.; Murefu, M.; Li, J.; Han, B. Potentials and limits of vegetation indices with BRDF signatures for soil-noise resistance and estimation of leaf area index. *IEEE Trans. Geosci. Remote Sens.* **2020**, *58*, 5092–5108. [CrossRef]
66. Defourny, P.; Bontemps, S.; Bellemans, N.; Cara, C.; Dedieu, G.; Guzzonato, E.; Hagolle, O.; Inglada, J.; Nicola, L.; Rabaute, T.; et al. Near real-time agriculture monitoring at national scale at parcel resolution: Performance assessment of the Sen2-Agri automated system in various cropping systems around the world. *Remote Sens. Environ.* **2019**, *221*, 551–568. [CrossRef]
67. Coradi, P.C.; Dubal, Í.T.P.; Bilhalva, N.D.S.; Fontoura, C.N.; Teodoro, P.E. Correlation using multivariate analysis and control of drying and storage conditions of sunflower grains on the quality of the extracted vegetable oil. *J. Food Proc. Preserv.* **2020**, *44*, e14961. [CrossRef]
68. Danao, M.G.C.; Zandonadi, R.S.; Gates, R.S. Development of a grain monitoring probe to measure temperature, relative humidity, carbon dioxide levels and logistical information during handling and transportation of soybeans. *Comput. Electron. Agric.* **2015**, *119*, 74–82. [CrossRef]
69. Wallays, C.; Missotten, B.; Baerdemaeker, J.; Saeys, W. Hyperspectral waveband selection for on-line measurement of grain cleanness. *Biosyst. Eng.* **2009**, *104*, 1–7. [CrossRef]
70. Lewis, M.A.; Trabelsi, S.; Nelson, S.O. Development of an eighth-scale grain drying system with real-time microwave monitoring of moisture content. *Appl. Eng. Agric.* **2019**, *35*, 767–774. [CrossRef]
71. Li, C.; Li, B.; Huang, J.; Li, C. Developing an online measurement device based on resistance sensor for measurement of single grain moisture content in drying process. *Sensors* **2020**, *20*, 4102. [CrossRef]
72. Liu, Z.; Wu, Z.; Zhang, Z.; Wu, W.; Li, H. Research on online moisture detector in grain drying process based on V/F conversion. *Math. Prob. Eng.* **2015**, *1*, 565764. [CrossRef]
73. Neethirajan, S.; Freund, M.S.; Jatas, D.S.; Shafai, C.; Thomson, D.J.; White, N.D.G. Development of carbon dioxide (CO_2) sensor for grain quality monitoring. *Biosyst. Eng.* **2010**, *106*, 395–404. [CrossRef]
74. Ubhi, G.S.; Sadaka, S. Temporal valuation of corn respiration rates using pressure sensors. *J. Stored Prod. Res.* **2015**, *61*, 39–47. [CrossRef]
75. Onibonoje, M.O.; Nwulu, N.I.; Bokoro, P.N. A wireless sensor network system for monitoring environmental factors affecting bulk grains storability. *J. Food Proc. Eng.* **2019**, *42*, e13256. [CrossRef]

76. Kodali, R.K.; John, J.; Boppana, L. IoT Monitoring System for Grain Storage. *IEEE Intern. Conf. Electron. Comput. Commun. Technol.* **2020**, *1*, 19988645. [CrossRef]
77. Sindwani, A.; Kumar, A.; Gautam, C. Prediction and Monitoring of stored food grains health using IoT Enable Nodes. In Proceedings of the 2020 IEEE International Conference on Computing, Power and Communication Technologies (GUCON), Greater Noida, India, 2–4 October 2020; p. 20130982. [CrossRef]
78. Parvin, S.; Gawanmeh, A.; Venkatraman, S. Optimized Sensor Based Smart System for Efficient Monitoring of Grain Storage. In Proceedings of the 2018 IEEE International Conference on Communications Workshops (ICC Workshops), Kansas City, MO, USA, 20–24 May 2018; p. 17896512. [CrossRef]
