OPTIMIZING N, P, K, AND S APPLICATION ACROSS LANDSCAPES IN THE NORTHERN GREAT PLAINS USING THE PLANT ROOT SIMULATOR (PRS™) TECHNOLOGY.

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ABSTRACT

Early papers on precision farming focused on variable rate fertilization and variable spraying technology (Roberts, 1996). The adoption of this 1st round of precision farming was acknowledged to be a "dead horse" (Mangold, 2000). These authors put forward the notion that farmers needed better tools to decide if the intensive management of fertilizer would result in a significant reduction in input costs, or a significant increase in crop yields. Western Ag Innovations Inc. has taken a significant step forward in quantifying the net returns that result from fertilizer decisions with the commercial adaptation of the Plant Root Simulator (PRS™) technology. Delivery of this technology to farmers has hinged upon the use of a Decision Support System called the PRS™ Nutrient Forecaster. This Knowledge-based computer tool has been utilized by growers in the Northern Great Plains for over 10 years, allowing them to assess the cost-benefit of a particular fertilizer and/or cropping decision on a field-by-field basis. The simulation engine in the PRS™ Nutrient Forecaster was used to optimize individual nutrient applications across many sites within a field. Analysis of the logistics required to deliver straight N, P, K, and S products to the 80 million acres of the Northern Great plains, crystallized the true limitation to variable rate or Precision Farming, the economic relating to fertilizer logistics.

This research paper squarely addresses logistics optimization. Our work focused on an intelligent solution optimization using a simulated annealing (SA) algorithm with the test for accuracy being the Forecaster simulation output deviations from the optimum yield on each site considering independent fertilizer nutrients. Field application of the technology indicated that finding a compromise in logistics using two best blends to re-blend in the field, resulted in more yield potential being realized that the straight rate controls, meanwhile simplifying the fertilizer handling.

INTRODUCTION

As knowledge of crop growth and field husbandry grows, we in Agricultural Research are faced with answering harder and harder questions. In the 1960's and 70's we focussed on the applied questions surrounding "What improves crop yield?". This era of empirical research had an explosion of field trials with fertilizer, crop varieties and managements being the "treatment" and final yields being the "result". This work was responsible for a significant improvement in crop yields known as the "Green Revolution".

In the 1980's and 90's, with the advent of GPS, satellite images and yield monitor technology, researchers jumped at the chance to answer even harder questions. We heralded an era of better, more precise, management because we could focus on "Where in the field 'What' crop yield occurred?". The answers generated by this level of Precision Farming did help explain temporally and spatially stable features that farmers intuitively understood to have control on crop yields. Examples like the old yard site, the saline area, or the patch of perennial weeds were readily seen and easily managed.

The equipment manufactures realized a new market potential and developed engineering solutions for GPS controlled, variable rate fertilizer application. A simple minded linear solution was implemented assuming that conventional soil testing told farmers where the soil was 'deficient' and a map would be created to simply add fertilizer to make the soil 'sufficient'. The fact is that precision farming at this level has generally failed to take off (Lowenberg-DeBoer, 2003, Walton etal., 2008). These authors offer a 'laundry list' of factors controlling technology adoption that is long and informative. However, we contend that there is one underlying flaw in adoption. We, as research scientist, have not adequately delivered tools to answer the most difficult research question: **WHY is 'what yield' where it is, and HOW does one apply this knowledge to optimize future yields?**

Dealing with the Why's and How's is much harder than the What's and Where's. It forces us as scientists to stop the simplistic empirical trials we are used to conducting and focus on putting the science back together in knowledge based tools that embody the underlying processes so as to predict future outcomes. Unfortunately, this new frontier of reconstructive science is too often threatening to the scientists with careers rooted in the past efforts of empirical reductionism.

In this paper we will describe a proven tool that reconstructs the soil-plant-climate processes so as to Optimize Farming practices. The Plant Root Simulator (PRS™) technology forms the base of this approach, as it has become a proven method to measure the soil nutrient supply for robust modeling. We will further describe how an interactive crop simulation, called the PRS™ Forecaster functions to extend the measured nutrient supply rates, along with salient crop growth drivers, to predict the fitness of the soil for plant growth. Finally, we will utilize this simulation engine to solve the logistical problems associated with applying fertilizer rates that are needed to optimize the net returns on across a hummocky landscape.

Re-thinking the WHY and HOW of Soil Nutrient Supply Power:

Assessing soil nutrient availability as a means of indicating the fitness for plants began with the pre and post war applications of "modern chemistry"

(Morgan, 1934). Since then numerous variants of dilute salts, acids, and bases have been used to extract an amount of nutrient that the plant could find and take up. The value of these testing protocols, therefore, hinged on the correlative relationship between the chemical extraction and actual plant uptake. Calibration studies relating soil test levels and fertilizer response followed the adoption of the first chemical extractions. The majority of these studies were performed between the mid-1950's and the early 1970's. This correlative index of soil nutrients and plant response was performed over many sites, soil types and climates to amass the often-referenced "regional database".

The aggregated scale that this data represented was a useful first approximation of whether a fertilizer response was probable given some extractable level. However, with any correlative index, situations exist where incorrect inferences are made simply because the specific situation is outside of the range of the original database or because time has reduced the utility of the calibrated extraction (Sumner, 2006). An example of this existed in the original "Field Fertilizer Investigations" used to create the calibrate soil testing database used in Saskatchewan. The researchers noted that in 1965 one site re-cropped to durum wheat did not respond to fertilizer N application. This site, noted to be "breaking", obviously had much higher N turnover from the freshly incorporated native prairie sod. Thus, the index of "extractable nitrate to 2 ft" failed in its prediction, indicating N was needed when the soil supply was adequate.

