DOI: 10.24996/ijs.2023.64.11.46

ISSN: 0067-2904

Sensors Work in Agriculture: Where Are We? What Are the Prospects?

Ahmed Asaad Zaeen[1]*, Laith Aziz Jawad[1], Lakesh K. Sharma[2], Tareq Zaid Hamood[3]

[1]Remote Sensing Unit, College of Science, University of Baghdad, Baghdad, Iraq
[2]Soil, Water, and Ecosystems Sciences Dept., University of Florida, USA
[3]Department of Computer Science, College of Science, University of Baghdad, Baghdad, Iraq

Received: 15/8/2022 Accepted: 10/1/2023 Published: 30/11/2023

Abstract

The increased food requirement puts intense pressure on the agriculture community to grow more from the same resources resulting in people leaving the farming business. This happened not exclusively due to the industrial pressure to produce more but to the lack of technology adoption among growers. The use of the sensor in agriculture is not new, but its adoption among agriculture producers is a challenge for industry and scientists. This study aimed to determine sensors used in agricultural fields with challenges and prospects. The study found that sensors have successfully been used at the industry level with highly skilled labor; however, their adoption is challenging in rural agriculture systems due to the lack of a support system. The study found that the sensors used in predicting crop parameters, yield, quality, insect attacks, leaf damage, and several plants are crucial parameters to study. Sensors, particularly ground-based active optical sensors, have performed well while developing algorithms where soil parameters, environmental factors, and sensors have successfully predicted crop yield and quality.

Keywords: Sensor, Remote Sensing, Agriculture, and Yield prediction.

عمل أجهزة الاستشعار في الزراعة: أين نحن؟ ما هي الآفاق؟

احمد اسعد زعين*1 ليث عزيز جواد1 لاكيش ك شارما2 طارق زيد حمود3

1وحدة الاستشعار عن بعد، كلية العلوم، جامعة بغداد، بغداد، العراق
2قسم علوم التربة والمياه، جامعة فلوريدا، الولايات المتحدة الامريكية
3قسم علوم الحاسوب، كلية العلوم، جامعة بغداد، بغداد، العراق

الخلاصة

تفرض الاحتياجات الغذائية المتزايدة ضغطًا شديدًا على المجتمع الزراعي لزيادة نموه من نفس الموارد مما يؤدي إلى ترك الناس أعمال الزراعة. لم يحدث هذا فقط بسبب الضغط الصناعي لإنتاج المزيد ولكن بسبب عدم تبني المزارعين للتكنولوجيا. استخدام المستشعر في الزراعة ليس جديدًا ، لكن اعتماده بين المنتجين الزراعيين يمثل تحديًا للصناعة والعلماء. هدفت هذه الدراسة إلى تحديد أجهزة الاستشعار المستخدمة في المجالات الزراعية مع التحديات والآفاق. وجدت الدراسة أن أجهزة الاستشعار قد تم استخدامها بنجاح على مستوى الصناعة مع العمالة الماهرة للغاية؛ ومع ذلك ، فإن اعتمادها يمثل تحديًا في أنظمة الزراعة الريفية بسبب عدم وجود نظام دعم. ووجدت الدراسة أن المستشعرات المستخدمة في التنبؤ بمعلمات المحاصيل،

*Email: ahmed.asaad@sc.uobaghdad.edu.iq

والمحصول، والجودة، والاصابة بالحشرات وتضرر اوراق النباتات هي عوامل أساسية للدراسة. لقد أدت المستشعرات، وخاصة المستشعرات الضوئية النشطة الأرضية ، أداءً جيدًا أثناء تطوير الخوارزميات ، حيث تنبأت معلمات التربة والعوامل البيئية وأجهزة الاستشعار بنجاح بإنتاجية المحاصيل وجودتها.

1. Introduction

The human population is increasing rapidly, leaving less farm income for the growers [1], and scientists are seeking new approaches to improve food productivity and nutrient efficiency [2]. The twenty-first century offers technology like soil sensors and normalized differential vegetative index (NDVI) to assist growers in producing high-quality crops.

Modern agricultural management depends on sensing methods like active optical and passive sensors: satellite and aerial images for accurate soil, crop, climate, and environmental conditions [3]. Sensing technology may play a role in the agriculture and food industries; for example, assessing the freshness or spoilage of fresh vegetables and fruit over processing and packaging can be achieved by employing an electronic nose [4,5].

Remote sensing technologies are non-destructive and can predict crop yield and nutrient requirements [6]. Sunlight rays reach the surface of the soil and crop; the beams are either absorbed, reflected, or transmitted, relying on light's wavelength and target characteristics. The difference in the chemical and physical properties of the target, texture, shape, and leaf color determines the portion of the absorbed, transmitted, and reflected light of a particular wavelength. Ahmed et al. (2020) [6] examined whether active sensors could be employed for yield prediction in the middle of the growing season for potatoes (Solanum tuberosum L.). chlorophyll index (CI) and NDVI data were acquired weekly from the active sensors, Crop Circle (CC) and GreenSeeker (GS). Indices measurements acquired at the 16th and 20th leaf growth stages were significantly associated with tuber yield. The regression analysis among potato yield as a dependent variable and vegetation indices, CI, and NDVI (as independent variables) could significantly enhance the forecast model's precision and improve the determination coefficient. The NDVI sensors could also determine nitrogen (N) use in plants and any deficiency [7]; detecting crop nutrient levels enables growers to determine the exact N requirements for high-yield output and perform a supplemental application. Soil sensors are valuable for determining soil's physical and chemical properties and moisture content [8]. Crops' water stress can be decreased through irrigation as determined by direct sensor readings from the field [9]. Sensing water stress within a field can increase yields and improve soil profile [10]. This article reviews the advanced sensor technology in practice to improve crop yield and farmer profit by improving efficiency and going through some points considered a gap in sensor work.

1.2 The Gap in Sensor Work

Many factors, such as saturation, could affect sensor work and its relationship changes [12]. Sharma et al. (2017) [12] determined that red wavelengths are weak at determining yield due to the impact of saturation. The saturation happens in later growth stages as leaves cover most of the area, contaminating sensor readings [13]. This occurs as the LAI approaches four and continues until the end of the growing season [13]. The second factor affecting sensor reading is soil type. The soil has a certain level of reflectiveness based on its composition [14]. The soil's mineral composition can increase the soil's reflectiveness, causing interference with NDVI readings [15]. Some soil types, like clay, are heavy in minerals that can increase the reflectiveness of soil [15]. Heavily irrigated soil and overall moisture content do not affect red or near-infrared light unless the water is still on leaves [14].

Isaev (2012) [16] mentioned that GreenSeeker's limitation is data logging frequency. GreenSeeker is programmed to record data faster than 1.0 HZ. However, the GS can record data once every second, negatively affecting the accuracy at the locations with a low reading. Since most studies were conducted by slow walking, recording frequency did not negatively impact the process. However, in the case of high-speed sensors installed on the tractor, long gaps between data locations negatively affect reading accuracy. Another gap issue mentioned by [17] is that when wheat grows under different nitrogen treatments, there is a slight difference in NDVI reading when the ground gets covered 100% by the plant, but the variability increases as the crop cycle progress. The highest variability was noticed at maximum head weight due to spike size and morphology similarity. There was a difference among cultivars at the heading and grain-filling stages.

2. Methodology

2. 1 How is Sensing Helping?

Spectral reflectance is the most standard sensing approach employed in agricultural measurements, in which spectral reflectance refers to the proportion of the reflected light to the incident light that is calculated as a function of wavelength [18,19]. Each target on the Earth's surface has a different reflectance curve depending on the target surface characteristics, known as the spectral signature. The visible regions (400-700 nm) to NIR and MIR (700-2500 nm) part of the electromagnetic spectrum are the wavelengths measured and most typically used in agricultural applications [20].

The spectral signatures offer valuable information about soil and crops' physiological and biological characteristics [20,21]. Radiometers, digital cameras, or spectrometers could be carried on different platforms, ground (truck or tractor), aircraft, and satellites to collect information. Successive measures of small-scale regions are derived from the sensor platform transferring, processing, and assembling measurement outcomes into an image [19].