79. Brabec, D.; Campbell, J.; Arthur, F.; Casada, M.; Tilley, D.; Bantas, S. Evaluation of wireless phosphine sensors for monitoring fumigation gas in wheat stored in farm bins. *Insects* **2019**, *10*, 121. [CrossRef] [PubMed]
80. Kumar, S.; Mohapatra, D.; Kotwaliwale, N.; Singh, K.K. Efficacy of sensor assisted vacuum hermetic storage against chemical fumigated wheat. *J. Stored Prod. Res.* **2020**, *88*, 101640. [CrossRef]
81. Asefi, M.; Jeffrey, I.; LoVetri, J.; Gilmore, C.; Card, P.; Paliwal, J. Grain bin monitoring via electromagnetic imaging. *Comput. Electron. Agric.* **2015**, *119*, 133–141. [CrossRef]
82. Gilmore, C.; Asefi, M.; Paliwal, J.; LoVetri, J. Industrial scale electromagnetic grain bin monitoring. *Comput. Electron. Agric.* **2017**, *136*, 210–220. [CrossRef]
83. Asefi, M.; Gilmore, C.; Jeffrey, I.; LoVetri, J.; Paliwal, J. Detection and continuous monitoring of localized high-moisture regions in full-scale grain storage bin using electromagnetic imaging. *Biosyst. Eng.* **2017**, *163*, 37–49. [CrossRef]
84. Gilmore, C.; Asefi, M.; Nemez, K.; Paliwal, J.; LoVetri, J. Three dimensional radio-frequency electromagnetic imaging of an in-bin grain conditioning process. *Comput. Electron. Agric.* **2019**, *167*, 105059. [CrossRef]
85. Nunes, C.F.; Coradi, P.C.; Jaques, L.B.A.; Teodoro, L.P.R.; Teodoro, P.E. Sensor-cable-probe and sampler for early detection and prediction of dry matter loss and real-time corn grain quality in transport and storage. *Sci. Rep.* **2023**, *13*, 5686. [CrossRef]
86. Li, B.; Mao, B. A grain loss prediction method based on integration of multiple classification models. *Concurr. Comput. Pr. Exp.* **2020**, *34*, e6116. [CrossRef]
87. Badgujar, C.M.; Armstrong, P.R.; Gerken, A.R.; Pordesimo, L.O.; Campbell, J.F. Real-time stored product insect detection and identification using deep learning: System integration and extensibility to mobile platforms. *J. Stored Prod. Res.* **2023**, *104*, 102196. [CrossRef]
88. Mendoza, Q.A.; Pordesimo, L.; Neilsen, M.; Armstrong, P.; Campbell, J.; Mendoza, P.T. Application of Machine Learning for Insect Monitoring in Grain Facilities. *AI* **2023**, *4*, 348–360. [CrossRef]
89. Coradi, P.C.; Oliveira, M.B.; de Oliveira, L.C.; Souza, G.A.C.; Elias, M.C.; Brackmann, A.; Teodoro, P.E. Technological and sustainable strategies for reducing losses and maintaining the quality of soybean grains in real production scale storage units. *J. Stored Prod. Res.* **2020**, *87*, 101624. [CrossRef]
90. Lima, R.E.; Coradi, P.C.; Nunes, M.T.; Bellochio, S.D.C.; Timm, N.S.; Nunes, C.F.; Teodoro, P.; Campabadal, C. Mathematical modeling and multivariate analysis applied earliest soybean harvest associated drying and storage conditions and influences on physicochemical grain quality. *Sci. Rep.* **2021**, *11*, 23287. [CrossRef] [PubMed]
91. Reimer, A.; Wiebe, K.; Rao, J.; Yao, B.; Gui, Y.; Jian, F.; Jayas, D.; Hu, C.M. A compact microwave device for monitoring insect activity in grain samples. *Biosyst. Eng.* **2018**, *175*, 27–35. [CrossRef]
92. Tan, C.; Zhou, X.; Zhang, P.; Wang, Z.; Wang, D.; Guo, W.; Yun, F. Predicting grain protein content of field grown winter wheat with satellite images and partial least square algorithm. *PLoS ONE* **2020**, *15*, e0228500. [CrossRef]
