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Changing the Cost of Farming: New Tools for Precision Farming
A White Paper
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Persistence Data Mining

Precision Farming – An Introduction and Challenges to Adoption

There are ongoing economic pressures in production agriculture to increase crop yields. However, high grain yield production comes at a cost of applying significant quantities of various agricultural inputs, i.e. nutrients, pesticides and irrigation. In traditional farming systems, producers attempt to apply these inputs at a uniform rate across a given field. However, due to inherent spatial variability in fields, not all areas may require the same levels of input. Although the spatial and temporal variability of yield limiting factors discussed above has been recognized for a long time (Rennie and Clayton, 1960; Malo and Worcester, 1975; Robert et al., 1990), farmers continued to manage their fields uniformly because they lacked the technology to manage for variability. With the introduction of new precision farming technologies such as global positioning systems (GPS), geographic information systems (GIS), remote sensing, and variable rate application technology (VRT) farmers now have the ability to manage their fields site specifically.

As more producers become aware of precision farming technology they are asking how precision farming can improve their productivity and profitability. Variable rate fertilizer application is promoted by industry as a way to increase efficiency and improve production. Environmentally, it seems correct to vary the amount of fertilizer in relation to crop need (Verhagen et al., 1995); however this will not appeal to farmers unless economic gain from VRT can be demonstrated.

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Producers have limited experience with this new technology and equipment and need unbiased information to determine whether VRT is a feasible option for their individual farming operations. The objectives of this White Paper are to review the challenges facing precision farming and present new tools to address these challenges to enable farmers to better utilize these effective solutions to high fertilizer costs and low commodity prices.

Variable Rate Application - Prescription Maps and Grid Soil Sampling

Field level studies have shown that organic C, total N, and NO_3-N have spatial dependence and variation (Cambardella et al., 1994). Using the ratio of nugget to total semi variance to classify spatial dependence, organic C, total N, and NO_3-N were strongly spatially dependent. Other studies have concluded that N uptake and crop response to N varies spatially within fields (Malzer, 1996; Dampney and Goodlass, 1997). Welsh et al. (1999) reported significant yield increases where 30% more additional N was applied to historically higher yielding parts of the field. Kachanoski et al. (1996) showed that optimal levels of N fertilization have spatial variability. The maximum yield increase and the economic yield increase over the check yield with no N applied were both strongly correlated with spatially optimal economic return of N (r=0.70 to 0.88). Variable rate application technologies enable farmers to adjust N rates to reflect these variations.

Accurate prescription maps are essential for effective VRT N fertilizer application (Sawyer, 1994; Ferguson et al., 1996). Grid soil sampling has most frequently been used to develop these prescription maps (Mueller et al., 2001). Past research has indicated several technical and economic limitations associated with this approach. There is a need to keep the number of samples to a minimum while still allowing a reasonable level of map quality.

However, Gotway et al. (1996) found that the optimum grid density may depend on the coefficient of variation. In many cases, where the spatial distribution is rather complex, much finer grid densities than those currently used commercially are required to produce accurate prescription maps. Mueller et al. (2001) indicated that a common commercial grid sampling scale of 100 m was grossly inadequate and that sampling at greater intensities only modestly improved prediction accuracy that would not justify the increase in sampling cost. Their data suggest that the use of the field average fertility values at their research field was not substantially worse than grid sampling. Schloeder et al. (2001) demonstrated that spatial interpolation of grid sampled data with limited sample size (n = 46) was mostly inappropriate. For most of their data sets the inability to predict, could be attributed to either spatially independent data, limited data, sample spacing, extreme values, or erratic behavior. Whelan et al. (1996) reported that in fields with less than 100 samples only very simple geostatistical methods such as inverse distance are appropriate. Sample sizes of 100 to 500 are needed for geostatistical methods such as kriging. Kravchenko and Bullock, (1998) studied several interpolation techniques, such as ordinary kriging, lognormal kriging, and inverse distance weighting, and found the best geostatistical methods to use depended on unique spatial properties in each field and could not be predicted in advance. McBratney and Pringle, (1999) reported that grid sampling at 20 to 30 m is generally needed when applying site specific management at a resolution of 20 by 20 m.

As can be seen, no one grid size or interpolation technique adequately describes the variability that exists in fields of a diverse population. If one fails to sample at a fine enough resolution to capture the spatial correlation in crop nutrient data, the interpolation methods and application maps developed from those methods will not be valid or accurate (Reich, 2000). However, the cost associated with grid sampling to the intensity required for accurate maps will be prohibitive in many cases.

The implementation of sustainable agricultural and environmental management requires a better understanding of the soil at increasingly finer scales for precision agriculture (Adamchuk et al. 2010). Conventional soil sampling and laboratory analyses cannot provide this information because they are time consuming and expensive. Remote soil sensing can overcome these shortcomings because the techniques facilitate the collection of larger amounts of spatial data using cheaper, simpler, and less laborious techniques. Diffuse reflectance spectroscopy using visible–near-infrared (vis–NIR) and mid-infrared (mid-IR) energies can be used to estimate soil organic carbon (OC) and soil nutrient composition (Stenberg et al. 2010). These sensors measure the amount of light that is diffusely reflected from the soil after radiation containing all the pertaining frequencies illuminates it. The parameter values cannot be directly deciphered from the vis–NIR or mid-IR spectra. To be useful quantitatively, spectra have to be exactly related to a set of known reference samples through the calibration of a prediction model, and these reference samples have to be representative of the range of soils the model is intended for. Some of the inaccuracies of calibrations may arise from the lack of sufficient absorption features, particularly in the vis–NIR, and from large soil type diversity in the calibration sets. By explaining and identifying these, we will achieve the maximum generalization capacity for the calibration of a particular soil property. In addition the density (one meter or less) of the remote sensed data will greatly increase the accuracy of the interpolation techniques needed to generate a very robust prescription map.

