
# Precision application of seeding rates for weed and nitrogen management in organic grain systems

**Loewen, S., Maxwell, B.D.M. Montana State University, United States.**

**A paper from the Proceedings of the**
**15th International Conference on Precision Agriculture**
**June 26-29, 2022**
**Minneapolis, Minnesota, United States**

***Abstract.***

*In a time of increasing ecological awareness, organic agriculture offers sustainable solutions to many of the polluting aspects of conventional agriculture. However, without synthetic inputs, organic agriculture faces unique challenges such as weed control and fertility management. Precision Agriculture (PA) has been used to successfully increase input use efficiency in conventional systems and now offers itself as a potential tool for organic farmers as well. PA enables on farm precision experimentation (OFPE) to systematically generate an understanding of crop response to varied inputs. We investigated the first principle relationship between cover and cash crop seeding density and yield output in a greenhouse experiment before testing this relationship in field settings on four Montana farms. In the field we explored the effect of varied seeding rates on harvested crop yield using OFPE; by seasonally repeating experimental input rates on fields, the seeding rates can be optimized spatially and temporally for maximized farmer net return. We optimized seeding rates by using machine learning crop response models trained on the experimental data. Random forest algorithms were used to construct predictive models that included yield responses from combine mounted sensors, input crop seeding rates, satellite information such as NDVI from previous growing seasons, topographic variables, and growing degree days. Using the predictive crop yield model, simulations revealed that optimized variable seeding rates maximized whole-field net returns and typically outcompeted farmer chosen or whole field optimized single field rates. The project aims to move forward with an open-source decision support tool that will enable farmers to practice OFPE with greater ease, thus encouraging adoption of both precision technologies and agroecological farming principles.*

***Keywords.***
*organic, precision agriculture, seeding rates, variable rate application, agroecology*

The authors are solely responsible for the content of this paper, which is not a refereed publication. Citation of this work should state that it is from the Proceedings of the 15th International Conference on Precision Agriculture. EXAMPLE: Last Name, A. B. & Coauthor, C. D. (2018). Title of paper. In Proceedings of the 15th International Conference on Precision Agriculture (unpaginated, online). Monticello, IL: International Society of Precision Agriculture.

## Introduction

The primary goals of agriculture are twofold: maintain nutritious and bountiful food sources for the planetary population and maintain or improve environmental conditions. One framework which envisages accomplishing these goals is that of agroecological intensification. Rather than sustainable intensification which still prioritizes yields(Garbach et al., 2017), agroecological intensification seeks first to improve environmental conditions then achieve quality and quantity of crops. Agroecological intensification can harness new technologies like precision agriculture to augment farmer knowledge of an area to achieve their goals (Duff et al., 2022). In organic agriculture, inputs can be optimized to reduce waste while improving yields, soil health, and farmers' net returns. In this way organic agriculture, which substitutes cover crops and manure for more harmful agrochemicals, can achieve resilient yields, quality products, and high net returns while maximizing ecosystem services in an agricultural setting.

The clearest method of deploying precision agriculture tools in organic operations is through optimized seeding rates of crops; this includes both harvestable cash crops, and soil health building cover crops. In organic systems, nitrogen fixing green manure cover crops (GM) are essential for supplying nitrogen for the following season's cash crops and limiting weed growth. In dryland organic production systems, GMs acquire nitrogen rich biomass at the expense of water loss. This balance must be finely tuned to provide optimum nitrogen and water for the following season, such that the cash crop's yield potential is reached, and net return is maximized for the farmer. Research has shown that pea (*Pisum sativum* L.) is the ideal plant to fix the most nitrogen with the least water loss in arid organic farm systems (Lawley & Shirtliffe, 2004; Miller et al., 2011; Wang et al., 2012; Zentner et al., 2004). By terminating the plant at first bloom stage, just before its maximal nitrogen fixation phase, crucial amounts of water are conserved (McCauley et al., 2012; Miller et al., 2011). It is well understood that increasing seeding rate of GMs increases nitrogen fixation asymptotically up to a maximum threshold (Mccauley et al., 2012; Usukh, 2010); seed increase also suppresses weed growth, and likely increases water consumption (Gan et al., 2007; Tully & McAskill, 2020). Using plot-based research, agronomists have established a broad range of applicable seeding rates for green manures across the NGP, though in reality optimum rates are site specific (Baird, 2007; Johnston et al., 2002; Spies, 2008).

Site specific seeding rates can now be managed using precision agriculture (PA) tools, including GPS, variable rate technology, and yield monitors. Many of these tools are already owned by organic farmers, though their on-farm application is limited (Finger et al., 2019; Griffin et al., 2017; Mitchell et al., 2018). Organic agriculture, while showing great potential, has been underfunded and under-researched, and basic organic agronomic principles poorly explored (Miles et al., 2017). Therefore, to bring the power of precision agriculture to organic operations we seek to determine the first principle relationship in a typical organic crop rotation sequence between seeding rate for both cover and cash crops and biomass production. We explored these relationships in a preliminary greenhouse study using the common organic grain crops pea and Kamut (*Triticum turanicum*), at varied densities, before expanding the project to field level operations and deployment. In the field a methodology of on farm precision experimentation (OFPE) was followed, in which rates of an input are randomly varied over an entire field to determine site specific optimums. OFPE, which relies on PA tools, is a mechanism to gain knowledge and adaptively manage crop inputs at the field and sub-field scales and can be applied in organic systems (Cook et al., 2018; Lacoste et al., 2022). By exploring the relationship between applied experimental seeding rates and the response of yield a field's spatial variability can be revealed, and if repeated over years the temporal variability can be optimized field by field (Lawrence et al., 2015). OFPEs were established on one field each on four separate farms across Montana to assess their applicability in organic grain production settings.

Greenhouse results confirm that varied pea seeding rates contribute to the varied levels of biomass production and fixed and available nitrogen (N). Field experiments were used to develop models to predict optimal site-specific green manure seeding rates and following year cereal crop seeding rates that maximized producer profitability in the organic fields where OFPE was applied. Results revealed yield responses to the varied rates that are spatially explicit, thus offering potential optimization strategies that could reduce input waste, increase yield, and provide more consistent net returns to organic farmers.

## Methods

### Greenhouse Experiment

The goal of the greenhouse experiment was to determine optimum green manure and cash crop seeding rates. Garden boxes measuring 50cm by 50cm and 25cm deep were filled with sterilized soil mixed with 50% sand to emulate the sandy, low nitrogen conditions typical of agricultural settings in north central Montana. The green manure tested was Arvika green peas (*Pisum sativum*), a common Montana crop and variety; the cash crop tested was Kamut, a typical organic cereal grown in Montana. Seeding rates encompassed a range well below and above typical farmer chosen rates and included pea rates at 0, 42, 78, 204 kg/ha (0, 7, 13, 34 seeds per box). Pea plants were grown for approximately eight weeks at optimal light and temperature growth conditions. Plants were terminated at first flowering stage, when roughly half the plants were flowering, which is the recommended termination stage to maximize N production and minimize water loss in arid conditions (McCauley et al., 2012). Pea plants were mixed into the soil and allowed to decompose over six weeks; the soil was kept moist and occasionally stirred. Kamut seed was planted into the boxes at four rates: 25, 50, 75, 100 seeds/box (30, 60, 90, 120 kg/ha) across each pea rate to create a full factorial design (4x4). Kamut was grown until maturity, which took approximately twelve weeks, then was harvested. The soil was sampled to track nitrogen gain and loss in the soil at multiple time points: at pea planting, pea termination, Kamut planting, and again following Kamut harvest. Data was analyzed with regression analysis using generalized linear models to determine the relationship between the green manure seeding rate and Kamut seeding rate and final Kamut biomass and yield response.

