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Review

An Overview on the Use of Infrared Sensors for in Field, Proximal and at Harvest Monitoring of Cereal Crops

Daniel Cozzolino *, Kenton Porker and Michael Laws

School of Agriculture, Food and Wine, Faculty of Sciences, The University of Adelaide, Waite Campus, PMB 1 Glen Osmond, Adelaide SA 5064, Australia; E-Mails: kenton.porker@adelaide.edu.au (K.P.); michael.laws@adelaide.edu.au (M.L.)

* Author to whom correspondence should be addressed; E-Mail: d.cozzolino@adelaide.edu.au; Tel.: +61-(0)-8-8313-6738.

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Abstract: Farmers are increasingly demanding rapid, cost-effective, easy-to-use and non-destructive methods for monitoring changes in the physical and chemical characteristics of crops and plants from the early stages of crop development until harvest. Remote and proximal sensor tools have been used recently to monitor different aspects of cereal production (e.g., fertilization, crop diseases). Most of these tools are characterized as non-destructive, non-invasive and easy-to-use, and most of them are based in near-infrared (NIR) spectroscopy. This article reviews recent and potential applications for the use of proximal sensors based on NIR spectroscopy to monitor dry matter (DM), yield, nitrogen and diseases in different cereal crops.

Keywords: near-infrared; yield; nitrogen; proximal sensors; harvest

1. Introduction

Farmers are increasingly demanding rapid, cost-effective, green and non-destructive methods for monitoring changes in the physical and chemical properties of crops throughout the lifecycle of the plant with the goal to establish the optimum harvest date, to improve agronomic management practices and to improve crop diagnostics, among other issues [1,2]. Concepts, like water and/or nitrogen use efficiency, have been around for decades [1–3]. However, these concepts have not been part of the decision making process, nor have they been used as metrics for evaluating the performance or a production system in real farm conditions due to lack of adequate tools and sensors [1–3]. In recent years, farmers, researchers and instrument manufacturers have been combining expertise and are looking for efficient solutions to solve different issues associated with the development of sensors and for ultimately improving current production or processes at the farm level [1–5]. Therefore, the development of tools that farmers can use to evaluate efficiency at the farm level will open a new era in agronomy and farming [1–5]. The exponential growth of sensor capabilities (e.g., infrared, hyperspectral, multi-spectral) and technologies (e.g., drones) allow exploiting these capabilities [1–5].

Proximal sensors are powerful tools and have been used for different purposes (e.g., in temporal analysis of crop field areas), providing added value for crop production, analysis and quantification of crop diseases and the analysis of soil physical and chemical properties [1–8]. More recently, sensor networks have been allowing for the collection of multiple types of *in situ* information, which can be conveniently exploited for controlling crop production or monitoring ecosystems by analysing different variables (e.g., light, temperature, humidity) [5,7,8]. This information can be also acquired using sensors deployed in different countries or areas where the data can be processed remotely, using web-based platforms [5,9]. For example, the use of wireless sensor technologies (WST) in specialty crops offers new features, both in terms of sensing and communications [9], allowing external service providers to access sensor data online, and as a diagnostic tool for any relevant crop production issue. A recent review by Ruiz-Altisent and collaborators [9] highlighted the advances in wireless sensor networking (WSN) technology and the development of low-cost, low-power, multifunctional sensor nodes. These authors emphasized that the application of these technologies for monitoring intensively-cultivated crops is new, since the necessary hardware has only recently become available, although other authors have demonstrated this type of application for specialty crops [1,6,9].

