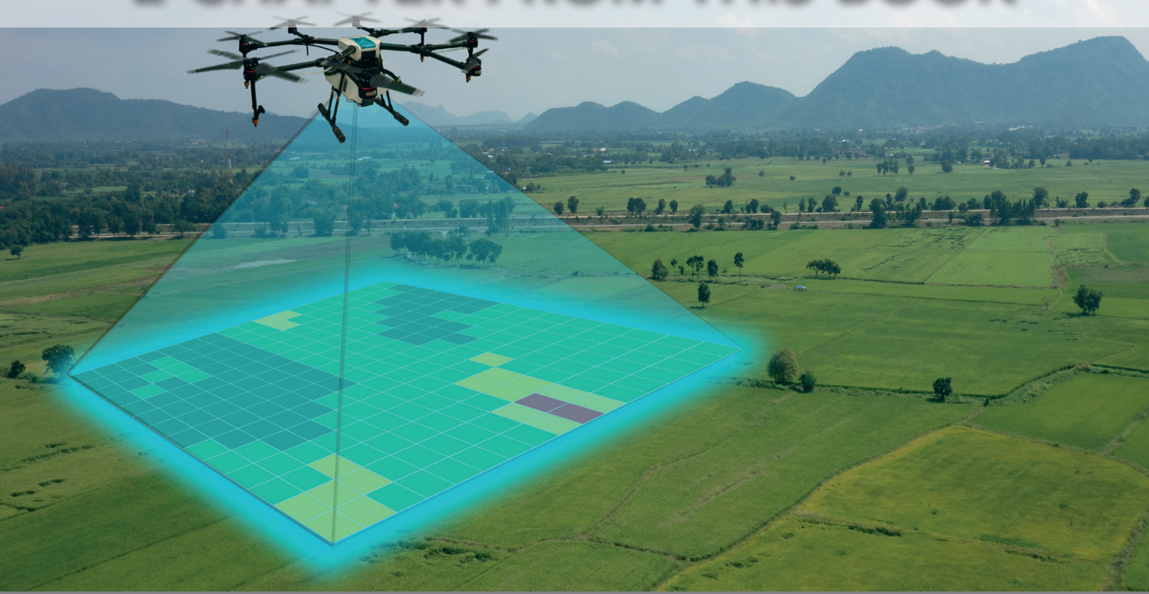
BURLEIGH DODDS SERIES IN AGRICULTURAL SCIENCE

Advances in sensor technology for sustainable crop production

Edited by Dr Craig Lobsey, University of Southern Queensland, Australia and Professor Asim Biswas, University of Guelph, Canada

E-CHAPTER FROM THIS BOOK



burleigh dodds SCIENCE PUBLISHING

Advances in proximal sensor fusion and multi-sensor platforms for improved crop management

David W. Franzen and Anne M. Denton, North Dakota State University, USA

1 Introduction

Other chapters in this book will describe numerous examples of the use of proximal and remote sensors as a tool to more easily evaluate crop growth and diagnose the need for application of amendments necessary to achieve improved plant health and ultimately more sustainable and profitable crop yield. Some of these sensors are also used to predict crop yield for its own value to crop marketing strategies and farm financial planning (Doraiswamy et al., 2007; Sabini et al., 2017; Donohue et al., 2018) or to use the information in formulas constructed to relate to in-season application of nitrogen (N) or other nutrients (Franzen et al., 2016; Sharma and Franzen, 2016; Ransom et al., 2019). In all of these evaluations, the relationship between sensor reading and crop health indicator or crop yield predictor is not perfect. It is therefore logical to consider whether the addition of other layers of sensor input from the area of interest would add strength to the relationship between sensor outputs and therefore increase predictability. The concept of using multiple layers of sensor information is not new and is supported by studies of methods to construct management zones for use in site-specific nutrient sampling and management (Khosla et al., 2002; Franzen et al., 2011). The use of a single method, such as

http://dx.doi.org/10.19103/AS.2022.0107.18

Chapter taken from: Lobsey, C. and Biswas, A. (ed.), *Advances in sensor technology for sustainable crop production*, pp. 307–326, Burleigh Dodds Science Publishing, Cambridge, UK, 2023, (ISBN: 978 1 78676 977 0; www.bdspublishing.com)

the use of topography, satellite imagery, aerial imagery, electrical conductivity sensor data, or multi-year crop yield map data, to produce zone boundary delineation resulted in significant correlation with intensively gridded soil sampling values in these studies; however, adding the zone boundary delineation information from two or more of these methods resulted in greater correlation and predictability.

Although there have been many studies and research publications on the use of sensors to direct the application of crop amendments, these have not resulted in acceptance of the technology in mainstream farmer use. According to Lowenberg-DeBoer and Erickson (2019), the three obstacles to adoption are cost, improved reliability of variable-rate technology tools, and demonstrated economic value.

Sensors to aid in crop management are either proximal (Viscarra Rossel and Adamchuk, 2013) or remote sensing tools. Sensors provide either a direct measurement, such as pH measurement at spaced points on-the-go with a proximal sensor, or an indirect measurement, such as relative crop growth using normalized differential vegetative indexes. A single sensor has unique capabilities and strengths of the data it generates, but it also is subject to limitations. To increase the reliability of variable-rate technology, the combined use of multiple sensors has been investigated to increase the predictability of sensors with yield and associated crop traits. The base sensor in most multi-sensor experiments tends to be proximal or remote electromagnetic radiation sensors and thermal sensors. Sensor data that has been added to the base sensor data to increase relationships of the base sensor output with yield, input need, or crop characteristic has been crop height, weather data, directed soil sampling data, electrical/magnetic conductivity proximal sensors, and combine/harvester yield sensors.

The development of high-speed personal computers has enabled the development of computer-modeling techniques such as neural network analysis and machine-learning algorithms to combine different sources of data that are somewhat related to the characteristic of interest, and to make improved predictions of the item with multiple sensor input (Salvador et al., 2020). An example of these techniques for non-yield prediction is relating satellite imagery and non-imagery sensor data to predict residual soil nitrate in northwest Minnesota, USA, after sugar beet (Gautam et al., 2011). Here, satellite imagery in the RGB range of vegetative indexes of the recently harvested sugar beet root crop is combined with data from an electrical conductivity sensor, active-optical sensor readings within the previously growing sugar beet crop, sugar beet canopy height measurements using a meter-stick, root yield, and surface soil elevation from differential GPS readings relative to other points in the study. These data were compared individually to residual soil nitrate values to a 60 cm depth after harvest, and together, using a radial basis function

Published by Burleigh Dodds Science Publishing Limited, 2023.

neural network (RBFNN) with 100 iterations. In addition, a back propagation neural network (BPNN) was examined for its utility, along with a modular neural network. The resulting prediction with the RBFNN had an r^2 of about 0.74 and a root mean square error (RMSE) of about 13%. The BPNN model had an r^2 of about 84% and an RMSE of about 10.6%, making the BPNN procedure most predictive. The modular neural network was not as predictive as the RBFNN or the BPNN. The prediction of soil nitrate after sugar beet using either of the neural network techniques was superior to any remote or ground sensor data input.

