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The Illuminating Role of Laser Scanning Digital Elevation Models in Precision Agriculture Experimental Designs – An Agro-Ecology Perspective

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1. Introduction

In his essay, The New Organon, Bacon (1561-1626) wrote *"So must we likewise from experience of every kind first endeavor to discover true causes and axioms; and seek for experiments of Light, not for experiments of Fruit. For axioms rightly discovered and established supply practice with its instruments, not one by one, but in clusters, and draw after them trains and troops of works."* (Donner et al., 1968). While Bacon's use of English is a bit opaque by today's writing styles, his statements are still very relevant and hold true for any significant area of inquiry when a key discovery or application is uncovered. Therefore, this chapter endeavors to indicate how laser scanning data streams, a 'light' based technology, enable the art, practice, and implementation of diverse investigations of agricultural systems, gaining insight into the various ecological processes involved. Our goal is to provide insight for others to similarly develop their 'trains and troops of works' according to their interests, which will, in turn, enrich all investigators of agricultural systems through the spread of shared knowledge and techniques.

Laser scanning data streams, when linked with multi-spectral, hyperspectral, apparent soil electro-conductivity (EC_a), or other kinds of geo-referenced data streams, aid in the creation of maps that allow useful applications in agricultural systems. These combinations of georeferenced information provide an opportunity to include several types of statistical analyses, permitting the best interpretation of the information conveyed by such maps, and provide the capability of building new, detailed, and more informative maps. Such maps have enabled a past, present, and, probably, future explosion '*of works*' leading to remarkably innovative methods for solving the problems of agricultural systems.

Several illustrations are presented to demonstrate a few of the numerous kinds of applications enabled by laser scanning data streams in agriculture. These illustrations focus on a Mississippi cotton field and a Nebraska corn field. Topics considered include (1) describing an approach to statistically evaluate impacts upon production by site-specific management practices (such as seeding rate, nitrogen and potassium applications, irrigation, and other farming operations), including the assessment of interactions among these practices and the topographical characteristics of crop fields, (2) assessing the accuracy of laser scanning data products, (3) evaluating the spatial distribution of the abundance, dispersion and other characteristics of agricultural variables as abstractions of agro-ecological populations of interest, and (4) a partial topographical analysis of yield involving two topographical attributes: laser scanning elevation data and the shallow apparent soil electrical conductivity (EC_a) measured by the Veris® cart (Veris Technologies, Salina, KS, USA), which is a proximal sensor system.

Global Positioning System (GPS) equipped hand-held loggers are another technology useful for obtaining geo-referenced scouting information such as crop phenology, soil fertility, and pests. These 'on the ground' measurements have extremely sparse sample sizes in comparison to the very dense pixel counts and small ground spatial distances (GSD) provided by laser scanning, proximal, or remote sensing sensors (Willers & Riggins, 2010). At the end of the production season, harvest yield monitors geo-spatially measure crop yield. Collectively, all of these kinds of information can be superimposed by a geographic information system (GIS) on a digital elevation surface built from a laser scanning mission of the agricultural field. Once assembled into a geo-database by additional geographic information system and remote sensing processing (de Smith et al., 2007; Jensen, 2000; Lillesand et al., 2008; Pouncey et al., 1999; Richards & Jia, 1999; Theobald, 2003; Willers et al., 2004), these data sets can be analyzed by advanced statistical methods (such as count model regression (Long, 1997; Willers et al., 2009b), general linear mixed analysis of covariance models (Gotway et al., 1997; Gotway & Hartford, 1996; Gotway & Stroup, 1997; Littell et al., 2006; Milliken & Johnson, 2002; Milliken et al., 2010; Willers et al., 2008b) or other geostatistical approaches (Oliver, 2010; Piepho et al., 2011; Schabenberger & Pierce, 2002). Such efforts by geographically supported experiments bring '*light*' — illuminating novel solutions to agricultural challenges and tasks. Laser scanning information is the key advance in such spatial experiments involving agricultural production systems.

1.1 Historical context

More than 15 years of on-farm research by the authors' on site-specific insect pest management from a precision agriculture (PA) perspective are beginning to lead toward ways of geographically evaluating whole-field and site-specific management practice combinations in commercial cotton fields (Burris et al., 2010; Milliken et al., 2010; Willers et al., 2004, 2008b). These different forms of geographically-based experimental designs are extensions of numerous concepts found in traditional experimental designs (e.g., completely random design (CRD), randomized complete block (RCB), Split-Plot, Lattices, etc.), yet they differ from traditional designs in several ways since they (1) can utilize the entire field or only certain parts of the field on demand, (2) are not restricted to the use of symmetrical, similarly sized small plots (or strips of plots), (3) excellently partition sources of variability due to both the planned treatment structure and the unplanned treatment structure (which includes one or more sources of field topography) and (4) exploit the geographical content of the site-specific experiment, especially the characteristics and travel paths of the farm equipment which apply site-specific applications. The inclusion of laser scanning data streams is one fundamental technology enabling this advance in statistical evaluation of PA practices.

Laser scanning maps field elevation at sufficient spectral, spatial and temporal resolutions which are typically smaller than the areal extent of a single swath (or harvest) element logged by the yield monitor. Since this scale of spatial resolution is possible, laser scanning information can resolve issues related to the modifiable areal unit problem (MAUP). This problem is comprised of two aspects (Gotway & Young, 2002). In the first instance, many statisticians have learned that different inferences are obtained when the same set of data is grouped into increasingly larger areal units. In the second instance, they have also found that variability in analysis results arise simply due to alternative specifications of areal units which create differences in their shapes at the same or similar scales.

Whenever the ground spatial distance of the pixels describing field topography are smaller than the swath element, then geographically-based methods of statistical analysis exploit the following characteristics of the variable-rate equipped machinery and the differential Global Positioning System equipped harvest yield monitors: (1) The travel path of the variable-rate sprayer (or largest implement) occurs in long strips (polygons) whose paths are polylines following either topographical contours or property boundaries, (2) Precision agricultural prescriptions are formulated to be applied to the polygon or polygons of interest coincident with the travel path of the applying machinery and can be spatially varied along that path, and (3) Demographic characteristics of these polygons of land are available at the level of a "plot", defined as areas which are geographically describable in interspersion, size, shape, and continuity. It follows that yields and other responses can be measured along harvest paths parallel to application paths. The precision agricultural practices are evaluated using analysis of covariance models to obtain regression effects describing the site-specific plot and control plot demographics with respect to a dependent variable such as yield. The process takes advantage of the fact that commercial fields are heterogeneous with respect to soil types, elevation, drainage patterns, and other characteristics. Digital topography maps describing these uncontrollable sources at sufficient spatial and temporal resolution are covariates to improve the statistical assessment of planned treatment effects on yield, or other crop responses. An illustration of this kind of analysis follows.

1.2 Illustration of laser scanning contribution to site-specific analyses

It is conceptually possible to establish a system of plots where standard management practices are applied and to insert within them smaller plots where an alternative management practice is applied (Figure 1). These plots assigned non-standard management treatments are referred to as "floating plots" and are also imbedded within the variable-rate application equipment paths and centered on the mid-line of the harvest equipment paths. The defining information of these floating plots can be collected from the prescription files created and used by the variable-rate controllers that treated them. The minimal size is defined by the variable-rate controller's reaction time to change discharge rates per georeferenced instructions, as well as other mechanical behaviors of the application equipment and additional preset experimental actions. This geographical overlapping process provides the necessary control data to perform a statistical evaluation of the efficacy of site-specific management decisions. All of the information is co-registered to a common geographical coordinate location which is the centroid of each harvest swath element (Willers et al., 2004).

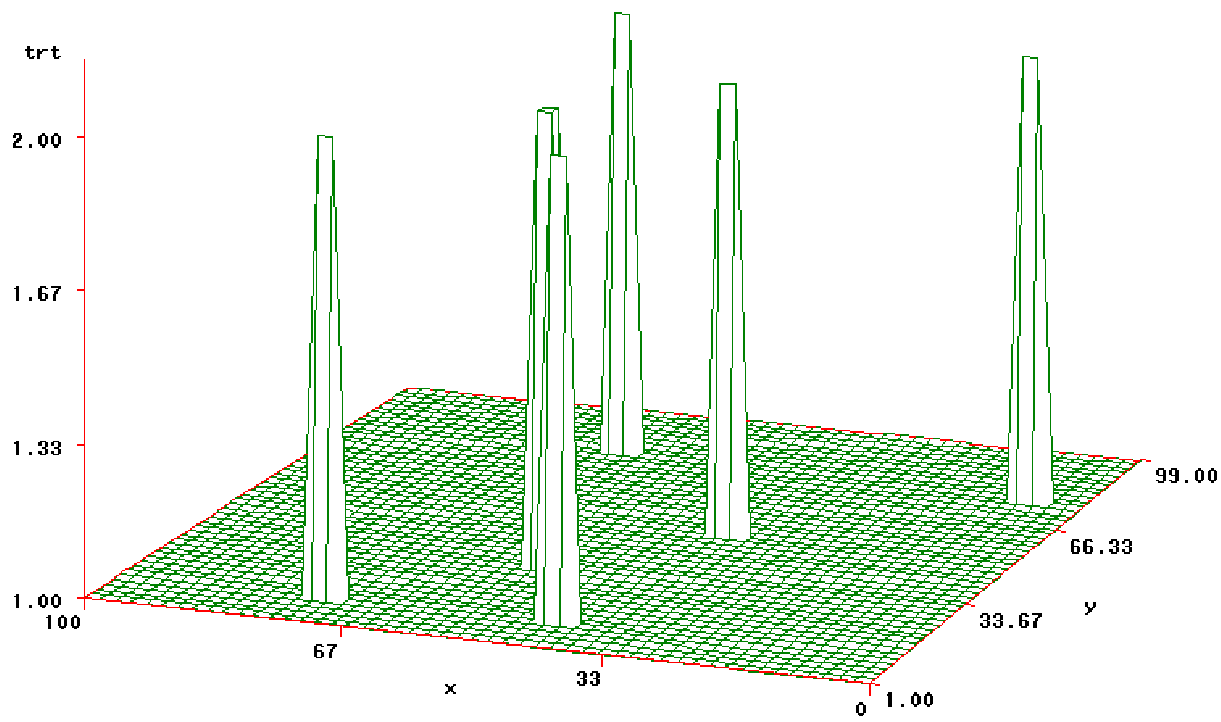

Fig. 1. Simulated treatment mean responses for a new management practice that is 2 times larger than the standard management practice (e.g., 1 unit) at several spatially selected locations in a simulated field.

While the actual 'plot layout' of any particular site-specific experiment can be quite diverse, a simplistic layout is proposed as illustrated in Figure 1, where the simulated 'field' is apportioned into a 100x100 grid of sub-plots in the '*x*' (i.e., Longitude or Easting) and '*y*' (i.e., Latitude or Northing) directions. Six floating plots were embedded to represent where a new treatment (or management practice) of two units will be spatially applied, while the rest of the field receives the standard (or traditional) management practice of one unit. Simulated response surfaces of two field topography characteristics that affect the yield (such as fertility levels (*e1*) and laser scanning elevation (*e2*)) are shown in Figs. 2A and 2B at the same spatial scale as the 'field' plots.

In this simulation, each sub-plot in the field grid was also modeled to contain a 6x6 lattice of points representing yield from harvest swath elements as measured by a yield monitor (Milliken et al., 2010; Willers et al., 2004, 2008b). Each yield point included a random error effect and the simulated yield for the experiment is shown in Figure 2C. The effects of both the conventional and new management practices were further modeled to interact with the topography characteristics (*e1* and *e2*), that were also simulated to have effects on the yield response.

A regression model was applied to these simulated data to estimate the yield response surface (Figure 2D) as a function of the levels (i.e., amounts, rates, elevation values, brightness values, etc.) of (1) the two environmental factors, (2) the conventional management practice applied to the standard plots, and (3) the new management practice applied to the floating plots. The simulated analysis shows that for some combinations of these two topography covariates, the new management tactic was not very effective at some locations (as indicated by troughs or absence of peaks in the yield response), while it was effective at other locations (as shown by the small peaks rising above the yield response).

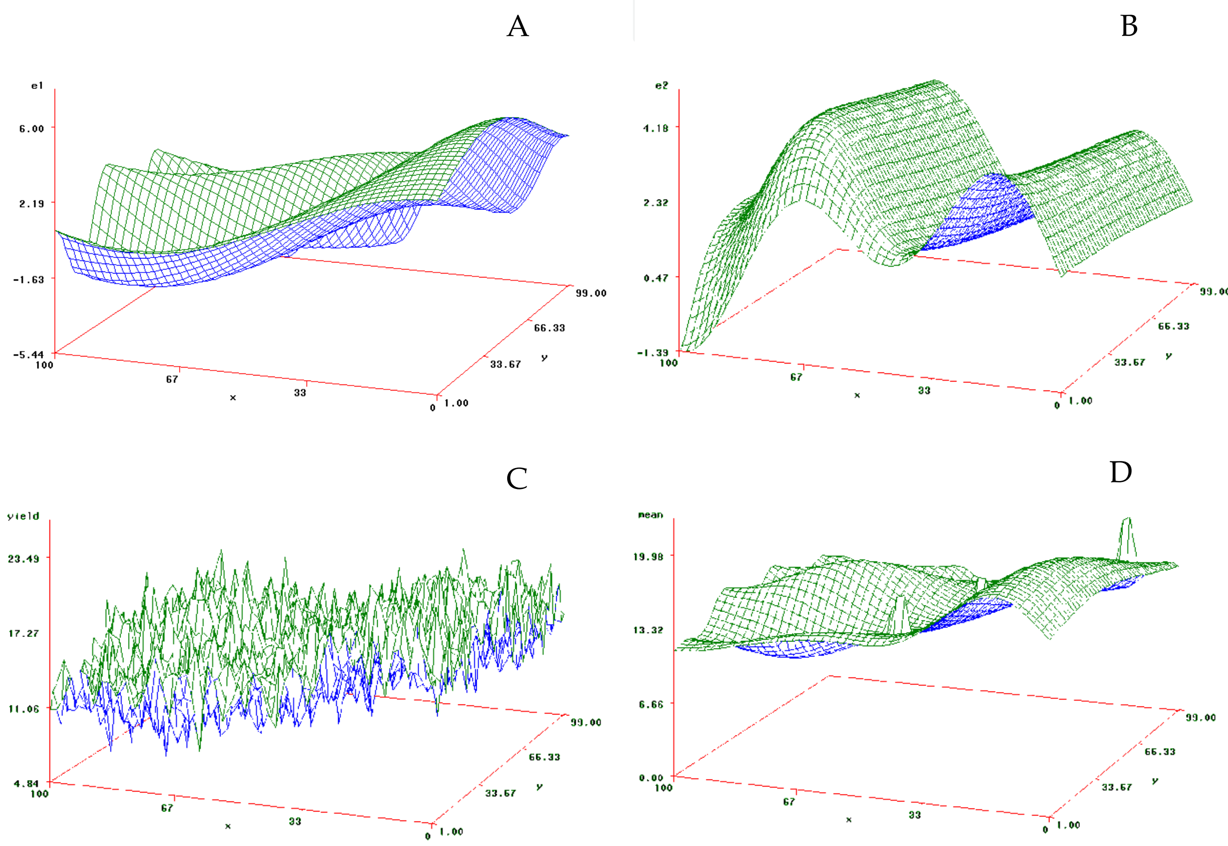

Fig. 2. Simulated response surfaces of A) first environmental factor (*e1*), B) second environmental factor (*e2*), C) mean yield estimates from a yield monitor obtained for each grid cell in both the *x* and *y* directions, and D) modeled yield response surface as a combination of the two environmental factors, the old management practice, and the new management practice which was spatially applied at different locations in the *x* and *y* directions.

