Advances in Soil Science

SOIL-SPECIFIC FARMING

PRECISION AGRICULTURE

Edited by

Rattan Lal and B. A. Stewart

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Preface

Faced with challenges of resource scarcity (water, nutrient, energy) and environmental degradation (nonpoint source pollution, gaseous emissions), it is important to identify and adopt innovative farming systems. Precision agriculture (PA), also called soil-specific farming or satellite farming, is a strategy of sustainable intensification of agroecosystems. The latter implies producing more from less land, water, agrochemicals, energy, and other finite resources. It also implies producing more with less of an ecological footprint, such as emission of greenhouse gases (e.g., N_2O, CH_4), depletion of soil organic carbon, and loss of topsoil by erosion. While initially developed for soil-specific application of fertilizers, the concept of PA can be adopted to address a range of inputs and farm operations such as tillage, irrigation, pesticides and herbicides, developing genotypes, and soil quality and variability. The strategy is to optimize resource use while addressing spatial heterogeneity in soil characteristics and site-specific abiotic and biotic stresses that limit agronomic production and aggravate environmental degradation.

PA technology utilizes Global Positioning System (GPS) and appropriate design support tools to target soil and crop management according to spatial and temporal variations in soil/site characteristics that constrain agronomic productivity, reduce use efficiency of inputs, impair environment quality, and jeopardize sustainability. The goal is to develop and strengthen the database on soil properties, terrain characteristics, and climate parameters with regard to spatial variability over the landscape, and use specific technologies to target these constraints.

Whereas the usefulness of PA technologies to sustainable intensification and prudential use of resources is widely recognized, adoption of these concepts has been slow even in developed countries. Thus, increasing adoption of PA necessitates addressing constraints related to farm size, technology, and policy. Can PA technology be made scale-neutral so that concepts are used both for large-scale commercial farmers as well as for smallholder agriculturalists of the tropics and subtropics? Is basic soil data available at the level of field-scale to adapt PA concepts to issues such as pest and weed management, microirrigation, depth of seeding and placement of fertilizer, and cluster planting? How can the essential inputs be made available to farmers in remote areas, and what policy interventions are needed to facilitate and promote a widespread adoption of PA?

Therefore, this volume specifically focuses on PA technologies and application of modern innovations to enhance use efficiency of inputs through targeted management of soils and crops. The 15-chapter volume discusses (1) historical evolution, (2) soil variability at different scales, (3) soil fertility and nutrient management, (4) water quality, (5) land leveling techniques, and (6) special ecosystems involving small landholders and coastal regions.

This book provides the technological basis of adopting and promoting PA for addressing the issues of resource scarcity, environmental pollution, and climate change. Specific attention is given to scale-related issues and concerns of small landholders.

The editors thank all the authors for their outstanding contributions and for sharing their knowledge and experiences. Despite busy schedules and numerous commitments, all authors managed to produce their chapters in a timely manner; we greatly appreciate that. The editors also thank the editorial staff of Taylor & Francis Group for their help and support in publishing this book. The office staff of the Carbon Management and Sequestration Center provided support with the flow of manuscripts between authors and editors and made valuable contributions, and their help and support is greatly appreciated. In this context, special thanks are due to Laura Hughes who formatted the text and prepared the final submission. Help from Jennifer Donovan in the early phases of the project is thankfully acknowledged. It is a challenging task to thank by listing names of all those

who contributed in one way or another to bringing this book to fruition. Thus, it is important to build upon the outstanding contributions of numerous soil scientists, agricultural engineers, and technologists whose research is cited throughout the book.

Rattan Lal
B.A. Stewart

Editors

Rattan Lal, PhD, is a distinguished university professor of soil science and director of the Carbon Management and Sequestration Center, The Ohio State University, and an adjunct professor of the University of Iceland. His current research focus is on climate-resilient agriculture, soil carbon sequestration, sustainable intensification, enhancing use efficiency of agroecosystems, and sustainable management of soil resources of the tropics. He received honorary degrees of Doctor of Science from Punjab Agricultural University (2001); the Norwegian University of Life Sciences, Aas (2005); Alecu Russo Balti State University, Moldova (2010); and the Technical University of Dresden (2015). He was president of the World Association of the Soil and Water Conservation (1987–1990); the International Soil Tillage Research Organization (1988–1991); the Soil Science Society of America (2005–2007); and is president-elect of the International Union of Soil Science. He was a member of the Federal Advisory Committee on U.S. National Assessment of Climate Change-NCADAC (2010–2013) and is a member of the SERDP Scientific Advisory Board of the US-DOE (2011–present); senior science advisor to the Global Soil Forum of the Institute for Advanced Sustainability Studies, Potsdam, Germany (2010–present); member of the Advisory Board of the Joint Program Initiative of Agriculture, Food Security and Climate Change (FACCE-JPI) of the European Union (2013–present); and chair of the Advisory Board of the Institute for Integrated Management of Material Fluxes and Resources of the United Nations University (UNU-FLORES), Dresden, Germany (2014–2017). Professor Lal was a lead author of IPCC (1998–2000). He has mentored 102 graduate students and 54 postdoctoral researchers, and hosted 140 visiting scholars. He has authored/coauthored 730 refereed journal articles and has written 12 and edited/coedited 58 books. In 2014, Reuter Thomson listed him among the world's most influential scientific minds.

B.A. Stewart, PhD, is director of the Dryland Agriculture Institute and a distinguished professor of soil science at West Texas A&M University, Canyon, TX. He is a former director of the USDA Conservation and Production Laboratory at Bushland, TX, past president of the Soil Science Society of America, and member of the 1990–1993 Committee on Long-Range Soil and Water Policy, National Research Council, National Academy of Sciences. He is a fellow of the Soil Science Society of America, American Society of Agronomy, Soil and Water Conservation Society, a recipient of the USDA Superior Service Award, a recipient of the Hugh Hammond Bennett Award of the Soil and Water Conservation Society, and was an honorary member of the International Union of Soil Sciences in 2008. In 2009, Dr. Stewart was inducted into the USDA Agricultural Research Service Science Hall of Fame. Dr. Stewart is very supportive of education and research on dryland agriculture. The B.A. and Jane Ann Stewart Dryland Agriculture Scholarship Fund was established in West Texas A&M University in 1994 to provide scholarships for undergraduate and graduate students with a demonstrated interest in dryland agriculture.

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1 Historical Evolution and Recent Advances in Precision Farming

David Mulla and Raj Khosla

CONTENTS

1.1 INTRODUCTION AND SCOPE OF CHAPTER

Precision farming is one of the top 10 innovations in modern agriculture (Crookston 2006). Precision farming is generally defined as doing the right practice at the right location and time at the right intensity. Since its inception in the early 1980s, precision farming has been adopted on millions of hectares of agricultural cropland around the world. The objective of this chapter is to review the history of precision farming and the factors that led to its widespread popularity. The specific focus is on the following aspects of precision farming: soil sampling, geostatistics and Geographic Information Systems (GIS), farming by soil, variable rate fertilizer, site-specific farming, management zones, Global Positioning System (GPS), yield mapping, variable rate herbicides, variable rate irrigation, remote sensing, automatic tractor navigation and robotics, proximal sensing of soils and crops, and profitability and adoption of precision farming. For each topic, reference to key groups of researchers and the breakthroughs that helped propel precision farming onward are identified. The chapter concludes with a vision for the future of precision farming.

1.2 SOIL SAMPLING

Spot applications of fertilizer were advocated as early as the 1920s (Linsley and Bauer 1929), but cheap fertilizer and labor combined with the increasing area of farms caused most farmers to shift to uniform applications (Franzen and Peck 1994) until the revolution in precision farming took place during the 1980s. Between the 1920s and 1970s, interest in the variability of soil fertility was primarily motivated by the need to accurately determine a field average soil fertilizer recommendation (Kunkel et al. 1971; Franzen 2007). Many scientists (e.g., Sig Melsted and Ted Peck from the University of Illinois) recognized that variability in soil fertility was large and that sparse soil sampling was likely to be a poor representation of average fertilizer requirements (Melsted 1967). Melsted and Peck designed an intensive grid sampling study (at spacings of 24.3 m) for the Mansfield field near Urbana, Illinois in 1961 with a view toward designing sampling strategies that minimized the cost of determining average soil fertility (Franzen 2007). The variability in soil test values prompted Melsted to suggest philosophically that customized fertilizer requirements were more efficient than a single uniform recommendation (Melsted 1967). Intensive grid sampling was continued in the same field at regular time intervals until about 1994 (Figure 1.1). However, there was little practical application of this concept until several decades later.

In Washington State, Irv Dow and colleagues conducted over 70 field trials on irrigated farms during the period from 1963–1970 in which variations in soil fertility were quantified using intensive soil sampling (Dow et al. 1973a,b). They concluded that "soil test variation is not random and may lend itself to mapping and differential fertilization." They opined that "fertilizing according to information from one composite sample results in erroneous fertility programs." Their solution

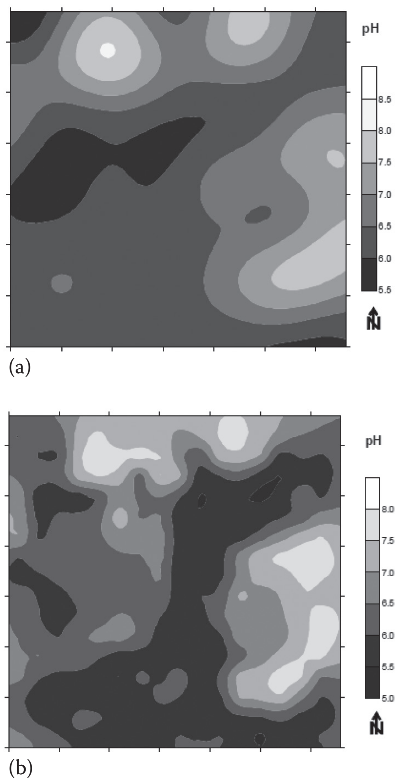

FIGURE 1.1 Interpolated soil pH values at Mansfield, IL from 1961 (a) to 1994 (b) based on intensive grid sampling by Melsted (1967) and his colleague Peck at 24.3 m intervals. (Courtesy of David Franzen.)

was to use "precision fertilization based on precision soil sampling." As with research conducted by Peck in Illinois, this idea languished for a decade because of the lack of technology to implement variable rate fertilization. Beginning in 1984, Mulla at Washington State University conducted intensive sampling for soil phosphorus across the eroded hilltops of the Palouse region (as reported in Veseth 1986). He found a good relationship between slope position and soil test phosphorus (P) values, modeled these relationships using geostatistics, and produced computerized contour and three-dimensional (3-D) maps of the relationships. He applied geostatistics and mapping techniques to this data as well as data collected previously by Dow from irrigated potato (*Solanum tuberosum*) farms in central Washington to show that applying variable rates of fertilizer was more efficient and cost-effective than applying uniform rates (Veseth 1986; Mulla and Hammond 1988; Hammond and Mulla 1989). Further, Mulla suggested that for accurate representation of spatial patterns in fertility, soil samples should be collected on a regular grid at spacings of between 30 and 60 m (Veseth 1986).

