

Rationale for field-specific on-farm precision experimentation

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ABSTRACT

Uncertainties in farming necessitate detailed knowledge of the production efficiencies to maintain sustainability. To accomplish ecologically based agriculture, with the goal of intensification by maximizing production and profit as well as minimizing environmental impact, we hypothesized that a site-specific knowledge base can be efficiently achieved through modern precision agriculture (PA) technologies at the field scale. The two goals of this study were to quantify the spatiotemporal variation of crop responses and the variables driving crop production, crop quality, and field-scale farmer net-return. We conducted on-farm experimentation (OFE) on several fields for three years where we varied nitrogen fertilizer rate as a management input, to induce changes in crop response. Using a Monte Carlo approach, we assessed the probability that crop responses varied across fields and between years. To determine the drivers of crop production, quality, and net-return, we performed sensitivity analyses to assess the impact of variation in the environment with the most influence on crop responses and farmer profits. Our analysis provided evidence that the degree of the response of winter wheat yield and protein content to variable nitrogen fertilizer rates are not homogenous across time and space. Elevation as a covariate to nitrogen fertilizer rate was the primary influence on predicted yields and protein across most fields, yet not among all fields and across years in fields. The drivers of net-return varied among fields and across years primarily between yield and protein. However, in some cases the most influential factor was the base price received, controlled by the grain elevators that growers sell to, indicating that in some fields and years, farmer's net-returns are dictated by variables outside of a farmer's control or ability to manage. These results provide basic evidence justifying the use of OFE for farm management and suggest that management needs to be specific to each field and point in time, with recommendations being made specifically for a field based on information gathered from that field. On-farm experimentation will enable farmers to identify these drivers and understand how their inputs influence yield and protein within fields. Using information provided by OFE with decision support systems can enable farmers to make informed management decisions that maximize their profits and increase the efficiency of chemical inputs, such as nitrogen fertilizer.

1. Introduction

In developed nations, the goal of agriculture has become agricultural intensification, synonymous with two objectives; maximization of crop production and the maximization of profits to accomplish economic sustainability (Elliot and Cole, 1989; Pretty, 2008; Talukder et al., 2020). Although harmful impacts of agriculture on neighboring ecosystems and human communities have been documented, little change in practices have been developed (Foley et al., 2011; Gliessman and Engles, 2014; Pretty, 2008; Tilman et al., 2011; Weiner, 2017). In addition, the uncertainties in agricultural production due to climate change and economics all necessitate more detailed knowledge of the efficiency of production within each farm to maintain sustainability

(Cambouris et al., 2014; McBratney et al., 2005). Results from other site-specific management studies indicate that a site-specific knowledge base will facilitate ecological intensification, defined as increased production through management based on ecological interactions, by maximizing production and profit as well as minimizing environmental impact (Bronson et al., 2006; Cambouris et al., 2014; Farid et al., 2016; Flowers et al., 2004; Huggins, 2010; Khosla et al., 2008; Koch et al., 2004; Link et al., 2008; Moshia et al., 2014). In addition, the intensification goal can be efficiently achieved through modern technologies at the field scale and collection of field specific data to inform management decisions (Cao et al., 2018). We begin by assessing the underlying assumption that crop field responses (e.g., grain yield or grain protein concentration) are site, time, and history of land use specific. Drawing

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on modern technologies to incorporate site-specific experimentation into adaptive management principles (Hecht and Crowley, 2020; Jackson et al., 2010; Lin, 2011) would overcome major drivers of variation in agroecological processes (e.g. crop responses to inputs) and increase resiliency of these systems. Our assessment started by determining if variation in crop responses were significant among fields and among years in the same field when crop species was held constant, and when nitrogen (N) fertilizer rates were experimentally varied on each field.

Field specificity of crop responses has been documented in small-holder farms in Africa where variation in crop yields varies between fields of the same farm based on soil fertility and geographic distance from the farmstead (Titttonell et al., 2005, 2007; Zingore et al., 2007b, 2007a, 2009). However, no such studies have been conducted in large scale industrial farms typical in the United States where all fields of the same farm typically receive the same management and fertilizer rate usage. This research differs from studies conducted in other systems due to the methods applied and the focus on how the distribution of crop responses to experimentally variable rates of N fertilizer vary in a given field across time, as well as compared to fields on the same farm that would typically receive the same management approach.

