10 Sensors for Site-Specific Management

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Site-specific management (SSM, also known as precision farming, precision agriculture, prescription farming, etc.) is a management strategy that seeks to address within-field variability and to optimize inputs such as pesticides and fertilizers on a point-by-point basis within a field. By reducing over-application and under-application of nutrients and pesticides, this strategy has the potential to improve profitability for the producer and also to reduce the threat of groundwater or surface water contamination from agrichemicals. SSM is being adopted by innovative producers across the country. Agricultural equipment manufacturers, farm input suppliers, and a host of other businesses are working along with public-sector research and education personnel to provide the necessary tools for farmers to implement this management strategy.

With the exception of grain yield, most data collection for commercially implemented SSM is done through laboratory analysis of collected samples. There is a tremendous need and opportunity for development of sensing technologies that will allow automated collection of soil, crop, and pest data. Sensors will allow the collection of data on a much finer spatial resolution than is currently feasible with manual and/or laboratory methods. These intensely sensed data should more accurately characterize within-field variability. Important soil variables to be sensed could include soil organic matter (important for herbicide and fertilizer application), nutrient level (for fertilizer application), pH (for liming rate and herbicide application), moisture (for seeding depth), and topsoil depth (for seeding and fertilizer application rates). Crop-related variables that could be sensed for input management include weed pressure and identification (for intermittent herbicide application), crop condition (for within-season fertilizer application), plant population, and crop yield.

Sensor technology currently lags behind the other enabling technologies necessary for SSM — positioning by the Global Positioning System (GPS), spatial mapping and analysis with Geographic Information Systems (GIS), and variable-rate control systems for fertilizer, herbicides, and seeding.

Development of sensors and technology for precise application of nutrients and pesticides was identified as one of the 1995 National Agricultural Engineering Research Priorities by ASAE, the society for engineering in agricultural, food, and biological systems. In 1993, the USDA National Agricultural Library and the Equipment Manufacturers Institute (EMI, an association of agricultural equipment manufacturers) co-sponsored a technology transfer project to identify sensor needs of the industry. Two of the top six priorities were sensors for soil property data and sensors to continuously measure crop yield.

Research and development efforts related to sensors for SSM are ongoing in a number of universities, government agencies and companies, both in the USA and abroad. This chapter reviews sensor developments and supporting scientific investigations from these organizations based upon the current literature and, in the case of industry, announced products. In addition to these developments, there are certainly a number of other continuing efforts which have not yet been reported. Also, readily available sensors that are only peripherally related to SSM, such as ground speed radar sensors, hydraulic system pressure sensors, or shaft rotational speed sensors are not discussed. Information on those types of devices is readily available from such references as Doebelin (1990) and Henry et al. (1991). An attempt has been made to give a comprehensive overview of those sensors and technologies that are applicable to measurement of soil-related and plant-related parameters important for SSM.

SOIL PROPERTY SENSING

Measurement of the soil properties that affect plant growth is a basic task in SSM. Although many soil properties (such as fertility levels) can currently be quantified by more traditional methods, widespread adoption of SSM will depend on automation to improve the efficiency of the soil property analysis process. The spatial and temporal intensity at which each property must be measured is a function of its variability. Some parameters, such as soil NO_3–N content and soil moisture content, can change rapidly (both spatially and temporally) and must be measured in real-time or near real-time to be useful for input control. Other parameters, such as organic matter content and topsoil depth will vary over a much longer time period, and can be measured off-line on a multi-year frequency. Likewise, spatial measurement intensity can be related to the spatial variation in the property being measured. Unfortunately, the necessary sampling intensity can only be determined after sampling on a fine mesh to determine the spatial variability, which is cost prohibitive without automated sensors.

There are two sources of error in soil testing — analysis error due to sub-sampling and analytical determination, and sampling error due to point-to-point variation in soils. With traditional soil testing, analysis error is relatively low; however, sampling error can be substantial since cost limits the sampling intensity. Real-time sensors can provide a sampling intensity several orders of magnitude greater than traditional methods. Therefore, a real-time soil sensor can tolerate much higher analysis errors while providing greater overall accuracy in mapping soil variability.

Soil Organic Matter

With many soil-applied herbicides, the application rate required for effective weed control increases as soil organic matter content increases. Organic matter variations as high as 2:1 were seen within an 80-m transect in a flat, apparently uniform field in Central Illinois (Sudduth & Hummel, 1993b); higher variations might be expected in areas with more variable topography or over longer distances. With this amount of variability, significant opportunity exists for cost savings and input optimization of soil-applied herbicides based on soil organic matter (SOM) content. Qiu et al. (1994) showed that up to one-half of preemergence herbicides applied in a typical Kentucky corn (*Zea mays* L.) field could be conserved using site-specific application based on variations in soil organic matter, texture, and weed competition. Soil organic matter content also affects N fertilizer needs. Many N recommendation algorithms allow a credit for the N-supplying power of the soil, which increases with increasing organic matter content.

The general observation that soils with greater organic matter contents appear darker formed the basis of the concept that electro-optical sensing of SOM might be feasible (Alexander, 1969). Researchers have investigated a number of approaches to automating this general concept, with varying degrees of success. Problems have occurred because soil color and/or reflectance are functions of properties such as moisture, texture, mineralogy, and parent material, as well as SOM.

Optical estimation of soil organic matter has been accomplished with color data and with wide-band and narrow-band spectral reflectance data. Soil color properties correlated with SOM have included the Munsell coordinates of hue, value, and chroma (Steinhardt & Franzmeier, 1979), as well as a number of Commission Internationale de l'Eclairage (CIE) color space coordinates (Page, 1974). In general, color has been a good estimator of SOM only when limits were imposed on the variability of other soil parameters that affect soil reflectance. A variety of data types and calibration methods have been used to correlate percent reflectance with SOM (Sudduth et al., 1991). The best results with visible reflectance data have been obtained with red light (Vinogradov, 1981), while the most predictive near infrared (NIR) wavelengths have ranged from 1700 nm to 2600 nm (Morra et al., 1991; Henderson et al., 1992).

Several researchers have developed optical SOM sensors to be used as a control input for variable rate herbicide application. These sensors have ranged from simple, single-wavelength devices to dedicated spectrophotometers capable of acquiring reflectance data at a number of wavelengths. Krishnan et al. (1980) correlated multiple-band reflectance characteristics in the 400 to 2400 nm range and SOM for ten Illinois soils at four moisture levels. Better correlations were obtained with visible range data than with NIR data. A first derivative model using optical density data yielded a coefficient of determination (r^2) of 0.85 with the calibration data set. Pitts et al. (1986) could not obtain satisfactory correlations when using this model with an expanded set of 30 Illinois soils ranging from 0.77 to 5.01% SOM. However, they were able to successfully predict a range of SOM for each of the 30 soils using an exclusion algorithm and polychromatic (white), green, and red reflectance data. The width of the prediction range for each soil was between 1 and 3% SOM, with an average width of 1.4% SOM.