Remote sensing has spectral, temporal, and spatial resolution [3,19], where the spatial resolution points out the smallest area recognized in the image, directly associated with image pixel size. In contrast, the spectral resolution points out the width and number of the fractions of the electromagnetic spectrum calculated by the sensor. The temporal resolution points out how often the remote sensing platform could take measures of a location; agriculture and farm managing applications generally demand (2-5m) spatial resolution with one to three days temporal resolution, one-pixel geolocation precision, 24-hour outcome delivery time, and regular production of atmospherically updated products [21].

Optical characteristics and nondestructive measurement of anthocyanin in plant leaf photobiology and photochemistry are the essential advantages of smart agriculture [22]. The sensors estimate leaf pigments such as chlorophyll, anthocyanin, and carotenoids; pigments are associated with the plant leaf structure and other metabolisms [23]. Sensors can calculate anthocyanin by discriminating the red and green wavelengths [22]. The pigment that could be distinguished using a sensor is the plant's chlorophyll content, an indicator of the plant's health. The plant's chlorophyll content is essential to perceive the photosynthetic capacity, canopy stress, and production of productivity [24].

Sensors such as leaf clips have measured the carotenoids from the photochemical reflectance index (PRI) equation derived from the red wavelength proportion. Sensors can detect the difference between daylight and dark on leaves, thus recognizing the application reflectance [25]. Sensors can assess leaf pigment content and activity using a reflectometer.

The leaf area index (LAI) determines the potential photosynthesis and crop yield model [26]. The classic methods for calculating LAI include (length × maximum width × 0.75) for each leaf for each plant or the laboratory procedure for determining LAI [27, 28]. Generally, LAI is stated as choosing the leaves area per ground area. Nevertheless, these methods are both time and cost-consuming.

Using sensing to estimate LAI is one of the most successful methods for obtaining accurate and valuable data; LAI could be derived from estimating the soil adjustment vegetation index (SAVIR) [29]. The hyperspectral indices evaluation for LAI can estimate and discriminate potato crops under various irrigation treatments. The role of RS in the last two decades in precision agriculture was due to the high demand to find innovative technology. Darker organic matter content has a higher significant absorption and lower spectral reflectance. This fact can be applied to any surface color changes so that soil with a dark color, due to significant organic content, would have higher absorption than soil with a light color [30]. The same concept was investigated, in the colored dissolved organic matter in lakes, based on changing the colors of the lake, where data was collected from satellite images, Landsat, IKONOS, and Advanced Land Imager (ALI). The IKONOS simulations provide a much more practical algorithm, while substantial uncertainty exists at the highest colored dissolved organic matter (CDOM) levels. Sensing is the science of gaining, processing, and interpreting images collected from the sensors placed on drones or satellites. This science could be applied to mineral exploration, either thermally recognizing the rock's spectral signature or localizing ore deposits. For instance, iron oxide is demonstrated brightly at visible wavelengths and decreased at NIR [31]. ASTRE image was used for mapping iron oxide, where band ratios, false color combinations, least square fitting, spectral angle mapper, and principal components analysis for mapping iron minerals were used in Hana district, Kerman province, Iran. The results displayed that the spectral angle mapper approach has high accuracy for mapping iron oxidation areas and minerals [32].

Accurate deployment information of crop or field features is provided within the high spectral resolution of the hyperspectral system, which can provide a considerable volume of data [33,34]. Moreover, Scotford and Miller (2005) [20] mentioned that interpreting measured data requires understanding hyperspectral sensors and properties; remote sensing could study crop nutrition, crop disease, water deficit or surplus, weed invasion, insect injury, plant population, flood management, and other fields.

2.2 Remote Sensing for Agricultural and Crop Management Applications

The consideration for selecting appropriate sensors and remote sensing datasets, based on some features, could differ among the applications [35]. Spatial resolution is on a spatial scale (pixel size) to collect data that differs from the required data, such as parcels, individual fields, states, and continents. The remote sensing instruments vary depending on satellite image sort; for example, IKONOS is 0.5m, the land sat thematic mapper is 30 m and 120 m (TIR; band 6), Advanced Spaceborne-Thermal Emission and Reflection Radiometer (ASTER) is 15, 30, and 90 m, SPOT (Satellite Pour observations de la Terre) is 60 km, LISS (Linear Imaging Self Scanning) is between 23 to 76.5 m according to the bands placed on it, AWiFS (Advanced Wide Field Sensors) is 56 m and image scene area is 710 km^2, and MODIS is 1 km. Increasing the spatial resolution means that the images show a more extensive area but less information. Even though the spatial resolution differs according to the differences among instruments such as satellites, aircraft, or drones, these images are still crucial for data acquisition. Higher spatial resolution images tend to have a lower temporal resolution [35].

The satellite images have different spatial and temporal resolutions, leading to flexible time and spatial resolution sources that would serve agricultural research. Alternative resources to collect images, such as an unmanned aerial vehicle (UAV), could have a higher spatial and temporal resolution which is more flexible, meaning the sensors placed on a UAV have an appropriate spatial and temporal resolution [35]. Sensors can be placed on a UAV to help monitor crop life stages, nutrient deficits, and crop surface models (CSMs) with high resolution (1cm/pixel), where red, green, and blue wavelengths are shown to have a high correlation between the linear models. Estimating biomass of barley by using CSMs derived from UAV-based RGB imaging [36].

UAVs are widely prevalent in agriculture due to efficient scheduling in the field with available remote sensing instruments compared to other remote sensing sources such as satellites and aircraft [37]. The UAVs are amounted to an image conquest system to determine biomass and nitrogen deficiency for different crops and vegetables; the UAV system comes with a primarily digital system for taking images of objects. Some sensors are equipped with multiple filters, where the more sophisticated camera's filter has many bands like near-infra-red (NIR), red edge, and thermal infrared or short wavelengths. Output images are either actual images (natural images) or false images. These sensors mounted on UAVs are passive sensors that the sun is the primary energy source. These sensors or cameras are multispectral or hyperspectral, working based on the incident spectrum [38]. The UAVs are used widely in precision agricultural applications due to being easy to use and attracting farmers [39]. The lower price, flexibility to collect data, and the massive information obtainable from the UAVs as images or mosaic forms are successfully exploited and invested in detecting nutrient deficiency and plant diseases [40], encouraging researchers and farmers to obtain and use this technology.

Acquiring data using UAVs could cover a large area affected by bacteria or fungi that would influence crop production, reducing profit [41], a new type of precision disease, and plant stress management. Several studies included plant pathology detection either by the multispectral or hyperspectral signature [42]. These techniques discriminated between healthy and unhealthy plant leaves through the reflectance at near-infrared (NIR), which showed a highly sensitive peak in the spectrum curve for unhealthy plants at early stages. The blue band did not show significant differences in spectral reflectance [42].

Aerial photography successfully monitored insect activity by detecting changes in plant leaves or the plant density influenced by insects [45]. The UAV is considered an essential method due to its ability to mount any sensor based on the study purpose; it is a technical tool for monitoring an environmental contaminant [44], including software that allows processing and collecting data from drones. Drones become the easiest and best technology ever used; the system is circulated with GPS, sunshine, and various facilities such as speed, altitude, resolution, Region of Interest (ROI), and accurate data collecting tools [45].

Decisions can be made based on interpreted data from images processed by software available online, such as MicaSence uploader, or purchased with a drone such as pix4D. Consequently, discrimination wavelengths are used to extract bands and use the algorithms to explicate collected data and calculate the NDVI [46], LAI based on crop canopy (CC) [47], soil-adjusted vegetation index (SAVI), green and red vegetation index (GRVI), and red, green blue vegetation index (RGBVI) [48].

Crops' productivity is significantly reduced due to water stress; water stress affects seed germination, plant growth, and photosynthesis [49]. Water stress reduces plants' transpiration and leaf structure moisture and increases leaves' temperature. Unmanned aerial vehicles are provided with sensors that know the canopy structure [50]. Water stress could be determined using UAVs with passive sensors attached to drones. These sensors, either hyperspectral or multispectral, have Middle infra-red (MIR) or short wave (SWIR) (1300 nm to 2400 nm), in which cell walls in spongy mesophyll structure reflect the incident radiation. This reflectance happens at 1450 nm and 1950 nm; consequently, the low absorbance and high reflectance lead to exposure to water stress [51]. Bellvert et al. 2014 [52] found that at thermal wavelengths with high resolution and size pixels, there was a decreased correlation between crop water stress index, indicating to map the spatial variability in water deficit and ψ, which suggested leaf water potential caused by the pixels’ interactions between leaf and soil.