We tested the rationale for empirically driven field-scale adaptive management based on within-field information. The two goals of this study were to quantify the spatiotemporal variation of crop responses and the variables driving crop production, quality, and farmer net-return. Specifically, the first goal was to determine and compare the variation in dryland winter-wheat production (yield) and quality (grain protein concentration) (1) across years in a given field, and (2) between fields of the same farm in a given year. The second goal was to assess the drivers of crop production, quality, and net-return of the farmers within and across years. Determining the generalizability of spatial and temporal variation in crop response to a primary management factor (in this case N fertilizer) allowed us to test the hypothesis that every field requires field-specific experimentation over several years to identify optimized management for that field, where optimization can be defined as maximized crop yield, quality, farmer net returns or a combination of these responses.

We hypothesize that yield and protein responses to N fertilizer rates will vary across years in the same field and between fields on the same

farm. Additionally, we hypothesized that weather related variables will be constant drivers of the variation in crop response between fields on the same farm. With this assessment, we provide empirical evidence for the value of on-field experiments which take advantage of modern farm equipment technologies to make experimentation logistically and economically efficient and acceptable to farmers.

2. Methods

2.1. Study sites and data

Empirically driven adaptive management requires iterative experimentation and data collection from fields as well as testing of our hypotheses on the spatial and temporal extent of crop response variability. Our research was conducted using data from farmers with a 10-year participation agreement to collaborate and learn with the On-Field Precision Experiments (OFPE) group at Montana State University. Farmers were chosen based on their experience with PA technologies (yield monitor and protein monitoring data), and ability to perform variable fertilizer/seed rate application (VRA) in dryland winter wheat production. Three conventional farms, with varying numbers of fields per farm were selected for this study based on their levels of data availability and quality (Fig. 1, Table 1).

Comparisons in this study were based only on data from years where winter-wheat was grown. The same variety was planted in each of the experimentation years for a given farm. Farm B planted the winter wheat variety Brawl in each year of experimentation across all fields, Farm D used the winter wheat variety Northern in each field since 2015, and Farm I planted the winter wheat variety Yellowstone in all years that winter wheat was grown.

Each field selected has been subjected to experimental variable rate N fertilizer experiments in at least two years and has yield data available for at least one year prior to experimentation. Fertilizer rates were experimentally applied by randomly placing treatments of various rates across each field with replication, stratified based on previous year crop yield (hypothesized best predictor of future yield). Experiments were thus a two-factor factorial assessment by application rate and previous yield (Figs. 2 – 14). Experimental N fertilizer rates in a given field were

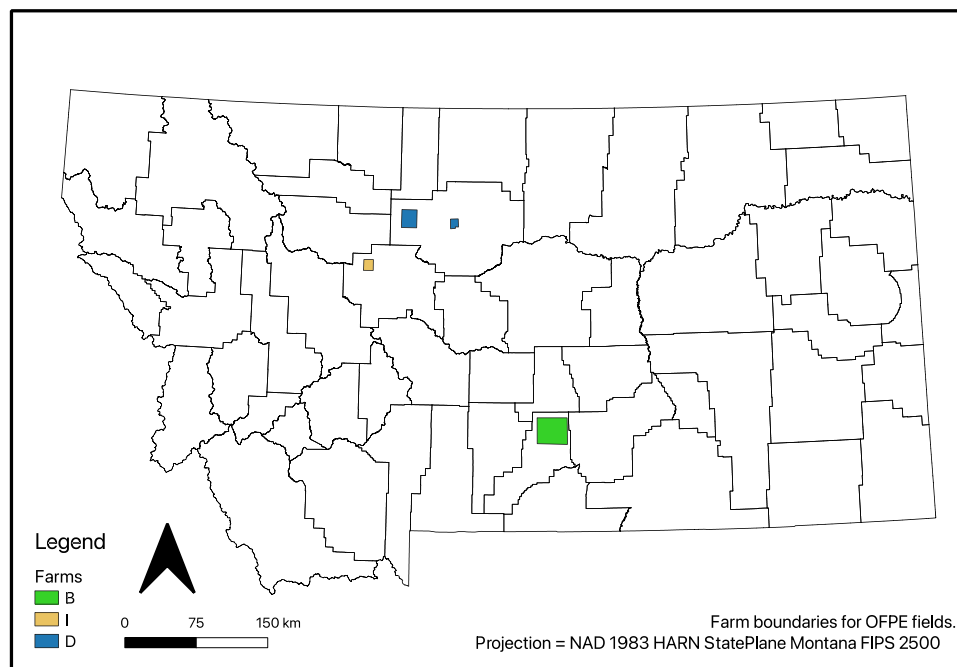


Fig. 1. Map of OFPE farm boundaries for the three selected farmer collaborators with Montana State University. Colors represent different farmers, while shapes represent general areas in which their respective fields are located.