There are several general forms of regression models useable in analyzing site-specific experiments. Investigating the best choice of statistical model for a particular geo-spatial combination of conventional and site-specific treatments and choice of applicator and harvester equipment configurations and which choice of topography covariate to use, is a large frontier for research. A key lesson learned in our research to date is that there are several constraints. The difficulty of defining optimal units of replication (Mead, 1988) includes (1) *a priori* definition of an adequate group of floating plots to serve as controls and where to place them, (2) the effects of uncontrollable spatial-temporal variability that is known but remains unmapped, and (3) effects of management practices that may differ for adjacent fields owned by different producers, especially with respect to insect and weed control (Anonymous, 2000; Dupont et. al., 2000). Another constraint is effectively projecting all of the data into the same coordinate system, such as the Universal Transverse Mercator grid (Bugayevskiy & Snyder, 1995). Different variable-rate or harvest equipment and sensor systems log their coordinate information in different formats as unprojected or projected values. A considerable amount of time is involved with co-registration of all data to a common coordinate system. As the number of farm fields increases, the process of resolving numerous data layers into a standard coordinate format becomes too excessive (Willers et al., 2009a).

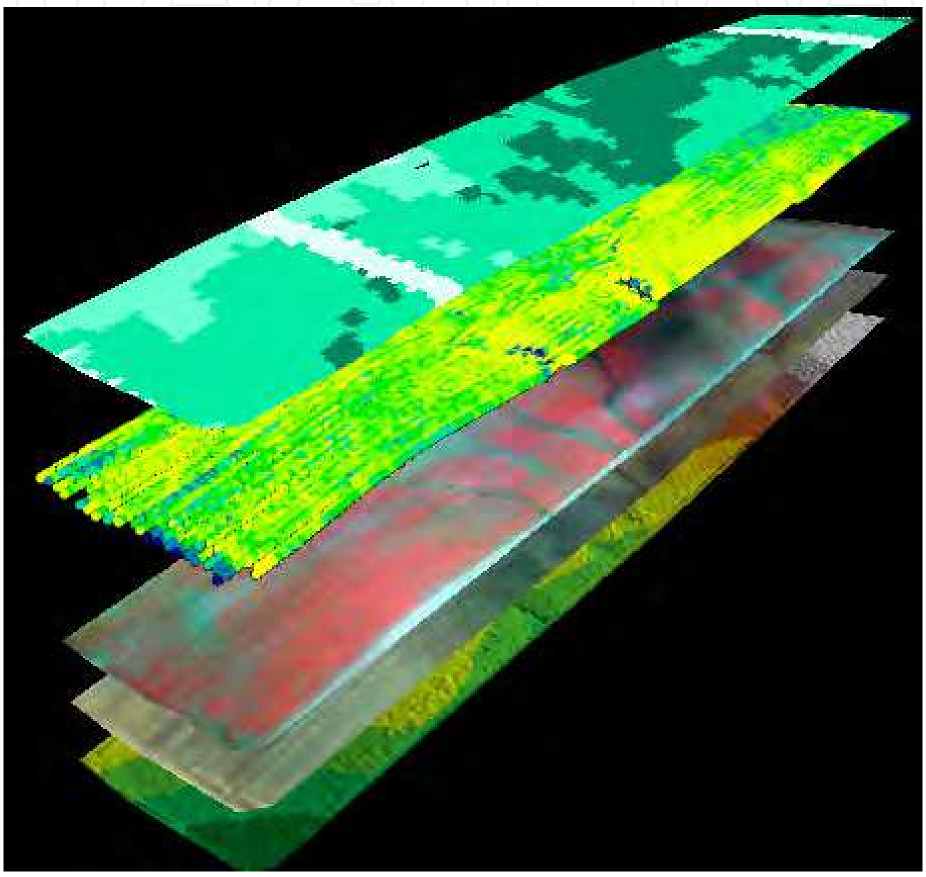

Fig. 3. Real-world data layers are shown to provide contrast to the hypothetical layers presented in Figures 1 and 2 (see Willers et al., 2004, 2008b).

In actual practice, as shown in Figure 3, the variable-rate controllers, yield monitors, and other types of sensors mounted on farm equipment or airborne platforms generate spatial information about agrichemical application rates, yields or other crop or soil attributes useful in analysis (Birrell et al., 1996; de Smith et al., 2007; Jensen, 2000; Kennedy, 1996; Pouncey et al., 1999; Richards & Jia, 1999; Sadler et al., 1998). The lowest layer of this figure is the laser scanned, digital elevation model. The layer above it is the multispectral bare-ground image (January 2002) and the next layer is the image of the crop development (June 2003), followed by the yield map. The topmost layer is the variable rate prescription map of three rates of plant growth regulator (PGR) (applied July 2003). This top layer also shows the embedded control strips (white bands) where no PGR was applied. As indicated in Figure 3, the digital elevation model from a laser scanning system is a foundational layer for the statistical analyses of precision agriculture management methods (Milliken et al., 2010; Willers et al., 2004, 2008b).

2. Solving questions of interest aided by laser scanning information

Questions of interest involved with applications of site-specific experimental designs can be classed into at least three types — does the question relate to (1) the evaluation of a single management tactic at a specific time or (2) a comparison between two or more management tactics at a specific time or (3) the evaluation of differences between two or more management tactics at different specific times of the season and/or different locations in a field. Methods of analyses for the latter two types of questions are not well developed; however, these kinds of questions are likely to be the most important to a commercial farm.

In site-specific experiments, it is likely that unplanned questions (that is, questions not specified *a priori* at the start of the production season) will arise, such as with the occurrence of dramatic, unexpected conditions during the crop production season. Farming operations can also be causes. Some possible operational causes are herbicide drift, mechanical injury to the crop during cultivation operations, or ruts caused by harvest equipment during wet soil conditions (which can cause effects lasting several seasons). If the effects of these unplanned causes can be mapped, then they can be included as effects in a statistical analysis.

Controlling the experiment-wise error rate (Milliken & Johnson, 2009) for planned or unplanned questions is another topic requiring deeper examination. It is likely that these error rate probabilities are going to be affected by the spatial, temporal, and spectral resolutions of the sensor systems involved. The major point with respect to these error rates is that laser scanning digital elevation models excellently support (Figure 3) on-farm experiments as well as other kinds of proximal and remote sensing data products. Utilization of such data streams shine '*light*' into the darkness of reality; otherwise, even if variable-rate controllers and harvest monitors are utilized, the results are only the *'fruit'* of the experimental exercise and, as a consequence, will have a small inferential space.

2.1 Sources of error and standards for laser scanning data streams

To function in the developing world of laser scanning data streams, the agricultural ecologist needs to have a working knowledge of how laser scanning systems acquire data, and how such data are processed and prepared for delivery to clients. There are many references (i.e., Lillesand et al., 2008) to provide such background. Nevertheless, it is necessary to briefly discuss sources of error and standards for laser scanning data to provide a common starting point. This discussion is anchored to a specific agricultural landscape (Figure 4), where more than 22 years of research on site-specific crop and site-specific insect pest management involving laser scanning, proximal and remote sensing systems, and crop yield monitors has been accomplished (Anonymous, 2000; Campenella, 2000; Dupont et al., 2000; Frigden et al., 2002; McKinion et al., 2009, 2010ab; Milliken et al., 2010; Willers et al., 1990, 1992, 1999, 2004, 2000, 2005, 2008ab, 2009ab; Willers & Riggins, 2010).

2.1.1 Lidar (laser scanning) background

Over the past decade, laser scanning (or light detection and ranging (lidar)), has become a primary method for collecting very dense and accurate elevation values. For data collected by a laser scanning system, the reflected pulses create a point cloud of elevation returns from the bare earth, vegetation, buildings, or any other features above the ground. Modern laser scanning systems are capable of recording multiple returns for each emitted lidar pulse reflected from a surface feature. In areas absent of any vegetation, only one pulse return would be recorded. Point clouds are comprised of lidar reflected returns which are processed and classified based upon whether the points represent ground or non-ground reflected returns. Non-ground returns may be further classified into feature categories such as grasses, shrubs, trees or woodlands, urban, withheld, noise, blunders, or any number of categories useful to a particular application.

Laser scanning has significant advantages over other methods of elevation data collection, including higher spatial resolution, vertical accuracies measured in centimeters, and penetration through forested and other vegetated areas. Laser scanning missions are typically acquired from aircraft which collect data in strips or swaths which comprise pulses rapidly collected at a rate that exceeds 150,000 pulses per second across large collection areas. Data acquisition may also be conducted by laser scanners mounted on mobile terrestrial platforms. However, in most applications, laser scanning data are processed to calibrate the data, classify ground and non-ground returns, and ultimately to produce high resolution, high accuracy digital elevation models. For agriculture applications, acquisition from aerial platforms provide data of sufficient pulse spacing and density for adequate terrain characterization providing multiple pulse returns per square meter of ground.

2.1.2 The LAS standard

The American Society of Photogrammetry and Remote Sensing (ASPRS) maintains data standards for remote sensing data through committees of subject matter experts from industry, government agencies, and academia. The lidar standard is copyrighted, maintained, and evolved by the ASPRS committees. The current standard for lidar data sets is the ASPRS Lidar Data Exchange Format Standard (or LAS) (ASPRS, 2004). Each LAS data file is a binary file that includes encoded information subdivided into three parts including the public header block, variable length records, and point data records. The LAS file format was developed to standardize the interchange, use, and implementation of 3-dimensional point cloud data between data producers and among users. The LAS standard was developed primarily for exchange of lidar point cloud data; however, the LAS data type supports the exchange of any 3-D collection of x,y,z data.

The public standard LAS binary file format is an interoperable file format well suited to encoding lidar data and has many advantages over proprietary data types that preclude interoperability, or over generic ASCII files which are characterized by large file sizes, inefficient implementation, non-standard structures, and slow processing. With the recent explosion in lidar technology and use, ASPRS has created a Lidar Division to keep abreast of data standards and implement new versions of the standards needed to support new hardware, sensor, and data technologies. The latest version of the LAS standard is version 1.4 which is pending final approval after public review. The updating of standards and creating new versions of the standard to accommodate the advance of technology is published on the ASPRS web site for the LAS working group at the following link:
http://www.asprs.org/Division-General/LAS-Working-Group.html

2.1.3 Laser scanning accuracy, guidelines, and base specifications

Three publications, NDEP (2004), ASPRS (2004) and FGDC (1998), provide guidance and formulas for determining elevation data accuracy. The Federal Emergency Management Agency (FEMA, 2003) has an early document that describes accuracy and quality assurance guidelines for laser scanning data. More recently, the United States Geological Survey (USGS, 2010) produced a document that has been circulated throughout the industry and is rapidly becoming the standard by which data are being evaluated whether for local, county, state, or national purposes. This document, commonly called the "version 13 specification", embodies an unprecedented emphasis on analyzing and understanding the lidar point cloud, including quantifying the sources of error in lidar data from initial acquisition to final delivery.

Prior to the version 13 specification, standards typically emphasized testing the final digital elevation model for accuracy; whereas, the version 13 specification addresses a sweeping range of aspects of error and uncertainty in the lidar data set. Considerations range from the initial coverage, to flight line overlap, and calculating and minimizing the relative error between adjacent laser scanning strips in their areas of overlap (Aguilar et al., 2010; Maas, 2002; Willers et al., 2008a). It is this relative error discrepancy (or step error) between adjacent strips that precludes or makes problematic the generation of a highly accurate continuous elevation surface for large agricultural landscapes.

Some of the common terms (NOAA, 2008) employed to describe lidar data as well as the errors that are encountered include the following:

- RMSE Z– abbreviation for root mean square error; a measure of the accuracy of the data similar to the measure of standard deviation if there is no bias in the data.
- Accuracy Z, Fundamental Vertical Accuracy (FVA) – a measure of the accuracy of the data in open areas at a high level of confidence (95%), calculated from the RMSE using the formula RMSE Z x 1.96 = FVA.
- Classification – data that have been processed to define the type of object that reflected the pulses; such can be as simple as unclassified (i.e., point not defined) to buildings and high vegetation. The most common is to classify the data set for points that are considered "bare earth" versus those that are not (i.e., unclassified).
- Return Number (First/Last Returns) – many lidar systems are capable of capturing the first, second, third, and ultimately the "last" return from a single laser pulse. The return number can be used to help determine what the reflected pulse is from (e.g., ground, tree, or understory).
- Point Spacing – how close the laser points are to each other, analogous to the pixel size of an aerial image; also called "posting density".
- Pulse Rate – the number of discrete laser "shots" per second that the lidar instrument is firing. Common systems used in 2008 are capable of 100,000 to 150,000 pulses per second. More commonly, the data are captured at approximately 50,000 to 70,000 pulses per second.
- Intensity Data – when the laser return is recorded, the strength of the return is also recorded. The values represent how well the object reflected the wavelength of light (for example, 1,064 nanometers) used by the laser system. These data resemble a black and white photo but cannot be interpreted in exactly the same manner.
- Real Time Kinematic Global Positioning System (RTK GPS) – satellite navigation that uses the carrier phase (a waveform) that transmits (carries) the Global Positioning

System signal instead of the Global Positioning System signal itself. The actual Global Positioning System signal has a frequency of about 1 megahertz, whereas the carrier wave has a frequency of 1500 megahertz, so a difference in signal arrival time is more precise. The carrier phase is more difficult to use (i.e., the equipment is more costly); however, once it has been resolved, it produces a more accurate position reading.

- Digital Elevation Model (DEM) – a surface created from elevation point data to represent the topography. Often a digital elevation model is more easily used in a geographic information system than the raw point data it is constructed from.

