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Potential for spectral imaging applications on the small farm: a review

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Advancements in optics and miniaturisation have resulted in multi- and hyperspectral imaging systems becoming more approachable in terms of cost, practicality and useability. Globally, the majority of farms are considered to be small farms (<2 hectares). Many spectral imaging applications have been associated with agricultural commodities over the years. However, due to the cost, technology hurdles and complex statistical modelling methods, these applications have mainly been implemented in larger monoculture settings where the method development time required can be met with and substantiated through higher profits gained and reduced labour in the long term. Recent years have seen advancements in spectral imaging technologies as well as open-source systems that have the potential for application on smaller, more diversified farms. There are many hurdles to face before spectral imaging technologies see widespread application on smaller farms, but technologies are advancing rapidly. Here, the current state of spectral imaging in small farm applications is evaluated, along with the potential for low-cost and open-source spectral imaging systems. Emphasis is placed on challenges which require addressing prior to approachable spectral imaging for the small farm.

Keywords: spectral imaging, small farm, precision agriculture, spectroscopy

Introduction

The world's population continues to grow while the number of farmers continues to decrease.[1,2] Mechanisation and technological advances in the last few decades have reduced the amount of labour necessary to maintain an operational farm. With a rise in the interest of hyper-localised cuisine there is an uptick in the number of small farms.[3] The term, small/family farm, can have a variety of meanings, land sizes, production outputs or income. In general, small farms are considered to be less than 2 hectares.[4] The US Department of Agriculture classifies a small farm as generating an income of less than $250,000 annually.[5] Recent data reports that there are approximately 690 million farms worldwide, with small farms (less than 2 hectares) accounting for 84 % of all farms and producing approximately 35 % of the world's food.[4] Agricultural operations have been a platform for advances in spectral imaging. However, due to the cost and specialised experience needed to establish and maintain spectral imaging technologies, previous applications have focused on automating larger

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monocrop farm processes such as soy, blueberries or corn.[6–8]

While large farms commonly focusing on a monoculture production have their own set of unique challenges to face in any growing season, smaller farms tend to be confronted with many and varied problems over the course of a growing season, associated with the need for production of a multitude of crops. In general, the goal of precision agriculture is to aid the growers and ease the requirement on labour while increasing quality of produce or livestock. In larger, monoculture farming operations farmers have typically relied on technological advances more so than smaller farms for a variety of reasons, including initial cost or amount of use. An investment of time by either the operator or the company producing the precision agricultural methods needs to be met with sufficient demand for justification of the time necessary to establish models and properly validate them. This is unequivocally easier to accomplish when you are developing one method for a monoculture farming system versus multiple methods for a smaller farm with crop diversity. However, as technology advances new opportunities arise for precision agricultural methodologies based on spectral imaging to be implemented on a smaller farming system.

A cornerstone of precision agriculture has been diffuse reflectance spectroscopy (DRS), which has a long-established history in the agricultural field, especially within the near infrared (NIR) spectral range.[9] In recent years, portable spectroscopic tools have become more cost approachable (<US$2000), offering similar results to benchtop counterparts, although typically are associated with lower levels of sensitivity and a reduced spectral range.[10] Third-party software companies have begun to market the spectrometers to application-specific end-users, though concerns about overstated performance capabilities is a potential pitfall. Technological advancements in recent years are driving the target market of portable and handheld spectroscopy applications from expensive lab-based methods towards lower-cost instrumentation that can be applied for everyday field use or citizen science-based methods. Corresponding to the rapid advancement is the concern that the technology is advancing more rapidly than a comprehensive understanding of the subject matter and there is a lack of proper validation models.

Hyperspectral imaging (HSI) collects spectral data, typically in the visible or NIR ranges and pairs the information with a set of images collected at each wavenumber. This creates three-dimensional data arrays, where m and n are spatial axes and λ is the spectral information.[11] This generates an image stack where each pixel has a corresponding spectrum within the entire image. Analogous to the technological pathway of the DRS spectrometers in the last decade, portable hyperspectral imaging systems are becoming more affordable in recent years, with multiple open-source spectral imaging cameras and Smartphone attachments appearing in the literature. Currently, these require custom-fitted accessories to be 3D printed with polylactic acid (PLA) filament and constructed with optics and electrical components purchased at low costs online. The most expense component is typically a decent quality C-mount lens. Some HSI systems are even operated with a Raspberry Pi computer (Raspberry Pi Ltd, Cambridge, UK) to keep the cost down.