Wollenhaupt et al. (1994) compared traditional sampling strategies with those that involved estimating composite sample grid cell averages or using individual grid point estimates on some fields in Wisconsin and sampled at spacings of 32.3, 64.6, or 69.9 m. Grid-point sampling was the most accurate strategy for making variable rate P or potassium (K) fertilizer recommendations, followed by grid cell compositing. Traditional sampling for field average soil fertility was inadequate. They also compared different methods for interpolation of soil fertility data, including Delaunay triangulation, inverse distance weighting, and kriging. The most accurate sample spacing was 32.3 m, similar to results found by Mulla in Washington State. Soil fertility map accuracy was significantly degraded at sample spacings of 69.9 m. Several excellent summaries of soil sampling techniques are provided in the literature for those who wish to learn more about this topic (Wollenhaupt et al. 1997; Mulla and McBratney 2000).

1.3 GEOSTATISTICS AND GIS

The seeds for quantifying soil spatial variability were sown by soil scientists during the 1970s and 1980s. Soil physicists, led by Don Nielsen, studied the spatial variability of soil moisture and soil hydraulic properties (Nielsen et al. 1973). The Nielsen group was interested in quantifying the spatial variability of water and solute transport at the field scale, and promoted the use of geostatistics as a tool for doing so (Vieira et al. 1981). On the other hand, soil pedologists, led by Richard Webster, were interested in using geostatistics to quantify the spatial variability of soil properties that could be used to improve the precision of soil mapping (Burgess and Webster 1980). While both groups quantified soil spatial variability using geostatistics, neither group was particularly interested in studying practical issues such as variable rate fertilizer management. The Webster group studied soil sampling strategies for estimating soil properties that could be used for soil classification (McBratney et al. 1981; Webster and Burgess 1984), and later became interested in strategies for accurate estimation of the semivariogram (Webster and Oliver 1992) and interpolation by kriging (Oliver and Webster 1990).

Influenced by Nielsen's studies of field scale variability, during 1985 David Mulla became interested in the relationship between soil fertility and landscape position for rainfed wheat (*Triticum aestivum*) farms in eastern Washington state and irrigated potato farms in central Washington state (as reported by Veseth 1986). He used geostatistics to map soil test P levels, and showed that soil fertility varied significantly from bottom slope to hill crest positions in wheat farms, and that P fertilizer recommendations for a field could be mapped into different zones (Table 1.1). Parallel research on the spatial variability of soil P was also conducted by Assmus et al. (1985). Mulla's research caught the attention of Max Hammond, a crop consultant working for CENEX Land O'Lakes and Soil Teq, and in 1986 Soil Teq from Waconia, Minnesota hired Mulla as a consultant to write software that automatically reclassified and mapped soil fertility sampling data into fertilizer recommendation zones, which Mulla called "management zones." This was the first combined use of geostatistics and GIS for precision

TABLE 1.1
Early Advances in Research on Soil Sampling, Geostatistics, and GIS in Precision Farming

Research Area	Nature of Contribution	Key References
Soil sampling	Grid sampling recommendations	Melsted (1967), Dow et al. (1973b), Mulla and Hammond (1988), Wollenhaupt et al. (1994)
Geostatistics and GIS	Map interpolation and reclassification for soil fertility data	Mulla and Hammond (1988), Mulla (1989, 1991, 1993)

farming (Mulla 1988; Mulla and Hammond 1988; Hammond et al. 1988). Fertilizer recommendation maps were burned onto an E-Prom device by Soil Teq, fitted into a computer in the cab of a fertilizer spreader, and used to guide the delivery of variable rate fertilizer applications starting in the late 1980s. The combined use of geostatistics and GIS for precision farming was detailed in a series of papers by Mulla (1989, 1991, 1993). The use of geostatistics in precision agriculture is extensively documented by Oliver (2010).

1.4 FARMING BY SOIL

Pierre Robert is often regarded as the father of precision farming because of his active promotion of the idea and organization of the first workshop, "Soil Specific Crop Management," during the early 1990s. In 1982, Robert defended his PhD dissertation under the direction of Richard Rust in the University of Minnesota's Department of Soil Science. The dissertation was titled "Evaluation of Some Remote Sensing Techniques for Soil and Crop Management" (Robert 1982). Robert's research on 15 Minnesota commercial corn (*Zea mays*)-soybean (*Glycine max*) farms showed that color infrared (CIR) aerial photography could be used to detect "problems relating to drainage, erosion, germination, grass and weed control, crop stand and damage and machinery malfunction." Robert suggested that CIR data could be used to build a "farm information and management system containing precisely located natural and cultural data to improve cost efficiency of future cultural practices. Such improvement could come, for example, from adjusting seed density, herbicide control, or fertilization in response to detected field problems" (Robert 1982). In Robert's dissertation, he repeatedly notes that anomalous reflectance patterns from row-cropped fields were associated with soil series boundaries. He noted that "The important contribution of remote sensing in soil and crop management is not as a real-time tool but as an input to a geographic soil and crop management data base system" (Robert 1982), indicating that farm management for the following cropping season could be improved using CIR images from the previous year in association with soil series maps. Robert spent the next 3 years developing a computerized soil mapping database in close cooperation with Rust (Figure 1.2). The concept of farming by soil in Minnesota was formally introduced into scientific literature by Rust (1985), Larson and Robert (1991), and by Vetsch et al. (1993).

Carr et al. (1991) and Wibawa et al. (1993) conducted long transect trials to compare a farming by soil fertilizer management strategy with a uniform strategy in Montana and North Dakota, respectively. Results from several fields in Montana showed that rainfed wheat grain yields differed significantly across soil types. However, there were no significant differences in economic returns for the uniform versus the soil-based fertilizer management strategy in Montana. In North Dakota, the economically optimum strategy for growing rainfed barley (*Hordeum vulgare*) and wheat was either a uniform nitrogen (N) fertilizer application based on composite soil samples or a variable rate N strategy that involved compositing soil samples and yield goals by soil mapping unit. Variable rate fertilizer applications based on grid soil sample spacings of 15.2 to 30.4 m were generally able to increase crop yield in comparison with the uniform strategy, but they also incurred extra costs that made these strategies unprofitable.

FIGURE 1.2 Pierre Robert explaining his computerized farming by soil map database (circa 1985) to Jim Anderson at the University of Minnesota.

1.5 VARIABLE RATE FERTILIZER

The idea of a variable rate fertilizer spreader was studied by several scientists during the early to mid-1980s, including John Hummel (Hummel 1985) working with the United States Department of Agriculture–Agricultural Research Service (USDA-ARS). Soil Teq of Waconia, Minnesota patented the first computer-controlled variable rate fertilizer spreading machine (Ortlip 1986; Schueller 1992). The system was apparently first tested in Minnesota using variable rate lime (Luellen 1985) or fertilizer applications (Schmitt et al. 1986). Guidance was possible using either dead reckoning or triangulation from radio beacons. Rates of fertilizer were varied according to digitized soil maps, hence the initial appellation "farming by soil" (Larson and Robert 1991). After 1987, using software written by Mulla from Washington State University, Soil Teq was able to vary rates of fertilizer application according to digital maps (Figure 1.3) that were based on soil fertility data obtained by grid sampling, hence the appellation "site-specific farming." This software evolved into Soil Geographic Information System (SGIS), which was marketed by SoilTeq and AgChem.

Gradually, the terms farming by soil and site-specific farming were replaced by variable rate technology (Sawyer 1994). Scientists at several U.S. universities started to investigate variable rate fertilizer applications in the late 1980s (Reichenberger and Russnogle 1989), including Mulla at

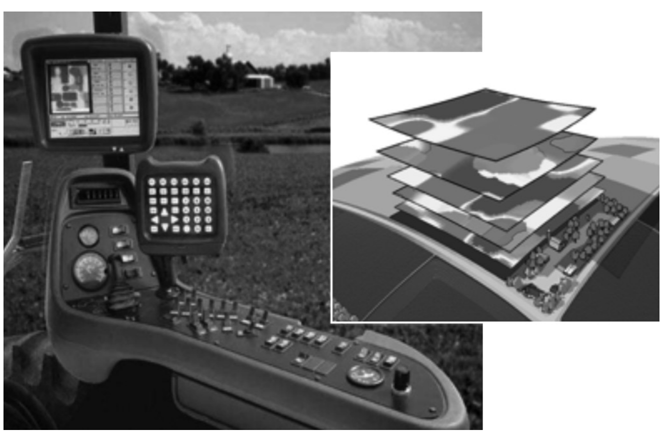

FIGURE 1.3 An early 1990s variable rate fertilizer applicator control system.

Washington State University (as reported by Miller 1988; Mulla et al. 1992), Kachanoski at the University of Guelph (Kachanoski et al. 1985) who had heard Mulla's reports on spatial variability of soil fertility at annual meetings of the W-188 Western Regional Committee on Spatial Variability, Searcy at Texas A&M (Borgelt et al. 1989, 1994) who used software written by Mulla, Robert at the University of Minnesota (Robert et al. 1990), and Jacobsen and Nielsen at Montana State University (Carr et al. 1991; Wibawa et al. 1993). Variable rate fertilizer applications were perceived as being both profitable and beneficial because they improved the efficiency of farm inputs, maintained or improved crop yield and quality, and protected water quality.

1.6 SITE-SPECIFIC FARMING AND MANAGEMENT ZONES

The philosophy of site-specific farming was distinct from farming by soil. Farming by soil posited that fertilizer requirements varied across soil series but were homogeneous within a given soil series. Site-specific farming posited that variability within soil series boundaries was significant, and the only way to identify fertilizer requirements was by grid or transect soil sampling across soil series boundaries. Field investigations involving these two contrasting philosophies were partially motivated by the need to document the profitability of variable rate fertilizer applications. To this end, Mulla and his colleagues from Cenex Land O'Lakes in Washington State established the first statistically rigorous field trials in 1987 comparing variable and uniform N and P fertilizer applications on commercial wheat farms (Mulla et al. 1992). Without GPS, they conducted long transect sampling at 15 m spacings across rolling landscapes, and used a manual controller to variably apply N and P according to a map developed by grouping and reclassification of soil fertility data from the transect sampling. While there were no statistically significant differences in crop yield between the uniformly and variably fertilized strips, the profitability of variable rate fertilizer was better than uniform management due to cost savings in fertilizer and improved protein content of wheat in the variably fertilized strips. Mulla introduced the concept of management zones into precision farming as a result of these and other early field trials on irrigated fields with variable rate fertilizer (Mulla 1991, 1993; Mulla et al. 1992). Management zones were relatively homogeneous regions within a larger field that differed from one another in fertilizer recommendations.