Building the DEM from the laser scanned point cloud can employ techniques that are quite diverse and are limited only by the creativity of the developers of any particular application. For example, Wang et al. (2008) process the point cloud to conduct vertical canopy structure analysis and 3D single tree modeling. Vu et al. (2009) developed a multi-scale, mathematical morphology approach to extract building features. Methods to reduce the processing time of these data intense points cloud are also keen areas of research (Han et al., 2009). Whatever the processing method employed for a specific application of the point cloud, the techniques exploit the *xyz* attributes for each return after filtering out blunders and random errors, employ various mathematical models to correct for systematic errors, and then employ various interpolation algorithms to produce the 3D surface of elevation at the appropriate spatial resolution for the intensity. Depending on the purpose of the DEM, that is, a bare earth DEM which describes elevational relief with features such as trees and buildings filtered out, or a digital surface model (DSM) which includes objects that are non-ground, the choices involved require specification of which return to use, be it the first return, the last return, or all returns.

For the agricultural DEMs used in this paper, two were processed by commercial vendors and made available thru either state or federal agencies (i.e., the background layers in Figures 4 and 7 (Mississippi) and Figures 5 and 16 (Nebraska). So, processing details for these 3D surfaces cannot be summarized. But, for the agricultural DEM in Figure 3 and the inset in Figure 4, as well as the DEM used for analyses in Figures 6 – 8 and 10 – 14, the point cloud processing can be summarized. First, the vendor removed systematic errors using proprietary procedures and orthorectified the point cloud returns to the vertical datum, NADV83 and the UTM Transverse Mercator grid for Zone 15 (North). Then a team of investigators (Willers, O'Hara and others) utilized the LAS file provided by the laser scanning vendor to (1) employ Terrascan® software to remove extreme instances of blunders and other random errors and then export the information as a comma delimited test file to upload into ArcMap® software for conversion into a set of point vector shapefiles for each strip (or line), including a tie-line strip acquired by the vendor. Next, these shapefiles were corrected for steps errors using the following algorithm and procedures.

The elevation data points in the overlap area of a tie-line strip were categorized into K groups indexed by k based on their coordinate and strip positions. Each group was characterized by $SubX_k$, $SupX_k$, $SubY_k$ and $SupY_k$ to define the set of points in group k as S_k so that $S_k = \{(i,j) \mid SubX_k \le x_{ij} < SupX_k \text{ and } SubY_k \le y_{ij} < SupY_k\}$. The number of points in strip (or line) i in group k was denoted by n_{ik}, so the total number of points in group k was:

$$n_k = \sum_{i=1}^{L} n_{ik} = |S_k| \tag{1}$$

The steps errors among the lidar flightline involved biases initially estimated by eye (also using Terrascan® software) to be about 15-20 cm. Therefore, to remove these step errors by mathematical programming, the variances of the adjusted elevations of points were minimized by determining the best values for a set of decision variables a_i. Let M_k be the mean elevation in group k before adjustment and A_k be the mean elevation in group k after adjustment ($k \in K$). Then, these mean values were found using:

$$M_k = \frac{\sum_{(i,j)\in S_k} e_{ij}}{n_k} \text{ and } A_k = \frac{\sum_{(i,j)\in S_k} (e_{ij} + a_i)}{n_k}. \tag{2}$$

And, then let V_k be the variance in group $k \in K$ after adjustment:

$$V_k = \sum_{(i,j)\in S_k} (e_{ij} + a_i - A_k)^2. \tag{3}$$

In order to minimize the error, the sum of the variances in each group was minimized by determining the values of decision variables a_i, according to the following unconstrained optimization problem:

$$\min_{a_i} \sum_k V_k = \sum_k \sum_{(i,j)\in S_k} (e_{ij} + a_i - A_k)^2. \tag{4}$$

Since (4) has a convex cost function, existing optimization solvers worked well to obtain a unique optimal solution for each strip. Once a line is adjusted, the estimated decision variable (a_i value) for flight line i was treated as a constant in subsequent iterations for the remaining strips. A custom C program supplemented the non-linear optimization routines found in Excel® to allow the estimation of the decision variables with respect to the tie-line. Once the step errors were adjusted among the point clouds of each strip, the non-linear surface tool of ERDAS® Imagine derived the 3D surface grid. See Willers et al. (2008a) for other details.

2.1.4 Sources of error in agricultural laser scanning data

A commercially prepared bare earth digital elevation model from 2009-2010 (feet Mean Sea Level (MSL)) provides the background layer in Figure 4, while a portion of a research derived, step error corrected digital elevation model (Willers et al., 2008a) from 2003 (m Height Above Ellipsoid (HAE)) is the smaller surface inserted near the top left of Figure 4. With some laser scanning data for at least one agricultural landscape now in hand, we further discuss sources of error for laser scanning data streams and data products.

Sources of error in laser scanning data involving agricultural landscapes can be generally grouped into three categories: systematic errors, random errors, and blunders. Systematic errors in laser scanning data are largely caused by biases in the measurements of bore-sighting parameters that relate to the system components and biases in the measurements made by the system that include Global Positioning System information, timing information, inertial measurements as well as potential biases in the scanner angles and ranges. Random errors arise mostly from the accuracy of the systems measurements including the position and orientation measurements from the Global Positioning System /Internal Navigation System (GPS/INS) component, mirror angles, and ranges. Blunders refer to gross errors that may be caused by the sensor system detecting something in the air (a bird) or some other measurement criterion that causes a very large discrepancy between the real-world surface and the lidar data. Blunders are often detected by identifying points which are statistical outliers in which the offsets between the points in consideration exceed the magnitude of normal random or systematic bias.

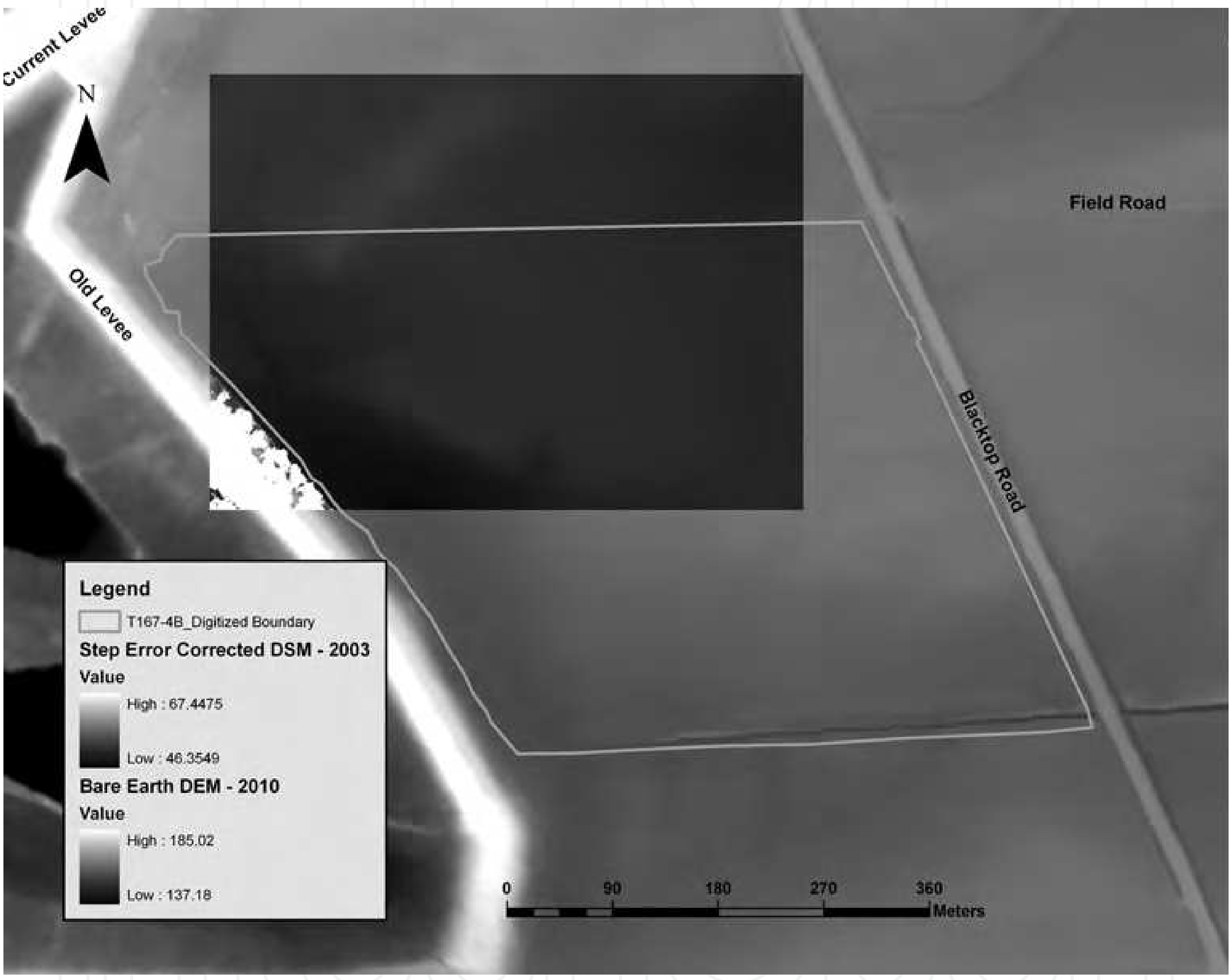

Fig. 4. Geographical detail of the areas of interest (AOI) involving a field location in Bolivar County, Mississippi, USA.

The reader should keep in mind that the literature on sources of error and standards is rapidly changing and quite detailed compared to this simple presentation on these topics (Baltsavias, 1999; Fritsch & Kilian, 1994; Huising & Pereira, 1998; Skaloud & Lichti, 2006; Vosselman, 2002). Nevertheless, our brief examination of sources of error in agricultural laser scanning missions provides a foundation upon which to build support for some '*trains of work*' that comprise other goals of this chapter. A second commercially supplied DEM of another agricultural landscape (Figure 5), located hundreds of kilometers away, is also utilized in this effort.

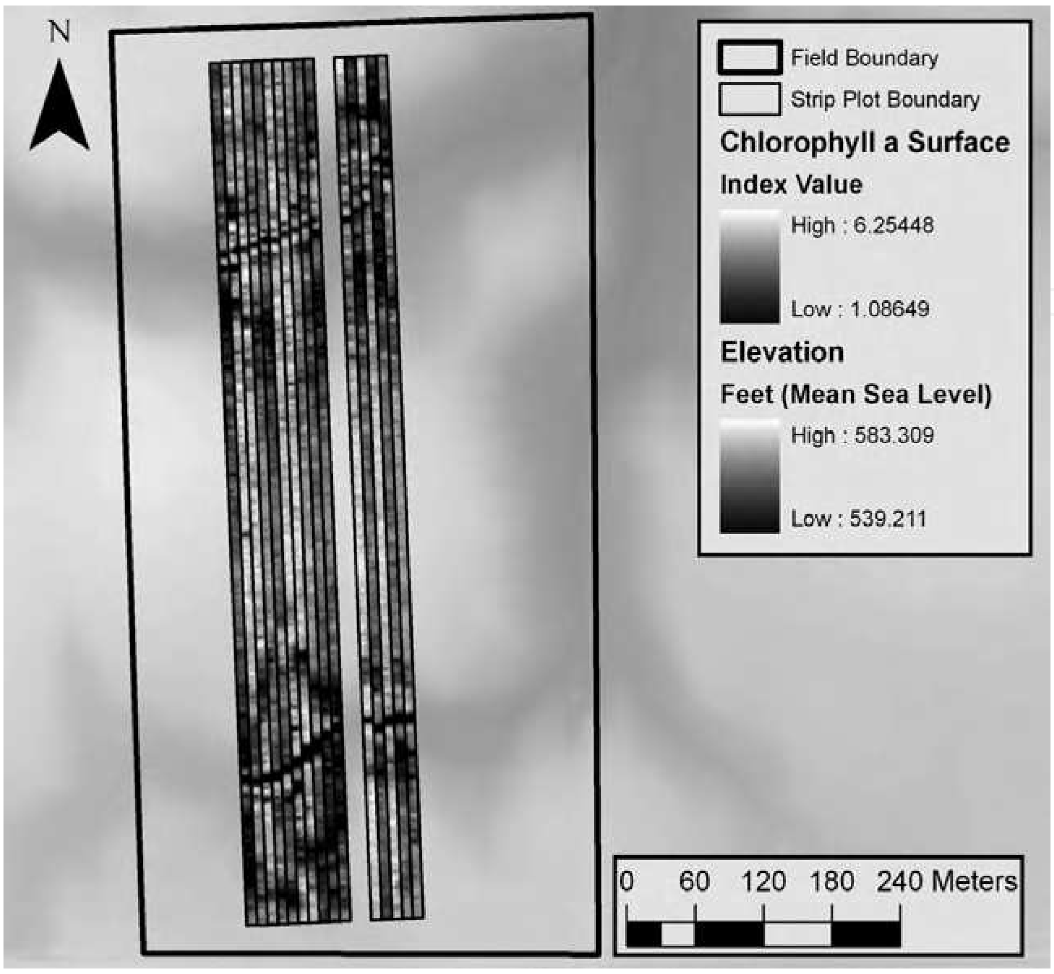

Fig. 5. Illustration of some of the geo-spatial relationships for a site-specific nitrogen experiment in a Nebraska corn field. The background is a laser scanning surface of elevational relief (Feet Mean Sea Level).

Section 2.2 is the first junction for the main journey path of this chapter; the previous discussion points were only collections of '*works*' meant to prepare the reader for some travel across a '*train*' of ideas. This journey covers several concepts involving laser scanning and agriculture and builds toward Section 2.5 as the final junction.

2.2 The population ecology interpretation of pixel attributes

Graphical techniques addressing the resolution of mixed populations of data distributions and other statistical properties of data distributions are discussed in D'Agostino and Stephens (1986) and King (1980). Many of these techniques are valuable in quality control methods and available in various software packages and have great value in image processing, including evaluations of laser scanning digital elevation models.

2.2.1 Population ecology experiments utilizing the attributes of pixels as abstractions of agro-ecosystems

High-resolution, laser scanning and multi-spectral imagery, when resolved with appropriate spectral and temporal resolutions, provide an opportunity to avoid errors in estimation of population statistics (such as mean abundance and interspersion). These digital raster layers permit sample data of an ecological population of interest to be collected from distinct habitats of crop growth (Willers et al., 2005; Willers & Riggins, 2010). When appropriately processed, the raster information can be linked to the ground sample data, allowing for the creation of additional data products describing the population characteristics as a geo-referenced map. The value of being able to build descriptive maps of population characteristics was elegantly discussed by Fleischer et al. (1999). Unlike Fleischer et al. (1999) methods to build their maps, this work, in an elementary fashion, considers the attributes of the image pixels to be surrogates of several important characteristics of biological populations through classification of the imagery attribute values, typically expressed as digital numbers (DN) or brightness values for each pixel of each band in the raster product. These pixel attributes are discrete abstractions of (primarily) the variability in the landscape or plant community structure across the crop. In the case of a digital elevation model, these pixel attributes are a continuous abstraction of the elevation relief of the laser scanned landscape. Therefore, just as is true for traditional data sets of ecological populations obtained by extensive ground survey samples, the collection of raster layer pixels of the agro-ecosystem of interest can have multiple populations of data distributions.