In recent years, much has been written about the application of HSI as a tool in the evolution of precision agriculture.[12–15] With the rise of socioeconomic trends emphasising the perceived allure of smaller, localised farming operations, spectral imaging as an application driven tool has been largely overlooked. This is perhaps due to the associated cost and lack of user-friendly functionality. Previous efforts in spectral imaging have been geared towards larger scale farming operations. Figure 1 shows multiple areas that have seen application of spectral imaging methods. These ventures have shown that spectral imaging capabilities have offered advantages for large-scale production through precision agriculture advances.[16–20] However, as open-source and lower-cost spectral imaging applications advance in scope and usability, there is potential to incorporate spectral imaging for smaller scale farming operations. Here, the aim is to evaluate the current state of spectral imaging regarding practicality, application and usability on a small farm setting, and discuss challenges facing wider spread application.

Systemic property management

Biodiversity

Monoculture farming has declined in recent years, while spatially heterogenous areas consisting of plant diversity are widely accepted to increase crop yields.[21] Differences in plant biodiversity comes from variations in evolutionary histories, genetic backgrounds and environmental conditions, which translates into above ground differences in physical transformations and chemical compounds that are synthesised by the plants.[22] Loss of biodiversity has been connected to often negative impacts on

Figure 1. Graphical representation of potential areas that hyperspectral imaging (HSI) can be implemented on a small-scale farm.

the ecosystem.[23] This loss can affect ecosystem stability, invisibility or nutrient use and retention.[24–27]

Typically, smaller farms place a considerable focus on biodiversity. This can stem from the need to rotate crops and livestock for nutrient cycling in the soil, or from the need to diversify revenue streams. The general idea is that rotating crops in a specific plot will increase annual production yields by reducing weeds, diversifying the nutrients in the soil and reducing the soilborne pathogens.[28–30]

Forest farming

Forest farming is one of several types of agroforesty farming practices that focuses on producing commodities under forest canopies.[31] Forest farming is gaining popularity in certain areas of the world, as the price for commodities such as ginseng, morel mushrooms and certain types of timber such as black walnut can regularly be sold at a premium price. Spectral cameras have previously been used to analyse tree canopies in forest settings.[32] It was found that spectral cameras paired with unmanned aerial vehicles (UAV)s were able to detect semi-individual tree crowns, dead trees and identification of tree species from spectral imaging data. This could be of use for scouting potential property to be used as forest farming sites for long-term investment crops that require years to harvest time, such as ginseng. The age of a ginseng plant is a critical indicator of its value, with older plants being worth more. Recent work has shown that HSI can predict the age of ginseng in years with high accuracy.[33,34] Portable HSI systems that could be durable enough to take into wooded areas would be a great value in the identification and age determination of ginseng plants. Ginseng can take dozens of years to mature and harvesting an immature plant can cause a loss of profits over time. Current open-source imaging systems are usually 3D printed and set on tripods. This is ideal for certain situations, but likely not a hike through a wooded area while searching for ginseng. As application and market potential grow, more durable imaging systems are likely to enter the market or as open-source projects.

Water supply

Key to any farming operation is water management, which includes finding sources and transferring it to the fields that are in need. First, when assessing potential property or land for establishing farming operations, existing platforms such as the Landsat program (NASA, Washington DC, USA) can be used to locate surface water sources on a property. Once sites have been selected and water sources are identified, irrigation systems and pumps can be installed to transport the water to the crops. Work in irrigation water quality with spectral cameras is relatively recent. In gardening zones close to saline aquifers, the salinity in the irrigated water source can be assessed and remediated if necessary.[35] Soil moisture content is another critical component of water management on a farm and can be estimated with spectral imaging methods for managing the water availability to the root zone just below the surface.[36] In terms of small farm applications, it may be possible to obtain a low-cost moisture meter to assess soil samples, while simultaneously collecting spectral images with an open-source spectral imaging system. From here, qualitative and, possibly, quantitative modelling could be attempted for rapidly assessing new potential crop sites on a farm. As farm production continues year after year, spectral imaging can also be applied as a means of assessing drainage and erosion issues on the property from livestock, rainwater or crop management. Comparing remote image cubes over the course of time for a property/field would provide insight into erosion issues, especially if correlated to soil analyses in these specified locations that could yield information on soil content over time.