Site-specific farming was studied in irrigated agriculture beginning in 1986 where high-cash-value crops such as potatoes were grown (Mulla and Hammond 1988; Hammond et al. 1988, Hammond and Mulla 1989). The profitability of these irrigated crops justified intensive grid soil sampling that could be used to define management zones for variable P and K fertilizer applications. Through the use of geostatistics, it was determined that the optimum grid spacing for soil sampling was ~61 m (Mulla and Hammond 1988; Mulla 1991).

The terms site-specific and precision farming were introduced into scientific literature by John Schueller from the University of Florida (Schueller 1991, 1992). He helped organize an important symposium on this topic at the 1991 Annual Meeting of the American Society of Agricultural Engineers (ASAE) in Chicago. According to Schueller (1991), "the continuing advances in automation hardware and software technology have made possible what is variously known as spatially-variable, precision, prescription, or site-specific crop production."

The use of management zones in precision farming has persisted to the present day, but the concept and definition has shifted (Table 1.2). Mulla (1991) offered the first definition: "Each management zone should ideally represent portions of the field that are relatively similar and homogeneous in soil fertility status so that a different uniform fertilizer recommendation can be made for each zone." Doerge (1999) broadened the concept by saying that management zones "are sub-regions of a field that express a homogeneous combination of yield limiting factors for which a single crop input is appropriate." Fraisse et al. (2001) introduced the k-means clustering approach for delineation of management zones. Khosla et al. (2010) summarized an extensive body of scientific literature for delineating management zones for precision farming.

TABLE 1.2
Early Advances in the Concept and Testing of Farming by Soil, Variable Rate Fertilizer, Management Zones, and Precision Farming

Research Area	Nature of Contribution	Key References
Farming by soil	Proposed concept	Robert (1982), Rust (1985)
Variable rate fertilizer	Machinery development and field testing	Hummel (1985), Luellen (1985), Ortlip (1986), Schmitt et al. (1986), Borgelt et al. (1989, 1994), Carr et al. (1991), Mulla et al. (1992)
Management zones	Proposed and tested concept	Mulla (1991, 1993), Mulla et al. (1992), Doerge (1999), Fraisse et al. (2001)
Precision farming	Proposed concept	Schueller (1991, 1992)

They found that the most common approaches for delineating management zones were based on soil properties such as soil texture and soil organic matter (SOM) content, followed by sensing technologies such as electrical conductivity mapping and remote sensing. Other less common approaches for delineating management zones included yield mapping followed by elevation differences across a field.

1.7 GPS

Precise determination of location is essential for precision farming, especially for mapping the variability in soil fertility or crop yield, and in locating farm machinery that can spread variable rates of fertilizer relative to the information in these maps. When interest in precision farming first developed, there were two distinct philosophies about how to determine location within a field. The first was to use radio-based triangulation with strategically placed beacons (Palmer 1991). The main advantage of this approach was the ability to determine machinery position in real time at submeter accuracy without postprocessing of data. The main disadvantages were loss of signal in rolling topography and time and effort to establish beacon positions (Auernhammer and Muhr 1991). The alternative was the GPS, which was established for military purposes in the late 1970s (Larsen et al. 1988; Tyler 1993). GPS accuracies of 3 m could be achieved by the military during the early 1990s based on differential postprocessing of the P code, or 5 m accuracies based on processing of the C/A code (Tyler 1993). A GPS receiver in a fixed position was required for differential correction. Civilian users without recourse to differential correction could only achieve accuracies of between 10–100m with GPS receivers before military selective availability (spoofing) was turned off in 2000. Differential correction became very popular with agricultural users during the 1990s as a way to obtain acceptable accuracies before selective availability was turned off (Tyler et al. 1997). Real-time differential correction became possible when the Coast Guard and several companies such as Omnistar began to establish networks of GPS base stations whose real-time positions could be broadcast to roving machines with an FM receiver (Tyler et al. 1997). This real-time differential correction approach was preferred to real-time kinematic positioning, where the phase of signals from at least four satellites were counted continuously at both the base and roving receivers. Loss of signal often occurred when the roving receiver passed behind a tree, building, or hill, causing failure of the real-time kinematic approach.

The primary interest in GPS for precision farming was initially as a method for identifying the location of a combine that was collecting real-time data on spatial variability in crop grain yield (Auernhammer and Muhr 1991; Schueller and Wang 1994; Auernhammer et al. 1994). More information about yield mapping is provided in Section 1.7 below. Later, interest in GPS shifted to its use in navigating agricultural machinery (Zhang et al. 1999) and autosteering (Keller et al. 2001). More information about these applications is described in Section 1.8 below.

1.8 AUTOMATED TRACTOR NAVIGATION AND ROBOTS

Precise automated navigation has been one of the most intense areas of research and implementation over the last three decades. The advantages of this approach include reduced operator fatigue, elimination of machinery overlaps and skips, and improved efficiency in fuel usage and product application. Navigation of agricultural machinery has been studied for at least 75 years since Andrew (1941) patented a method for automated plowing of circular fields based on the distance to center using a cable spool system. Reid and Searcy (1987) used near-infrared computer vision to distinguish straight rows of crop from bare soil that could be used for straight-line navigation. Dust and vibration of the camera were the main limitations of computer vision (Reid et al. 2000; Wilson 2000). Triangulation of agricultural machinery positions using radio beacons (Palmer 1991, 1995) or microwave signals (Searcy et al. 1989b) required good line of sight and significant setup of equipment in the field.

The most frequent approach to precise automated navigation involves GPS, first proposed by Larsen et al. (1988). O'Connor et al. (1996) pioneered the use of real-time kinematic (RTK) GPS for automatic steering of a tractor along straight lines. This system initially involved four separate GPS receivers mounted on a tractor as well as a nearby GPS base station. An electrohydraulic steering unit on the tractor was automatically guided by the GPS. Accuracy of the RTK GPS method was better than a 2.5-cm standard deviation, which is better than accuracy (15–33 cm std. dev.) of the U.S. Federal Aviation Agency's Wide Area Augmentation System (WAAS), or the accuracy (5–12.5 cm std. dev.) of the commercial OmniStar system. A series of patents were subsequently issued for GPS-based navigation (Greatline and Greatline 1999; Keller et al. 2001; McClure 2005; Collins et al. 2006; McKay and Anderson 2007), leading to rapid commercialization and adoption of autosteer technology in agriculture, including the Beeline Navigator, which first appeared in Australia. Thuilot et al. (2002) used RTK GPS to guide a tractor along curved paths, which is more difficult than navigating along straight lines. Their accuracy was generally better than 2m deviations from prescribed pathways. Recent attempts to improve accuracy of navigation often involve multiple sensors, including GPS, geomagnetic direction sensors, and machine vision (Zhang et al. 1999). Japan has been a leader in adoption of all types of autosteer navigation technology, particularly on the small agricultural fields of Hokkaido Island (Torii 2000). Automated navigation of tractors can take various forms, including manual guidance with a lightbar, assisted steering, or autosteer (Berglund and Buick 2005), depending on the monetary investment.

1.9 YIELD MAPPING

The concept of detailed spatial mapping of crop yield was initially developed and tested by Schueller and Bae (1987) before the availability of GPS. They used variations in engine speed as a surrogate for grain flow to the combine, which was operated under constant throttle and cutting head height. Position of the combine was determined using real-time microwave ranging, with between 0.5 and 6 m accuracy. Variations in crop yield were aggregated to blocks of 10 × 10 m to reduce variability in measurements. Because measuring variations in engine speed could be inaccurate due to slippage of wheels and other factors, Bae et al. (1987) and Searcy et al. (1989a) also studied yield monitors that were based on measurements of the volume of grain leaving the grain auger. Grain volume flow in the combine could be estimated based on the rate of revolution of a rotating paddle in the auger. Each paddle had a fixed volume capacity for grain.

More sophisticated indirect techniques for measuring grain flow in the combine were developed by Vanischen and Baerdemaeker (1991), who used measurements of deflection in a curved plate caused by the impact of grain flow mass. Accuracy of this approach required sensitive measurements of swath width and combine speed, as well as filtering of the raw data signal from the deflection of the curved plate to overcome vibration and distortion effects. Most commercial yield monitoring devices are based on deflection of plates or fingers or on impact of grain on impact plates

(Pierce et al. 1997). Stafford et al. (1991, 1996) evaluated two other methods for yield mapping (Figure 1.4); namely; gamma ray detectors whose signal is attenuated based on the amount of grain flow, and a capacitative sensor whose response varies with the dielectric constant of the air/grain mixture. Neither technique was entirely satisfactory.

Errors in measuring grain yield with yield monitors are generally less than 5% (Pierce et al. 1997). The most common errors arise from inaccurate estimates of cutting swath width or combine travel distance; the latter is estimated from combine speed. Cutting swath width can be in error when overlap occurs between successive passes of the combine so that the effective cutting swath is less than the width of the cutting head. Use of centimeter-accuracy GPS systems on the combine can significantly reduce errors in estimating travel distance and can prevent cutting head overlap on successive passes of the combine. The primary error that persists in yield monitor data occurs when the combine turns around at the edge of a field. Because of a time lag between the measurement of grain yield relative to the location where the crop was harvested, the first few data points for crop yield after a combine turns will generally be too low.

Attempts to explain spatial variability of crop yield were initially based on the hypothesis that patterns in yield were determined by relationships with soil series mapping units. To test this hypothesis, Karlen et al. (1990) produced a detailed soil series map in an 8-ha field by intensive soil coring and profile descriptions in the Coastal Plains region of South Carolina (Karlen et al. 1990). They then studied spatial variations in corn, wheat, and sorghum (*Sorghum bicolor*) yield for this field from 1985–1988. Results showed that spatial variations in crop yield were extensive, and were significantly different across soil mapping units (Table 1.3). The best indicator of spatial patterns in crop yield was depth to argillic horizon, but spatial variation within soil map units was nearly as large as the variation in yield among map units. Sudduth et al. (1996) studied spatial relationships between crop yields and soil or topographic factors on two fields in central Missouri from 1993 to 1995. Using data from over 300 sampling locations, they found that advanced regression techniques could explain from 51%–77% of the variability in crop yield. The most important factor affecting crop yield was elevation, followed by topsoil depth, organic matter content, and soil test phosphorus. Both Karlen et al. (1990) and Sudduth et al. (1996) noted that there was significant variation in crop yield from one year to the next in response to variations in precipitation, but the primary focus of their analysis was on spatial variation.