Better Tools for VRT – Remote Soil Sensing

Due to the technical and economic limitations associated with grid soil sampling described above, better tools are needed to fully realize the potential VRT technologies can provide**.** Persistence Data Mining's program utilizes remote soil sensing to provide the powerful new tools needed to enhance Precision Farming adoption today.

Remote sensing is a technology that can be used to obtain various spatial layers of information about soil and crop conditions (Adamchuk et al., 2003). It allows detection and/or characterization of an object, series of objects, or landscape without physical contact. Typically remote sensing is conducted by positioning a sensor above the object (target) being observed. Platforms that support the sensors vary, depending on the altitude above the target. Today three main observation platforms are used to collect remote sensing data: UAV-based, aircraft-based and satellite-based. Ground-based sensors also have been used for certain specific applications and research studies.

Sensors commonly used for remote sensing are part of either passive or active systems. Active systems, such as radar, supply their own source of energy to illuminate target surfaces. Passive systems, like a common photo camera, detect reflected solar energy. Although several concepts involving active systems have been developed at the research level, primarily passive systems are used in commercial applications related to site-specific management.

During the last half of the century, remote sensing instrumentation developed from simple optical systems into complex digital sensors, allowing rapid and high quality scanning of the Earth’s surface. Computation algorithms have been developed to process remotely sensed data and to produce different types of images. Spatial, spectral, and temporal resolutions are the main characteristics of any remote sensing system.

Spatial resolution refers to the smallest area (pixel) that can be distinguished in the image. Each pixel becomes a data point. As with photography, the distance between the sensor and the target, as well as the viewing angle, defines the field of view (i.e., size of the area represented by a single image or scan). Most images and data sets used in site-specific management have spatial resolutions ranging from less than 1 meter to 20 meters or more. Smaller pixel size usually is more expensive and requires more storage space and computation power.

Spectral resolution defines the ability of the system to differentiate between levels of electromagnetic radiation across different wavelengths (portions of spectrum). The number of sensed portions of the spectrum (bands) and their width also characterize the spectral resolution of the system. Some sensors (especially photographic) produce only black and white, color, or color infrared images, while others allow recording multi-spectral (typically less then 10) or hyper-spectral responses (can be more than a hundred). Panchromatic images also can be used to represent total reflectance combined from visual and near-infrared bands

Remote Soil Sensing Specifications

Persistence Data Minings platform utilizes remote sensed hyper-spectral imaging to map nitrogen, phosphorous, potassium, organic matter and pH with a consistently calibrated remote sensor. The technology initially creates a Normalized Difference Elemental Index (NDEI) map from the imagery. The NDEI relates the reflectance in the near-infrared (NIR) region and short-wave infrared (SWIR) to determine concentration of total nitrogen, phosphorous, potassium, organic matter and pH. A spatial yield potential map is then developed from the NDEI data. Remotely sensed imagery of soil, can offer an attractive alternative to the use of a standard soil sampling methods. Remotely sensed prescription maps are not affected by inaccuracies inherent in chemical wet lab processing. In field testing reduces soil respiration which changes the chemical composition in transport and processing. Correlation analysis shows a significant reduction in user error as related to the care of samples and sample taking methodology. The imagery data enables uniformity of sampling across soil types and textures in a post till process. The derived regression equations used to estimate soil nutrient concentrations will also have the potential to predict micronutrients for more precise fertilizer aplications. Ferguson et al. (2004) suggest that accurately characterizing yield potential within a field and thus spatial N demand is necessary for site specific N management.

Persistence Data Mining, Spatial N, P, K Recommendations and the Future

From the remote soil sensing data Persistence Data Mining develops variable rate Nitrogen (N), Phosphorus (P) and Potassium (K) application maps. The user inputs the N, P, and K recommendation equations appropriate for their area.

Fertilizer savings from \$15.00 to \$40.00+ per acre can be achieved utilizing this system as well as 10 to 13 percent yield increases. The system is also environmentally effective in reducing fertilizer over application leading to runoff and leaching into ground water. By combining an effective suite of well researched and documented procedures, Persistence Data Mining has developed an industry leading fertilizer management system that can begin to fully utilize VRT’s vast potential.

The commoditization in the Ag retail sector is creating an increasingly flatter environment, the opportunity to replace the weak net margins commodities generate with creative value-added systems such as Persistence Data Mining with strong net margins is promising. A way that companies can be successful in a flat environment is by enabling their customers with effective technologies. Those who can create value through leadership, collaboration, and creativity will transform the industry, as well as strengthen their relationships with their existing clients. The last twenty five years in technology has just been the warm up act, now we are going to get into the main event, an era when technology will transform every aspect of business, every aspect of life, and every aspect of society (T.L. Friedman, 2015).

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