2.2.2 Applications of the probability plot with laser scanning elevation (surface) models

Using laser scanning information for the agricultural landscape contained within the field boundary shown in Figure 4, some issues regarding the step error (Crombaghs et al., 2000; Luethy & Ingensand, 2001; Willers et al., 2008a) are examined by a technique known as probability plotting (D'Agostino & Stephens, 1986).

Inclusion of several local heuristics (e.g., planting date, soil topography, and crop phenology) is useful to best interpret the information provided by the probability plot. For example, since there are up to seven years of time between the two laser scanning missions (Figure 4), a potential question of interest to the producer owning these fields is "What are the estimates of soil erosion rates at different geographical areas in these fields?" However, before answering this question, the prudent analyst should first ask and answer another question "How comparable are the two digital surface elevation models given that different vendors and laser scanning systems produced them?" The probability plot is a useful tool for examination of the second question which leads then to other kinds of decisions involving the first.

It is a small exercise (in a spatial software package) to load, subtract, and then save a new raster layer of the elevational differences between the two laser scanning missions. The difference raster is then exported as a flat file for use in a statistical software package to build the probability plot. Presented in Figure 6 is a probability plot of the difference in laser scanned elevations between 2003 and 2009-2010. The occurrence of several bends and a sharp discontinuity of the attribute values of the output raster created by the subtraction of the two parent rasters clearly show that several unique populations of differences are present, even though the parent rasters of elevation share a common field boundary. Of interest is that the metadata provided by the vendors claims vertical accuracies on the order of 9 cm and 15 cm. The probability plot indicates differences in elevational relief which negatively and positively exceed the maximum tolerance of 15 cm.

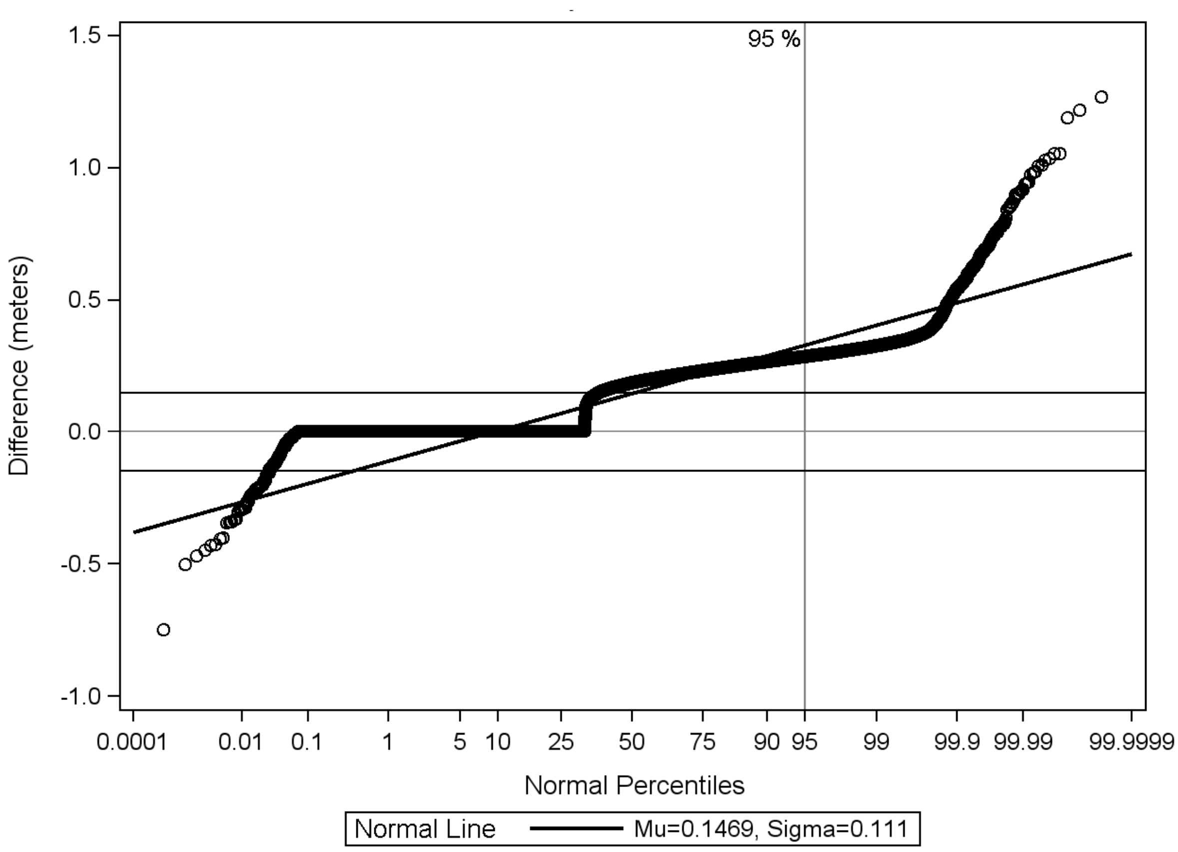

Fig. 6. Probability plot of the elevation difference between a 2009-2019 digital elevation model and a step error corrected (Willers et al., 2008a), 2003 digital elevation model.

In Figure 7 are indications of various geometric patterns in a surface map of change between these two digital elevation models. The east-west linear bands of different widths and intensity are due to different tillage operations between the acquisitions. While each laser scanning data set may have met the standards for each separate mission, the effects of textural change due to tillage and remnant step errors within the 2009-2010 data product, combine to cause combinations of both random and systematic sources of error. The producer's question of interest cannot be effectively answered until (at least) the step error effect in the most recent mission is corrected. The probability plot served a useful purpose in showing sources of different kinds of errors between the two elevation layers.

Traditionally, the description of ecological populations by image analysis is accomplished by applications of one or more classification (Richards & Jia, 1999) procedures to the raster image acquired over the agricultural landscape of interest. However, we have found that it is best to first analyze the raster data content by conversion of the raster image product into a flat file format, which can be statistically processed into a probability plot. Since raster layers can have large numbers of individual pixels, a straightforward way to demonstrate the existence of multiple populations of data distributions is to examine the shape of the probability plot constructed from the flat file of the respective raster layer. If multiple data distributions are present, the plot will not be a straight line (D'Agostino & Stephens, 1986) under the assumption of a single distribution, which is typically the normal distribution (other distributions, such as the exponential, can also be specified). If more than one data distribution is indicated, the next task is to find the meaningful groupings of these populations of data distributions in a manner which relates to the ecological structure of the crop. These meaningful groupings are established through concurrent geographic information system and statistical operations in both the data and geographical spaces of the respective agricultural landscape.

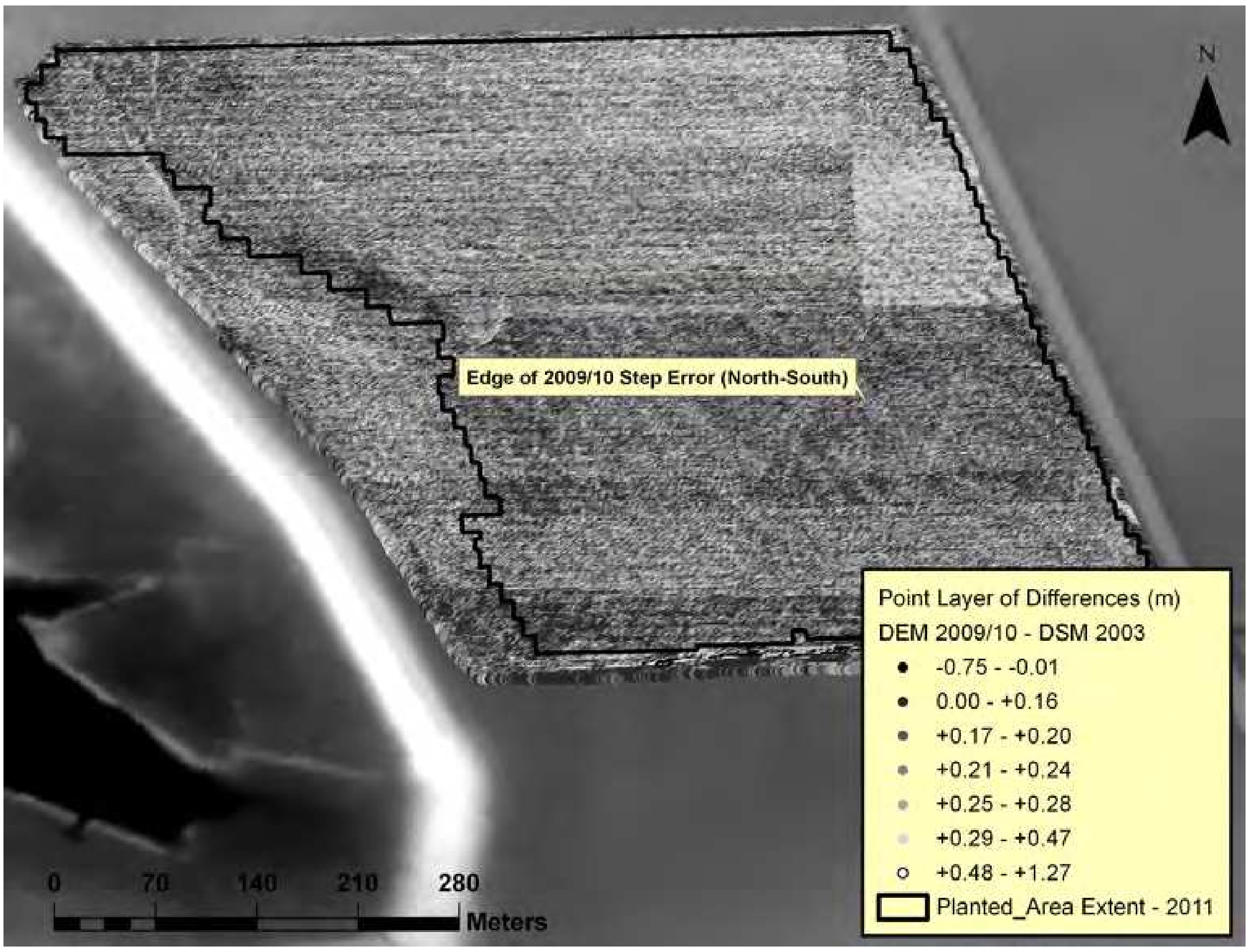

Fig. 7. Potential step error revealed by differences of the 2009/2010 bare earth DEM and the step corrected 2003 DSM.

2.3 Geographical space and data spaces and the Pearson correlation statistic

Previous geographical analysts have elaborated on the concepts of the data space and the geographical space (Berry, 1998; Hargrove & Hoffman, 1999). These concepts merit a brief review at this time and both involve the Cartesian coordinate system (Pignani & Haggard, 1970) as the basic tool for their construct. The elegance and utility (Hogben, 1968 ; Stewart, 2008) of a Cartesian coordinate system can too frequently be undervalued by the agricultural analyst due to too much familiarity. However, with the data density and the spatial resolution obtained by laser scanning digital elevation models, the planar Cartesian coordinate systems referred to as the data space and the geographical space are exceptionally '*illuminating*'.

In Section 2.1, it was discussed that laser scanners create an x, y, z point cloud which can be processed into a surface, or raster layer (de Smith et al., 2007; Lillesand et al., 2008), of elevational relief known as a digital elevation model. Using this surface as an illustration for definitions, the digital elevation model is a map forming a continuous surface, where the system of pixels creates a regular grid of cells over an area (Berry, 1998). The x and y axis position of each pixel cell in the surface grid of elevation represents the information in the geographical space. The z axis of each pixel represents the continuous numeric value of elevation in the data space. If more than one layer of remote sensing information exists for a given area, the data space across the geographical space can be described in more than one dimension (or layer). In such cases, the scale of support (Gotway & Young, 2002) or the congruency of the ground spatial distances of the pixels among the different surfaces (elevation, crop vegetative index, yield, etc.) is an important consideration to guard against source of measurement errors in a geo-spatial analysis (Berry, 1998).

Pearson Correlation Coefficients, N = 428,825
Prob > |r| under H0: Rho=0

	b1	ndvi_04	ndvi_11
b1	1.00000	0.30410	0.47413
Corrected Elevation (meters HAE)		<.0001	<.0001
ndvi_04	0.30410	1.00000	0.47168
ATAN NDVI (August 2004)	<.0001		<.0001
ndvi_11	0.47413	0.47168	1.00000
ATAN NDVI (August 2011)	<.0001	<.0001	

Table 1. Tabular representation of the Pearson correlation coefficients describing relationships among three raster layers for the field T167-4B (Figure 4) using information only in the data space without concomitant application of information in the geographical space of these mapped features from the agricultural landscape.

The Pearson correlation statistic is one metric many analysts seem most interested in using with geo-spatial analyses. For many investigators of agricultural systems, Pearson correlation values, such as those presented in Table 1, are typical. In such instances, low values of correlation, while significant, often do not generate an immense level of confidence in using either laser scanning elevation data or imaging data as resources to create a site-specific prescription, or especially build confidence to also go through the expense of preparing one to upload to the controller of a variable-rate equipped farm implement. One reason for reluctance is the sample size (Table 1, top line) involved with raster layers. One traditional dogma is that whenever sample sizes are large enough, significance can be obtained almost anytime. When analyzing raster layers, this traditional view needs careful consideration. Further, such reluctance is particularly acute if the examination of the scatter plots between pixel pairings of two sensor layers is especially non-informative; that is, the scatter plot is without clear representation of either liner or quadratic trends (Figure 8). It is obvious from results found in Table 1 and Figure 8 that without concurrent application of information from the geographical space, the utility of discerning features for site-specific applications is quite limited if information from only the data space is examined.

Conceptual perceptions derived exclusively from the examination and interpretations of only the data space become other extensions of the modifiable areal unit problem (Gotway & Young, 2002). Therefore consequences of an overemphasis upon only the data space of proximal and remote sensor system data streams is unbalanced — it is best to strike a balance among the information content provided from both the geographical and data spaces of these sensor layers (Berry, 1998; Hargrove & Hoffman, 1999). The demonstration of ways to strike such a balance between the data and geographical space domains are the topics of Sections 2.4 and 2.5. In fact, by clever processing in both the data and geographical spaces, the occurrences of experimental evidence of the kind presented in Table 1 or Figures 6 - 8, are actually indicators of opportunities for discovery and progress, particularly if good quality laser scanning DEMS are available.