### On Farm Precision Experimentation of Seeding Rates and Harvest Yield

In the field portion of this project, on farm precision experimentation (OFPE) was used to generate field scale experiments to determine potential optimum rates of nitrogen-fixing green manure cover crops, and cash crops such as wheat, barley, or Kamut, and on one farm bloodmeal was varied to determine its optimum input rate. Rates were varied randomly across the field in order to understand within field spatial variation based on continuous georeferenced yield monitor combine data. As all organic farmers face weed challenges, variation in weed density was manually sampled. A total of four separate Montana certified organic farms collaborated on this project, and each farm conducted experiments on one field. Farms are here referred to as farms A:D. The first three farms conducted OFPE with seeding rates of green manures and cash crops, and farm D experimented with varied rates of bloodmeal, an organically approved source of nitrogen, on wheat cash crops. The acreages of the fields varied from 32 to 93 hectares.

Initially one field per farm was extensively soil sampled (approximately one sample for every two acres). The samples were analyzed for total nitrogen content in Montana State University's Environmental Analytics Laboratory (EAL) and were used to build a fertility map of each field. Wherever possible, the fertility map, previous yields, and other geographic variables were used to stratify GM seeding rate strips across the field to maximize variability within each randomized replicated strip. Experiments were initially designed to incorporate five rates of pea at 1.5X, 1.0X, 0.75X, 0.5X and 0X of farmer selected rates. These were planted with standard planters owned by each farmer. Given differences in equipment and ever-changing field and weather conditions, the exact number and level of different rates was not followed precisely. In year two, differing seed rates of cereal crop were planted on top of the green manure variable strips such that each green manure rate had every level of the cereal crop overlaid. Cereal seed rates were to similarly be 1.25X, 1.0X, 0.75X, and 0.5X of recommended organic rates. These were target rates, and in practice rates were adjusted by farmers' specific needs as seen below.

The farms joined the project at different times and experiments therefore started in different years. In 2019 farmer A planted peas on a 32-hectare field (soil sampled) at rates of 0, 60, 90, and 135kg/ha, and tilled them in after approximately eight weeks. In 2020 they planted barley over the same field at 60, 75, and 90 kg/ha, but unfortunately hail damage wiped out 90% of the crop, and the remaining plant matter was removed as hay bales. Barley was again planted at the same rates in the spring of 2021, and harvested at the end of July 2021. In spring 2020 farmer B planted peas at 70, 90, 110, 130 kg/ha on a 32-hectare field till them in in summer and planted winter wheat at a single rate in fall 2020. In spring 2020 farmer C planted peas at rates of 80, 100, 120, and 140 kg/ha across a 93 hectare field and tilled them in approximately eight weeks later. Winter wheat was planted in fall 2020 across the field at varied rates of 55, 70, 85, and 100 kg/ha. Farmer D planted spring wheat at a uniform rate across a 67-hectare field. Bloodmeal was applied across the growing wheat at rates of 0, 3.5, 7, 15, 20 kg of N/ha. Yield data were collected from the combine monitors. Crop and weed biomass data were collected during the growing season to track how the varied seeding rates affected crop and weed growth. Approximately 60 points were chosen at random across each field and stratified on seeding rate. Samples of both crop and weed species were taken as conducted by Bussler et al. (1995).

### Statistical Analysis

Point data from the seeder (as applied map) and combine (yield map) were added to a square 10m x 10m grid of the field. Normalized Difference Vegetation Index (NDVI) and topographic information and satellite data were compiled via Google Earth Engine using satellite information from NASA's Modis and Landsat 8 instruments (He et al., 2018) and were also added to the data set. Means of points were taken when more than one point existed per cell. To remove border effects, headlands, as measured by 30 m from the field edge, were removed from analysis. From this accumulated data set random forest models were constructed to find optimized seeding rates for minimized weed presence and maximized yield. Moran's I test, linear models and random forest models were tested in R (Version 1.1.453 – © 2009-2018 RStudio, Inc.), on data sets assembled in QGIS. Moran's I test was used to verify that the seeding rate variable interacted spatially and affected weeds and yields differently in different parts of the field. The random forest model used for each field varied based on input data, but a typical model is seen below.

*Model 1 = Yield ~ f {Pea Seed Rate, Barley Seed Rate, Elevation, X, Y, Slope, Aspect, Topographic Position Index, Weed Biomass 2019-2021, NDVI 2019-2021, Precipitation 2021, Bulk Density, Clay Content, Soil pH, Soil Water Content, Soil Carbon Content, Nitrate at 10 and 30cm}*

Model 1 included yield as the response variable to seeding rate of pea and wheat, and topographic variables: elevation, x and y coordinate points, slope, aspect, and Topographic Position Index; also included were the season's weed values as found from interpolated sample data; satellite data including: Normalized Difference Vegetation Index (NDVI) from the harvest year, the year prior to harvest, and two years prior to harvest, the current year precipitation, bulk density, clay content, pH, water content, and soil carbon; and soil sample data including: nitrate to six inches, and nitrate to 24 inches. Based on the predictions of this model ideal seeding rates were estimated for maximized yield across each grid cell. As an example, a subset of the variables collected for the above method is shown in maps in figure 1 including topographic variables (1A), satellite variables (1B), manually sampled variables (1C), and machine variables (1D).

### Economic Analysis

Net returns were calculated based on farmers' reported costs of seed and price received for product. Prices received in our tested harvest years ranged from \$13 a bushel to \$23 a bushel. To compare these to historic conditions, a data set tracking organic prices from grain elevators over the last 21 years was used. Varied fixed rates collected from the USDA were also included over these years (Table 1). To ascertain the probability that one method would outcompete another, a Monte Carlo simulation analysis was conducted using the 21 years of economic data such that the simulation outcome of yield and recommended seeding rates was tested across every year of economic data. In this way we found the probability that one method (farmer chosen rates, optimum average rates, or variable seeding rate) was better than the others given varied economic conditions.

Table 1

Economic values used in modeling including price received for organic wheat from 2020 to 2021, and fixed costs

| Year | Organic Price Recieved ($/bu) | Fixed Costs ($) |
|---|---|---|
| 2000 | 6.17 | 88.16 |
| 2001 | 6.24 | 86.83 |
| 2002 | 6.56 | 85.23 |
| 2003 | 6.60 | 92.04 |
| 2004 | 6.33 | 89.96 |
| 2005 | 6.30 | 97.35 |
| 2006 | 6.51 | 102.76 |
| 2007 | 10.26 | 108.35 |
| 2008 | 20.09 | 117.70 |
| 2009 | 11.12 | 138.08 |
| 2010 | 10.85 | 143.26 |
| 2011 | 11.48 | 152.12 |
| 2012 | 10.07 | 158.03 |
| 2013 | 11.38 | 161.50 |
| 2014 | 14.65 | 166.40 |
| 2015 | 16.43 | 163.27 |
| 2016 | 14.92 | 163.14 |
| 2017 | 13.66 | 171.68 |
| 2018 | 15.67 | 176.65 |
| 2019 | 12.07 | 181.78 |
| 2020 | 10.67 | 177.93 |
| 2021 | 10.47 | 182.41 |