In this chapter, examples of the use of multi-sensor approaches to crop production management and prediction will be explored. The ultimate goal for the use of these sensors is to increase crop yield with an economy of inputs for the financial advantage of the grower and the conservation enhancements from their use that lead toward a more environmentally friendly and sustainably productive agriculture.

2 Use of plant height and proximal/remote sensing

Differences in crop height intuitively indicate that a taller crop is healthier and requires fewer amendments compared to a shorter crop. Several studies have evaluated the use of corn height alone with the prediction of corn yield (Boomsma et al., 2009; Yin et al., 2011a,b). Crop height differences themselves may not be a direct result of a single variable. In a series of Indiana experiments over tillage treatments, there were sometimes differences in yield and corn height between no-till compared to deeper tillage treatments (Boomsma et al., 2009); however, the differences in height were not consistently related to yield. The differences within row of height due to delayed emergence appeared to have a greater relationship to yield than the mean height over a length of row. In Yin et al. (2011a,b), differences in corn height were determined over a range of N rates; thus, the differences in corn height were related to yield, with the implication that corn height might be used to direct in-season N fertilization if relative height to a sufficient N area was considered. These experiments were conducted using meter sticks or similar analog measurements that would not be practical for most commercial agricultural management. The use of an acoustic sensor, which has industrial uses such as measuring liquid volumes in storage tanks and for assembly-line purposes to help maintain quality, has been investigated in some studies (Shrestha et al., 2002; Sui et al., 2013; Sharma and Franzen, 2016; Yuan et al., 2018). Other methods of sensor-based plant height measurements include use of 3D cameras (Hämmerle and Höfle, 2016) and LiDAR and UAS-based platforms (Verela et al., 2017), combined with previously determined digital elevation models. These additional methods have not been combined with other sensors to provide relationships to crop yield to date. Acoustic height measurements were combined with active-optical sensor data in corn (Sharma and Franzen, 2014) and in sunflower (Schultz et al., 2018). In corn, the relationships of RedNDVI and RedEdgeNDVI with yield were increased with height data, while in sunflower, the relationship of active-optical sensor data with yield was low in oil-seed sunflower and the sunflower height relationship with yield was high. In confection sunflower, which generally has a broader leaf surface, the RNDVI and RENDVI relationship with yield was stronger and sunflower height increased the yield and sensor relationship. The combination of active-optical sensor data and sunflower height did not result in a stronger relationship of the height data with sunflower seed yield in oil-seed sunflower. In Oklahoma (Martin et al., 2012), a formula using the combination of corn plant height, distance between plants, and active-optical sensor NDVI resulted in improved corn yield prediction.

In sugar beet, prediction of root yield and sugar yield is important to aid in sugar processing planning for sugar cooperatives in the Red River Valley of Minnesota and North Dakota. Production is monitored to make certain there is enough sugar to meet demand while limiting production so as not to glut the market, which results in low prices and unprofitable production. The use of satellite imagery has been useful by the industry to produce regional yield estimates (Beeri et al., 2004).Also, the use of satellite imagery alone has been useful since the late 1990s for sugar beet farmers to anticipate the nitrogen release from sugar beet leafy-top residues for the subsequent crop (Daberkow et al., 2003; Franzen, 2004). The use of active-optical sensors was examined for use in estimating root yield and sugar yield at multiple harvest dates, since root yield increases from early pre-harvest (mid-late August) until the soil is frozen, typically anytime from late October to early November (Bu et al., 2016). Although red NDVI and red-edge NDVI were useful yield predictors at most locations and harvest timings, the addition of canopy height increased the prediction of root yield and sucrose yield at most harvests, particularly when the measurements were made early in the season from V6 to V8.

3 Sensors and weather data

Most regional and national crop yield forecasts combine remote sensing from satellites and weather station data (AMIS, 2016). Some models also include additional input from crop growth models and background soil information (Paudel et al., 2021). Crop growth models use weather information as an important part of their formulas. Weather information comes from sensors for rainfall, solar radiation, temperature, and other crop growth influencing measurements. Weather data is generally from sensors placed at some distance to specific land. Therefore, the weather data is site-specific only to the extent of the spatial distance between sensor locations. Satellite imagery or other remote sensing tools are spatial in nature, so combining imagery within a model produces a spatial crop growth model (Kasampalis et al., 2018; Zhao et al., 2020). The scale of the sensor tools defaults ultimately to the smallest scale input, with the assumption that the weather data is relatively accurate at that scale even though it was not measured at that smaller scale. For temperature, relative humidity, and solar radiation, that assumption is probably correct; however, for rainfall, particularly in regions where seasonal rainfall is largely dominated by thunderstorms, that assumption is not correct (Patrick and Stephenson, 1990; Hatfield et al., 1999). It is important, therefore, that if weather data is included in a multi-sensor approach the weather station should ideally be within or adjacent to the field where a spatial decision on inputs is intended to be made.

In a study of US national maize yield, the base model for yield was weather-based only (Peng et al., 2018), with the weather-based model based on temperature, precipitation, and vapor pressure deficit. Adding satellite imagery-derived enhanced vegetative index increased the predictability of the weather-only-based model.

Adding rainfall data as average precipitation from date of planting to date of harvest most consistently improved the relationship of corn yield to active-optical sensor values alone or sensor values together with corn height, and potato yield with active-optical sensor reading (Sharma et al., 2018). The interesting aspect of this study, conducted in North Dakota (corn) and Maine (potato), was the most often the weather station with rainfall data considered in the study was up to 50 km away from the experimental area. So although the seasonal rainfall at the experiment site was more or less than that of the nearest weather station whose rainfall data was considered, the data was nonetheless helpful to the analysis.

A three-US-state study (Thompson et al., 2015) was conducted to explore differences between an active-optical sensor approach to in-season N application compared to N rate predictions using the MAIZE-N model (Setiyono et al., 2011). The MAIZE-N model incorporates weather data together with soil data, particularly an estimate of soil organic matter mineralization, along with crop price and N costs into an in-season N rate prediction. Although the active-optical sensor used (RapidSCAN CS-45 Handheld Crop Sensor – Holland Scientific, Lincoln, NE, USA) correctly predicted N rate at 7 of 11 sites, the model approach predicted 9 of 11 sites correctly. The authors suggested that the use of a combination of the two approaches may make the model approach more responsive to in-season variations in N availability to corn.

