Decision Support From On-Field Precision Experiments

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Abstract.

Empirically driven adaptive management in large-scale commodity crop production has become possible with spatially controlled application and sub-field scale crop monitoring technology. Site-specific experimentation is fundamental to an agroecosystem adaptive management (AAM) framework that results in information for growers to make informed decisions about their practices with their local data. Crop production and quality response data from combine harvester mounted sensors and internet available remote sensing allows spatial variability assessment of the experimentally applied input as well as the impact of environment and management covariates that also spatially vary across the field. Repeating the experiments and gathering year-specific economic and weather data allows for incorporating temporal variability into simulation models driven by the locally parameterized crop response models. Field-specific simulation allow comparison of input management alternatives to identify practices that provide the greatest profitability, minimization of pollution from the inputs and economic resilience. Communication of information to farmers through carefully designed decision support will determine if precision agriculture (PA) provides transparent interactive algorithms that empowers farmers to become more knowledgeable agroecologists, or becomes the end point of industrialized agriculture that removes human decisions from agriculture.

Keywords.
Adaptive management, optimization for profitability and resilience, local data.

Introduction

The Agroecology Lab at Montana State University is keenly aware of the requirement of local information to make accurate agroecological recommendations. Prior to PA it seemed like most of our ability to apply ecology in agroecosystems was limited to application of general principles rather than making specific recommendations (Maxwell and Luschei 2005; Luschei et al. 2001; Maxwell 1999). Incorporating ecological knowledge into management made local recommendations cost prohibitive for farmers to gain knowledge of the spatial and temporal variability in ecological processes required to inform management.

Precision agriculture (PA) technologies have provided a new ability to capture local data on which an agroecological understanding can be obtained and used in specific management recommendations (Duff et al. 2022; Bullock et al. 2019). Furthermore, the refinement of testing management hypotheses has been accentuated with on-farm experimentation (OFE). OFE makes farm managers the researchers and the scientists left to build the tools to conduct the research to objectively test the management hypotheses. Taking the final stages of research to the fields on which decisions about agronomic inputs are made allows understanding of the complexities of agronomic management on a field specific basis (Lacoste et al., 2022). Crop metrics, such as yield, vary spatially within a field due to a range of edaphic properties and management practices even when meant to be held constant. In addition, crop response varies over time due to factors such as weather (Hegedus & Maxwell, 2022a), yet the response of crops to varying agronomic input rates also varies, indicating the potential for site-specific agronomic management to increase profitability and sustainability when informed by OFE (Trevisan, et al. 2021). On-farm experimentation augments small plot research at agricultural research centers to directly inform management decisions on specific fields (Cook et al. 2004; Maxwell & Luschei, 2005).

Precision technologies like variable rate application (VRA) devices that respond to georeferenced maps to conduct experiments across fields allow automation of experiment establishment that can systematically account for spatial variability in response to inputs like crop seeding rate, fertilizer, and herbicides. In addition, repeating the experiments over years allows for assessment of temporal variability in crop response and economic outcomes. Quantifying these different forms of variability allows for estimates of uncertainty in field-specific input management recommendations. Also available are a vast array of spatially explicit covariates of crop response that can help account for spatial variability. On-Field Precision Experimentation (OFPE) has developed a mechanism to provide response functions that provide locally parameterized input decision support systems (DSS). Ultimately, the increased abilities allow scientists to assess the agroeconomic value of the site-specific information and the technology to obtain it.

This paper examines the issues that have become apparent over the past 6 years of implementing OFPE to improve input recommendations on a set of rainfed winter wheat farms. Specific objectives were to: 1) determine the value of the information and applications to the farmer and society, and 2) identify appropriate presentation of outcomes in the DSS to enhance sustainability and resilience of the agroecosystem.