It was with an understanding of these shortfalls in correlative indices that several key research groups began to investigate a mechanistic approach to predicting plant nutrient needs. In the early 1960's both Nye at Oxford and Barber at Purdue began extending their lab results on nutrient movement to root systems. The late Stanley A. Barber was one of the first to visualize the importance of soil nutrient flux in a pioneering study of radioactive ^{32}P uptake and accumulation in wheat plants (Barber, 1947). Later research would build on these tracer studies and result in the mechanistic description of the soil supply and plant uptake (Barber, 1995).

The PRS™ Technology is a further iteration of Barber's concept. Measuring the soil nutrient flux to a "simulated" root can provide valuable research data on the dynamic mechanisms controlling soil fertility. More importantly, extending these flux measurements to predict the potential plant uptake and subsequent nutrient deficit, is what farmers and growers require. This paper describes how soil nutrient supply rates can be extended, through a computer-forecasting model, to result in a dynamic prediction of crop response and fertilizer needs.

Ion Flux measurement with the PRS™ Technology:

The Plant Root Simulator™ (PRS™) Technology utilizes both anion and cation exchange membranes encapsulated in either an orange or purple plastic probe. When chemically pre-treated, these membranes exhibit surface characteristics and nutrient sorption phenomena that resemble a plant root surface. When buried in moist soil, the PRS™-probe will provide an assessment of nutrient supply rates by continuously absorbing charged ionic species over the burial period in much the same way as a plant root would.

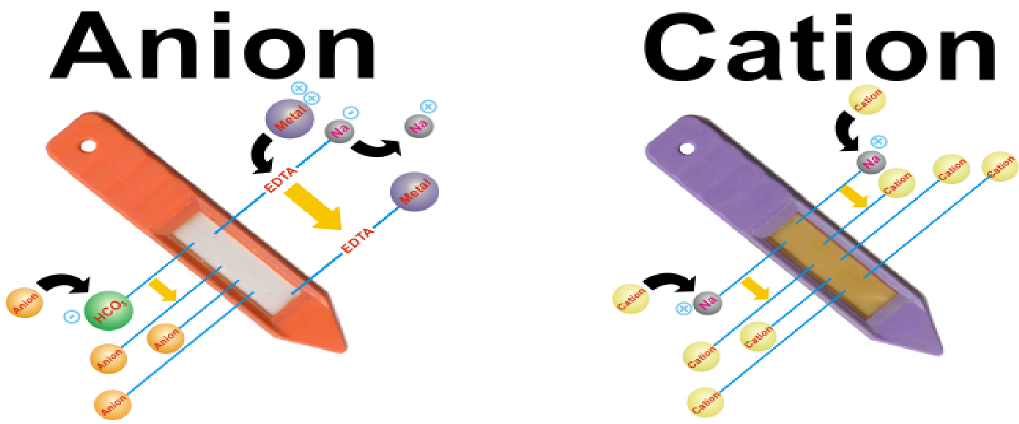


Figure 1. PRS™- Anion and Cation probes. The balls and lines show a schematic of sorption process.

Functionally testing the ion supply rate of a soil in controlled or known conditions is a necessary starting point for one to build a forecast of the whole-season potential plant uptake. Ion flux, measured with the PRS™-probe, is sensitive to the same factors that drive plant production, namely water and heat. These relationships are relatively easy to scale from a known condition to one that is wetter or drier, and/or cooler or warmer. The ability to scale the PRS™-probe measurements with climatic factors provides superior datum on which to build an integrated soil-climate-plant model.

Modeling Potential Plant Uptake - First Attempts

Most of the intensive modeling efforts in the past began with chemical extraction data, and some assessment of the "labile" and "stable" soil nutrient pools (Godwin and Jones, 1991; Jones et al., 1991). The approach of assessing pool size and turnover rates to model the contribution of stable nutrient forms to the "plant available pool" has been most often applied to N. Typically, commercial labs have applied either simplified linear release estimates from generalized soil organic matter levels (Karamanos et.al., 1992) or N "credit" for legumes, manure, or other high N residues (http://www.agviselabs.com/tech_art/precisionn.php). Crediting or estimating N release using any of these methods certainly can improve the extractable N tests' inferences in some soil types and management regimes. However, since the kinetics of release from these credited pools are often assumed to be some "average" for a climatic region, there will always be instances where generalized credits fail despite having an accurate account of the inputs to these calculations.

The task of accounting for mineralization or soil nutrient buffer power has focused much of the soil research toward nutrient pool fractionation and turnover studies. However well intentioned this work may be, the conceptual plant-soil diagram of Williams (Figure 2) illustrates a larger oversight. From the plants' perspective, the intensity of nutrients in soil solution and the quantity factors buffering the soil solution are only as important as the mass of root system growing and taking up nutrients. The central role of rooting volume in potential plant uptake has been clearly illustrated with the Barber model. Sensitivity analysis reveals that factors controlling roots have a much greater impact than most of the soil supply factors. Clearly, the soil testing industry's focus on chemical extractions that are "rapid, repeatable and extract a given quantity of the available pool" are misguided if we accept that the rooting volume of the plant is the principal factor governing nutrient uptake. Thus the convention of multiplying extractable concentrations by 2 to obtain a mass of nutrient in the acre furrow slice cannot be simply equated to be the lbs/acre of available nutrient irrespective of the specifics in plant rooting volume.