Worner (1989) developed a portable spectrophotometer suitable for collection of multiple-wavelength visible/NIR reflectance data in the laboratory.

Smith (1991) modified this spectrophotometer for improved performance and reliability, and used it to collect reflectance data on the same set of 30 Illinois soils used by other researchers (Pitts et al., 1986; Sudduth & Hummel, 1993b). Analysis of combined field capacity and wilting point moisture level data by stepwise multiple linear regression yielded an r^2 of 0.61 and a standard error of prediction (SEP) of 0.79% SOM.

Griffis (1985) developed and tested a SOM sensor consisting of an incandescent source and silicon phototransistor mounted in a light-proof housing. An r^2 of 0.75 was obtained in laboratory tests with a set of 18 air-dry Arkansas soils ranging from 0.33 to 3.41% SOM. Kocher and Griffis (1989) reported on an elevating chain and horizontal belt system that was used to convey soil past the sensor developed by Griffis (1985). In laboratory tests with sieved, air-dry soil, the conveying mechanism-sensor combination was successful in locating a step change in soil type.

Gunsaulis et al. (1991) studied the effect of soil surface structure on reflectance from a red (660 nm) light-emitting diode (LED) source. Surface preparation was by sieving the air-dry soil and then scraping or rolling the surface before obtaining reflectance measurements. Two sensor geometries were tested, one that measured only diffuse reflectance and one that measured both diffuse and specular reflectance components. The 20 Arkansas soils used ranged from 0.47 to 2.1% SOM. The best results ($r^2 = 0.61$) were obtained with absorbance data from the diffuse-specular sensor, the largest sieve size (3.66 mm) and a scraped soil surface. Attempts to minimize surface structure effects by passing the soil through small sieves and rolling the surface smooth resulted in weaker ($r^2 = 0.40$) correlations with SOM. Improved results ($r^2 = 0.73$) were obtained with multiple linear regression on data obtained from both sensors.

Fernandez et al. (1988) correlated Munsell color with SOM for a given soil catena, which is a sequence of soils similar in terms of age, parent material, and climatic conditions, but having different characteristics due to variation in relief and drainage. They hypothesized that the relationship between color and SOM would be closer within a catena than those previously reported for wider geographic areas. Samples collected from three soil series in each of two catenas yielded strong correlations between SOM and the Munsell value parameter (moist soil $r^2 = 0.92$, dry soil $r^2 = 0.94$). Different calibrations were required at the two moisture levels, and the calibrations developed were applicable only within the catenas studied, containing only silt loam and silty clay loam soils.

Shonk et al. (1991) built upon the work of Fernandez et al. (1988) and developed a real-time SOM sensor intended to be recalibrated for each new soil catena. The sensor consisted of compact transmitter and receiver modules that utilized light reflectance to measure SOM. Light emitting diodes (LEDs) were arranged in an array around a photodiode to focus an intense beam of light on the soil surface directly below the photodiode. The position of the LEDs assured equal illumination of the sensed surface by each diode, minimizing specular, or surface, reflectance. The field of view of the photodiode was constrained to the most intensely illuminated area of the soil surface and sensor height was 25 mm above the soil surface. Laboratory tests using red (660 nm) LEDs as the light source on soil samples collected from five representative Midwestern U.S. fields yielded strong correlations ($r^2 = 0.80$ to 0.98) for soils obtained within a single catena and prepared to a single moisture content. Coefficient of determination values were greater for moist soils than air-dry soils. A linear relationship was found between light reflectance and SOM for two catenas, both having fine and medium textured soils. For field operation, the sensor was mounted to a tractor tool bar and operated below the soil surface to minimize the effect of soil moisture, soil surface roughness, plant cover, and crop residues on the sensor output. Field tests showed a curvilinear relationship between sensor output and SOM ($r^2 = 0.84$ to 0.95), with new calibrations developed for changes in travel speed or sensing depth (Shonk et al., 1991).

The sensor developed by Shonk et al. (1991) was licensed for commercial development and used to control the rate of a granular herbicide formulation applied by a pneumatic metering system (McGrath et al., 1990). The probe was mounted to the front of a custom applicator and operated at a depth of 10 cm and speeds of up to 19 km hr^{-1}. Soil samples were collected from each different soil catena to develop a specific sensor calibration curve. McGrath et al. (1990) noted that moisture and surface preparation significantly affected sensor output, and stated that calibration should be carried out under conditions similar to those encountered at the time of chemical application. The variable rate application system satisfactorily applied herbicides in a number of field tests, and weed control was reported as excellent in all cases.

Sudduth and Hummel (1991) conducted laboratory tests using a representative set of 30 Illinois mineral soils and concluded that NIR data analyzed by partial least squares regression (PLSR) held the most promise for prediction of SOM. PLSR, a latent variable regression method, was used to reduce the set of collinear independent variables (reflectances) to a smaller set of orthogonal components which represented most of the variability in the original data and contained a reduced amount of random measurement noise (Martens & Naes, 1987). The analysis technique was evidently able to minimize the effect of moisture, resulting in improved SOM prediction as compared with single-wavelength sensing. Excellent correlation ($r^2 = 0.92$, SEP = 0.34 % SOM) was obtained when the NIR data were smoothed to a 60-nm data point spacing and the wavelength range was reduced to 1720 to 2380 nm, for a total of 12 reflectance points used (Sudduth & Hummel, 1991).

A rugged, portable NIR spectrophotometer was developed to implement this prediction method and laboratory and field tests were completed (Sudduth & Hummel, 1993a,b). The sensor used a circular variable filter spinning at 5 Hz to sequentially provide monochromatic, chopped light from a broadband quartz-halogen source. A fiber optic bundle transmitted the monochromatic light to the soil surface, allowing remote mounting of the major portion of the sensor. A lead sulfide photodetector captured the energy diffusely reflected from the soil surface. The output from the detector was conditioned by an AC-coupled preamplifier and input to a PC through a 12-bit A/D converter. The effective sensing range was from 1630 to 2650 nm, on a 52 nm bandpass. The portable spectrophotometer predicted organic matter in the laboratory, across a range of soil types and moisture contents, with a predictive capability ($r^2 = 0.89$, SEP = 0.40% SOM) approaching that of data obtained on the same soils with a research-grade spectrophotometer. Field operation of the prototype sensor did not yield acceptable results (SEP = 0.91% SOM), due at least in part to errors introduced by the movement of soil past the sensor during the scanning process (Sudduth & Hummel, 1993b). Additional laboratory tests of this NIR sensor with soils obtained from across the continental USA showed that acceptable soil organic matter predictive capability could be maintained with a single calibration equation for soils from the lower U.S. Corn Belt. Calibrations obtained for wider geographic areas suffered from a significant decrease in accuracy. A similar sensitivity analysis carried out on the soil reflectance database compiled by Stoner and Baumgardner (1981) confirmed these results (Sudduth et al., 1990).