Methods

The research conducted developed the OFPE framework to identify the profit maximizing input rates that could be applied site-specifically with VRA within a field and compare the site-specific approach with a uniform application rate selected by either the farmer or using the response functions parametrized with OFPE (Hegedus 2022). The proof of concept was to vary nitrogen fertilizer rates (N-rates) with VRA, harvest winter wheat with combine mounted yield monitor and grain protein analyzer to understand spatial variability and repeat OFPE over years to understand temporal variability to ultimately make the best recommendations for input management, in this case N-rates. Eight geographically separated farmers with a winter wheat focus were chosen based on their experience with PA technologies (yield monitor, and protein monitoring data), and ability to perform variable fertilizer and seed rate application (VRA) in dryland winter wheat production. Four conventional farms and 4 certified organic farms with varying numbers of fields per farm were selected for the study. OFPE establishment, data organization and analysis details are described in Hegedus (2022). Yield and protein datasets, as-applied N data from the farmer's VRA equipment was georeferenced to the observed yield and protein data. Beyond data collected from the machines on the field, remotely sensed covariate data from open sources were gathered. These data were obtained or derived from Google Earth Engine (Gorelick et al. 2017) and aggregated to the locations of the yield and protein observations. This prevented any loss of information due to averaging and aggregating observations to a scale above their observed level.

All analyses were conducted in R using version 4.1.0 (R Core Team, 2021). All data were assessed to quantify spatiotemporal differences in crop responses. After grain yield and grain protein concentration datasets were compiled, field-specific ecological models characterizing the response of grain yield or grain protein concentration to variable N fertilizer rates and environmental factors were trained. Model selection was conducted using the methods of the OFPE framework (Hegedus 2022; Hegedus & Maxwell, 2022b). In most fields, a random forest model was used for characterizing grain yield and grain protein concentration relationships to as-applied N rates. In one field, grain yield was modeled using a modified version of a Bayesian non-linear function (Lawrence et al., 2015) and grain protein concentration was modeled with a modified version of a non-linear sigmoid model, called the beta function (X. Yin et al., 2003). In two other fields, grain protein concentration was best predicted by a generalized additive model. Detailed description of the model types and the selection process for each field used can be found in Hegedus & Maxwell (2022b).

All models were trained with crop production or quality (grain yield or grain protein) as the response variable and as-applied N as the explanatory variable. All remotely sensed covariate data were initially included in each model, but automated feature selection was performed during the model fitting process for each. Crop responses models were then used to simulate management outcomes in each field under varying weather conditions to identify and evaluate site-specific N-rate management.

Agricultural management studies are limited by the reality that only one fertilizer rate can be applied in a given area of a field in a year. Thus, models are required to predict how crop responses change under different management strategies with varying N-rate fertilizer application schemes. Models are also required to derive optimum N-rate fertilizer strategies, as multiple N fertilizer rates cannot be applied in the same location of a field and compared. Accordingly, a simulation approach using the OFPE framework defined in Hegedus (2022) was used to develop and evaluate site-specific N management that accounts for the tradeoff in net-return and nitrogen use efficiency (NUE).

Weather plays a vital role in crop production, as precipitation and temperature are important drivers of crop growth. Farmers cannot control weather conditions; however, they can adjust management strategies based on recent weather conditions and expectations of future weather. For example, farmers tend to apply more N fertilizer when they expect to receive high precipitation and lower N fertilizer rates when they expect a year to be dry. Yet farmers ultimately do not know how weather will behave in an upcoming year, so simulation is important for assessing how the outcomes of N management vary in different weather conditions, specifically in years with varying precipitation. In this paper, the historical weather record for each year was used to identify the driest, wettest, and most average year from 2000 – 2021. These years were selected to assess how robust the profitability and N rate strategies were when accounting for uncertainty in future weather conditions. A 10m grid was generated for each field, to which remotely sensed data from selected years were aggregated to the centroids of each cell to create the simulation datasets. The field-specific crop response models trained on observed data were then used to predict grain yield and grain protein responses across a field in the datasets that represent different weather conditions.

