REVIEW

APPLICATION OF SPECTROSCOPY TECHNOLOGY FOR NUTRIENT MONITORING IN COCOA PLANTATION: A REVIEW

Nurfadzilah, M.[1*], Nawi, N. M.[2], Wong, M. Y.[2] and Mahirah, J.[3]

[1] Division of Cocoa Upstream Technology, Cocoa Research and Development Centre, Malaysian Cocoa Board, Jalan Jengka 23, P.O. Box 34, 28000 Temerloh, Pahang, Malaysia
[2] Institute of Plantation Studies, University Putra Malaysia, 43400 Serdang, Selangor, Malaysia
[3]Department of Biological and Agricultural Engineering, Faculty of Engineering, University Putra Malaysia, 43400, Serdang, Selangor, Malaysia
**Corresponding author: nurfadzilah@koko.gov.my*

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ABSTRACT – *The fundamental component of food security is adapting agricultural systems to sustenance production improvements and reducing inputs and the negative consequences of climate change. Precision agriculture developments in recent years have considerably boosted the efficacy of managing spatially variable agronomic irrigation inputs such as pesticides, seeds, water and fertilizers. The growing number of innovations using cutting-edge technologies to monitor field crop for varied temporal and spatial changes is responsible for these advancements. This review compares the applicability, cost, limitations, and advantages of using spectroscopy technology for nutrient monitoring in cocoa plantations with conventional methods. This paper highlights basic information on cocoa crops, then focuses on fertilizer applications, and management in each of the chosen cocoa-producing countries. Concerns about the nutrient adequacy of the soil and the monitoring of nutrient availability in the soil and leaves by using conventional and Near-Infrared Spectroscopy (NIRS) are discussed. The limitations of the conventional analysis method and technology of NIRS are also discussed. A general overview of how each of these sectors benefits from the use of NIRS, along with specific applications related to each sector, is also presented. Therefore, we briefly present the advantages of this technology and demonstrate its potential for nutrient monitoring in cocoa plantations.*

Keywords: Cocoa, near infrared spectroscopy, nutrient, monitoring and limitation

INTRODUCTION

The cocoa tree, or *Theobroma cacao* L., is a major tree cultivated for chocolates, beverages, cocoa mass, and cocoa powder. It originated in the upper Amazon basin region and has an economic lifespan of 30-40 years (Somarriba *et al*., 2021). It is one of the most important commodities in the world and is grown by 5-6 million smallholder farmers (Tosto *et al*., 2022). The world's top ten cocoa producers are currently Cote d'Ivoire (27.9%), Ghana (16.5%), Cameroon and Nigeria in West Africa (15.3%), Indonesia in Southeast Asia (16.6%), Ecuador (4.4%), Brazil (7.0%), Peru (1.2%), the Dominican Republic (1.7%), and Colombia (1.6%) in Latin America (Figure 1) (Kozicka *et al*., 2018). For many farmers, cocoa is their only source of financial income. In 1980, 63% of cocoa was grown by estates, but it shifted to smallholders. In 2020, about 88% of cocoa was grown by smallholders in Malaysia, with a production of 706 metric tons (Malaysian Cocoa Board, 2021). Regrettably, this industry has experienced a decline from the 1990s to the present day. Several factors have been identified to explain the decreasing trends, including the impacts of pests and disease, inadequate maintenance practices (Asante *et al*., 2022), and the high production cost of inorganic fertilizer (Olagunju *et al*., 2021).