Most of the applications of NIR spectroscopy described in the literature essentially rely on spot measurements [9]. Nowadays, the availability of hyperspectral cameras and spectrographs has provided exciting new possibilities for online defect detection, which were not achievable with the use of sensors based only on the visible (VIS) range of the electromagnetic spectrum (e.g., detection of defects in fruits) [9]. For example, broadband images (e.g., grey-scale and colour images) are inappropriate for detecting specific quality attributes (other than colour attributes or certain surface blemishes that are visible), because many chemical components (pigments, sugar, starch, water, protein, *etc.*) are sensitive to specific narrow wavebands in or beyond the visible region [9]. Spectral imaging technologies, which acquire single or multiple images at selected wavelengths, might be used to detect specific quality attributes in a wide range of crops and horticultural products [9]. Spectral imaging may be categorized into multispectral and hyperspectral imaging. Multispectral imaging acquires spectral images at a few discrete narrow wavebands (the bandwidth may range between 5 and 50 nm). Hyperspectral imaging, on the other hand, acquires tens or hundreds of spectral images at congruous wavelengths or wavebands over a specific spectral region [9,10–12]. While acquisition speed is still an issue in modern instrumentation, the use of focal plane array cameras may solve this issue [9]. Hyperspectral imaging integrates the main features of imaging and spectroscopy to acquire both spectral and spatial information from the product simultaneously, thus making it especially suitable and more powerful for inspecting horticultural and food products, whose properties and characteristics often vary spatially [10–12]. As reviewed by other authors, hyperspectral imaging is commonly implemented in one of the two sensing modes: push broom or line scanning mode and filter-based imaging mode [10–13]. In in-line scanning mode, the imaging system line scans the moving product items, from which three-dimensional (3D) hyperspectral images, also called hypercubes, are created. In filter-based imaging mode, spectral images are acquired from the stationary product items for a sequence of wavebands using either a liquid crystal tuneable filter (LCTF) or an acousto-optic tuneable filter (AOTF) [14,15]. Line scanning mode is most commonly used because it is relatively easy to implement, particularly when real-time, online applications are needed. Filter-based hyperspectral imaging systems require more complicated calibration and are not suitable for online applications [14,15]. A hyperspectral imaging system needs to consist of a high performance digital camera covering the spectral region of interest, a large dynamic range, low noise level and good quantum efficiency [9,11,12]. Moreover, an imaging spectrograph, which disperses line images into different wavelengths, is an essential component for a line scanning hyperspectral imaging system [9,11,12]. It should have an appropriate optical resolution and spectral response efficiency with minimal aberrations. In addition to this, it is critical to have an appropriate DC-regulated light source that is highly stable, with a smooth spectral response [9,11,12]. Those who have sufficient knowledge and experience in optics and imaging may use off-the-shelf optical components to assemble a hyperspectral imaging system to achieve cost savings and to meet their specific application needs in the laboratory [9,11,12]. The availability of fast and relatively cheap diode array spectrometers allows acquiring an NIR spectrum in as little as 50 ms [9,11,12]. These types of instruments have boosted research and development towards a wide range of commercial applications [9,11,12]. However, the widespread use of this technology depends on several factors, such as cost and availability of instruments and the type of application (online, in field). In most of these applications, model robustness in terms of accuracy and precision is the most important factor to be considered [9,11,12].

This article reviews some applications on the use of proximal sensors based on the near-infrared (NIR) to monitor dry matter (DM), yield, nitrogen, pest and diseases in different cereal crops.

2. Analysis of Crops and Plants

2.1. Measurement of Dry Matter (Moisture) and Yield

In the context of climate change, environmental adaptation of crops and sustainable agriculture, the determination and monitoring of water status in plants is of significant importance in order to schedule irrigation times and volumes, preserve water or to manipulate composition. Near-infrared (NIR) spectroscopy in the wavelength range above 1000 nm is becoming widely used to monitor stomatal conductance of plant canopies in the lab and in the field [4,16].

It is generally accepted that dry matter (DM) yield is one of the most important parameters in crop production, as it is directly related to production costs. This parameter greatly influences the concentration of nutrients in the whole plant [17–22]. However, taking measurements of DM (water) in plants or crops on the farm is not straightforward, presenting several logistical and technical challenges [17–22].

In recent years, the use of NIR spectroscopy for online measurements of DM has been made possible by the availability of in field portable NIR instruments that have facilitated the direct selection of samples in the field for this parameter without pre-processing (in field analysis) [17–22].

More complex morphological characteristics, such as tiller density, auxiliary formation, shoot branching and spike/spikelet morphology, are considered to be better monitored using three-dimensional scanning, as recently shown in maize [23,24]. According to these authors, the combination of three-dimensional analysis with NIR spectral reflectance data might be considered as a future tool for improving both DM and morphological characteristics in crops [23,24]. In recent years, "on the go" or in field NIR spectroscopy methods have been also evaluated to predict nitrogen and water content in different cereal crops [25,26].