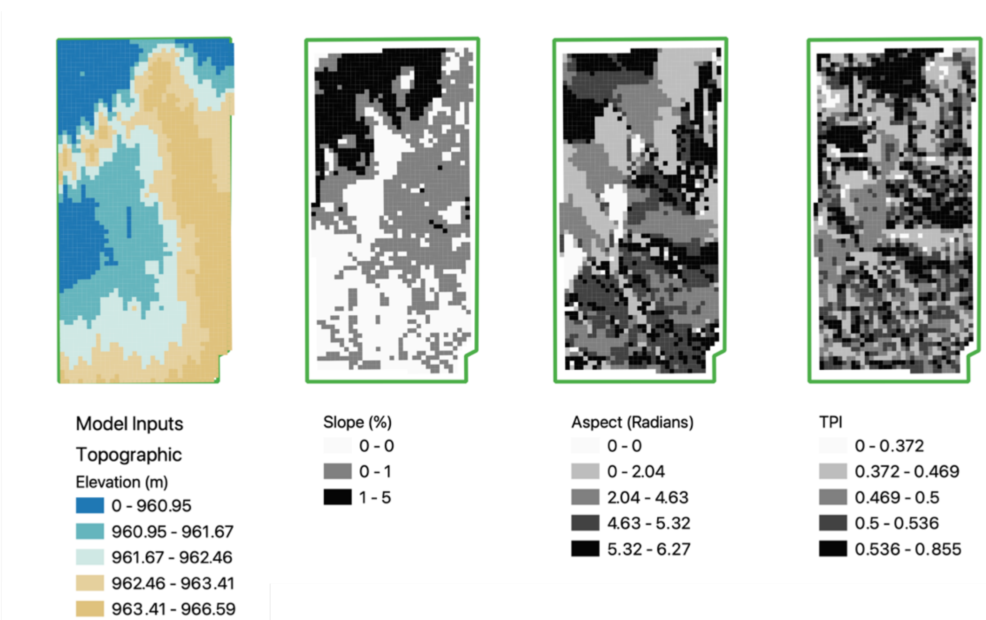


**Figure 1A) 32 hectare Field A showing topographic input variables for modeling including panel 1) elevation, panel 2) slope, panel 3) aspect, and panel 4) topographic position index (TPI).**

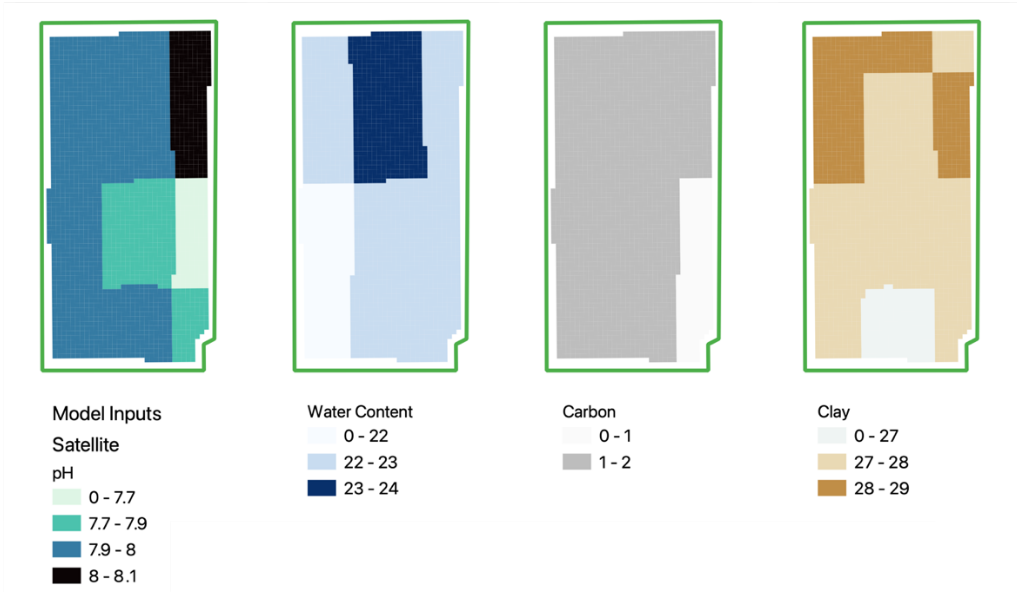


**Figure 1B) 32 hectare Field A showing satellite input variables for modeling including panel 1) pH, panel 2) water content, panel 3) carbon content (%), and panel 4) clay content (%).**

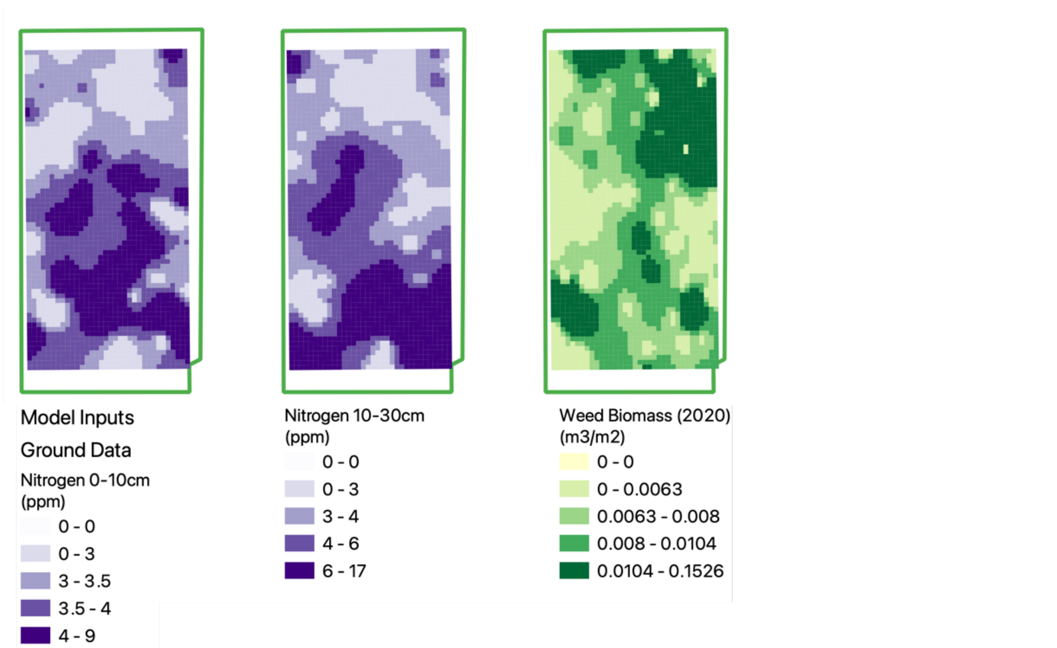


**Figure 1C) 32 hectare Field A showing on the ground collected data for modeling including panel 1) nitrate 0-10cm, panel 2) nitrate 10-30cm, and panel 3) sampled weed biomass in cubic meters per square meter.**

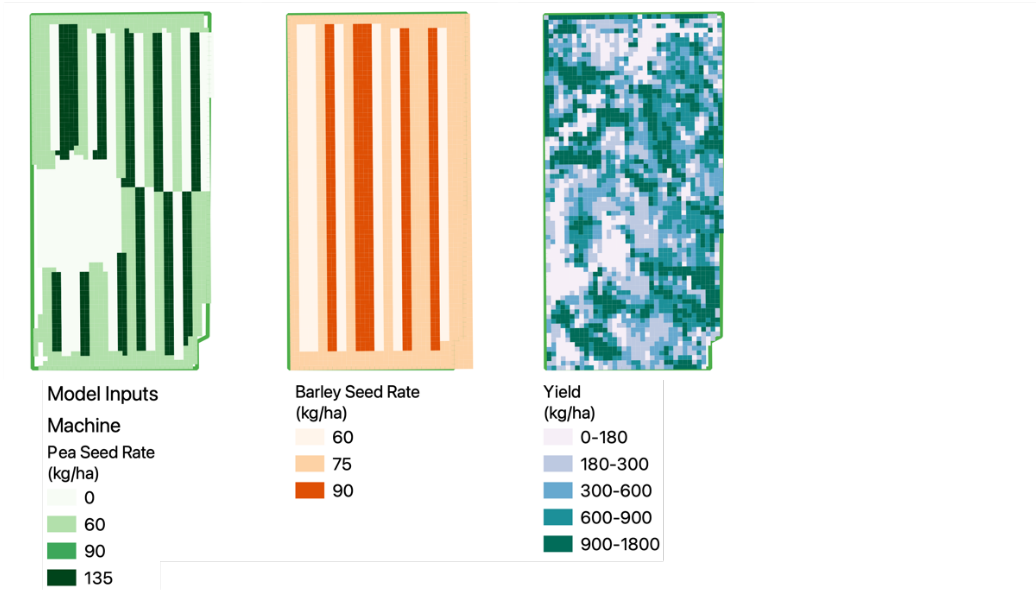


**Figure 1D) 32 hectare Field A showing on the machine collected data for modeling including panel 1) experimental pea seeding rates from 2019 (missing patch too wet to seed), panel 2) experimental barley seeding rates from 2020 (repeated in 2021 due to hail 2020), and panel 3) yield results from barley harvest 2021.**