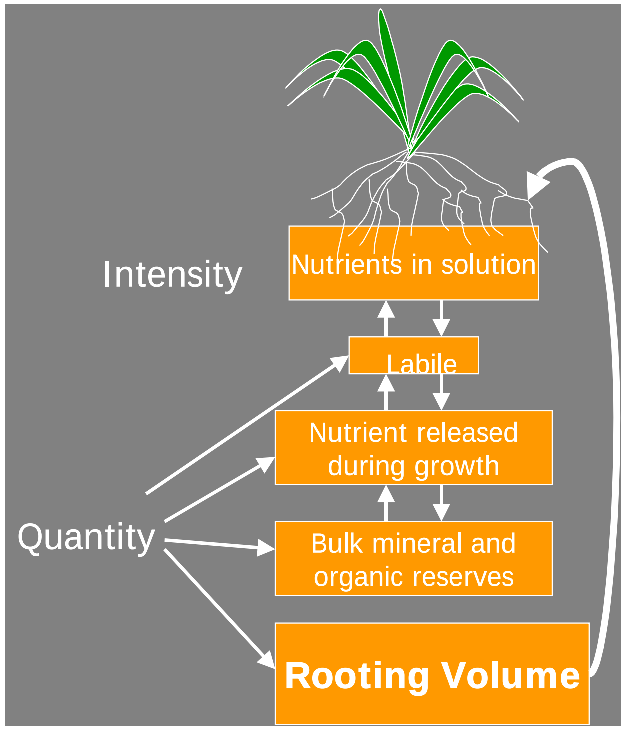
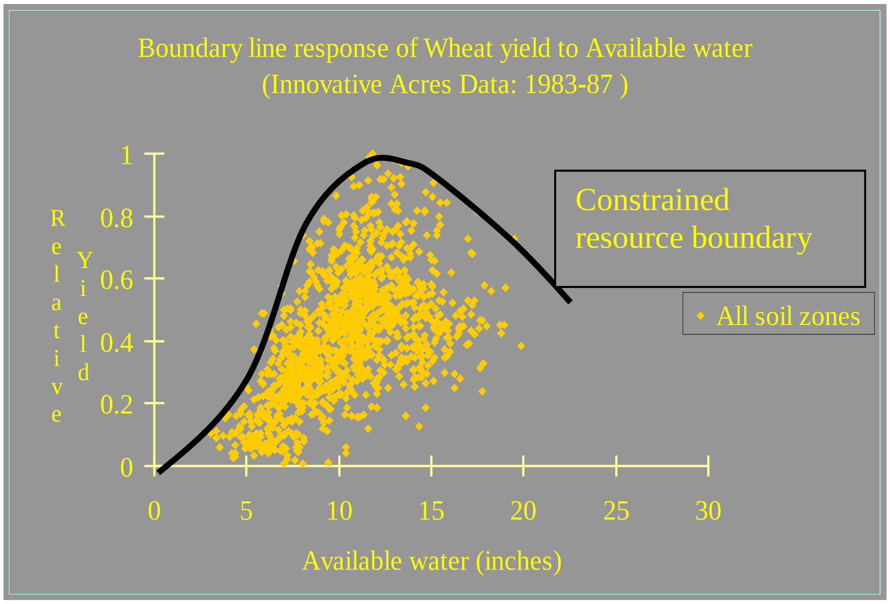


Figure 2. Quantity/Intensity relationships between nutrient pools as seen by plant roots (after Williams, 1970).

Constrained Resource Modeling approach

In 1997 an effort was made to tie together the utility of a functional test of soil nutrient supply rate with a mechanistic nutrient uptake model. The very detailed concepts of Barber's Flux model were used along with more highly aggregated modeling efforts applied to grain yield and nutrient responses (Flaten et al., 1988). The modeling approach began by simplifying the soil-climate-plant system and systematically adding complexity that accounted for the most likely exceptional scenarios. Resources defined by this procedure have a fundamental impact on the soil-climate-plant system. The entire approach, called "Constrained Resource Modeling", proved a useful level of aggregation for crop nutrition modeling in western Canada.

Selecting an appropriate scale of aggregation for the resources controlling yield is essential to developing a model that is understood by the grower. For example, the supply and demand for water can be mechanistically modeled with daily precipitation data, infiltration, drainage, root suction potentials, transpiration and water demand for photosynthesis. The net outcome of such a mechanistic description should result in different levels of plant growth with changes in precipitation. However, at the scale the grower sees, the constraint to yield by water has a more simplified functional description. Too little water available during the growing season means low yield. Increases in water result in increased yields. Although the grower also knows, that past some point, too much water restricts yield. The grower has just defined the generic bell-shaped curve that results when the finite resource (water) is the only factor constraining yield, illustrated in Figure 3. With over 1200 site yields plotted against available water, the boundary clearly forms where water is the only constraint to more yield. The lower yields at equivalent levels of available water often occur, however, the



reason for the lower yield is some factor other than water.

Figure 3. Scatter plot of relative spring wheat yield as a function of the available soil water showing the boundary of the resource constraint (de Jong, 1988).

Similar treatment of other critical constraining factors such as heat, soil texture, soil density, soil pH, and soil EC resulted in a set of overriding controls that growers identify with. Selecting grower-tracked data as the key input variables also eliminated a common problem of most research-derived mechanistic models; that being the requirement for scientific data on the soil and/or crop to be measured and entered into the model (Acock et al., 2001).

The PRS™ Nutrient Forecaster – a dynamic management tool

Conventional soil testing labs perceive their role as being the “data or information provider”, with output to farmers focusing on colorful and easy to read reports (Vaughan, 2000). In our experience we see many growers frustrated with the inability to practically manage their business with such data or information.

Most growers began soil testing with the implicit assumption that measuring the soil will then allow for better management. However, over time, the “regionally calibrated database” became obsolete and the range of possible recommend outcomes from the database became more predictable to growers. Such depreciation in the value of the regionally calibrated database is inevitable since the knowledge contained in this data matrix is fixed within the specific characteristics (i.e. management, crop variety, fertilizer type, rates, etc.) of the calibration studies. Growers demand a knowledge-based tool with much more power and inference space. To that end, we feel that the PRS™ Nutrient Forecaster has greatly extended the ability of growers to incorporate new knowledge into their mental model of the soil-climate-plant system.