Lamb et al. (1997) were the first to quantitatively compare spatial and temporal variations in continuous corn crop yield over a 5-year period for a 1.8-ha field in Minnesota. The field was divided into 60 grid cells of area 279 m^2 each. The highest and lowest crop yields for a given year differed between 2762 and 4519 kg/ha from one grid cell to another depending on the year, but spatial

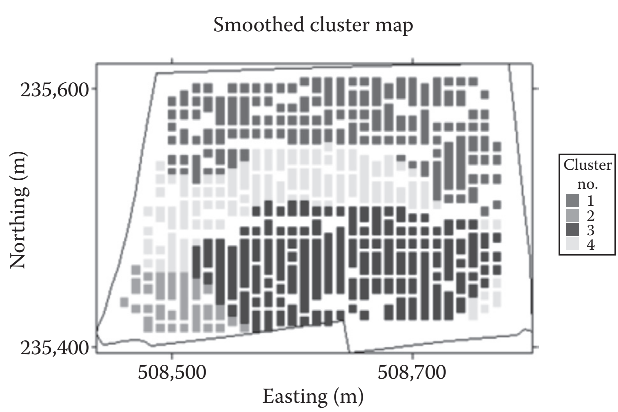

FIGURE 1.4 Clustered yield map for winter barley based on 3 years of data (1993–1995) in Cashmore field, UK. (Courtesy of John Stafford.)

TABLE 1.3
Early Advances in Research on GPS, Machinery Navigation, and Yield Mapping for Precision Farming

Research Area	Nature of Contribution	Key References
GPS	Technology adaptation to farming and testing	Larsen et al. (1988), Auernhammer and Muhr (1991), Tyler (1993)
Machinery navigation and autosteer	Technology development and testing	Reid and Searcy (1987), Palmer (1991), O'Connor et al. (1996), Greatline and Greatline (1999), Keller et al. (2001)
Yield mapping	Technology development and field testing	Bae et al. (1987), Schueller and Bae (1987), Searcy et al. (1989a), Karlen et al. (1990), Stafford et al. (1991)

patterns in crop yield were not temporally stable. Yield maps for the first 4 years of the study could only explain half of the spatial variability in grain yield for the last year of the study. These results showed that the magnitudes of both spatial and temporal variability were important, but temporal variability was not predictable from one year to the next.

McBratney and Whelan (1999) studied spatial and temporal variability in wheat crop yield in four fields located in Australia from 1995–1996. They noted that temporal variations across years were larger in magnitude than spatial variations within a year. This led them to propose the concept of using uniform field management techniques when yield stability across years was poor and variable management when yield was stable across years. Their null hypothesis was stated as: "given the large temporal variation evident in crop scale relative to the scale of a single field, then the optimal risk aversion strategy is uniform management." Blackmore et al. (2003) found that wheat yield variability across four fields in England for 6 years was unpredictable from one year to another, despite significant spatial variability in yield during any single year. They suggested that managing for the spatial variability that exists in a given year is better than trying to predict management needs from the previous year(s) yield map(s).

The focus on spatial and temporal variation in crop *yield* tends to overlook an important issue. For variable rate management, what is really critical is the crop *response* rather than the crop yield. Mamo et al. (2003) studied spatial and temporal variations in the response of a corn crop to variable rates of N fertilizer from 1995 to 1999 in Minnesota. Half of the field responded to N fertilizer in a given year, while 60% of the responsive areas were stable across years. A variable rate fertilizer strategy would have reduced N rates overall by 69 to 75 kg/ha in comparison to a uniform application of fertilizer. This study showed that crop yield by itself is a poor indicator of the crop response to N fertilizer. The implication is that defining management zones based on differences in crop yield is not generally an efficient approach for developing a variable rate fertilizer application strategy. Similar conclusions were reached by Scharf et al. (2006) in Missouri, who showed that economically optimum N rates were more strongly controlled by soil N supply than yield-controlled N uptake patterns.

1.10 VARIABLE RATE HERBICIDE APPLICATION

Weeds tend to occur in patches rather than in uniform coverage across fields, and if these patches exceed threshold populations, they can reduce crop yield and vigor (Coble and Mortensen 1992). Before the advent of Roundup Ready crops, there was significant interest in variable rate applications of preemergent or postemergent herbicides (Wiles et al. 1992).

Haggar et al. (1983) fitted an optical sensor to a handheld weed sprayer to test the concept of optically activated spot spraying. The optical sensor estimated the ratio of red to near-infrared reflectance of weeds on a background of bare soil. Guyer et al. (1986) and Thompson et al. (1990, 1991) suggested the concept of mapping weed locations using either machine vision, remote sensing, video cameras on tractors, or manual counts, and then spraying the field at a uniformly low rate with a higher dosage of herbicide in areas with weed patches. Thompson et al. (1990, 1991) believed that this approach would work well in fields where weed patches tend to occur in the same locations from one year to another. Thompson et al. (1991) discussed the potential for real-time mapping of weed populations in a growing crop, but this approach was rejected due to the difficulty of discriminating weeds from crop and low spatial resolution of aerial imagery. Felton and McCloy (1992) proposed a spot herbicide sprayer that was based on detection of weeds using red and near-infrared reflectance. This research led to the development of a commercial spot sprayer in Australia known as DetectSpray. Stafford and Miller (1993) built a variable rate herbicide sprayer that applied a low uniform rate of herbicide throughout the field and a higher rate where weed patches had been previously mapped (Figure 1.5). Sprayer position relative to the weed map was determined using differential GPS techniques. Weed patches were mapped using a model airplane equipped with a 35-mm color photography camera; this was the first use of an unmanned aerial vehicle for precision farming. Further development of the map-based approach to variable herbicide spraying in Europe was subsequently restricted as a result of legal rulings relating to an infringement of the SoilTeq patent for map-based variable rate applications.

Johnson et al. (1995a) mapped weed density in 12 corn or soybean fields in Nebraska for a single year. This research showed that weeds tended to occur in patches, and many areas of the field tended to be weed-free. They suggested that variable rate herbicide spray could be targeted to weed patches if the density of weeds in those patches exceeded an economic threshold. Research by Johnson et al. (1995b) then mapped weed patches for 2 years in 18 Nebraska corn and soybean fields. Results of this research showed that locations of weed patches were not stable from one year to the next.

As a result of research by Johnson et al. (1995b), interest in weed mapping soon turned to real-time mapping of weeds using photodetectors and variable herbicide spraying (Beck and Kinter 1998a,b) with what became known as WeedSeeker. Hanks and Beck (1998) evaluated two commercial sensors, DetectSpray and WeedSeeker, for their ability to identify and spray weeds; the former used passive reflectance, while the latter had an active sensor consisting of gallium-based light-emitting diodes. DetectSpray and WeedSeeker were both initially designed to sense green vegetation on a background of bare soil and were not appropriate for use in fields where crops and weeds were mixed together. Weeds were sprayed whenever detected by either system. When used in fields

FIGURE 1.5 Variable rate herbicide applicator developed by Stafford and Miller (1993).

where crops had already germinated, a spray hood was installed over the weed sensors and sprayer nozzles to prevent the application of glyphosate herbicide to growing crops. WeedSeeker performed better than DetectSpray in variable ambient lighting conditions because of its active sensor system. Sensor-based weed control reduced the volume of herbicide applied by 63%–85% relative to a uniform spray application (Hanks and Beck 1998). Using machine vision, Giles and Slaughter (1997) found that variable herbicide spray reduced application rates by 66%–80% in vegetable crops relative to a uniform spray application. Tian et al. (2000) developed a variable rate herbicide sprayer that used a low-resolution color video camera to identify clusters of weeds growing between rows of corn or soybean. Herbicide spray could be varied nozzle by nozzle depending on the weed density. For low-density weed cover, tests of this system showed that herbicide application amounts could be reduced by 71% relative to a uniform application rate (Tian 2002).

1.11 VARIABLE RATE IRRIGATION

Water conservation is a pressing issue in the face of drought and competition for water resources by agricultural, municipal, and industrial users. Overirrigation wastes water and leads to leaching and runoff losses that carry soluble pollutants such as nitrate-N and pesticides to ground or surface waters. McCann and Stark (1993) patented a method for variable application of irrigation water and chemicals applied through center pivot irrigation systems (Table 1.4). Aerial photography or soil sampling was used to identify management zones requiring different amounts of irrigation. Each nozzle on the irrigation spray boom could be independently controlled using a solenoid valve. A microprocessor was used to determine the location of each nozzle relative to mapped irrigation zones, and a control program then turned the nozzle on or off in order to deliver the required amount of water for that location. Variable rate irrigation was field-tested by King et al. (1996), who found that this method was able to accurately deliver recommended variations in irrigation water depth and associated nitrogen fertilizer requirements. Variable rate irrigation through linear move systems was developed by Fraisse (1994) at Colorado State University in parallel with the Washington State research by McCann and Stark (1993). In South Carolina, Omary et al. (1997) and Camp et al. (1998) placed multiple manifolds on a center pivot in order to have the flexibility of delivering one of eight possible rates of irrigation to any portion of the field.

Evans et al. (1996) collaborated with the Nelson Irrigation company in Walla Walla, Washington to install variable rate irrigation controllers on a center pivot system in a commercial farm. Thirty zones having two to four nozzles were cycled on and off by a master controller on an RS485 bus to achieve desired rates of water application. Water demands could be calculated using a potato growth simulation model based on landscape, soil, and climatic information. They found that the performance of the variable rate irrigation system was excellent, and that the main limitation in implementing the system "lies in the ability to interpret spatially variable data and develop rational and

TABLE 1.4
Early Research Advances in Variable Rate Herbicide for Weed Control and Variable Rate Irrigation

Research Area	Nature of Contribution	Key References
Variable rate herbicide	Technology development and testing	Haggar et al. (1983), Guyer et al. (1986), Beck and Kinter (1988a,b), Thompson et al. (1990, 1991), McCloy and Felton (1992), Stafford et al. (1993)
Variable rate irrigation	Technology development and testing	McCann and Stark (1993), Fraisse (1994), Evans et al. (1996)

coherent site-specific crop management prescriptions" (Evans et al. 1996). Distortion of irrigation spray patterns by wind was also a particularly vexing problem.

1.12 REMOTE SENSING

Remote sensing applications in precision agriculture are primarily based on reflectance of the sun's visible and near-infrared light by soils or crops. Remote sensing does not require contact between the sensor and the soil or crop and is usually achieved using cameras mounted on satellites, airplanes, towers, or unmanned aerial vehicles. Proximal sensing, discussed in Section 1.13 below, differs from the traditional definition of remote sensing in that proximal sensing involves sensors placed on ground vehicles rather than aerial platforms.

The earliest applications of remote sensing in agriculture were primarily focused on estimating crop yield (Pinter et al. 1981; Wiegand et al. 1991), although Al-Abbas et al. (1974) conducted laboratory studies of the spectral properties of corn leaves with various levels of nutrient stress. Robert (1982) used color infrared aerial photography in Minnesota for diagnosis of "problems related to drainage, erosion, germination, grass and weed control, crop stand and damage, and machinery malfunction."