In an eight-US state study on exploring commonalities in corn N rate recommendations, active-optical sensor readings, soil moisture measurements, satellite imagery, on-site weather station data, and soil sampling preseason and in-season were evaluated using machine-learning methodology (Qin et al., 2018). An important feature of the most successful machine-learning-derived models in this effort was including soil hydrological status. The soil hydrological status was measured using the available soil moisture holding capacity, dictated by soil texture with depth, and the ratio of in-season rainfall to the available water holding capacity. Sites that did not perform well in the model probably did not adequately measure soil moisture changes through the growing season. One site that did not perform as well with the model was the Durbin site in North Dakota, which has about 50% clay content (Smectite dominant, illite about 20% of total clay content). The North Dakota climate differs from other states in the study because summer transpiration often exceeds rainfall during the same period. That results in capillary water movement from groundwater at depths below the depth of soil moisture measurements. The deeper groundwater may also hold nitrate that would not be considered in the model. A greater water supply than that predicted by rainfall and soil moisture measurements would also result in greater yield than that predicted. For most sites, however, the use of active-optical sensors, on-site weather data, and soil moisture measurements were adequate to predict economically optimum N rates.

In the same eight-US state study, the economic optimum nitrogen rate (EONR) algorithms used in each state were compared among the states (Ransom et al., 2020). In this analysis, there was no state algorithm that was common to all states. The study concluded that additional factors needed to be considered to produce a more regionally effective algorithm. In subsequent analysis, these algorithms were evaluated with the addition of active-optical sensor readings, satellite image values, weather data, and soil characteristics (Ransom et al., 2021). The active-optical sensor and satellite image-based algorithms were improved in performance when weather data (from at-site weather stations) and soil characteristics were included. Weather parameters that were most useful were evenness of rainfall and abundant and well-distributed rainfall.

Winter wheat yield prediction at the in-field scale has been conducted in the southern US Great Plains since about 2000 using red normalized difference vegetation index (NDVI) standardized using growing degree days from planting. The standardization of NDVI using growing degree days is referred to as in-season estimate of yield (INSEY). Including weather data, consisting of total rainfall from September to December and temperature from September to December, improved the r^2 of the relationship between measured and predicted yield from 0.620 to 0.768 at one location and 0.476 to 0.698 at a second location (Aula et al., 2021).

Using a multi-spectral camera mounted on a UAV to collect red-green-blue (RGB) imagery from fields in Finland, a sequential series of flights, timed according to a certain interval of cumulative temperatures, were conducted to produce a temporal map of RGB during crop growth (Nevavuori et al., 2020). Yield monitor sensor data from field harvests were used to train the spatial neural network-derived model for the relationship between sensor readings and crop yield. In this study, the conclusion was that data from the first month of crop growth was sufficient to build a yield model from a series of UAV flight data obtained using cumulative temperature from weather data. Time-series remote sensor readings have also been important in rice prediction models. Setiyono et al. (2014) used satellite imagery based on synthetic aperture radar (SAR), which is radar-based, and unaffected by cloud cover, which is often a problem in major rice-growing regions of Asia. The rice growth SAR model is developed using temporally separated multi-image acquisition. Leaf area index (LAI) is a common product of an SAR image. Another rice yield estimation model was developed using soil data to estimate soil nitrogen dynamics and weather data from a regional source, corrected to more local weather stations when available. Although each of the models, the SAR-based model and the weather/soil-based model, was effective in predicting rice yield, the combination of models was more effective than either by itself.

Using Sentinel-2 satellite imagery, 109 wheat fields in NE Australia were scanned during the growing season for a relationship to wheat yields. Although the red-edge chlorophyll index and optimized soil-adjusted vegetation index (OSAVI), using satellite imagery only explained over 70% of yield variation, addition of weather data, specifically the crop stress index (SI) developed for this region in Australia, increased the prediction to over 90% of yield variation. The SI consisted of the actual evapotranspiration divided by the potential evapotranspiration. Both parameters are dependent on rainfall, wind speed, temperature, and other weather-related variables from weather stations in the area.

Crop yield modeling was examined in Nebraska, USA, over 134 irrigated and 94 rainfed maize fields (Sibley et al., 2014). Use of the satellite-derived Moderate Resolution Image Spectroradiometer (MODIS) sensor, a crop model (Hybrid-Maize) with either MODIS or Landsat imagery, and the Hybrid-Maize model applied to MODIS and Landsat data was compared. The MODIS methods were consistently poor at yield prediction, whereas the best was the Hybrid-Maize model applied to Landsat imagery. The Hybrid-Maize model includes maize growth related to soil and weather parameters, while the Landsat imagery, R-band NDVI, was the best predictor (R^2 0.54–0.63).

In machine-learning exercises relating satellite imagery NDVI and weather data to potato yield in autumn-winter and spring-summer crops in Mexico, the most successful approach for the autumn-winter crop was using a random forest (RF) approach, while for the spring-summer crop a support vector machine linear (svml) approach was best. For the RF approach, the most important variables supporting the model were the NDVI, total cloud cover, consideration of previous crop yield, solar radiation, and evaporation. For the svml approach, LAI measured each month, NDVI, total cloud cover, precipitation, and evaporation were most important in yield prediction. A combination of satellite imagery and weather data was important for national potato production prediction.

Predicting sunflower seed yield is a greater challenge. As seen in the failure of active-optical sensor red NDVI and red-edge NDVI to relate to sunflower yield in North Dakota (Franzen et al., 2019), similar problems have also been observed in Spain (Trepos et al., 2020). The sunflower yield crop model used (SUNFLO) to predict yield based on time, soil, and climate; management practices including crop nitrogen content, plant transpiration, leaf expansion, senescence and biomass accumulation as a result of nitrogen deficits; and weather data including temperature, radiation, and water availability. The crop forecast models without LAI from satellite imagery resulted in poor yield estimates with large errors, generally overestimating yield. Including LAI tended to reduce errors, with a smoothed LAI over the study area reducing errors the most. The resulting model was an improvement, but it still resulted in general yield overestimation. The explanation for yield overestimation was the lack of consideration of weeds, diseases, and other pests in the fields. Disease and insect pests can particularly attack formally healthy sunflowers at or near heading, late in the season (Berglund, 2007).

Soybean yield is also best predicted using a combination of satellite imagery NDVI and climatic data. Soybean yield is greatly influenced by late-season environmental conditions, particularly soil moisture stress (Licht et al., 2013). If the season is favorable in soil moisture for late season growth and pod-fill, then NDVI can be a good predictor of yield. However, in a study of soybean fields in Russia, the satellite NDVI saturated in values mid-season when the rows closed over the soil, and climatic data was important to add to the model to predict soil moisture condition and ultimately yield (Stepanov et al., 2020). A similar approach was also taken in a study of Brazil soybean yield prediction (Schwalbert et al., 2020). Satellite imagery and weather data were significant, but relatively poor predictors of yield 70 days before harvest; however, the prediction was greatly improved at 40 days before harvest with updated weather data.

