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Article

On-Farm Precision Experiments (OFPE) framework: tapping local data to optimize crop sub-field scale decisions

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Abstract: Precision agriculture and open-source data repositories provide a plethora of field-specific ecological data about agroecosystems, but few mechanisms have been developed to turn that information into management recommendations for crop production. The On-Farm Precision Experiments (OFPE) framework is an agroecological model-based methodology to improve crop manager's abilities to make field-scale agronomic input decisions. This work evaluates the use of field-specific experiments that employ open-source data and the data emanating from precision agriculture technologies to gain local knowledge of the spatial and temporal variability in agroeconomic performance at the sub-field scale. Quantification of the temporal variability in crop response to inputs (e.g., crop seeding rates, crop rotations, fertilizers, other soil amendments, pesticides, etc.) allows for estimation of the probability that a future management scenario will outcompete another, in terms of crop yield, crop quality, farmer net return, or environmental quality. The challenge is to integrate OFPE into applied management with minimal disruption of stakeholder practices while drawing on historic knowledge about the field and economic constraints. OFPE is the basis of a decision support system that includes a six-step cyclical process that harnesses precision agriculture technology to apply experiments and gather field-specific data, incorporates modern data management and analytical approaches, and generates management recommendations as probabilities of outcomes. The OFPE framework allows field managers to assess the tradeoffs in agronomic input management between the maximization of crop production, quality and profits from production while considering environmental effects.

Keywords: Agroecology; Crop modeling; Crop production; Decision support system; Ecological management; On-farm experimentation; Optimization

1. Introduction

While crop productivity has increased due to initiatives like the Green Revolution, the rate of crop yield increase has slowed since 1985 [1]. With a projected two-fold increase in crop demand from 2005 to 2050, agriculture will need to increase productivity yet again, albeit with a higher priority on sustainability [2]. The challenge of moving toward more sustainable agriculture includes identification of practices that will simultaneously increase farm profits, promote environmental stewardship, enhance the quality of life of farmers and rural communities, and increase agricultural production [3]. Crop production gains have primarily been the result of application of inputs like fertilizer. To achieve sustainability, agricultural practices must recognize the tradeoffs, in regard to agronomic inputs, that are required to increase production while maintaining the resource base on which agriculture relies [4-5]. Transitioning industrial agriculture towards a sustainable future will not be achieved by a single leap from conventional practices to complete sustainability but will require incremental development of knowledge of the interacting factors that contribute to variability in crop response and the resulting tradeoffs between production, profitability, and environmental impact. The tools and technology of

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precision agriculture (PA) hold great potential for sustainable management through quantification of the tradeoffs of agronomic inputs at the field scale where input management decisions are made [6-7].

Industrial agriculture in developed nations contributes the most to agricultural inefficiency and pollution, but has also been the primary adopter of precision agriculture tools and technology due to the economy of scale in industrial farm operations [8-9]. PA is generally regarded as a management approach based on a collection of tools that use spatial information to inform agricultural production practices at a subfield scale. Early adoption of PA has been predominantly based on GPS guidance technology, crop yield maps, and decision support tools that draw on the spatial information. PA is often perceived as a replacement of local stakeholder knowledge, giving rise to farmers' fears of the use of the technology for farmer replacement and the potential of "ecological dystopias" [10-11]. On-farm experimentation (OFE) is provided as a mechanism to improve upon local knowledge, use locally parameterized agroecological models, and incorporate and augment the farmers' knowledge necessary for locally relevant decision making, rather than replacing traditional knowledge [6].

OFE brings farmer research to the fields on which decisions about agronomic inputs are made and approaches the complexities of agronomic management on a field specific basis [12]. Crop metrics within a field, such as yield, vary spatially due to soil and climate variability and variations in management practices, even when management has focused on holding outcomes constant. In addition, crop responses vary over time due to factors such as weather [13], and 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 OFPE [13-14]. OFE shifts the lens of agronomic research to "operational research", by using observations from farms rather than from the closest geographic research station to inform management decisions [15-16]. The benefits of OFE have been well studied and include increased productivity, profits, and adoption of sustainable practices [17]. Although designed to inform spatially varying agronomic input rates, even a single year of experimentation potentially provides information that balances sustainability and profit more effectively than over spatially uniform management [18].

The objectives of this paper were to detail Montana State University's On-Field Precision Experiments (OFPE) methodology and outline the generation and evaluation of management options for sustainable agronomic inputs. This paper presents a proof of concept of OFPE, first describing the methodology and then summarizing results of several examples where OFPE was applied in both conventional and organic dryland wheat systems in the Northern Great Plains (NGP) of the United States. In conventional fields OFPE was used to optimize top-dress nitrogen fertilizer applications, and in organic systems was used to establish optimum seeding rates of green manure cover crops as well as cereal cash crops. In total OFPE has been applied in twenty-eight fields over the last six years, quantifying within-field spatial and temporal crop responses to whichever input was varied. This system has the unique aspect of including crop quality (grain protein concentration) as well as grain yield as economically significant response variables.

2. Materials and Methods

2.1. Overview

The goal of the OFPE framework was to provide farmers, or any user (e.g., crop consultant, researcher, etc.), a method for generating management recommendations that can aid in decision making to increase sustainability as well as production, profit, and sustainability. Management recommendations for farmers using the OFPE framework were derived and evaluated through a six-step process (Figure 1).