The prototype NIR sensor was redesigned for improved accuracy, faster data collection, and improved portability (Sudduth & Hummel, 1993c). Changes were made to the optical design of the sensor for increased spectral resolution and improved signal/noise ratio. Electronic modifications reduced the complexity and amount of off-line computation required to process the reflectance signal to usable form, and a dedicated single-board computer was implemented for system calibration and optical performance evaluation. Bandwidth of the revised instrument was 45 nm, wavelength instability was essentially eliminated, and reflectance data could be obtained on-line within 10 s. Although optical performance and reliability were improved, the ability of the sensor to estimate soil organic matter was essentially unchanged from the initial prototype.

Soil Moisture

Whalley and Stafford (1992) reviewed a number of sensing methods applicable to soil water content measurement for SSM. They categorized these as noncontact methods, including near infrared reflectance (NIR), ground penetrating radar (GPR), and microwave reflectance; and contact methods, including microwave, capacitance, and resistance.

Optical sensing of soil moisture using NIR takes advantage of the several water absorption bands in the NIR spectrum. Researchers have used data obtained at two (Christensen & Hummel, 1985; Kano et al., 1985) or three (Dalal & Henry, 1986) wavelengths, and have usually obtained good correlations ($r^2 > 0.9$) between soil moisture and reflectance. A disadvantage to the NIR approach is that it is only responsive to the water content at the measurement surface.

Price and Gaultney (1993) developed a real-time optical sensor for soil moisture based on measuring the relative reflection of light from the soil surface illuminated by three sequentially pulsed laser diodes at 750, 810, and 840 nm. A maximum likelihood classifier algorithm was used to determine the most likely moisture content of the soil. In laboratory tests conducted on 29 soils encompassing three soil textures (loam, silt loam, and silty clay loam) and five soil moisture tensions, the sensor was able to classify 82% of the samples correctly into moist (0.01, 0.03, or 0.05 MPa) or dry (0.1, or 1.5 MPa) categories. In field tests, at speeds of 2 to 3 km hr^{-1}, the sensor correctly classified 82% of the soil samples. As long as soil type did not vary greatly, the sensor could estimate soil moisture with sufficient accuracy for planting depth control, where the objective is locating the drying front where soil moisture transitions from dry to moist in a relatively small depth increment.

The portable NIR spectrophotometer developed by Sudduth and Hummel (1993a) for organic matter measurement also was usable to measure soil moisture. Spectral reflectance data obtained in the laboratory (Sudduth & Hummel, 1993b) were correlated with laboratory determined gravimetric moisture for 30 Illinois soils. Moisture content was predicted with a SEP of 1.88% ($r^2 = 0.94$) for a data set including soil moisture tensions of 0.033, 0.33, and 1.5 MPa, and air-dry soil. In terms of the coefficient of variation (CV), the prediction of soil moisture was more accurate than the prediction of SOM.

Microwave reflectance measurements of soil water were examined theoretically by Whalley and Bull (1991). They reported that microwave reflectance would likely give good estimations of the surface water content to a depth of approximately 0.1 m; however, they envisioned difficulties in calibration of the reflectance signal and in the dependance of the dielectric constant on soil type. Ground penetrating radar (GPR), which measures the time delay of a reflected signal to quantify the depth to a dielectric interface, may have some promise for soil moisture measurement. Truman et al. (1988) noted that the dielectric constant of a saturated soil layer is much greater than that of an unsaturated soil, making it possible to locate that interface by GPR.

Whalley et al. (1992) developed a capacitance-based soil moisture sensor that was designed to be installed on a single soil-engaging tine. Field tests were promising, although there was some dependence of sensor calibration on dry bulk density of the soil. Whalley (1991) also developed a microwave soil moisture sensor designed to be incorporated into a narrow cultivator tine. Good calibrations were obtained in a soil bin with uniform soils, but calibrations for structured soils were not as good, due to the small sampling volume of the sensor.

Soil electrical resistance measured between two soil engaging tines or shanks was used in the development of a moisture-seeking planter controller (Carter and Chesson, 1993). Soil electrical resistance was found to change rapidly with depth near the soil moisture front, allowing control of seed placement based on measured resistance. Use of such a sensor to measure actual soil moisture could be complicated by the dependence of soil electrical conductivity on soil salinity and clay content, along with soil moisture (Rhoades et al., 1989).

Since soil conductivity is a function of soil salinity, clay content, and water content, soil conductivity measurements have the potential for providing estimates of within-field variations in these properties for SSM; however, care must be taken to understand the effects of the other, nonestimated properties on the conductivity measurement. In areas without saline soils, spatial variation in soil moisture content is often a major factor determining variations in bulk soil conductivity. Kachanoski et al. (1988) found that soil electrical conductivity was highly correlated with soil water content stored in the top 0.5 m, within a single field and on a single measurement date. Sheets and Hendrickx (1995) measured electrical conductivity along a 1950 m transect in New Mexico during a 16-mo period and found a linear relationship between conductivity and profile soil water content. Independent measurements of soil water at several calibration points along the transect were required for each measurement date. In both of these studies, soil conductivity was measured using commercial electromagnetic induction (EM) ground conductivity meters, the EM-31 and EM-38 (Geonics Ltd.[1], Mississauga, Ontario, Canada). These portable meters allow immediate, noncontact measurements of soil conductivity. They can be coupled with GPS location equipment and data loggers, and pulled across a field using an all-terrain vehicle (ATV) to rapidly map conductivity variations over large areas (Jaynes et al., 1995a).

Soil Nutrients

At present, the focus of the commercial implementation of SSM is on yield mapping and variable rate fertilizer application; however, unlike yield mapping, where yield monitors are already commercially available, automated soil nutrient sensors are still in the early development stages. There is an ongoing need to develop automated systems to decrease the cost of soil nutrient sampling and improve the accuracy of soil nutrient maps. Current real-time nutrient sensor development has concentrated on N sensors, due to the economic importance of N fertilizers, potential environmental problems associated with excessive NO_3–N in water, and the considerable temporal and spatial variability of NO_3–N. The variability of soil NO_3–N levels dictates that sampling occur within a short time prior to fertilizer application and at a very high sampling intensity. Since K and P are immobile nutrients, and soil pH changes relatively slowly, mapping of these soil properties need not be carried out every year, allowing the cost of traditional soil sampling techniques be spread over multiple years.