Landsat imagery was investigated for diagnosis of agricultural problems by Robert (1982), but difficulties in processing satellite remote sensing data at that time prevented meaningful results. Zheng and Schreier (1988) and Bhatti et al. (1991) were the first to use aerial and satellite imagery, respectively, for the specific purpose of estimating spatial patterns in soil fertility that could be used to guide variable rate fertilizer applications. Zheng and Schreier (1988) found that potassium fertilizer recommendations for a bare field in British Columbia could be reduced relative to uniform applications if rates were varied according to spatial patterns in soil organic matter content identified using color aerial photographs. Bhatti et al. (1991) found that spatial patterns in soil organic matter from Landsat satellite imagery for bare soil on a commercial farm in Washington State were strongly related to patterns in soil phosphorus and wheat yield. They proposed that areas with low organic matter content and low crop productivity "could be managed with customized fertilizer and tillage practices" for environmental protection. During this early period in precision farming, satellite remote sensing imagery with Landsat was limited to 30 m spatial resolution with a return frequency of no better than 15 days. These factors, coupled with the problem of acquiring satellite imagery during cloudy days, limited the application of satellite imagery to precision farming during the 1990s.

Attention soon turned to using remote sensing to detect nitrogen deficiency in corn and other crops. Blackmer et al. (1995) used canopy reflectance measurements of single leaves with a spectroradiometer to confirm previous research by Walburg et al. (1982) that showed an increase in reflectance in the green spectrum (550 nm) with nitrogen stress. Blackmer et al. (1995, 1996a) then used black and white aerial photography of stressed and unstressed corn plants in Nebraska with a camera that filtered all light except green. Results showed an excellent relationship between canopy reflectance and grain yield across a large range of crop nitrogen stress. In a companion paper, Blackmer and Schepers (1996b) showed that crop nitrogen stress was accurately detected using the brightness of red in a digitized aerial color photograph of a cornfield in Nebraska. Bausch and Duke (1996) developed a green vegetation index (GVI) defined by the ratio of near-infrared to green (NIR/G) reflectance that accurately predicted differences in nitrogen stress for irrigated corn in Colorado. Research results showing that remote sensing could accurately identify areas of nitrogen stress in crops led directly to the development of proximal sensors (described in Section 1.13) for precision management of crop nutrient deficiencies.

Until launch of the commercial Ikonos satellite in 1999, there were few instances where satellite remote sensing was used for precision farming applications (Mulla 2013). Ikonos collected reflectance data using blue, green, red, and near-infrared bands at 1–4 m spatial resolution with a return frequency of 3 days, leading to immediate applications in precision farming such as diagnosis of crop nitrogen stress, fungal infestations, and soil drainage problems (Seelan et al. 2003). A second commercial satellite, Quickbird, launched in 2001, collected reflectance in the blue, green, red, and near-infrared bands at 0.6–2.4 m spatial resolution with a return frequency of 1–4 days. Quickbird normalized green normalized difference vegetation index (NGNDVI) data were used by Bausch and Khosla (2010) to identify locations experiencing crop N stress.

High-resolution, high-return-frequency commercial satellites launched from 2008–2009 included RapidEye, GeoEye1, and WorldView2. These satellites have spatial resolutions ranging from 6.5 to 0.5 m (Mulla 2013) and return frequencies ranging from 5.5 days to 1.1 days. Thus, they are highly suitable for applications in precision farming. More interestingly, these satellites offer additional spectral bands in comparison with earlier satellites. RapidEye collects reflectance data in the blue, green, red, red-edge, and near-infrared bands. Red-edge reflectance is highly sensitive to the chlorophyll status of growing crops. GeoEye1 collects reflectance data in the blue, green, red, and two near-infrared bands. The images in Google Earth are commonly obtained using GeoEye1 imagery. WorldView2 collects imagery in purple, blue, green, yellow, red, red-edge, and near-infrared bands. Despite the improvement in return frequencies for commercial satellites, difficulties persist in acquiring satellite imagery when needed due to cloud cover and competition for imagery among civilian and military users.

Remote sensing has been used in precision farming for a variety of purposes, including estimating spatial variability in soil organic matter (Bhatti et al. 1991; Mulla 1997; Fleming et al. 2004), in crop yield (Yang et al. 2000; Boydell and McBratney 2002; Garcia Torres et al. 2008), in crop water stress (Barnes et al. 1996; Meron et al. 2010; Rud et al. 2014), in insect infestations (Franke and Menz 2007; Prabhakar et al. 2011), in crop disease (Muhammad 2005; Huang et al. 2007; Mirik et al. 2011), and in weed infestations (Zwiggelaar 1998; Lamb and Brown 2001; Thorp and Tian 2004; Lopez-Granados 2011). By far the most common application of remote sensing in precision farming, however, is for detection of spatial and temporal patterns in crop nutrient deficiencies (Bausch and Duke 1996; Haboudane et al. 2002; Miao et al. 2007, 2009; Tremblay et al. 2012; Nigon et al. 2014).

In many of these applications, various combinations of spectral bands known as spectral indices are used to detect the property of interest (Haboudane et al. 2002, 2004; Thenkabail 2003; Mulla 2013). The spectral index most commonly used when a growing crop is present is the normalized difference vegetative index (NDVI) (Rouse et al. 1973), which is based on the sharp contrast in reflectance between the red and near-infrared portions of the spectrum. Plant pigments absorb radiation in narrow wavelength bands centered around 430 nm (blue or B) and 650 nm (red or R) for chlorophyll a and 450 nm (B) and 650 nm (R) for chlorophyll b. Wavelengths with low absorption characteristics conversely have high reflectance, particularly in the green (550 nm) wavelength. Remote sensing of crops in the near-infrared spectrum (particularly at 780, 800, and 880 nm) responds to crop canopy biomass and leaf area index (LAI), leaf orientation, and leaf size and geometry. NDVI has been used to detect crop nutrient deficiencies, patterns in crop yield, insect and weed infestations, and crop diseases (Mulla and Miao 2015). NDVI values are often not a good indicator of crop status due to either interference from bare soil reflectance or to insensitivity to changes in leaf chlorophyll in closed canopy crops when leaf area index values exceed 2 or 3 (Thenkabail et al. 2000).

As a result, there has been significant research effort devoted to finding broadband multispectral indices that can be used as an alternative to NDVI (Sripada et al. 2006, 2008; Miao et al. 2009). In general, there are three classes of broadband multispectral indices used in precision farming. These include soil-adjusted vegetation indices, ratios of green and near-infrared reflectance bands, and ratios of red and near-infrared reflectance bands (Thenkabail 2003; Mulla 2013). Soil-adjusted vegetation indices reduce reflectance from bare soil that interferes with the interpretation of reflectance from a growing crop before canopy closure. Red ratio indices typically are sensitive to absorption of radiation by leaf chlorophyll, while green ratio indices are sensitive to leaf pigments other than chlorophyll. In commonly used red and green ratio indices, either the red or green or the near-infrared reflectance can appear in the numerator of the ratio.

Hyperspectral remote sensing data involves the collection of reflectance data over the entire visible and near-infrared spectra in narrowbands typically of 10 nm or narrower width. In contrast, multispectral data typically involves reflectance in broadbands, 50 nm or wider, centered in the blue, green, red, and lower near-infrared portion of the spectrum. All of the broadband spectral indices calculated with multispectral data can be calculated as narrowband spectral indices using hyperspectral imaging. The advantage of doing this is that specific plant or soil responses that would be obscured by other plant or soil reflectance characteristics using broadband multispectral imagery become clear with narrowband hyperspectral imagery. For example, plants contain different pigments whose light absorption peaks at specific narrow wavelengths. Plant pigments such as chlorophyll strongly absorb radiation, particularly at wavelengths such as 430 (blue or B) and 660 (red or R) nm for chlorophyll a and 450 (B) and 650 (R) nm for chlorophyll b (Pinter et al. 2003). Other plant pigments such as anthocyanins and carotenoids absorb strongly at different wavelengths (Blackburn 2007). Crop reflectance also responds to changes in crop biomass, LAI, canopy structure, and leaf density in the red and near-infrared wavelengths. A narrow red band centered at 687 nm is sensitive to crop LAI and biomass, while a narrow near-infrared band centered at 970 nm is sensitive to crop moisture status (Thenkabail et al. 2010). Further examples of linking specific soil and crop characteristics with narrowband reflectance are given by Thenkabail et al. (2010). Hyperspectral imaging can be used to estimate narrowband spectral indices that have no analog in multispectral imagery. For example, several researchers have used red-edge reflectance in the spectral region between 700 and 740 nm to construct spectral indices that are sensitive to crop nitrogen status (Guyot et al. 1988; Datt 1999; Clarke et al. 2001; Haboudane et al. 2002; Gitelson et al. 2005; Fitzgerald et al. 2010; Shiratsuchi et al. 2011).

Interest is growing in the use of low-altitude unmanned aerial vehicles (UAVs) as a platform for remote sensing in precision farming (Zhang and Kovacs 2012). Imagery collected with UAVs can be high enough in resolution to view individual plants and leaves, although images at such high resolution have to be mosaicked to obtain complete coverage of a field. UAVs have been used to assess crop LAI, biomass, plant height, nitrogen status, water stress, weed infestation, and yield and grain protein content (Berni et al. 2009; Swain et al. 2010; Samseemoung et al. 2012; Bendig et al. 2013). Current limitations to using UAVs include governmental restrictions on their usage, light payloads, low power, and limited flight times.

1.13 PROXIMAL SENSING OF SOILS AND CROPS

Proximal sensing has been widely used in precision farming to map spatial patterns in soil or crop properties. Early advances in proximal soil sensing were initially based on geophysical prospecting techniques that were used to discover mineral reserves buried deep in the earth (Parasnis 1973). Two categories of geophysical prospecting techniques have been adapted for proximal sensing of soil in precision farming: electrical resistivity/conductivity methods and electromagnetic induction methods. Halvorson and Rhoades (1974) adapted electrical resistivity mapping methods to the problem of mapping soil salinity in agricultural fields based on the four-probe Wenner array developed in the mining industry. Wenner array probes were simply metal spikes inserted in soil along a straight line at fixed spacing. A battery supplied current to the soil through two of the spikes, while the other two served as voltage probes. The depth of measurement could be controlled by varying the spacing between metal electrodes. Carter et al. (1993) built on the research by Halvorson and Rhoades (1974) to pioneer continuous mobile electrical conductivity measuring equipment for soil salinity mapping. The mobile apparatus consisted of a battery attached to four equally spaced chisel blades mounted on a tractor. This apparatus was the inspiration for the Veris electrical conductivity mapping system (Christy and Lund 1998) based on equally spaced electrode disks that is widely used in precision farming. Colburn (1991) patented a device for a resistivity-based sensor mounted behind a moving fertilizer spreader that was claimed to accurately vary fertilizer rate in response to differences in soil nitrate-N concentrations, soil cation exchange capacity, organic matter content, and soil moisture. This device, called Soil Doctor, was widely marketed for applications in precision farming, although many scientists were skeptical of its accuracy in the absence of rigorous scientific testing.