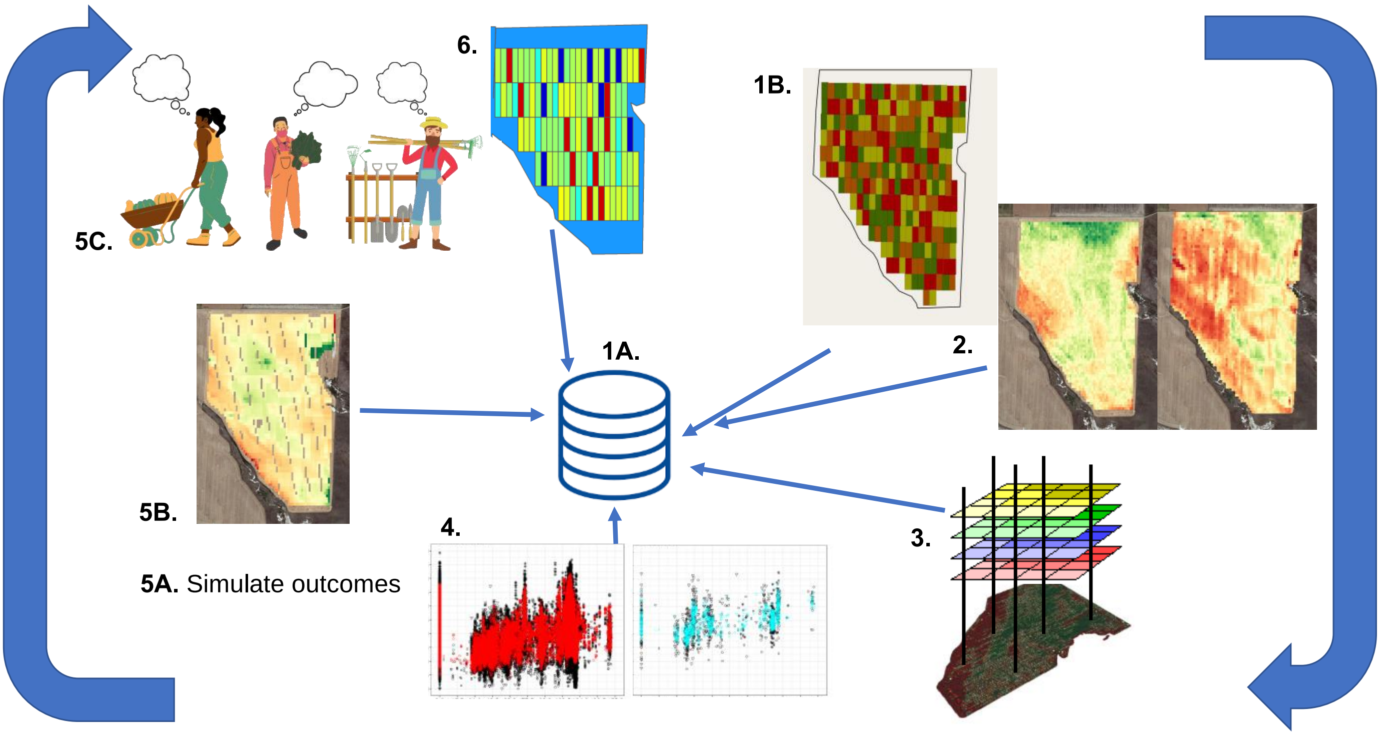

Figure 1. Overview of the OFPE methodology for generating optimized nitrogen fertilizer rates, beginning with 1A) Creation of a database management system, 1B) the creation of an initial field experiment, 2) collection of field-specific data from sensors mounted on farm equipment, gridded internet available weather data and open-source satellite imagery, 3) aggregation of data from the disparate datasets, 4) parameterization of ecological crop response models, 5A) generation of optimized (profit maximized and pollution minimized) agronomic input rates, 5B) simulation of management outcomes under varying weather and economic conditions, 5C) evaluation of recommendations, and 6) selection of future management based on a management strategy and/or continued experimentation. Each year begins with either step 1B or 6 which cyclically feed into step 2.

First, a database management system was required to facilitate the storage and organization of ecological field-specific data (1A), followed by the development of on-farm experiments that were implemented to assess the ecological relationship between the crop and the agronomic input of interest (1B). PA equipment and technology were used for the application of experiments and collection of field-specific data [6, 13]. Data from farms and open-source data repositories were gathered (2) and combined to generate analysis ready datasets for ecological modeling (3). Statistical and machine learning models that characterize the ecological interactions among crop responses, the environment (topographic, weather, and edaphic features), and experimentally varied agronomic inputs were trained with data aggregated from on-farm and internet-available open sources, such as remote sensing data from satellites (4). Simulations were used to predict the probability of outcomes under variable conditions (5A) to generate agronomic input recommendations while considering uncertainty in future weather and economic conditions, where year associated data from the past, including non-sequential years, were sampled to emulate potentially anomalous futures [19]. Based on predetermined goals and modeled crop responses across simulations, optimized input rates were identified on a site-

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specific basis (5B). Management outcomes, ranging from farmer's status quo rates to site-specific optimized rates, were evaluated and presented to farmers and crop managers in a probabilistic framework, leaving decisions about future management in the hands of the farmers (5C). Finally, a farmer or crop manager decided on the management for next year and continued to apply experimental rates to further experimentation, data collection, and ecological understanding of crop responses on the field with the goal of reducing areas reserved for experimental blocks to allow for increased farmer profitability (6). Currently, all steps of the OFPE framework are automated and available as an open-source R package called *OFPE* via GitHub (https://github.com/paulhegedus/OFPE).

The OFPE framework was demonstrated in dryland winter-wheat systems in Montana, USA but can be applied in other systems by substituting response variables or spatially varying explanatory variables. The OFPE framework was developed with the objective to optimize top-dress nitrogen fertilizer rates based on maximizing farmer profits and sustainability of nitrogen fertilizer use. The OFPE framework has also been applied in certified organic fields to identify optimized cash crop and cover crop seeding rates based on maximizing profit from wheat grain yields. Adoption of the OFPE framework by the Data Intensive Farm Management (DIFM) project's trials in eight states and multiple countries [20] demonstrates the flexibility and adaptability of the approach, as the field-specific nature of the methodology relies only on data from a specific field and performs model selection to identify the form that best characterizes crop responses in a specific field [21].

Five principles distinguish the OFPE framework from other agronomic decision-making approaches: First, experiments are intended to inform management on the field where OFPE was conducted under the assumption that field history can have a significant impact on response to inputs [13]. Second, all variables used to predict crop responses are from open-source or farmer owned data that are available up to the time of application decision[19]. Third, predictive ecological models built specifically for each field evolve as new data are collected in subsequent years capturing temporal dynamics due to weather and economic variability [21]. Fourth, the manager can simulate management outcomes given different weather and price conditions that most closely match the current year when a decision is made or explore a possible range of outcomes under different assumed conditions. Finally, after predicted conditions are identified, the manager can compare different management application approaches (site-specific variable rate application, model selected uniform rate application, a farmer selected uniform rate, or application of the minimum rate possible) and determine the probability (based on uncertainty in outcomes) that site-specific management will produce a higher return on investment compared to other approaches.