# Results

## Greenhouse Study

Results from the greenhouse study confirmed the first principle relationship that seeding rates of green manure affected nitrogen availability for the following cash crop. When the peas were terminated at first flower stage, the presence of root nodules indicated that they were fixing nitrogen. Soil from each box was sampled throughout the experiment and N levels in parts per million (ppm) can be seen at each experimental time point in figure 2. When peas were planted the soil had a mean level of soil nitrate of 4.12 ppm. When the peas were terminated eight weeks later soil N had been consumed by the pea plants and nitrate levels declined to a mean of 3.26 ppm. After the six-week decomposition period of the pea biomass a significant amount of N was added to the soil (p-value = 0.009) and the N level rose to an average level of 12.46 ppm. This is highlighted to verify that nitrogen fixation did indeed occur within the pea plant root. Finally, at Kamut harvest the soil N levels fell to 0.700 ppm as the cereal crop consumed nearly all of the plant available N in the soil converting it into plant biomass and harvestable Kamut seed.

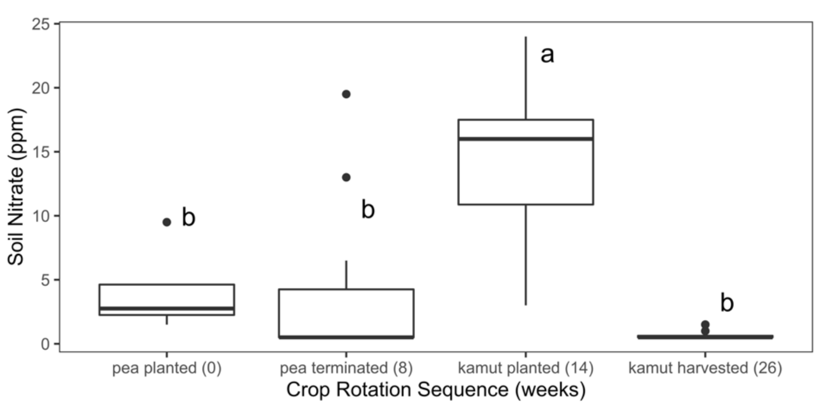


**Figure 2) Soil nitrogen levels in ppm at each experimental point, from the original soil the peas were planted into, to the stage when peas were terminated, to the Kamut planting stage, and finally at the end of the experiment when the Kamut was harvested.**

Nitrogen change was tracked in each individual box such that the effect of pea seeding rate could be assessed. In figure 3 we can see how pea seeding rates created varied levels of change in nitrate between pea and kamut seeding times; as pea seeding rates rise the plant available nitrogen also rises. While the specific curve is somewhat unclear due to high variation; there does appear to be an optimum; there is weak evidence (p-value = 0.19) to support our model showing that soil nitrate reaches a peak at around 90 kg/ha pea seed rate and then begins tapering off as higher pea seeding rates become detrimental to pea growth as predicted by plant competition models (Freckleton et al., 2009).

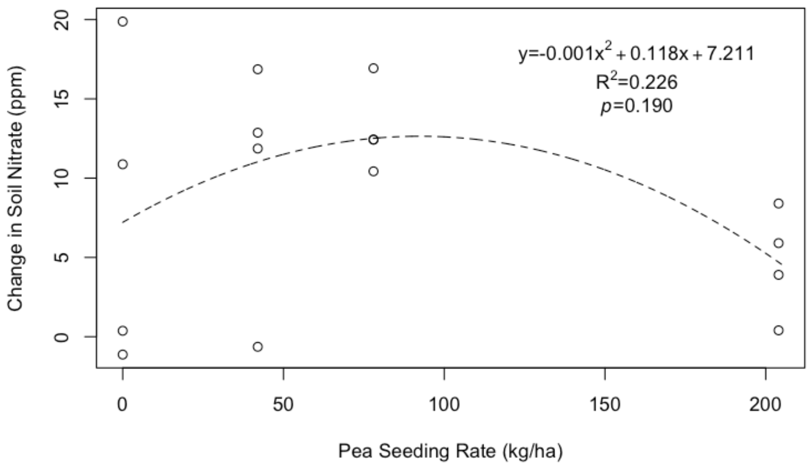


**Figure 3) Change in soil nitrate in ppm between original pre-experiment soil and soil at the point of Kamut planting when pea biomass had decomposed. Each point represents each individual planting box and its soil contents.**

In the next stage of the experiment, we tracked how Kamut and pea seeding rates would affect final Kamut yield. In figure 4, the curve shown fits a quadratic curve wherein the yield gains slow as seeding rates rise, reaching a maximum yield around the maximum tested seeding rate of Kamut. As Kamut seeding rate rises we found strong evidence that overall Kamut yield also rises reaching a peak level around a seeding rate of 120 kg/ha ($p = 0.027$). In figure 5 we see the effect of the pea seeding rate on Kamut yield. In this situation we are tracking how the pea seeding rates affected the following crop's yield. These results show a very similar trend to the soil nitrogen affects from pea seeding rate seen in figure 3. Here again we see weak evidence that pea seeding rate creates a maximum response in Kamut yield around the 100kg/ha mark ($p = 0.160$). While repetitions were insufficient to show significance (of $\alpha = 0.05$), we can nevertheless observe likely and predicted trends wherein low and high seeding rates are beyond optimum levels. These trends highlight the ability of a pea green manure crop to provide nitrogen to the following crop, while specific seeding rates of both the green manure and the cash crop are important in finding optimums.