2.3 How Do Sensors Help the Food Industry?

Volatile organic compounds (VOCs) are a byproduct of daily physiological functions typically released from plants and trees. The specific quantities of VOCs indicate crop and field situations; for instance, humidity, temperature, light, fertilization, soil condition, insects, and plant diseases impact the discharge of VOCs [53]. Electronic noses are typically applications in farming to diagnose crop disease, identify insect invasion, and observe foodstuff quality. The electronic nose comprises a set of gas sensors with an expansive selectivity partially interfering and an electronic pattern recognition approach with multi-change statistical data processing instruments. The electronic nose is programmed to compare the profile of VOCs emitted from healthy plants or fruits with the diseased ones.

Assessing the freshness or spoilage of harvested-farm products during the processing and packaging operation can be conducted by using an electronic nose [4,5]. The VOCs imply fruit ripening and compounds that activate fruit maturation, such as ammonia, [54,55] ethanol and ethylene, and trans-2-hexenal [56,57]. Brezmes et al. 2001 [58] utilized an electronic nose to monitor changes in aroma profile during apple storage to assess the quality after harvesting peaches, pears, and bananas [56, 59] and to detect spoilage in potatoes [60]. Most investigations are still in the preparatory stage because of limitations, such as stability, calibration, selectivity, longevity, and standardization of gas collection apparatus [61].
Electronic noses and electro-antennogram monitor pheromone trap coverage area to captivate insect herbivores [62,63]. New studies stated that the electronic nose could specify earlier stages of insect invasions by noticing VOCs released by injured plants [64,65].
Rady and Guyer 2015 [66] mentioned the efficiency of selected wavelengths to predict sucrose and glucose of potato tubers of Russet Norkotah and Frito Lay 1879 cultivars to classify potatoes according to sugar levels relevant to the frying industry. Slices were scanned using 12.7 mm as tubers via VIS/NIR band ratio (446-1,125 nm). Artificial neural networks and the partial least squares regression were involved in building prediction models; R (RPD), correlation coefficients, were 0.95 (3.02) and 0.78 (1.61) for RN and FL using slice samples, and 0.97 (3.89) and 0.81 (1.72) for RN and FL, respectively, for whole tubers. R(RPD) for sucrose models were 0.78 (1.57) and 0.71 (1.43) for RN and FL with slice samples and 0.94 (2.82) and 0.80 (1.64) for whole tubers.

2.4 How Do Sensors Help with Nutrient Uptake and Yield Prediction?

Electrochemical sensors in agriculture are used to directly measure soil chemistry, such as pH and nutrient content [8], where two electrochemical sensors are commonly used to calculate the activity of specified ions in the soil (K+, H+, NO3-, Na+, etc.), first, ion-

selective electrode (ISE) sensors, and second, ion-selective field-effect transistor (ISEFT) sensors. ISE and ISEFT sensors can investigate plants' uptake of ions [67].
Furthermore, Mladenova et al. 2017 [68] mentioned that the correlation between soil moisture and evapotranspiration indices could provide critical information for predicting corn and soybean yields more than vegetation indices. The significance of the correlation relied on the interannual variability in yield measured at a given location. Soil moisture was studied as a factor for yield prediction. [1, 69] found that soil moisture was negatively associated with the yield of wheat grain ($r= ^{-}0.68$ and $^{-}0.53$) at the depths (0–15 and 15–30 cm, respectively) at stage 5 of physiological growth. However, at stage 7 of Feeke's physiological growth, there was no association between soil moisture and wheat grain yield at any depth. Also, Soil Bulk density was negatively associated with the final grain yield ($r = ^{-}0.35$).

The plant's request determines the nutrient rate, which depends on the growth rate and nutrient content situation. Nitrogen, Phosphorous, and Potassium as macro-nutrients are actively absorbed. Observing ion concentrations of the plant is a significant opportunity for growers to design fertilization procedures to enhance production, where ion-selective sensors are used to detect an assortment of ions. The Nitrogen ion in soils or plants, such as potato and vegetable fertilization regimes, is monitored using ISE sensors [70, 3].

The ion-selective electrode measures concentrations of ions such as iodide, chloride, fluoride, sodium, potassium, cadmium, and in plants and soil to examine the plant metabolism, nutrition, and toxicological consequences on plants [71,72].

The active optical sensor can work efficiently and non-destructively without weather conditions and solar elevation [73]. Active optical sensors can quickly collect canopy NDVI data and other indices of crops. GreenSeeker works with red (656 ± 10 nm) and near-infrared (774 ± 10 nm). The quantitative relationship between NDVI and indices of growth (LAI, DM (dry matter), and GY (grain yield)) give positive associations. The precision (R^2), accuracy (k), and standard deviation of the RNDVI dynamic model for two types of rice are 0.999, 1.017; 0.9084**, 0.803**; and 0.0232, 0.0170, respectively. The consequences indicate that the RNDVI dynamic model could accurately reflect crop growth and forecast dynamic modifications in high-yield crop populations, supplying a primary method for observing rice growth status [73]. These two bands are used widely to monitor nutrient conditions and crop growth; for instance, Osborne (2007) [65] utilized GreenSeeker in monitoring wheat growth and nutrient condition, showing that extracted NDVI values significantly with nitrogen content and dry matter.

As a standard, active optical sensors predict yield in the fields without nitrogen limitation. In contrast, fields that suffered from nitrogen limitation gave a lower yield prediction from sensor reading, indicating a need for supplemental nitrogen. The Red NDVI and red edge NDVI were utilized in corn yield prediction. The V6 of the growth stage, Red NDVI, and red edge NDVI gave a similar association with yield. In contrast, the red-edge NDVI was superior to the red NDVI at V12, indicating that red-edge NDVI would still be actively helpful until the late season of nitrogen application [6].

The LAI is a direct biophysical parameter for observing crop conditions, which provides specific physical information regarding canopy functioning [75]. The NDVI and LAI were utilized in yield prediction; it was found that NDVI and LAI have similar efficacy as a spatial yield variability prediction factor, which provided high correlations of 0.8 at specific times during the growing season. Sharma (2014) [76] used ground-based active optical sensors

(GBAO) to predict crop yield. Two GBAO sensors, GreenSeeker (GS) and crop circle (CC), within forty-six trials of N-rate for corn crop at (V6) and (V12) of leaf growth stages with plant height manually factor.

The relationship between GS, yield, and INSEY (INSEY= in-season estimate of yield = sensor NDVI/ growing degree-days from planting data) was enhanced by multiplying the sensor-NDVI by corn height at V6. The GreenSeeker GS and CC were used to identify the plants' sulfur deficiency [76]. Both sensors detected that the sensor reading values (NDVI) decreased at an increased N rate. Practitioners can use this connotation to test areas with an early-season sulfur deficiency.

Raun et al. (2002) [77] developed the GS algorithm for corn, connecting corn yield calculated in field experimentations with an in-season yield estimation, where GS data and NDVI were used to derive INSEY, divided by growing degree days from the planting date. “The algorithm depicted by the regression association between corn yield and INSEY employed to vary nitrogen rate of corn crop utilizing the difference between corn yield forecasted and the corn yield forecasted from a nitrogen-rich sector, within variety and field of interest, multiplied the 1.25 % nitrogen in corn grain estimate divided by a nitrogen fertilizer application efficiency factor (values from > 0 to 1)”.

The algorithm that Holland and Schepers (2010) [78] developed for the CropCircles sensor and corn crop calculated the ratio of the vegetarian index for corn plants in comparison with the reference plants that were considered to have a sufficient supply of nitrogen. The acceptable index (SI) ratio was supposed to keep the same during the growing season's residue unless further nitrogen fertilization was added. A good association was found between SI and yield estimation [79].