2.2. Step 1A. Database Management Preparation

Deployment and development of the OFPE framework centers around a data management system that stores and facilitates organization of the spatiotemporal data collected by PA equipment and satellites. Prior to implementation of the OFPE framework, a database needed to be created to contain farm and field information, such as: boundaries, grain yield, grain protein, agronomic input, and remotely sensed data. Development of the OFPE framework in this work used a secure PostgreSQL spatial database housed on a cloud-based virtual machine to store farm and field information from farmer collaborators. A key component of the OFPE framework was gathering open-source data that is expected to have an ecological relationship with yield or grain protein concentration. In our case, vegetation index data, weather variables, and soil characteristics were gathered from freely available repositories and used as predictors in crop response functions and for simulating outcomes in different years. This database also contained all the open-source, on-farm, and as-applied data gathered from experimental fields. The data management system serves as the keystone of the "ecosystem" needed for digitally informed agriculture [20].

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2.3. Step 1B. Experimentation

The first step in the OFPE framework was the generation of field-specific experiments. Experiments can be generated in any design selected by the user in the OFPE framework, to be flexible to context-specific research objectives, and to comply with restrictions due to farm equipment. To identify optimal input rates, experiments should attempt to apply each experimental rate representatively across the entire field to capture potential subfield variation of crop responses. Experimentally varying agronomic inputs, such as nitrogen fertilizer or crop seed, underpins the OFPE framework by generating the datasets required for modeling field-specific crop responses [20]. OFE using PA technology can take many forms, ranging from random assignment of agronomic input rates stratified on previous data, such as yield, to more structured experimental designs [22]. Best practices of PA based OFPE include trial plots that exceed 120 meters to allow equipment to change rates between plots and widths equivalent to at least two equipment passes to generate statistically qualified designs [23-24]. Designing experiments in the OFPE framework is available online as an open-source web application (http://trialdesign.difm-cig.org/home).

Prior research indicated that repeated PA based experimentation in dryland Montana systems for 6-8 years were necessary to fully parameterize (capture temporal variability) Bayesian empirical models of grain yield and grain protein concentration responses to experimentally varied nitrogen fertilizer rates [25]. However, the number of years that experimentation is required may vary by field, depending on the uncertainty introduced by climate change induced increases in the probability of extreme weather events and shifting temporal trends in precipitation and temperature [26]. A backlog of experimental data from years with a diverse range of weather conditions increases the likelihood that a given model can accurately simulate crop responses in unknown conditions of future years [21].

Initial experiments in a field with the OFPE framework require experiments that cover an adequate range of agronomic input rates from which a relationship between crop responses and the input can be identified. Beyond representation of rates, initial experiments should also spatially represent the entire field (Figure 2).

Figure 2. Conceptual diagram of an example experimental layout in the OFPE framework. Different colors represent different rates of the agronomic input.

We hypothesize that as experimentation is repeated on a given field, the range of rates represented each year, as well as the amount of the field covered in experimental rates, can be minimized to diminish the influence of experimentation on management while retaining statistical relevance. Yet, minimization of the experimental area while retaining statistical efficacy of the experiments continues to be an open research question. After

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experiments are designed for a given field, they are reviewed by the farmer to incorporate any agronomic adjustments they may wish to make.

2.4. Step 2. Data Collection

The second step in the OFPE process involved data collection from farms and open internet sources. The field experimental design map was given to a farmer for application, typically using variable rate application (VRA) technology, was read by their input machine (e.g., seeder, sprayer, etc.), and the rates were applied accordingly. The application data was downloaded from the equipment and imported into the data management system to account for differences between the prescription and actual application due to practical limits on machinery. After harvest, crop response data were gathered from monitors mounted on combines. Crop response data included yield monitor data but can also include other crop response metrics, such as crop quality like grain protein concentration.

With the aim of supporting a low-cost decision support system, the OFPE framework only utilized data collected from normal farm operations and data available from open sources. This means that the OFPE process did not require data that comes at an additional cost in terms of time or money. Thus, in addition to data collected on farms, data from open-source data repositories were utilized to provide field specific information not gathered from farmer's equipment. These data include information about the crop or environment which can be useful prior to input application as they provide current field conditions such as water availability, crop condition, or weed presence. Multiple open-source data repositories provide easily accessible environmental data , such as Google Earth Engine [27]. Examples of supplementary data collected from Google Earth Engine include vegetation index, water index, topographic, weather, and soil characteristic data (Table 1).

Table 1. Table of covariate data types gathered from Google Earth Engine to create predictive models for crop yield and protein datasets gathered from on-farms.

Data Type	Data Sources	Resolution	Years Collected	Description
Normalized Difference Vegetation Index (NDVI)	Landsat 5/7/8	30 m	L5: 1999-2011 L7: 2012-2013 L8: 2014 - present	Landsat is an ongoing USGS and NASA collaboration. Bands (NIR, red) L5/L7: B4 and B3 L8: B5 and B4
Normalized Difference Water Index (NDWI)	Landsat 5/7/8	30 m	L5: 1999-2011 L7: 2012-2013 L8: 2014 - present	Landsat is an ongoing USGS and NASA collaboration. Bands (NIR, red) L5/L7: B2 and B4 L8: B2 and B5
Elevation	USGS NED	~10 m (1/3 arc second), ~23 m (3/4 arc second)	1999-present	USGS National Elevation Dataset. Measured in meters.
Aspect	USGS NED	~10 m (1/3 arc second), 30m	1999-present	Direction the surface faces, function of neighboring elevations, in radians. Also calculated for each E/W and N/S direction as cosine and sine.
Slope	USGS NED	~10 m (1/3 arc second), 30m	1999-present	Rate of change of height from neighboring cells, in degrees. Measured in degrees.
Topographic Position Index (TPI)	USGS NED	~10 m (1/3 arc second), 30 m	1999-present	Measure of divots and low spots as a function of neighboring elevation.
Precipitation	DaymetV3	1 km	1999-present	Estimates from the NASA Oak Ridge National Laboratory (ORNL). Measured in mm.
Growing Degree Days (GDD)	DaymetV3	1 km	1999-present	Estimates from the NASA Oak Ridge National Laboratory (ORNL).
bulkdensity	OpenLandMap	250 m	1999-present	Soil bulk density (fine earth) 10 x kg / m3 averaged over 6 standard depths (0, 0.1, 0.3, 0.6, 1 and 2 m).
claycontent	OpenLandMap	250 m	1999-present	Clay content in % (kg / kg) averaged over 6 standard depths (0, 0.1, 0.3, 0.6, 1 and 2 m).
sandcontent	OpenLandMap	250 m	1999-present	Sand content in % (kg / kg) averaged over 6 standard depths (0, 0.1, 0.3, 0.6, 1 and 2 m).
pH (phw)	OpenLandMap	250 m	1999-present	Soil pH in H_2O averaged over 6 standard depths (0, 0.1, 0.3, 0.6, 1 and 2 m).