2.2. Measuring Nitrogen and Mineral (Macro and Trace Elements) Status in Crops

It has been reported by several authors that one of the major causes for low nitrogen (N) use efficiency (NUE) in the current N management practices is the poor synchrony between soil N supply and crop demand [27–30]. Routine laboratory methods for the determination of N concentration in crops are based on methods, such as Kjeldahl distillation (Association of Official Agricultural Chemists, 1990) or Dumas. These methods are widespread and used in many routine laboratories, even though time-consuming and expensive [20–22,25,26].

In recent years, it has been demonstrated that NIR spectroscopy can be implemented to more efficiently determine N concentrations in grass samples [20–22], where an NIR-based system replacing wet chemistry methods with online field screening constitutes a more direct strategy to select for improved N uptake efficiency and total N concentration [20–22,25,26].

One of the potential advantages of using NIR spectroscopy for in field crop monitoring is the analysis of fresh plant materials (e.g., leaf, whole plant) without the need for drying, grinding or sending the sample to the lab [17–19]. This approach has been tested in wheat and other cereal crops by several authors [20–22,25,26]. Recently, the use of visible (VIS) and NIR spectroscopy has been reported in order to measure trace elements in leaves of rice [31]. In that paper, two wavelength selection methods applied to VIS-NIR spectra were investigated to determine the levels of iron (Fe) and zinc (Zn) in rice leaf samples [31]. The overall results reported by these authors indicated that VIS-NIR spectroscopy, combined with different chemometrics tools, was very efficient in terms of accurate determination of trace elements in rice leaves [31].

3. Determining Grain Composition at Harvest

Several authors have evaluated the feasibility of using NIR spectroscopy for at harvest applications [21,23,24]. In routine analysis of cereal grains, the spectrum of the sample is typically measured from fine ground powders or from the bulk of whole grain [32–34]. In some cases (e.g., breeding), single-seed samples can be also used and analysed using NIR spectroscopy in order to measure different chemical properties. For example, maize kernels can be classified according to characteristics, such as starch composition, hardness, avidin or mycotoxin levels [22,35]. However, samples still need to be sent to the lab, causing unavoidable time delays and cost.

Research and development on the use of NIR spectroscopy on agricultural harvesters have presented new opportunities (and challenges) to develop novel platforms that will enable large-scale screenings of crops for several characteristics [21,23,24]. These so-called high throughput techniques could bring remarkable progress to plant research and open new possibilities in farm management [20–24].

The use of NIR spectroscopy on agricultural harvesters reduces the labour and expenditure required for the determination of relevant properties. In contrast to conventional sample-based methods, NIR spectroscopy on agricultural harvesters secures a good distribution of measurements within plots and covers substantially larger amounts of plot material [20–24]. Consequently, agricultural harvesters equipped with NIR instruments will reduce the unavoidable errors associated with traditional sampling and produce more representative measurements of the plot material. This approach can also be used successfully to determine DM, starch and crude protein contents in several grains at the farm level [20–24].

In silage maize, the potential of this technology has also been reported for the determination of DM, starch and soluble sugars [17,18,20–24]. The use of NIR spectroscopy on agricultural harvesters might also represent a high-throughput phenotyping technique with substantially reduced sampling error, whereas spectral reflectance of plant canopies facilitates the determination of dynamic traits in a non-invasive mode [20–24].

The prediction of constituent concentrations using NIR spectroscopy on intact single seeds has been most successful for plants with small seeds and those with a relatively uniform distribution of seed constituents, such as rapeseed, wheat, sunflower achenes or soybean seeds [36–40]. The potential of NIR spectroscopy for non-destructive determination of quality parameters, including oil and protein contents in shell-intact cottonseed, was also reported [41]. Determination of amino acid nitrogen (AAN) in tuber mustard was also reported by other authors. Moving window partial least squares (PLS), combined with Savitzky–Golay smoothing, was used for the wavelength selection. Based on the various divisions in the calibration and prediction sets, an effective modelling approach with good stability was proposed by these authors [42]. These results confirmed that the long-wave NIR region contains enough information for the quantification of AAN in tuber mustard. The authors selected the wavelengths between 1700 to 2350 nm as the most appropriate region to develop the PLS models [42]. These results can serve as valuable references for designing spectroscopic instruments for quality evaluation of tuber mustard [42]. The determination of protein and starch, as well as the effect of sample presentation during the analysis of grain at harvest was also investigated [43].

