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# Optimizing crop seeding rates on organic grain farms using on farm precision experimentation

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ABSTRACT

Organic agriculture is often regarded as less damaging to the environment than conventional agriculture, though at the expense of lower yields. Field-specific precision agriculture may benefit organic production practices given the inherent need of organic farmers to understand spatiotemporal variation on large-scale fields. Here the primary research question is whether on-farm precision experimentation (OFPE) can be used as an adaptive management methodology to efficiently maximize farmer net returns using variable cover crop and cash crop seeding rates. Inputs of cash crop seed and previous-year green manure cover crop seed were experimentally varied on five different farms across the Northern Great Plains from 2019 to 2022. Experiments provided data to model the crop yield response, and subsequently net return, in response to input (seeding) rates plus a suite of other spatially explicit data from satellite sources. New, field-specific spatially explicit optimum input rates were generated to maximize net return including temporal variation in economic variables. Inputs were spatially optimized and using simulations it was found that the optimization strategies consistently out-performed other strategies by reducing inputs and increasing yields, particularly for non-tillering crops. By adopting site specific management, the average increase in net return for all fields was \$50 ha $^{1}$. These results showed that precision agriculture technologies and remote sensing can be utilized to provide organic farmers powerful adaptive management tools with a focus on within-field spatial variability in response to primary input drivers of economic return. Continued OFPE for seeding rate optimization will allow quantification of temporal variability and subsequent probabilistic recommendations.

## 1. Introduction

Conventional agriculture has produced ever higher yields at the cost of degrading surrounding ecosystems. Fueled by the Green Revolution and economies of scale, farms have become larger, and higher yielding, but often accompanied by environmental pollution (Pellegrini and Fernández, 2018; Pretty, 2018). On larger farms with more and larger fields, less is known about the local variation present across the management domain. This loss of knowledge exacerbates input overuse as farmers blanket the land with inputs to reduce temporal and spatial variation to increase yields and decrease perceived economic risk.

Organic agriculture and precision agriculture are alternative methods of farming designed to confront the challenges of conventional agriculture head on. Organic agriculture strives toward agroecological intensification by adopting environmentally sustainable practices (Eyhorn et al., 2019). The primary organic practice focuses on long term soil health through local nutrient cycling rather than inputs of synthetic chemicals (Hammermeister, 2020). The main detraction of organic systems is a tendency towards reduced crop yield (Seufert et al., 2012; Seufert and Ramankutty, 2017). Precision agriculture views spatial variability opportunistically, and uses geo-referencing technologies to correlate input levels to sub-field soil attributes and local yield potentials, thereby reducing input waste and building higher yields in responsive areas of a field (International Society of Precision Agriculture, 2021). Precision agriculture holds much promise for increasing production and mitigating environmental damage, however, beyond yield maps and automated steering, the technology has seen low adoption by farmers due to the complexities of its application, the lack of spatial information resulting in recommendations, and the absence of clear economic advantage in its use (Mitchell et al., 2018). While agroecological intensification could take advantage of the research conducted in organic and precision agriculture, and the philosophies are less antithetical than often perceived (Duff et al., 2022), a system to enable the practices in tandem has been lacking.

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On Farm Precision Experimentation (OFPE) is a novel methodology to deploy precision agriculture, on-farm experimentation, and data science in any agricultural system to increase agronomic input efficiency and net-returns (Hegedus et al., 2023). The method utilizes field-scale data to gain an understanding of field-specific variation to optimize farm input strategies at the sub-field scale. Using OFPE, farmers experimentally apply varied rates of an input across their field, then harvest with a georeferenced yield monitor to determine yield response to varied rates of any input (Hegedus et al., 2022). Other remotely sensed data are collected including commonly used plant and soil indices (Gulhane et al., 2023), and response models use these data to predict profit maximizing variable input rates within the specified field. Crop prediction models can be updated over time using multiple years of data and experimentation, and in this way farmers can continuously learn about the temporal aspect of the crop responses while building ever greater optimization into their system to generate higher net returns. OFPE builds upon the established notion of precision agriculture by placing an emphasis on local experimentation to empirically determine optimized input rates that are field specific, with the understanding that every individual field will have unique internal spatial and temporal variation and thus its own unique history of responses (Hegedus et al., 2023). OFPE could be particularly relevant in organic systems where there may be more spatial variability (in pests and fertility) and currently OFPE lacks any detailed exploration in organic systems (Bullock et al., 2019; Lacoste et al., 2021).

Most studies focusing on varied input rates have examined fertilizer and herbicides, but seed is also an important input that can be varied (Šarauskis et al., 2022). Site-specific prescriptions have been previously developed using mapping and sensing technologies. Under the mapping-based prescription method, data are collected about field variability such as soil-based indices, and previous yield, to generate management zones. Input rates are prescribed to the zones to maximize yield or profit. A sensing-based approach uses real (or near-real) time sensor data to build a prescription map using proximal soil sensors like those found on Veris machines, or multispectral cameras on drones among others. The advantages of a sensing-based approach allow for real time characterization of the soils to understand temporal-based attributes such as soil moisture (Munnaf et al., 2020). These research methods emphasize the development of management zones to prescribe input rates; they seek variables which drive changes in the relationship between input and yield to improve input placement (Munnaf et al., 2022). While these methods are important, they are also complex and costly. Determining which soil attributes are most important in a wide variety of agronomic settings is complex, and often relies on mechanistic models of plant-soil interactions which are difficult to extrapolate from one field, or portion of a field, to another. These methods also rely on the need to extensively soil sample and deploy proximal sensors, which are costly, and unavailable to most farmers (Corwin and Scudiero, 2020). Comparably, OFPE is inexpensive and is novel in its aim to use only free data: openly available data from satellites sensors, and data which is already generated by the farmers' own equipment (Hegedus et al., 2023). OFPE is novel in its comparative disinterest with determining the specific soil variables driving yield prediction, rather it seeks a field by field empirical determination of optimal input rates without previous understanding of the soil spatial variability.

Here the first detailed field exploration of precision agriculture deployment in organic systems using OFPE is presented. The project targeted areas uniquely relevant to organic agriculture including non-herbicide weed management and cover crop use. Five separate farms from across the Northern Great Plains, some with multiple fields, were involved in OFPE from 2019 to 2022 for a total collection of eleven site-years of data. The farms experimented with different inputs including annual cash crop seeding rates, as well as non-harvested previous-year green manure cover crop seeding rates. Seeding rates were thought to offer a unique application of OFPE in organic systems by offering both weed competition and a source of nitrogen from cover crops through manipulated seeding rates (Carr et al., 2020; Loewen, 2023). After collecting field-specific data to model each site-year, four different input strategies and their net returns were compared. The strategies included the actual experimental rate (AER) (i.e. cost of the experiment placed in the field), the simulated returns of the typical farmer chosen rate (FCR) defined as the rate the farmer themselves expressed as their chosen rate applied uniformly across the field, the simulated returns of a single optimum uniform rate (OUR) applied consistently across the field, and finally the simulated returns of an optimum variable rate (OVR) where rates were allowed to vary across the field to maximize net return. To explore temporal variation without having multiple years of experimentation on each field, annual variation in input costs and prices received over the last ten years was included in the modeling process to account for major drivers of temporal variability in net return. The study's specific objectives were 1) to use OFPE to spatially optimize seeding rate inputs of rain-fed cash and cover crops on organic farms on each field. 2) To determine if simulated variable rate strategies were consistently more profitable than the optimum uniform rate or the farmer chosen rate. Finally, 3) to quantify the economic costs and benefits of deploying OFPE. It was hypothesized that OVR would be more profitable than OUR which would in turn be more profitable than FCR. It was also hypothesized that there would be a cost associated with implementing the experiment, that is that AER would be less profitable than FCR.

## 2. Methods

### 2.1. Study sites

To accomplish the objectives of this study, freely available field data were collected and compiled in order to efficiently and accurately model organic cash crop yield and subsequent net return from across farmer collaborator's fields. Details on employing the OFPE method, including yield monitor data accumulation and cleaning, were described by Hegedus et al. (2023). All farms involved in the study were certified organic for at least several years before experimentation began, ranging from four to 35 years of organic experience. Farm A was based in south-east Manitoba, and experiments were placed on two fields over several years comprising site-years 1–3, and 5–8 (Table 1). On Farm A various annual crop seeding rates including spring wheat, hemp, and oats were experimentally varied. The organic fertilizer (presumably nitrogen) on all fields on Farm A were sourced from uniformly applied chicken manure spread annually in the fall. Farm B was in south-east Montana, and experimented on one field in 2021 and was designated site-year 4. As opposed to all other farms, which experimented with seeding rate, this farm experimented with blood-meal as an organically approved top dress fertilizer (presumably nitrogen) on uniformly seeded winter wheat. Farms C-E were in north-central Montana and experimented with the effects of annual winter wheat seeding rates as well as the nitrogen-fixing green-manure cover crop which proceeded the wheat by one season. Tilling in the green-manure crop in mid-summer provided fertility to the next-year cash crop, a typical practice in organic rain-fed grain farming (Carr et al., 2020; Miller et al., 2011). Each of these last three farms harvested a cereal crop, following a pea green manure plow down, in 2021 (Table 1). Climate anomalies in precipitation and growing degree days were calculated from Dayment based on 30 year averages, these data were not included in modeling as there was not enough spatial resolution to see variability across fields in these variables, but are included in Table 1 as a general reference to site-year-specific growing conditions (Thornton et al., 2022). Numerous other experiments were planned and established over the four years of collaboration but weather conditions, including drought, wind damage, and hail storms, prevented their completion. The experiments were intentionally conducted in a field-specific manner, having encountered significant field spatial and temporal variation differences on conventional farms in the same region (Hegedus and Maxwell, 2022). Fig. 1