Soil health

In addition to erosion control, the overall health of the soil should be able to promote crop growth. Nitrogen is a key component of soil health and promotes the production of amino acids, proteins and nucleic acids in the plants through uptake from the root system. Spectral imaging has aided in evaluating the total amount of nitrogen available in soil.[37] This can prove useful in pairing the spatial component of a potential produce growing plot. Geographically plotting total nitrogen over a field can assist the grower in understanding where soil may need to be amended or where the soil is healthy enough to begin sowing seed. Arbuscular mycorrhizal fungi (AMF) extract phosphorus from the soil through hyphae and share the phosphorus with root systems of plants increasing nutrient uptake. Recently, X-ray computed tomography has been used as a means of mapping hyphae density in soil to suggest optimal growing regions.[38] This potentially could impact the selection of food crops in forest farming. If a spectral camera operating in the NIR or MIR range could predict the hyphae density of possible future growing plots for something such as ramps or ginseng in forest farming, then optimal growing conditions could be identified that would produce stronger, healthier and faster growing crops. Variation in crop yield has been documented through aerial hyperspectral cameras.[39] As an alternative to labour-intensive grid sampling, remote sensing can provide information on quantification of such soil attributes as pH, macro and micronutrients, and iron content.[40] Quantification is typically more challenging with spectral imaging than qualitative classification. With open-source spectral imaging systems being in the very early stages of development it will take some time to develop reliable quantification predictive modelling. As these technologies advance there is unlimited soil health analysis potential with spectral imaging. Collecting soil samples from traditional grid searching patterns and waiting for results to be calculated from a laboratory can be supplemented with real-time processes.

Plant health

Maintaining optimal plant health is essential to producing productive crop yields and seeds for the next growing season. Typically, early plant stressors are only found after applying destructive analysis techniques.[41] Vegetable plants can be susceptible to a variety of diseases and having a screening method in place to detect potentially diseased plants before they spread to other plants in a garden would be helpful. Because spectral imaging systems collect information at many colour bands and, potentially, near infrared bands, information on diseased plants outside the red, green and blue colour bands that we as humans notice is possible. If a suspected diseased plant is imaged and detected, it can be identified and removed from the field before rendering an entire crop useless. Previously, HSI has been used to identify plants carrying fungal blight in tomato fields in hopes of containing the disease spread before consuming larger parts of the fields.[42] Tomatoes require a significant amount of labour involved with planting, staking and continuously monitoring for insects such as hornworms. Labour involved in harvesting of tomatoes on a routine basis, even on a smaller farm is more involved than other crops such as soybeans. In these situations, blight can quickly spread plant-to-plant and destroy a tomato crop, which can significantly damage fiscal yields. There is potential for low-cost spectral imaging devices to be attached to UAVs and monitor a small field for signs of blight. In addition to plant blights, plant stressors such as powdery mildew, water stress or rot can be rapidly identified through drone-based spectral images.

Toxin detection

Aflatoxin and other mycotoxins are potentially carcinogenic by-products of fungi found in grain crops. Mycotoxins can be detected by spectral imaging in grains.[43] Yellow rust or stripe rust can also be found in wheat and is difficult to detect by eye. However, early disease detection with spectral cameras has been shown to be effective.[44] Detecting toxins early in the growing process is critical to stopping the spread of toxin production in the crop. Crop rotation may also show promise in reducing these issues, which is something common to smaller farming operations. An example of a particular crop that can produce toxins are fiddlehead ferns. These ferns are often sold to restaurants and home cooks. Fiddleheads have toxins that have to go through multiple rounds of boiling to remove toxigenic effects before consuming. A possible application could work towards identification of high amounts of toxins as a food safety measure, or qualitatively detect toxins after processing the fiddlehead ferns.