To generate optimized N fertilizer rates based on maximized profit and minimized potential for pollution, the field-specific crop response models were used to predict grain yield and grain protein concentration every 10m across each field in each simulated weather condition. At every point in a given field, crop responses were predicted for every N rate from 0 to 168 kg N ha^{-1}, from which the optimum N fertilizer rate was identified. After grain yield and grain protein concentration were predicted at a given rate for each N rate, net-return was calculated as;

$$NR = yield * P - CA * AA - FC - ssAC \qquad \text{Equation 1}$$

where *NR* is the net-return (\$ ha^{-1}) received and a function of the product of the *yield* (kg ha^{-1}) and the price received (*P)*, minus the cost of the applied input (*CA*) multiplied by the as-applied rate of the input (*AA*), the fixed costs (*FC*) associated with production (\$ ha^{-1}) that do not include the input, and the cost per hectare of the site-specific application (*ssAC*). As Montana farmers receive a premium/dockage to the base price received for wheat based on grain protein concentration, the price received for calculating net-return was (Hegedus & Maxwell, 2022b; 2022c);

$$P = Bp + (B0pd + B1pd * protein + B2pd * protein^2) \qquad \text{Equation 2}$$

where *P* is the final price received (\$ kg^{-1}), *Bp* is the base price received (\$ kg^{-1}), *B0pd* is the intercept of the protein premium/dockage function set by the grain elevator, *B1pd* is the coefficient on the grain protein concentration (protein, %) and *B2pd* is the coefficient on the squared protein term to account for non-linearity in the relationship.

To simultaneously account for maximization of profit and minimization of the potential for N pollution, NUE was predicted at every point for every N rate. Efficiency was modeled using a support vector regression model developed from intensive soil and plant tissue sampling conducted over two years in four of the fields (Hegedus 2022). Ecological and biogeochemical covariates important to NUE included topographic and edaphic variables, normalized difference vegetation index (NDVI), normalized difference water index (NDWI), and precipitation. The optimum N fertilizer rate for any given point in the field was then identified as the rate that maximized profit and efficiency. Under the assumption that nitrogen use efficiency cannot exceed 100% (1.0), 1 – NUE represents the proportion of nitrogen not used by the crop, or nitrogen use inefficiency (NUI). Desiring maximization of net-return and minimization of nitrogen use inefficiency, the conceptual optimum N fertilizer rate at each point was the rate at which the distance between net-return and nitrogen inefficiency was greatest (Eqn. 1). Rather than solving for a multi-objective optimum, the tradeoff in net-return and efficiency was incorporated into derivation of optimum N fertilizer rates by calculating the dollar value of NUI. At every point, NUI was multiplied first by the amount of N fertilizer applied at each location in the field, and then by the cost of N fertilizer to generate a value of nitrogen inefficiency. The value of NUI at each point was then subtracted from the net-returns at each point and the optimum N fertilizer rate for each point was identified as the N rate at which net-return was maximized and the cost of adding one unit of N was greater than the increase in net-return or the maximized distance between the two relationships (Fig. 1).