Canola is mostly grown as a spring crop in Canada, North Dakota, and some northern areas in Montana and Minnesota. Yield prediction is important for the canola oil industry in this region. Knowing that canola grows as a rosette for the first 30 days of the season, then bolts to form heads and flowers, with the length of flowering important for final yield, largely dictated by temperature and soil moisture status, a study across the Canadian Prairies was conducted using as a primary tool estimates of soil moisture obtained from the SM Ocean Salinity Mission (SMOS) satellite (White et al., 2020). Additional tools were climatic variables and NDVI derived from the Advanced Very High Resolution Radiometer (AVHRR) platform, currently used as an input for canola yield

Published by Burleigh Dodds Science Publishing Limited, 2023.

models. The NDVI-based model alone predicted 41.2% of yield variation, while adding satellite-derived soil moisture increased prediction to 74.2%.

4 Multi-sensor approaches

Most studies that investigate yield prediction or traits associated with yield prediction using multiple tools utilize one set of electromagnetic sensor-based vegetative indexes and the output from an unrelated tool, such as weather data or crop height. Studies are now being conducted that utilize machine learning to combine multiple vegetative indexes in their analyses. Osco et al. (2020) combined red NDVI, red-edge NDVI, green NDVI, and soil-adjusted vegetative index (SAVI) in several machine-learning analyses for the prediction of leaf N concentration and maize plant height at V12. This study was conducted on an N rate X maize hybrid experiment in maize in NE Mato Grosso do Sul, Brazil. The dimensions of the study were approximately 60 m × 30 m. The algorithms were conducted on spectral bands alone, on the vegetative indices derived from the spectral bands, and the models compared were RF, REPTree, K-Nearest Neighbor with K = 1, 5, and 10, singular boundary method-radial basis function (SBM-RBF), support vector machine polynomial (SVMP), linear regression, and radial basis function regression. Of all the methods, the RF method using the vegetative indexes performed best, with a RMSE of 1.9 g kg^{-1} for leaf N concentration and 0.17 m for plant height.

A multiple vegetative index approach was also applied to an N rate study in maize in Mississippi, USA. Although yield prediction using a single vegetative index was optimized using the OSAVI or the Simplified Canopy Chlorophyll Content Index (SCCCI), the combination of Green Atmospherically Resistant Index (GARI), red-edge NDVI, and green NDVI was the best yield predictor at V6-7 (r^2 = 0.70); the SCCCI and SAVI were best at V10-11 (r^2 = 0.90); and SCCI, Green Leaf Index (GLI), and Visible Atmospherically Resistant Index ($VARI_{green}$) were the best predictors at tasseling (r^2 = 0.93).

Leaf nitrogen estimation in maize was studied using a 'fusion' of bands and 18 vegetative indices from a hybrid by nitrogen rate experiment in Beijing, China (Xu et al., 2021). The analysis was based on development of cover-adjusted spectral indices (CASIs), where CASI = VI/(1+FV_{cover}), where VI is the vegetative index selected, and FV_{cover} indicates the fraction of vegetative cover. The vegetative indices were extracted from multispectral imagery with high spatial resolution. The FV_{cover} was also calculated from the RBG imagery, as area of vegetation divided by total area. A random frog algorithm was used to identify the five most optimal characteristics among the VIs. Then a partial least squares method was utilized to investigate relationships between leaf nitrogen concentration and an optimal set of CASIs/Vis at three growth stages of corn (V12; R1; R3). The CASIs at the R1 growth stage were most related to leaf nitrogen content with an r^2 of 0.59, an RMSE of about 22%, and an NRMSE (normalized root mean square error) of about 8.4%. The removal of soil information from the analysis resulted in greater relationships between leaf nitrogen concentration and CASIs/VIs.

Use of all spectral bands in a wheat variety experiment involving 1170 lines in Spain was superior in yield prediction compared to individual vegetative indexes (Montesinos-Lopez et al., 2017). The bands used were 250 discrete narrow bands that ranged from 392 nm to 851 nm. Mid-season imagery was more predictive than early or late-season flights. Also, the use of all bands was most predictive over all environments. Prediction of yield was best under early heat and under irrigation, and poorest under the drought environment.

A combination of vegetative indices was explored individually for ground proximal sensors (chlorophyll meters) and multispectral imagery from an airplane flying at 330 m elevation and a drone operated at 80 m elevation was explored in maize (Gabriel et al., 2017). The ground proximal sensors individually or combined were more related to experiment nitrogen availability than the aerial sensors. In the suite of possible aerial-based VIs, the TCARI (transformed chlorophyll absorption in reflectance index) = $3[(R_{700}\text{-}R_{670}) - 0.2(R_{700}-R_{550})/(R_{700}/R_{700})]$and OSAVI = $(1+0.16) \times ((R_{800}-R_{670})/(R_{800}+R_{670} + 0.16)$ were most related, particularly when evaluated as TCARI/OSAVI. In the case of aerial image relationship, the best relationship with maize nitrogen concentration was achieved when soil interference was eliminated. The ground proximal sensors were applied to the leaves only, so soil had no effect; however, obtaining information from the leaf-clipping derived proximal chlorophyll sensors was laborious and slow compared to either aerial data source (Barzin et al., 2020).

Thermal sensors have historically been studied for their use in identifying differences in transpiration/evaporation from soil or crop canopy surfaces, drought conditions (Jones et al., 2021), and pest/disease infestation (Pineda et al., 2021). Lately, thermal sensors have been linked directly or in combination with remote sensing and proximal light sensors. A recently developed proximal tool, Crop Circle Phenom (Holland Scientific, Inc., Lincoln, NE, USA) was studied for its use in improving corn N status prediction. The instrument includes sensors with red, red edge, and near-infrared wavelengths, a thermal sensor for determining the difference between crop canopy temperature and air temperature ΔT, and a sensor for determining the fractional photosynthetically active radiation (fPAR). The best prediction of crop nitrogen status was made using a machine-learning tool, eXtreme Gradient Boost (XGBoost) that included the vegetative indexes calculated by the sensor tool, the ΔT, the fPAR, and adding in drainage, tillage, and pre-plant nitrogen rate (Cummings et al., 2021).

A suite of proximal soil sensing tools was utilized in a study on a small pasture in Brazil to characterize its soils. The tools consisted of an apparent magnetic susceptibility sensor, an apparent electrical conductivity sensor,

Published by Burleigh Dodds Science Publishing Limited, 2023.

a volumetric water sensor, a portable gamma-ray radiation sensor, a cone-penetrometer, and an x-ray fluorescence sensor. Readings were compared to laboratory analysis of soil clay content, water content, cation exchange capacity (CEC), organic carbon, and sum of bases. The use of the x-ray fluorescence sensor was most highly correlated with organic carbon, clay content, and bulk density, while other tools were more highly correlated with sum of bases, CEC, and water content. The use of a combination of tools was superior in correlation to the use of only one tool (Vasques et al., 2020).

Imagery from a UAV fit with sensors able to capture thermal, infrared, and RGB spectral bands, as well as plant height using Structure from Motion and LiDAR to predict soybean yield at R4/R5 in a large soybean variety trial. Machine-learning tools RF and XGBoost were used to obtain highly predictive algorithms ($r^2 > 0.9$) from the UAS-generated sensor data (Herrero-Huerta et al., 2020).