4. Monitoring Plant Pests and Diseases

Various spectroscopic and imaging techniques have been recently evaluated for the detection of symptomatic and asymptomatic plant diseases as reviewed by both Lee and colleagues [44] and Sankaran and colleagues [45]. Some of the methods used by different authors included fluorescence imaging, hyperspectral imaging, infrared spectroscopy, fluorescence spectroscopy and VIS-multiband spectroscopy [4,44,45]. In particular, the use of NIR spectroscopy (950 and 1650 nm) was explored to determine the percentage of fungal infection in rice samples of yellow-green *Aspergillus* (aflatoxigenic fungal infections) [44,45]. A rapid identification method for aflatoxin B1 in paddy rice samples was developed by using NIR spectroscopy under a wavelength range of 1000 to 2500 nm. Paddy rice samples were collected from both natural and artificial infection with aflatoxin B1 in order to build PLS calibration models [46]. The best predictive model to detect aflatoxin B1 in paddy rice was obtained using a standard normal variate detrending (SNV-D) spectra, resulting in a correlation of 0.85 and a SEP (standard error of prediction) of 3.21% [46]. These results showed that NIR spectroscopy could be a useful method for determining aflatoxin B1 in paddy rice and might be used to monitor aflatoxin fungal contamination in postharvest paddy rice during storage [46]. The use of VIS-NIR spectroscopy has been applied and evaluated as a method for the detection of plant diseases, monitoring of stress, injury and diseases in plants by several authors [44–49]. It has been reported by several authors that VIS-NIR spectroscopy allows the determination of physiological stress levels in the plants, and some of these wavelengths might be related to a specific disease even before the symptoms are visible [44,45]. In recent years, the monitoring or measurement of fungal-derived toxins in cereals, such as aflatoxins, deoxynivalenol and other mycotoxins, has been reported by several authors [50–52]. The use of NIR spectroscopy has been also reported for the detection of insect contamination or to detect insect damage in cereals [53].

5. Final Considerations

Adapting and using advanced technologies is a promising way to efficiently and reliably improve management farming practices, as well as to move towards the application of best management practices in the process and commercialization of agricultural products and commodities. Different studies have shown the important role of proximal sensors based on NIR spectroscopy in the analysis of crops. More recently, the use of NIR spectroscopy on agricultural harvesters has shown the potential to reduce the manpower and expenditure required for the determination of relevant properties in different crops, as well as reducing the sampling error, and it delivers more representative measurements of the plot. The measurement of quality parameters, such as protein and dry matter during harvest, are continuing to come online and being successfully used by farmers in Australia, Canada, Europe and the USA.

The accuracy and robustness of the NIR calibration used in the field compared to those used in the lab should be sufficient even when they are used to predict the quality attributes of the product specimen that were not used in the model calibration. Calibration models to be used in practice should be based on large datasets, encompassing several origins, climate conditions, seasons and operational conditions, such as temperature, and optimized towards robustness by incorporating appropriate spectral pre-processing.

The potential savings, reduction of analysis time, cost and the environmentally-friendly (reagentless) nature of this technology places proximal sensors based on NIR spectroscopy as a very attractive technique with a bright future to be used in farm applications for crop properties. It is clear that the breadth of these applications, either in routine use or under development, is showing no sign of diminishing. The development of hyperspectral imaging, micro-spectroscopy and new algorithms (topics not covered in this report) will place NIR spectroscopy as one of the most useful tools in crop monitoring and as the preferred in field technology in the near future.

The application of NIR technology across the entire food supply chain, such as in the hands of landholders with large (many square km) and small (less than one hectare) holdings, in all food processing plants and for retailers and consumers is not unrealistic [54]. Batten [54] also added that the limits of the technology must be appreciated and any misuse monitored by a spectroscopy specialist. It is in this context that one of the main barriers to the development of these applications is the lack of academic education in spectroscopy and chemometrics in disciplines related to plant and soil sciences. However, without a doubt one, of the biggest challenges for the use of NIR spectroscopy will be the interpretation of the spectra obtained, as well as the mathematical models through multivariate analysis or chemometrics in order to develop robust and reliable applications for crops.

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Author Contributions

All authors contributed equally to the conception and writing of the paper.

Conflicts of Interest

The authors declare no conflict of interest.

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