**Table 1**
Agronomic conditions across the five farms (A-E), each with one or two fields applying On Farm Precision Experimentation for a total of eleven site-years of data. Each unique field and year combination was treated individually for crop yield modeling purposes and was given a site-year ID. Annual climate anomalies were calculated from a 30-year average (1991–2021) from Daymet (Thornton et al., 2022), regional yields were from conventional 3–5 year averages from USDA (Montana) and the Government of Manitoba.

| Site-year ID | Year | Farm-Field | Crop | N Source | Hectares | State/ Province | Precipitation anomaly (+/- mm) | GDD anomaly (+/-C) | Observed Yield (t ha $^{1}$) | Regional Average Yield (t ha $^{1}$) |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 2020 | A 1 | Wheat* | Manure | 32 | Manitoba | 154 | +48 | 3.48 | 3.99 |
| 2 | 2021 | A 1 | Hemp* | Manure | 32 | Manitoba | 111 | +366 | 0.60 | 0.62 |
| 3 | 2022 | A 1 | Oat* | Manure | 32 | Manitoba | +151 | 139 | 3.28 | 3.60 |
| 4 | 2021 | B 1 | Winter wheat | Bloodmeal* | 130 | Montana | 138 | +412 | 1.08 | 3.76 |
| 5 | 2019 | A 2 | Wheat* | Manure | 71 | Manitoba | +134 | 112 | 3.01 | 3.99 |
| 6 | 2020 | A 2 | Hemp* | Manure | 71 | Manitoba | 159 | +52 | 0.95 | 0.62 |
| 7 | 2021 | A 2 | Wheat* | Manure | 71 | Manitoba | 115 | +366 | 3.09 | 3.99 |
| 8 | 2022 | A 2 | Oat* | Manure | 71 | Manitoba | +150 | 138 | 3.36 | 3.60 |
| 9 | 2021 | C 1 | Winter wheat* | Pea GM* | 93 | Montana | 157 | +278 | 3.48 | 3.76 |
| 10 | 2021 | D 1 | Barley* | Pea GM* | 32 | Montana | 113 | +287 | 0.58 | 3.90 |
| 11 | 2021 | E 1 | Winter wheat* | Pea GM* | 32 | Montana | 122 | +274 | 1.82 | 3.76 |

* Experimentally varied input; GM = green manure; N = nitrogen; GDD = growing degree days

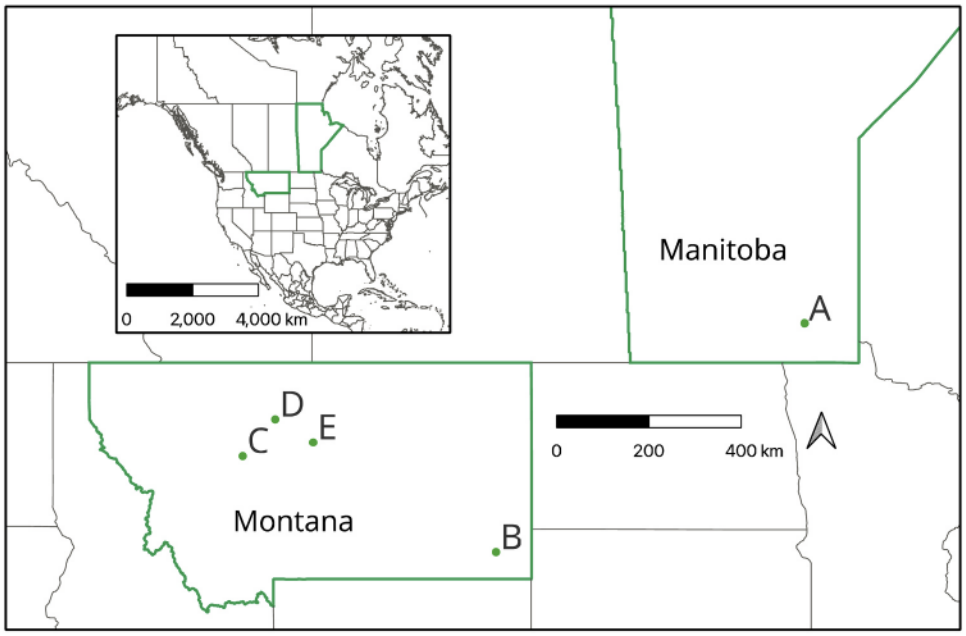



**Fig. 1.** Rain-fed organic farm locations across the Northern Great Plains in both Canada and the USA. Farm A, in south-east Manitoba, experimented with annual crops across two fields from 2019 – 2022; Farm B, in south-east Montana, experimented with bloodmeal across one field in 2021 to increase spring wheat production; Farm C-E, in north-central Montana, experimented on one field each with a two-year rotation of a green-manure crop, followed by a cereal cash crop harvested in 2021.

### 2.2. Experimental design and data collection

The workflow of the project involved on field experimentation, data collection, machine learning modeling, followed by analysis of simulated outcomes to compare rate input strategies (Fig. 2). Experimental prescriptions were designed by increasing seeding and fertilizer rates above and below farmer chosen rates. It was assumed that each farmer, using their own experience and know-how of local conditions (field, weather, variety, etc.) and working in consultation with an agronomist, would make an appropriate choice on a baseline uniform rate around which to choose the other seed rates for each site-year. In this way a standard experiment allowed variation of approximately 40 % in either direction of the farmer chosen *status quo* rate, similar to other OFPE seed rate experiments (Trevisan et al., 2021). Unlike the seeding rate experiments, the bloodmeal experiment included a zero rate. Efforts were made to stratify the rates on previous yield maps when they existed, otherwise rates were randomized across the field. Rates were generally placed in a checkerboard design across the field, however in several instances farmers reverted to a simpler strip trial design due to equipment failures of variable rate applicator technology. Strip design is a capable method, though less statistically optimal, and has the advantage of being able to be manually deployed by a farmer with little additional effort (Piepho et al., 2011; Pringle et al., 2004).

Data were collected from farm machinery and satellite sources and aggregated to a 10 m x 10 m grid for analysis. As-applied seeding or bloodmeal rates, were collected from farmer's tractor monitors, and yield data were collected from combine mounted yield-monitors which were calibrated at least annually. Seed rates were manually verified through plant counts (Supplemental Table 1). Yield data were cleaned in a standard fashion by removing outliers where yield values or distance

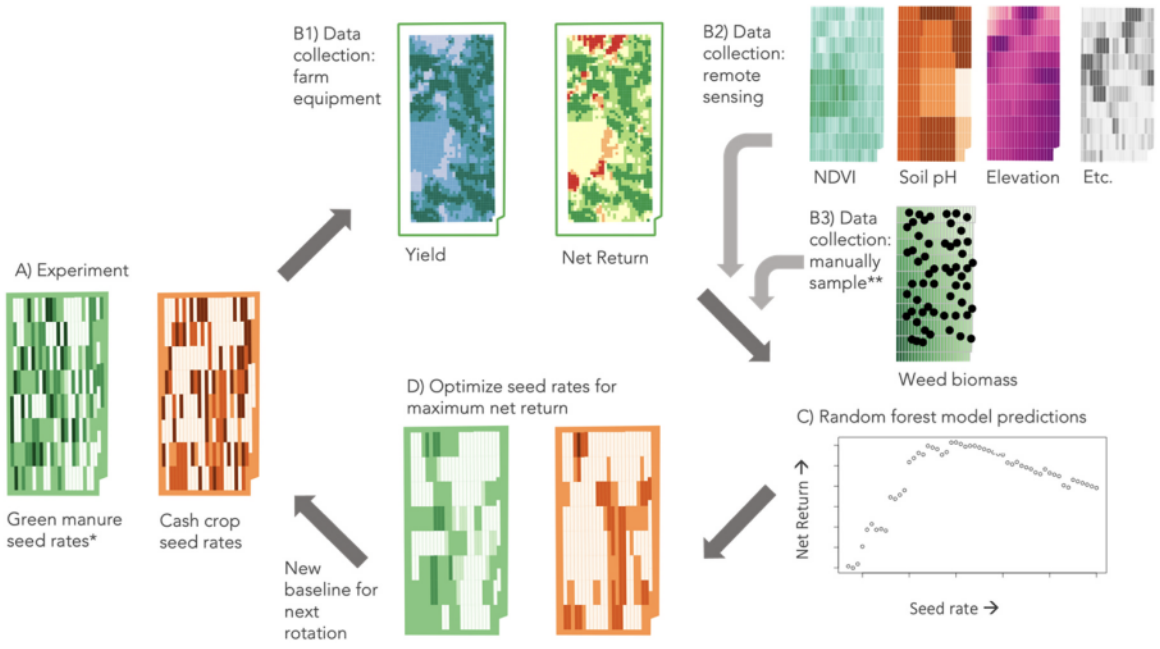



**Fig. 2.** Workflow of organic On Farm Precision Experimentation (OFPE) from a 32 hectare example field with a two-year rotation. A) Experimental seeding rates varied across whole field for one or two-year rotation. B1) Collect data from farm equipment, B2) remote sensing (many more variables can be included), B3) and optionally from manually sampled sources (*i.e.* could include soil or plant sample data). C) Use random forest model to predict net return (via yield) as a response to seeding rate (with other factors from B as covariates) for every cell on the field. D) Find optimum variable seed rates to maximize net return, forming new optimized base layer for future OFPE.