The photosynthetic rate of leaves depends strongly on nitrogen content, where any nitrogen deficiency could affect the photosynthetic rate [80], so selecting a particular wavelength to determine corn nitrogen status is very important [80, 81]. Shanahan et al. (2003) [82] suggested employing NDVI and Green NDVI (GNDVI), using two spectrums, NIR and the other 500-600 nm. Active-optical sensors, such as GS and CC, release four light bands, which are blue (460 nm), green (555nm), red (680 nm), and NIR (800 nm), where any difference in nitrogen rate and sampling date affects the NDVI reading. The results showed an increase in chlorophyll content correlated strongly with the nitrogen treatment $r^2 \geq 96$. Hansen and Schjoerring (2003) [83] said that NDVI could be employed effectively in assessing growth and small grains’ development.

Moges et al. (2005) [84] mentioned that sensor readings at Feekes growth stages (5) were correlated with grain yield more than other development stages. Raun et al. (2001) [85] mentioned that the sensor-based estimated reading could describe 83% grain product variability. At the same time, Inman et al. (2007) [86] found that the variability over space and time may affect the association between sensor reading and yield. The discrepancy in measuring yield was related to sampling date, seasonal changes, hybrid variation, nitrogen fertilization, and spatial differences [86, 87].

2.5 Factors and Parameters That Could Help in Improving Sensing Technology

2.5.1 Plant Height and Sensors for Yield Prediction

Plant height is used as a criterion for studying the vegetation growth of corn crops [76], where the height of corn plants is affected by all the soil water content [88], soil texture, cultivation methods, and fertilizer application rate [89]. Plant height could be measured by employing high-resolution ultra-sound distance sensing of crop canopy [90].

The canopy height of sugar beet (*Beta Vulgaris L*) is multiplied by GS data to calculate leaf nitrogen concentration, sugar beet top nitrogen content, and dry matter yield [91]. The nitrogen content of sugar beet tops is associated with the two-dimensional leaf area and density. Multiplying NDVI reading times of canopy height results in a leaf volume instead of a leaf area index. Also, the NDVI reading was associated with alfalfa plant height (Medicago sativa L), where surface area coverage and plant height were developed simultaneously. Still, grasses were not associated with plant height, where surface coverage was nearly continuous [92].

Researchers considered plant height an indicator to assist crop prediction besides other sensors, where measuring plant height dramatically improved the relationship between the active optical sensor and crop yield [93]. A practical manual measuring plant height is not accepted for US commercial corn production. Therefore, commercial acoustic height and active optical sensors were utilized at two-corn growth stages (V6 and V12), supplying an improved yield association compared to the manual method. At V6, the improvement was more significant than in V12 regarding the relationship between active optical sensor readings multiplied by acoustic sensor reading and yield.

Researchers used light detection and ranging (LIDAR) to have a better crop height measurement [94], where a LiDAR-based high-throughput phenotyping (HTP) system was the tool developed for cotton plant phenotyping in the field. The HTP technique consists of two Dimensions LIDAR and Real-Time Kinematic-Global Positioning System (RTK-GPS) mounted on a high-clearance tractor. Three rows of cotton plots were scanned by LIDAR concomitantly from the top, and the RTK-GPS was employed to supply the spatial coordinates of the point cloud during data assembly.

LIDAR was utilized in the Lab to test a single plant using 0.5º angle resolution, where results showed an R^2= 1.00 and RMSE = 3.46 mm compared to manual measures. Utilizing the exact angular resolution in the field tests, they achieved R^2 =0.98 and 65 mm as RMSE compared to manual measurements. The HTP system benefits from extensive field applications because it provides highly accurate measurements.

2.6 Leaf Area Index (LAI) for Yield Prediction

The leaf area index was studied alongside NDVI sensors to create a perfect relationship in marketable potato yield (MPY) [12]. Sensor readings were taken at each growing stage and then multiplied by the proprietor-proxy leaf area index (PPLAI). This was done to see the impact of NDVI and PPLAI on MPY [12]. The method showed a healthy relationship between the N rate and NDVI-PPLAI than NDVI alone in MPY [12]. In addition, the method determined an inverse relationship between the rate of N application and S deficiency in the soil [12]. The LAI apparently can be used to determine MPY, where the PPLAI must be recorded in real-time rather than a system recommendation to correlate with sensor readings [12].

2.7 Red-Edge Wavelength: A High Performance to Detect Nutrients Deficiency

The symmetrical feature of the first derivative reflectance in the red edge wavelength range (690 nm to 730 nm) is related to the changes in leaf chlorophyll content. This could be beneficial for noticing leaf chlorophyll content under various growing states [95, 11]. Leaf reflectance arranged between 680 and 750 nm is a measurement of vegetation indexes; consequently, reflectance and transmittance are correlated to chlorophyll concentration, leaf maturity, and leaf area index (LAI) [96]. The red edge demonstrates a high correlation between total chlorophyll content and crops' growth, but the red edge wavelength is still unrelated to a single stress issue. Factors such as insects or air pollution may reduce the correlations between red-edge wavelength and chlorophyll content [97]. Miller et al. (1990) [98] suggested that the red edge model helps explain the correlations between remote sensing and environmental changes derived from a high-resolution sensor. The red-edge region did show double peaks based on low pigment concentration, which suggested mapping vegetation stress [99]. Sibanda et al. (2017) [100] found that the soil background did not impact the red edge; consequently, the red edge was an excellent estimator for the LAI, chlorophylls a and b, and nitrogen stressed discrimination. The red edge position (REP) determined by linear derivative from a wide wavelength range. Thus, the red edge peak could mitigate the differences between low or high nitrogen concentrations [101]. Curran et al. (1990) [102] mentioned that the red-edge wavelength could be influenced by background, such as dead pine needles, in a study that leads to extrapolation at all but low canopy levels. The red edge position estimated the carotenoids due to the correlations between chlorophyll and carotenoid content [103]. Red edge is found feasible to assess the water stress based on the correlation with crop stress [104]. Several methods, such as inverted Gaussian or linear curves, correlated the red edge and crop parameters [105, 106].

3. What are the Prospects?

As a result of using active optical sensors, a smartphone application can be developed to help farmers directly detect and control nutrient deficiency and develop a fertilization recommendation for nitrogen supplements. Also, a smartphone application can be developed to identify and control plant insects and diseases that can help farmers immediately in the field. Since the GreenSeeker and Crop Circle work on the reflected light from crop leaves as an indicator of chlorophyll content, which gives sight of plant health regarding nutrients, the suggestion is to add a thermal band to help detect plant diseases is possible. In this case, growers can control plant health regarding nutrients and pathogens and delineate a map of plant conditions. Satellite imaging provides large-scale coverage but faces a hard limitation with any weather issue. Connecting the GreenSeeker online with a system would help send the data directly from the field to the office. The new remote sensing technology can evolve with several field measurements, such as groundwater estimation and management, which simulate traditional field data. Also, the advanced research in field emissivity estimations using thermal wavelength benefits scientists and growers by increasing the amplitude of knowledge [107,108].

3. **Conclusion**

The sensors could be used in agriculture to predict crop parameters such as crop yield and quality. Still, their consistency in data collection (e.g., NDVI, rainfall) and environmental variations were the biggest hurdles that needed more attention. However, using soil moisture, rainfall, LAI, and crop height with sensors are promising parameters that could help sensors provide reliable data and algorithms. It has been found that crop height and rainfall data were more effective than soil moisture and LAI derived from NDVI because they were impractical to use on large fields. Satellite imagery and UAVs were less valuable than ground-based active optical sensors due to easy use, no specific time required, and no conflict with atmosphere issues such as clouds, dust, and sunlight. However, developing more science, such as crop scouting and essential potato activity, could quickly be performed with ground devices. Still, UAVs can cover vast areas in a short period.