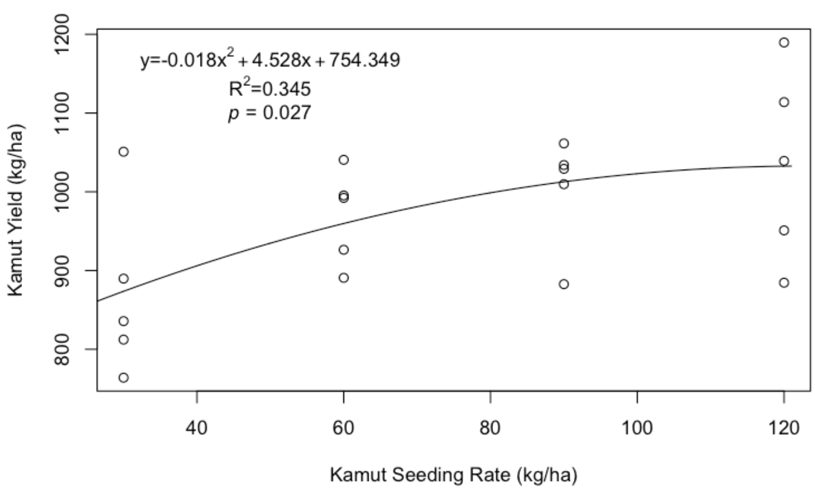


**Figure 4) Kamut yield per garden box as a function of varied Kamut seeding rates.**

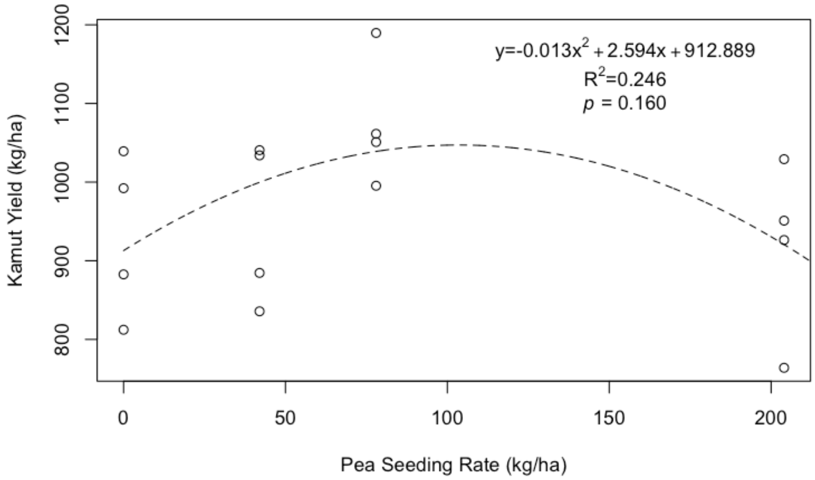


**Figure 5) Kamut yield per garden box as a function of pea seeding rate.**

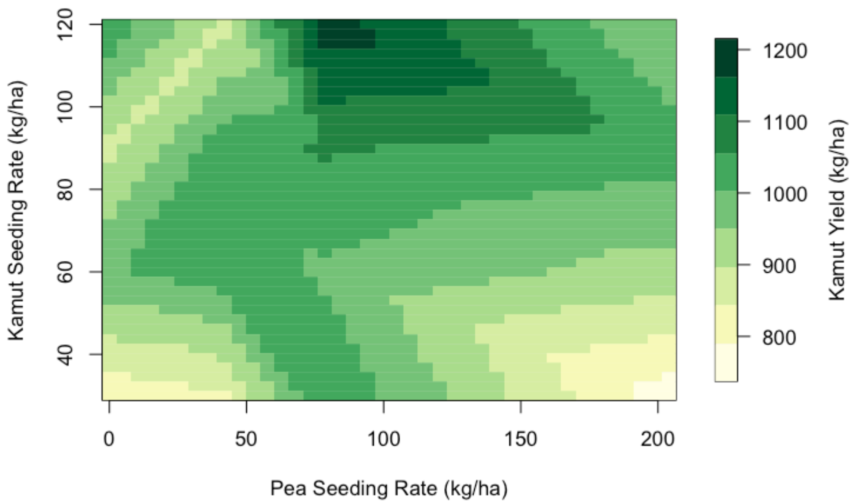


**Figure 6) Kamut yield as a function of Kamut seeding rate and underlying pea seeding rates, highlighting the ability to find overlapping optimums.**

By combining pea and Kamut seeding rates, we determined overlapping seeding rates that lead to the highest yielding combinations. As noted earlier optimum pea seeding rate appears around the 90-100kg/ha zone, and Kamut yields respond to this as shown by the dark green area rising through the center of figure 6. Kamut yields tended to increase towards the higher rates tested, but appeared responsive to specific levels of pea seeding rates. We expect this trend then to be replicable for spatially variable field locations where each specific field space will be optimizable for both green manure and cash crop seeding rates. This was an important step in validating the proof of concept for our field experiments with varied pea and cereal crop seeding rates.

### On Farm Precision Experimentation of Seeding Rates and Harvest Yield

A list of final outcomes is shown in tables 2 and 3. A specific example of the results is shown from farm A in compiled maps shown in figure 7A-D. From farm A we can see the output from simulations as generated using model one from methods in the random forest model. These simulations predict yield and net return values based on three input scenarios. In the first scenario we set the seeding or bloodmeal rates as a single rate that would be typically chosen by a farmer (FRM) and spread across the whole field; in the example shown this is pea green manure followed by the cash crop of barley. The second scenario shows optimized average rates (OAV) across the whole field based on maximizing net return using only one rate across the field. The third scenario displays optimized variable rates (VRT) of pea and barley across each cell of the field. The fourth panel of figure 7 illustrates new randomized experimental rates that incorporate half of the field and the other half uses the newly discovered optimum rates as a baseline for improving farmer net return. This final situation represents our recommendation for the farmer to continue experimentation over future years even as they add optimized zones to their management.

Table 2

Agronomic results from four experimental farms including their nitrogen source, cash crop, actual yield, and simulated results of predicted yields based on farmer chosen rates (FRM) optimum average rates (OAV), and optimum variable rates (VRT) *for farm D bloodmeal was varied not pea seeding rates

| Farm | Nitrogen Source | Cash Crop | Actual Yield (kg/ha) | FRM Pea Seed Rate (kg/ha)* | FRM Cash Crop Seed Rate (kg/ha) | FRM Yield (kg/ha) | OAV Pea Seed Rate (kg/ha)* | OAV Cash Crop Seed Rate (kg/ha) | OAV Yield (kg/ha) | VRT Pea Seed Rate (kg/ha)* | VRT Cash Crop Seed Rate (kg/ha) | VRT Yield (kg/ha) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| A | Pea | Barley | 675.0 | 90 | 75 | 675.0 | 60 | 60 | 660.6 | 62.45 | 61.02 | 669.0 |
| B | Pea | Winter wheat | 1585.2 | 129 | NA | 1560.6 | 116 | NA | 1622.4 | 115.00 | NA | 1660.8 |
| C | Pea | Winter wheat | 3102.6 | 100 | 70 | 3098.4 | 70 | 49 | 3093.0 | 82.11 | 59.97 | 3124.2 |
| D | Blood meal | Spring wheat | 981.0 | 20 | NA | 1002.6 | 0 | NA | 975.6 | 0.00 | NA | 975.6 |

Table 3

Simulated economic results from four experimental farms including net returns under farmer chosen rates (FRM), predicted optimum average rates (OAV), and predicted optimum varied rates (VRT). Also listed are the probabilities that the variable rate outcompeted the farmer chosen or optimum average rates given 21 years of economic variability

| Farm | Nitrogen source | Cash Crop | Net Return FRM ($/ha) | Net Return OAV ($/ha) | Net Return VRT ($/ha) | %VRT > FRM | %VRT > OAV |
|---|---|---|---|---|---|---|---|
| A | Pea | Barley | 153.72 | 179.39 | 180.51 | 100 | 100 |
| B | Pea | Winter wheat | 272.75 | 306.11 | 323.68 | 100 | 100 |
| C | Pea | Winter wheat | 964.21 | 981.33 | 983.66 | 100 | 67 |
| D | Blood meal | Spring wheat | 36.05 | 82.78 | 82.78 | 100 | 0 |

In scenario one, shown in figure 7A, farmer chosen rates of pea (90 kg/ha) and barley (75 kg/ha) are shown in panels 1 and 2, followed by yield and net return in panels 3 and 4. Due to low rainfall in 2021, yields were relatively low on this field (675 kg/ha as seen in table 2). This effect is picked up in the model and when farmer chosen rates were simulated across the field the predicted yield was similarly low (658.8 kg/ha), generating a predicted net return of $153.72/ha. The red and orange areas of the map denote the poorest performing areas of the field and they tend to correspond to weedy areas of the field (figure 1C), and to areas of higher elevation (figure 1A). Net returns were likely low in those areas due to weed competition and lack of moisture. These effects highlight the variability at play across the field.