watercontent	OpenLandMap	250 m	1999-present	Soil water content (volumetric %) for 33kPa and 1500kPa suctions predicted and averaged over 6 standard depths (0, 0.1, 0.3, 0.6, 1 and 2 m).
carboncontent	OpenLandMap	250 m	1999-present	Soil organic carbon content in x 5 g / kg averaged over 6 standard depths (0, 0.1, 0.3, 0.6, 1 and 2 m).

An important aspect of the OFPE framework was the temporal constraint placed on covariate data. All farmers face a point in time at which decisions about inputs must be made. With modern satellite data collected at a weekly or daily resolution, farmers now have access to up-to-date data at and before the time of an application decision. Thus, temporal data used in crop response models of the OFPE framework were collected up to the decision point to maximize the amount of information available at the time of decision making [19].

2.5. Step 3. Data Aggregation

Aggregation of data consisted of georeferencing all the data from different monitors and sensors to common locations within fields while rectifying variation in the resolution of data from disparate sources that can introduce uncertainty [28-29]. The resolution of collected covariate data ranged from 10 m for some vegetation index data to 1 km for weather data such as precipitation and growing degree days. On the other hand, the temporal resolution of grain yield and protein measurements are 3 to 10 seconds, respectively, with spatial resolution across fields thus depending on the velocity and cutter bar width of the harvester. Development of the OFPE framework was conducted using a scale of 10 m for data aggregation, though users of the framework have the power to decide the scale appropriate for their system based on their data. Variability is lost when smoothing over space, and the 10 m scale was selected to minimize loss of information when taking the median of multiple observations in one grid cell. The 10 m scale was the smallest resolution at which open-source data in the development process were gathered, meaning that no upscaling of open-source data was required. Many of the open-source datasets used were collected or calculated at resolutions greater than 10 m yet no attempts at downscaling were made. Thus, uncertainty was introduced when using coarse resolution data at the 10 m scale because information about fine scale variation was missing. Downscaling is beyond the scope of this paper but represents an area in which future research can benefit the OFPE project.

Grids were overlayed on each field, and all data collected on-farms and from remotely sensed information were aggregated to the centroid of each 10 m grid cell. The scale selected for aggregation determined the degree to which variation in measurements are smoothed. As-applied or as-planted data were also aggregated to the centroid of grid cells via a spatial intersection of the grid points and the experimental data. The aggregation process resulted in datasets at a user defined scale for each field, that contained the crop responses, experimental rates, and all remotely sensed covariates (Figure 3).

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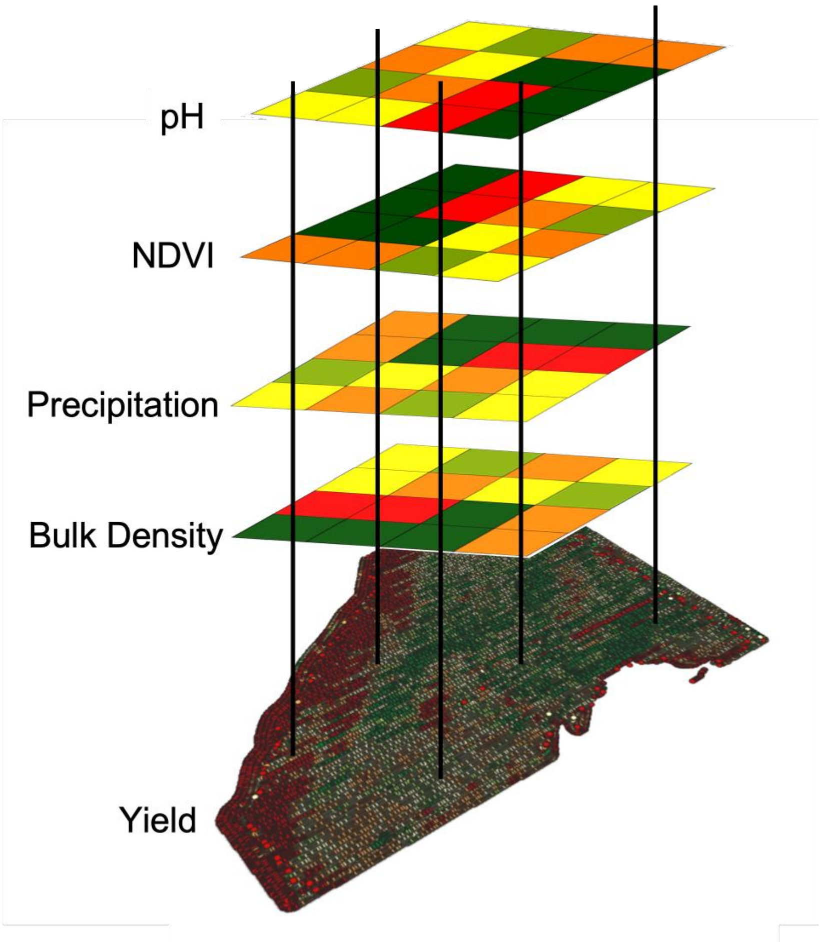

Figure 3. Conceptual diagram of the aggregation process. In this example, measurement values for a sample set of cells of remotely sensed raster data (pH, NDVI, precipitation, and soil bulk density) are georeferenced to grain yield points via spatial intersection.