References

[1] W. B. Meyer and B. L. Turner, "Human population growth and global land-use/cover change," *Annual review of ecology and systematics*, pp. 39-61, 1992. URL: http://www.jstor .org/stable/2097281?origin=JSTOR-pdf

[2] J. Spiertz, "Nitrogen, sustainable agriculture and food security: a review," *Sustainable agriculture,* pp. 635-651, 2009. URL: 10.1007/978-90-481-2666-8_39

[3] S. Li, A. Simonian, and B. A. Chin, "Sensors for agriculture and the food industry," *The Electrochemical Society Interface*, vol. 19, no. 4, p. 41, 2010.URL: https://iopscience.iop.org/article/10.1149/2.F05104if/pdf

[4] I. A. Casalinuovo, D. Di Pierro, M. Coletta, and P. Di Francesco, "Application of electronic noses for disease diagnosis and food spoilage detection," *Sensors,* vol. 6, no. 11, pp. 1428-1439, 2006.URL: https://doi.org/10.3390/s6111428

[5] A. K. Deisingh, D. C. Stone, and M. Thompson, "Applications of electronic noses and tongues in food analysis," *International journal of food science & technology,* vol. 39, no. 6, pp. 587-604, 2004. URL: https://doi.org/10.1111/j.1365-2621.2004.00821.x

[6] A. A. Zaeen, L. Sharma, A. Jasim, S. Bali, A. Buzza, and A. Alyokhin, "In-season potato yield prediction with active optical sensors," Agrosystems, Geosciences & Environment, vol. 3, no. 1, p. e20024, 2020. https://doi.org/10.1002/agg2.20024

[7] S. M. Samborski, N. Tremblay, and E. Fallon, "Strategies to make use of plant sensors-based diagnostic information for nitrogen recommendations," *Agronomy Journal*, vol. 101, no. 4, pp. 800-816, 2009. URL: https://doi.org/10.2134/agronj2008.0162Rx

[8] V. I. Adamchuk, J. Hummel, M. Morgan, and S. Upadhyaya, "On-the-go soil sensors for precision agriculture," *Computers and electronics in agriculture,* vol. 44, no. 1, pp. 71-91, 2004.URL: https://doi.org/10.1016/j.compag.2004.03.002

[9] D. Fangmeier, D. Garrot, C. Mancino, and S. H. Husman, "Automated irrigation systems using plant and soil sensors," *ASAE Publication,* no. 4-90, pp. 533-537, 1990. URL: shorturl.at/jlQZ8

[10] R. Cakir, "Effect of water stress at different development stages on vegetative and reproductive growth of corn," *Field Crops Research,* vol. 89, no. 1, pp. 1-16, 2004.URL: https://doi.org/10.1016/j.fcr.2004.01.005

[11] N. Milton, B. Eiswerth, and C. Ager, "Effect of phosphorus deficiency on spectral reflectance and morphology of soybean plants," Remote sensing of environment, vol. 36, no. 2, pp. 121-127, 1991.URL: https://doi.org/10.1016/0034-4257(91)90034-4

[12] L. Sharma, S. Bali, J. Dwyer, A. Plant, and A. Bhowmik, "A Case Study of Improving Yield Prediction and Sulfur Deficiency Detection Using Optical Sensors and Relationship of Historical Potato Yield with Weather Data in Maine," Sensors, vol. 17, no. 5, p. 1095, 2017.URL: https://doi.org/10.3390/s17051095

[13] C. Wiegand, A. Gerbermann, K. Gallo, B. Blad, and D. Dusek, "Multisite analyses of spectral-biophysical data for corn," Remote Sensing of Environment, vol. 33, no. 1, pp. 1-16, 1990.URL: https://doi.org/10.1016/0034-4257(90)90051-M

[14] J. R. Sims and V. A. Haby, "Simplified colorimetric determination of soil organic matter," Soil Science, vol. 112, no. 2, pp. 137-141, 1971.URL: shorturl.at/wzCLW

[15] M. K. John, "Colorimetric determination of phosphorus in soil and plant materials with ascorbic acid," Soil Science, vol. 109, no. 4, pp. 214-220, 1970.URL: shorturl.at/EOSUV

[16] D. Isaev, "Assessment of GreenSeeker in Peanut Disease Detection," 2012.URL: shorturl.at/cKWZ2

[17] S. R. Sultana, A. Ali, A. Ahmad, M. Mubeen, M. Zia-Ul-Haq, S. Ahmad, S. Ercisli, and H. Z. Jaafar, "Normalized difference vegetation index as a tool for wheat yield estimation: a case study from Faisalabad, Pakistan," The Scientific World Journal, vol. 2014, 2014.URL: https://doi.org/10.1155/2014/725326

[18] M. Govender, K. Chetty, and H. Bulcock, "A review of hyperspectral remote sensing and its application in vegetation and water resource studies," *Water Sa*, vol. 33, no. 2, pp. 145-151, 2007. URL: https://hdl.handle.net/10520/EJC116430

[19] R. Smith, "Introduction to interpreting digital RADAR images," *MicroImages Tutorials, Learning Geospatial Analysis, 2001 www. microimages. com*, 2006. URL: https://www.microimages.com/documentation/Tutorials/radar.pdf

[20] I. Scotford and P. Miller, "Applications of spectral reflectance techniques in northern European cereal production: a review," *Biosystems Engineering*, vol. 90, no. 3, pp. 235-250, 2005.URL: https://doi.org/10.1016/j.biosystemseng.2004.11.010

[21] S. Moran, G. Fitzgerald, A. Rango, C. Walthall, E. Barnes, W. Bausch, T. Clarke, C. Daughtry, J. Everitt, and D. Escobar, "Sensor development and radiometric correction for agricultural applications," *Photogrammetric Engineering & Remote Sensing*, vol. 69, no. 6, pp. 705-718, 2003. URL: https://doi.org/10.14358/PERS.69.6.705

[22] A. A. Gitelson, M. N. Merzlyak, and O. B. Chivkunova, "Optical properties and nondestructive estimation of anthocyanin content in plant leaves," *Photochemistry and photobiology*, vol. 74, no. 1, pp. 38-45, 2001. URL: https://doi.org/10.1562/0031-8655(2001)0740038OPANEO2.0.CO2

[23] D. A. Sims and J. A. Gamon, "Relationships between leaf pigment content and spectral reflectance across a wide range of species, leaf structures and developmental stages," *Remote sensing of environment*, vol. 81, no.2-3, pp. 337-354, 2002. URL:https://doi.org/10.1016/S0034-4257(02)00010-X

[24] A. Gitelson, A. Viña, V. Ciganda, D. Rundquist, and T. Arkebauer, "Remote estimation of canopy chlorophyll content in crops," *Geophysical Research Letters*, vol. 32, no. 8, 2005. URL: https://doi.org/10.1029/2005GL022688

[25] J. Gamon and J. Surfus, "Assessing leaf pigment content and activity with a reflectometer," *The New Phytologist*, vol. 143, no. 1, pp. 105-117, 1999. URL: https://doi.org/10.1046/j.1469-8137.1999.00424.x

[26] G. Asrar, M. Fuchs, E. Kanemasu, and J. Hatfield, "Estimating absorbed photosynthetic radiation and leaf area index from spectral reflectance in wheat 1," *Agronomy Journal*, vol. 76, no. 2, pp. 300-306, 1984. URL: https://doi.org/10.2134/agronj1984.00021962007600020029x

[27] C. Francis, J. Rutger, and A. Palmer, "A rapid method for plant leaf area estimation in maize (Zea mays L.) 1," *Crop Science*, vol. 9, no. 5, pp. 537-539, 1969. URL: https://doi.org/10.2135/cropsci 1969.0011183X000900050005x

[28] B. E. Law, T. Arkebauer, J. L. Campbell, J. Chen, O. Sun, M. Schwartz, C. Van Ingen, and S. Verma, "Terrestrial carbon observations: Protocols for vegetation sampling and data submission," ed: Citeseer, 2008. URL: shorturl.at/BFKU4

[29] S. Ray, G. Das, J. Singh, and S. Panigrahy, "Evaluation of hyperspectral indices for LAI estimation and discrimination of potato crop under different irrigation treatments," *International Journal of Remote Sensing*, vol. 27, no. 24, pp. 5373-5387, 2006. URL: https://doi.org/10.1080/014311160 600763006

[30] T. Kutser, D. C. Pierson, L. Tranvik, A. Reinart, S. Sobek, and K. Kallio, "Using satellite remote sensing to estimate the colored dissolved organic matter absorption coefficient in lakes," *Ecosystems*, vol. 8, no. 6, pp. 709-720, 2005.URL: shorturl.at/ikxz4

[31] W. Loughlin, "Principal component analysis for alteration mapping," *Photogrammetric Engineering and Remote Sensing*, vol. 57, no. 9, pp. 1163-1169, 1991. URL: shorturl.at/GJOPQ

[32] A. Shirazi, A. Hezarkhani, A. Shirazy, and I. Shahrood, "Remote sensing studies for mapping of iron oxide regions, South of Kerman, Iran," *International Journal of Science and Engineering Applications*, vol. 7, no. 4, pp. 45-51, 2018.