*green manure year precedes cash crop year and is optional.

**example of weed sample points used to interpolate weed biomass across field.

to the next point were above four standard deviations from the mean value or distance (Hegedus and Maxwell, 2022; Sudduth et al., 2012). All satellite data were collected via Google Earth Engine. Satellite data on plant information included Normalized Difference Vegetation Index (NDVI), Normalized Difference Red Edge (NDRE), and red edge chlorophyl index (CIRE); satellite data on soil information included Normalized Difference Water Index (NDWI), soil bulk density, sand content, clay content, pH, soil water content, and carbon content; satellite or drone collected lidar data on topographic information included slope, elevation, topographic position index (TPI), and aspect in eastness and northness following standard GIS practices (Fig. 3 & Supplemental Table 2)(Amatulli et al., 2018). Satellite data classified as "this year" were collected from January 1st of the year of harvest to March 31st. In that way future models could be updated with current information up to the point at which a spring crop seeding rate decision must be made. To understand as much field variation as possible satellite indexes that change over time including NDVI, NDRE, CIRE, and NDWI were collected for the prior year, and two years prior to the harvest year. Previous year yield data, and previous year variable seeding rate data, were included in the analysis when they were available. Latitude and longitude were included in the full model as a standard practice to understand spatial variation not captured in the other terms in the model (Janatian et al., 2017; Walsh et al., 2017; Wang et al., 2017). As there can be discrepancy on this technique (Javadi et al., 2022), model results with and without latitude and longitude are shown in supplemental (Supplemental Table 4). To remove border effects, headlands, as measured by 30 m from the field edge, were removed from analysis (Hegedus et al., 2023).

All organic farmers face weed challenges, so, variation in weed density was manually sampled. Approximately two points per hectare were sampled using a 0.25 $m^2$ ring. To non-destructively ascertain plant biomass, plant volume was estimated by height and width for the crop species and similarly for up to the three most dominant weed species following the method of (Bussler et al., 1995). Weed data by species was too limited to present full field variation so all weed data were compiled to an "all-weeds" biomass variable and kriged across the field (Figs. 3–9), using ordinary kriging with R packages gstat and automap (Hiemstra and Skoien, 2023; Pebesma and Graeler, 2022). Weeds were estimated from sampling and interpolating across fields and it is recognized as the most uncertain variable we estimated. Therefore, it is important to note that observance of spatial autocorrelation was a prerequisite for including interpolated weed data in the modeling process. We further only included the variable in a site-year model if it showed improvement in random forest model prediction (via variable importance estimation), and did not have a high Variable Importance Factor (VIF). All other variables included in the model are freely available, and in future studies weed distribution and abundance may well be assessed with remote sensing (Esposito et al., 2021; Mattivi et al., 2021).

### 2.3. Crop response models

A random forest model was used to predict yield across each field using a wide set of variables (Fig. 2). Other model types were tested but, as has been found elsewhere, based on RMSE random forest models tend to produce the most accurate predictions (Hegedus et al., 2022). The random forest method is well designed to ignore poor model predictors added to the modeling process but is computationally expensive, so, certain features were dropped from the models. The Boruta package in R identified 'unimportant' variables which could be dropped, (Kursa and Rudnicki, 2010). Variable Importance Factor (VIF) is a measurement of multicollinearity and as a rule of thumb values exceeding ten are problematic (James et al., 2021); model variables were assessed using the R package 'car', and any with a VIF over ten were dropped (Fox and Weisberg, 2018). Variables with more than 30 % of the data missing from a field due to machine or incomplete satellite data were dropped (Storey et al., 2016; Trémas et al., 2015). Before feature selection the full field-specific models included all variables in Equation 1 (Table 2 and Fig. 3). Following feature selection, hyperparameters of the models were

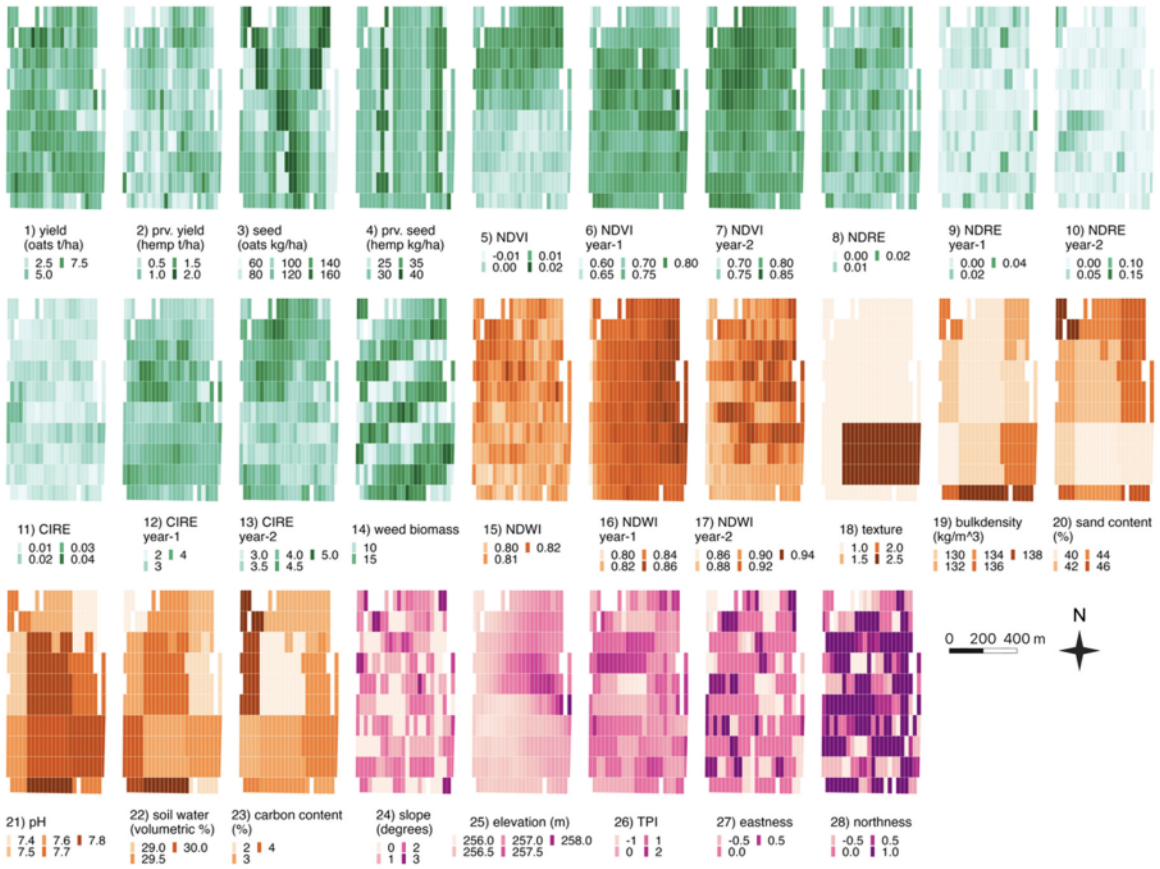



**Fig. 3.** Example maps from site-year three, a 32-hectare field in south-east Manitoba planted to oats in 2022. The maps show all possible input variables in the full model before feature selection for that site-year model. Those pictured in green (1 14) represent plant variables, those in brown (15 23) represent soil variables, and those in pink (24 28) represent topographic variables. Maps 1–4 are farm machinery data, the remaining maps show satellite data. Individual maps show data split into management cells of 24 m wide by 120 m long. Areas in the north-west and north-east of the field were not seeded due to excessive moisture. Only sand content, due to multi-collinearity, was dropped from the model for this site-year (Table 2).

tuned in R using the tidymodels and ranger packages (Kuhn, Wickham, 2022; Wright and Ziegler, 2017). Tuning involved optimizing mtry (number of variables sampled at each node at each ensemble tree) and ntree (total number of ensemble trees) based on lowest RMSE to arrive at best models for each site-year (Table 2). Models were trained on the data set aggregated to 10 m x 10 m cells, however when building new optimized prescriptions for every field, the new rates were upscaled to a 24 m x 120 m grid cell to match field equipment size and constraints. The width is 2x a standard 12 m wide seeder, and the length used is the recommended length to get the most accurate response from combine mounted yield monitors (Guaci et al., 2022). All data analysis was conducted in R, including random forest modeling, and GIS mapping (R Core Team., 2022).