Table 1

Crop histories, field sizes, and years in VRA treatment for each field for given farmers. The farm identifier corresponds to the map above and is used instead of the farmer's name for privacy.

Farm	Field	Field size (ha)	Crop History ¹ : 2014 / 2015 / 2016 / 2017 / 2018 / 2019 / 2020	Years N rate treatment
B	B1	79	SF / WW / CF / WW / CF / WW / CF	2017, 2019
	B2	94	WW / CF / WW / CF / SF / WW / CF	2016, 2019
	B3	90	CF / SW / WW / CF / WW / CF / SW	2016, 2018
	B4	64	SW / CF / WW / CF / WW / CF / WW	2016, 2018, 2020
	B5	45	CF / WW / CF / WW / CF / SF / WW	2017, 2020
D	D1	46	CF / WW / CF / WW / CF / WW / CF	2017, 2019
	D2	48	WW / SW / WW / CF / WW / CF / WW	2016, 2018, 2020
	D3	20	SW / SW / WW / CF / WW / CF / WW	2016, 2018, 2020
	D4	191	WW / CF / WW / CF / WW / CF / WW	2018
I	I1	64	NA / WW / CF / WW / CF / WW / CF	2017, 2019
	I2	128	P / WW / CF / SW / CF / WW / CF	2017, 2019
	I3	64	CF / NA / NA / CF / WW / WW / WW	2019
	I4	94	SW / CF / WW / CF / WW / CF / WW	2016, 2018, 2020

1 WW = winter wheat, CF = chemical fallow, P = peas, SW = spring wheat, SF = safflower, NA = Not Available

not identical across years, just as weather was not identical between years. However, given these differences we assess how similar crop responses are. In the event that crop responses were similar, we glean useful information for farmers and scientists alike that different N rates and weather conditions don't affect crop responses. Across all fields in Farm I in 2019, the farmer was not able to apply experimental rates and only their starter rate of 16.8 kg ha⁻¹ were applied. Similarly, operators in field D3 and B3 in 2018 were unable to apply experimental rates.

The response variables of interest are crop productivity (grain yield in kg ha⁻¹) and quality (% protein of grain), both of which are gathered from monitors mounted on farmers' harvesters. Data from yield monitors are gathered on average every three seconds and have become standard equipment on most modern combines. All yield monitors are

calibrated every spring by the farmers, according to their respective manufacturing instructions. Grain protein concentration (%) was measured with a CropScan 3000 H near-infrared monitor (Clancy, 2019). These data are subjected to cleaning before analysis, including adjusting for the lag between measurements and the location the measurement characterizes. Additionally, observations within 30 m of the field boundary were removed, and outliers were removed where the yield/protein values or distance from the next point in time were above or below 4 standard deviations from the mean value or distance (Blackmore and Moore, 1999; Sudduth et al., 2012; Sudduth and Drummond, 2007).

For both yield and protein datasets, as-applied N data from farmers' application equipment was georeferenced to the observed yield and protein data. Beyond data collected from the machines on the field, open-source data that characterizes crop productivity, weather, and soil characteristics were gathered (Table 2). These data were obtained or derived from Google Earth Engine (Gorelick et al., 2017) and aggregated to the locations of the yield and protein observations. Aggregating data to the location of the yield and protein observations prevented any loss of information about crop responses due to averaging and upscaling. However, the open-source data gathered and hypothesized to characterize ecological relationships with the responses (Table 2) were gathered at a coarser resolution, inducing uncertainty because of the lack of fine scale variation in covariate measurements at the resolution yield and protein observations were gathered at.

2.2. Assessment of spatiotemporal differences in crop responses

All analysis was conducted in R using version 4.1.0 (R Core Team, 2021). The first objective of the study was to assess the spatiotemporal differences in crop responses. We assessed the sub-field scale spatiotemporal variation in crop responses for each field each year by comparing the crop response distribution of a given field and year 1) to the distribution of the crop response for the given field from all other years, and 2) to the distribution of the crop response for all other fields of the same farm in the given year. Comparing the probability that crop responses were greater for a given field and year than crop responses from the same field in all other years indicates variation across time, while variation across space was assessed by comparing the probability that crop responses were greater for a given field than all other fields cropped in the same year.