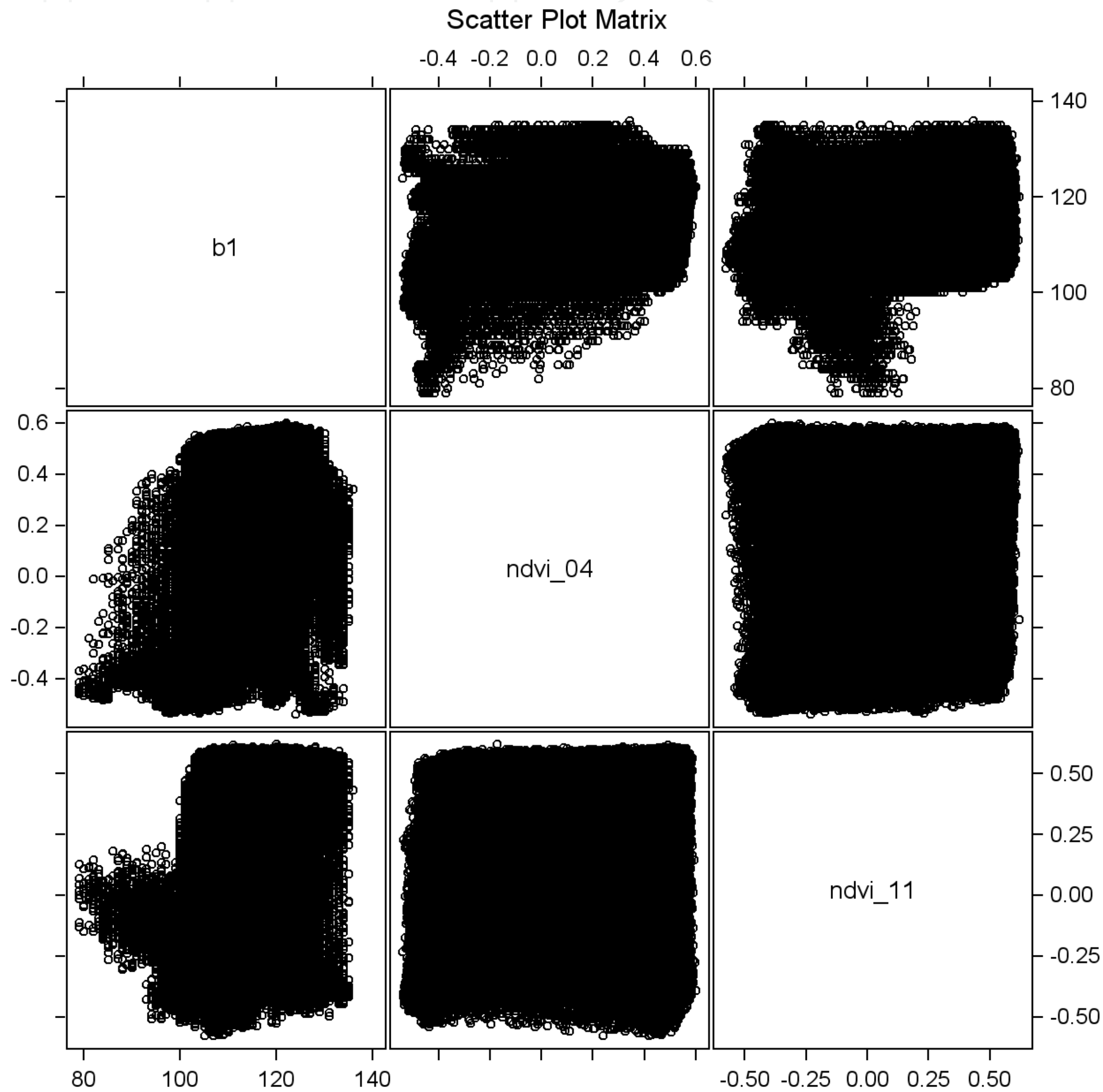

Fig. 8. Scatter plot of the three raster layers for the field T167-4B depicting a graphical representation of the data space of these three raster layers.

2.4 Building crop management zones with laser scanning and remote (or proximal) sensing data streams – development of a categorical, pseudo-likelihood classifier

The task here is to shed '*light*' on how laser scanning digital elevation models contribute an important role in agricultural data analyses of numerous kinds of geo-referenced data streams. Specifically, it is desired to convey an important advance in understanding how to complete statistical analyses of the kind introduced in Section 1.2; especially, whenever both the data attribute and geographical spaces of geo-referenced data streams are concurrently put to work, despite smudged scatter plots or small Pearson correlations. These efforts begin with a terse examination of a technique known as 'maximum likelihood classification' (Strahler, 1980). Additional details and refinements are presented in Willers et al. (2012).

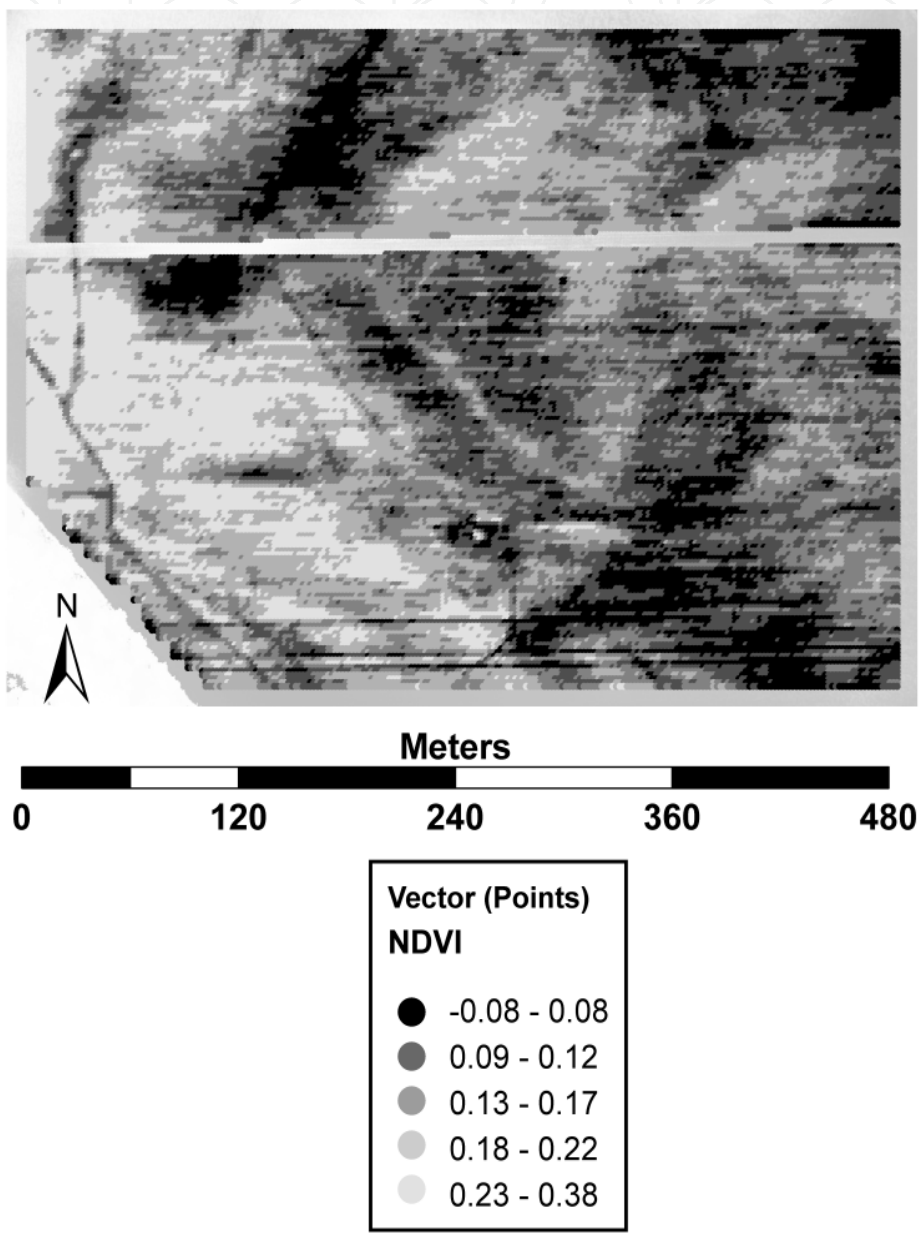

Fig. 9. NDVI ranges as a point vector layer for 2004 subset of two cotton fields.

Figure 9 shows the normalized difference vegetation index (Rouse et al., 1974) representation of the crop conditions for the sub-region previously delineated (Figure 4) during late June of the 2004 production season. In addition to the cotton portion, tall trees are the lightest gray tones beneath the north arrow at the lower left.

Figure 10 presents the laser scanning elevations for the equivalent landscape sub-region shown in Figure 9 (and Figure 4). It was derived from a much larger digital elevation model (Willers et al., 2008a) used to extract this subset for exploratory analyses with the Strahler (1980) algorithm. (Note the trees in the lower left corner, which were excluded in the bare-earth digital elevation model (2009-2010 acquisition) which is the background layer in Figure 4.)

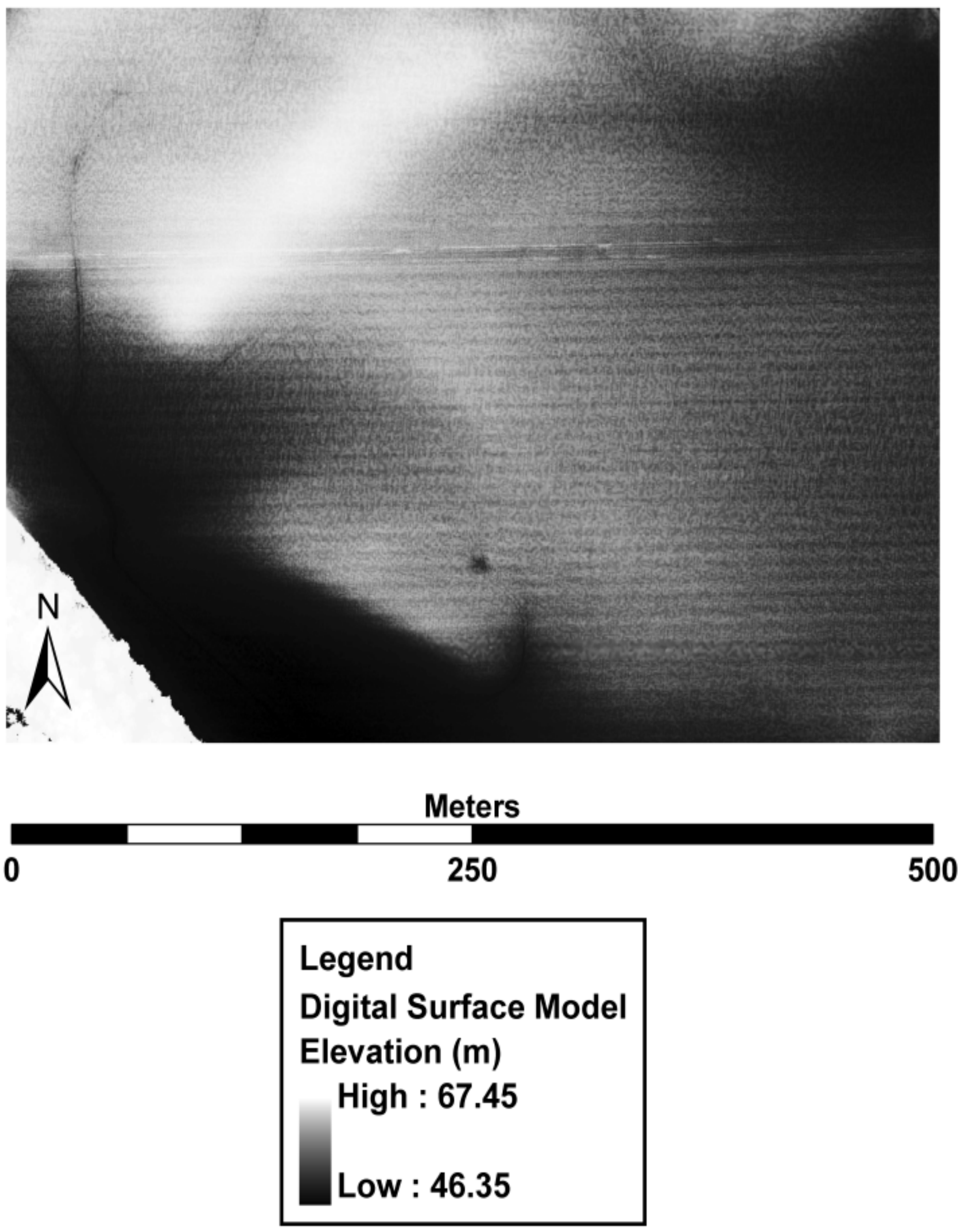

Fig. 10. Step error corrected (Willers et al., 2008a) laser scanning elevations from 2003 for the same region of the two cotton fields.

By making several modifications to the maximum likelihood classification function of Strahler (1980), it is possible to create a new raster layer where the attributes of each pixel are predicted improper probability values, as shown by (5):

$$\hat{p}(\mathbf{x}:\hat{\boldsymbol{\mu}},\hat{\boldsymbol{\Sigma}}) = \left(\begin{bmatrix} x_1 - \hat{\mu}_1 \\ x_2 - \hat{\mu}_2 \end{bmatrix}^T \hat{\boldsymbol{\Sigma}}^{-1} \begin{bmatrix} x_1 - \hat{\mu}_1 \\ x_2 - \hat{\mu}_2 \end{bmatrix} \right\} \right) \quad (5)$$

where $\hat{\mu}_1$ = the estimated mean normalized difference vegetation index value of that input raster (Figure 9), $\hat{\mu}_2$ = the estimated mean elevation of the laser scanning input raster (Figure 10), and ∑-hat provides the estimated covariance parameters between x_1 and x_2 for each pair of input pixels. From an inspection of expression (1), it is obvious that the means or the covariances for normalized difference vegetation index and elevation can be influenced by values from pixels that involve non-crop features. Consequently, it is an important point to remember while processing of the pixels in each input raster layer by (5), that one important geographic information system pre-processing step is to exclude pixels for non-crop features (i.e., trees and field road) that may occur within the field boundary polygon.