### 2.4. Economic optimization

Economic data were collected from a range of sources encompassing the years 2013–2022 to estimate net return based on predicted yields (Bertramsen and Dobbs, 2002; USDA, 2022; Würriehausen et al., 2015; Personal communication: Manitoba Harvest). Data included price received for winter wheat, spring wheat, oats, hemp, and barley, the seed costs for each of these crops, and their associated fixed costs over the course of those years. From these data net return was established (Eq. 2).

$$NR = Y * PR \quad (IR_1 * IC_1 + \ldots + IR_x * IC_x + FC) \tag{2}$$

Where *NR* was the net return received by a farmer in a given year; *Y* was the yield of the harvested crop in the given year, *PR* was the price received for the crop in the given year and *FC* was the fixed costs (custom services, fuel, lube, electricity, repairs, straw bailing, interest on operating inputs, labor, capital recovery of machinery and equipment, taxes and insurance, and general overhead). The first input rate ($IR_1$) and input cost ($IC_1$) were used when seeding rates or bloodmeal rates were included in the OFPE. Not all fields had a second input, but when pea seeding rates as green manures were experimented with, $x = 2$, and the pea seeding rate and input cost from the year pea was seeded, were represented with ($IR_2$) and input cost ($IC_2$). If bloodmeal was the value varied, seed costs were included in the fixed costs. Price received as well as costs of seed were measured in USD kg $^{1}$, and fixed costs and net return were measured in USD ha $^{1}$. Full economic data can be found in Appendix material (Supplemental Table 3).

Objective one was accomplished by using the crop response models to find economically optimum (profit maximizing) seeding rates in every cell across the field thereby spatially optimizing inputs. Economically optimum seeding rates were generated for each site-year for the year of harvest, and these rates were also generated for each of the previous ten years based on the historical economic data described above. By including this series of possible net return outcomes, past economic variability revealed how often one seeding rate strategy outcompeted another and this accomplished objective two. Finally, objective three was accomplished by quantifying the specific average amount ($) by which the optimized (profit maximized) rate strategies, OVR and OUR, outcompeted FCR on a field specific basis.

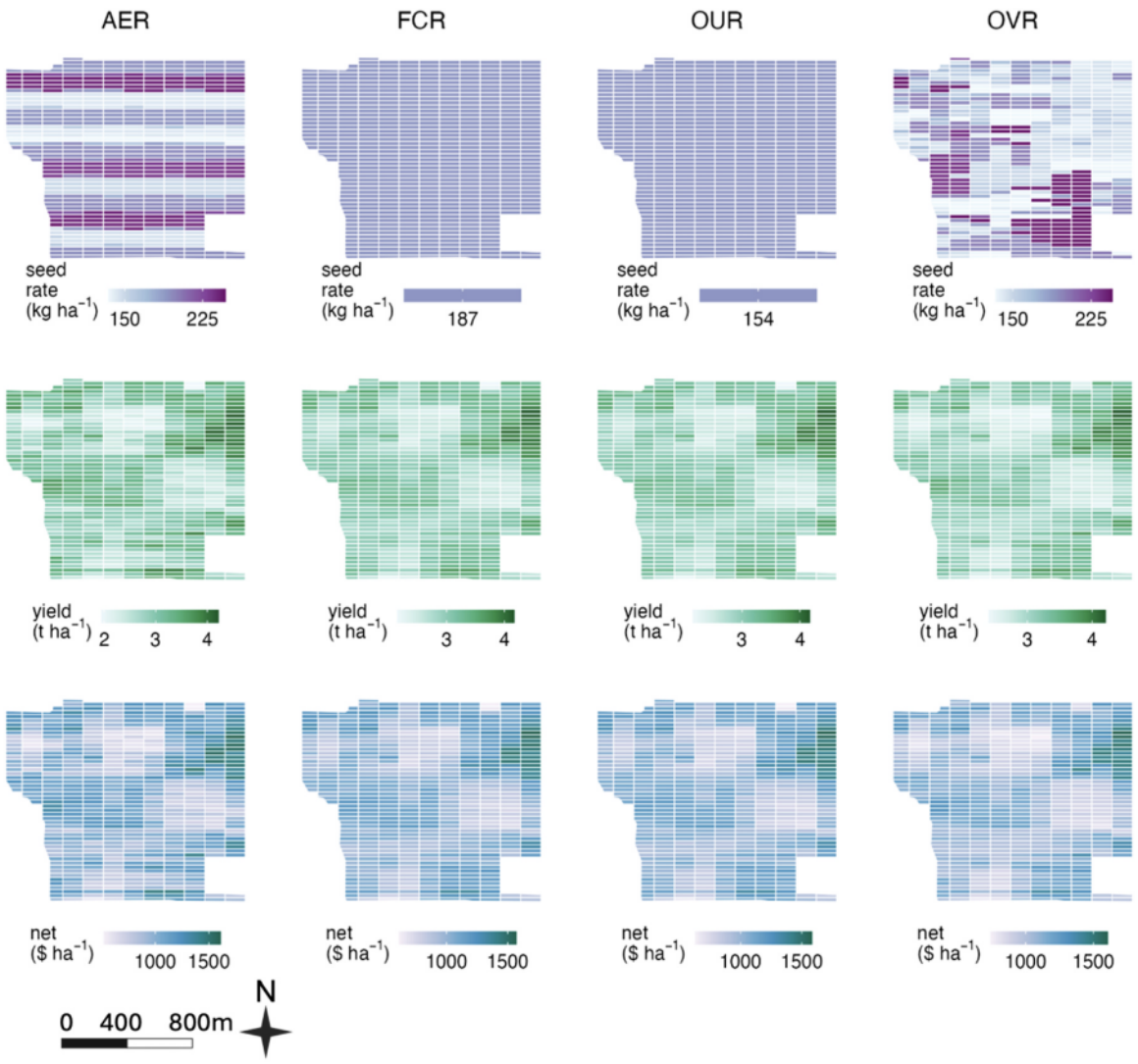



**Fig. 4.** Maps of the seed rates (top row) and resulting yields (middle row) and net-returns (bottom row) to the four management strategies in site-year 5. This experiment featured variable spring wheat seeding in south-east Manitoba from 2021 on a 71-hectare field, individual cells are 24 m wide by 120 m long. The management strategies were the actual experimental rate (AER), farmer chosen rate (FCR), optimum uniform rate (OUR), and optimum variable rate (OVR). AER shows actual input rates and actual yields and net returns, all others are simulated.

## 3. Results

### 3.1. Spatial optimization using field specific models

Through OFPE and simulation, inputs were spatially optimized on all fields. The exception was the bloodmeal application on site-year 4, where the OVR and OUR were both zero with negligible crop response across bloodmeal rates. Of the eleven site-years tested, two are highlighted below to exemplify both the one-year cash crop only seed rate variation (Fig. 4) and the two-year rotation of green manure seeding rates followed by cash crop seeding rates (Fig. 5). Spatial variation of inputs could be large and obvious, as in OVR for site-year 5 (Fig. 4), or subtle like the OVR strategy in site-year 10 (Fig. 5). The resultant calculated changes in yields and net return using the crop response models appear minor on the generated maps, however the cumulative changes in net return were meaningful at the field scale. For example, site-year 5 was a single year rotation of spring wheat in non-drought conditions and demonstrated substantial changes in net return and recommended seeding rates between strategies (OVR, OUR and FCR; Table 3). The AER on field site-year 5 had a net return $27.16 ha $^{1}$ less than FCR; this was the estimated cost of the experiment for this site-year. The FCR for the wheat crop planted in site-year 5 was 187 kg ha $^{1}$, while the OUR was calculated to be just 154 kg ha $^{1}$. The reduction in seeding rate did not have a large effect on yield using the OUR strategy, so primarily offered the farmer savings through reduced seed costs. The OVR also tended to reduce seed input over the entire field relative to the FCR, thus saving costs. However, the OVR model also found areas on fields where increased plant density offered an economically significant yield advantage on site-year 5, thus offering an economic incentive for an optimized prescription for variable seeding rates (Fig. 4). Calculated net return for OVR increased by $58.63 ha $^{1}$ over the FCR management on site-year 5 (Table 3).