5 Statistical tools for fusing multi-sensor data

A common theme of all studies that include multi-sensor data in prediction of any crop attribute is the use or comparison of statistical tools to combine the data sources. Some options for combining data are:

- egression in some form, linear, quadratic, or some transformed model;
- neural networks;
- machine-learning tools; and
- deep learning tools.

Among statistical approaches for sensor fusion problems in agriculture, most fall into the group of supervised learning problems in that there is a ground truth available that can be measured for at least some of the data. This is unlike clustering or pattern detection problems where no labeled data is available. To be yet more specific, sensor fusion is often used in regression problems, where a variable is to be predicted that is continuous, for example, yield or crop health indicators. Classification, or the prediction of categorical target variables, can also be of interest for problems like identifying diseased plants (Moshou et al., 2011). A more general discussion that includes a broader set of machine-learning goals can be found in Liakos et al. (2018).

The most basic approaches to regression problems assume that a linear combination of basis functions can be used for prediction. Such approaches are called linear regression, even while the basis functions themselves do not have to be linear functions of the independent variables. Regression using quadratic or higher order basis functions can still be linear in the parameters that are optimized and would then be considered as linear regression in the statistics literature. Yin et al. (2011a) compare linear, quadratic, square root, logarithmic, and exponential basis functions for assessing the relationship of corn yield with plant height.

Linear regression problems are more straightforward to solve than nonlinear ones, and there is less ambiguity about the assumptions that were made. Except when physical reasons suggest selecting a specific model, it is normally recommended to use linear models where those are sufficient. Most available implementations of linear regression also return information on the importance of different independent variables as part of the result. Like other regression approaches, linear regression is vulnerable to overfitting, especially when many independent variables or basis functions are included. In such cases, regularization is recommended, which serves the purpose of reducing the number of non-zero fit parameters, such that only important independent variables and basis functions are considered in the final model. Least absolute shrinkage and selection operator (LASSO) is an example of a regularization and variable selection algorithm that is used for example in Aula et al. (2021). Using regularization is especially important when the independent variables are highly correlated.

Instead of using regression models directly, combined features can be precomputed. The simplest examples are indices like the NDVI or the LAI. A common statistical way of deriving combined features is principal component analysis (PCA), which returns orthogonal combinations of features ordered starting with highest variance. Basso and Liu (2019) give examples of the use of vegetation indices and PCA for the purpose of crop yield forecasting. They also discuss examples of using the output of physical models as input into statistical models such as used by Ratjen and Kage (2015).

Many sensor fusion problems are too complex to yield good results using only linear methods either directly or on derived features that were explicitly specified. Nonlinear regression algorithms can be useful for these cases, including artificial neural networks (ANN), support vector regression (SVR), and tree-based methods. SVR is a mathematically elegant approach to nonlinear regression that uses the concept of kernels for encoding assumptions about the learning problem. Unfortunately, in SVR the model size depends on the size of the training data, and in many learning contexts, it is desirable to prescribe the size of the model.

Tree-based techniques are relatively fast and are good for reducing noise due to less relevant features. Regression trees are constructed by identifying the most important feature at every level. Individual regression trees typically do not yield the highest prediction quality, but they can be useful for creating explainable models, since the number of features that contribute to a prediction is usually small, and its impact on the prediction straightforward, see, for example, Hamann et al. (2011). To achieve high accuracy, ensembles

Published by Burleigh Dodds Science Publishing Limited, 2023.

of trees should be used, such as RF. RF models are constructed by creating a large set of regression trees, each from a subsample of training data points, and then computing the predicted value as the average of the predictions of each individual tree. Osco et al. (2020) conclude that an RF model is a suitable technique for predicting leaf nitrogen and plant height in maize.

Among the most popular statistical prediction models are neural networks of various designs. The choice of model has a strong impact on what solution can be achieved, making it important to understand their characteristics. One of the simplest assumptions is that predictions should be based on proximity to known examples, which is used in RBFNN and SVR with Radial Basis Function kernels. While an assumption of overall proximity is straightforward, it suffers from the shortcoming that distances are calculated over all independent variables. For sensor fusion, the relevance of different input sources toward the predicted quantity may differ vastly, and it has been shown that RBFNN may be less suitable to such problems than, for example, backpropagation neural networks (BNNs) (Gautam et al., 2011).

Among the oldest and most versatile neural network designs are BNNs, which are also sometimes referred to as feed-forward neural networks or multilayer perceptrons. The most common design has a layer of input nodes that are connected to a layer of hidden nodes, which in turn is connected to a third layer that represents the outputs. The hidden layer allows these neural networks to represent nonlinearities in a way that does not have to be prescribed explicitly. The BNN was one of the top-performing networks in Gautam et al. (2011).

A breakthrough for the recognition of objects in images and for understanding text input was the development of deep learning (LeCun et al., 2015). Deep neural networks have substantially more than one hidden layer and can directly learn features within data that do not have to be structured, such as images or text, thereby resolving or reducing the need for encoding features explicitly. The success of deep neural networks relied on some general algorithmic improvements, in particular, the prevention of overfitting through dropout of nodes, which can be compared with the regularization that was mentioned earlier in the context of regularized linear models. Moreover, some of the most successful types of deep learning networks were constructed such that they are effective at encoding specific derived features. For example, convolutional neural networks, CNNs, were designed to represent image features regardless of where in an image they occur. For this purpose, they have convolutional layers that represent information on what happens within the vicinity of a point in an image. CNNs also have max-pooling layers that combine information regardless of where in the image it is found. A typical use of this capability would be plant identification (Grinblat et al., 2016).

Some deep learning networks have been designed to be particularly effective at encoding temporal relationships, in particular, recurrent neural networks (RNN) and extensions of RNNs that can capture long-term relationships and are called long-short term memory (LSTM) models. Jia et al. (2019) demonstrate the success of LSTM models in crop monitoring. They also show that when temporal aspects are to be combined with spatial machine learning, domain adaptation (DA) is a common and often successful approach. DA is a special case of transfer learning. In transfer learning, a machine-learning model is used on a data set that is different from the one that is used in prediction. DA refers to the special case that the data only differ in the time at which the data were collected.

6 Conclusion and future trends

There is much evidence that proximal and remote sensing technology can be used to improve crop management by farmers and their industry partners. There is also much evidence in the value of the use of multiple sensors over the use of one alone. Partnering sensors with different strengths to achieve a better prediction and management consequence will likely improve management decisions and promote more sustainable agricultural practices. However, this is dependent on the value obtained through investment in additional data sources (e.g. sensors). The challenge now is to provide the end-user with a package of sensor and analytical tools to make the use of these technologies simple to use, easy to maintain, and produce a minimal burden. The integration of relevant tools into a plug-and-play package, with sufficient developmental research support to support their value will be critical to the movement of these sciences into commercial adoption.