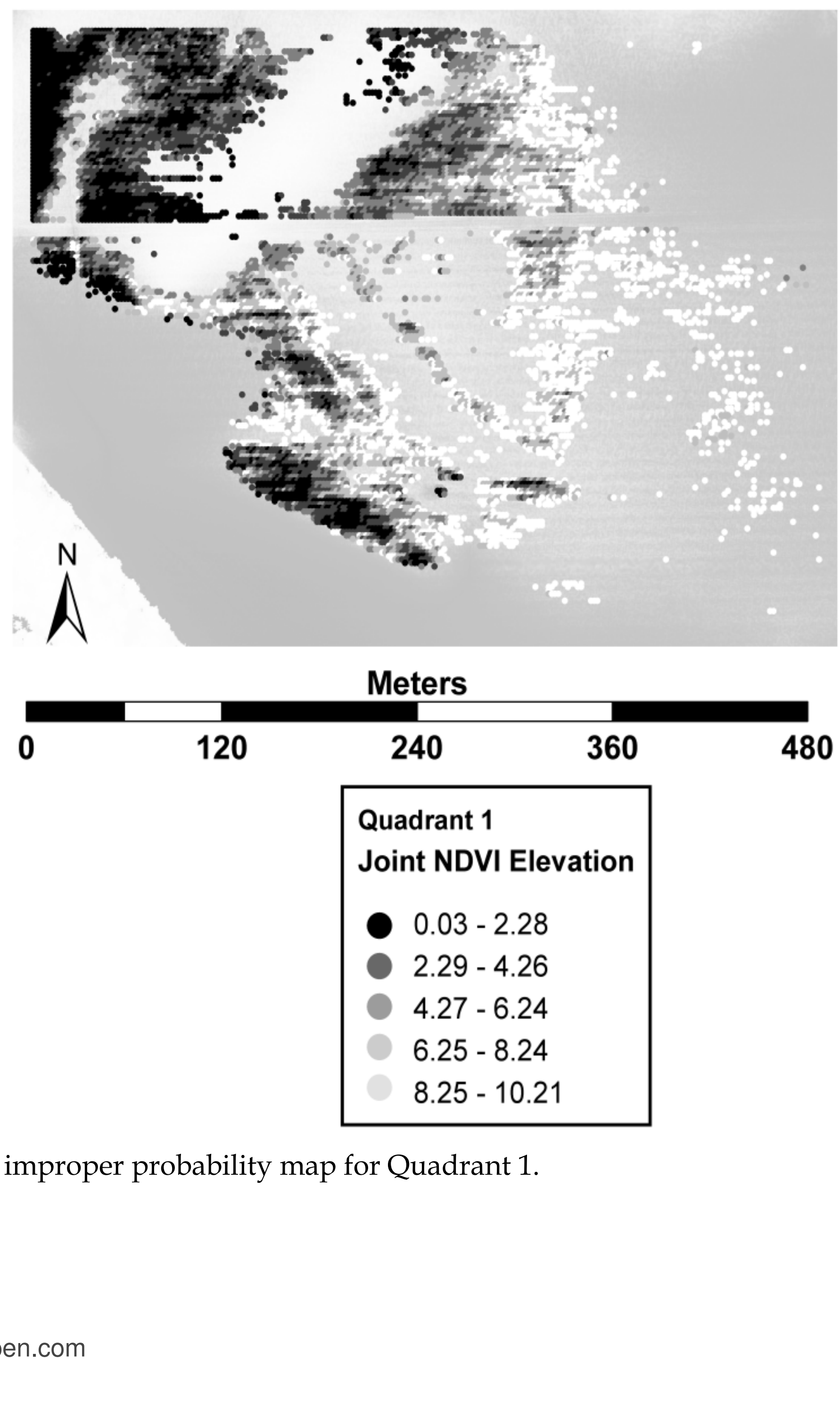

Fig. 11. Joint improper probability map for Quadrant 1.

While working with values from laser scanning elevation and other proximal and remote sensing data streams with equation (5), it was learned that the attributes for the two raster input layers are not required to be of the same units (for example normalized difference vegetation index is unit-less, elevation is in meters (HAE or MSL), and EC_a data is in mS/m). An interesting fact found while using (5) was that many improper probabilities predicted on the left-hand side were of similar magnitudes, whose frequency histogram was concave in shape, often symmetrical, and exhibited higher frequencies to the left and right of a central minimum frequency. Since (5) is the Mahalanobis distance (McLachlan, 1999), and by its form, involves the squaring of positive and negative distances from the centroid, the distance differences of the predicted value of any point pair does not indicate direction with respect to the centroid mean.

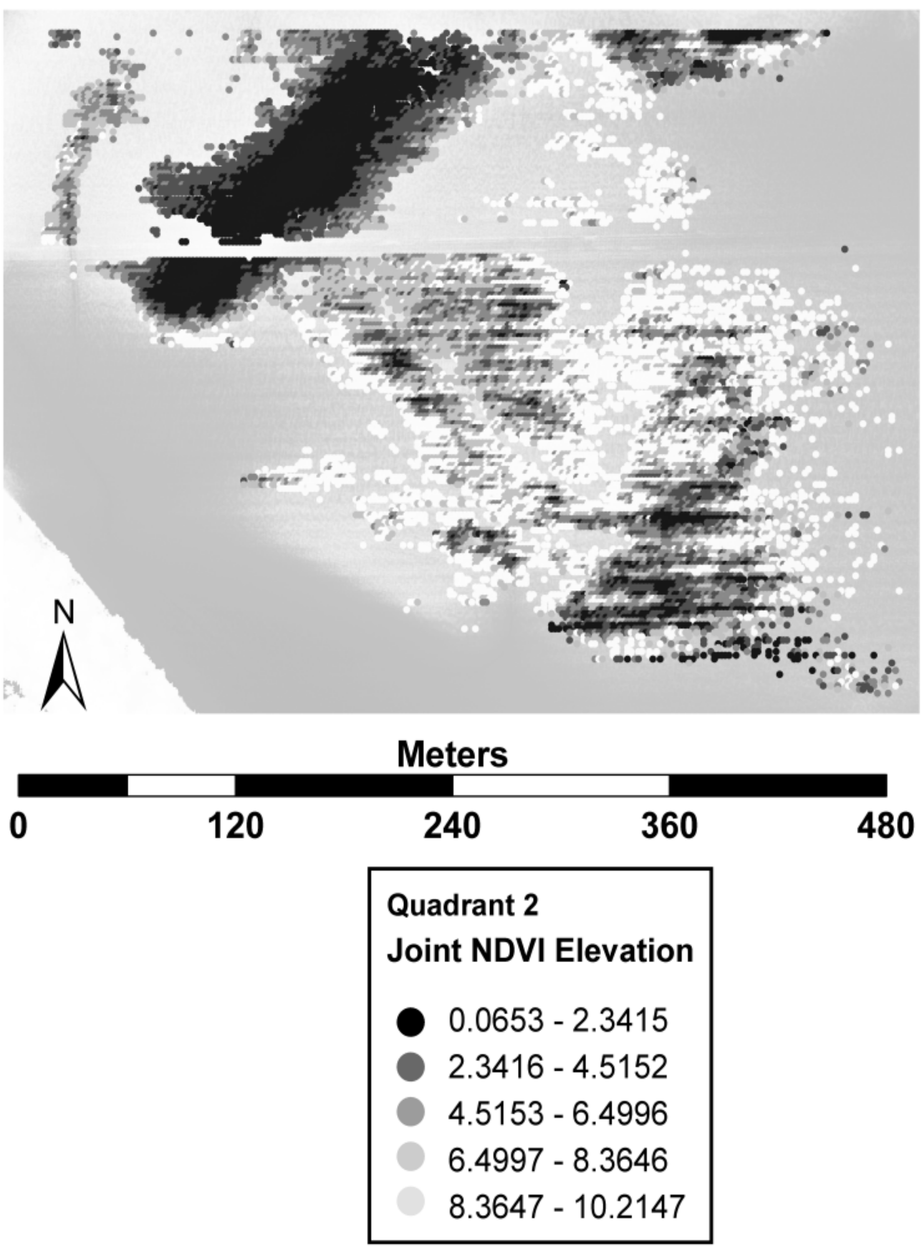

Fig. 12. Joint improper probability map for Quadrant 2.

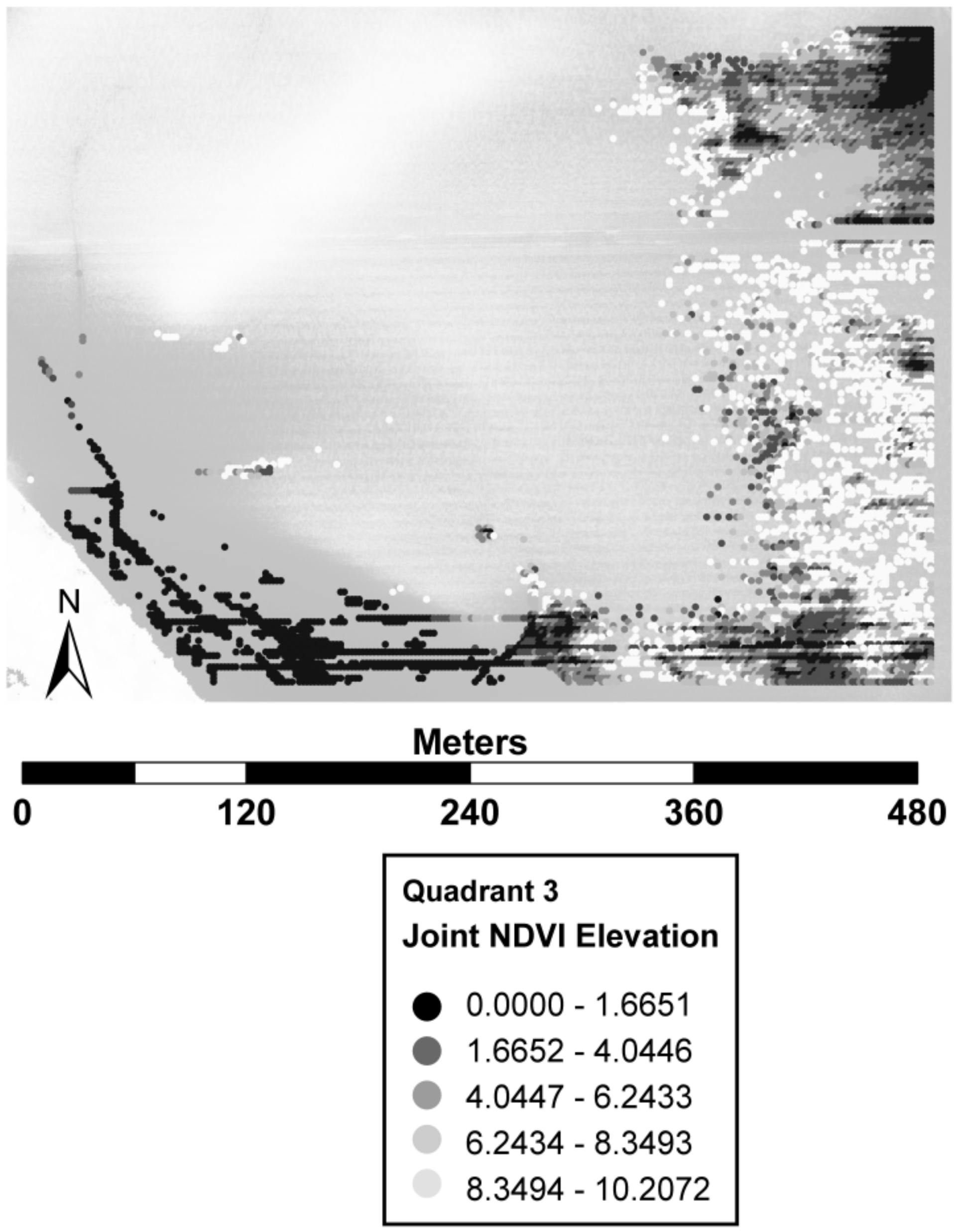

Fig. 13. Joint improper probability map for Quadrant 3.

The second step required was to then determine the Cartesian quadrant for each output pixel with respect to the centroid origin of the data space comprised of the normalized difference vegetation index and elevation. This Cartesian quadrant attribute referenced each output pixel using the traditional labeling (I, II, III, and IV) of a Cartesian coordinate system (Pignani & Haggard, 1970) and defined a new attribute named QUADRANT for the left-hand side predictions (these labels refer to the nominal partitioning of the input raster's data space).

Using these codes the predicted values on the left-hand side of (5) could be displayed in the geographical data space (the UTM coordinate grid), as shown in Figures 11-14. It was remarkably insightful to see that these predicted values, when geographically sorted by their nominal quadrant labels, depicted an irregular but spatially distinctive pattern of dispersion. Such results indicate the advantage gained by the researcher who employs a laser scanning DEM and works concurrently in both the data and geographical spaces. Therefore, it does pay to examine the older literature to learn useful concepts which can refine applications of a newer technology such as laser scanning. After all, often ideas are explored in theory long before technology can produce the methodologies to verify, use, or disprove the ideas.

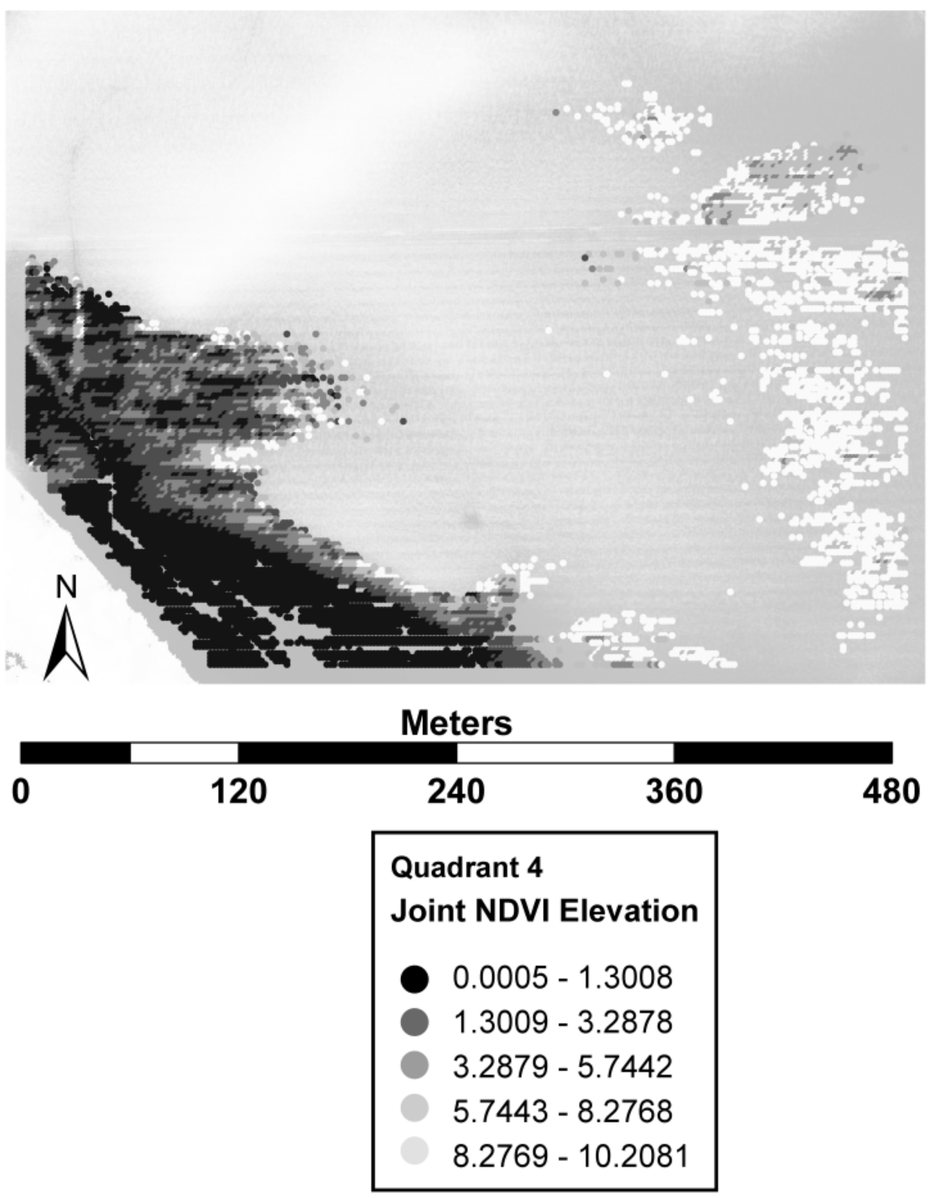

Fig. 14. Joint improper probability map for Quadrant 4.