2.6. Step 4. Data Analysis

Crucial to the OFPE framework was the development of ecological models that were used to characterize the relationships between the observed crop responses, experimentally varied agronomic inputs, and the remotely sensed environmental variables. Modeling the response of crops to agronomic inputs has long been a subject of agronomic research, which has not reached a consensus on one approach that adequately captures the variability across space and time for a given crop response [30-31]. Minimization of uncertainty related to the characterization of crop responses to agronomic inputs requires model selection performed on a trial by trial basis, as the form of a model appropriate for one field is not always consistent with neighboring fields, or even the same field in different years [32]. Additionally, when modeling crop responses, the bias-variance tradeoff must be considered. Crop responses to varying agronomic input rates do not always present a clear pattern, meaning that assumptions of a specific functional form or shape increase uncertainty and lead to models with reduced ability to accurately predict future crop responses compared to models that do not assume data takes a specific shape [21]. Increased predictive power translates into a higher confidence in management recommendations and evaluation of optimized input rates [19, 21].

The OFPE project has considered multiple crop response model types for experimental nitrogen fertilizer. These included a non-linear model assuming a logistic form, a non-linear model assuming a beta function [33] a generalized additive model, random forest regression, a Bayesian multiple linear regression model, and a Bayesian non-linear

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model [25]. This set of models was used in a selection process to determine the model type that best predicted crop responses in each field. This model list is not exhaustive but meant to represent a spectrum of approaches. Different models may be incorporated into the OFPE framework and current research includes exploration of other machine learning approaches such as AdaBoost, Stacked Autoencoders, and Convolutional Networks [34-36].

2.7. Step 5A. Optimization

Crop response models were necessary to find optimum agronomic input rates because optima cannot be found directly via experimentation. At any given point in a field, only one experimental rate can be applied, meaning that the true "optimum" was not observable [37]. Optima thus must be identified via models in which crop responses were predicted under a range of experimental rates. The definition of an optimum rate, and whether single or multi-objective optimization was required, varies based on the user of the OFPE framework and the agronomic system.

One example of a single-objective optimization includes a scenario where a barley farmer using nitrogen fertilizer and selling to a brewer requires low protein content to minimize the haziness of the beer. In this case, the optimum fertilizer rate for a given location in a field would be the rate that minimizes grain protein concentration. Another example of single objective optimization is a farmer growing wheat for a baker that requires high protein content for their dough. The optimum fertilizer rate for a given location in the field would be identified in this case as the rate that maximizes grain protein concentration. Optimization goals can also vary in the metric of interest. In most systems, the motivation for farmers is not quality (e.g., protein content), but maximization of production relative to costs, which leads to profit. In corn or soybean systems this would require identifying optimum rates that simply maximize net-return, or the price received for their yield minus expenses. In dryland winter-wheat systems of Montana, farmers receive a premium or dockage based on grain protein that is added or subtracted from the base price received for wheat, making profit maximization more complex, while remaining a single-objective optimization problem [38]. When farmer profits are the primary goal, an optimum nitrogen fertilizer rate would be the rate at which farmer net-return is maximized and the cost of higher fertilizer rates is not compensated by an increase in revenue.

While individual farmers typically pursue net profit as their broad objective, the future of agriculture requires an emphasis on sustainability. The OFPE framework creates the infrastructure for farmers to move beyond considerations of simply profits and consider sustainable environmental stewardship as well with multi-objective optimization. While nitrogen is a major macronutrient for crops, contributing to yield and protein, Northwest and NGP soils are subject to soil acidification and nitrate loss to both leaching and denitrification due to excess nitrogen fertilizer use [39-40]. Thus, sustainable agriculture requires defining an optimum nitrogen fertilizer rate based on the tradeoff between profit and environmental quality. One approach for assessing the environmental impacts of nitrogen fertilizer requires models that estimate nitrogen use efficiency on a subfield scale basis to inform crop managers on the potential and the cost of nitrogen loss [41]. In this case, an optimum could be considered as the nitrogen fertilizer rate at which net-return is maximized and the value of nitrogen lost from a system (contributing to acidification or leaching) is minimized.

To gain insight into how minimizing nitrogen application influences farming profitability, a multi-objective approach was implemented, taking both net return maximization and nitrogen application minimization into account. The nitrogen minimization objective was a naïve approach only aiming to reduce the pounds of fertilizer per acre applied to farmer fields. The implemented algorithm found a set of solutions balancing the two objectives, which allowed us to analyze the change in net return of solutions focusing on reduced fertilizer [42].

2.8. Step 5B. Simulation

Simulation is an important aspect of decision support systems because it allows users to assess the potential for variation in the efficacy of management strategies in a probabilistic format given historic local performance. Unpredictable weather and economic conditions induce uncertainty to any management recommendations, since the optimal agronomic input rate at a given point in a field may change depending on any variation in weather conditions [19]. The optimum recommendation under one weather condition may not be appropriate for another, and a field manager can only take a best guess at what the weather will be like in a future year. Additionally, many farmers do not have control or information on the economic conditions at a future harvest date when their crop is sold, further introducing uncertainty into management recommendations, as optimum rates assuming a farmer will receive one price for their crop may not be consistent with an optimum rate under a different price scenario.

The OFPE framework used a bootstrap Monte Carlo simulation approach to propagate these uncertainties as a distribution of predicted net returns. This error propagation provided management outcomes that allowed a probabilistic perspective on risks in decision making (Figure 4).