Figure 7B shows simulated results from a scenario in which one optimum rate was selected based on the results of our experiment. In this instance we note that the model selected the lowest allowable rates for an optimized single rate. This is likely an effect of the very dry year that was the last year of this experiment. In low precipitation years lower plant densities perform better as they use less water. By lowering the seeding rates our model predicted an increase in yield; due to decreased seed costs and increased yield a higher net return of $179.39/ha was found. These net returns come from both lowering seeding rates where they are not conducive to further yield growth, and from increasing yield by reducing intra-crop competition for water.

These gains are further improved upon when variable rate of both pea and barley are planted across the field (figure 7C). In this scenario we simulated the farmer planting specific varied rates of both cover and cash crop to maximize net return. We saw further yield gains here as areas of the field that the model predicts can support higher plant densities are enabled to do so. In this way those prime growing areas of the field increase plant matter and consequent yield. Similar to the greenhouse experiment where higher cover crop densities produced higher cash crop yields, higher cover crop densities were predicted to improve cash crop outcomes. Through experimentation we have been able to pinpoint those areas and select them for increased plant densities in future seasons. This method maximized net returns to a predicted $180.51/ha level, an increase of $26.79/ha above what the regular farmer used rates are predicted to have generated.

To compare these methods against each other statistically, we used 21 years of historic economic data to understand how economic variation may favor one method over another. A compilation of these results for each farm is shown in Table 3. Following the example of farm A to this table we see that the variable rate scenario outcompetes both the farmer chosen rates, and the optimum average rates, in every year of economic conditions sampled. This same result was seen in farm B where the variable rate scenario fully outcompeted the other two scenarios 100% of the time. On farm C there was less certainty. While the variable rate scenario outcompeted the farmer chosen rates every time, the variable rate only outcompeted the optimum average scenario 67% of the time. This emphasizes that while variable rate is typically the best input rate strategy, the optimum average rate is a close second. Indeed on farms A, B, and C, the optimum average net return was considerably higher than the farmer chosen rate, but much closer to the optimized variable rate method.

Farm D was the exception to the trends seen on the other farms. In this situation the farmer applied blood meal in order to experiment with the effect of varied rates of nitrogen directly on their cash crop of spring wheat. While our goal as researchers was to learn about the variation in the field and optimize input rates, a broader result showed that blood meal had very little effect on the wheat yield. Due to its poor showing, any use of the product (which cost the farmer $1 per pound of nitrogen added per acre), reduced the farmer’s net return. Due to the experiment, the farmer discontinued their use of the product and is exploring other organic nitrogen inputs instead. The optimized rate of bloodmeal is zero on every grid cell of the field; so in this instance the optimized variable input rate never outcompetes the optimized single rate. The results of these experiments highlighted the variability present across every field tested, and the ability to vary input seeding rates or other inputs to maximize farmer net return.

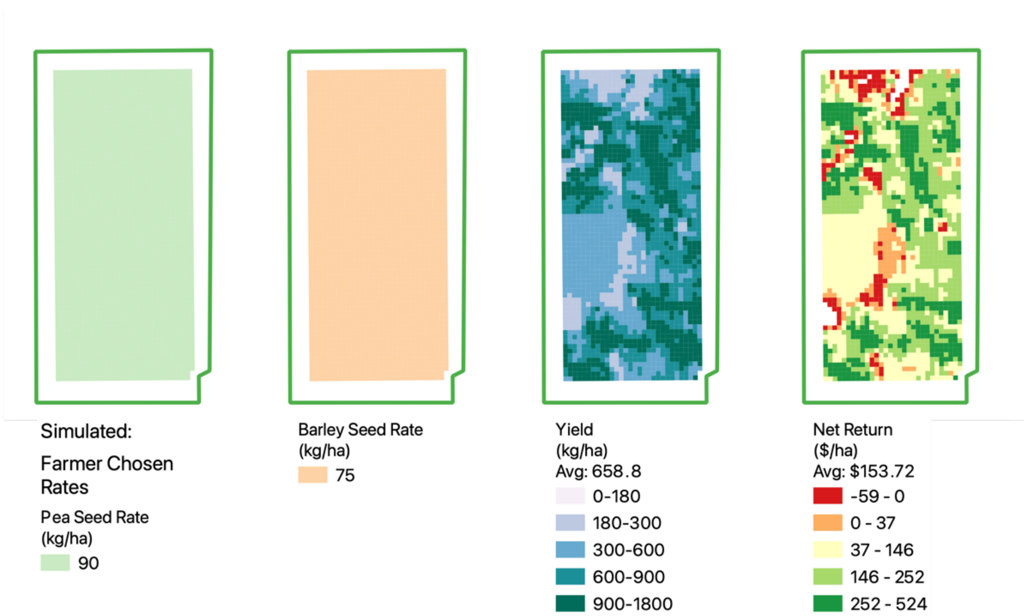


**Figure 7A) 32 hectare Field A showing simulated results of applying farmer chosen single rates. Panel 1) pea seeding rate, panel 2) barley seeding rate, panel 3) simulated yield from random forest model shown in model 1, and panel 4) net return given seeding rates and simulated yield.**

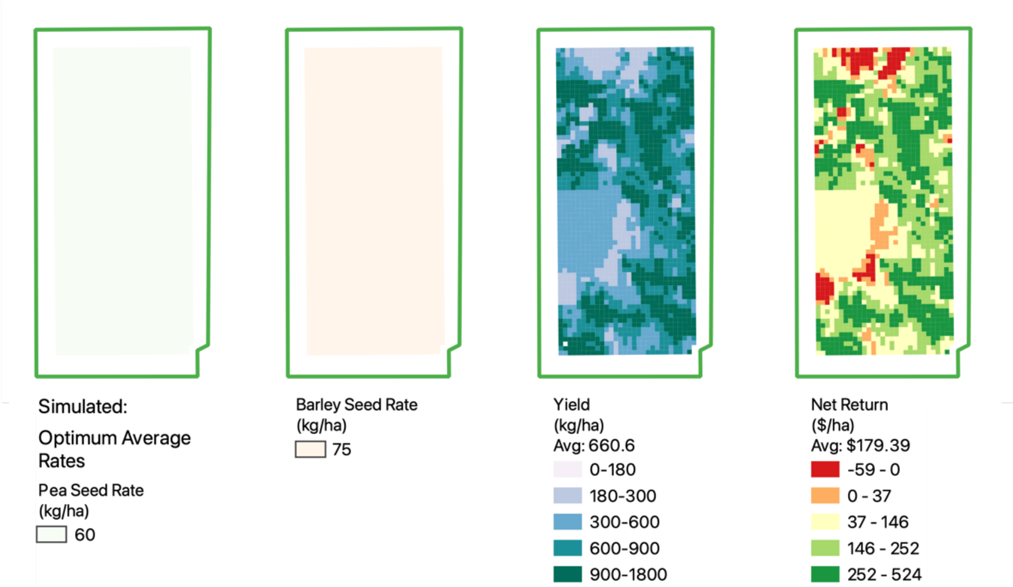


**Figure 7B) 32 hectare Field A showing simulated results of applying optimum average rates for pea (panel 1) and barley (panel 3) which the model predicts would garner highest net return without varying rates. Panel 3) simulated yield given these rates, and panel 4) net return given these seeding rates and simulated yield.**