There were several drawbacks of the Wenner array of electrodes for soil salinity mapping. First was the difficulty of ensuring good contact between electrodes and dry soil, and second was the need to eliminate site-specific calibration of electrical resistivity measurements with soil samples that were analyzed in the laboratory. To overcome these limitations, Rhoades and Corwin (1981) began working with Geonics Ltd. of Canada, who were commercial suppliers of electromagnetic induction probes for geophysical prospecting in the mining industry. Rhoades and Corwin (1981) suggested the development of a noncontacting electromagnetic induction probe that could be used specifically for shallow sensing of soil materials, and this suggestion led to the development of the EM-38 electromagnetic induction probe (Figure 1.6) that is widely used in precision farming (Lesch et al. 1992; Doolittle et al. 1994; Sudduth et al. 1995; Kitchen et al. 1999, 2003). Electromagnetic induction is a process where an electrical field generated above ground induces current loops in the soil that are proportional in magnitude to the soil's electrical conductivity. The primary current loops in the soil induce a secondary electromagnetic field whose strength is proportional to the current flowing in the loops. This secondary field is then measured by a receiver above ground to estimate soil electrical conductivity.

The commercially available EM-38 electromagnetic induction unit from Geonics Ltd. of Canada became a preferred tool to map soil salinity (Corwin and Lesch 2003). Lesch et al. (1992) reported the advantage of using an EM-38 unit that enhanced their ability to accurately predict spatial soil salinity patterns with 60% to 90% fewer soil samples. They concluded that EM-38 readings were a more practical and cost-effective tool for accurate mapping of spatial salinity patterns at the field scale than soil sampling. Likewise, Doolittle et al. (1994) in Missouri were able to quantify and map variations in the depth to claypan soils that restrict infiltration, influence the lateral movement of soil water and agrichemicals, and limit crop production. They found that EM techniques were noninvasive, less labor-intensive, more economical, and could produce large quantities of data in a relatively short period of time. Sudduth et al. (1995) continued the work of Doolittle et al. (1994) and found that by automating the process of collecting EM-38 data, they could map variations in soil properties over large areas for site-specific nutrient management. Kitchen et al. (1999) studied the relationships in spatial maps from EM-38 data and grain yield monitors. They found a significant relationship between yield maps and apparent electrical conductivity maps in nine out of 13 site years of data. Later, Kitchen et al. (2003) measured apparent soil electrical conductivity using a Veris electrical conductivity unit developed by

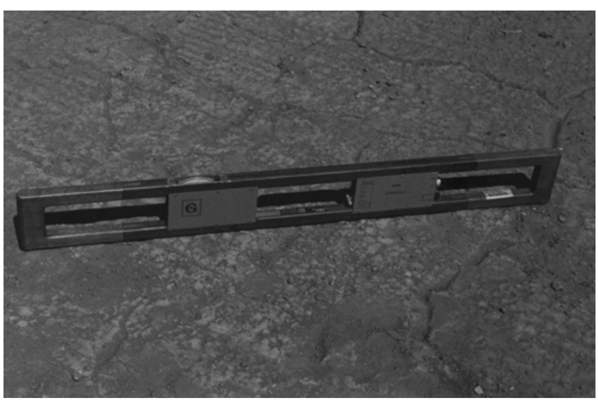

FIGURE 1.6 First commercial unit (circa 1980) of the Geonics EM-38 single dipole electromagnetic induction conductivity meter. (Courtesy of Dennis Corwin.)

Christy and Lund (1998) across three states (Missouri, Kansas, and Colorado), under four different crops (maize, wheat, soybean, and sorghum), and indicated that sensor-based soil information can greatly assist farmers in understanding yield variations for planning management decisions in precision farming.

Early proximal sensing in precision farming was also focused on the use of *in situ* reflectance methods to assess spatial patterns in soil organic matter content (Shonk and Gaultney 1988; Sudduth et al. 1991). Soil organic matter content is often correlated with other soil properties such as moisture content and nitrogen mineralization, each of which can affect potential crop yield. In addition, certain classes of crop protection chemicals are adsorbed by soil organic matter content. In either case, varying the rate of fertilizer or pesticide according to levels of soil organic matter content was the motivation for developing proximal sensing techniques for soil organic matter content. Gaultney et al. (1991) patented a device to measure soil organic matter content in real time that was based on laboratory calibration curves that depended on soil texture. The device consisted of an array of red-light-emitting diodes surrounding a photodiode sensor, both of which could be mounted on a chisel blade dragged by a tractor. McGrath et al. (1990) used the organic matter sensor to vary rates of herbicide applied in Midwestern fields, with good success at controlling weeds. Sudduth et al. (1991) developed an organic matter sensor that was based on near-infrared reflectance (Figure 1.7). When tested in the laboratory, the sensor was able to accurately detect differences in SOM content even when soil moisture content varied. However, field trials were initially unsatisfactory because reflectance values were sensitive to soil roughness (Hummel et al. 1996).

Electrochemical sensing of soil chemical properties was an important emphasis in early precision farming research (Colburn 1991; Adsett and Zoerb 1991; Birrell and Hummel 1993). Adsett and Zoerb (1991) adapted an ion-selective electrode that measured nitrate-N concentrations in soil solution to a real-time proximal sensor. A rather cumbersome apparatus was developed that sampled soil, mixed and stirred it with water, and then used the ion-specific electrode to measure nitrate concentrations on the go. The sample container was then dumped in the field and rinsed out automatically before taking another soil sample. Birrell and Hummel (1993) tested an ion-sensitive field effect transistor (ISFET) for nitrate-N concentration measurements in the laboratory. They found that samples could be analyzed every 1.5 seconds through a cycle that involved sample injection and washing of the sample container. ISFET sensors are smaller and have a faster response and higher signal-to-noise ratio than ion-specific electrodes. However, they also have greater electronic drift, requiring frequent recalibration. Flat surface ion-selective probes were developed by Adamchuk et al. (1999) and patented (Adamchuk et al. 2002) for real-time automated mapping of soil pH,

FIGURE 1.7 Soil organic matter sensor based on NIR reflectance. (From Sudduth, K. A. et al., Soil organic matter sensing: A developing science. In: G. A. Kranzler (ed.), *Automated Agriculture for the 21st Century.* ASAE Publication 11–91, St. Joseph, MI, pp. 307–316, 1991.)

while Adamchuk et al. (2003) developed ion-selective probes for real-time automated mapping of soil nitrate and potassium levels.

Interest in proximal sensing of crops is not new. Scientists and farmers alike will visually inspect crops to nondestructively estimate crop health status. Their visual inspection may often lead to a management decision such as fertilizer, irrigation, or pesticide application. Human eyes are in fact a pair of reflectance-based optical sensors. However, human eyes require experience to discern subtle differences in crop appearance due to various biotic and abiotic stresses. Machine-based optical sensors, on the other hand, can be used repeatedly without bias or need for experience. In the early 1970s, Leamer and his coworkers at the USDA-ARS unit in Weslaco, Texas, and his colleague Silva from the electrical engineering department at Purdue University, recognized the need for an instrument that would scan a specific field target through the visible and thermal infrared spectrum (Leamer et al. 1973). They designed and developed an instrument and provided specifications and plans to Exotech Inc. to build a sensor that could be used in fields for crop sensing. The instrument was built by Exotech, who also contributed many engineering concepts and the electronic circuits required to measure the reflected or emitted energy and to produce an electrical signal proportional to the energy detected by the instrument (Leamer et al. 1973).

The instrument (Exotech model 20-B Spectroradiometer) consisted of two systems, each made up of an optical unit and a control unit. One system covered the spectral range 0.37–2.52 μ; the other system covered the spectral range 2.76–13.88 μ. The optical units of the two systems were mounted side by side on a tiltable base mounted on an aerial lift truck. Separation between the objective lenses was about 30 cm to minimize parallax. The system was configured such that it can be operated separately or in the tandem, boresighted mode (Leamer et al. 1973). The control units were mounted in a camper-type equipment van and were connected to the optical units by 60 m of armored cable. Preamplifiers and auxiliary electronics in the optical units were designed to operate without picking up interference over this length of cable. The entire system was designed to operate in an outdoor environment.

The Laboratory for Applications of Remote Sensing (LARS) at Purdue University was among the early pioneers and leaders in advancing the science of remote sensing and its applications in agriculture. Much of the early work in the area of crop sensing came from LARS under the leadership of Bauer, Baumgardner, and many of their graduate students (Al-Abbas et al. 1974; Bauer 1975; Ahlrichs and Bauer 1978; Kumar et al. 1979; Daughtry et al. 1980; Walburg et al. 1982).

The 1980s witnessed the introduction of optical sensing into agriculture as a complementary monitoring tool to estimate crop health, growth, abiotic stresses, and crop yield (Bell and Xiong 2007). Daughtry et al. (1980), using an advanced version of Exotech Spectroradiometer (Exotech 100A), investigated the effects of various management practices (soil moisture, planting date, nitrogen fertilizer, and cultivar) on spring wheat crop canopies. They suggested that LAI, biomass, and percent soil cover can potentially be monitored by crop canopy sensing. Likewise, Walburg et al. (1982) studied the effects of N rates on growth, yield, and reflectance characteristics of corn canopies and reported that spectral reflectance differed significantly with N rate. Wanjura and Hatfield (1987) reported that vegetation indices had greater sensitivity to plant vegetation reflectance than did the reflectance of a single wavelength. Early work that utilized crop canopy sensing was primarily done to understand cause and effect relationships and to identify particular wavebands, their simple ratios, or various vegetative indices that were most effective in distinguishing the treatments of interest (Chappelle et al. 1992; Blackmer et al. 1994; Filella et al. 1995). Reflectance near the 550-nm wavelength was found to be the best at distinguishing nitrogen treatments in soybean (Glycine max [L.] Merr; Chappelle et al. 1992). Blackmer et al. (1994) reported similar findings for nitrogen in corn canopies. Around the same time, Filella et al. (1995) reported that reflectance at 550 and 680 nm was significantly correlated with canopy chlorophyll content across five N treatments in wheat canopies.

Around the same time, engineers Solie and Stone and agronomist Raun at Oklahoma State University were working on developing rapid ways of estimating leaf nitrogen concentrations and crop biomass using sensing technology (Solie et al. 1996). Stone developed a sensor with two detectors working in synchrony; one measured the incoming radiance and the other faced the plant canopy and measured the reflected radiance (Table 1.5). The irradiance reflected was divided by the incoming irradiance to determine reflectance (Bell and Xiong 2007). One of the limitations among the crop sensing devices of the 1980s and 1990s was that they were passive sensors (i.e., without their own sources of light energy). Hence, they were limited by the time of day when sensor readings were acquired in the field with and without cloud cover, and the need for constant white plate calibration (Rutto and Arnall 2009). To address this limitation, in 1998, the Oklahoma team joined hands with Mayfields (future founders of N-Tech Industries and manufacturers of the GreenSeeker™ sensor), who owned much of the relevant intellectual properties for active optical sensors, which they purchased from John Deere & Company, Moline, IL (Rutto and Arnall 2009). The team felt that the development of active sensors (sensors that have their own source of light energy) was necessary for such sensing devices to be incorporated into in-field and in-season precision nutrient recommendations.