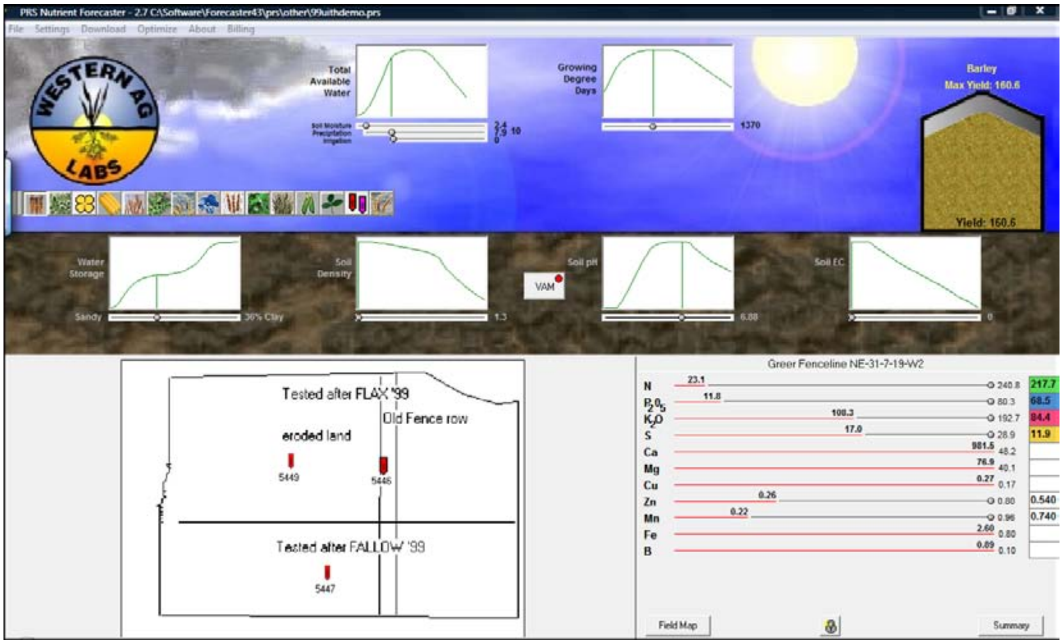


Figure 4. Screen Capture of the PRS™ Nutrient Forecaster. Upper curves show the constrained resource relationships driving yield. Online demo available for viewing at [(http://www.westernaglabs.com/demo/demo.html)](http://www.westernaglabs.com/demo/demo.html).

In the fall of 1997, Western Ag Labs Ltd. became the first to apply the complete PRS™ Technology as a replacement for the conventional soil test extractions and calibrated database recommendations. Growers readily accepted the constrained resource modeling approach and the inherent assumptions that are graphically displayed in the shape of each resource vs. yield function. The adoption of this technology as a basis for crop nutrition planning and nutrient management followed rapidly. Today, more than 12M acres have been managed with the knowledge derived from this dynamic management tool. The key to its' adoption has been the success in distilling down and aggregating the soil-climate-plant processes and controls to match those commonly understood by growers. Having data inputs and outcomes that are readily known by growers allows the PRS™ Nutrient Forecaster to be validated with the growers own experience base. Lynch and Gregor (2001) have researched several decision support systems in Australia and confirm that simple validation points, and wide trialability are key features in systems exhibiting high utility to growers. Further research including collating grower experiences with the PRS™ Nutrient Forecaster is underway in western Canada (Wildfong et al., 2010).

Optimizing the WHY: Leveraging Nutrient Interactions.

In order to optimize the yield in each landscape position, the resource constraints in these landscape positions need to be understood. Obviously if there are multiple constraints in soil nutrient supply, there is the potential to optimize yield with different combinations of N, P, K or S. This concept builds squarely on the proven concept of synergistic nutrient interactions within crops (Fageria, 2001; IPNI, 1999).

The following screen captures from the PRS™ Forecaster Model are useful in illustrating how a constrained resource model will leverage the interactions between nutrients to derive a best dollar outcome. In Figure 5a, with zero fertilizer applied, the Forecaster Model predicts the best ROI to added P fertilizer. When $3.00/ac of P is applied, the N "response" changes from a flat ROI to a steeply increasing ROI (Figure 5b). With $3.00/ac of N fertilizer applied the ROI curves arrive at the same slope (Figure 5c), indicating an optimized state for input cost and net profit. However, fixing this "fertilizer blend" of N and P at 1:1 and varying the rate upward, no longer results in an optimum state (Figure 6a).

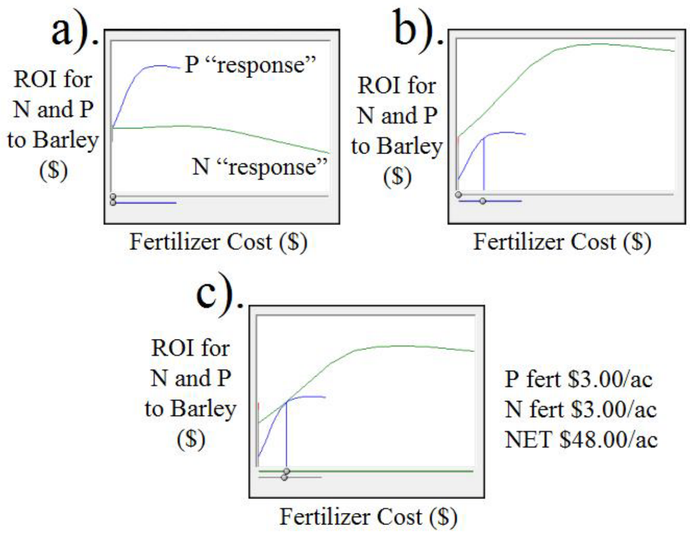


Figure 5. Return On Investment (ROI) from both N (green) and P (blue) fertilizer dollars in a state of **a).** No $ of Fertilizer Cost incurred, **b).** $3.00/ac of P Fertilizer Cost and **c).** $3.00/ac of P and $3.00/ac of N fertilizer.