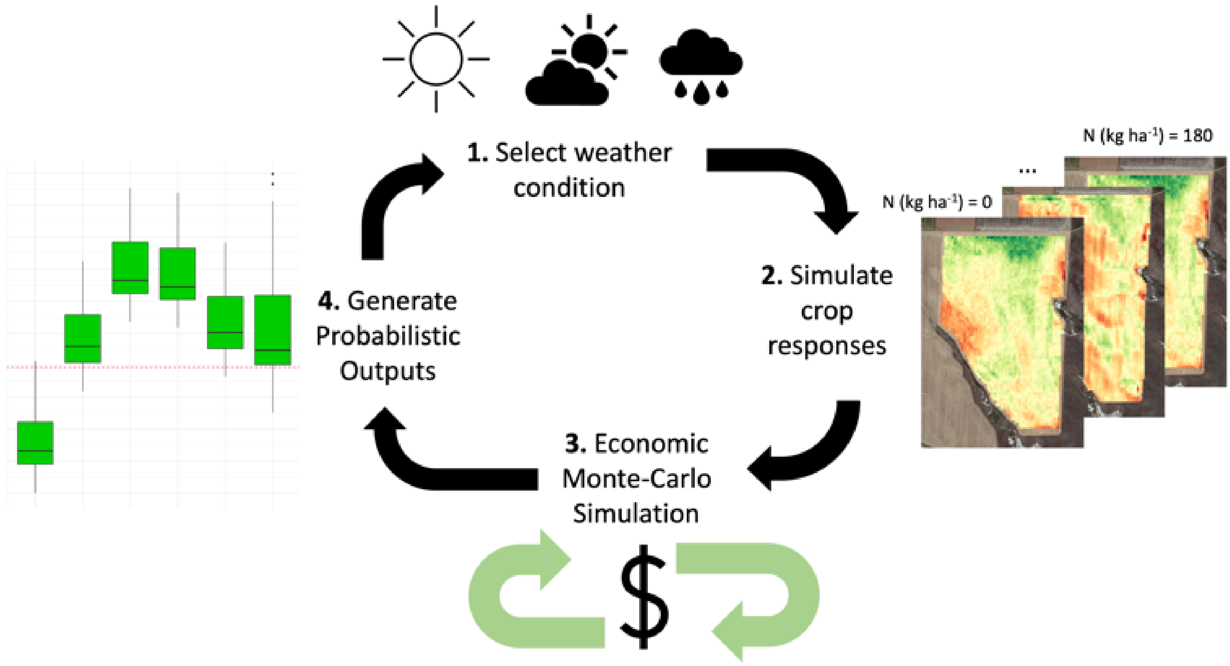

Figure 4. Overview of the OFPE framework simulation and optimization process. Simulations begin with the selection of weather conditions to forecast management outcomes in, typically as a selection from a year in the past. Then the data from that year are used to predict crop responses at every location in the field for a range of agronomic input rates, for example nitrogen fertilizer. The third step is a Monte Carlo simulation where economic conditions and weather data from previous years are used to account for uncertainty in future economic conditions. Finally, the repeated sampling of different economic scenarios enables the evaluation of management in a probabilistic format and the identification of optimum input rates based on economic uncertainty.

The OFPE framework can be adapted to assess a range of different management strategies to compare against site-specific management, such as applying a uniform rate selected by the farmer, a full-field uniform optimized rate, or none of the agronomic input (in the case of fertilizer or herbicide, for example). Again, due to the flexibility of the OFPE framework, the optimization scheme from which rates were selected can be varied.

To address the uncertainty of management recommendations due to weather, the OFPE framework required users to select a year from the past that they expect would be representative of an upcoming year. Years from the past can also be selected randomly or non-sequentially to emulate a future anomalous year that is more likely due to predicted

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climate change. After selecting a year, data for covariates from the selected field-specific model were used to predict crop responses under the simulated conditions. Forecasted crop responses in the new conditions were made at every location in the field for a range of experimental rates. This led to the second layer of the simulation, where another year from the past was randomly selected and the economic parameters were used to calculate net-return. Based on net-return, optimized rates at each location in the field were identified, as well as the net-return from the other strategies. Random sampling of different years was repeated for a given number of iterations, typically >1000, and the optimums and management outcomes were tracked and evaluated after the simulation of different management scenarios had completed.

The flexibility of the OFPE framework allowed users to define the degree to which uncertainty is incorporated in the simulation. For example, if a farmer knows the cost of their input and price received for the crop prior to deciding input management strategy, they could run the simulation with a fixed economic scenario rather than drawing randomly from previous years in the Monte Carlo simulation. Additionally, farmer decision makers have control over what and how many weather conditions they include in a simulation. For example, if a farmer was confident in the consistency of the weather in their fields, they could run the simulation using the same conditions as the prior year, but if they were less certain, they may use simulations to compare management outcomes from years with varying weather conditions. The simulation aspect of the OFPE framework enabled farmers and crop managers to assess how management would change under climate change, by selecting a set or a single anomalous year from the past that may have not occurred in sequence but might represent a new condition. The simulation step was thus a crucial juncture in the OFPE framework where farmer involvement and knowledge of their system was required to inform data driven management.

2.9. Step 5C. Evaluation

As optimum agronomic inputs cannot be empirically evaluated because only one input rate can be applied at any given point in the field at any given time, the crop response models fit in the fourth step of the OFPE framework were crucial for evaluating the profitability and sustainability of optimum rates and rates of different management strategies. Site-specific optimum rates were found by using crop response models to make site-specific predictions under varying agronomic input rates, but the model was also required to predict the site-specific crop responses under a farmer's status quo management, or any other selected management strategy. The OFPE framework evaluated different strategies in probabilistic terms, where at each iteration of the simulation, the mean net-returns of each strategy were compared. Given a strategy of interest, such as a site-specific approach, the number of times that the strategy yielded a higher net-return, or other metric of interest, compared to the other strategies was recorded and divided by the total number of iterations simulated. In this way farmers were provided the probability that a given management strategy outcompeted another management strategy. The farmer then had the choice to select from any of the management strategies, leaving the ultimate decision about management up to the farmer. While presented with a site-specific and full-field optimized strategy, the farmer may elect to continue with business as usual if they like the odds of that strategy outperforming the optimized approaches.