Site-year 10 (Barley preceded by pea green manure in Montana) represented a two-year rotation, which occurred during a drought in 2020 and 2021 (-113 mm precipitation anomaly, Table 1). In this instance the seeding rate changes were less obvious than site-year 5, and net return gains from FCR to OUR were $34.21 ha $^{1}$ (Fig. 5, Table 4). There was very little difference between the OUR and OVR, the net return increase to OVR was only $0.19 ha $^{1}$; which is likely as a result of the overwhelming effects of drought. Despite the low crop response to seeding rates in low precipitation years the calculated optima did identify areas where seeding rates could increase, thus enabling slightly

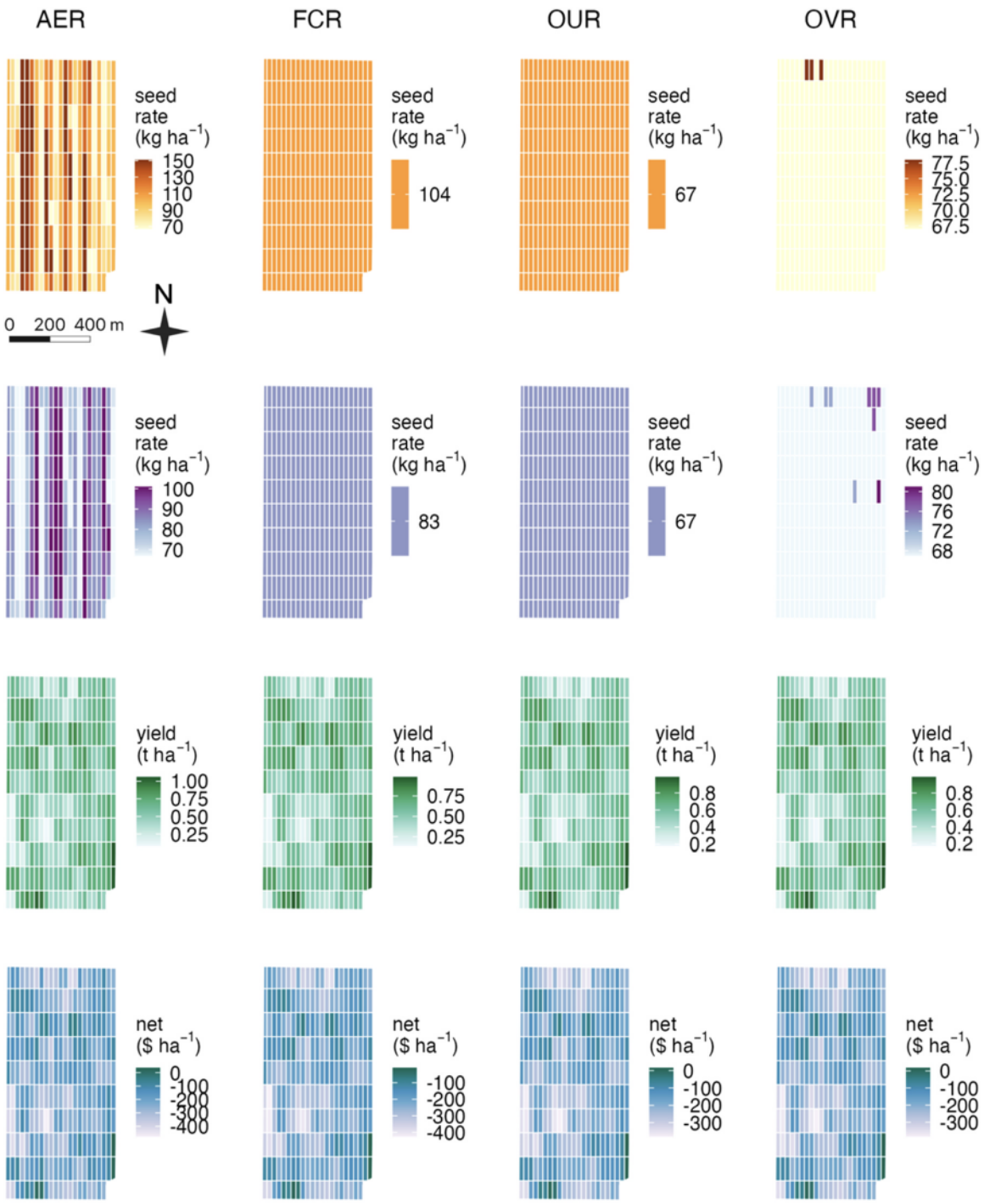



**Fig. 5.** Results from site-year 10 (barley preceded by pea green manure) on a 32 hectare field in north-central Montana harvested in 2021, individual cells are 24 m wide by 120 m long. Pea green manure seed rate (top row), the subsequent barley cash crop seed rate (second row), their respective simulated yields (third row), and calculated net returns (bottom row), for each of four seeding rate strategies (columns), including the actual experimental rate (AER), farmer chosen rate (FCR), optimum uniform rate (OUR), and optimum variable rate (OVR). AER shows actual input rates and actual yields and net returns, all others are simulated.

better chances of increasing net return. The specific examples illustrated here demonstrated the specifics of where and how input rates could be spatially optimized to provide an advantage to the farmer.

The random forest models to predict subfield cash crop yield used in this study were field and year specific. Through model variable selection field-specific models were developed that included different variables than the initial full model. The input variables, and their importance to crop yield prediction were quite different field to field and year to year (Fig. 6). This exemplified the variability seen between the fields examined and emphasized the requirement to estimate optimization and compare strategies using field specific models (Hegedus and Maxwell, 2022). The variable importance plots were useful in visualizing the differences among model years, and were also a starting point for unpacking potential driving variables in the models. For example, in site-year 5 seeding rate was a very important driver of the model, however in site-year 10 seeding rate is near the bottom of the list. The variable importance plots were useful for understanding which variables were driving the sub-field scale patterns in crop yield (Fig. 5). While

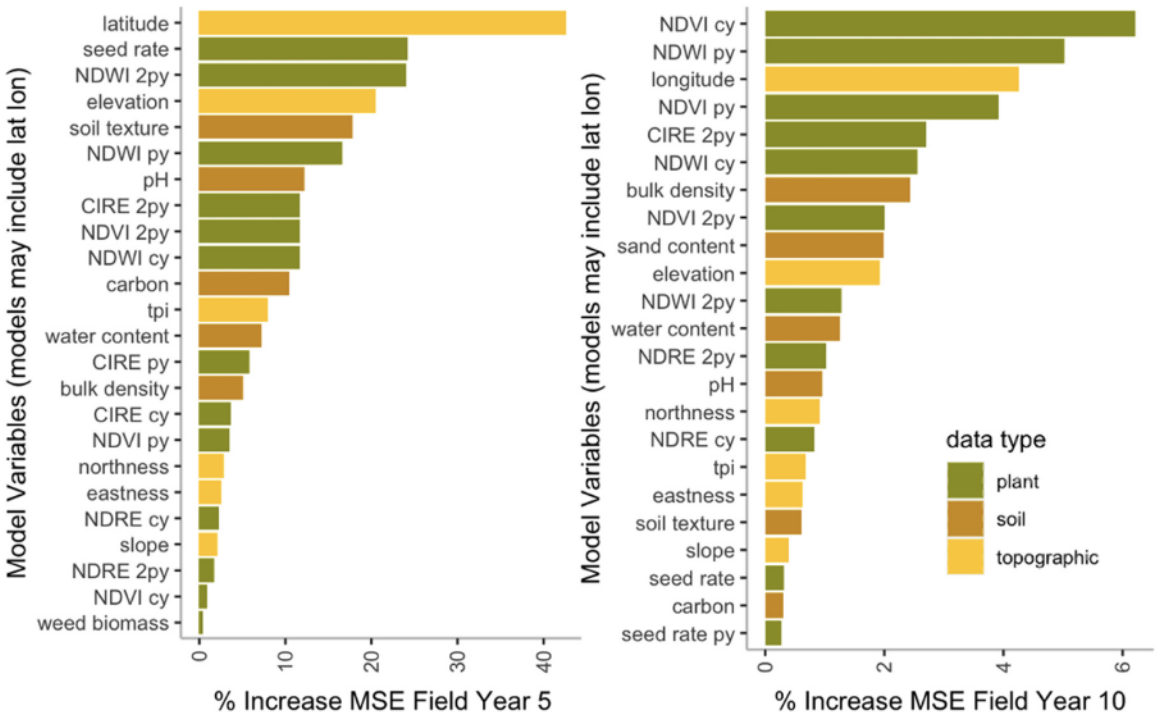



**Fig. 6.** Variable importance plot derived from the random forest model for site-year 5 and site-year 10, where every variable was measured based on the increase in MSE if that variable was randomly permuted within the modeling process. More important variables can be interpreted as important to predictions of crop yield. Each model for each site-year had a different variable importance plot (Supplemental Figure 1). The variables were broken down into data-type categories of plant, soil, and topographic variables.

latitude and longitude can be included to inform about spatial variation not accounted for by other variables they should not be regarded as mechanistic drivers of yield. When they were removed from the models the model prediction accuracy declined slightly (Supplemental Table 4) but the relative importance of the variables in each model remained largely unchanged (Supplemental Table 5). When considering all site-year models collectively, the top predictors of yield, as determined by random forest model variable importance, were elevation, NDVI (two years prior), CIRE (two years prior), NDVI (one year prior), and NDWI (one year prior).

### 3.2. Comparison of Management Strategies

Input optimization strategies were compared for profitability within fields, and also across site-years by simulating temporal variability in outcomes using the variability in cost of seed and prices received for the cash crop (Fig. 7). Simulated yields were assumed to be constant over time (2013–2022) and based on the OFPE we conducted, cash crop yields were also compared within fields and across site-years (Fig. 8). Based on the observations it was possible to compare profitability among the different input application strategies OVR, OUR, FCR, and AER (Fig. 9). Averaged optimum (OUR and OVR) input rates tended to be lower when compared with the FCR strategy (Fig. 7); this was particularly evident under drought conditions in 2021 (Table 1: site-years 2, 4, 7, 9, 10, and 11; precipitation anomalies 111 mm, 138 mm, 115 mm, 157 mm, 113 mm, 122 mm respectively). All optimum green manure seeding rates were found to be lower than the FCR (Fig. 7: 9.1–9.3). In a few instances however, input rates increased when optimized, such as in site-year 8, an oat rate experiment in above average precipitation conditions (+150 mm precipitation anomaly) in Manitoba (Table 1). At site-year 8 the OUR of oats was increased relative to the FCR, resulting in higher yield and net return (Fig. 7 & 8). Optimized seeding rates were seen to increase at site-years 2, 8 (only OUR) and 11; elsewhere seeding rates were reduced relative to the FCR.