Applying an increased rate of the 1:1 blend will result in greater yield and increased net (Figure 6a). Although it is clear that the ROI on P fertilizer has decreased greatly, meanwhile the N fertilizer ROI curve is still rising steeply. Allowing the PRS™ Nutrient Forecaster model to rearrange the blend rate based on optimum ROI yields a Net of $98.00/ac. This gain is achieved by allowing the interaction of N and P to be played out as less P ($4.50/ac) and more N ($9.50/ac), result in a substantially higher yield of barley.

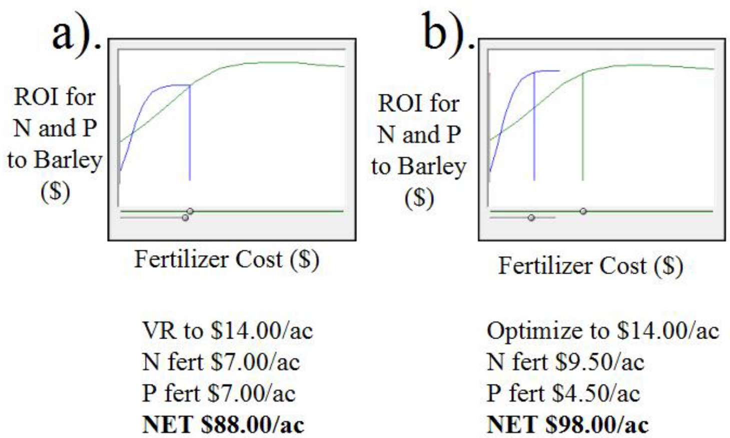


Figure 6. Return On Investment (ROI) to $14.00/ac of added N and P fertilizer with, a). Variable Rate (VR) with a 1:1 fixed blend of N:P and b). PRS™ Forecaster Optimized solution with interaction of N and P.

These differing outcomes in N, P, K or S leverage the biological reality that nutrient interaction can result in the same yield, with different levels of soil nutrient and/or fertilizer supplied. This synergistic interaction between nutrients, present in the PRS™ Forecaster, does not exist in other crop simulation models. Modeling yields using the interactions that exist between nutrients allows for a more realistic optimization based on dollars of nutrient input and dollars of yield output. Thus the thinking that one blend with a variable application rate will be best for each site, is a gross oversimplification.

Optimizing the WHY: A Field Scale Trial.

The optimization field site selected in 2001 was located on the NW 01-07-20 W2, near Ceylon, Saskatchewan, Canada. The soil type was a Mollosol mapped as an Amulet/Brooking clay loam complex in the Canadian Soil Classification System. The relief on the site was significant as the Missouri Coteau begins to rise on this quarter section. Topography was logged using the Flexi-coil task controller attached to a John Deere Starfire receiver with WAAS correction. Figure 7 shows the relative sampling sites and field boundaries overlaid on the topography.

Three fields were separated for the experiment. Field 1 was not included in the study since the site was underseeded to sweet clover and could not be sprayed for volunteer canola. Field 2 was 54 acres in size and was selected as the site for optimization of net return using the PRS^{TM} Nutrient Forecaster. Field 3 comprised 18 acres and was used as the average fertilized control.

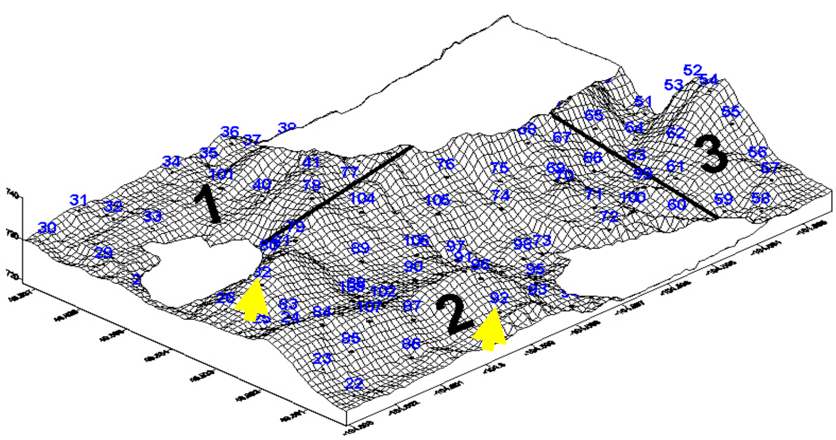


Figure 7. Topography and sample points where soil data was collected using the PRS^{TM} technology. Yellow arrows denote sites 82 and 92.

In the fall of 2001, eighty-six (86) soil samples were taken in a “smart” or directed sampling scheme. This involved sampling equivalent number of upper level, mid-slope and lower-level positions in a balanced manner, thus allowing meaningful interpolation across the site. Field 2 had 46 sample sites that were analyzed for PRS^{TM} nutrient supply rate, texture and stored water. Field 3 contained 23 sampling sites.