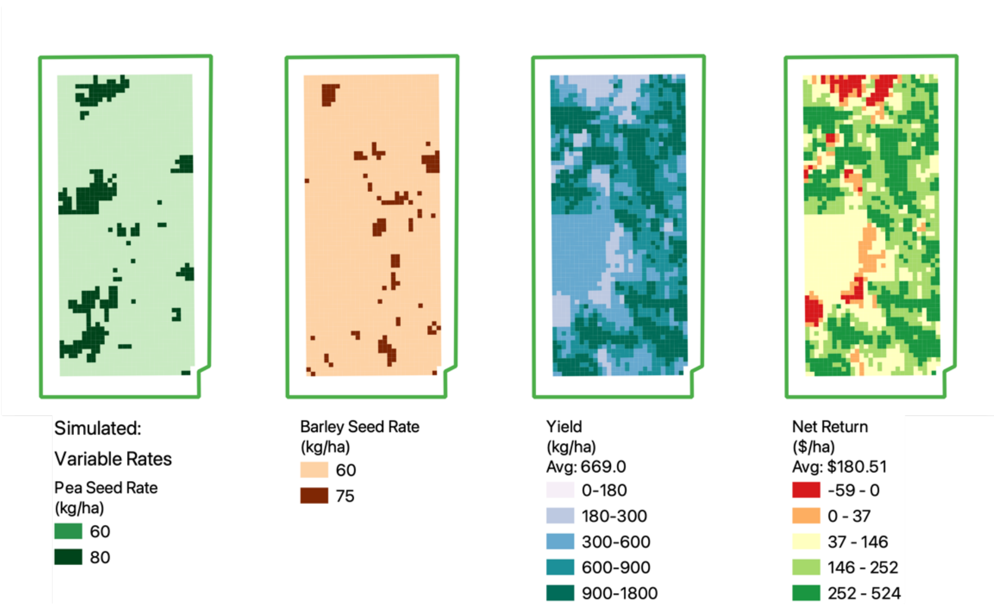


**Figure 7C) 32 hectare Field A showing simulated results of applying optimum variable rates for pea (panel 1) and barley (panel 3) the model predicts would garner highest net return given the option of varying rates in every cell across the field. Panel 3) simulated yield from random forest model shown in model 1 given variable rate seeding rates, and panel 4) net return given these seeding rates and simulated yield.**

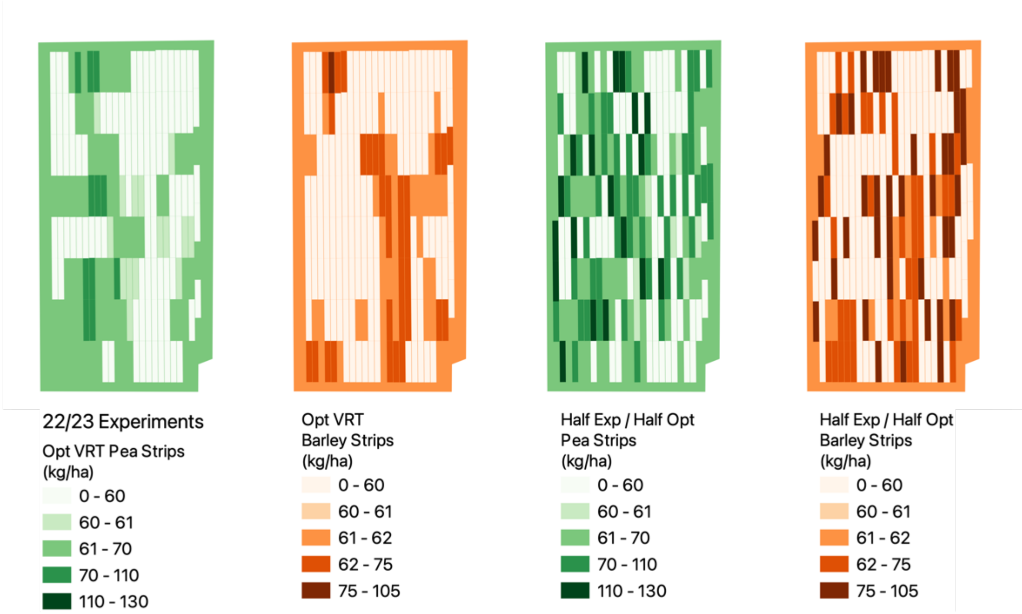


**Figure 7D) 32 hectare Field A showing optimum variable rates given actual seeder capabilities in width (21m) and length given speed of variable rate change (73m); panel 1) optimum variable pea rates, 2) optimum variable barley rates, and in panels 3 and 4) half the strips are randomized for continued experimentation. These are the rates we would recommend for the farmer the following seasons this rotation repeats.**

# Discussion

It is well understood that spatial variability across fields can and should be accounted for in farming practices. In pre-modern agriculture, farmers managed small areas of land, understood the variation across their domain, and were able to effectively manage it to maximize yield returns. Using the power of precision agriculture we can begin to steer industrial agricultural operations, be they organic or otherwise, back toward these more holistic management methodologies (Garbach et al., 2017; Lacoste et al., 2021). From this experiment we were able to generate greater understanding of field variability, which was inherently known to exist, and begin showing farmers a methodology of understanding how that variability interacts with their crop, and how they can maximize their benefits from it by responding to that field variability with their own varied input rates. Specifically, we were able to see this in practice through varied seed inputs of cover and cash crop across organic farms in Montana.

Moving forward, these results can be harnessed to deploy optimized input rates on fields that have been experimented on. Continued long term experimentation is crucial; while an initial sequence of experiments revealed and built upon understandings of spatial variability, continued experimentation will reveal temporal variability, an equally key component of farm variation (Lawrence et al., 2015). In arid Montana, a focus on temporal variability will concentrate on precipitation, the key weather variability of concern for farmers. The lack of variability in precipitation patterns within the results shown here is limitation that will be overcome with repeated experimentation in the future. Each farmer has expressed a keen interest in continued experimentation, and results will vary year to year as the climate naturally moves through wetter and dryer cycles.

It hoped that the results of this project can help farmers mitigated the effects of climate change, which are already impacting agriculture (Liu et al., 2022; Ray et al., 2019). Because this project and its outcomes focus on the ability of farmers to adaptively manage using constantly updated in-field conditions, the OFPE methodology is a prime example of how farmers can prepare to manage in an era of climate change. Since the models respond to real conditions, as the climate continues to change, farmers can update their management practices to suit.

There are many possible future directions of this work. Because the project aims to provide free information to farmers, it will be useful to incorporate as much remote sensing data as possible.

Many satellite soil and vegetation indexes are incorporated into our models, and moving forward these indexes will likely improve in both scale and accuracy and thus predictive power. It is hoped that sampling methods for weed and soil can be replaced in the coming years with accurate remote sensing variables. This is a transition that appears well on its way (Robb et al., 2021). While much work has been done to make this projects methods available to farmers (see http://trialdesign.difm-cig.org/demo, and https://github.com/paulhegedus/OFPE), we hope to improve these designs and make them ever more accessible to farmers, consultants, and researchers alike.

# Conclusion

Our goals in this research were to first determine that varied seeding rates of green manure cover crops can affect yield in subsequent cash crop harvests, and secondly to determine that these rates could be varied in a way to determine actual field site specific optimums for farmers using PA. The greenhouse results highlighted in figure 7 showed that optimum overlapping rates of green manure and cash crop rates could be found. In the field experiments where farmers deployed OFPE over whole fields we were able to determine site specific optimums for both cover and cash crops that were shown to outcompete farmer chosen rates. Through these experiments we have established OFPE in organic systems as a viable method of deploying underutilized PA technologies in order to improve farmer net returns.

Our results have shown that natural variability can be incorporated and built upon in farm management strategies. This mode of thinking, enabled by precision technologies, practiced with on farm experimentation, and conducted by farmers for their own net gain, can allow farmers to work in concert with local ecologies and work with variability rather than against it. Precision technology then can allow for holistic and agroecologically managed farms that are healthier for nature, farmers, and the broader human population, creating long term resiliency for these agroecological spaces and their interconnected surroundings.

### Acknowledgements

Thank you to Western Sustainable Agriculture Research and Education for funding this project, and the farmer collaborators who contributed so much time and effort.