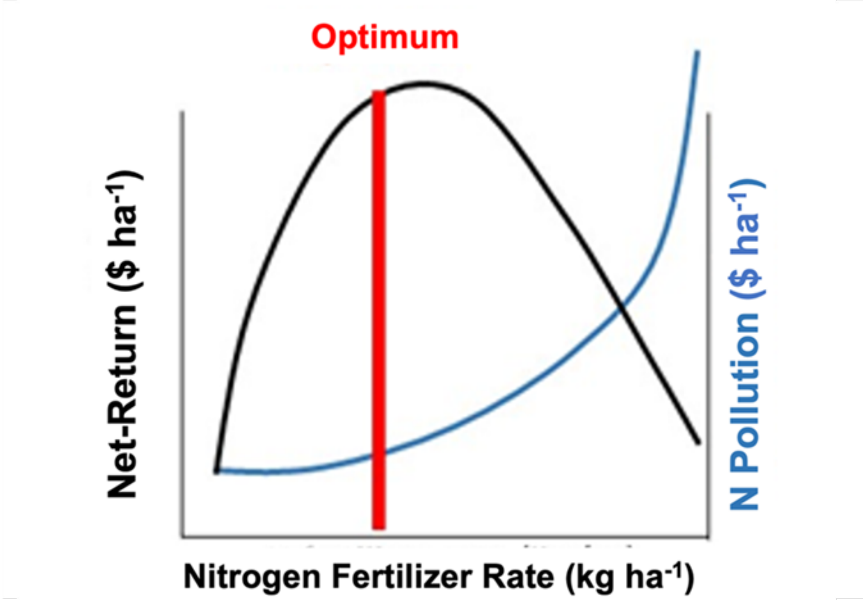

Figure 1. Conceptual diagram of the optimization process for finding the nitrogen fertilizer rate at each point that maximizes net-return and minimizes nitrogen use inefficiency, calculated as 1 – nitrogen use efficiency.

Unless a farmer has entered a contractual agreement with a buyer defining the price they will receive for their crop, farmers face uncertainty in economic conditions for an upcoming year. The same goes for weather. This uncertainty was addressed through a Monte Carlo simulation where actual economic conditions from 2000 – 2021 were randomly selected at each iteration and used to calculate net-return (Hegedus et al., 2022). This repetition and variation allow net-return and the value of NUI to vary across the simulation and for the reporting of probabilistic outcomes. The Monte Carlo economic simulation was conducted for every field and weather condition to generate a distribution of outcomes under the varying economic conditions.

Utilizing simulations provides a method for identifying optimized site-specific N fertilizer rates under varying weather and economic conditions, but also allows for the comparison of site-specific management to other management strategies. Site-specific optimized N fertilizer rates, hereby referred to as the SS.Opt strategy, was compared to five alternative management strategies. The first strategy was the application of applying zero N fertilizer (Min.Rate). The second strategy was the application of a uniform farmer selected N fertilizer rate (FS), and the third was a full-field uniform N rate that balances the tradeoff between net-return and NUE (FF.Opt). The FF.Opt was derived in a similar fashion to SS.Opt rates, however, was identified as a single rate across the entire field where the net-return was maximized when accounting for the cost of inefficiency. The fourth strategy was a scenario where the actual experimental from the most recent year of OFPE in each field was applied, labeled as Actual below, and represents the cost of experimentation when compared to other strategies. The fifth and final strategy was the application of zero N fertilizer with the assumption that a farmer would have been able to receive organic prices (Org.Price) and where a uniform 15% reduction in yield was assumed to be due to weeds. The Min.Rate and Org.Price approaches take a drastic shift towards sustainable management by completely foregoing the application of N fertilizer management and represent the transformation of an agroecosystem from conventional management to organic management. The Min.Rate approach characterizes the years during which farmers must cease conventional management yet cannot receive organic prices for crops, while the Org.Price scenario describes management outcomes when the transition to organic management is completed, and they can receive the premium price.

At every iteration of each simulation, the average net-return and total nitrogen applied from the SS.Opt strategy was compared to each of the other strategies, and the number of iterations in which the SS.Opt approach generated a higher net-return (profitability) or applied less nitrogen (sustainability) was recorded. The probability that the SS.Opt approach outperformed other management strategies regarding net-return or total N applied was calculated as the number of iterations the SS.Opt approach yielded higher net-returns or applied a lower amount of nitrogen compared to each other strategy, divided by the number of iterations in the simulation. Farmers do not currently receive a dockage to their net-returns based on the value of NUI. The value of NUI was subtracted from the net-return calculated at each point to identify the N rate that maximizes profit while considering efficiency, however, to make realistic comparisons to other strategies, the value of NUI was added back to net-return to report and compare the profitability of optimized strategies with the other management scenarios.

Results

General results of OFPE applied to rainfed winter wheat fields demonstrated significant field-to-field and year-to-year variability in crop response data, functions used to characterize the data and profit maximizing management approaches for applying top-dress nitrogen fertilizer. Results confirmed the expectation that OFPE must be integrated into management of each field and continued every year following the AAM philosophy. Hence the automation of experimentation that can be accomplished with PA technologies is crucial for implementation of optimized science-based management.