93. Shahhosseini, M.; Martinez-Feria, R.A.; Hu, G.; Archontoulis, S.V. Maize yield and nitrate loss prediction with machine learning algorithms. *Environ. Res. Lett.* **2019**, *14*, 124026. Available online: https://iopscience.iop.org/article/10.1088/1748-9326/ab5268 (accessed on 20 October 2023). [CrossRef]
94. Silva, E.E.; Baio, F.H.R.; Teodoro, L.P.R.; Junior, C.A.S.; Borges, R.S.; Teodoro, P.A. UAV-multispectral and vegetation indices in soybean grain yield prediction based on in situ observation. *Remote Sens. Appl. Soci. Environ.* **2020**, *18*, 100318. [CrossRef]
95. Han, J.; Zhang, Z.; Cao, J.; Luo, Y.; Zhang, L.; Li, Z.; Zhang, J. Prediction of Winter Wheat Yield Based on Multi-Source Data and Machine Learning in China. *Remote Sens.* **2020**, *12*, 236. [CrossRef]
96. Wan, L.; Cen, H.; Zhu, J.; Zhang, J.; Zhu, Y.; Sun, D.; Du, X.; Zhai, L.; Weng, H.; Li, Y.; et al. Grain yield prediction of rice using multi-temporal UAV-based RGB and multispectral images and model transfer—A case study of small farmlands in the South of China. *Agric. For. Meteorol.* **2020**, *291*, 108096. [CrossRef]
97. Zhang, K.; Ge, X.; Shen, P.; Li, W.; Liu, X.; Cao, Q.; Zhu, Y.; Cao, W.; Tian, Y. Predicting rice grain yield based on dynamic changes in vegetation indexes during early to mid-growth stages. *Remote Sens.* **2019**, *11*, 387. [CrossRef]
98. Gaso, D.V.; Berger, A.G.; Ciganda, V.S. Predicting wheat grain yield and spatial variability at field scale using a simple regression or a crop model in conjunction with Landsat images. *Comput. Electron. Agric.* **2019**, *159*, 75–83. [CrossRef]
99. Guo, C.; Tang, Y.; Lu, J.; Zhu, Y.; Cao, W.; Cheng, T.; Zhang, L.; Tian, Y. Predicting wheat productivity: Integrating time series of vegetation indices into crop modeling via sequential assimilation. *Agric. For. Meteorol.* **2019**, *272*, 69–80. [CrossRef]
100. Martinez-Feria, R.A.; Licht, M.A.; Ordóñez, R.A.; Hatfield, J.L.; Coulter, J.A.; Archontoulis, S.V. Evaluating maize and soybean grain dry-down in the field with predictive algorithms and genotype-by-environment analysis. *Sci. Rep.* **2019**, *9*, 7167. [CrossRef]
101. Li, H.; Chen, S. A neural-network-based model predictive control scheme for grain dryers. *Dry. Technol.* **2019**, *38*, 1079–1091. [CrossRef]

102. Dai, A.; Zhou, X.; Liu, X.; Liu, J.; Zhang, C. Intelligent control of a grain drying system using a GA-SVM-IMPC controller. *Dry. Technol.* **2018**, *36*, 1413–1435. [CrossRef]
103. Liu, X.; Li, B.; Shen, D.; Cao, J.; Mao, B. Analysis of grain storage loss based on decision tree algorithm. *Procedia Comput. Sci.* **2017**, *122*, 130–137. [CrossRef]
104. Nyabako, T.; Mvumi, B.M.; Stathers, T.; Mlambo, S.; Mubayiwa, M. Predicting *Prostephanus truncatus* (Horn) (Coleoptera: Bostrichidae) populations and associated grain damage in smallholder farmers' maize stores: A machine learning approach. *J. Stored Prod. Res.* **2020**, *87*, 01592. [CrossRef]
105. Duan, S.; Yang, W.; Wang, X.; Mao, S.; Zhang, Y. Forecasting of grain pile temperature from meteorological factors using machine learning. *IEEE Access* **2019**, *7*, 130721–130733. [CrossRef]