2.10. Step 6. Decision Making

The final steps of the OFPE framework occurred after the farmer was confronted with probabilistic outcomes from the simulation. After the farmer selected their strategy, they chose the extent to which experimentation and optimization rates are distributed across their field. These are represented as three possible routes: full deployment of their selected strategy (optimized or not), full experimentation, or a mix of both. In option one a farmer can adopt and apply their selected management strategy. In option two the farmer can begin the OFPE process again with another full field experiment. In option three a farmer can elect to adopt and apply the selected strategy in combination with further experimentation. In this case experimental rates are distributed spatially across the field at a lower density than full experimentation. Note that determining the number of experimental plots, where experimental plots are located, and the extent to which non-experimental treatments add to the information being collected represent a further optimization problem and are currently being studied. While the first option is available to farmers, continued experimentation through the second or third approaches is highly recommended for two reasons. First, experimentation is crucial for increasing the statistical power of the field specific crop response models, and second, as more data are gathered, models can be refined for updating management recommendations.

3. Results

We applied the OFPE framework for managing inputs in rain-fed agroecosystems of the NGP as a proof of concept. Each step of the process (Figure 1) was completed across multiple years in different systems (organic and conventional) in fields distributed geographically across the state of Montana, USA. The OFPE framework was applied in conventional winter-wheat fields where nitrogen fertilizer was the experimentally varied agronomic input, and the goal was to optimize fertilizer rates based on maximization of profit and minimization of the risk of nitrogen pollution. Results from this research indicated that site-specific optimized rates from the OFPE process improved net-returns compared to application of a farmer selected uniform fertilizer rate in 100% of the seven fields tested and three simulated weather conditions [43]. However, in only 50% of cases did site-specific fertilizer rates from OFPE optimization reduce the total amount of nitrogen fertilizer applied to fields compared to a strategy applying a farmer selected uniform nitrogen fertilizer rate [43]. These results suggested that while site-specific management had a high probability of generating increased profits for farmers, the probability that site-specific management reduced nitrogen fertilizer use was equivalent to a flip of a coin. However, one could also argue that by site-specifically applying the nitrogen to maximize net return and nitrogen use efficiency, versus uniform application of the same total amount across the field, more of the total nitrogen was taken up by the crop and thus less available as a pollutant.

When comparing a multi-objective approach of maximizing profit while minimizing pollution to an approach that only focused on minimizing pollution, there was no significant difference in resulting net return between these site-specific optimization approaches [42]. However, when comparing either optimization approach to uniform fertilizer rate applications of 100, 120, or 140 lbs/acre, the predicted net return from both the optimized approaches were higher than the predicted net return of the uniform rates. This indicated that site-specific fertilizer approaches that directly account for sustainability focused objectives in the decision process not only improve net return but also reduce environmental impacts.

OFPE was also conducted on five organic farms across Montana, as well as one farm in Manitoba, Canada. Seeding rates of both nitrogen fixing green manure cover crops and cash crops were assessed as experimentally varied inputs in these systems. The method was carried out to find optimum seeding rates when optimizing for maximized net returns. Variable rate site-specific management tended to outcompete other management strategies, though in several instances a single uniformly applied optimum rate was found to be as likely to produce the greatest net return as optimized variable rates across the field [44]. In general, optimum seeding rates were found to be considerably lower than typically chosen farmer rates. This may be in part due to organic farm seed rates being intentionally high to create competition with weeds in their system. Further research in this area will pursue organic OFE as a multiple objective optimization situation to maximize annual net returns while simultaneously minimizing current and future weed pressures. A series of different crops including barley, wheat, oats, hemp, and peas were

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tested, highlighting the versatility of the OFPE method in creating optimums for any farm input.

The iterative process of OFPE becomes a monitoring mechanism resulting in improved agroecological models. The framework created a data environment for application of modern analytical methods. For example, initial modeling efforts demonstrated the potential of machine learning approaches for spatially explicit modeling of the functional relationship between nitrogen fertilizer and crop yield [13]. A novel convolutional neural network (CNN) architecture called Hyper3DNetReg [36], was tested to tackle the yield prediction problem as a two-dimensional regression task. That is, it took in a two-dimensional multi-channel input raster and, unlike previous approaches, output a two-dimensional raster, where each output pixel represented the predicted yield value of the corresponding input pixel. Experimental results showed that, when using training sets with reasonable data representativeness, the Hyper3DNetReg models improved predictions over other traditional and more recent machine learning methods [36]. This implied that the Hyper3DNetReg network modeled the mapping from the feature space to the yield value space better than other approaches. Therefore, a method to generate N-response curves that were specific to each location of the field using Hyper3DNetReg models was proposed [35]. Initial results using two different winter wheat fields showed that different regions of the field have different responses to the N fertilizer (Figure 5) and thus allowed further refinement of approaches to identify site-specific input management.