During the past few years, several different systems for field analysis of soil nutrients have become available. Test kits, such as those provided by LaMotte and Hach, are available for the major soil nutrients (N in both NO_3–N and NH_4–N forms, K, and P_2O_5), soil pH, and many of the micronutrients. The tests are generally colormetric methods using chemical reagents or chemical test strips. The colorimetric analysis methods range from visual comparison of the color development to a color chart or color comparator disks, to the use of pocket colorimeters or spectrometers. Most chemical test strips are visually compared with standard color charts to determine the concentrations; however, newer systems like the Agri-Lab from Spectrum Technologies (Plainfield, IL) and Reflectoquant Analysis System have a digital test strip analysis system to provide the concentrations directly. Several laboratory studies have shown that ion-selective electrodes can be used to measure soil nutrients (Dahnke, 1971; Yu, 1985). Hand-held Cardy meters for NO_3–N, K and Na ions which are based on ion selective membranes and provide a reading in a matter of minutes are commercially available (Spectrum Technologies). The accuracy of field tests with all of these portable units depends more on the individuals conducting the test than the inherent accuracy of the test method, making quality assurance difficult. With these test kits, results are

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[1] Mention of a trade name, proprietary product, or specific equipment does not constitute a guarantee or warranty by the USDA-ARS or the University of Missouri and does not imply the approval of the named product to the exclusion of other products that may be suitable.

obtained immediately in the field; however, the labor and time required for soil sample collection makes them less than perfect for SSM soil analysis.

Adsett and Zoerb (1991) reported on real-time NO_3–N sensing using ion selective electrodes. An automated field monitoring system consisting of a soil sampler, NO_3–N extraction unit, flow cell, and controller was laboratory and field tested. Their soil sampling concept, based on a chain saw bar, appeared to have potential as a continuous soil sampler; however, the consistency of the sample varied with soil type, relative forward speed, compaction, and soil moisture content. The soil sample consistency affected the performance of the NO_3–N extraction system and the mixing and filtration system required improvement. The NO_3–N extraction time and methodology were limiting factors in the system. Additional research was planned to improve the mixing and extraction phases. Thottan et al. (1994) reported on subsequent laboratory work on the effects of different soil/extract ratios and extract clarity on electrode response and electrode response time. They found that there was no significant difference ($\alpha = 0.05$) among different soil/extract ratios (1:15, 1:5, 1:3) and no significant difference among final NO_3–N concentration indicated in either decanted, filtered, or soil/extract suspension samples. Normalizing the response of the electrode for time showed that 80% of final concentration was consistently indicated within 12 s, 40% within 6 s, and 10% within 4 s, which they felt was within the time required for rapid in-field measurements.

Ion selective field effect transistors (ISFETs), which are based on the same chemical principles as ion selective electrodes, have several possible advantages such as small dimensions, low output impedance, high signal-to-noise ratio, fast response and the ability to integrate several sensors on a single electronic chip. ISFETs have the disadvantage, however, of greater long-term drift and hysteresis than ion selective electrodes. The use of a dynamic measurement system such as flow injection analysis (FIA) minimizes the effects of drift and hysteresis and exploits the specific properties of ISFETs. Birrell and Hummel (1993) investigated the use of a multi-ISFET sensor chip to measure soil NO_3–N in a flow injection analysis (FIA) system using different flowrates (0.04–0.19 mL s^{-1}), injection times (0.25–2 s), and washout times (0.75–2 s). The multi-ISFET/FIA system was successfully used to measure soil NO_3–N in manually extracted soil extracts ($r^2 > 0.9$) using a 0.5 s washout time and a 0.75 s injection time (Hummel & Birrell, 1995). A prototype automated extraction system was tested; however, the extraction system did not consistently provide soil extracts that could be analyzed by the FIA/ISFET system and required considerable improvement. The rapid response of the system allowed samples to be analyzed within 1.25 s and the low sample volumes required by the multi-sensor ISFET/FIA system made it a likely candidate for use in a real-time soil nutrient sensing system.

While ion selective electrodes have been used in soil nutrient testing for many years, the disadvantage of real-time sensors based on this technology is that a soil sample must be acquired, mixed with an extractant and a soil extract obtained for analysis. A noninvasive technology would provide significant advantages in the development of real-time soil nutrient sensors. Preliminary studies by Upadhyaya et al. (1994) found that the signals from gamma ray irradiation were not strong enough for practical real-time soil NO_3–N sensing and that nuclear magnetic resonance (NMR) techniques were infeasible, while dielectric dispersion methods showed some encouraging results but were not investigated further. Dalal and Henry (1986) used NIR reflectance to measure total N (r^2>0.92) in soils with some success; however, the prediction capability of NIR at lower concentrations of total N (Kjeldahl total N < 0.05%) was poor and it was not possible to predict total N across a wide range of soil colors. Dalal and Henry (1986) found that for certain soils the NIR technique erroneously predicted total N and the standard error of prediction increased. Upadhyaya et al. (1994) used NIR reflectance in conjunction with partial least squares regression (PLSR) and Fast Fourier Transform (FFT) analysis techniques to sense mineral soil NO_3–N (0–300 mg kg^{-1} NO_3–N). The correlation between the NIR methods and standard NO_3–N methods was high (r^2 > 0.9), if the correlation was blocked by moisture content (air dry, 10%, 15%) and N fertilizer source (NH_3NO_3, $Ca(NO_3)_2$). The standard error of prediction ranged from 6–38 mg kg^{-1}; however, when the two fertilizer sources and three moisture contents were pooled the correlation decreased (r^2 = 0.70) and the standard error increased to 43 mg kg^{-1}. Upadhyaya et al. (1994) found that both the FFT and PLSR analyses reasonably predicted the soil mineral-N content, although the standard prediction error was fairly high and needed to be reduced for successful application of this technique.

Researchers at the Georgia Institute of Technology developed an integrated optical ammonia sensor capable of measuring a range of NH_3 levels from less than 0.1 to 1000 mg kg^{-1} (Hartman et al., 1995) for quantifying NH_3 volatilization from cropland (Walsh et al., 1990). The sensor was based on an optical waveguide structure using an interferometric mode. The main focus of the project was on optimizing fertilizer use through improving application methods, and while NH_3 volatilization was not a direct indicator of N availability in the soil, NH_3 emissions were seen as indicators of soil chemistry as it related to soil fertilizer management techniques (Babbitt, 1991).

Crop Technology (Houston, TX) has developed and brought to the market a variable N application system. The original prototype used soil slurry electrical resistivity to estimate soil NO_3–N concentrations (Colburn, 1986). The currently available system uses rolling coulters as electrodes to determine soil NO_3–N levels (Crop Technology, 1991); however, no information has been made publicly available on the operating principles of the sensor.