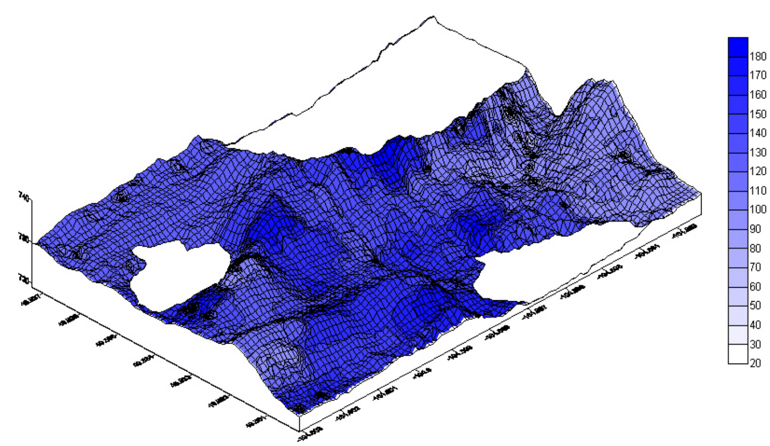
Water Redistribution:

Using the topography and slope percentage, a simple water budget was calculated to spatially proportion the 8 inches of growing season precipitation in our “what if” scenario. Yield forecasts and nutrient responses are greatly influenced by the Total Available water. Hence upper-slopes having a steep gradient are likely to be less responsive to fertilizer simply due to a limitation in water infiltration and storage. Field 2 water settings ranged from a low of 5.10 inches at site 82, to a high of 9.71 inches at site 92 (Figure 7).

Rates of N, P, and K:

The PRS™ Nutrient Forecaster model was initialized with the soil nutrient supplies, soil texture and water redistribution data for each of the 46 sites in Field 2. The model was then constrained to spend $40/ac for a total of $2160.00 on Field 2. Allocation was allowed based on the N, P or K response curve at each location. The N, P and K nutrient prices were set at $0.41/lb, $0.35/lb, $0.15/lb, respectively. The Barley produced was given a value of $2.00/bu. The allocation of these resources was free to flow from site to site within Field 2 until a maximum Net Return after fertilizer was found. Fertilizer applications ranged from 0 to 85 lb/ac actual N (Figure 8). Phosphorus and potassium rates ranged from0 to 48 lb/ac and 0 to 78 lb/ac, respectively (Figure 9).

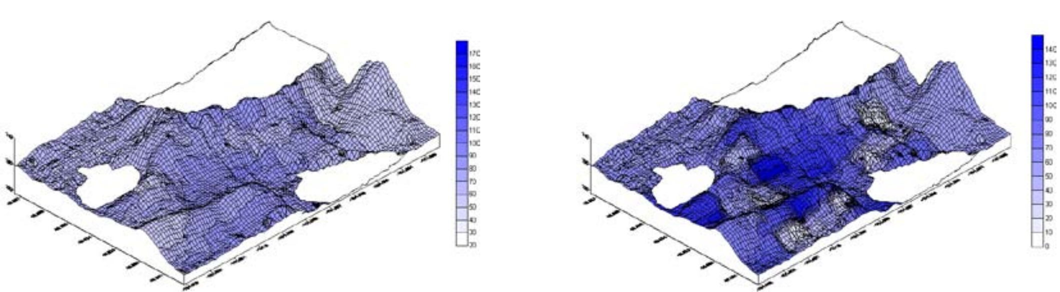
The same constrained-resource model was then used to develop an average best blend for Field 3. Nutrient supply rates, texture and water inputs were averaged across the 23 sample locations. The optimum return for $40/ac of inputs (total of $720) was calculated using the same nutrient price inputs. Figures 2-4



show the actual rates of products applied on the site using the Flexi-coil 50 series Task controller.

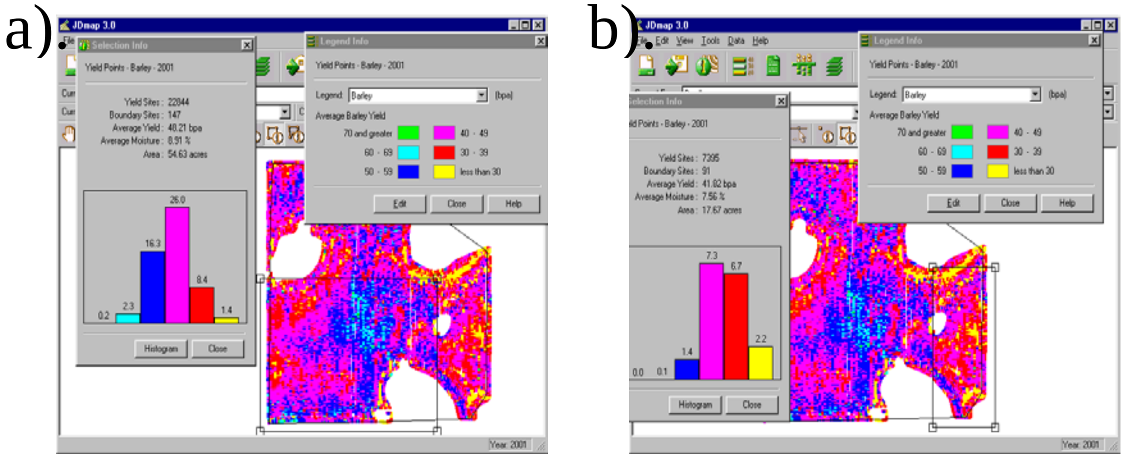
Figure 8. As applied map of 46-0-0 in lbs product per acre overlaid on topography.
Figure 9. As applied maps of 11-52-0 and 0-0-62 in lbs of product per acre, respectively.

The growing season precipitation set in the “what if” scenario was 8



inches. Actual growing season precipitation on the site was 3.5 inches. The stored water present after the winter period was estimated at 2 to 3 inches. Running the same water redistribution assumptions resulted in total water ranging from 4.0 to 6.8 inches of water. Maximum barley yields Forecast with the original 8 inch “what if” scenario ranged from 63 to 115 bu/ac. Maximum yields Forecast using the observed precipitation and soil moisture settings were calculated to be between 30 to 80 bu/ac. Actual yield range on the field was 20 to 80 bu/ac (Figure 10a).