[33] M. Govender, P. Govender, I. Weiersbye, E. Witkowski, and F. Ahmed, "Review of commonly used remote sensing and ground-based technologies to measure plant water stress," *Water Sa*, vol. 35, no. 5, 2009.URL: 10.4314/wsa.v35i5.49201

[34] J. Sanyal and X. X. Lu, "Application of remote sensing in flood management with special reference to monsoon Asia: a review," *Natural Hazards*, vol. 33, no. 2, pp. 283-301, 2004. URL: shorturl.at/bejsY

[35] J. A. Berni, P. J. Zarco-Tejada, L. Suárez, and E. Fereres, "Thermal and narrowband multispectral remote sensing for vegetation monitoring from an unmanned aerial vehicle," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 47, no. 3, pp. 722-738, 2009. URL: 10.1109/TGRS.2008.2010457

[36] J. Bendig, A. Bolten, S. Bennertz, J. Broscheit, S. Eichfuss, and G. Bareth, "Estimating biomass of barley using crop surface models (CSMs) derived from UAV-based RGB imaging," *Remote sensing*, vol. 6, no. 11, pp. 10395-10412, 2014.URL: https://doi.org/10.3390/rs61110395

[37] K. C. Swain, S. J. Thomson, and H. P. Jayasuriya, "Adoption of an unmanned helicopter for low-altitude remote sensing to estimate yield and total biomass of a rice crop," *Transactions of the ASABE,* vol. 53, no. 1, pp. 21-27, 2010.URL: https://elibrary.asabe.org/abstract.asp?aid=29493

[38] N. J. Stehr, "Drones: The newest technology for precision agriculture," *Natural Sciences Education,* vol. 44, no. 1, pp. 89-91, 2015.URL: https://doi.org/10.4195/nse2015.04.0772

[39] C. Zhang and J. M. Kovacs, "The application of small unmanned aerial systems for precision agriculture: a review," *Precision agriculture,* vol. 13, no. 6, pp. 693-712, 2012.URL: https://link.springer.com/article/10.1007/s11119-012-9274-5

[40] H. Nicolas, "Using remote sensing to determine of the date of a fungicide application on winter wheat," *Crop Protection,* vol. 23, no. 9, pp. 853-863, 2004. URL: https://doi.org/10.1016/j.cropro.2004.01.008

[41] Y. Pederi and H. Cheporniuk, "Unmanned aerial vehicles and new technological methods of monitoring and crop protection in precision agriculture," in *2015 IEEE International Conference Actual Problems of Unmanned Aerial Vehicles Developments (APUAVD)*, 2015, pp. 298-301: IEEE. URL: 10.1109/APUAVD.2015.7346625

[42] J. Abdulridha, R. Ehsani, and A. De Castro, "Detection and differentiation between laurel wilt disease, phytophthora disease, and salinity damage using a hyperspectral sensing technique," *Agriculture,* vol. 6, no. 4, p. 56, 2016.URL: https://doi.org/10.3390/agriculture6040056

[43] J. Riley, "Remote sensing in entomology," *Annual review of entomology,* vol. 34, pp. 247-271, 1989.URL: https://doi.org/10.1146/annurev.en.34.010189.001335

[44] M. Lega, J. Kosmatka, C. Ferrara, F. Russo, R. Napoli, and G. Persechino, "Using advanced aerial platforms and infrared thermography to track environmental contamination," *Environmental Forensics,* vol. 13, no. 4, pp. 332-338, 2012.URL: https://doi.org/10.1080/15275922.2012.729002

[45] U. Mahajan and B. R. Bundel, "Drones for normalized difference vegetation index (NDVI), to estimate crop health for precision agriculture: A cheaper alternative for spatial satellite sensors," in *Proceedings of the International Conference on Innovative Research in Agriculture, Food Science, Forestry, Horticulture, Aquaculture, Animal Sciences, Biodiversity, Ecological Sciences and Climate Change (AFHABEC-2016), Delhi, India*, 2016, vol. 22. URL: shorturl.at/acqTW

[46] D. Fawcett, J. Bennie, and K. Anderson, "Monitoring spring phenology of individual tree crowns using drone-acquired NDVI data," *Remote Sensing in Ecology and Conservation,* vol. 7, no. 2, pp. 227-244, 2021.URL: https://doi.org/10.1002/rse2.184

[47] J. I. Córcoles, J. F. Ortega, D. Hernández, and M. A. Moreno, "Estimation of leaf area index in onion (Allium cepa L.) using an unmanned aerial vehicle," *Biosystems Engineering,* vol. 115, no. 1, pp. 31-42, 2013.URL: https://doi.org/10.1016/j.biosystemseng.2013.02.002

[48] J. Bendig, K. Yu, H. Aasen, A. Bolten, S. Bennertz, J. Broscheit, M. L. Gnyp, and G. Bareth, "Combining UAV-based plant height from crop surface models, visible, and near-infrared vegetation indices for biomass monitoring in barley," *International Journal of Applied Earth Observation and Geoinformation,* vol. 39, pp. 79-87, 2015. URL: https://doi.org/10.1016/j.jag.2015.02.012

[49] T. A. C. Joca, "Respostas fisiológicas envolvidas na tolerância à restrição hídrica e estresse luminoso em Orchidaceae epífitas," 2020. URL: http://hdl.handle.net/11449/192334

[50] J. Berni, P. Zarco-Tejada, G. Sepulcre-Cantó, E. Fereres, and F. Villalobos, "Mapping canopy conductance and CWSI in olive orchards using high resolution thermal remote sensing imagery," *Remote Sensing of Environment,* vol. 113, no. 11, pp. 2380-2388, 2009. URL: https://doi.org/10.1016/j.rse.2009.06.018

[51] J. Gago, C. Douthe, R. E. Coopman, P. P. Gallego, M. Ribas-Carbo, J. Flexas, J. Escalona, and H. Medrano, "UAVs challenge to assess water stress for sustainable agriculture," *Agricultural water management,* vol. 153, pp. 9-19, 2015.URL: https://doi.org/10.1016/j.agwat.2015.01.020

[52] J. Bellvert, P. J. Zarco-Tejada, J. Girona, and E. Fereres, "Mapping crop water stress index in a 'Pinot-noir vineyard: comparing ground measurements with thermal remote sensing imagery from an unmanned aerial vehicle," *Precision agriculture,* vol. 15, no. 4, pp. 361-376, 2014. URL: https://link.springer.com/article/10.1007/s11119-013-9334-5

[53] S. Sankaran, A. Mishra, R. Ehsani, and C. Davis, "A review of advanced techniques for detecting plant diseases," *Computers and electronics in agriculture*, vol. 72, no. 1, pp. 1-13, 2010. URL: https://doi.org/10.1016/j.compag.2010.02.007

[54] P. Ivanov, E. Llobet, A. Vergara, M. Stankova, X. Vilanova, J. Hubalek, I. Gracia, C. Cané, and X. Correig, "Towards a micro-system for monitoring ethylene in warehouses," *Sensors and Actuators B: Chemical*, vol. 111, pp. 63-70, 2005.URL: https://doi.org/10.1016/j.snb.2005.06.064

[55] C. Pinheiro, C. M. Rodrigues, T. Schäfer, and J. G. Crespo, "Monitoring the aroma production during wine–must fermentation with an electronic nose," *Biotechnology and Bioengineering*, vol. 77, no. 6, pp. 632-640, 2002.URL: https://doi.org/10.1002/bit.10141

[56] C. Baratto, G. Faglia, M. Pardo, M. Vezzoli, L. Boarino, M. Maffei, S. Bossi, and G. Sberveglieri, "Monitoring plants health in greenhouse for space missions," *Sensors and Actuators B: Chemical*, vol. 108, no. 1-2, pp. 278-284, 2005. URL:https://doi.org/10.1016/j.snb.2004.12.108

[57] U. Herrmann, T. Jonischkeit, J. Bargon, U. Hahn, Q.-Y. Li, C. A. Schalley, E. Vogel, and F. Vögtle, "Monitoring apple flavor by use of quartz microbalances," *Analytical and bioanalytical chemistry*, vol. 372, no. 5, pp. 611-614, 2002.URL: shorturl.at/finoV