Yield was always highest under the OVR management strategy (Fig. 8) regardless of whether input rates were higher or lower (Fig. 7). Yields were typically shown to increase when moving from the FCR to the OUR to the OVR strategy (Fig. 7). Though in some instances yield gains were negligible, such as in site-year 5 where moving from FCR to OUR showed no improvement in yield. In this instance, only reductions in seeding rate allowed the net return to increase. Under the AER conditions yields were usually lower than FCR, though not always. Occasionally, due to random chance, AER was shown to produce more yield than FCR such as site-years 2 and 10. Optimization was set to maximize net return which often resulted in either reduced inputs, or increased yields, and typically both occurred (Supplemental Table 6).

In terms of net return, OVR tended to outcompete OUR, which tended to outcompete FCR, which tended to outcompete AER as hypothesized (Fig. 9). The dollar spread between OUR and OVR was less when wheat was the cash crop (site-years 1, 4, 5, 7, 9, 11) than the other cash crops tested. The spread between OUR and OVR was less under drought conditions (Table 1 & Fig. 9); drought conditions included site-years 2, 4, 7, 9, 10, and 11. Despite very different moisture conditions, the hemp crops (site-years 2 and 6) showed large gaps between management strategies, highlighting the potential of this crop for variable rate management.

### 3.3. Quantification of net return differences

Net returns were always shown to increase relative to FCR when inputs were optimized under either the OVR or OUR strategy. Each strategy was compared against a baseline of the FCR to clarify the net return results and to make them more telling to farmers (Fig. 9). The results demonstrated and quantified gains in adopting the profit maximizing strategy, and whether the gain in profit represented enough economic advantage to offset the costs and time required to employ OFPE. Depending on the site-year, average improvements (across all 10

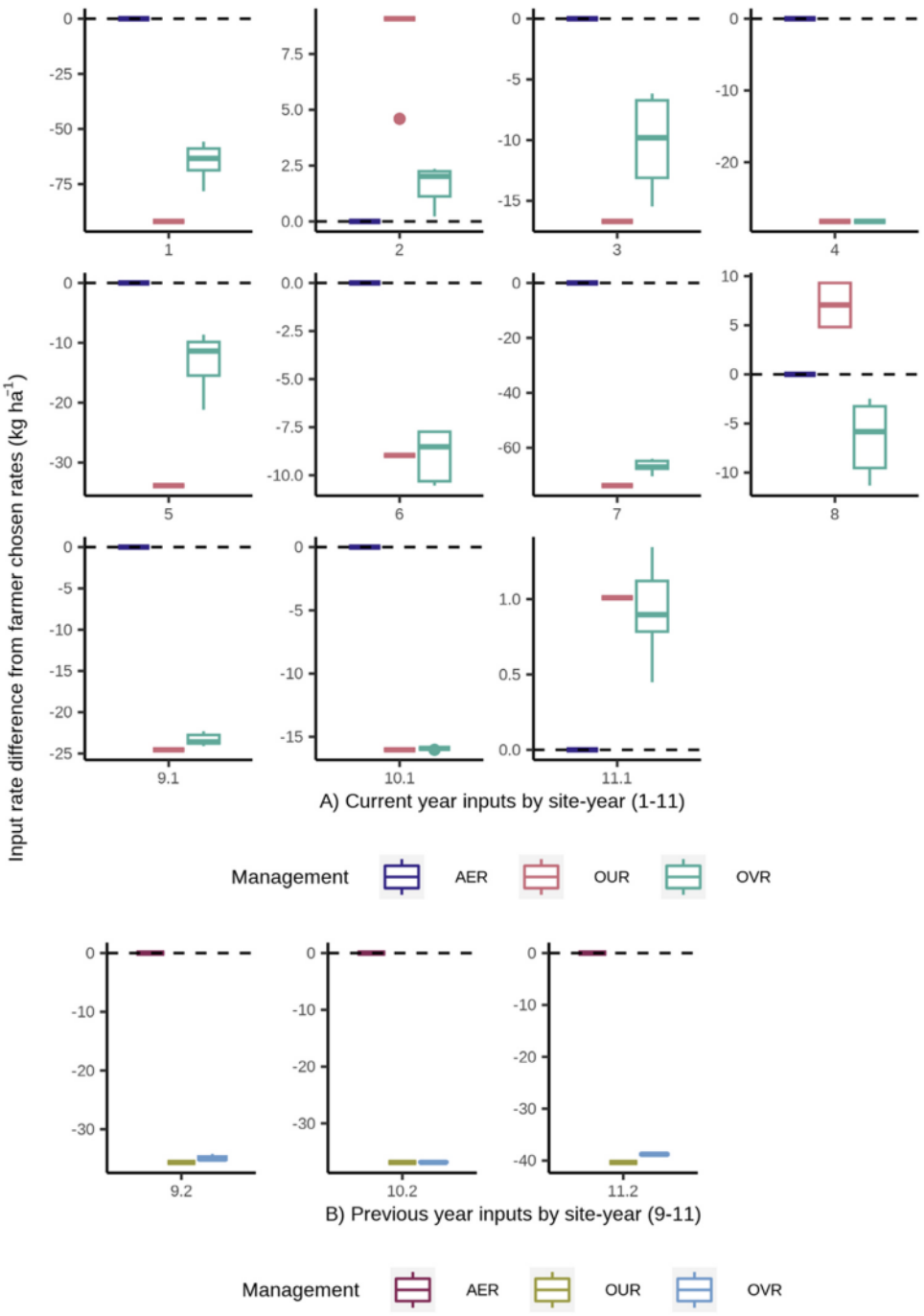



**Fig. 7.** A) The current year input rates of four different management strategies on site-years 1–11, and B) the previous year input rates for pea green manure for site-years 9–11. Management strategies included actual experimental rates (AER), farmer chosen rates (FCR), optimum uniform rates (OUR), and optimum variable rates (OVR). All were shown here relative to the FCR, which here was 0, and shown as a horizontal black dashed line. Each box represented a range of outcomes given the experimental or optimized rates on 10 years of historical economic data.

years of economic variation) were as low as \$3.35 ha $^{1}$ in site-year 8 under OUR management (an oat experiment in Manitoba), to as high as \$105.36 ha $^{1}$, in site-year 6 under OVR management (a hemp experiment in Manitoba) (Fig. 9, Supplemental Table 6). While results were field specific, the average increase across all site years when adopting OVR management, over FCR, was \$50.01 ha $^{1}$. Implementing OFPE usually cost the farmer on average across all site-years \$6.90 ha $^{1}$. In site-years 2 and 10 the farmer actually made money from running the experiment (Supplemental Table 6).

## 4. Discussion

In this crop seed rate study optimized variable rates (OVR) provided the greatest increase in net return over the farmer chosen rates, though the optimized uniform (OUR) strategy also increased net return. These results largely confirm the hypothesis and findings from conventional systems (Bullock et al., 2020; Hegedus and Maxwell, 2022), that the OFPE method is applicable in organic systems. Net returns increased across all site-years on average by \$50.01 ha $^{1}$. While conventional farmers have seen relatively small gains in variable rate technology (Bullock et al., 2020; Lawrence et al., 2015; Pedersen and Lind, 2017),