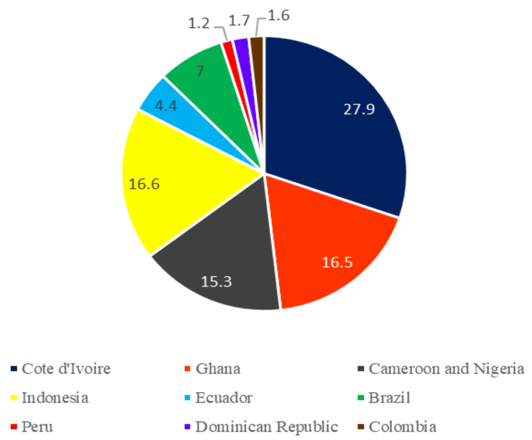

Figure 1. World cocoa producer

In 2020, the fertilizer consumption of Malaysia was 1,952.1 kg/ha, which increased from 177 kg/ha in 1971 and is growing at an average annual rate of 6.24% (Knoema, 2021). Numerous studies have revealed that prolonged exposure to inorganic fertilizer will negatively affect microbial communities and change the physical and chemical characteristics of soil, leading to environmental issues (Lian *et al*., 2022). According to Qaswar (2022), inorganic N fertilizer significantly alters the soil's AL^{3+} phase, releasing net AL from Al-hydroxides on clay minerals in acidic soil, reducing base cation saturation, and enhancing soil acidity. Mineral fertilizer use has expanded dramatically during the last few decades. According to Food and Agriculture Organization (FAO) statistics for 2018, global requests for N, P, and K fertilizer increased by 7.3%, from 186,895 thousand tons in 2014 to 200,522 thousand metric tons in 2018.

Monitoring plays an essential role in agricultural management and production (Mdemu *et al*., 2020). Monitoring is critical in agricultural administration and production. Through effective and thorough monitoring, producers can pinpoint corrective and preventive actions to optimize input while maximizing production. The primary methods for observing and evaluating the growth and development of cocoa are destructive methods, depending on human labor or instruments, and labor-intensive, and time-consuming, necessitating the preparation of samples using risky and expensive chemicals (Ibrahim *et al*., 2022). The gathering of ground data mainly relies on traditional monitoring techniques. Current technologies cannot provide accurate time and space information (Dibs *et al*., 2017). The traditional approach to obtaining nutritional content analysis was unsafe. The plant parts were oven-dried, weighed, and pulverized in the lab after the cocoa seedlings were harvested. Furthermore, they were combined to create a composite sample for total N analysis using the Kjehdahl method (Prastowo *et al*., 2021) and for analysis of phosphorus, potassium, calcium, magnesium, zinc, copper, and iron using the dry ashing method (Flores *et al*., 2022). This method requires laborious methods and expensive chemicals. Therefore, to expand the precision of nutrient analysis determination, it is required to develop non-destructive, intelligent, real-time, rapid and precise systems for determined quality parameters.

Optics, Acoustic analysis, ultrasonics, X-ray imaging, near-infrared spectroscopy (NIRS), ultrasonics, hyperspectral imaging (HIS), Raman spectroscopy, magnetic resonance (MR)/magnetic resonance imaging (MRI), and optical coherence tomography are general modern non-destructive methods that are widely used to investigate the estimation of available nutrients and fruit quality (Ibrahim *et al*., 2021). Additionally, one can make a real-time choice created on practical wavelength data for a variety of items and assess several quality factors for the same products (Tamburini *et al*., 2015). A few papers highlighted the use of spectroscopy to determine the cocoa bean quality parameter (Ernest *et al*., 2020), analyze nutrients (Nanganoa & Njukeng, 2018), and measure and evaluate the quality of cocoa beans (Munawar *et al*., 2022). In this review, 1) we explore the nutrient management and application in cocoa plantations; 2) the limitations of current management; 3) the sensing system for monitoring nutrient content; and 4) the application of spectroscopy to monitor nutrient content in other crops. The current study aimed to monitor changes in nutrient content and quality metrics using non-destructive methods based on NIR wavelength.

NUTRIENT MANAGEMENT AND APPLICATIONS

A major problem for the agricultural land-use system is handling soil productiveness to achieve adequate crop production without hurting the environment (Wessel & Quist-Wessel, 2015). In cocoa plantations, a high nutrient requirement is needed for growth and yield, where the increase was very rapid in the first five years and reached a plateau after the fifth year, with subsequent increases based mostly on nutrient export in higher output (Ling, 1984). Nutrient management differs from one country to another. In this topic, we discussed nutrient management for cocoa plantations, starting with the largest cocoa manufacturing country, Cote d'Ivoire, and ending with the smallest one, Malaysia.

Cote d'Ivoire

With an average yield of 200-500 kg/ha and a declining trend over time, Cote d'Ivoire has the lowest yields per land area in the world. This yield is significantly less than on-station yields production, which averages 2000 kg per hectare (Gyou *et al*., 2015). The primary full-sun, monoculture cocoa systems in Cote d'Ivoire are the cause of this condition, since their short-term output increases result in a serious long-term depletion of soil nutrients. Currently, the extension services recommend one single fit-all formula called "engrais cacao" with a formulation of 0% N, 23% P_2O_5, 19% K_2O, 10% CaO, 6% MgO, and a minor quantity of S and Zn (Kêbê *et al*., 2005). The suggested dose was 400 kg/ha per year. Nevertheless, applying a single-fit-all formula to whole soil categories is inappropriate. A variety of factors, including the soil's origin, cultural practices, the surrounding environment, and the crops that are grown influence the unique fertility potential of each type of soil.