[58] J. Brezmes, E. Llobet, X. Vilanova, J. Orts, G. Saiz, and X. Correig, "Correlation between electronic nose signals and fruit quality indicators on shelf-life measurements with pink lady apples," *Sensors and Actuators B: Chemical*, vol. 80, no. 1, pp. 41-50, 2001.URL:https://doi.org/10.1016/S0925-4005(01)00867-X

[59] J. Brezmes, M. L. Fructuoso, E. Llobet, X. Vilanova, I. Recasens, J. Orts, G. Saiz, and X. Correig, "Evaluation of an electronic nose to assess fruit ripeness," *IEEE Sensors Journal*, vol. 5, no. 1, pp. 97-108, 2005. URL: https://ieeexplore.ieee.org/document/1386228

[60] B. de Lacy Costello, R. Ewen, H. Gunson, N. M. Ratcliffe, and P. T. Spencer-Phillips, "The development of a sensor system for the early detection of soft rot in stored potato tubers," Measurement Science and Technology, vol. 11, no. 12, p. 1685, 2000. URL: shorturl.at/bgsY8

[61] N. Hounsome, B. Hounsome, D. Tomos, and G. Edwards-Jones, "Plant metabolites and nutritional quality of vegetables," Journal of food science, vol. 73, no. 4, 2008.URL: https://doi.org/10.1111/j.1750-3841.2008.00716.x

[62] T. C. Baker and K. Haynes, "Field and laboratory electroantennographic measurements of pheromone plume structure correlated with oriental fruit moth behaviour," Physiological entomology, vol. 14, no. 1, pp. 1-12, 1989.URL: https://doi.org/10.1111/j.1365-3032.1989.tb00931.x

[63] S. Schütz, B. Weiβbecker, and H. Hummel, "Biosensor for volatiles released by damaged plants," Biosensors and Bioelectronics, vol. 11, no. 4, pp. 427-433, 1996.URL: https://doi.org/10.1016/0956-5663(96)82738-2

[64] W. G. Henderson, A. Khalilian, Y. J. Han, J. K. Greene, and D. C. Degenhardt, "Detecting stink bugs/damage in cotton utilizing a portable electronic nose," Computers and electronics in agriculture, vol. 70, no. 1, pp. 157-162, 2010.URL: https://doi.org/10.1016/j.compag.2009.09.019

[65] K. A. Weerakoon and B. Chin, "Detecting insect infestation using a carbon/polymer composite based sensor array," ECS Transactions, vol. 33, no. 8, pp. 85-89, 2010.URL: https://iopscience.iop.org/article/10.1149/1.3484110/meta

[66] I. E. Mladenova, J. D. Bolten, W. T. Crow, M. C. Anderson, C. R. Hain, D. M. Johnson, and R. Mueller, "Intercomparison of Soil Moisture, Evaporative Stress, and Vegetation Indices for Estimating Corn and Soybean Yields Over the U.S," IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 10, no. 4, pp. 1328-1343, 2017.URL: https://doi.org/10.1109/JSTARS.2016.2639338

[67] V. I. Adamchuk, J. W. Hummel, M. T. Morgan, and S. K. Upadhyaya, "On-the-go soil sensors for precision agriculture," Computers and electronics in agriculture, vol. 44, no. 1, pp. 71-91, 2004.

[68] I. E. Mladenova, J. D. Bolten, W. T. Crow, M. C. Anderson, C. R. Hain, D. M. Johnson, and R. Mueller, "Intercomparison of Soil Moisture, Evaporative Stress, and Vegetation Indices for

Estimating Corn and Soybean Yields Over the U.S," IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 10, no. 4, pp. 1328-1343, 2017.URL: https://doi.org/10.1109/JSTARS.2016.2639338

[69] K. Girma, K. Martin, R. Anderson, D. Arnall, K. Brixey, M. Casillas, B. Chung, B. Dobey, S. Kamenidou, and S. Kariuki, "Mid-season prediction of wheat-grain yield potential using plant, soil, and sensor measurements," Journal of Plant Nutrition, vol. 29, no. 5, pp. 873-897, 2006.URL: https://doi.org/10.1080/01904160600649187

[70] M. Errebhi, C. J. Rosen, and D. E. Birong, "Calibration of a petiole sap nitrate test for irrigated 'Russet Burbank'potato," Communications in Soil Science & Plant Analysis, vol. 29, no. 1-2, pp. 23-35, 1998.URL: https://doi.org/10.1080/00103629809369926

[71] S. Brouder, M. Thom, V. Adamchuck, and M. Morgan, "Potential Uses of Ion-Selective Potassium Electrodes in Soil Fertility Management," Communications in soil science and plant analysis, vol. 34, no. 19-20, pp. 2699-2726, 2003.URL: https://doi.org/10.1081/CSS-120025214

[72] S. Plaza, Z. Szigeti, M. Geisler, E. Martinoia, B. Aeschlimann, D. Günther, and E. Pretsch, "Potentiometric sensor for the measurement of Cd2+ transport in yeast and plants," Analytical Biochemistry, vol. 347, no. 1, pp. 10-16, 2005/12/01/ 2005.URL: https://doi.org/10.1016/j.ab.2005.09.030

[73] X. Liu, R. Ferguson, H. Zheng, Q. Cao, Y. Tian, W. Cao, and Y. Zhu, "Using an Active-Optical Sensor to Develop an Optimal NDVI Dynamic Model for High-Yield Rice Production (Yangtze, China)," Sensors, vol. 17, no. 4, p. 672, 2017.URL: https://doi.org/10.3390/s17040672

[74] S. L. Osborne, "Utilization of existing technology to evaluate spring wheat growth and nitrogen nutrition in South Dakota," Communications in soil science and plant analysis, vol. 38, no. 7-8, pp. 949-958, 2007.URL: https://doi.org/10.1080/00103620701277916

[75] S. Liang, G. Feng, M. C. Anderson, W. P. Kustas, M. M. Alsina, L. Sanchez, B. Sams, L. McKee, W. Dulaney, W. A. White, J. G. Alfieri, J. H. Prueger, F. Melton, and K. Post, "Daily Mapping of 30 m LAI and NDVI for Grape Yield Prediction in California Vineyards," Remote Sensing, Article vol. 9, no. 4, pp. 1-18, 2017.URL: https://doi.org/10.3390/rs9040317

[76] L. K. Sharma, "Evaluation of active optical ground-based sensors to detect early Nitrogen deficiencies in corn," North Dakota State University, 2014.URL:shorturl.at/ksUW6

[77] W. R. Raun, J. B. Solie, G. V. Johnson, M. L. Stone, R. W. Mullen, K. W. Freeman, W. E. Thomason, and E. V. Lukina, "Improving nitrogen use efficiency in cereal grain production with optical sensing and variable rate application," Agronomy Journal, vol. 94, no. 4, pp. 815-820, 2002.URL: https://doi.org/10.2134/agronj2002.8150

[78] K. Holland and J. Schepers, "Derivation of a variable rate nitrogen application model for in-season fertilization of corn," Agronomy Journal, vol. 102, no. 5, pp. 1415-1424, 2010.URL: https://doi.org/10.2134/agronj2010.0015

[79] K. H. Holland and J. S. Schepers, "Use of a virtual-reference concept to interpret active crop canopy sensor data," Precision Agriculture, vol. 14, no. 1, pp. 71-85, 2013.URL: https://link.springer.com/article/10.1007/s11119-012-9301-6

[80] L. E. Gentry and F. E. Below, "Maize productivity as influenced by form and availability of nitrogen," Crop Science, vol. 33, no. 3, pp. 491-497, 1993.URL: https://doi.org/10.2135/cropsci1993.0011183X003300030015x

[81] A. Belay, A. Claassens, and F. Wehner, "Effect of direct nitrogen and potassium and residual phosphorus fertilizers on soil chemical properties, microbial components and maize yield under long-term crop rotation," Biology and Fertility of Soils, vol. 35, no. 6, pp. 420-427, 2002.URL: https://link.springer.com/article/10.1007/s00374-002-0489-x