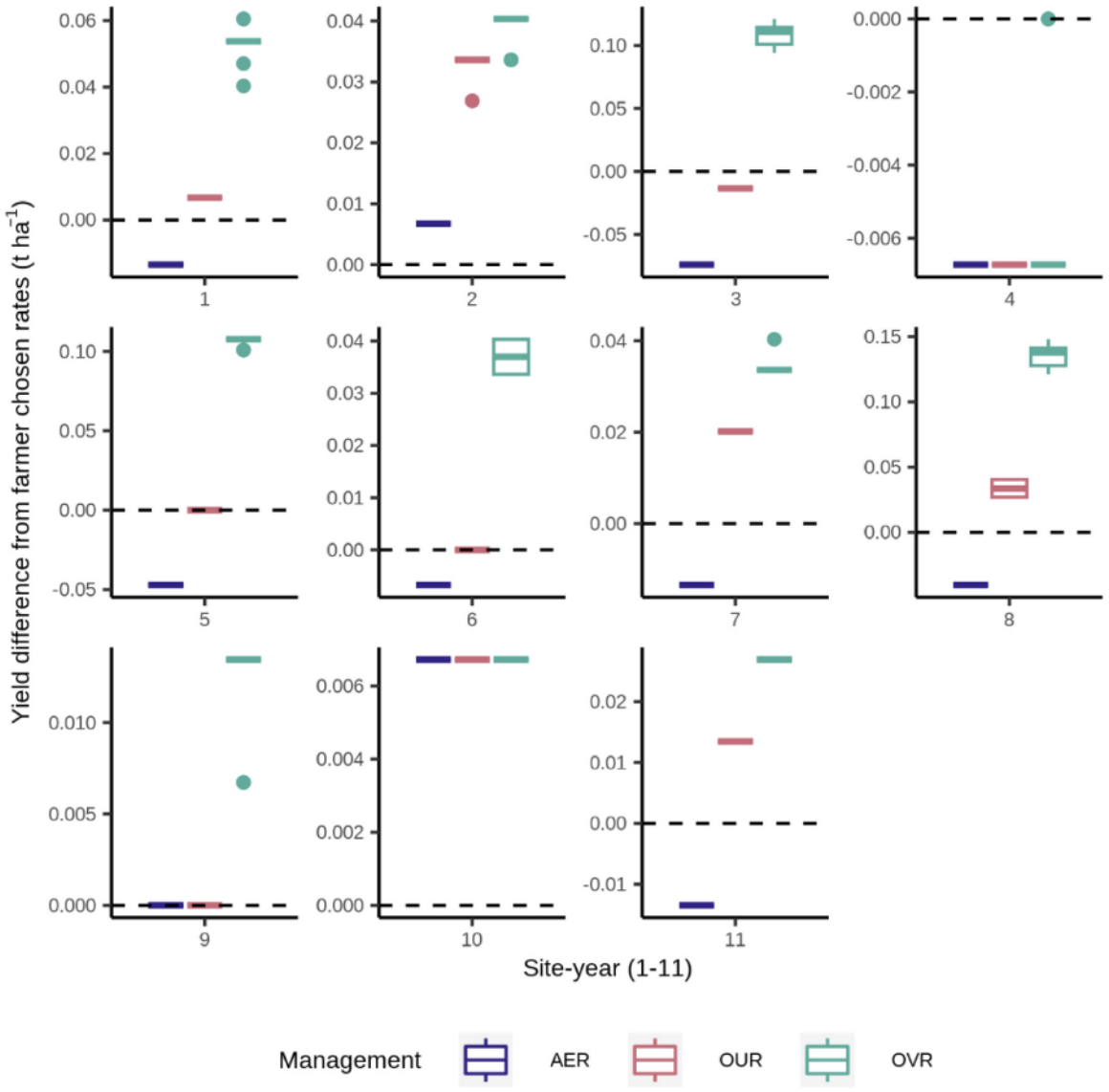



**Fig. 8.** The cash crop yields for four different management strategies. Management strategies included actual experimental rates (AER), farmer chosen rates (FCR), optimum uniform rates (OUR), and optimum variable rates (OVR). All were shown here relative to the FCR strategy, which here was set to 0, and shown as a horizontal black dashed line. Each box represented a range of outcomes given the experimental or optimized rates over 10 years of historical economic variables.

this study found substantial possibilities for increased net returns for organic farmers using precision agriculture. In conventional systems optimized input rates, such as soybean seed or nitrogen fertilizer, have been inconsistent, showing both increases and decreases of input rates when optimized (Hegedus, Ewing, et al., 2022; Rothrock et al., 2022). Despite low adoption rates, organic farmers may benefit the most from precision agriculture (Mitchell et al., 2018).

OFPE is a new method of site-specific seed rate optimization, and its deployment in organic systems is novel. It is unique in its pursuit of optimal input rates through in-field experimentation, which is designed to update each growing season, and use freely available data (Bullock et al., 2019; Hegedus et al., 2023). Other site-specific seeding studies have explored optimal input rates by dividing fields into management zones and generally assigning areas with higher yield potential higher seeding rates. This can be problematic in collecting enough data to create the management zones prior to experimentation as the data collection often calls for the use of expensive sensors like Veris machines, whereby the OFPE method prioritizes data which is already available (Javadi et al., 2022; Kazlauskas et al., 2022; Monzon et al., 2018). Additionally, there can be an issue in assuming a "King's treatment" (higher inputs in higher yield potential zones) approach to inputs on a field. While this may often be true (Munnaf et al., 2022) it has been shown that the opposite treatment is sometimes the case depending on the input and the location (Bastos et al., 2020). By taking a blank slate approach through OFPE, the experiments can inform the optimal rates rather than delineating them based on a mechanistic understanding of the underlying soil conditions. Where there is a lack of prior understanding of spatial field response to a certain input, OFPE may be the preferred method providing required experimentation to create more flexible management zones. In particular it may be beneficial where the input in question is not well studied such as organic hemp seeding rates like those studied here. Future work could examine a comparison of these two approaches for short- and long-term accuracy.

We have shown here that variable seed rates can improve crop yields and more importantly, net returns; in particular we see those improvements benefiting a non-tillering crop like hemp, more than the cereals which were tested. In some instances higher seed rates are beneficial where the increased plant density enables the crop to take advantage of increased resource availability, or as is common in organic systems, being able to outcompete weeds through increased density (Beavers

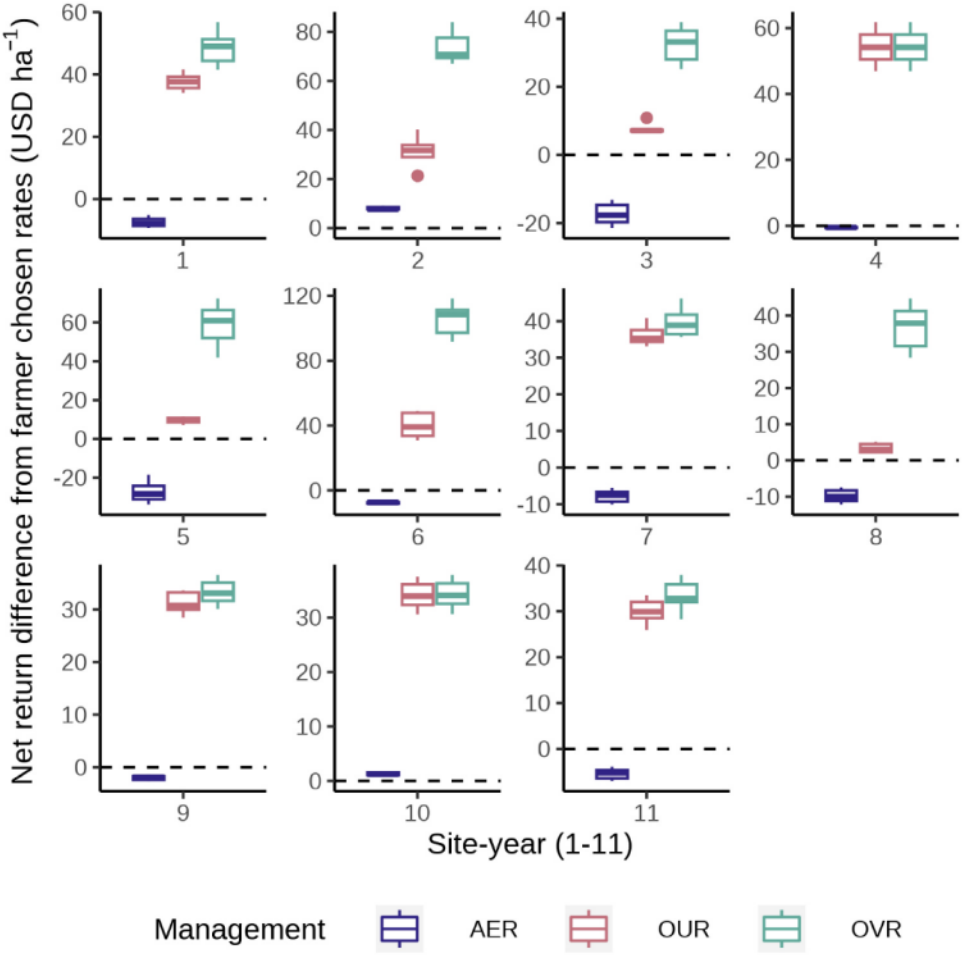



**Fig. 9.** The average net returns for four different management strategies including actual experimental rates (AER), farmer chosen rates (FCR), optimum uniform rates (OUR), and optimum variable rates (OVR). All were shown relative to the FCR strategy, which here was set at $0.00, and shown as a horizontal black dashed line. Each box represented a range of outcomes given the experimental or optimized rates on 10 years of historical economic data.