Based on simulations using OFPE parameterized yield and protein functions, site-specific application of nitrogen fertilizer consistently produced higher full-field net returns than the nitrogen fertilizer rate that the farmer would have applied uniformly across the field. A uniform applied rate determined by using the predictive equations from the OFPE data occasionally out-performed the site-specific application approach based on profitability (Fig. 2).

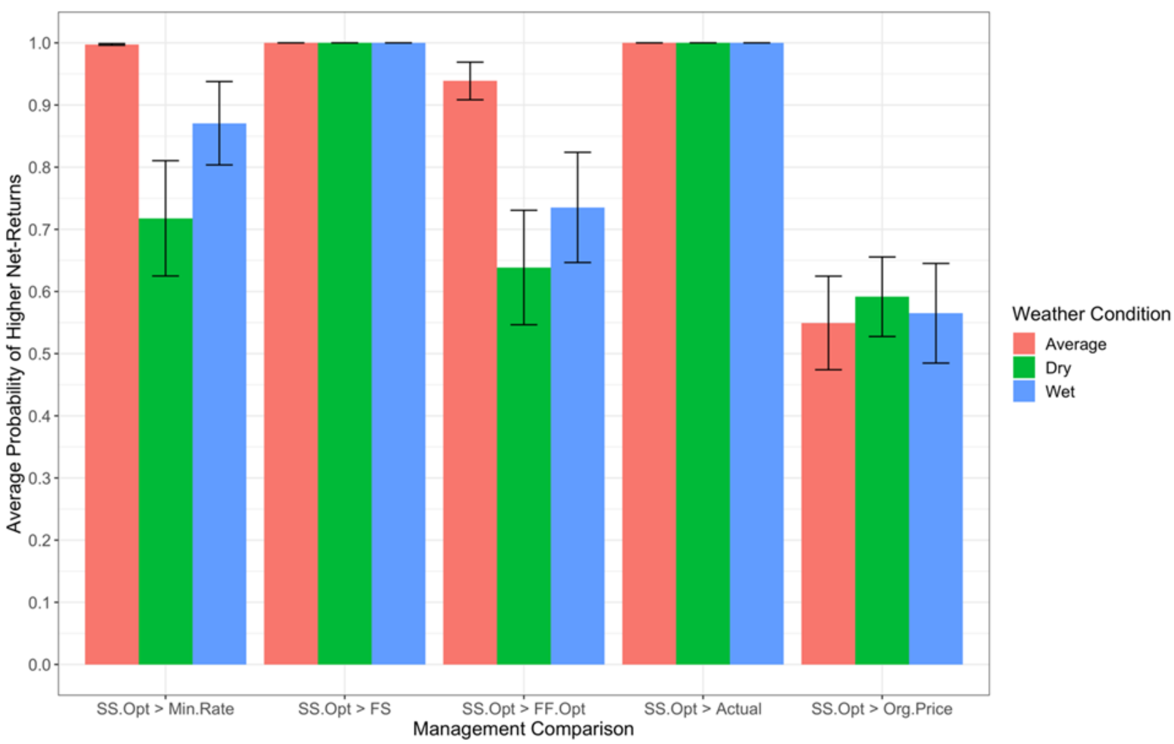

Figure 2. Average probability across fields that the SS.Opt approach yielded a higher net-return compared to each of the other five strategies in the different weather conditions. The error bars represent the 95% confidence interval derived from the distribution of average probabilities across fields.

Site-specific applied N-rates fertilizer that maximized farmer profits often add more total nitrogen to fields (positive values) than the other strategies (Fig. 3).