Field 2 average yield was 48 bu/ac (Figure 10a). The yield map indicated that upslope positions experienced limited yield (25-35 bu/ac). This was expected since both water and nutrients were limited. Low slope regions that had higher total water available, yielded well above the average (60-70 bu/ac). The histogram of yield showed that 16.3 of the 54 acres was found to yield in the 50-59 bu/ac yield class. Only 9.8 acres are in the yield classes less than 39 bu/ac



(Figure 10b).

Figure 10. Yield maps showing acres within each yield class on **a.)** the PRS™ Forecaster Optimized (field 2) and **b.)** the average rate of the ‘best blend’ (field 3).

Conversely, on the control field only 1.5 of the 18 acres were in the greater than 50 bu/ac class and nearly 50% of the acres yielded less than 39 bu/ac (Figure 10b). This data indicates that the low slope positions in the control field did not produce to the same yield potential because the fertilizer blend applied was the average considering upslopes, midslopes, and lowslopes. This increasing of yield on the midslopes at the expense of the lowslopes was the main factor in causing the reduced average yield (42 bu/ac) on the control field. Optimized redistribution of fertilizer dollars within the field in this study resulted in 6 bu/ac or $19.50/ac more return. However, the additional 16 hours needed to individually carry each fertilizer product out and make a second pass across the field would have an opportunity cost of $47/acre. Thus, the benefit of optimizing is more than lost in the cost of logistics.

A further logistics solution must be considered that will simplify the optimization and eliminate the costs associated with delivering individual products. It is entirely possible that two custom blends could be created that, when re-blended on each site in the field, would approximate a best solution of the individual products. It would be theoretically possible to program the PRS™ Forecaster model solve this problem by trying every blend. Such a solution, known as the "brute force" approach, is untenable given the size of the search space. For example, given the possible dry commercial fertilizers and the rate steps needed for N, P, K and S, over 1 trillion blend combinations must be searched in order to find the two optimal blends. This computation would take 7 years of computation PER site. Thus on the farm field with 100 sites, the computation would take 700 years to render an answer for one state of the PRS™ Forecaster constraints. Therefore, to efficiently accomplish this task we required an Artificial Intelligence solution called Simulated Annealing (SA).

Optimizing the HOW: Simulated Annealing for selecting blends to deliver to the field.

The simulated annealing (SA) blend optimization can be performed on the PRS™ Forecaster Optimized solution as a means of simplifying the logistics of applying nitrogen, phosphorus, potassium, and sulfur individually. The SA solution required looking at the compromise of over-application of some nutrients for the benefit of simplifying the blend selection. In order to accommodate this change, the PRS™ Forecaster Model required knowledge of the antagonistic nutrient interactions to be added (Figure 11).

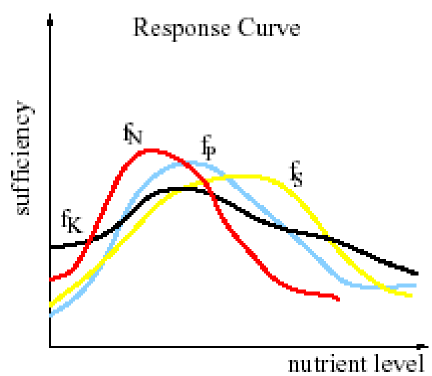


Figure 11. Nutrient response curves required for blend compromises using the PRS™ Forecaster enhanced with Simulated Annealing.

The antagonism of over-applying is shown to be less severe for P, K and S. Meanwhile N over-application is more antagonistic to optimal yield. This new version of the PRS™ Forecaster rendered a solution to both a 40 site field and a 100 site field (Figure 12). It is readily apparent that a CPU time of 20 to 100 seconds can render two blends that when re-blended are within 99% of the true optimal yields on each site. When contrasted to the hundreds of years required to have the model alone test every blend combination, the SA solution is obviously significant and needed tool for simplifying the logistics of blend delivery for Optimized Forecaster Farming.

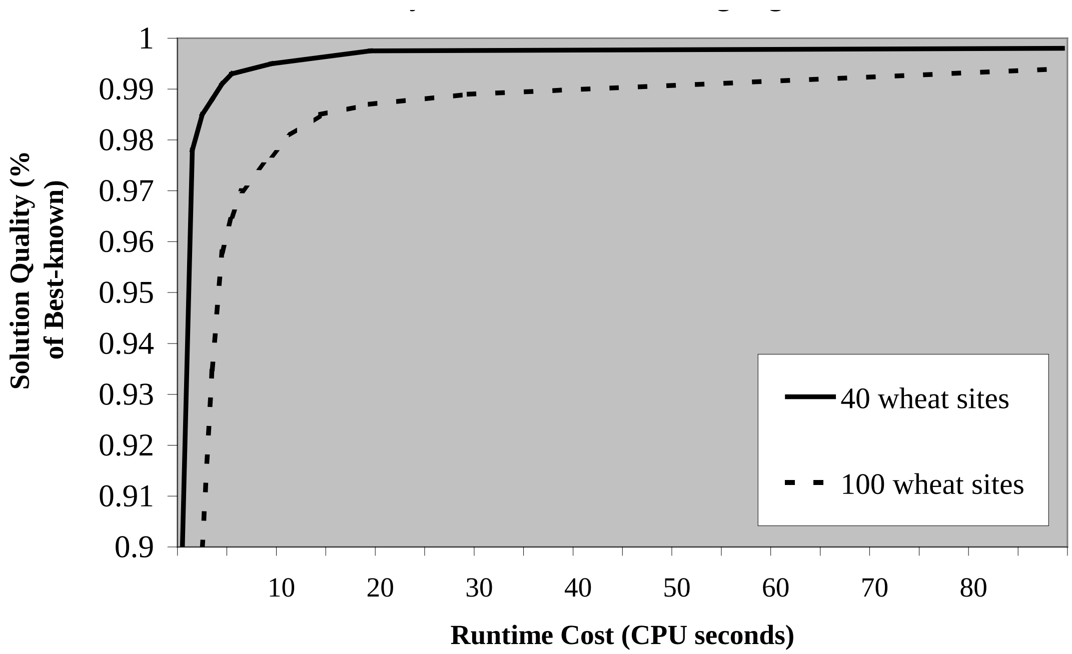


Figure 12. Simulated Annealing solution for 2 best blends to Optimize the logistics needed for N, P, K and S deliver to a field with 40 and 100 individual sites.