106. Li, J.; Su, Z.; Li, Y.; Zhao, H.; Chen, X. Online temperature-monitoring technology for grain storage: A three-dimensional visualization method based on an adaptive neighborhood clustering algorithm. *J. Sci. Food Agric.* **2023**, *103*, 6553–6565. [CrossRef] [PubMed]
107. Qu, Z.; Zhang, Y.; Hong, C.; Zhang, C.; Dai, Z.; Zhao, Y.; Gu, Z. Temperature forecasting of grain in storage: A multi-output and spatiotemporal approach based on deep learning. *Comput. Electron. Agric.* **2023**, *208*, 107785. [CrossRef]
108. Abdelsamea, M.M.; Gaber, M.M.; Ali, A.; Kyriakou, M.; Fawki, S. A logarithmically amortising temperature effect for supervised learning of wheat solar disinfestation of rice weevil Sitophilus oryzae (Coleoptera: Curculionidae) using plastic bags. *Sci. Rep.* **2023**, *13*, 2655. [CrossRef] [PubMed]
109. Yang, H.; Zhao, H.; Zhang, D.; Cao, Y.; Teng, S.W.; Pang, S.; Li, Y. Auto-identification of two Sitophilus sibling species on stored wheat using deep convolutional neural network. *Pest. Manag. Sci.* **2022**, *78*, 1925–1937. [CrossRef] [PubMed]
110. Jian, F.; Chelladurai, V.; Jayas, D.S.; Demianyk, N.D.G. White, Interstitial concentrations of carbon dioxide and oxygen in stored canola, soybean, and wheat seeds under various conditions. *J. Stored Prod. Res.* **2014**, *57*, 63–72. [CrossRef]
111. Barreto, A.A.; Abalone, R.; Gastón, A.; Ochandio, D.; Cardoso, L.; Bartosik, R. Validation of a heat, moisture and gas concentration transfer model for soybean (*Glycine max*) grains stored in plastic bags (silo bags). *Biosyst. Eng.* **2017**, *158*, 23–37. [CrossRef]
112. Taheri, S.; Brodie, G.; Gupta, D. Optimised ANN and SVR models for online prediction of moisture content and temperature of lentil seeds in a microwave fluidized bed dryer. *Comput. Electron. Agric.* **2021**, *182*, 106003. [CrossRef]
113. André, G.S.; Coradi, P.C.; Teodoro, L.P.R.; Teodoro, P.E. Predicting the quality of soybean seeds stored in different environments and packaging using machine learning. *Sci. Rep.* **2022**, *12*, 8793. [CrossRef]
114. Aznan, A.; Gonzalez Viejo, C.; Pang, A.; Fuentes, S. Rapid detection of fraudulent rice using low-cost digital sensing devices and machine learning. *Sensors* **2022**, *22*, 8655. [CrossRef]
115. Carneiro, L.C.; Coradi, P.C.; Rodrigues, D.M.; Lima, R.E.; Teodoro, L.P.R.; Santos de Moraes, R.; dos Santos Bilhalva, N. Characterizing and Predicting the Quality of Milled Rice Grains Using Machine Learning Models. *AgriEngineering* **2023**, *5*, 1196–1215. [CrossRef]
116. Abdipour, M.; Ramazani, S.H.R.; Younessi-Hmazekhanlu, M.; Niazian, M. Modeling oil content of sesame (*Sesamum indicum* L.) using Artificial Neural Network and Multiple Linear Regression Approaches. *JAOCS* **2018**, *95*, 283–297. [CrossRef]
117. Patrício, D.I.; Rieder, R. Computer vision and artificial intelligence in precision agriculture for grain crops: A systematic review. *Comput. Electron. Agric.* **2018**, *153*, 69–81. [CrossRef]
118. Lutz, E.; Coradi, P.C. Applications of new technologies for monitoring and predicting grains quality stored: Sensors, Internet of Things, and Artificial Intelligence. *Measurement* **2021**, *188*, 110609. [CrossRef]
119. Weiss, M.; Jacob, F.; Duveiller, G. Remote sensing for agricultural applications: A meta-review. *Remote Sens. Environ.* **2020**, *237*, 111402. [CrossRef]