A probabilistic approach was used to compare yields and protein between individual fields and years for two reasons. First, compared to pooled distributions, the distributions of crop responses of fields and

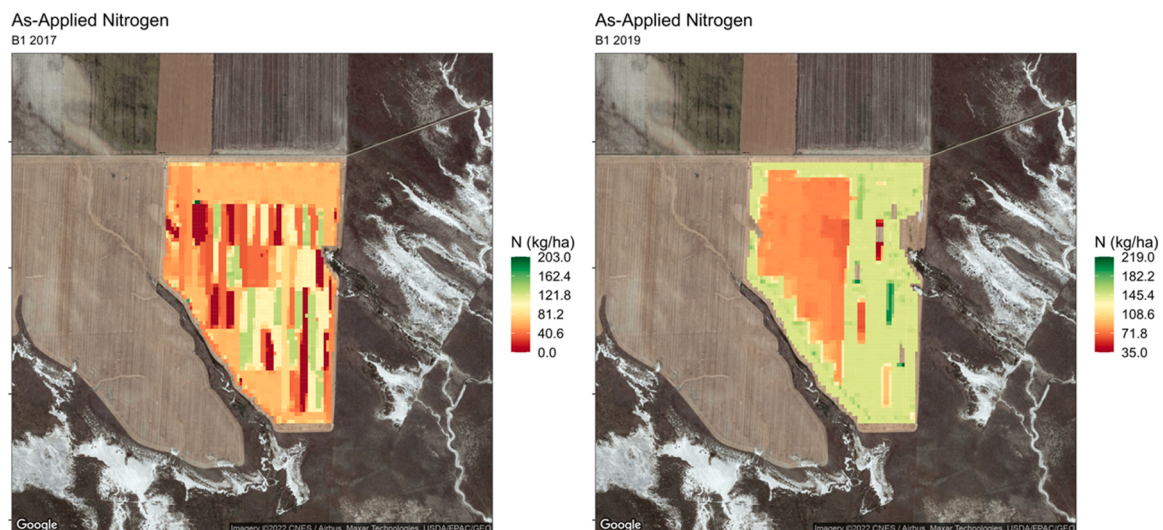


Fig. 2. As-applied N fertilizer experiments in field B1, plotted from data gathered from farmer's equipment.

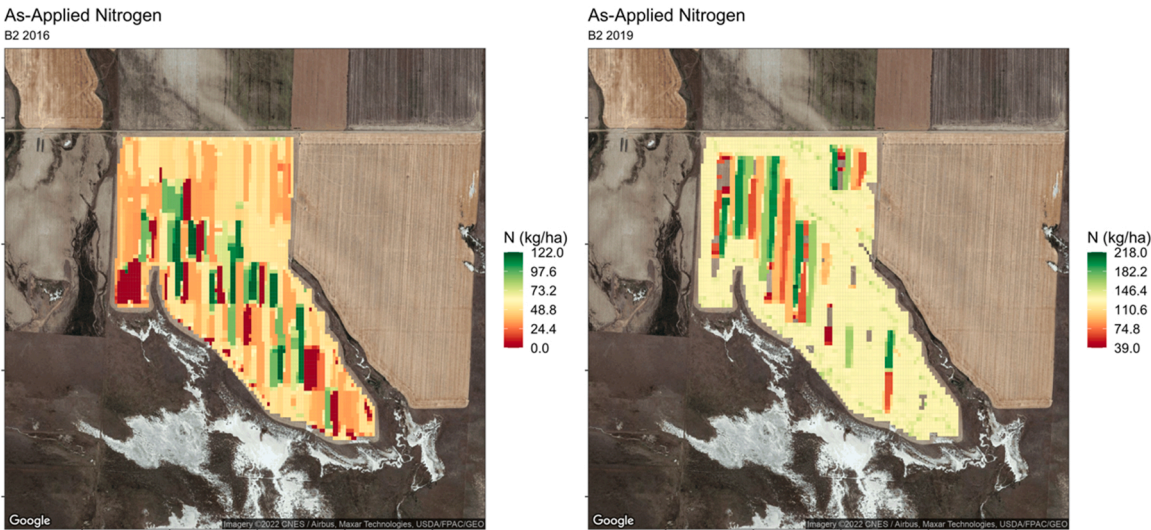


Fig. 3. As-applied N fertilizer experiments in field B2, plotted from data gathered from farmer's equipment.