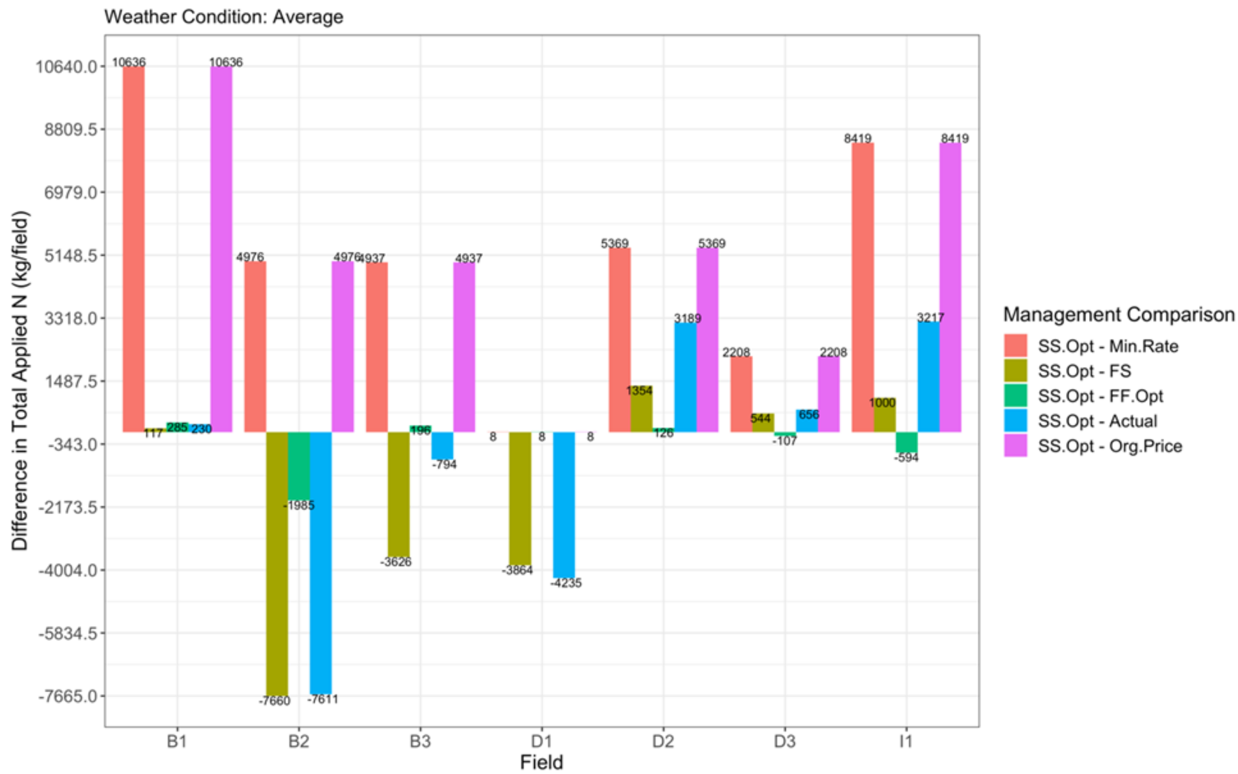

Figure 3. The difference in total N applied across 7 different conventionally managed fields with the SS.Opt approach compared to each of the other five strategies in simulations where the most average year from 2000 – 2021 was selected for each field. Labels are rounded to the nearest whole number. Negative differences indicate that the SS.Opt approach applied less N fertilizer than the comparison approach while positive differences indicate that the SS.Opt approach applied more total N fertilizer across the field than the total N applied with the comparison approach.

When nitrogen fertilizer rates were optimized for profit and pollution prevention there were many cases where a uniform application of nitrogen fertilizer across the field was best, but in many cases the uniform fertilizer rate was 0, especially in relatively dry years (Fig. 4). Although, the potential legacy effects of fertilizer applied in dry years is not known.