An integrated system of soil sample collection, automated sample preparation and chemical analysis with decision support software has been developed by Tyler Ltd. (McGrath et al., 1995). The sampler automatically collected samples across the field and packaged them in plastic bags that were connected to form a long band. The banded samples were then analyzed using an automated laboratory workstation set up near the field. The initial preparation of the automated workstation required 90 minutes and then samples could be analyzed at a rate of 1 min^{-1}. Macro-nutrient concentrations (NO_3–N, NH_4–N, K, P, Ca, Mg), particle size (<10μ, 10–100μ), overall humus, alkali-soluble humus, sequioxides, carbonates and soil acidity were determined (McGrath et al., 1995). The analysis results were then input into an expert system to determine fertilizer recommendations.

Soil Texture, Structure, and Physical Condition

Soil physical characteristics are extremely important for crop production. Soil structure or degree of aggregation influences root growth, hydraulic conductivity, and aeration due to the size of the pores present in the soil matrix. The structure of the soil surface, or seedbed, is important in providing good soil-seed contact for germination. The presence and location of a restrictive layer, such as a hardpan, plowpan, or claypan, can be a major factor in crop growth. In a more general sense, the soil physical condition can be viewed as those physical characteristics that are important for plant growth and are influenced by tillage operations. The ability to precisely manipulate a soil from an initial to a desired final physical condition implies the need for sensors to assess this property (Schafer et al., 1981).

Zuo et al. (1995) used a fiber optic displacement sensor to evaluate air-dry soil aggregate size in the laboratory. This commercial sensor provided an output signal proportional to the distance from the sensor to the soil surface. The spatial pattern of peaks in the sensor output correlated well with soil aggregate size. This measurement also was relatively insensitive to the distance between the sensor and the soil surface. Stafford and Ambler (1990) reported on a computer vision system used to assess seedbed structure. Tests indicated that data from the vision system compared well with the traditional sieve analysis for aggregate size.

Stafford and Hendrick (1988) investigated variations in soil strength for sensing of compaction-induced hardpans, as an input to a tillage control system. They found that the forces on a small blade mounted behind a subsoiler tine and projecting down into undisturbed soil were indicative of soil strength. A tillage control system was proposed where tillage depth would be continuously varied in response to the location of the maximum soil strength, assumed to be at the level of the pan. Raper et al. (1990) successfully used ground penetrating radar (GPR) to sense hardpan depth for two soils in a soil bin. They also noted that information on the relative density of the hardpan might be contained in the GPR signal, but this analysis was hampered by the absence of digital data recording in the GPR unit they used.

Soil physical condition sensing for tillage control was investigated by Young et al. (1988). They used time series analysis techniques, including autoregressive modeling, applied to instantaneous draft (horizontal force) measurements from wedge and blunt vertical chisels. Mean draft, residual draft, and the autoregression coefficients were sufficient to characterize soil physical condition, but they noted that a major difficulty of their work was the need to specify the desired soil condition based upon agronomic considerations. Smith et al. (1994) built upon this work and investigated coulter draft forces as an indication of soil condition. Roytburg and Chaplin (1995) proposed using soil resistance force, as measured with an extended octagonal ring transducer, as an indicator of the changes in soil condition during tillage.

Soil conductivity measurements can provide information on soil texture, in addition to estimating soil water content as discussed earlier. Williams and Hoey (1987) used EM measurements of soil conductivity to estimate within-field variations in soil clay content. Doolittle et al. (1994) related EM measurements to the depth of a claypan horizon by means of an exponential regression (r^2 = 0.81). An automated EM sensing system was then used to map claypan depth across a number of fields by Kitchen et al. (1995). They obtained calibration measurements of claypan depth with a soil probe at a number of locations within a field to remove the effects of temporal variations in soil water content and temperature. Since soil conductivity integrates texture and moisture availability, two characteristics that both vary over the landscape and also affect productivity, EM sensing of conductivity shows some promise in interpreting grain yield variations, at least in certain soils (Sudduth et al., 1995; Jaynes et al., 1995a, Kitchen et al., 1995). EM data also have been used to estimate other soil properties related to clay content, including cation exchange capacity (McBride et al., 1990) and atrazine partition coefficients (Jaynes et al., 1995b).

CROP SENSING

Crop Stress and Nutrient Status

Generally, fertilizers are applied to crops according to soil fertility recommendations based on soil samples. However, for nutrients such as N that exhibit significant temporal variations, climatic conditions between soil sampling and the period of maximum N intake cause considerable uncertainty on how much fertilizer to apply. The development of sensors that monitor crop nutrient status during the growing season could allow a reduction of initial fertilizer application rate, with additional fertilizer applied during the growing season if the crop experiences nutrient stress.

Benedict and Swindler (1961) reported on an inverse relationship between reflectance and chlorophyll in soybeans and showed that reflectance measurements could be used to follow changes in chlorophyll content. Thomas and Oerther (1972) found that the N content in pepper (*Capsicum frutescens*)leaves was highly correlated with reflectance at 550 nm and 675 nm (r^2= 0.86 and 0.81, respectively) and reported that the prediction error was <0.7% N content. Al-Abbas et al. (1974) analyzed the spectra of normal and nutrient deficient (N, P, K, S, Ca, Mg) corn leaves and found that the nutrient deficiencies led to a reduction of leaf chlorophyll content, which then altered leaf color, spectral reflectance and transmittance in the visible region of the spectrum (500–750 nm). Thomas and Gausman (1977) investigated the effects of leaf chlorophyll and carotenoid concentrations on reflectance at 450, 550, and 670 nm for eight different crops, concluding that the 550 nm wavelength was superior to the 450 and 670 nm wavelengths for relating reflectance to either total chlorophyll or carotenoid concentration.

A portable leaf chlorophyll meter (SPAD-501 later replaced by the SPAD-502, Minolta Corp.) has been developed. The later version of the meter has two light-emitting diodes, active at 650 and 940 nm. The chlorophyll content of a small section of the leaf is determined using the ratio of transmittance at 650 nm, which is affected by leaf chlorophyll content, and transmittance of light at 940 nm, which is not sensitive to chlorophyll content and serves as a reference. The meters have successfully been used to determine leaf chlorophyll in rice (*Oryza sativa* L.) (Takebe et al., 1990), sorghum (*Sorghum bicolor* L. Moench) (Marquardt and Lipton, 1987), tomato (*Lycopersicon esculentum* L.) (Tenga et al., 1989) and corn (Dwyer et al., 1991; Wood et al., 1992; Schepers et al., 1992). Dwyer et al. (1991) reported that the individual regressions of chlorophyll meter readings and

chlorophyll content for each growth stage and hybrid combination were not significantly different, and a single regression equation using all the data was valid.