7 Where to look for further information

Several journals are particularly rich sources of information regarding the use of sensors in agriculture. These journals include *Agronomy Journal* (https://acsess.onlinelibrary.wiley.com/journal/14350645), *Sensors* (https://www.mdpi.com/journal/sensors), *Remote Sensing and Environment* (https://www.journals.elsevier.com/remote-sensing-of-environment), *Computers and Electronics in Agriculture* (https://www.sciencedirect.com/journal/computers-and-electronics-in-agriculture), *Remote Sensing* (https://www.mdpi.com/journal/remotesensing), and *Precision Agriculture* (https://www.springer.com/journal/11119).

A book was released in 2021 that provides a broad view of research into the use of sensors in agriculture: *Sensing Approaches for Precision Agriculture*, Ruth Kerry and Alexandre Escola, eds, Springer Cham (https://doi.org/10.1007/978-3-030-78431-7).

Published by Burleigh Dodds Science Publishing Limited, 2023.

Also, recent proceedings from the ISPA (International Society of Precision Agriculture), https://www.ispag.org/, and the European Society for Precision Agriculture, https://www.ecpa2021.hu/, may also be helpful, as well as attending their future conferences.

8 References

AMIS (2016). Crop yield forecasting: methodological and institutional aspects. Agricultural Market Information System, Food and Agriculture Organization of the United Nations. Available at: http://www.amis-outlook.org/fileadmin/user_upload/amis/docs/resources/AMIS_CYF-Methodological-and-Institutional-Aspects_web.pdf.

Aula, L., Omara, P. E., Nambi, E., Oyebiyi, F. B., Dhillon, J., Eickhoff, E., Carpenter, J. and Raun, W. R. (2021). Active optical sensor measurements and weather variables for predicting winter wheat yield. Agron. J. 113(3):2742–2751 doi:10.1002/agj2.20620.

Barzin, R., Pathak, R., Lofti, H., Varco, J. and Bora, G. C. (2020). Use of UAS multispectral imagery at different physiological stages for yield prediction and input resource optimization in corn. Remote Sens. 12(15):2392 doi:10.3390/rs12152392.

Basso, B. and Liu, L. (2019). Chapter four - seasonal crop yield forecast: methods, applications and accuracies. Adv. Agron. 154:201–255.

Beeri, O., Zhang, X., Newcomb, T., Carson, P. and Wagner, G. (2004). Using Landsat images to map quality and quantity sugar beet yield. 2004 *Sugarbeet Research and Extension Reports*. Vol. 35, p. 125. Sugarbeet Research and Education Board of Minnesota and North Dakota, Fargo, ND. Available at: https://www.sbreb.org/wp-content/uploads/2018/09/Production5.pdf.

Berglund, D. R. (2007). Sunflower production. Available at: https://www.ag.ndsu.edu/extensionentomology/recent-publications-main/publications/A-1331-sunflower-production-field-guide.

Boomsma, C. R., Vyn, T. J., Brewer, J. C., Santini, J. B. and West, T. D. (2009). Corn yield responses to plant height variability resulting from tillage and crop rotation systems in a long-term experiment. In: *17th Triennial Conference of the International Soil Tillage Research Conference Proceedings*.

Bu, H., Sharma, L. K., Denton, A. and Franzen, D. W. (2016). Sugar beet yield and quality prediction at multiple harvest dates using active-optical sensors. Agron. J. 108:273–284.

Cummings, C., Miao, Y., Paiao, G. D., Kang, S. and Fernandez, F. G. (2021). Corn nitrogen status diagnosis with an innovative multi-parameter Crop Circle PhenoM sensing system. Remote Sens. 13(3):401 doi:10.3390/rs13030401.

Daberkow, S., McBride, W. and Ali, M. (2003). Implications of remote sensing imagery and crop rotation for nitrogen management in sugar beet production. *Proceedings of the 2003 AAEA, Montreal, CA, 27-30 July, 2003*. file:///C:/Users/david.franzen/Downloads/sp03da01%20(1).pdf.

Donohue, R. J., Lawes, R. A., Mata, G., Gobbett, D. and Ouzman, J. (2018). Towards a national, remote-sensing-based model for predicting field-scale crop yield. Field Crops Res. 227:79–90. doi:10.1016/j.fcr.2018.08.005.

Doraiswamy, P.C., Akhmedov, B., Beard, L., Stern, A. and Mueller, R. (2007). Operational prediction of crop yields using MODIS data and products. p. 45-49. In: *ISPRS WG VIII/10 Workshop 2006 Remote Sensing Support to Crop Yield Forecast and Area Estimates* Barath, B., Royer, A. and Genovese, G. (Eds), Stesa, Italy. Available at: https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.222.4442&rep=rep1&type=pdf#page=52.

Franzen, D. W. (2004). Delineating nitrogen management zones in a sugar beet rotation using remote sensing: a review. J. Sugar Beet Res. 41(1):47–60. Available at: https://www.researchgate.net/profile/Dave-Franzen/publication/237133722_Delineating_Nitrogen_Management_Zones_in_a_Sugarbeet_Rotation_Using_Remote_Sensing_-_A_Review/links/5473404d0cf216f8cfaecab0/Delineating-Nitrogen-Management-Zones-in-a-Sugarbeet-Rotation-Using-Remote-Sensing-A-Review.pdf.

Franzen, D. W., Kitchen, N., Holland, K., Schepers, J. and Raun, W. (2016). Algorithms for in-season nutrient management in cereals. Agron. J. 108(5):1775–1781.

Franzen, D. W., Long, D., Sims, A., Lamb, J., Casey, F., Staricka, J., Halvorson, M. and Hofman, V. (2011). Evaluation of methods to determine residual soil nitrate zones across the northern Great Plains of the USA. Prec Agri. 12:594–606. doi:10.1007/s11119-010-9207-0.

Franzen, D. W., Schultz, E. C., DeSutter, T. M., Sharma, L. K., Ashley, R. and Bu., H. (2019). Sunflower type influences yield prediction using active optical sensors. Agron. J. 111(2):881–888. doi:10.2134/agronj2018.07.0440.

Gabriel, J. L., Zarco-Tejada, P. J., Lopez-Herrera, P. J., Perez-Martin, E., Alonso-Ayuso, M. and Quemada, M. (2017). Airborne and ground level sensors for monitoring nitrogen status in a maize crop. Biosys. Eng. 160:124–133. doi:10.1016/j.biosystemseng.2017.06.003.

Gautam, R., Panigrahi, S., Franzen, D. and Sims, A. (2011). Residual soil nitrate prediction from imagery and non-imagery information using neural network technique. Biosys. Eng. 110(1):20–28.doi:10.1016/j.biosystemseng.2011.06.002.

Grinblat, G. L., Uzal, L. C., Larese, M. G. and Granitto, P. M. (2016). Deep learning for plant identification using vein morphological patterns. Comp. Elec. Agric. 127:418–424.