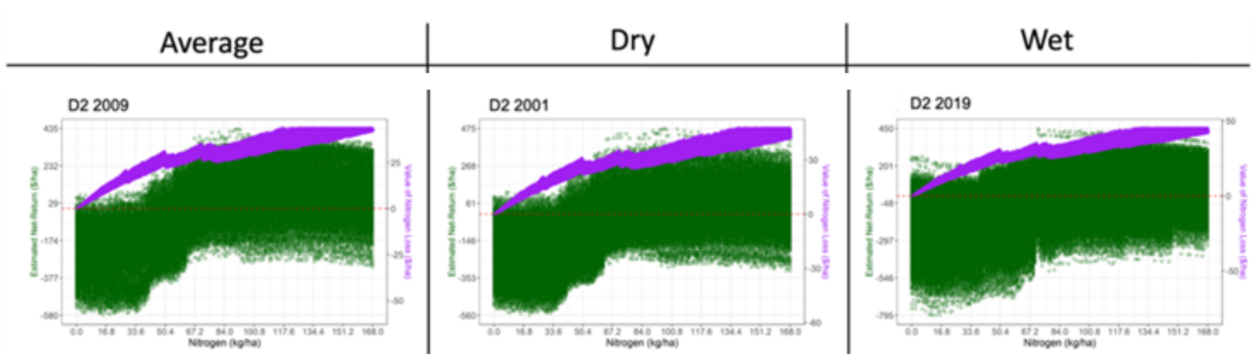

Figure 4. Predicted net-return (left axis, green) and predicted value of nitrogen loss calculated from the nitrogen use inefficiency (right axis, purple) plotted against as-applied nitrogen rate. The distribution of points at each nitrogen rate are from predictions at that rate from every point in the field. Predictions were made using an average base price of \$0.2 kg^{-1} and an average cost of N of \$1.14 kg^{-1}. Note that scales are dependent on the field and weather condition to represent the variation across fields.

Discussion

The first objective of assessing the value of PA to farmers is notably absent from the precision agriculture literature and is indicative of how the Agronomy discipline has historically promoted new technologies (e.g. synthetic fertilizers, pesticides including herbicides, VRA equipment, GPS applications, DSS applications), without an assessment of their economic value to farmers or the direct/indirect environmental impact of the technology on society. New agronomic associated industries gain the economic advantage from new technologies and the farmer producer's return on investment (ROI) has often been minimized. Precision technology facilitating OFPE can easily place focus on economic response variables like farmer ROI and pollution potential of assessed inputs or greenhouse gas emissions. In most cases, results may best benefit society including the farmers and PA industry by explicitly assessing the outcomes of profit and environmental impact as a multi-objective optimization problem.

A simplified optimization might be expressed as the maximized difference between the most profitable nitrogen fertilizer rate (N-rate) and the potential cost of the portion of N lost to the system that can become a pollutant (Fig. 1 and Fig. 4). Each yield point or polygon in a field can estimate the N-rate to maximize farmer profit and minimize pollution potential utilizing NUE as calculated here (Hegedus, 2022). The method suggest by Hegedus (2022) is deficient in that it simply assigns the cost of the amount of nitrogen lost rather than its potential environmental impact or cost of mitigating the impact. Regardless of problems it demonstrates how one might utilize OFPE analysis to identify a site-specific management application that accomplishes or optimizes between two objectives.

Other optimizations that could be important might assess the best input approach to maximize economic resilience. Where field economic resilience is defined as the stability in full-field net returns over a 10-year time horizon given a range of variable weather and climate conditions from previous years.

Summary

Experimentation is integral to adaptive management and can be demonstrated by the manipulation of inputs (fertilizers, pesticides, crop species for rotation and crop seeding rates) to maximize profits and simultaneously minimize negative impacts from inputs. Thus, input management becomes an optimization problem that explicitly quantifies the tradeoffs between different methods of applying inputs or selecting rates of inputs. Adaptive management recognizes and aims to understand uncertainty in the managed system and acknowledges that there may be multiple optima that can be presented to the producer as alternative ways to manage. Alternative management approaches are evaluated based on their probability of "success" at accomplishing the goals, given the uncertainty associated with predicting production and quality over different years. Alternative management approaches are tested against the previous best performing approach. Experimentation is a central tenet to adaptive management, that repeatedly applied in agroecosystems over time feeds an iterative decision-making process that balances learning and producer goals in the face of uncertainty associated with crop production, maintenance of environmental quality and resilience.

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