Ghana

In the 1980s, the Cocoa Research Institute of Ghana (CRIG) recommended a single fertilizer formula, called Asase Wura (0% N, 165% P_2O_5, 200% K_2O

kg/ha, and a small amount of calcium, sulfur, and magnesium). In local trials, this fertilizer was able to increase cocoa yields by an average of 206%, but with major variations among farmers (Appiah *et al*., 2000). However, the recently recommended inorganic fertilizer by the Cocoa Research Institute of Ghana was 75% N, 165% P_2O_5, 200 K_2O, 344% CaO, and 250% MgO (Snoeck et al., 2009). However, based on the study done by Quaye *et al*. (2021), the occurrence of farmers' replies to the application of fertilizer fluctuated from 47% to 92%. The usual fertilizers used were granular fertilizers such as Asase Wura (91%), cocoafeed (87%), cocoa master (71%) and liquid fertilizers such as Sidalco (91%),

Nigeria

In addition to the topsoil needing to be rich in organic matter, cocoa demands profound, well-drained soil and a high nutritional content. The soil texture of Nigerian cocoa farms should be clayey, ideally with sandy clay loam within four inches of the soil surface and sandy clay under 10 to 15 inches, to confirm that the crops receive enough humidity in the dry months (Ogbeide & Ibiremo, 2021). In Nigeria, fertilizer practices were recommended by the Cocoa Research Institute of Nigeria, with the application of 50-100 kg of N, 120 kg of P_2O_5, and 250 kg of K_2O for mature (6 years and above) land previously cropped.

Indonesia

In Southeast Asian cocoa smallholders' systems, fertilizer use is uncommon, and extensive nutritional shortages are typical (Oberthür *et al*., 2018). Unfortunately, West Africa and Malaysia, with circumstances unrelated to Indonesia's agricultural regions, shaped most of our understanding of nutrients. Because of the unpredictable impacts of weather and disease, Indonesian farmers frequently perceive the use of fertilizer as dangerous, and there is still countless doubt among farmers. A crucial part of a change procedure would be knowledge that surges farmers' certainty as they accomplish fertilizer. In Indonesia, the common use of inorganic fertilizer, as recommended by the Mars Cocoa Academy, amounted to 160 kg N, between 30 and 60 kg P, 90 and 165 kg of K, 11 and 17 kg Mg, and 110 and 470 kg Ca per year.

Malaysia

In Malaysia, for mature cocoa in the field, the common fertilizers applied to apply the necessary nutrients to sustain its growth are NPK Blue with the formulation of 12% N, 12% P_2O_5, 17% K_2O, 2% MgO, and 8% S with the amount of 1.2 kg per tree (Lee *et al*., 2013). However, in 2016, the Malaysian Cocoa Board officially launched a controlled release fertilizer known as MCB F1-HyFer during Malaysian Chocolate and Cocoa Day 2016. This fertilizer formulation was derived through several years of study by identifying nutrient need in cocoa, and the addition of zeolite increased fertilizer efficiency by 20-24% as compared to common-use fertilizer (Helmi *et al*., 2016).

This review shows that five countries producing cocoa have used inorganic fertilizers in common for yield production. An effective utilization of every nutrient by the plant is guaranteed by balanced feeding. Inadequate nutrition causes the depletion of the soil's insufficient nutrients, as well as low yields, inefficient fertilizer use, and low farmer profits. Measurement of nutrient availability in soil and leaves is necessary to determine the efficacy of fertilizer use. It is an important parameter to measure the deficiency or excess fertilizer applied to cocoa trees.