Water and food safety

In general, spectroscopy instruments offer agricultural practices many advantages in terms of rapid and non-destructive screening for commodities.[45] Recent advances in low-cost spectrometers have placed market entry for handheld spectrometers at approximately the same cost as a new cellular phone. Careful consideration should be placed on the application at hand when it comes to smaller scale farming practices, and if a handheld spectrometer could be an appropriate methodology or if a spectral camera is of needed. For example, a handheld spectrometer may be able to rapidly discriminate between species of pepper seeds. However, if one wanted to check seeds for potential fungal issues that were not visible with the human eye, a spectral imaging system may be of use.[46] Also, the data processing requirement for spectral imaging is greater than typical spectroscopy methods, due to the need to save image stacks associated with each spectral imaging sample. One needs to weigh the pros and cons of the two systems in regard to their needs on the farm and determine which is of use for a particular application.

Food security and safety on any farm is paramount. Blockchain food production systems and traceability have advanced in the last 20 years. In the case of a foodborne disease outbreak, the causative agents can be theoretically traced to the source. A common cause of foodborne disease outbreak can be the water source.[47] Spectral imaging applications have also been applied to water quality monitoring.[48] There is potential application in real-time source monitoring of water quality with hyperspectral imaging. Regarding a smaller farm, water monitoring could potentially be conducted for coliform counts, but, first, representative sampling will need to be sorted out for a continuous water source. For example, coliforms may be detected, but how many image cubes should be analysed for a confident level of detection.

Applications involved in water quality safety as well as the safety of the farmer's finished product focus on rapid and non-destructive methods.[49] These are advantages that spectral imaging can offer. Previously, much work has been published about the potential for spectral imaging in water and food safety. This can be seen by using traditional spectral imaging cameras for imaging nutrient-based agar plates for the classification of pathogenic bacteria colonies.[50,51] At a microscopic level, pathogenic bacteria have been classified by morphological features (rods, cocci, corkscrew shapes) and various taxonomical levels such as family, species and serovars.[52,53] Hyperspectral microscopy has also shown comparable classification accuracies to gold-standard identification methods such as polymerase chain reaction.[54] Spectral imaging for detecting foodborne pathogens has shown promise, but the challenge is again in representative sampling. Practical implementation is not at a level where an affordable solution could be applied at a small farm with stricter limitations on available labour and costs. However, advancements in low-cost microscopes such as the Foldscope® (Foldscope Inc., Palo Alto, CA, USA)[55] and the Jiusion Microscope (1000×) (London, UK) open new low-cost possibilities. Pairing open-source spectral imaging systems, such as the one described by Salazar-Vazques,[56] with a standard dissecting stereo microscope, generating image cubes that can be uploaded to ImageJ software for analysis could soon open avenues to low-cost spectral imaging options for small farm application.

Rapid food quality assessment

One of the most common applications for spectral imaging in agriculture is the purpose of commodity quality grading.[57] In the poultry industry, muscle myopathies such as woody breast are deemed poor quality and detrimental to consumer preference, with typical 5–10 % market occurrence.[58] Hyperspectral imaging technologies have been implemented to detect woody breast conditions in chicken breast fillets. Wold *et al.*[59] found that an online NIR spectral imaging system was able to classify woody breast syndrome at an accuracy >99 %.[59] While expensive online systems may not be practical for a smaller scale farm, as open-source spectral imaging systems advance there is potential for a handheld or small stationary system to be implemented during onsite processing for a few dozen or hundred birds. Similar to how miniaturised and handheld SWIR instruments are being implemented for protein characterisation in poultry meat.[60] Pork, beef and lamb have also all seen spectral imaging applications developed for similar quality assessing, marbling and myopathy detection, analogous to the poultry industry.[61–66] Regarding smaller scale farming, open-source imaging systems have only started to emerge in the past few years. As these systems progress so does the potential for improving quality production in small-scale agriculture. Secondary or further processed cuts of meat are considered value-added products and with some additional butchery on site can increase farm revenue. Spectral imaging systems can assist with quality grading of cuts and fat marbling in the butchering process by potentially setting up a camera mounted to a tripod. This may not yield immediate results for the cuts being processed at the moment, but as a research tool that can later be modelled to predict which cuts can be used for selling as is, or which may be used for stew meats, which may benefit from lower and slower cooking. There is an inherent cost vs value assessment planning requirement with this step of the operation. One can determine if the time spent collecting data and building models is worth the effort. Future applications could see opportunities for spectral imaging to offer categorical classification of marbling or muscle myopathies at the time of butchering, so that identified cuts can be used for further processing where those specific characteristics can be remediated into another product and not wasted.