Schepers et al. (1992) found that factors such as crop growth stage, hybrid, and timing and type of N fertilization all affected the feasibility of calibrating the SPAD-502 chlorophyll reading to leaf NO_3–N concentrations across all conditions; however, both Schepers et al. (1992) and Wood et al. (1992) found that the chlorophyll meter readings correlated as well or better with yields than did leaf N concentrations. Schepers et al. (1992) proposed normalizing SPAD-502 readings relative to an adequately fertilized area of the field, so that the normalized data would essentially be internally calibrated for each field, hybrid, stage of growth and cultural practice. Blackmer et al. (1993) reported that the chlorophyll meter readings were affected by within row plant spacings and that plants having extreme spacings should be avoided when using the chlorophyll meter, since plant spacing had a greater effect on chlorophyll meter readings than leaf N concentrations. Blackmer and Schepers (1994, 1995) used a sufficiency index (SI = field meter reading/reference meter reading from adequately fertilized area) and provided additional N fertigation during the season when the index decreased below 0.95, to prevent yield loss. Schepers (1994) reported that while leaf N concentration increased with luxury consumption of N, the chlorophyll meter did not respond to luxury consumption, simplifying calculation of the sufficiency index to distinguish between N deficient crops and N sufficient crops.

The studies mentioned above all investigated reflectance characteristics of single leaves, however many papers report on the use of canopy reflectance measurements to determine the physiological condition of crops. Such canopy reflectance measurements may be acquired by means of remote sensing techniques, or through the use of close-range sensors attached to equipment operating within a field. Although changes in leaf reflectance are important stress indicators, differences in leaf area index (LAI) are frequently more useful for spectrally separating healthy from stressed plant canopies (Knipling, 1970). Changes in LAI can result in changes in spectral reflectance of crop canopies in the infrared and near infrared without any change in the reflectance properties of individual leaves (Colwell, 1974). Stanhill et al. (1972) reported that the spectral response of N-deficient wheat (*Triticum aestivum* L.) was primarily related to total phytomass and that leaf optical properties were secondary. Although Walburg et al. (1982) and Hinzman et al. (1986) were able to distinguish between corn and wheat canopies with different levels of N fertilization, the differences in spectral response between treatments were a result of soil cover differences, LAI, and leaf pigmentation values, all of which changed with N treatment.

Takebe et al. (1990) reported on the use of a Canopy Green Meter (Model CP-1, Minolta Corp.) which used a ratio of the spectral reflectances of the crop canopy at 800 and 550 nm to the spectral reflectance of a standard white surface to determine an index called Green Color Intensity. The intensity of solar radiation affected measurements and problems were encountered with measurements taken during sunny or windy periods and early in the morning or late in the evening; however, meter readings for a rice canopy were highly correlated to the total N and chlorophyll content (r^2 = 0.81 and 0.86, respectively) from the second leaf from the top of the canopy. Blackmer et al. (1994) found that leaf reflectance at 550 nm was highly correlated ($r^2 = 0.90$) to both chlorophyll meter readings and leaf N content for four hybrids grown with five different N application rates. Blackmer et al. (1995) used aerial photography to measure the light reflectance centered on 550 nm from a field and showed a linear relationship between grain yield and measured light reflectance values from a single site with one hybrid and 10 N application rates. Bausch et al. (1994) developed a reflectance index using spectral reflectance measurements of the crop canopy in the blue (450–520 nm), green (520–600 nm), red (630–690 nm) and NIR (760–900 nm) wavelengths, similar to the sufficiency index developed by Schepers et al. (1992) from SPAD readings. The reflectance index was calculated as the NIR/green ratio from the treatment area divided by the NIR/green ratio from the reference area with adequate N. There was almost a 1:1 relationship between the reflectance index and sufficiency index, except during early vegetative growth when soil background effects caused differences.

Stone et al. (1995) reported on the development of a tractor-mounted crop nutrient sensor based on spectral reflectance. The integrated sensor consisted of photodiode detectors and interference filters for red (671 ± 6 nm) and NIR (780 ± 6 nm) spectral bands with a 0.46m wide by 0.075 m long spatial resolution, an ultrasonic sensor to measure the height of the reflectance sensor and a signal processing system. The detector used the plant-N-spectral-index (PNSI), which was calculated as $|(NIR + red)/(NIR - red)|$. Stone et al. (1995) found that the PNSI was correlated to total N uptake in wheat forage at different locations and stages of growth. The PNSI was used for variable rate N application. Wheat grain yields increased significantly with N top dressing in both the fixed rate and variable rate treatments compared to the check plots; however, no significant differences in yield were found between the fixed and variable rate treatments. Solie et al. (1995) used geostatistics to investigate the spatial variation of the PNSI, to estimate the unit application size. The range of spatial dependence depended on location of the transect and the direction of travel with respect to the orientation of rows. Solie et al. (1995) determined that the fundamental application cell size was between 0.21 and 0.83 m long, by the sensor width of 0.46 m.

Several researchers have used machine vision and image analysis to detect plant stress. Omasa et al. (1987) reported on the development of an instrumentation system for obtaining whole-leaf chlorophyll fluorescence images. Chlorophyll fluorescence is a sensitive indicator of the effects of stress on the photosynthetic process. Okamura et al. (1993) used imaging to determine the green chromaticity of the youngest leaf of musk melon (*Cucumis melo* L.) plants to detect the start of water stress in the plants. Casady et al. (1994) used machine vision to determine various features of rice plants, such as projected plant area, plant height and width, and leaf width, which were used in conjunction with SPAD chlorophyll readings to develop several models representing the relationship between these mid-season measurements and rice grain yield. Kole et al. (1995) studied the use of machine vision to measure the top projected leaf area of lettuce (*Lactuca savita* L.) leaves and used the rate of change in projected area to investigate the effect of nutrient stress.

Plant Population

Plant population may vary considerably across a field, either due to planting or emergence problems or because of pest infestations. In addition, variable rate planters are now available, which allow changing of seeding rate based on productivity variations within a field. A sensor that could determine plant population would be desirable in either case, as population has been shown to have a significant effect on corn yield across soil types.

Birrell and Sudduth (1995) reported on a combine mounted sensor to map corn population at harvest. The sensor consisted of a spring loaded rod attached to a rotary potentiometer, mounted on the row dividers on the combine head. The sensor was tested under normal harvesting conditions at three different operating speeds. Heavy weed infestations caused significant errors at low speeds. The accuracy of the sensor was speed dependent, and population prediction error using the raw sensor outputs were <70, <20 and <5% (with one exception) for the 3.2, 5.6 and 8.0 km h^{-1} tests. However, by using different time-based and distance-based filtering techniques, the error could be reduced to <10% for the slowest speed, and to <5% for the faster speed. The sensor consistently identified gaps in the row regardless of combine speed and weed infestation levels.

Plattner and Hummel (1995) investigated the use of photoelectric sensors to measure the distances between adjacent plants in a row, along with the stem diameter of each plant. An emitter projected a light beam across the row to a receiver as the sensor traveled down the row. The light and dark intervals resulting from plants breaking the beam and forward velocity of the sensor were used to determine the distance between plants. Preliminary results indicated the sensor could operate at ground speeds of up to 3 m s^{-1} with plant spacing accuracies of ±3%.