LIMITATIONS OF CURRENT MANAGEMENT

Besides pruning, fertilization is one of the most important agricultural practices on cocoa plantations (Tosto *et al*., 2023). To monitor whether nutrients through fertilizer application are enough, measurements have to be adopted to measure the nutrient availability in the soil and leaves of the cocoa tree. Nutrients like nitrogen, phosphorous, and potassium are essential for plant growth since they are a major source of sustenance for plants and soil. Traditional measuring techniques, such as field and laboratory tests, can offer precise estimates of the soil and leaf nutrient contents at tested points, but it takes a long time and costs more money to produce for an entire research project. In Malaysia, the analysis price for a soil sample is RM160.00 (total nitrogen, total phosphorus, available phosphorus, total potassium, calcium, pH, total carbon, magnesium, cation exchange capacity (CEC), moisture, organic carbon and cost for leaves samples are RM100 (nitrogen, phosphorus, potassium, calcium, magnesium, cuprum, iron, and zinc). If there are 25 samples for soil and 25 samples for leaf nutrient analysis, it is required for RM 6,500.00 per location of the specific study. If there are more than five specific studies, it will cost more than RM 32,500 to run the analysis. Each soil sample in China costs around ¥165 (RM 107) to be analyzed in a lab to determine its nitrogen, total phosphorus, and total potassium concentrations. The overall charge of collecting the spatially overt estimations of the soil qualities for the entire part, if a plan with a spatial resolution of 100 m x 100 m for the zone of 50 km x 50 km is created using the conventional method, will be ¥2965 million (RM 1918 million) (Peng *et al*., 2019). This cost does not include the cost of travel and transportation, labor work and time for the assortment of soil and leaf samples in the field. Furthermore, to be properly understood, soil test values must be calibrated to crop response (Ichami *et al*., 2022); yet, in many developing countries, the lack of data required to do this is a significant hindrance. Testing of plant tissue in conjunction with soil analysis is necessary to identify micronutrient deficits that might interfere with plant responses to macronutrients. High chemical analysis costs limit the use of soil and leaf testing to assess limiting nutrients over a large area (Bekunde *et al*., 2010). Therefore, to increase the accuracy of the nutrient content, it is imperative to advance intelligent, non-destructive, quick, real time, and precise systems for monitoring quality criteria.

SENSING SYSTEM FOR MONITORING NUTRIENT CONTENT

With the introduction of remote sensing technologies in agriculture, it is now possible to extract data on the "status of the field crop" and track crop development. One of the most interesting new advances in this field is hyperspectral imaging (HSI), which combines spectroscopy and imaging (Hagen and Kudenov, 2013). A spectral image produces a three-dimensional (3D) dataset, often known as a data cube, whereas imaging delivers concentration at each pixel of the image. In contrast, spectroscopy yields a single spectrum. Multispectral imaging (MSI) and traditional RGB imaging techniques are among the other pioneering technologies. Spectrum imaging technology and optical sensing have enabled the development of more advanced MSI and HIS devices with a wide range of agricultural applications, including field crop monitoring (Liu *et al*., 2021) and food quality inspection (Qin *et al*., 2013). The main benefit of spectrum imaging in agriculture is the non-destructive extraction of precise phenotypic data across a wide spatial range and in a predetermined amount of time (Yang *et al*., 2017). The data will be processed and used for comprehensive data-driven analysis, and to make technological choices to raise agricultural productivity (Elgendy *et al*., 2022). The science of gathering and computing data on certain characteristics of events, matters, or resources without coming into physical contact with the target of surveillance is known as remote sensing (RS) technology (Kundu *et al*., 2021). The electromagnetic radiation applied for remote sensing travels through space at the speed of light in the form of harmonic wave patterns of varying wavelengths (Wójtowicz *et al*., 2016). The most useful wavelengths in remote sensing cover visible light (VIS), with wavelengths between 400 and 700 nm, near-infrared (NIR), with wavelengths between 700 and 1100 nm, shortwave-infrared (SWIR) rays (1100-2500 nm), mid-infrared (MIR) rays (2.5-50 µm), far-infrared (FIR) rays (from 50 µm to 1 mm), microwave rays (from 1 mm to 1m), and radio waves (1-30,000 m) (Omia et al., 2023). Despite being useful for scene analysis, not all of this information is visible to the naked eye. In this chapter, we focused on near-infrared (NIR) in determining the nutrient content in soil and leaves.