Optimizing the HOW: Field Trial of the SA solution.

In 2004, specialized large scale field equipment was fitted with the control units necessary to implement the 4690 rate changes throughout the 135 acre site at St. Denis, Sk. Control strips with “average fertilizer rates” (solid color) were placed north to south in each of the test fields (Figure 13).

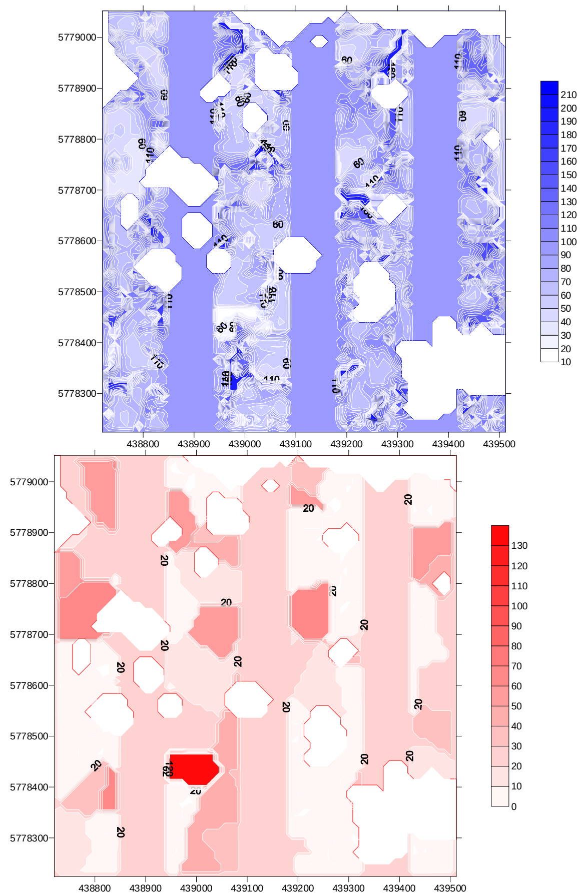


Figure 13. St. Denis site rate maps to be applied for optimized Blend 1 (31.0-12.5-0-10.0) and Blend 2 (12.4-5.0-37.5-3.5) respectively.

The PRS™ Forecaster Optimization ran using a simulated annealing algorithm to select the two best blends that could be re-blended to accommodate every rate step. Figure 13 shows that a both Blend 1 and Blend 2 had locations in the field where they would be both dominant and "make-up" blends. These maps reinforce the complexity of the optimization. As such a simplified one blend with make up for the hilltops, is far from the state of the art in optimizing profit from each position in the landscape.

The SA search for this field site ran for 1 day. The blends that resulted were calculated back to individual N, P, K and S rates and, in turn, run back through the PRS™ Forecaster as a means of comparison to the optimal nutrient rates. Table 1 lists the % CV between the SA selected blends and the individually derived optimal nutrient rates. Utilizing the two blends listed in Figure 13, the deviation for Sulfur (S) was highest at 3.14 % of the mean rate. The SA derived blends for nitrogen (N) and phosphorus (P) varied by less than 1 % of the mean rates.

Table 1. Mean rates and variance as calculated by the SA optimized fertilizer blends.

Fertilizer	N lb/ac	P lb/ac	K lb/ac	S lb/ac

Rates	31.991	12.983	8.130	10.325
Variance	0.186	0.092	0.014	0.324
CV%	0.58	0.71	0.18	3.14

Rethinking the WHY and HOW: Conclusions

To allow for Optimization of the plant-soil-climate system, the first step is to functionally assess the constraints of that system. Conventional soil testing using chemical extractions and correlative plant response data initially was a useful tool for "field average" management. However, with little new work done to calibrate for new varieties, new management practices, and soil changes, the value of these regional databases has depreciated in the eyes of the grower. A mechanistic approach to building a crop nutrition plan is possible using the PRS™ Technology. This technology utilizes both the strength of a functional test for soil nutrient supply and the power of a mechanistic computer model tailored for growers. Such a tool has allowed farmers to come closer to the true goal of variable rate fertilization, that being optimization of ROI to fertilizer. This search for the highest net return to the total dollars spent on fertilizer is not simply a zone by zone, or even site by site, compromise. Instead, the ROI for the entire field can be optimized by considering the constraints at each site and optimizing the specific response curves by passing fertilizer dollars around from site to site to obtain the highest profit. Our field validation of this technology found a net yield advantage of $19.50/ac, despite having less than half of the normal forecasted rainfall. The most inciteful conclusion of this work however, was that without simplified logistics the benefit of optimization was easily overshadowed by the cost of delivering individual nutrients to the field.

An artificial intelligence technique called Simulated Annealing (SA) was employed to search a vast domain (> 100 trillion) of blend products that, when re-blend on the fly, produce near optimal rates of N, P, K and S. The SA routine selected could render a solution within 99% of the optimal within 100 CPU seconds, making this solution compatible with the "real-time" modeling approach inherent in the PRS™ Nutrient Forecaster.

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