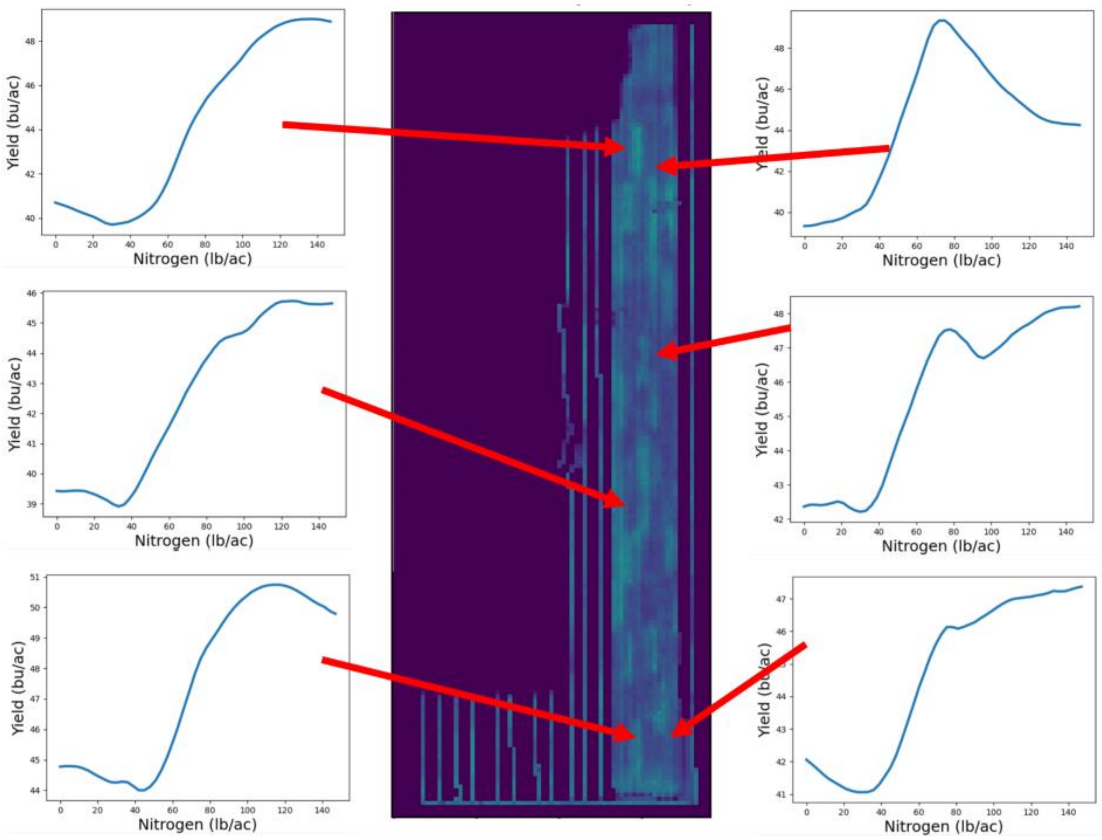

Figure 5. Example of the type of N-response curves generated for different regions of a rain-fed winter wheat field.

OFPE can also advance objectives of enhancing environmental quality and conserving on-farm biodiversity. Plant and insect diversity was assessed on two farms in Montana as proof of concept that small uncropped areas can increase on-farm biodiversity [45]. A linear regression of diversity as a function of distance from uncropped areas demonstrated that plant diversity declined significantly with distance from uncropped areas and into the crop field on both farms (p-value 0.13 and p-value = 0.011). In addition, insect diversity declined significantly with distance from uncropped areas and into the crop field (p-value < 0.0005). We hypothesized that beneficial ecosystem services such as pollination or pest predation would be increased adjacent to areas with higher plant and insect diversity (i.e., ecological refuges). Biodiversity data was integrated with open-source and PA data in a random forest model [45]. The model indicated that distance from uncropped area was the most important explanatory variable for yield and that yield decreased significantly with distance from uncropped area on one farm (p-value < 0.0001). Thus, expanding the OFPE framework to include on-farm conservation was key to clarifying the relationship between on-farm biodiversity and yield, and to inform agronomic decisions that affect environmental quality and net return.

A further application of OFPE towards on-farm conservation occurs when consistently low-yielding or high-maintenance areas within a field are identified. Farmers may elect to remove these areas from production rather than adjusting their input rates. Thus, particularly unproductive areas in fields serve as opportunities to demonstrate how the OFPE framework can be applied to on-farm precision conservation. Crop response models were integrated with ecological data on plant, insect, and landscape diversity to assess potential tradeoffs of removing land from production and conserving it as habitat [6]. Managing for on-farm biodiversity generated a suite of beneficial ecosystem services such as enhanced pest suppression, weed seed predation, and crop pollination, though accompanying negative impacts included increased pest habitat, weed pressure, and yield reduction [46-49]. The tradeoff analysis weighed the potential costs of lower yields and exacerbated pest issues against the potential benefits of saved input costs and enhanced ecosystem services. The application of the OFPE framework to on-farm precision conservation enabled stakeholders to quantify environmental benefits and agronomic impacts of patch habitat within production fields. This multi-objective approach aimed to optimize crop yield and environmental quality and aid farmer decision-making for on-farm conservation, and thus represented a useful expansion of the OFPE framework to aid in environmental quality and farm sustainability.

4. Discussion

Only around 10% of farmers with PA technology use variable rate applications, with the lack of decision support aids being one of the main barriers to adoption [50-51]. A farmer with PA technology benefits from decision support systems that facilitate the organization, storage, and translation of data to management recommendations [1, 50, 52]. Decision support systems are central to making management recommendations for agronomic inputs by facilitating collection and analysis of crop response and remote sensing information from farms and open-source datasets. As a big-data industry, PA is overcoming prior barriers to adoption surrounding the management and analysis of data by attracting profound investment and interest in agronomic data analytics and software development [53-54]. Open-source decision support systems that use data that farmers generate or can obtain free will prevent farmers having to pay to make informed decisions.

The OFPE framework alone may not be immediately adopted by farmers due to the data infrastructure and digital requirements but provides the logical underpinning of a decision support system provided to farmers as an open source or low-cost software, possibly through non-profits or a farmer cooperative [55]. Harnessing field-specific data, combined with on-farm experimentation, facilitates empirically driven adaptive management, where field-specific agronomic input decisions are generated and updated from iterative analyses of experimental data gathered on the given field [56-58]. While increasing adoption of variable rate technology remains a challenge, developing, providing, and training farmers and crop consultants on a low-cost decision support system can remove barriers to adoption surrounding the price associated with managing and exploiting field-specific data. While full automation of the framework could result in removing the farmer from the decision process, the OFPE framework was designed as a decision aid that augments farmer knowledge of field-specific performance obtained through a range of learning approaches.

5. Conclusions

The OFPE framework provides farmers with a methodology for harnessing the data and tools from PA to make management decisions. The flexibility and adaptability of the framework means it can be adapted to optimize agronomic inputs based on any reasonable user defined criteria. Utilized by the DIFM project in fields across the world, the framework has been employed to generate site-specific agronomic input recommendations, demonstrating the broad applicability of the framework to work across different agroecosystems [20].

Supplementary Materials: Not Applicable.

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Data Availability Statement: Data supporting this research are sensitive and not available publicly due to requests from the farmer collaborators. The data contains geographic data that can be tied to farmer's properties, as well as yield and net-return information that are related to their livelihoods. Other data are gathered from open-sources online but are also geographically tied to farmer's land and even with geographies anonymized would still reflect defining characteristics of the farmer's property. All data are available to qualified researchers from Montana State University by contacting Paul Hegedus (paulhegedus@montana.edu) or Bruce Maxwell (bmax@montana.edu) in the Department of Land Resources and Environmental Sciences. If data is requested, users will be subject to sharing and use restrictions to protect the privacy of farmer collaborators.

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