[82] J. Shanahan, K. Holland, J. Schepers, D. Francis, M. Schlemmer, and R. Caldwell, "Use of crop reflectance sensors to assess corn leaf chlorophyll content. p. 135–150. Digital imaging and spectral techniques: Applications to precision agriculture and crop physiology. ASA Spec. Publ. 66. ASA, Madison, WI," ASA Spec., 2003.URL: https://acsess.onlinelibrary.wiley.com/doi/book/10.2134/asaspecpub66

[83] P. Hansen and J. Schjoerring, "Reflectance measurement of canopy biomass and nitrogen status in wheat crops using normalized difference vegetation indices and partial least squares regression," Remote sensing of environment, vol. 86, no. 4, pp. 542-553, 2003.URL: https://doi.org/10.1016/S0034-4257(03)00131-7

[84] S. Moges, W. Raun, R. Mullen, K. Freeman, G. Johnson, and J. Solie, "Evaluation of green, red, and near-infrared bands for predicting winter wheat biomass, nitrogen uptake, and final grain yield," Journal of Plant Nutrition, vol. 27, no. 8, pp. 1431-1441, 2005.URL: https://doi.org/10.1081/PLN-200025858
[85] W. R. Raun, J. B. Solie, G. V. Johnson, M. L. Stone, E. V. Lukina, W. E. Thomason, and J. S. Schepers, "In-season prediction of potential grain yield in winter wheat using canopy reflectance," Agronomy Journal, vol. 93, no. 1, pp. 131-138, 2001.URL: https://doi.org/10.2134/agronj2001.931131x
[86] D. Inman, R. Khosla, R. M. Reich, and D. G. Westfall, "Active remote sensing and grain yield in irrigated maize," Precision Agriculture, journal article vol. 8, no. 4, pp. 241-252, October 01, 2007.URL: https://link.springer.com/article/10.1007/s11119-007-9043-z
[87] J. F. Shanahan, J. S. Schepers, D. D. Francis, G. E. Varvel, W. W. Wilhelm, J. M. Tringe, M. R. Schlemmer, and D. J. Major, "Use of remote-sensing imagery to estimate corn grain yield," Agronomy Journal, vol. 93, no. 3, pp. 583-589, 2001.URL: https://doi.org/10.2134/agronj2001.933583x
[88] I. Hussain, K. Olson, and S. A. Ebelhar, "Impacts of tillage and no-till on production of maize and soybean on an eroded Illinois silt loam soil," Soil and Tillage Research, vol. 52, no. 1, pp. 37-49, 1999.URL: https://doi.org/10.1016/S0167-1987(99)00054-9
[89] E. J. Kladivko, D. R. Griffith, and J. V. Mannering, "Conservation tillage effects on soil properties and yield of corn and soya beans in Indiana," Soil and Tillage Research, vol. 8, pp. 277-287, 1986.URL: https://doi.org/10.1016/0167-1987(86)90340-5
[90] T. W. Katsvairo, W. J. Cox, and H. M. Van Es, "Spatial growth and nitrogen uptake variability of corn at two nitrogen levels," Agronomy Journal, vol. 95, no. 4, pp. 1000-1011, 2003.URL: https://doi.org/10.2134/agronj2003.1000
[91] D. Franzen, G. Wagner, and A. Sims, "Application of a ground-based sensor to determine N credits from sugarbeet," Sugarbeet Research and Extension Reports, vol. 34, pp. 119-123, 2003.URL: https://www.sbreb.org/wp-content/uploads/2018/09/soil4.pdf
[92] J. Payero, C. Neale, and J. Wright, "Comparison of eleven vegetation indices for estimating plant height of alfalfa and grass," Applied Engineering in Agriculture, vol. 20, no. 3, p. 385, 2004.URL: https://elibrary.asabe.org/abstract.asp?aid=16057
[93] L. Sharma and D. Franzen, "Use of corn height to improve the relationship between active optical sensor readings and yield estimates," Precision agriculture, vol. 15, no. 3, pp. 331-345, 2014.URL https://link.springer.com/article/10.1007/s11119-013-9330-9
[94] S. Sun, C. Li, and A. H. Paterson, "In-Field High-Throughput Phenotyping of Cotton Plant Height Using LiDAR," Remote Sensing, vol. 9, no. 4, p. 377, 2017.URL: https://doi.org/10.3390/rs9040377
[95] C. Wu, Z. Niu, Q. Tang, and W. Huang, "Estimating chlorophyll content from hyperspectral vegetation indices: Modeling and validation," Agricultural and forest meteorology, vol. 148, no. 8, pp. 1230-1241, 2008.URL: https://doi.org/10.1016/j.agrformet.2008.03.005
[96] D. Horler, M. Dockray, and J. Barber, "The red edge of plant leaf reflectance," International journal of remote sensing, vol. 4, no. 2, pp. 273-288, 1983.URL: https://doi.org/10.1080/01431168308948546
[97] J. Vogelmann, B. Rock, and D. Moss, "Red edge spectral measurements from sugar maple leaves," Title Remote Sensing, vol. 14, no. 8, pp. 1563-1575, 1993.URL: https://doi.org/10.1080/01431169308953986
[98] J. Miller, E. Hare, and J. Wu, "Quantitative characterization of the vegetation red edge reflectance 1. An inverted-Gaussian reflectance model," Remote Sensing, vol. 11, no. 10, pp. 1755-1773, 1990.URL: https://doi.org/10.1080/01431169008955128
[99] P. J. Zarco-Tejada, J. R. Miller, G. Mohammed, T. L. Noland, and P. Sampson, "Vegetation stress detection through chlorophyll a+ b estimation and fluorescence effects on hyperspectral imagery," Journal of environmental quality, vol. 31, no. 5, pp. 1433-1441, 2002.URL: https://doi.org/10.2134 /jeq2002.1433
[100] M. Sibanda, O. Mutanga, and M. Rouget, "Testing the capabilities of the new WorldView-3 space-borne sensor's red-edge spectral band in discriminating and mapping complex grassland

management treatments," International Journal of Remote Sensing, vol. 38, no. 1, pp. 1-22, 2017.URL: https://doi.org/10.1080/01431161.2016.1259678

[101] M. A. Cho and A. K. Skidmore, "A new technique for extracting the red edge position from hyperspectral data: The linear extrapolation method," Remote sensing of environment, vol. 101, no. 2, pp. 181-193, 2006.URL: https://doi.org/10.1016/j.rse.2005.12.011

[102] P. J. Curran, J. L. Dungan, and H. L. Gholz, "Exploring the relationship between reflectance red edge and chlorophyll content in slash pine," Tree physiology, vol. 7, no. 1-2-3-4, pp. 33-48, 1990.URL: https://doi.org/10.1093/treephys/7.1-2-3-4.33

[103] Y. Tang, R. Wang, and J. Huang, "Relations between red edge characteristics and agronomic parameters of crops," Pedosphere, vol. 14, no. 4, pp. 467-474, 2004.URL: shorturl.at/qrtxz

[104] I. Filella and J. Penuelas, "The red edge position and shape as indicators of plant chlorophyll content, biomass and hydric status," International journal of remote sensing, vol. 15, no. 7, pp. 1459-1470, 1994.URL: https://doi.org/10.1080/01431169408954177

[105] T. Dawson and P. Curran, "Technical note A new technique for interpolating the reflectance red edge position," 1998.URL: https://doi.org/10.1080/014311698214910

[106] L. Liu, J. Wang, W. Huang, C. Zhao, B. Zhang, and Q. Tong, "Estimating winter wheat plant water content using red edge parameters," International Journal of Remote Sensing, vol. 25, no. 17, pp. 3331-3342, 2004.URL: https://doi.org/10.1080/01431160310001654365

[107] B. R. Da Luz and J. K. Crowley, "Spectral reflectance and emissivity features of broad leaf plants: Prospects for remote sensing in the thermal infrared (8.0–14.0 μm)," Remote sensing of environment, vol. 109, no. 4, pp. 393-405, 2007.URL: https://doi.org/10.1016/j.rse.2007.01.008

[108] M. K. Jha, A. Chowdhury, V. Chowdary, and S. Peiffer, "Groundwater management and development by integrated remote sensing and geographic information systems: prospects and constraints," Water resources management, vol. 21, no. 2, pp. 427-467, 2007.URL: https://link.springer.com/article/10.1007/s11269-006-9024-4