The seafood industry has also witnessed many publications in the use of spectral imaging for seafood quality grading and fraud detection, such as mislabelled or adulterated fish.[67] Aquaculture is trending in small farming communities, especially if farmers have access to ponds or small lakes where fish can be raised and harvested. Spectral imaging technologies here can gauge fish quality as they are being harvested for sale from the ponds and lakes. In terms of pond/lake management, HSI can identify vegetation issues that may correlate to those discussed in the systemic property management potential for HSI.

Spectral imaging hardware

Primary components of a spectral imaging system include a light source, wavelength dispersion device and an area detector, which obtains both spatial and spectral information from the sample.[45] High functioning spectral cameras collecting data in the visible, NIR and mid-infrared (MIR) spectral ranges come at a high cost and are typically sold to large corporations and research institutions. Typically, the light source component of a spectral imaging system can be a low-cost component, consisting of tungsten halogen or LED lamps. More expensive arc lamps such as mercury or xenon-based lamps can be used in more specific applications. The wavelength dispersion device is another key component. In higher cost platforms, acousto-optical and liquid crystal tuneable filters may be used, while lower-cost systems operating in the visible or shortwave NIR range may employ a simple glass diffraction gradient. The area detector of a spectral camera is commonly a complimentary metal-oxide semiconductor (CMOS) or a charge coupled device camera (CCD). As miniaturisation technology progresses, spectral imaging platforms are becoming increasing available and entering wider consumer markets at more affordable pricing each year. Still, a system that is built to be durable for application in agricultural settings is going to cost US$10,000—30,000. These prices place ready-to-use spectral imaging technologies out of the budgetary reach of a small-scale farmer. However, in the past few years open-source spectral imaging systems are being introduced through published literature. As spectral imaging technologies continue to be integrated into real-world applications, their value is realised and more attention is being placed on low-cost and approachable spectral imaging instrumentation.

Several publications exist in the recent literature pertaining to building a low-cost spectral camera with a 3D printer, optics and hardware purchased through online distributors, and some programming abilities, typically in Python. Salazar-Vazquez and Mendez-Vazquez designed an open-source spectral imaging system built with low-cost parts and 3D printed components.[56] The system collects images at 2.07 mm resolution between 400 nm and 1052 nm. It operates with a tungsten halogen lamp, uses a plastic diffraction gradient and is controlled through a Raspberry Pi®. The total cost of building the imaging system was around US$500. Open-source projects also share their design files with the public which is streamlining the development of others to develop their own spectral imaging systems. Current open-source spectral imaging systems are showing potential and are necessary in the evolution of the technology to progress towards more widespread application usage.

Portability and durability are both key issues for developing spectral imaging systems that can be used in small farm applications. The physical nature of operating a small farm can be demanding on tools, and any spectral imaging system will need to withstand an occasional bit of wear and tear. Another concern is access to proper validation tools such as greyscale tiles at varying degrees of reflectivity, needed to assure photometric linearity for routine or periodic data collection verification checks. Low-cost materials or light sources with known spectral peaks may also be used as a wavelength verification procedure when appropriate. Verifying the radiometric and wavelength position performance of any system is crucial to ensure data validity, but perhaps more so with open-source spectral imaging systems. As open-source technologies have time to progress and evolve more application-driven instruments will be developed and the potential for readily available portable and durable spectral imaging systems will be accessible.