PEST SENSING

Site-specific sensing of crop pests such as insects and weeds would allow control measures such as crop protection chemicals to be applied only when and where needed. Researchers have been able to detect some insect species by acoustic methods (Hendricks, 1989). Work is ongoing to adapt this technology for remote, in-field sensing of insect pests (McKinion, 1996).

In the area of weed detection, the ability to discriminate green vegetation from soil by ratioing the intensities of visible and near-infrared radiation reflected from a surface was demonstrated nearly 20 yr ago (Hooper et al., 1976). Relatively simple two-wavelength sensors can locate green plant material on a background of bare soil and control spray nozzles to spotspray for fallow weed control (Felton and McCloy, 1992). Similar sensors have been used to control spray application of herbicides between the rows of a row crop (Merritt et al., 1994, Woebbecke et al., 1995a). Hanks (1995) reported on a sensor/nozzle unit that had been developed in cooperation with Patchen California, and tested on an 8-row toolbar for controlling weeds in row middles. The Weedseeker (Patchen, Los Gatos, CA) projected a 5-mm-wide band of light onto the soil when positioned 30 to 90 cm above the soil surface, and could detect green plant material as small as 0.1 cm^2.

Research scientists also have attempted to distinguish weed species from crop species on the basis of spectral properties (Franz et al., 1991a) or plant geometry (Woebbecke et al., 1995b; Tian & Slaughter, 1993; Franz et al., 1991b). Guyer et al. (1986) concluded that there is significant potential for image processing to identify weeds, particularly since only the crop species needs to be identified from among a range of weed species; however, Thompson et al. (1990) reported that weed detection between the rows of a drilled cereal crop was severely limited due to the crop canopy, even at early stages in the crop growth cycle.

The high cost and complexity of machine vision systems and the voluminous quantities of data to be processed, have led some researchers to conclude that, for the foreseeable future, site-specific weed control will be based upon the development of maps that will control sprayer output (Thompson et al., 1991). Geographic information systems can be used to store maps of weed distributions and to predict weed densities from historical data (Brown et al., 1990; Stafford and Miller, 1993). Mapping of weeds at opportune times such as flowering and senescence for control during the subsequent season could enhance the accuracy of the map, as well as provide information on the species of the weed infestation (Thompson et al., 1991). The use of a map to control herbicide application during the next season is valid because many weed species appear in well-defined patches that remain relatively static from year to year (Brown et al., 1990).

SENSING OF HARVEST PARAMETERS

Crop Yield

Within-field variation of crop yield is an important input for site-specific decision making. Crop yield is an integrator of many varying crop and soil parameters, such as moisture, nutrients, or pest problems. Linking spatial information on both yield and soil properties through a GIS system allows for diagnostic determination of the predominant factor(s) controlling crop production. This information then becomes the basis for developing precision input strategies. Additionally, yield measurements can provide feedback on the effect of variable rate application of inputs, allowing refinement of the application plan for future years. There have been yield sensors developed for crops such as potatoes (*Solanum tuberosum* L.), forage, and hay, but most yield sensing efforts have focused on grain crops.

Combine-based quantification of spatial variations in grain yield requires the successful integration of several sensors and information sources. Grain flow rate must be measured at some point on the combine, usually as the material enters the grain tank. The grain transport dynamics of the combine must be modeled and used to adjust the measured grain flow to recreate the actual rate of grain entering the combine header (Searcy et al., 1989). Combine forward velocity must be measured or determined to convert from grain harvest rates per unit time to harvest rates per unit area, or yield. In drilled grains, the width of cut must be measured to provide an accurate measure of yield. Combine position within the field must be determined and that data integrated with the other data streams. Finally, all these data must be combined and processed to provide interpretable grain yield maps. Several grain flow sensors are either on the market or in commercial development. In addition, a

number of other prototype units have been developed by public sector researchers (i.e., Wagner & Schrock, 1989; Vansichen & DeBaerdemaeker, 1991). More information on specific grain yield sensors can be found in another chapter of this publication (Pierce et al., 1997, this publication).

Vansichen and DeBaerdemaeker (1993) developed a technique for measuring corn silage yield using torque transducers on the silage blower shaft and cutterhead drive shaft. They found that these torque signals, integrated more than a 2500 kg load of silage, were good estimators of silage flowrate. Blower shaft torque was the better estimator, possibly due to a greater effect of material property variations (e.g., stalk toughness) on cutterhead torque requirements. Auernhammer et al. (1995) developed a radiometric yield measurement system for a self propelled forage harvester. This system used a radioactive source and detector placed on opposite sides of the forage harvester discharge chute to measure the mass of material flowing through the chute. They reported relative standard errors on a trailer-load basis of 7.1% for a calibration developed using data from 20 fields. The error could be reduced significantly by calibration within individual fields. They found that material moisture did not significantly affect the calibration, but that different calibrations were required for different forage crops.

Wild et al. (1994) reported on a hay yield measurement system for round balers. They used strain gages on the tongue and axle to weigh the baler plus bale, both on-the-go and in a stationary mode, after the bale was completely formed and tied. Accelerometers were mounted adjacent to the strain gages to measure vertical accelerations during operation. When stationary, yields could be measured with errors <2%. The authors stated that instantaneous yield determination on-the-go was still under investigation, in order to develop an acceptable system.

Wilkerson et al. (1994) developed a real-time cotton (*Gossypium hirsutum*) flow sensor for yield mapping. An array of lights and a photodetector array were installed on opposite sides of the cotton picker discharge chute, in order to measure the light attenuation due to cotton passing through the sensor. In laboratory tests, integrated sensor output correlated well with total cotton mass passing through the sensor ($r^2 = 0.93$). Settings for cotton flow rate and blower air flow rate also were found to affect the calibration of the sensor.

A potato yield sensing system was described by Campbell et al. (1994), building upon the work of Rawlins et al. (1995). Idler wheels instrumented with load cells were installed under the conveyor on a commercial potato digger, to weigh the harvested potatoes. Association of these weights with field location was done by measurement of conveyor speeds and lengths for calculation of the delay time from digging to weighing. Hofman et al. (1995) described the use of a weighing conveyor system for measuring sugarbeet (*Beta vugaris* L.) yield.

Harvest Swath Width

Swath width measurement is important for narrow row or broadcast crops, such as wheat, since use of a fixed swath width may significantly distort the actual crop yield. Vansichen and DeBaerdemaeker (1991) used a commercial ultrasonic distance transducer to measure actual cutting width for harvesting wheat. They reported that the sensor had an accuracy of better than 2 cm when a clear crop edge was present. The need for additional work on this type of sensor was noted.