Hamann, A., Gylander, T. and Chen, P. Y. (2011). Developing seed zones and transfer guidelines with multivariate regression trees. Tree Genet. Genomes 7(2):399–408.

Hämmerle, M. and Höfle, B. (2016). Direct derivation of maize plant and crop height from low-cost time-of-flight camera measurements. Plant Methods 12:50 doi:10.1186/s13007-016-0150-6.

Hatfield, J. L., Prueger, J. H. and Meek, D. W. (1999). Spatial variation of rainfall over a large watershed in Central Iowa. Theor. Appl. Climatol. 64(1–2):49–60.

Herrero-Huerta, M., Rodriguez-Gonzalvez, P. and Rainey, K. M. (2020). Yield prediction by machine learning from UAS-based multi-sensor data fusion in soybean. Plant Methods 16:78 doi:10.1186/s13007-020-00620-6.

Jia, X., Khandelwal, A., Mulla, D. J., Pardey, P. G. and Kumar, V. (2019). Bringing automated, remote-sensed, machine learning methods to monitoring crop landscapes at scale. Agric. Econ. 50(S1):41–50.

Jones, H. G., Hutchinson, P. A., May, T., Jamali, H. and Deery, D. M. (2021). A practical method using a network of fixed infrared sensors for estimating crop canopy conductance and evaporation rate. Biosys. Eng. 165:59–69. doi:10.1016/j.biosystemseng.2017.09.012.

Kasampalis, D. A., Alexandridis, T. K., Devan, C., Challinor, A., Moshou, D. and Zalidis, G. (2018). Contribution of remote sensing on crop models: a review. J. Imaging 4(4):52, doi:10.3390/jimaging4040052.

Khosla, R., Fleming, K., Delgado, J. A., Shaver, T. M. and Westfall, D. G. (2002). Use of site-specific management zones to improve nitrogen management for precision agriculture. J. Soil Cons. 57:513–518.

LeCun, Y., Bengio, Y. and Hinton, G. (2015). Deep learning. Nature 521(7553):436–444.

Liakos, K. G., Busato, P., Moshou, D., Pearson, S. and Bochtis, D. (2018). Machine learning in agriculture: a review. Sensors (Basel) 18(8):2674. doi:10.3390/s18082674.

Licht, M. A., Wright, D. and Lenssen, A. W. (2013). Soybean response to drought. *Agriculture and Environment Extension Publications*. 190. Available at: https://lib.dr.iastate.edu/extension_ag_pubs/190.

Lowenberg-DeBoer, J. and Erickson, B. (2019). Setting the record straight on precision agriculture adoption. *Agron. J.*:1552–1569. doi:10.2134/agronj2018.12.0779.

Martin, K. L., Raun, W. R. and Solie, J. B. (2012). By-plant prediction of corn grain yield using optical sensor readings and measured plant height. J. Plant Nutr. 35(9):1429–1439.

Montesinos-Lopez, O. A., Montesinos-Lopez, A., Crossa, J., de los Campos, G., Alvarado, G., Suchismita, M., Rutkoski, J., Gonzalez-Perez, L. and Burueno, J. (2017). Predicting grain yield using canopy hyperspectral reflectance in wheat breeding data. Plant Methods 13(4):4 doi:10.1186/s13007-016-0154-2.

Moshou, D., Bravo, C., Oberti, R., West, J. S., Ramon, H., Vougioukas, S. and Bochtis, D. (2011). Intelligent multi-sensor system for the detection and treatment of fungal diseases in arable crops. Biosys. Eng. 108(4):311–321.

Nevavuori, P., Narra, N., Linna, P. and Lipping, T. (2020). Crop yield prediction using multitemporal UAV data and spatio-temporal deep learning models. Remote Sens. 12(23):4000 doi:10.3390/rs12234000.

Osco, L. P., Junior, J. M., Ramos, A. P. M., Furuya, D. E. G., Santana, D. C., Teodoro, L. P. R., Gonçalves, W. N., Baio, F. H. R., Pistori, H., Junior, C. AdS. and Teodoro, P. E. (2020). Leaf nitrogen concentration and plant height prediction for maize using UAV-based multispectral imagery and machine learning techniques. Remote Sens. 12(19):3237 doi:10.3390/rs12193237.

Patrick, N. A. and Stephenson, D. (1990). Spatial variation of rainfall intensities for short duration storms. Hydrol. Sci. J. 35(6):667–680 doi:10.1080/02626669009492471.

Paudel, D., Boogaard, H., de Wit, A., Janssen, S., Osinga, S., Pylianidis, C. and Athanasiadis, I. N. (2021). Machine learning for large-scale crop yield forecasting. Agric. Syst. 187:103016.

Peng, B., Guan, K., Pan, M. and Li, Y. (2018). Benefits of seasonal climate prediction and satellite data for forecasting U.S. maize yield. Geophys. Res. 45(18):9662–9671. doi:10.1029/2018GL079291.

Pineda, M., Baron, M. and Perez-Bueno, M.-L. (2021). Thermal imaging for plant stress detection and phenotyping. Remote Sens. 13(1):68 doi:10.3390/rs13010068.

Qin, Z., Myers, D. B., Ransom, C. J., Kitchen, N. R., Liang, S., Camberato, J. J., Carter, P. R., Ferguson, R. B., Fernandez, F. G., Franzen, D. W., Laboski, C. A. M., Malone, B. D., Nafziger, E. D., Sawyer, J. E. and Shanahan, J. F. (2018). Application of machine learning methodologies for predicting corn economic optimal nitrogen rate. Agron. J. 110(6):2596–2607. doi:10.2134/agronj2018.03.0222.

Ransom, C. J., Kitchen, N. R., Camberato, J. J., Carter, P. R., Ferguson, R. B., Fernandez, F. G., Franzen, D. W., Laboski, C. A. M., Myers, D. B., Nafziger, E. D., Sawyer, J. E.

and Shanahan, J. F. (2019). Statistical and machine learning methods evaluated for incorporating soil and weather into corn nitrogen recommendations. Comp. Elec. Agric. 164:104872 doi:10.1016/j.compag.2019.104872.

Ransom, C. J., Kitchen, N. R., Camberato, J. J., Carter, P. R., Ferguson, R. B., Fernandez, F. G., Franzen, D. W., Laboski, C. A. M., Nafziger, E. D., Sawyer, J. E., Scharf, P. C. and Shanahan, J. F. (2020). Corn nitrogen rate recommendation tools' performance across eight US Midwest corn belt states. Agron. J. 112(1):470–492. doi:10.1002/agj2.20035.

Ransom, C. J., Kitchen, N. R., Sawyer, J. E., Camberato, J. J., Carter, P. R., Ferguson, R. B., Fernandez, F. G., Franzen, D. W., Laboski, C. A. M., Myers, D. B., Nafziger, E. D. and Shanahan, J. F. (2021). Improving publicly available corn nitrogen rate recommendation tools with soil and weather measurements. Agron. J. 113(2):2068–2090 doi:10.1002/agj2.20627.