Spectral imaging software

A commonly discussed barrier to the incorporation of spectral imaging platforms is the initial startup costs. There are multiple open-source software platforms available for processing and analysing the data cubes that are collected. Maintaining cost-prohibitive software over the course of the imaging system's lifespan can also be a barrier. It would not be advantageous to offer an open-source spectral imaging system and then design the file outputs to be processed and analysed through a high-priced subscription service. The profit margin in small-scale agriculture is a concern, and a successful incorporation of spectral imaging technologies will need to focus on open-source analytical possibilities. There are obvious cost benefits with this option, but several disadvantages must be addressed when using open-source applications. First, scripting in open-source languages is a learned skill and spectral imaging applications built in these platforms add additional complexities due to incorporation of large multidimensional data cubes. Therefore, someone with a statistical background and experience with open-source programming languages will need to establish the software applications. On the spot troubleshooting and debugging object-based or Java scripting languages can be challenging unless the end-user is experienced in the language. Second, the inherent advantages and disadvantages of open-source platforms results in scripts, functions or programs that should be validated for the application. This would require testing the potential application on a trial set of samples before establishing a calibration method.

R-studio is freely available and uses an object-based scripting language. Packages can be downloaded and installed within the localised R environment that can process images. Packages such as "dplyr", "chemometrics" or "mdatools" are freely available in R-studio and are beneficial for working with spectral imaging datasets. In 2014, *NIR news* published a tutorial series on processing spectral images in R.[68] Packages that are specific for image processing such as "raster", "imager" or "magick" are needed to handle large image sets in the R environment.

Another object-based language platform similar to R where image processing can be accomplished, is Python. Also, recent low-cost hyperspectral cameras have been developed running operational coding for data collection through Python scripting.[56] Both of these object-based open-source platforms offer the user endless customisable options in terms of ability. However, the learning curve can be steep, and the end-user may need some understanding of the coding language to troubleshoot as needed.

Applications can also be developed by R-studio or Python, which can greatly increase the ease of access and speed of use. R-studio offers ShinyApps, while Python offers Dash. Both allow a user to script out programs that relate input and output of user defined programs in an easy-to-use graphical user interface (GUI). Results can be calculated, and figures can be plotted within the apps, giving the user a quick visual representation of the data. For example, a user collects images of a basil leaf and wants to determine if this is an optimal time to harvest. The app could load a calibration model, predict the new data extracted from a hypercube and generate a qualitative result in a matter of seconds. Currently, there are no elegant cellular-phone based apps for R-studio, although these are in stages of development. Servers can maintain applications that can be accessed from cell phones with wi-fi.

ImageJ is another open-source software platform for image processing developed by the US National Institute of Health. There are many basic and advanced built-in functions available for extracting regions of interest (ROI) and analysing the data. Mathematical image processing steps such as subtracting backgrounds are easily performed. If one needs to alter some of the built-in functions or create their own specific functions one would need to program in the Java language. Another option is pairing ImageJ with R-studio through the Bios7 platform. This is an open-source platform that can run ImageJ and R simultaneously in one user-friendly GUI. Bi07 was developed by Marcel Austenfeld for ecological modelling and can integrate ImageJ with R-studio in one GUI, which may speed up application processes.[69] This would again require some knowledge in programming to setup applications that are of use in a small farm setting.

The previous platforms are all open-source methods that require some language-based user understanding. Hypertools is another spectral imaging platform that was developed for Matlab.[70] This is an open-source program that can quickly analyse spectral datacubes and additionally perform many multivariate data analysis methods. While the package is freely downloadable, the user must have Matlab software installed, which costs approximately US$2000.

In the past few years, many third-party software companies have started to produce their own image processing programs. One must approach these options with caution as there are some defined advantages, such as ease of use, but companies can potentially oversell their capabilities in multivariate algorithms with buzz words. One must also consider the needs of their own small farm in considering the image collection and access needs. R-studio and Python both offer servers for hosting applications. Typically, a small number of applications can be hosted on a server at the free level, which could then be accessed by multiple people working on the farm at various times and locations, assuming they have wi-fi connection.

The current state of spectral image analysis programs offers benefits and disadvantages in terms of time and effort required to initialise applications on the farm. Certainly, open-source platforms are an avenue of exploring low-cost options for small farm implementation. Currently, setting up these methods and complicated multivariate analyses in an open-source software program would require someone with experience in a niche set of analytical skills. Producing a spectral imaging analysis program on a small farm would first require prioritising need and projected benefit of a spectral imaging system. As it may be easier in certain situations to deploy a traditional low-cost handheld spectroscopy method using the SWIR wavelength region. In situations where spectral imaging has a marked benefit and can reasonably be deployed, for example, the cost of labour and method development is not more costly than the savings, priority applications can be flagged. From here, applications can be developed one at a time with the largest potential application addressed first. Once image collection, processing and analysis can be completed the programming functions can be loaded and maintained on a ShinyApp server.