**Table 2**
Model selection on the variables used in each of the eleven site-year models, beginning with the full model each model was trimmed down through feature selection to reduce computation time, reduce multicollinearity, and account for missing data.

| Model | Model variables |
|---|---|
| Full model | (1) $yield_y \sim yield_{y\ 1} + seed\ rate_y + seed\ rate_{y\ 1} + NDVI_y + NDVI_{y\ 1} + NDVI_{y\ 2} + NDRE_y + NDRE_{y\ 1} + NDRE_{y\ 2} + CIRE_y + CIRE_{y\ 1} + CIRE_{y\ 2}$ + weed biomass + $NDWI_y + NDWI_{y\ 1} + NDWI_{y\ 2}$ + soil texture + bulkdensity + sand content + pH + soil water content + carbon content + slope + elevation + TPI + eastness + northness + latitude + longitude |
| | *Model variables removed by field:* |
| Site-year 1 | $seed\ rate_{y\ 1}$, $CIRE_{y\ 1}$, sand content |
| Site-year 2 | $CIRE_{y\ 1}$, sand content |
| Site-year 3 | $yield_{y\ 1}$, sand content |
| Site-year 4 | $yield_{y\ 1}$, $seed\ rate_{y\ 1}$, longitude, weed biomass |
| Site-year 5 | $yield_{y\ 1}$, $seed\ rate_{y\ 1}$, sand content, longitude, $NDRE_{y\ 1}$, X |
| Site-year 6 | sand content, longitude, $NDRE_{y\ 1}$ |
| Site-year 7 | sand content, longitude |
| Site-year 8 | sand content, longitude |
| Site-year 9 | $yield_{y\ 1}$, longitude, carbon content |
| Site-year 10 | $yield_{y\ 1}$, latitude, weed biomass, $NDRE_{y\ 1}$, $CIRE_y$, $CIRE_{y\ 1}$ |
| Site-year 11 | $yield_{y\ 1}$, sand content, latitude, bulkdensity, $NDWI_{y\ 1}$, weed biomass, carbon content, $CIRE_y$, $CIRE_{y\ 1}$ |

**Table 3**
Quantified results from site-year 5 (spring wheat crop fertilized with manure in Manitoba) indicating rate, yield, and net return of the four strategies averaged across all field cells and all economic years.

| | AER | FCR | OUR | OVR |
|---|---|---|---|---|
| Avg seed rate (wheat kg ha $^{1}$) | 187 | 187 | 154 | 174 |
| Avg yield (t ha $^{1}$) | 3.01 | 3.05 | 3.05 | 3.16 |
| Avg net return ($ ha $^{1}$) | 1088.17 | 1115.33 | 1125.06 | 1173.96 |

AER = Actual Experimental Rate; FCR = Farmer Chosen Rate; OUR = Optimum Uniform Rate; OVR = Optimum Variable Rate

**Table 4**
Quantified results from site-year 10 (barley preceded by pea green manure in Montana) indicating rate, yield, and net return of the four strategies averaged across all field cells and all economic years.

| | AER | FCR | OUR | OVR |
|---|---|---|---|---|
| Avg seed rate (pea kg ha $^{1}$) | 104 | 104 | 67 | 67 |
| Avg seed rate (barley kg ha $^{1}$) | 83 | 83 | 67 | 67 |
| Avg yield (t ha $^{1}$) | 0.58 | 0.57 | 0.58 | 0.58 |
| Avg net return ($ ha $^{1}$) | 298.43 | 299.73 | 265.52 | 265.33 |

AER = Actual Experimental Rate; FCR = Farmer Chosen Rate; OUR = Optimum Uniform Rate; OVR = Optimum Variable Rate

et al., 2008). In other instances, yields decline with higher seed rates as disease, pest pressure and lodging can increase (Bastos et al., 2020; Laghari et al., 2011). Since negative affects like weeds and diseases, and positive affects like nitrogen availability, vary across the field, these represent ways in which seed rates can be optimized. While there tended to be smaller opportunities for the cereals to contribute via optimized seed rate to increased net returns (they tended to have similar OUR and OVR net returns), the hemp in both site-years had a large increase in net return from OUR to OVR. Hemp has fewer plastic abilities as compared to tillering crops like oat or wheat (Browne et al., 2006), it has more expensive seed, and has demonstrated highly variable response to spatial conditions as well as seed rate (Darby et al., 2016; Hammami et al., 2022; Stafecka et al., 2016). This highlights the potential for hemp, a relatively understudied crop, as a target for future variable seed rate applications.

Organic agriculture is predicated on the farm manager understanding the complex bioeconomic interactions in the agroecosystem. To gain agroecosystem understanding farmers rely on generational knowledge and personal experience to make informed decisions. OFPE is the basis for bringing objectivity and science into the decision process associated with applying inputs in these complex agroecosystems accelerating knowledge gain over a traditional trial and error approach. The OFPE method encourages learning, and is not solely a decision making aid (Bramley et al., 2022; Cook et al., 2018; Toffolini and Jeuffroy, 2022). To demonstrate the effect to farmers, a variety of OFPE strategy outcomes are shown in terms of net return, and comparably how often one strategy outperforms another. Given all this information the farmer can decide whether to utilize the newly designed precision agriculture approach or not. Rather than use an arbitrary cost of precision agriculture, which will vary from farmer to farmer, we can display the cost of the experiment, and the potential net return benefits in the future, and allow the farmer to decide based on that information, if they would like to pursue precision seeding rates using OFPE. There is considerable skepticism in the farm community regarding black box modeling and prescriptive software (Altieri and Nicholls, 2020; Daum, 2021). Future decision support tools should therefore delineate possible outcome strategies, given known economic and climatic variability, in response to different input management strategies. A decision support tool which encouraged experimentation and attempted to augment farmer knowledge with their own site-specific data, rather than replace the farmer with an automated prescription, will be more successful, both in adoption rates, and in helping to create more sustainable organic farms (Prost et al., 2023). Ideally these tools would leave the management decisions up to the farmer but provide extra data and support that a farmer could use to improve decision making. The OFPE method encourages learning, not decision making in and of itself.

The primary drawback of this study and analysis was a lack of consistently repeated experiments over time. Organic farming has been found to have greater yield stability over time than conventional (Schrama et al., 2018), nevertheless more data collection over time will improve the applicability of these models (Hegedus et al., 2022). The models developed are time and site specific, though designed with enough flexibility to be updated to future conditions based on future remotely sensed variables (Hegedus et al., 2023). In this manner updated models ought to be able to make predictions based on real-time up to date field conditions, an important consideration in light of climate change (Lawrence et al., 2018). However, the models are only trained on one season of climate data each and moving forward there will likely be greater variation in model outputs as they adjust to variable climatic conditions. The point is exemplified in this study from fields experimented on during drought. Under drought conditions the lowest input rates were selected by the model as optimum, yet this was under anomalous conditions, and higher rates would be expected as optima in wetter conditions. This was particularly disappointing where the field systems received soil nitrogen from green manure cover crops, and it was hoped to uncover the potential for cover crop seed rates to be optimized.

The temporal variability was addressed in this study by incorporating economic changes from year-to-year, and that alone was instructive to a decision maker, but climate data will add crucial information moving forward. Key to future research will be reproduction of these rainfed field-specific experiments to engage with temporal variability in yield in response to variable precipitation over years. The specific weather experienced by each site-year undoubtedly played a role in determining the outcome of the experiment and the resultant optimization strategy found through the random forest modeling process. This highlights the future need for longer term experiments to further tease out the temporal based variation across each field.

Another component of future work will be examining weeds in greater detail. Weeds are an important factor in organic production, and integrated weed management is becoming ever more important in conventional agriculture as well due to the negative effects of chemicals on the environment, and the rise of herbicide resistant weeds (Heap and Duke, 2018; MacLaren et al., 2020; Monteiro and Santos, 2022). In this study weeds were treated as an independent variable in the models but were not the focus of analysis as a response variable. Seeding rate's impact on net return was focused on, however organic farmers make other choices when conducting their operations such long-term management of weed seed banks this may be more important than short term net return. Indeed, the results indicate that reducing seeding rates leads to higher net returns, but an organic farmer may in fact wish to maintain higher seeding rates to increase competition with weeds and reduce weed seed production (Merfield, 2019). Future projects could therefore examine weed abundance as a response variable as well as crop yield to minimize the trade-off between reduced crop yield and the long-term benefit of reduced weed seed production.

## 5. Conclusion

Precision agriculture is underused in organic agriculture despite its strong potential to inform and refine crop management. Most technologies introduced to crop production have resulted in erosion of farmer profits, and organic production is largely driven by a rejection of input technologies. Organic farmers reject the advantage of variation suppressing chemicals, and this disadvantage leads to lower yields relative to conventional agriculture. However, lower yields are offset by higher net returns due to lower input costs and price premiums. Successful management of organic systems is more dependent on managing with variation because variation suppressing inputs are not available. Thus, awareness of spatial variation in organic agroecosystems will allow precision agriculture technology and resultant data to uniquely benefit organic farms by helping to manage heterogeneity. Despite low adoption rates, organic farmers may benefit the most from precision agriculture.

Objectives of this research were met whereby data from full field varied seed rate experiments on organic farms revealed through simulation optimum rates to maximize net return, which were an improvement upon other simulated strategies by as much as 50 $ ha $^{1}$, while the cost of deploying the experiment itself averaged $7 ha $^{1}$. By experimenting with varied input rates across individual organic fields, optimized rates different than the FCR were found to maximize net return. The OFPE approach resulted in increased economic returns for organic farmers. In addition, this study demonstrated how farmers can decide if precision agriculture technology is a good investment for them, and is also useful for researchers to form the basis for development and deployment of new decision support tools designed specifically for organic farmers. The primary limitation in this study was a lack of repetition of OFPE over time, but future work will repeat experiments and improve characterization of field-specific temporal variability. Organic agricultural inputs were optimized with precision agriculture tools to enable decision making that responds to field-specific spatial and temporal variability. Where uncertainty in economics and climate are becoming increasingly intense, an adaptive management tool like

OFPE can provide up-to-date information that can empower organic farmers managing large scale farms to continue high levels of quality production under uncertain conditions. Agroecological practitioners can harness the power of precision agricultural tools to lead the way in both sustainable and high-tech farming.

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## CRediT authorship contribution statement

**Bruce D Maxwell:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Data curation, Conceptualization. **Sasha Loewen:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data Availability

Data will be made available on request.

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## Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.fcr.2024.109593.

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