Ratjen, A. M. and Kage, H. (2015). Forecasting yield via reference-and scenario calculations. Comp. Elec. Agric. 114:212–220.

Sabini, M., Rusak, G. and Ross, B. (2017). Understanding satellite-imagery-based crop yield predictions. Available at: http://cs231n.stanford.edu/reports/2017/pdfs/555.pdf.

Salvador, P., Gomez, D., Sanz, J., and Casanova, J. L. (2020). Estimation of potato yield using satellite data at a municipal level: A machine learning approach. Int. J. Geo-Info. 9(6):343 doi:10.3390/ijgi9060343.

Schultz, E., DeSutter, T., Sharma, L., Endres, G., Ashley, R., Bu, H., Markell, S., Kraklau, A. and Franzen, D. (2018). Response of sunflower to nitrogen and phosphorus in North Dakota. Agron. J. 110: 1–11.

Schwalbert, R. A., Amado, T. J. C., Corassa, G. M., Pott, L. P., Prasad, P. V. V. and Ciamtitt, I. A. (2020). Satellite-based soybean yield forecast: integrating machine learning and weather data for improving crop yield prediction in southern Brazil. Agric. Forest Meteorol. 284 doi:10.1016/j.agrformet.2019.107886.

Setiyono, T. D., Nelson, A. and Holecz, F. (2014). Remote sensing based crop yield monitoring and forecasting. *FAO Expert Meeting Proceedings*. Available at: http://www.fao.org/fileadmin/templates/rap/files/Project/Expert_Meeting__17Feb2014_/P2-4_Setiyono_2014_Remote-Sensing_based_Crop_Yield_Monitoring.pdf.

Setiyono, T. D., Yang, H., Walters, D. T., Dobermann, A., Ferguson, R. B., Roberts, D. F., Lyon, D. J., Clay, D. E. and Cassman, K. G. (2011). Maize-N: a decision tool for nitrogen management in maize. Agron. J. 103(4):1276–1283.

Sharma, L. K. and Franzen, D. W. (2016). Comparison of two ground-based active-optical sensors for in-season estimateion of corn (Zea mays, L.) yield. J. Plant Nut. 39:957–966.

Sharma, L. K., Bali, S. K., Zaeen, A. A., Baldwin, P. and Franzen, D. W. (2018). Use of rainfall data to improve ground-based active optical sensors yield estimates. Agron. J. 110(4):1561–1571.

Sharma, L. K. and Franzen, D. W. (2014). Use of corn height to improve the relationship between active optical sensor readings and yield estimates. Precision Agric. 15(3):331–345.

Shrestha, D. S., Steward, B. L., Birrell, S. J. and Kaspar, T. C. (2002). Plant height estimation using two sensing systems. In: *Proceedings of the ASAE Annual International Meeting, 2002.* CD-ROM, St. Joseph, MO.

Sibley, A. M., Grassini, P., Thomas, N. E., Cassman, K. G. and Lobell, D. B. (2014). Testing remote sensing approaches for assessing yield variability among maize fields. Agron. J. 106(1):24–32.

Stepanov, A., Dubrovin, K., Sorokin, A. and Asseva, T. (2020). Predicting soybean yield at the regional scale using remote sensing and climatic data. Remote Sens. 12(12):1936 doi:10.3390/rs12121936.

Sui, R., Fisher, D. K. and Reddy, K. N. (2013). Cotton yield assessment using plant height mapping system. J. Agri. Sci. 5(1): 23–31. doi:10.5539/jas.v5n1p23.

Thompson, L. J., Ferguson, R. B., Kitchen, N., Franzen, D. W., Mamo, M., Yang, H. and Schepers, J. S. (2015). Model and sensor-based recommendation approaches for in-season nitrogen management in corn. Agron. J. 107(6):2020–2030. doi:10.2134/agronj15.0116.

Trepos, R., Champolivier, L., Dejoux, J.-F., Al Bitar, A., Casadebaig, P. and Debaeke, P. (2020). Forecasting sunflower grain yield by assimilating leaf area index into a crop model. Remote Sens. 12(22):3816 doi:10.3390/rs12223816.

Varela, S., Assefa, Y., Vara Prasad, P. V., Peralta, N. R., Griffin, T. W., Sharda, A., Ferguson, A. and Ciampitti, I. A. (2017). Spatio-temporal evaluation of plant height in corn via unmanned aerial systems. J. Appl. Remote Sens. 11:036013 doi:10.1117/1.JRS/11/036013.

Vasques, G. M., Rodrigues, H. M., Coelho, M. R., Baca, J. F. M., Dart, R. O., Oliveira, R. P., Teixeira, W. G. and Ceddia, M. B. (2020). Field proximal soil sensor fusion for improving high-resolution soil property maps. Soil Syst. 4(3):52. doi:10.3390/soilsystems4030052.

Viscarra Rossel, R. A. and Adamchuk, V. I. (2013). Chapter 6. Proximal soil sensing. In: Precision Agriculture for Sustainability and Environmental Protection Oliver, M., Bishop, T. and Marchant, B. (Eds). 99–118. doi:10.13140/2.1.2799.1847.

White, J., Berg, A. A., Champagne, C., Zhang, Y., Chipanshi, A. and Daneshfar, B. (2020). Improving crop yield forecasts with satellite-based soil moisture estimates: an example for township level canola yield forecasts over the Canadian Prairies. Int. J. Appl. Earth Obs. Geoinf. 89:102092 doi:10.1016/j.jag.2020.102092.

Xu, X., Fan, L., Li, Z., Meng, Y., Feng, H., Yang, H. and Xu, B. (2021). Estimating leaf nitrogen content in corn based on information fusion of multiple-sensor imagery from UAV. Remote Sens. 13(3):340 doi:10.3390/rs13030340.

Yin, X., Jaja, N., McClure, M. A. and Hayes, R. M. (2011a). Comparison of models in assessing relationship of corn yield with plant height measured during early- to mid-season. J. Agric. Sci. 3(3):14–24.

Yin, X., McClure, M. A., Jaja, N., Tyler, D. D. and Hayes, R. M. (2011b). In-season prediction of corn yield using plant height under major production systems. Agron. J. 103(3):923–929.

Yuan, W., Li, J., Bhatta, M., Shi, Y., Baenziger, P. S. and Ge, Y. (2018). Wheat height estimation using LiDAR in comparison to ultrasonic sensor and UAS. Sensors 18:3731. https://doi.org/10.3390/s18113731.

Zhao, Y., Potgieter, A. B., Zhang, M., Wu, B. and Hammer, G. L. (2020). Predicting wheat yield at the field scale by combining high-resolution Sentinel-2 satellite imagery and crop modelling. Remote Sens. 12(6):1024 doi:10.3390/rs12061024.