Data processing and storage

An underlying question that will need to be addressed in any practical HSI application on a smaller agricultural setting relates to the storage and processing of data. Large data files are generated by spectral imaging systems. Typically, collecting, storing and processing image stacks is computationally cumbersome, requiring large storage spaces. Larger agricultural systems institute data management practices, which are often accredited by international operating standards (ISO) guidelines. Another option is secure cloud-based storage, which removes the need for onsite servers to host storage options but comes with a monthly cost and needs to be assessed for privacy standards. As food safety guidelines evolve in coming years for more farm-to-table traceability, data verification and traceability are becoming more of a necessity for small and moderate sized farms to operate. In the unfortunate situation of a foodborne disease outbreak traceability is key, which would include any spectral imaging platforms that lend themselves to product quality and safety decisions.

Cloud-based storage is likely the most realistic and affordable option for small-scale farmers in the short term. Both qualitative and quantitative multivariate models for processing HSI data can be stored in cloud-based computing platforms for a monthly fee, then applications can be accessed with a user-friendly GUI, which a end-user could upload data, select processing parameters, then download results to be processed and stored.

Another issue to address is the need for updating and maintaining calibration files. Seasonal variation can cause calibration files to become less accurate and will likely require data from several years for optimisation, as these tend to be living calibration files requiring periodic updating. If a program is coded to receive new spectral imaging results and self-updates this would take the responsibility from the end-user. However, the realistic answer is that there would need to be some monitoring of the samples going into the calibration file to update over time. Establishing a 95 % confidence interval for example and flagging samples that should be further investigated by the grower to assure that both natural variation is adequately represented and that the outliers are truly perturbations in the sampling cycles.

Barriers to marketplace application

Perhaps one of the largest barriers to market entry is the stigma that precision agriculture has in small farming communities. Here, pride and knowledge is passed down through generations in traditional agricultural practices, which tend to divert from technological-based platforms that have been adapted by large-scale monoculture operations. As time progresses, precision agriculture is being integrating into small farming operations. For example, hydroponic growing operations can be operated through cell phone applications that continuously monitor growing conditions. Nutrients can then be put on a time release, temperatures can be adjusted for indoor growing operations or lighting can be altered for optimal growing conditions with sensors relaying information to a cell phone or central PC management station. When considering such hydroponic growing conditions, HSI could be incorporated into these production systems to monitor plant leaves for signs of disease or stress that may not be visible to the human eye until it is too late to attempt to remedy a situation. This has the potential to increase yield.

Addressing the previously mentioned data processing and storage needs of spectral imaging systems on a small farm is a necessity. Introduction of cloud-based computing services could ease the application of spectral imaging technologies into small farming operations. Customisable data processing solutions is a sizable hurdle that needs to be addressed as well. Spectral imaging datasets can be customised for a particular solution. Third-party software companies have begun marketing portable spectroscopy solutions for potential clients. Occasionally, these companies market solutions to challenges such as food security that are perhaps outside the scope of what is capable with the spectrometer being sold. For example, it would be extremely challenging if not impossible for a portable NIR spectrometer to address food safety issues such as bacterial or allergen presence on food surfaces at an adequate limit of detection, while lacking comprehensive validation.[71] It is certain that as portable spectral imaging technologies advance these same challenges of overzealous marketing campaigns will be an issue. It will be the task of diligent applied spectral imaging methods to address the reality of these approaches as they enter the marketplace.

Conclusions

As with larger scale monoculture farms, smaller farms face a myriad of challenges. Precision agriculture exists to ease the burdens placed upon operating a farm and being profitable while feeding a community. There is a long-documented history of applying spectral imaging technologies to agricultural production. Significant strides in recent years have been made towards lower costs and portable spectral imaging systems. As these technologies progress there is an abundance of potential for application in smaller farms as well. Here, the challenges for technology implementation are different, and as open-source and low-cost spectral imaging systems evolve and advance, there is abundant potential for application that can improve the processes of growing food and livestock in the years to come.

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