Near-infrared (NIR) Spectroscopy

Near-infrared (NIR) spectroscopy has become the furthermost appealing and commonly used technique for food and agriculture analysis and quality management over the last four decades. It is a non-destructive analytical instrument that allows for a quick and simultaneous qualitative and quantitative assessment of a wide variety of samples' chemical composition and physical properties (Ozaki *et al*., 2021). NIR spectroscopy is becoming increasingly relevant for agricultural monitoring (Beć *et al*., 2022). The advancement of near-infrared spectroscopy allows for the creation of a unique, dependable, and rapid tool. This enables the execution of diverse studies, particularly in data collection, without compromising research resources (Pasquini, 2018). NIRS examines the light imitated from a trial after being irradiated by wavelengths ranging from visible (VIS 400-700 nm), near-infrared (NIR 700-1,100 nm) and shortwave infrared (SWIR 1,100 - 2,500 nm). This can provide information on the physical and chemical properties of the sample. A single spectral measurement can concurrently record a variety of different plant attributes, and it requires little to no sample preparation (Petit Bon *et al*., 2020). Additionally, the measurements are non-destructive, allowing for the tracking of trait changes over time while avoiding interference with the organism.

Although NIRS data are easy to collect and produce a lot of information quickly, they also need a lot of post-processing, including chemometrics and multivariate statistical studies. Usually, the building of calibration models connecting spectra and reference trait data allows for the exploitation of spectral information. A representative subset of the entire data set, in terms of the spectral variation range treated, is used to build calibration models (Foley *et al*., 1998). The attribute values of fresh samples are forecast from their spectra using models that connect crop spectra to independently measured traits in the calibration dataset. Partially least squares regression (PLSR; Wold *et al*., 1983), 2D correlation plots (Darvishzadeh *et al*., 2008), and principle components analysis (Dreccer *et al*., 2014), are a few statistical techniques commonly used to predict trait data from spectra. However, it has been shown that the efficiency of these approaches, notably PLSR, in assessing plant attributes varies substantially depending on species and growth situations (Fu *et al*., 2020). Machine learning techniques are gaining prominence in a variety of industries due to their improved predicted accuracy. Machine learning, specifically deep learning approaches, can improve the statistical analysis of high quantity data by employing a sequence of neural networks (Mishra and Passos, 2021).

Principles of Near-infrared Spectroscopy (NIRS) for Plant Characterization

The leaf's spectral reflectance is determined by its low reflectivity in the observable region of the spectrum (400–700 nm), which is caused by sturdy fascination with photosynthetic pigments, and its high reflectivity in the near-infrared region (700–1,100 nm), which is caused by high light scattering in the leaf mesophyll tissue (Vasseur *et al*., 2022). The cellulose, water, protein, and lignin contents of plant tissues, for instance, have an impact on the reflectance intensity in the SWIR region of the spectrum (1100-2,500 nm) (Rascher *et al*., 2010). Because of their high water content, healthy leaves emit infrared radiation at their temperature (emissivity between 0.97 and 0.99). In contrast to the blue, yellow, and red blue, light bands, which are captivated by photoactive pigments, the green light band (550 nm), which is imitated effectively, gives the leaves their green color. As a result of this absorption at various wavelengths, a spectrum of light reflectance is created, and can be interpreted as a "signal" of the physical and chemical characteristics of the leaf. To study leaf composition, functionality, and diversity, it is particularly helpful to understand the physical relationship between leaf characteristics and light reflection. Depending on their structure and chemical makeup, various leaves will have various spectral signatures. For instance, the wavelengths absorbed by chlorophyll A and B in the visible spectrum (400–700 nm), the spectral red edge (700–760 nm), and proteins in the SWIR (1,300–2500 nm) are related to the amounts of nitrogen in leaves (Kokaly, 2001). Due to the extremely short effective photon penetration distance at these wavelengths, structures like palisade cell density have a significant role in determining the spectrum reflectance in the SWIR (SWIR 700-1,300 nm). The amount of infrared light that is absorbed depends on the molecule's overall modification in dipole moment as a result of its vibrational motion. A net energy transfer from the radiation to the molecule will be seen when the vibrations are accompanied by a change in dipole moment and when the frequency of the vibrations matches the frequency of infrared radiation. This results in a change in the amplitude of the molecular vibration. That is, the molecule gets excited to a higher energy level as a result of the vibration absorbing the infrared radiation (Kulkarni *et al*., 2014).