2.5 Application - nitrogen and corn yields in a Nebraska field

Another area of possible use for laser scanning is for nitrogen (N) management in corn production. Nitrogen management to optimize crop production is a complex process involving such factors as applied N, soil nitrogen supply, crop nitrogen demand, and the economics of profit maximization, all of which can vary spatially and temporally. Because of the complexity of addressing these challenges, current nitrogen management practices generally result in low nitrogen use efficiency (NUE), estimated to be as low as 30-40% for cereal crops, such as corn (Cassman et al., 2002; Raun & Johnson, 1999). Unused nitrogen can eventually contaminate surface and groundwater, creating environmental and health concerns in addition to economic losses for agricultural producers. Low nitrogen use efficiency can be attributed to such things as poor synchronization between soil nitrogen supply and crop demand, uniform application rates of nitrogen fertilizer to spatially variable landscapes, and failure to account for temporally variable influences on crop nitrogen need (Shanahan et al., 2008).

To address the issues of low nitrogen use efficiency, research projects are evaluating the use of active crop canopy sensors to assess in-season plant nitrogen status and apply in real-time spatially-variable nitrogen applications; thereby increasing nitrogen use efficiency (Raun et al., 2002; Solari et al., 2010). Active canopy sensors generate their own source of modulated light and measure canopy reflectance in the visible (400-700 nm) and near-infrared (NIR) (700-1000 nm) parts of the electromagnetic spectrum. Solari et al. (2010) developed an algorithm on small plots in central Nebraska to direct in-season nitrogen applications in corn. Using a sufficiency index (SI), site-specific nitrogen was applied according to the equation:

$$N_{app} = 317 \times \sqrt{0.97 - SI_{sensor}}$$

where SI_{sensor} was the ratio of reflectance measurements from N-stressed to N-sufficient areas. However, they indicated the need to evaluate this algorithm across a broader range of soil and climatic conditions.

Research to address low nitrogen use efficiency has also involved the development of management zones, defined as dividing a field into sub-regions with homogeneous yield-limiting factors or regions of similar production potential (Doerge, 1999). A variety of crop or soil data layers have been used to develop management zones within fields; however, these efforts have produced mixed results, characterizing homogeneous production areas well in some years, but not in others. Schepers et al. (2004), as well as Shanahan et al. (2008), suggested a responsive in-season nitrogen application approach combining management zones and crop-based remote sensing as a possible strategy to increase nitrogen use efficiency.

In 2008, a study was conducted on an irrigated cornfield in central Nebraska to evaluate the algorithm proposed by Solari et al. (2010) against a conventional uniform nitrogen management approach, and, also, to explore the usefulness of an integrated management zone and active sensor approach for improved nitrogen management. The study location consisted of Hastings silt loam and Hastings silty clay loam soils ranging from 0 to 11% slope. The field had substantial change in elevation (~8-10 m), resulting in multiple landscape classifications within the study. Multiple spatial data layers were collected prior to planting to characterize spatial patterns of soil properties within the field. These layers included soil optical reflectance, apparent soil electrical conductivity (EC_a), laser scanning elevation, and slope. The laser scanning for this study was mapped during leaf-off conditions, at a 2-m spatial resolution. The field was also grid soil sampled (Oliver, 2010) to characterize field variation in soil chemical properties.

Hybrid selection, planting date, seeding rate, and field operations were at the producer's discretion. The sensor algorithm proposed by Solari et al. (2010) was evaluated using five different nitrogen application treatments as follows:

1. 45 kg N ha^{-1} at planting (45 At Planting)
2. University of Nebraska-Lincoln soil-based algorithm at planting + split application (per University of Nebraska-Lincoln recommendations)
3. 45 kg N ha^{-1} at planting + sensor algorithm delivered N (45 At Planting + variable-rate)
4. 90 kg N ha^{-1} at planting + sensor algorithm delivered N (90 At Planting + variable-rate)
5. High N (280 kg N ha^{-1}) reference at planting (N-Reference)

Treatments 1 and 5 were included to provide limiting and non-limiting nitrogen conditions to evaluate nitrogen response across the landscape as well as to provide the nitrogen reference (N-Ref) for calibration of the sensor algorithm. Treatment 2 served as a comparison to sensor algorithm treatments 3 and 4, with the nitrogen application rate determined via the University of Nebraska soil-based nitrogen recommendation algorithm. The sensor algorithm treatments 3 and 4 consisted of a combination of at-planting nitrogen (either 45 or 90 kg ha^{-1}) and in-season (~V13-V14 growth stage) nitrogen, with in-season nitrogen rates determined by the sensor algorithm (Solari et al., 2010). A uniform base amount of nitrogen was applied at-planting because previous work (Varvel et al., 1997) has shown that, in high yielding conditions, nitrogen stress prior to the V8 growth stage causes yield losses that cannot be corrected with additional in-season nitrogen application. The purpose of including the two at-planting nitrogen rates (45 and 90 kg nitrogen ha^{-1}) was to determine the appropriate amount of at-planting nitrogen required to avoid an early season nitrogen stress before delivery of in-season nitrogen using the sensor algorithm. Treatment 5 (N-Reference) received 280 kg ha^{-1} at-planting to provide an adequate reference for in-season nitrogen application.

The experimental design consisted of field-length strips (12 cornrows per strip) of each treatment replicated 3 times across the variable landscape. For treatments 1, 2 and 5, nitrogen was applied around planting time at spatially uniform rates. All treatments were applied at the appropriate times and rates using a high-clearance applicator, with the sensor algorithm treatments (3 and 4) being applied at approximately the V13/V14 growth stage at all fields. To determine the in-season nitrogen application rates for the two sensor algorithm treatments, active canopy reflectance sensor readings were first mapped for the N-Ref strips in each replication. Sensor reflectance in visible (VIS_{590}) and near infrared (NIR_{880}) was used to calculate chlorophyll index (CI_{590}) values according to Gitelson et al. (2003, 2005) using the equation:

$$CI_{590} = \frac{NIR_{880}}{VIS_{590}}$$

To acquire sensor readings, four sensors were mounted on the front of a high-clearance vehicle approximately 0.8 to 1.5 m above the crop canopy. The output from each sensor included pseudo-reflectance values for the two parts of the spectrum needed for CI_{590} calculation.

In-season variable nitrogen rates for 45AP + variable-rate and 90AP + variable-rate treatments were determined based on the algorithm described by Solari et al. (2010). This was done by calculating average CI_{590} for each N-Ref treatment. Next, 45AP + variable-rate and 90AP + variable-rate treatments were mapped and additional nitrogen need was determined on-the-go using a sufficiency index (SI) calculated by:

$$SI_{590} = \frac{CI_{target}}{CI_{N\ Ref}}$$

where CI_{target} is the CI_{590} value of a nitrogen target area and $CI_{N\ Ref}$ is the CI_{590} value of a non-nitrogen limiting area. At physiological maturity, the field was harvested by the producer using a commercial combine equipped with a yield monitor and differential global positioning system.

2.5.1 Ordinal categorical partitioning of the data space

In Section 2.3, a brief elaboration of the concepts of the geographical space and the data space was presented. At this time, an additional partitioning of the data space will be introduced — the ordinal categorical partition, which is only made possible through a high resolution, laser scanning digital elevation model.

To establish an ordinal categorical partition for the Cartesian coordinate data space of interest, the origin of reference is that formed by the centroid of the attribute means of any two topographical characteristics. The attribute values of one are plotted on the abscissa while the attribute values of the other (where both are co-located in the geographical space) are plotted on the ordinate axis. In the present case (Figure 15), the mean (*x, y*) pair, (4.22, 4.76) defines the centroid origin, where *x* is the natural logarithm of the range transformed (Lillesand et al., 2008, p. 504) apparent soil electrical conductivity ($EC_{a)}$ readings and *y* is the natural logarithm of the range transformed laser scanning elevation values (feet mean sea level).

Once plotted for ecological investigations, it is useful to recode the elevation and apparent soil electrical conductivity (EC_a) data space into an ordinal, categorical data partition (Figure 15) as opposed to the nominal categorical partition discussed in Section 2.4. To establish this ordinal partition, one examines the sign pairs of the Cartesian coordinate systems data space with respect to the centroid mean. For agriculture, it is reasonable to ordinally recode (as described in Willers et al. 2012) these quadrants in the following order: (a) associate the sign pair (+,+) to topography quadrant Q-IV, (b) the sign pair (+,-) to topography quadrant Q-III, (c) the sign pair (-,+) to topography quadrant Q-II, and (d) the last sign pair (-,-) with topography quadrant Q-I. Consequently, with respect to the statistical analysis domain, these ordinal topography quadrants represent 'topography blocks' within the design structure of the site-specific experiment (Mead, 1988; Milliken and Johnson, 2009).

The abscissa is defined by the natural log of range transformed attributes for the apparent soil electrical conductivity EC_a readings and the ordinate axis is defined by the natural log of range transformed attributes for elevation (feet mean seal level); thus, the origin of this Cartesian system is the centroid means of these two attributes. Each individual point pair in the scatter plot shows the corn yield value according to 15, natural breaks, color ramped classes (see legend inset at left of figure).

Data from Hunnicutt08 was analyzed previously (Roberts et al., 2012) using different classification techniques than those outlined in this chapter. In their work, Roberts et al. (2012) evaluated the relationship between crop response variables (CI_{590} and Yield) and apparant soil electrical conductivity (EC_a), soil optical reflectance, and landscape topography. In the Hunnicutt08, apparent soil electrical conductivity was significantly related to CI_{590} and yield, and was subsequently used to delineate management zones using the software Management Zone Analyst (University of Missouri, USDA-ARS, Columbia, MO). Management Zone Analyst delineated 2 zones within the field, with spatial patterns closely aligned with topography quadrants 1 & 3 and 2 & 4 of Figure 16. Higher positions in the landscape for this field ($Zone_{MZA}$ 1 and topography quadrants 2 & 4) corresponded to higher organic matter and more productive soils, while lower areas in the landscape corresponded to eroded drainage ways ($Zone_{MZA}$ 2 and topography quadrants 1 & 3).

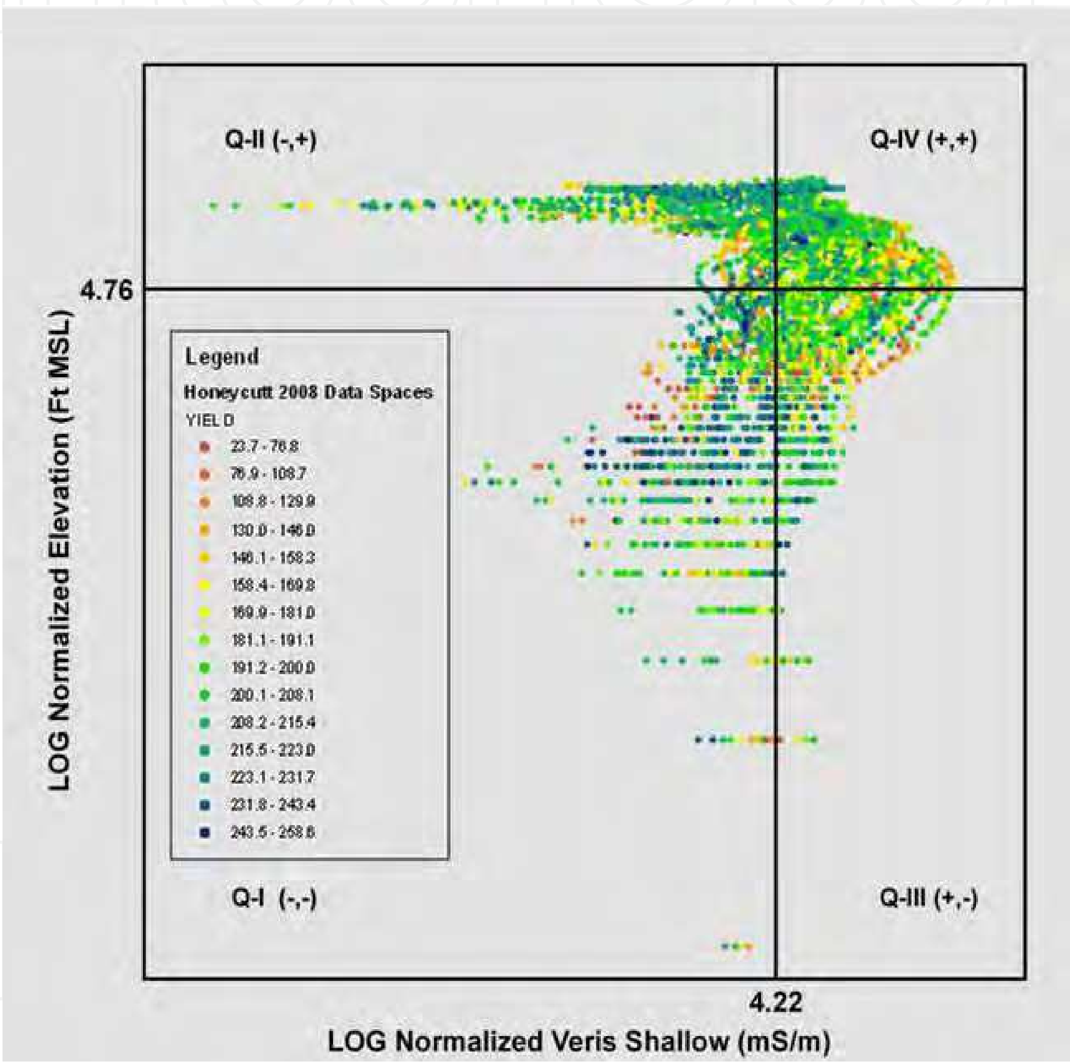

Fig. 15. The Hunnicutt 2008 nitrogen experiment structured in the data space according to (1) topography quadrants.