The year 2002 marked the commercial release of the GreenSeeker active sensing device (Raun et al. 2002) by N-Tech Industries (Ukiah, CA). Since then other proximal crop-sensing devices such as Crop Circle active sensor (Holland Scientific, NE), the Yara N-Sensor ALS (active light sensor) by Yara International, Norway; and Isaria Crop Sensor by CLAAS, Germany have become commercially available. These reflectance-based active sensors are being widely used to guide variable rate nitrogen fertilizer applications around the world (Shanahan et al. 2008; Samborski et al. 2009; Kitchen et al. 2010).

Initially, the majority of the commercially available active sensors were reflectance-based sensors and were providing either NDVI or a modification of the NDVI readings. However, more recently there are fluorescence-based active sensors that are commercially available such as the Multiplex Fluorescence sensor by Force-A, France, and the MiniVeg laser-induced chlorophyll fluorescence sensor by Fritzmeier, Germany. Fluorescence sensors utilize either ultraviolet or laser light sources, or both, to stimulate a plant's chlorophyll to emit fluorescent light. Green plants emit fluorescence in the blue-green (440–520 nm) and in the red to far-red (690–740 nm) regions of the light spectrum when excited with a potent light source (Buschmann et al. 2000). Different combinations of red and far-red fluorescence ratios obtained with different excitation wavebands can be used to calculate a multitude of indices for the plant status (Tremblay et al. 2011). A fluorescence-based index called

TABLE 1.5
Early Research Advances in Remote Sensing, Proximal Sensing of Soils, and Proximal Sensing of Crops for Precision Farming

Research Area	Nature of Contribution	Key References
Aerial remote sensing	Ability to identify spatial patterns, identification of sensitive wavelengths	Robert (1982), Zheng and Schreier (1988), Bhatti et al. (1991), Blackmer et al. (1995), Barnes et al. (1996), Bausch and Duke (1996), Blackmer and Schepers (1996b), Haboudane et al. (2002), Thenkabail (2003)
Proximal sensing of soils	Development and testing of technology	Rhoades and Corwin (1981), Shonk and Gaultney (1988), Colburn (1991), Gaultney et al. (1991), Sudduth et al. (1991), Lesch et al. (1992), Carter et al. (1993), Doolittle et al. (1994), Christy and Lund (1998), Adamchuk et al. (1999)
Proximal sensing of crops	Development and testing of technology	Leamer et al. (1973), Daughtry et al. (1980), Walburg et al. (1982), Chappelle et al. (1992), Solie et al. (1996), Raun et al. (2002)

the nitrogen balance index (NBI) was developed to detect N variability by the ratio of chlorophyll content to the flavonoid content (Cartelat et al. 2005). In a recent study, Longchamps and Khosla (2014) reported early detection of nitrogen variability at the five-leaf growth stage of maize using the Multiplex 3 fluorescence sensor. They also reported that the fluorescence readings were not influenced by soil background noise when used at the recommended height of measurement. Such findings are significant for precision farming and are leading the way to enhance our ability to manage nutrients more efficiently. Interestingly, fluoresensing is not new. Lorenzen (1966) demonstrated that chlorophyll fluorescence can be used to assess plant chlorophyll content and photosynthetic activity through the state of photosystem II. However, such measurements were made in a dark chamber on a potted plant by inducing fluorescence with a laser beam. Today, similar measurements can be acquired using commercially available fluorescence sensors in broad daylight and in motion above the crop canopy. One can therefore envision that in the near future as technology and science continue to progress, scientists and farmers will be working with many innovative proximal crop sensors that are yet to be developed and commercialized to further the goals of precision farming.

1.14 ENVIRONMENTAL BENEFITS OF PRECISION FARMING

Precision farming allows for variation in the rate of applied fertilizer, manure, and pesticides to better match spatial patterns in soil fertility and pesticide adsorption, and to respond to changing temporal patterns in crop nutrient stress and infestations of weeds, insects, and disease. In addition, with autosteer technology, precision farming reduces overapplication of chemical inputs due to overlap between successive passes of chemical applicator machinery. All of these factors lead, conceptually, to improved environmental quality and sustainability (Larson et al. 1997; Bongiovanni and Lowenberg-DeBoer 2004).

The use of precision farming to reduce the risks of pesticide leaching to groundwater in sandy soils were first studied by Mulla et al. (1996) at a field site in Washington State. Measured concentrations in carbofuran applied at 8.1 kg ha^{-1} a.i. were measured to a depth of 1.8 m at 57 locations throughout the field and this data wad used to calibrate the convective-dispersive equation for pore water velocity, dispersion coefficient, and retardation factor. Results showed that there was significant spatial variability in pesticide leaching risks. Over half of the field was at high risk for leaching losses, and these losses could be significantly reduced by applying low rates of carbofuran in high-risk leaching areas. Spatial patterns in leaching risk were controlled primarily by variations in water movement rather than variations in soil organic matter content, making the *a priori* identification of high-risk leaching areas challenging.

Khakural et al. (1994, 1999) and Mulla et al. (2002) measured the impact of variable rate herbicide applications on herbicide losses in runoff, tile drainage, and eroded sediment for a fine textured soil in Minnesota. These studies showed that variable rate herbicide applications based on spatial patterns in soil organic matter content, soil pH, or weed populations resulted in significant reductions of herbicide applied to soil and subsequent reductions in the amount lost to surface waters relative to uniform herbicide applications. A number of other researchers showed that spatial variability in soil properties and weed populations could be used as the basis for variable rate herbicide applications that could lead to significant reductions in the amount of herbicide applied to fields (Mortensen et al. 1995; Johnson et al. 1997).

Mixed results have been found by a number of researchers concerning the environmental benefits of variable rate nitrogen fertilizer applications using either assessments of residual soil N and nitrogen use efficiency (NUE) or simulation modeling (Bongiovanni and Lowenberg-Deboer 2004). Hergert et al. (1996) compared uniform versus variable rate applications of N fertilizer in irrigated corn in Nebraska. They found that residual N concentrations in soil were significantly lower for variable rate N applications than uniform applications, but there were no differences in NUE for either strategy. On the other hand, Redulla et al. (1996) found no significant differences in residual soil N or NUE between uniform and variable rate N applications in irrigated Kansas corn fields.

Whitley et al. (2000) studied N leaching in irrigated potatoes grown in Washington State using either uniform or variable rate N applications. They found that N leaching was reduced in lower landscape positions with variable rate N application relative to uniform application.

A variety of simulation models have been used to assess the benefits of variable rate N applications on water quality. Larson et al. (1997) used Leaching Estimation and Chemistry Model (LEACHM) in rainfed corn produced in Minnesota to show that N leaching was reduced with variable rate N applications relative to uniform applications on a loamy sand, but not on a loamy soil. The Environmental Policy Integrated Climate (EPIC) model was used by Rejesus and Hornbaker (1999) and by English et al. (1999) to show that N losses to surface waters were reduced using variable rate N application in Illinois and Tennessee, respectively. Delgado et al. (2005) used the Nitrogen Loss and Environmental Assessment Package (NLEAP) model in Colorado to show that N leaching in irrigated corn could be reduced using variable rate N applications. Variable rate N applications were particularly effective at reducing N leaching losses in management zones with low crop productivity where crop uptake of N was limited.

1.15 PROFITABILITY OF PRECISION FARMING

Since the inception of precision farming, scientists, farmers, and practitioners alike have questioned the economic feasibility of precision farming. The perceptions among the early users of precision farming were (1) that it is technologically and resource-intensive and time consuming and hence it would be cost-prohibitive, and (2) that it primarily increases system efficiencies and not necessarily output (Napier et al. 2000). These perceptions were further strengthened by the limited number of early studies evaluating agronomic and economic gains of precision farming (Table 1.6). Hammond (1993) reported that variable management is unlikely to cause increases in crop yield or quality in high or intermediate fertility areas of the field. Furthermore, a majority of those early studies reported that precision farming was not profitable or that profitability was mixed at best (Lowenberg-DeBoer and Boehlje 1996). Table 1.6, adopted from Lowenberg-DeBoer and Boehlje (1996), summarizes the findings of 11 early studies evaluating the economics of precision farming. Five of the 11 studies reported precision farming as not being profitable, four studies reported mixed or inconclusive results, and only two studies showed potential profitability. They attributed the

TABLE 1.6
Profitability Findings from Eleven Precision Farming Studies

Study and Year	Crop(s)	Conclusion: Precision Farming Profitable or Not?
Beuerlein and Schmidt (1993)	Corn, soybean	No
Carr et al. (1991)	Wheat, barley	Mixed
Fiez et al. (1994)	Wheat	Yes, potentially
Hammond (1993)	Potato	Inconclusive
Hayes et al. (1994)	Corn	Yes, potentially
Hertz and Hibbard (1993)	Corn	No
Lowenberg-DeBoer et al. (1994)	Corn	No
Mahaman (1993)	Corn	Mixed
Wibawa et al. (1993)	Wheat	No
Wollenhaupt and Buchholz (1993)	Corn	Mixed
Wollenhaupt and Wolkowski (1994)	Corn	Mixed

Source: Modified and adapted from Lowenberg-DeBoer, J., and M. Boehlje, Revolution, evolution or dead-end: Economic perspectives on precision agriculture. *Proc. 3rd Intl. Conf. Precision Agriculture*, pp. 923–944, 1996.

failure to demonstrate economic gains to two primary reasons: (1) these studies compared whole-field gains to precision farming treatments, and (2) the findings depended heavily on the cost of sampling and variable rate applications that exceeded any gains made in yields. Lowenberg-DeBoer and Boehlje (1996) argued that whole-field profit maximizing conditions differ from the site-specific conditions and that there has to be a more economical, less expensive way of preparing variable rate prescription maps for precision farming. In a follow-up study, Lowenberg-DeBoer and Swinton (1997) suggested that many previous studies failed to indicate whether problems with the technology or with its management were behind the apparent low profitability findings.

The limitations identified by Lowenberg-DeBoer and Boehlje (1996) and others (Khosla and Alley 1999) highlighted the need to develop techniques to replace expensive grid soil sampling for the purpose of variable rate management of crop and soil inputs. Khosla et al. (2002) reported significant agronomic gains from using site-specific management zones to variably apply nitrogen in comparison with conventional uniform applications of nitrogen across the entire field. A more detailed, in-depth study on economic feasibility by Koch et al. (2004) clearly documented for the first time significant economic gains from using precision farming. An increase in net return was reported ranging from \$18.21 to \$29.57 ha^{-1} higher for variable-rate N application than for uniform N management (Koch et al. 2004). Interestingly, most studies in the late 1990s and early 2000s focused on the precision nutrient management aspects of precision farming, logically so, because this was the first precision farming technology that was technically feasible (Lowenberg-DeBoer and Swinton 1997).