Application of NIRS

Various fields have widely used NIRS to determine the chemical properties of substances. For example, NIRS is widely used to characterize food products (Shen *et al*., 2022), pharmaceuticals (Velez *et al*., 2022), agriculture (Jang *et al*., 2022), and environmental monitoring and ecological studies (Grabska *et al*., 2021; Munawar *et al*., 2021). Meanwhile, in plant science, the application of NIRS is important because it helps increase production, increasing the cost efficiency for biodiversity characterization (Jackson *et al*., 2022), identifying plant stress (Zahir *et al*., 2022) and disease (Tan *et al*., 2022), and predicting differences in leaf palatability, digestibility, and decomposability through lignin and fiber content between species. Ibrahim *et al*. (2022) claimed that Vis-NIR spectroscopy has demonstrated its efficacy and usefulness in labs and production lines for monitoring quality parameters in watermelon cultivars. Additionally, it may be applied to a variety of items and utilized to assess many quality characteristics for the same product, enabling real-time decision-making based on applied wavelength data. A crop nutrition detection model for pears was created by combining chemical analysis test results with near-infrared reflection spectrum imaging technology to collect the leaf scale spectral image, computer image analysis software to process the spectral digital image, and spectral data extraction (Fan *et al*., 2022). Another study by Mohd Hilmi Tan *et al*. (2022) applied NIRS ranging from 900-1700 nm to detect fungus infection on oil palms. They found that the optimal wavelengths are identified at 1310 and 1452 nm, where 1310 nm could be related to ergosterol concentration and 1452 nm is attributed to water content. This work used ergosterol to detect *Ganoderma boninense* in oil palm, and it has proven to be a reliable alternative methodology for analyzing the incursion of such metabolites. To estimate quality metrics, dry matter, and crude protein in fresh, un-dried grass, Murphy *et al*. (2022) conducted a study to produce near-infrared spectroscopy (NIRS) calibrations. This study found that NIRS accurately estimated fresh grass dry matter content (R^2=0.86 SEP=9.46g kg^{-1}, RPD = 2.60) and crude protein content (R^2=0.84 SEP=20.38g kg^{-1}, RPD=2.37). The study's calibrations made it possible to analyze pasture quality more quickly, allocate and use pasture more precisely, and further the development of precision grassland agriculture concepts.

In a different work by Tang *et al*. (2022) NIRS was used to quickly identify the nitrogen content of rubber leaves to estimate the rubber yield and fertilizer content of rubber trees. The experiment's results showed that by combining dimensionality reduction and clustering to achieve a more complete and consistent distribution of the area proportion information, the expected values of leaf pixels for nitrogen content can be updated. Based on the study, a nitrogen detection model for rubber leaves may be established using the clustering method based on KPCA-GMM because the accuracy of the model can also be substantially enhanced. Meanwhile, Munawar *et al*. (2021) investigated the use of NIRs in the 1000-2500 nm wavelength region for quick and non-destructive measurement of cocoa bean fat content. According to the findings, the fat contents of cocoa beans may be predicted and determined using a correlation coefficient (r) of 0.89 and a ratio of prediction to deviation (RPD) index of 2.87 for raw spectra and a r of 0.92 and an RPD of 3.18 for baseline spectra adjustment. As a result, NIRS is a viable option for assessing cocoa bean quality in a timely and non-destructive manner.

In conclusion, researchers have made significant efforts to find a better way to use NIRS in agriculture. Such NIRS application capacity can be employed efficiently in the optimization process of cultural activities, particularly fertilization, to assess the quality of cocoa growth and production.

FUTURE PERSPECTIVES AND CONCLUSIONS

Contrary to traditional laboratory tests, which are time-consuming and only yield single-point observations, spectroscopy techniques have various advantages. Numerous geotechnical and geological devices can incorporate spectroscopic techniques because of technological advancements in the creation of tiny sensors. This technique can be developed using fiber optic sensors that can determine the material's elemental composition. The difficult parts of it include designing and creating a portable cone and a user-friendly interface data reading system that allows non-experts to gather the data. On board, where the data may be studied in real-time for in-depth analysis, chemometric methodology and statistical methods can be employed for data analysis.

In conclusion, the spectroscopy technique has been proven in different fields, including nutrient analysis, fruit quality, and the detection of pests and diseases. NIRS has been utilized to accurately assess the nutrient content and level of fruit quality while taking into account the cost of analysis and assessing fruit quality. NIRS is a valuable technology for qualitative and quantitative assessments involving a variety of sample types utilized in a wide range of industries. It is a promising method for effectively gathering information about how plants and crops function, the response of crops toward the environment, plant metabolism, and ecological strategies. NIRS allows for time and money savings (spectrum capture only takes a few seconds) while avoiding the use of harmful chemicals. Additionally, samples can be analyzed in their natural form without a destructive method. Thus, NIRS facilitates the application of phenomics to ecology by enabling the creation of huge databases of features at various temporal, geographical, and taxonomic scales.

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