Roberts et al. (2012) concluded that the sensor-based algorithm used in their study may need to be adjusted according to management zones to account for differences in crop nitrogen response. In addition to the proximal ground-based sensors used to delineate zones by Roberts et al. (2012), spatial patterns identified in Figure 16 suggest that laser scanning digital elevation models would also be useful to identify spatial patterns of soil variability and crop response to nitrogen.

The floating plots in Figure 16 would require a variable-rate ground sprayer that can apportion its application swath into polygons that are 9.2 m wide by 18 m long, to apply the alternate management practice in each specific topography zone (that is, the four zones indicated by the red, yellow, green and blue colors).

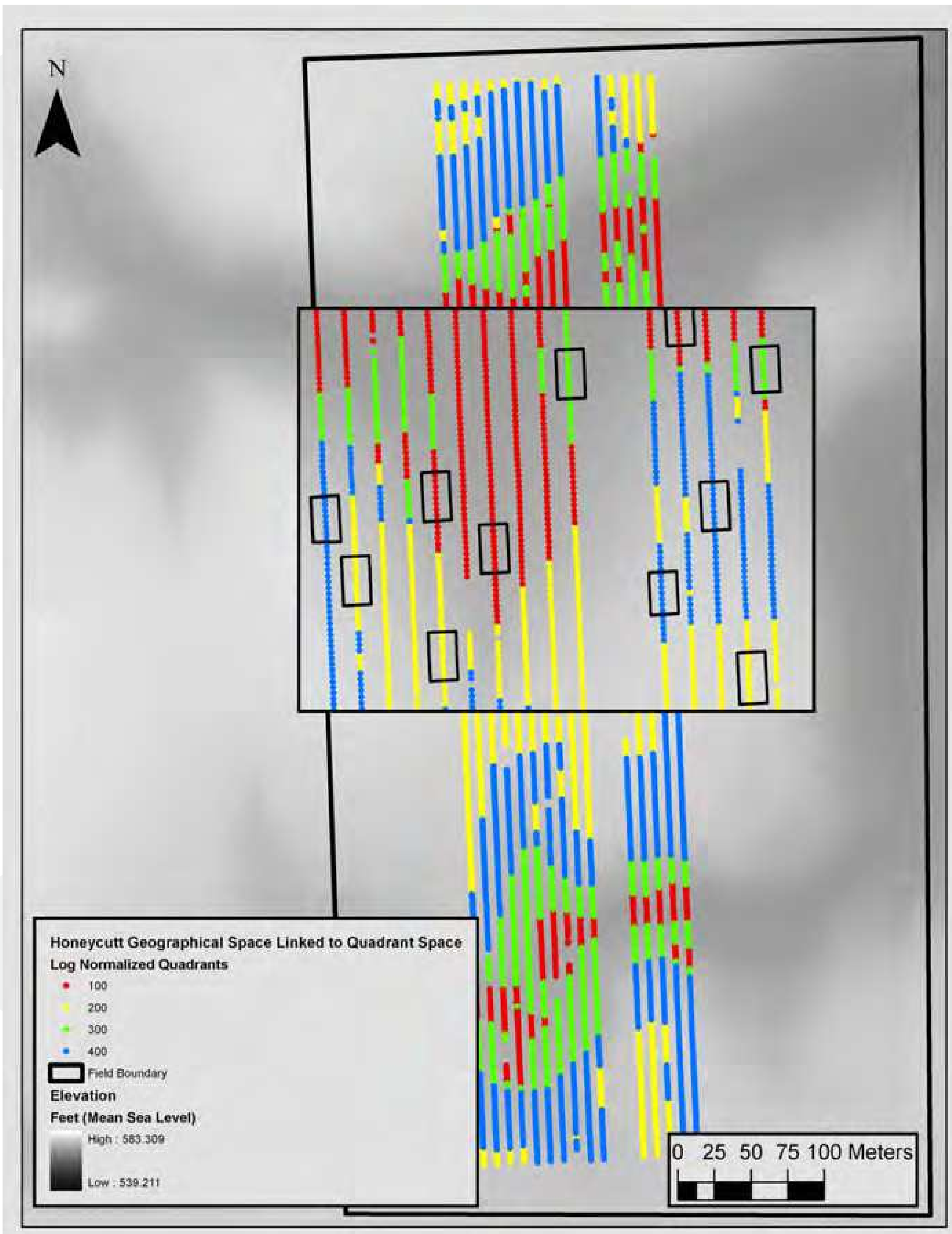

Fig. 16. The strip-plot plan of the Hunnicutt 2008 corn nitrogen experiment showing the topography blocks (see text) and examples of imbedded floating plots within the harvest paths of the combine.

2.5.2 Value of topographical partitions for site-specific experimental designs

The chief aim of a good experimental design is to (1) define the question to be tested, (2) define the experimental units and apportion these experimental units into homogenous populations, (3) define and describe the appropriate treatments or treatment combinations to obtain data to answer the question, and then (4) employ an appropriate randomization scheme to assign the treatments to the sensible structure of the experimental units (Mead, 1988; Milliken & Johnson, 2009). In agricultural experiments, availability of a laser scanning digital elevation model leads to significant improvements in experimental design. Evidence of this capability is presented in this section.

In Section 1.2, information addressing the issue of a system of floating plots was discussed (see also Milliken et al., 2010). The methodology involving an ordinal, categorical partition of two topographical attributes represents the first description of how to establish the geographical location of these floating plots in commercial fields. This method of choosing floating plot locations exploited the data and geographical spaces of information obtained by a laser scanning system and a second type of sensor system. More research is necessary to define the minimum size of these floating plots for optimal efficiency in a site-specific experimental design.

This same procedure generates another process which establishes the geographical extent of an asymmetrical, irregularly shaped set of topography blocks as a statistical construct useful for inclusion within the design structure component (Milliken & Johnson, 2002, 2009) of a site-specific experimental design (Milliken et al., 2010; Oliver, 2010; Schabenberger & Pierce, 2002; Willers et al., 2004, 2008b). The results presented in Table 2 provide evidence that the topography zones (as geographical 'blocks') successfully remove the influence of topography effects on the crop yield response variable as compared to where these topography layer attributes in the data space are only employed as covariates (compare sets of P-values at the far right column) and if the analysis is a traditional, randomized complete block experimental design.

Experimental Design Type	Covariance Parameters			Tests of Fixed Effects (Type 3)				
	Cov Parm	Subject	Estimate	Effect	Num DF	Den DF	F Value	Pr > F
Traditional (Randomized Complete Block)	Intercept	BLOCK	1.8393	LIDAR	1	5871	5.43	0.0198
	Residual		1094.19	ECSH	1	5871	9.59	0.0020
				LIDAR*ECSH	1	5871	9.38	0.0022
Site-Specific (Randomized Complete & Topography Blocks)	Intercept	T_BLOCK	2.8635	LIDAR	1	5862	0.28	0.5974
	Intercept	BLOCK* T_BLOCK	23.6590	ECSH	1	5862	2.15	0.1423
				LIDAR*ECSH	1	5862	2.08	0.1493
	Residual		1080.23					

Table 2. Summary statistics for two situations, where the topography covariates are employed for a traditional randomized complete block experimental design or are employed as covariates for a site-specific topography block experimental design.

3. Conclusion – agricultural laser scanning's '*trains and troops of works*'

This chapter is the logical supplement of two previously published works (Willers et al., 2009a; Willers & Riggins, 2010). A common theme of the collection is the illustration of how geo-spatial information of appropriate spatial, temporal and spectral resolution is a valuable resource for agro-ecological investigations. This work concludes with two major points.

The first point is that without the development of a suite of adequate tools and procedures to manage the copious flows of information for the experimenter, consultant, farm technician, farm supplier, or producer, the *fruit* that laser scanning provides for insight into the structure and function of agro-ecological systems will never be harvested. At the present time, the application of laser scanning and other remote sensing tools resides in the domain of specialists and not in the domain of the agriculturalist. The answer(s) needed to achieve a shift in the domain of usage and audience is not an easily resolved problem.

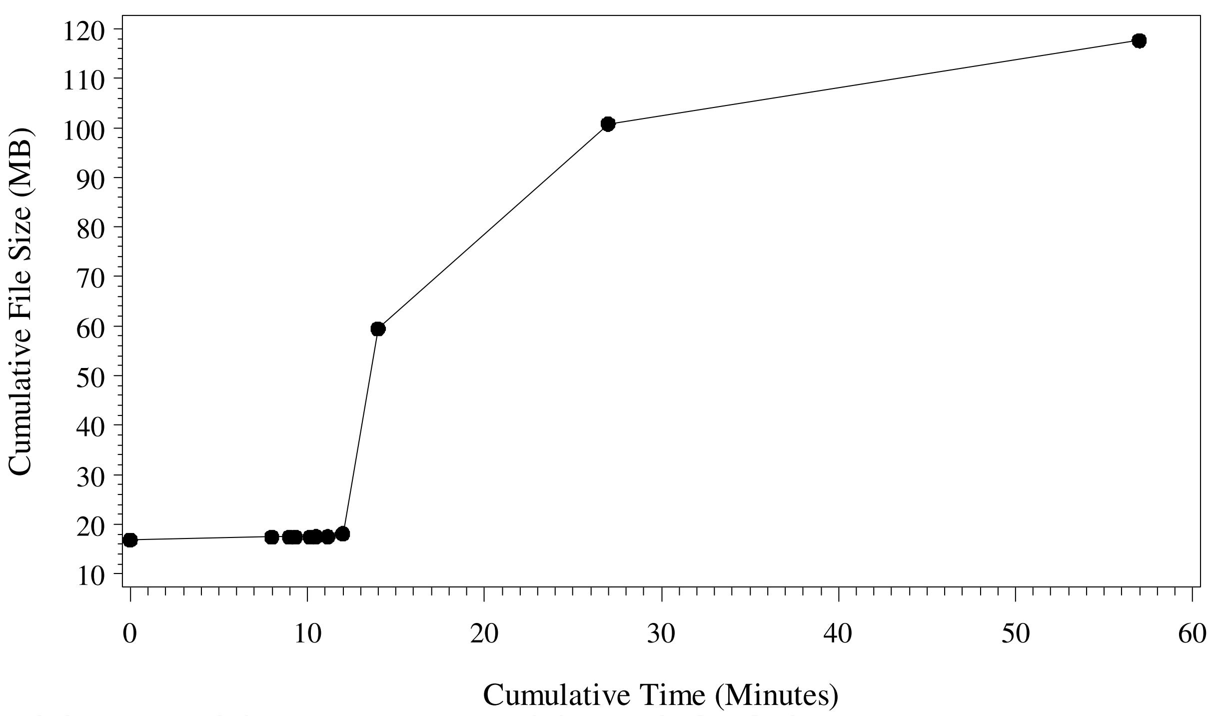

Fig. 17. Illustration of the relationship between cumulative time and cumulative file size for a task combining laser scanning elevation model with a raster layer of arctan normalized difference vegetation index values for one field on a commercial farm.

One simple example provides some indication of the kind of focus required among cross disciplinary skills and task(s) to make such a shift in usage. Employment of methods like those of Milliken et al. (2010) or Oliver (2010) indicates that usage of these mathematical approaches is limited because a comprehensive data processing and computing infrastructure for on-farm, in the field agricultural activities, does not exist (Schuster et al., 2011). We provide on example of the problem. Figure 17 shows the cumulative time required for a specialist to complete a task involving the combining of a digital elevation model layer with a normalized difference vegetation index (NDVI) layer to produce an output layer similar to Figures 11-14. The figure shows that the total time required can approach 60 minutes, while the cumulative file sizes involved increase to just a few megabytes. In real-farm applications, gigabytes of data are collected. Interestingly, the step involving some automation (the sharp inflection point near 12 min) is a step completed rather promptly.

Unless a formal infrastructure for precision agriculture is developed that significantly reduces processing time and establishes interoperability, all of the theories, ideas, techniques, data, and mathematical models developed through years of government and university research and industry investment will be underutilized or fall into disuse. Consequently, a "Henry Ford" type of construct is needed to reduce the time required to process and produce meaningful analyses for clients and reduce the amount of labor needed. For such a complex, multifaceted problem, it will take multiple consortiums of investigators to discover ways to make laser scanning information and other remote sensing data streams affordable and easily available to agricultural systems. Aside from establishing the capability of gathering data from using sensors in the field and on farm machinery, there is the overriding need to promptly use the huge amounts of data for rapid decision-making. At its core, the fundamental limitation on data-intensive agriculture is the lack of interoperability for data in different formats and the time constraints between data collection and results being available for the end user.

The second concluding point is the opportunity and need for additional confirmatory experimentation, built on exploratory experimentation procedures introduced in Sections 2.2 – 2.5. If a probability plot examination of the features of an agricultural landscape indicate the presence of more than one data distribution (D'Agostino & Stephens, 1986), then concurrent processing in the geographical space is required. Creation of a Cartesian coordinate system whose origin is a centroid formed by the arithmetic means of the data space obtained from two sensor systems, where at least one is elevation mapped by laser scanning, should reveal different autocorrelations among groups established by the categorical data partition of such a centroid. If differences in spatial autocorrelation among categorically derived groups are evident, then such evidence dictates that different management zones exist in the field and each requires different rules for their site-specific management. Without access to laser scanning information, investigators could model the spatial autocorrelation of their data attributes with an isotropic semivariogram and consequently not recognize the reality that more than one spatial random field (Oliver, 2010; Schabenberger & Pierce, 2002) determines the properties of the first (the mean) and second (the variance) moments of the data space comprised of the measured variables of interest. Thus, the modifiable areal unit problem, when examined in the '*light*' provided by laser scanning digital elevation models, is actually an indication of opportunity (not problems) with respect to the goals and philosophy of precision agriculture (Barnes et al., 1996; Moran et al., 1997; Oliver, 2010; Plant et al., 2001; Willers & Riggins, 2010).

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