Crop Moisture

The moisture content of the crop being harvested is an important attribute. The efficiency and throughput capacity of the harvester, the storability of the crop, and the viability of harvested seeds are affected by the crop's moisture content. Harvested crop moisture content changes as the harvest season progresses and the crop matures, but also with changes in weather during the harvest season. In addition, rapid moisture content changes occur during a harvest day. Finally, harvest moisture content varies depending upon location within the harvested area. Hunt (1965) reported >1% variation in the moisture content of shelled corn between the ends of 15-m long rows. Accurate comparisons of yield levels at different locations require that measured yield level be adjusted to remove the moisture content variable.

The sensing and measurement of moisture in a biological material is complicated because water may be present in several different forms (Young, 1991). Water may be present in a biological material as water of hydration, which is chemically bound to the constituents. This water is typically not considered in moisture content measurement. Water may be physically bound within the material by surface forces in excess of the forces that act on normally condensed water, water may be present as normally condensed moisture, and moisture may be present that has passed through the cell walls and entered into the cytoplasm of the cell. These last three forms of moisture are exchanged between the material and its surroundings, and thus, enter into the sensing and measurement of moisture content. Many moisture sensing technologies, such as oven methods, desiccant drying, distillation methods, chemical methods, and gas chromotography, are unsatisfactory for real time moisture measurement because of the lengthy time required to complete the analysis. These methods also require the sample to be ground, which may result in the gain or loss of moisture from the sample.

Sensing technologies that have application for real time moisture content analysis use indirect measurement based upon some property of the material that varies with moisture content. Electrical methods, based on either the conductance or capacitance properties of the biological material, are widely used in the grain marketing industry. These methods are rapid, simple, and may be nondestructive (Young, 1991); however, conductance-type moisture sensors, whether of the bulk or single kernel design, usually crush the sample since, in addition to moisture and temperature, conductance is a function of the pressure exerted on the test material by the electrodes (Young, 1991; Bonifacio-Maghirang et al., 1994). Extensive tests have been conducted to validate the calibrations of commonly used commercial moisture meters (Paulsen et al., 1984), including capacitance-type meters. Sensors based on the rate of change of capacitance with moisture content are often installed in the clean grain transport system of a combine to sense moisture content of the grain flow stream. These units sense the dielectric constant of a mixture of air, water, and dry matter surrounding them, and are relatively unaffected by uneven moisture distribution within the sample volume. While they are capable of moisture measurement across a wider range than the conductance-type sensors (Young, 1991), they are susceptible to error due to coating with plant juices that are released in the threshing section of the combine.

Other indirect methods of moisture measurement, such as spectrophotometric methods and nuclear methods, have been developed. Norris (1964) reported on the use of NIR spectroscopy in an instrument developed for measuring moisture content of grain and seeds. Early moisture meters based on this method required the sample to be ground prior to moisture measurement, but recent commercial introductions have featured transmittance spectroscopy of unground samples (Williams, 1987). The NIR approach also has been used in development of a portable meter for measurement of the moisture content of grass and forage crops (Stafford et al., 1989) Microwave spectroscopy has shown promise for moisture measurement (Kraszewski & Nelson, 1994). Nuclear magnetic resonance can provide rapid, highly accurate moisture measurement, and a commercial unit for use in the food and grain milling industries is available. All of these technologies require expensive and, sometimes, bulky equipment. While these sensing technologies have been proven, considerable additional development is necessary before they can economically used for real time sensing of moisture content of biological materials on mobile field equipment.

EMERGING ISSUES IN SENSORS FOR SITE-SPECIFIC MANAGEMENT

From the above discussion, the degree of activity in sensor development for SSM data collection is evident. However, the state of the technology varies considerably from one sensed property to another. Grain yield sensors are now a reasonably mature, commercialized technology. Some sensors, such as those for soil organic matter, have been the subject of much research effort, and may be usable in a commercial setting following additional development efforts. Other sensors, such as those for discrimination of weed plants from crop plants are still early in the research and development cycle, and much additional basic and applied research will be necessary to bring them to commercial fruition.

The efforts of public sector scientists and engineers are important in development of sensors for SSM, especially for those sensing technologies which are early in the development cycle. The long-term research and development efforts required to bring a sensor from concept to a viable technology are often beyond the capabilities (financial and/or technical) of companies in the agricultural sector. Certainly there are sensors that have been and will be developed in the private sector, but much initial development work will continue to be done at universities and in government agencies.

Another important issue impacting sensor development and the SSM industry in general is that of standardization. Pressures of standardization are being felt on several levels, from the need for standard data interchange formats, to electronic communication standards, to standard methods of sensor (and SSM system) evaluation. For example, developers of SSM data analysis programs want to be able to import data from a variety of sources (including sensors) in standard formats, and then export standard control maps which can be used to drive variable-rate application hardware.

Makers of agricultural equipment want to develop standard electronics communication protocols for mobile equipment, such that intelligent subsystems on the equipment may be connected over a simple data bus, rather than requiring complex, dedicated wiring harnesses to be installed. Stone and Zachos (1993) described the application of the J1939/ISO11783 vehicle network standard to agricultural equipment. This standard provides support for SSM message information to be transferred along the data bus, in addition to the more conventional equipment operating messages (Stone, 1995). The potential adoption of this standard by manufacturers of agricultural equipment has important implications for developers of SSM sensing systems. It may one day be possible to transmit data from a sensor over the data bus, combine that data with GPS location data, and store the combined data set in a dedicated computer onboard the tractor. The standard also defines a virtual terminal device, which provides a display and keyboard for the operator to interact with multiple onboard systems, including sensor systems (Stone & Zachos, 1993).

Schueller (1995) has called for the adoption of standard procedures to test the performance of SSM systems, including sensors, similar to the Nebraska Tractor Tests, which provide unbiased performance data for comparison between tractor models. Standard tests should be conducted using methods developed to repeatably model real-world operating conditions. Results of these tests would provide the potential SSM user with objective comparisons of competing systems and sensors. Although the test results might not be indicative of actual field performance in all cases, they would provide a starting point from which other evaluations could be developed.

SUMMARY

Site-specific management (SSM) requires the collection, coordination, and analysis of massive quantities of data. Widespread adoption of SSM as a management strategy will require improvements in the accuracy, efficiency and economics of the data collection and manipulation process. These improvements will be obtained, in large part, through the use of electronic sensors for collection of SSM data. Sensors will also play an important role in improving data collection techniques for agronomic research in SSM. The current state-of-the-art of SSM sensors varies widely. Grain yield sensors are a relatively mature technology and are commercially available. Other sensors are well on the way to commercialization, while still others are currently the subject of basic engineering research efforts. Future research and development efforts will undoubtedly provide new and improved sensors, leading to opportunities for improved profitability and reduced environmental impact through the adoption of SSM.

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