120. Khanal, S.; Kc, K.; Fulton, J.P.; Shearer, S.; Ozkan, E. Remote Sensing in Agriculture-Accomplishments, Limitations, and Opportunities. *Remote Sens.* **2020**, *12*, 3783. [CrossRef]
121. Jaques, L.B.A.; Coradi, P.C.; Lutz, É.; Teodoro, P.E.; Jaeger, D.V.; Teixeira, A.L. Nondestructive technology for real-time monitoring and prediction of soybean quality using Machine Learning for a bulk transport simulation. *IEEE Sens. J.* **2022**, *23*, 3028–3040. [CrossRef]
122. Lutz, É.; Coradi, P.C.; Jaques, L.B.A.; de Oliveira Carneiro, L.; Teodoro, L.P.R.; Teodoro, P.E.; de Souza, G.A.C. Real-time equilibrium moisture content monitoring to predict grain quality of corn stored in silo and raffia bags. *J. Food Proc. Eng.* **2022**, *45*, e14076. [CrossRef]
123. Jaques, L.B.A.; Coradi, P.C.; Müller, A.; Rodrigues, H.E.; Teodoro, L.P.R.; Teodoro, P.E.; Steinhaus, J.I. Portable-mechanical-sampler system for real-time monitoring and predicting soybean quality in the bulk transport. *IEEE Trans. Instrum. Meas.* **2022**, *71*, 2517412. [CrossRef]
124. Dubal, Í.T.P.; Coradi, P.C.; dos Santos Bilhalva, N.; Biduski, B.; Lutz, É.; Mallmann, C.A.; Flores, E.M.M. Monitoring of carbon dioxide and equilibrium moisture content for early detection of physicochemical and morphological changes in soybeans stored in vertical silos. *Food Chem.* **2024**, *436*, 137721. [CrossRef]
125. Jaques, L.B.A.; Coradi, P.C.; Rodrigues, H.E.; Dubal, Í.T.P.; Padia, C.L.; Lima, R.E.; Souza, G.A.C. Post-harvesting of soybean seeds–engineering, processes technologies, and seed quality: A review. *Intern. Agroph.* **2022**, *36*, 59–81. [CrossRef]
126. Santana, D.C.; Teodoro, L.P.R.; Baio, F.H.R.; dos Santos, R.G.; Coradi, P.C.; Biduski, B.; Shiratsuchi, L.S. Classification of soybean genotypes for industrial traits using UAV multispectral imagery and machine learning. *Rem. Sens. Appl. Soci. Environ.* **2023**, *29*, 100919. [CrossRef]

127. Bilhalva, N.; Coradi, P.C.; Biduski, B.; Mallmann, C.A.; Anschau, K.F.; Müller, E.I. Early detection of quality alterations in corn grains stored in vertical prototype silos using real-time monitoring of carbon dioxide and equilibrium moisture content. *Food Bioprod. Proc.* **2023**, *140*, 242–258. [CrossRef]
128. Coradi, P.C.; Maldaner, V.; Lutz, É.; da Silva Daí, P.V.; Teodoro, P.E. Influences of drying temperature and storage conditions for preserving the quality of maize postharvest on laboratory and field scales. *Sci. Rep.* **2020**, *10*, 22006. [CrossRef]
129. Coradi, P.C.; Lutz, É.; dos Santos Bilhalva, N.; Jaques, L.B.A.; Leal, M.M.; Teodoro, L.P.R. Prototype wireless sensor network and Internet of Things platform for real-time monitoring of intergranular equilibrium moisture content and predict the quality corn stored in silos bags. *Exp. Syst. Appl.* **2022**, *208*, 118242. [CrossRef]
130. Coradi, P.C.; Lemes, Â.F.C.; Müller, A.; Jaques, L.B.A.; Dubal, Í.T.P.; Bilhalva, N.D.S.; Teodoro, P.E.; Steinhaus, J.I.; Maier, D.E. Silo–dryer–aerator in fixed and thick layer conceptualized for high quality of grains applied in different social scales post-harvest: Modeling and validation. *Dry. Technol.* **2021**, *40*, 1369–1394. [CrossRef]