In the following years, novel technologies and improved management techniques continued to accelerate the adoption of precision farming, including, but not limited to, precision autoguidance, lightbar, autopilot systems, active crop sensing, precision irrigation systems, and smart sampling (Jones 2004; McClure 2005; Inman et al. 2007; Shaner et al. 2008). Griffin et al. (2005) investigated the economics of using a lightbar and autoguidance GPS navigation technologies and found that a high-precision real-time kinematic (RTK) GPS system was less profitable to operate compared with no GPS use on a farm. However, when a farmer begins using GPS, its profitability increases with the level of GPS precision (Griffin et al. 2005). They found that the lightbar was the most profitable navigation technology; however, as farm size increases, RTK-GPS becomes profitable and it outranks lightbar-GPS-based precision farming operations (Griffin et al. 2005). More recently, Shockley et al. (2011, 2012) demonstrated that autosteer technologies can influence machinery selection and replacement decisions, increase net returns, and reduce production risk. This is even more significant because their work incorporated over 500 real-world cropland fields from farms in Colorado, Kansas, and Nebraska.

The economics of precision farming continue to improve as technologies and management techniques improve. However, a major factor that previously has and will continue to greatly influence the economics of precision farming is commodity prices. During the last decade we have witnessed substantial fluctuations in commodity prices. For example, corn prices have gone from approximately \$80 Mg^{-1} in early 2000 to over \$200 Mg^{-1} recently (USDA-ERS 2014). Such increases in commodity prices are a welcome relief for farmers and have resulted in higher economic gains and investment of such gains back into innovative technologies and techniques, including precision farming. However, recent declines in commodity prices may start to reverse the growing adoption of precision farming.

1.16 ADOPTION OF PRECISION FARMING

Precision farming has been termed the most significant innovation introduced to U.S. agriculture in the mid- to late 1980s (Napier et al. 2000). Yet its adoption rate, at least for the first 10 to 15 years, did not meet expectations. Yapa and Mayfield (1978) indicated a number of reasons that could lead to nonadoption of an innovation. These include, but are not limited to, lack of sufficient information, lack of favorable attitude, lack of economic means to acquire technology, and lack of physical availability of technology. Nowak (1992) narrowed the reasons down to two major factors: willingness and ability to adopt. Rogers (1995) argued that adoption of technological innovations will not occur unless potential adopters become aware that a problem exists that can be resolved in a more efficient manner by new technologies. The early practitioners of precision farming highlighted the problem they were trying to address. However, the perception that it amounts to mere improvement in efficiency of farming was not enough to attract adopters. Nowak (1992) emphasized that the willingness to adopt depends on access to information about the technology, confidence in that information, and belief that the information provides a basis for favorable outcomes. Fairchild and Duffy (1993) suggested that profitability is one favorable outcome desired by virtually all producers in a market economy and it is a necessary condition for extensive, voluntary technology adoption. It is therefore no surprise that the pace of adoption of precision farming techniques and technologies was slow at best until the mid- to late 1990s because there was no clear evidence of economic feasibility or profitability associated with precision farming (Lowenberg-DeBoer and Boehlje 1996). By early 2000, it was widely recognized among the precision farming community that for adoption of precision farming to occur, the technology needed to be relevant in addressing problems, be easy to use, and above all be profitable to farming (Napier et al. 2000; Kitchen et al. 2002). Batte and Arnholt (2003) examined case studies of six leading-edge adopters and found that profitability was the biggest motivating factor in using precision agriculture tools.

The first decade of the twenty-first century saw accelerated adoption of precision farming. Over the past decade, the adoption and use of different precision agricultural technologies among producers and commercial agricultural businesses increased steadily (Whipker and Akridge 2006). There are a number of reasons that can be attributed to the change in pace of adoption of precision farming techniques and technologies over the past decade: (1) certain components of precision farming such as precision nutrient management have been thoroughly tested and evaluated and were being reported to enhance efficiency, productivity, and profitability in an environmentally responsible manner (Franzen et al. 2000; Khosla et al. 2002; Koch et al. 2004), (2) positive change in commodity prices that increased multifold over the last 10 years (USDA-ERS 2014), which led to higher net returns to farmers and their respective investment into advanced technologies, (3) introduction of new technologies such as autoguidance systems that in addition to improving efficiencies and profitability, reduced farmers' fatigue and allowed them to work longer hours (Griffin et al. 2005), and (4) enhanced capacity and availability of a skilled labor force, trainers, and practitioners who understood both technology and agriculture. While these may only serve as a partial list of factors responsible for the enhanced level of adoption over the last decade, it does reflect on bridging the gap in many areas as pointed out by Nowak (1992), Fairchild and Duffy (1993), and Kitchen et al. (2002).

Unique partnerships among industries, the media, and academic institutions have enabled monitoring and documentation of change, progress, and adoption of precision farming among U.S. farmers. For the past 15 years, Purdue University in partnership with CropLife Media and recently Trimble Inc., has employed a survey tool to quantify changes in precision technologies, their respective adoption rates, and predicted future trends by agricultural retailers, practitioners, and farmers. Figure 1.8 reflects a summary of the most recent survey conducted in 2011 (Whipker and Erickson 2013). It lists the top 11 precision technologies that have gained popularity and adoption among farmers, agricultural retailers, and practitioners. The top two are both related to precision guidance that allow farmers to increase speed of field operations, work longer days, provide greater flexibility in hiring labor, have a more appropriate placement of inputs, and reduce overlap or chemical use (Griffin et al. 2005). It is interesting to note that some of the latest innovations such as crop and soil sensing devices that are still undergoing extensive research across academic institutions are being adopted by very few farmers and practitioners. Overall it is encouraging that about 60% of the agricultural retailers surveyed are offering precision farming services to their clientele. Review of the survey reports from previous years (data not presented) indicates that precision farming technologies and its adoption continue to grow among farmers.

While some may term the adoption of precision farming as slow, it is still remarkable given that precision farming was a new concept only about 25 years ago. In contrast, machine harvesters and

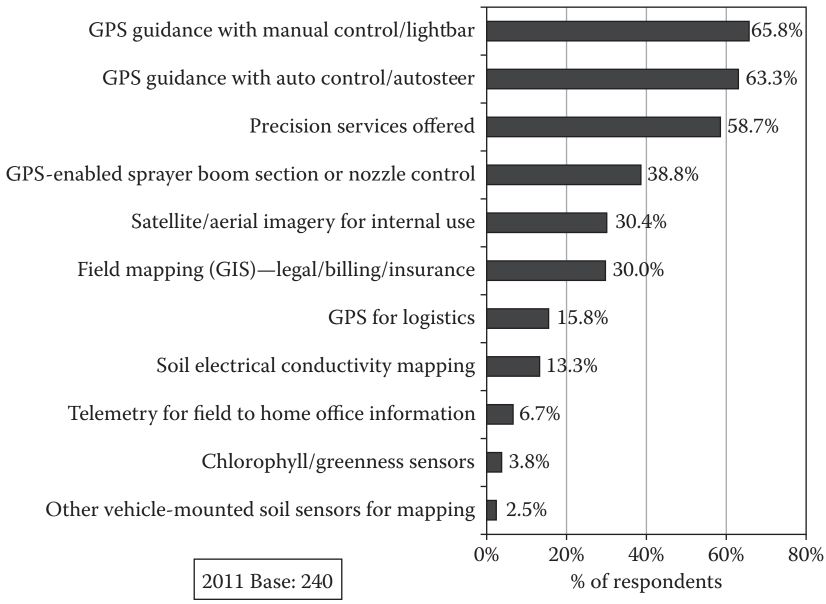

FIGURE 1.8 Summary of a nationwide survey reflecting the use of precision technologies across agricultural states in the United States. (Modified and adapted from Whipker, L. D., and B. Erickson, 2011 Precision agriculture services dealership survey results. Staff paper, Department of Agricultural Economics, Purdue University. W. Lafayette, IN, 2013.)

combines that are used today by most farmers in North America and elsewhere were invented in the early 1800s, commercialized in the late 1800s, and it took over 50 years or more since commercialization before they were used in large numbers on agricultural farms (Wikipedia 2014). Nevertheless, precision farming technologies continue to evolve and change and its impacts are reflected in overall production, efficiency, and environmental footprints of farming operations.

1.17 SUMMARY AND FUTURE TRENDS

The history of precision agriculture has shown that it is more strongly influenced by technological innovations rather than innovations in information analysis and decision support. For example, when first introduced, GPS and yield monitors were viewed as technological advances that could be added to existing farm equipment to add value. Later, agribusiness began embedding both GPS and yield monitors onto farm combines as part of the standard sales package. This combination of technology is now widely adopted by farmers so that it is used by practitioners of precision farming as much as by practitioners of conventional farming. The addition of GPS to farm equipment enabled many other technological breakthroughs in precision farming, such as autosteer, and furthermore, machine location was essential for variable rate fertilizer application technology.

In contrast, information analysis and decision support systems for deriving management zones or making variable rate recommendations have not largely been embedded in routine farm operations. In many cases these functions are performed by crop retailers, consultants, and agribusiness service providers for a fee. There seems to be a trend toward more focus on information analysis and decision support systems in precision agriculture (McBratney et al. 2005). In particular, large corporations and researchers are beginning to focus their attention on big data issues, involving combinations of spatially and temporally varying yield monitor, soil fertility, crop stress, and climate data. This data is overlain from many separate farming operations with a view toward identifying and modeling relationships with soil or landscape features that could be used to create knowledge that informs precision farming decisions. In general, the volume, variety, and value of large databases is increasing, while the scale at which management decisions are being visualized and implemented is becoming finer. Increasingly, there is likely to be a trend toward stronger reliance on forecasting precision farming operations based on short-term weather forecasts and expert system simulation models and delivering recommendations to farmers via the Internet and smartphones.

Within the technology realm, there is an increasing convergence between proximal sensing and robotics. Sensors mounted on aerial and ground robots are increasingly being used to scout for and mitigate damages caused by crop stress. Significant research efforts are being directed toward improved software algorithms that are devoted to improved navigation and coordination between swarms of aerial and ground robots deployed in large agricultural fields. However, this convergence between robotics and proximal sensing will not be successful without increased emphasis on information analysis and decision support systems that allow massive amounts of data collected with these technologies to be quickly and accurately turned into useful recommendations and management strategies. A wide range of analytic tools are increasingly being used for this purpose, including partial least squares analysis, neural network analysis, and computer vision.

The spatial and temporal resolution of remote sensing information has dramatically improved since the inception of precision farming. In the early years of precision farming, spatial resolutions of satellite data were on the order of 30 m, while temporal resolutions were on the order of weeks to months. Today, spatial resolutions are as good as several centimeters, while temporal resolutions are as good as a few days. With this level of spatial and temporal resolution, it is likely that precision farming practitioners will be able in the near future to develop customized management recommendations on a weekly basis for every single plant growing in their field.

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