# References

Baird, J. M. (2007). *Optimal seeding rates for organic production of field pea and lentil*.

Bussler, B. H., Maxwell, B. D., & Puettmann, K. J. (1995). Using Plant Volume to Quantify Interference in Corn ( Zea mays ) Neighborhoods Author ( s ): Brett H . Bussler , Bruce D . Maxwell and Klaus J . Puettmann Published by : Cambridge University Press on behalf of the Weed Science Society of America Stable UR. *Weed Science Society of America*, *43*(4), 586–594.

Cook, S., Lacoste, M., Evans, F., Ridout, M., Gibberd, M., & Oberthür, T. (2018). *An On-Farm Experimental philosophy for farmer-centric digital innovation*. *5*(October).

Duff, H., Hegedus, P. B., Loewen, S., Bass, T., & Maxwell, B. D. (2022). *Precision Agroecology*.

Finger, R., Swinton, S. M., El Benni, N., & Walter, A. (2019). Precision Farming at the Nexus of Agricultural Production and the Environment. *Annual Review of Resource Economics*, *11*(1), 313–335. https://doi.org/10.1146/annurev-resource-100518-093929

Freckleton, R. P., Watkinson, A. R., & Rees, M. (2009). Measuring the importance of competition in plant communities: Forum. *Journal of Ecology*, *97*(3), 379–384. https://doi.org/10.1111/j.1365-2745.2009.01497.x

Gan, Y. T., Wang, J., Bing, D. J., Miller, P. R., & McDonald, C. L. (2007). Water use of pulse crops at various plant densities under fallow and stubble conditions in a semiarid environment. *Canadian Journal of Plant Science*, *87*(4), 719–722. https://doi.org/10.4141/P06-117

Garbach, K., Milder, J. C., DeClerck, F. A. J., Montenegro de Wit, M., Driscoll, L., & Gemmill-Herren, B. (2017). Examining multi-functionality for crop yield and ecosystem services in five systems of agroecological intensification. *International Journal of Agricultural Sustainability*, *15*(1), 11–28. https://doi.org/10.1080/14735903.2016.1174810

Griffin, T. W., Miller, N. J., Bergtold, J., Shanoyan, A., Sharda, A., & Ciampitti, I. A. (2017). Farm's sequence of adoption of information-intensive precision agricultural technology. *Applied Engineering in Agriculture*, *33*(4), 521–527. https://doi.org/10.13031/aea.12228

He, M., Kimball, J. S., Maneta, M. P., Maxwell, B. D., Moreno, A., Beguería, S., & Wu, X. (2018). Regional crop gross primary productivity and yield estimation using fused landsat-MODIS data. *Remote Sensing*, *10*(3). https://doi.org/10.3390/rs10030372

Johnston, A. M., Clayton, G. W., Lafond, G. P., Harker, K. N., Hogg, T. J., Johnson, E. N., May, W. E., & McConnell, J. T. (2002). Field pea seeding management. *Canadian Journal of Plant Science*, *82*(4), 639–644. https://doi.org/10.4141/P02-001

Lacoste, M., Cook, S., McNee, M., Gale, D., Ingram, J., Bellon-Maurel, V., MacMillan, T., Sylvester-Bradley, R., Kindred, D., Bramley, R., Tremblay, N., Longchamps, L., Thompson, L., Ruiz, J., García, F. O., Maxwell, B., Griffin, T., Oberthür, T., Huyghe, C., … Hall, A. (2022). On-Farm Experimentation to transform global agriculture. *Nature Food*, *3*(1), 11–18. https://doi.org/10.1038/s43016-021-00424-4

Lawley, Y. E., & Shirtliffe, S. J. (2004). Optimum seeding rates for three annual green manure crops : the effect of weed competition. *Soils and Crops Workshop*.

Lawrence, P. G., Rew, L. J., & Maxwell, B. D. (2015). A probabilistic Bayesian framework for progressively updating site-specific recommendations. *Precision Agriculture*, *16*(3), 275–296. https://doi.org/10.1007/s11119-014-9375-4

Liu, J., Desjardins, R. L., Wang, S., Worth, D. E., Qian, B., & Shang, J. (2022). Climate impact from agricultural management practices in the Canadian Prairies: Carbon equivalence due to albedo change. *Journal of Environmental Management*, *302*(PA), 113938. https://doi.org/10.1016/j.jenvman.2021.113938

McCauley, A. M., Jones, C. A., Miller, P. R., Burgess, M. H., & Zabinski, C. A. (2012). Nitrogen fixation by pea and lentil green manures in a semi-arid agroecoregion: Effect of planting and termination timing. *Nutrient Cycling in Agroecosystems*, *92*(3), 305–314. https://doi.org/10.1007/s10705-012-9491-3

Mccauley, A., Miller, P., Holmes, J., Burgess, M., Jones, C., & Check-off, F. (2012). *Fertilizer Facts*. *61*.

Miles, A., DeLonge, M. S., & Carlisle, L. (2017). Triggering a positive research and policy feedback cycle to support a transition to agroecology and sustainable food systems. *Agroecology and Sustainable Food Systems*, *41*(7), 855–879. https://doi.org/10.1080/21683565.2017.1331179

Miller, P. R., Lighthiser, E. J., Jones, C. A., Holmes, J. A., Rick, T. L., & Wraith, J. M. (2011). Pea green manure management affects organic winter wheat yield and quality in semiarid Montana. *Canadian Journal of Plant Science*, *91*(3), 497–508. https://doi.org/10.4141/cjps10109

Mitchell, S., Weersink, A., & Erickson, B. (2018). Adoption of precision agriculture technologies in ontario crop production. *Canadian Journal of Plant Science*, *98*(6), 1384–1388. https://doi.org/10.1139/cjps-2017-0342

Ray, D. K., West, P. C., Clark, M., Gerber, J. S., Prishchepov, A. v., & Chatterjee, S. (2019). Climate change has likely already affected global food production. *PLoS ONE*, *14*(5), 1–18. https://doi.org/10.1371/journal.pone.0217148

Robb, B. C., Olsoy, P. J., Mitchell, J. J., Caughlin, T. T., Delparte, D. M., Galla, S. J., Fremgen-

Tarantino, M. R., Nobler, J. D., Rachlow, J. L., Shipley, L. A., & Forbey, J. S. (2021). Near-infrared spectroscopy aids ecological restoration by classifying variation of taxonomy and phenology of a native shrub. *Restoration Ecology*, *October*. https://doi.org/10.1111/rec.13584

Spies, J. M. (2008). The Effect of Field Pea ( Pisum sativum L .) Basal Branching on Optimal Plant Density and Crop Competitiveness Permission to Use. *The Effect of Field Pea ( Pisum Sativum L .) Basal Branching on Optimal Plant Density and Crop Competitiveness Permission to Use*, 113.

Tully, K. L., & McAskill, C. (2020). Promoting soil health in organically managed systems: a review. *Organic Agriculture*, *10*(3), 339–358. https://doi.org/10.1007/s13165-019-00275-1

Usukh, B. (2010). *the Impact of Lentil and Field Pea Seeding Rates on Dinitrogen*. *January*.

Wang, X., Gan, Y., Hamel, C., Lemke, R., & McDonald, C. (2012). Water use profiles across the rooting zones of various pulse crops. *Field Crops Research*, *134*, 130–137. https://doi.org/10.1016/j.fcr.2012.06.002

Zentner, R. P., Campbell, C. A., Biederbeck, V. O., Selles, F., Lemke, R., Jefferson, P. G., & Gan, Y. (2004). Long-term assessment of management of an annual legume green manure crop for fallow replacement in the Brown soil zone. *Canadian Journal of Plant Science*, *84*(1), 11–22. https://doi.org/10.4141/P02-188