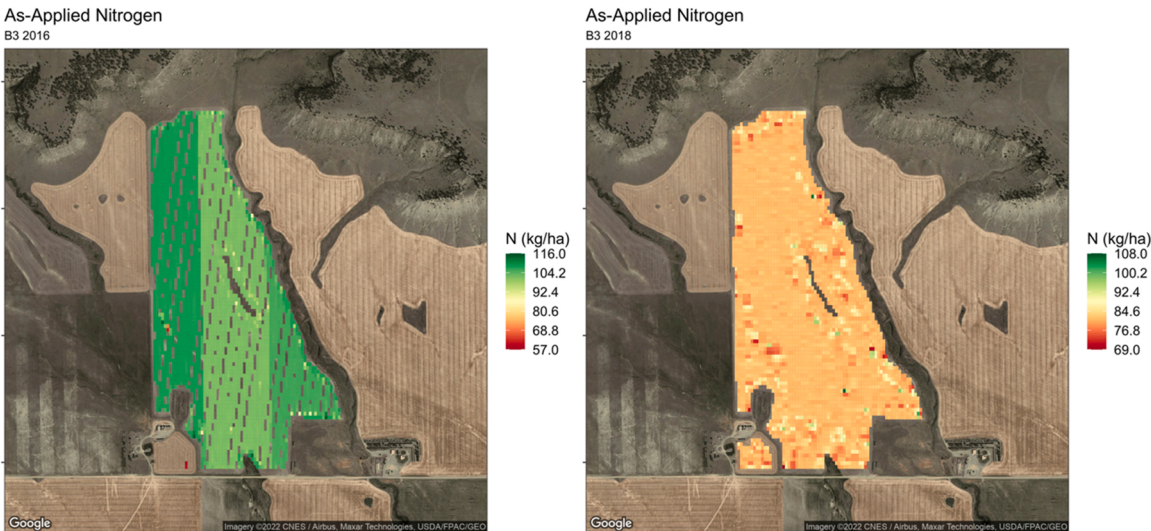


Fig. 4. As-applied N fertilizer experiments in field B3, plotted from data gathered from farmer's equipment.

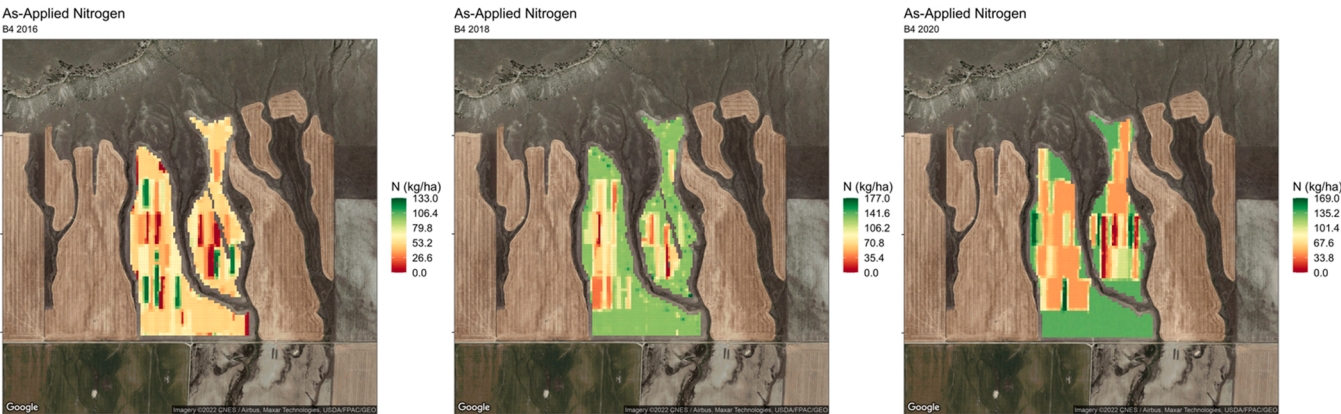


Fig. 5. As-applied N fertilizer experiments in field B4, plotted from data gathered from farmer's equipment.

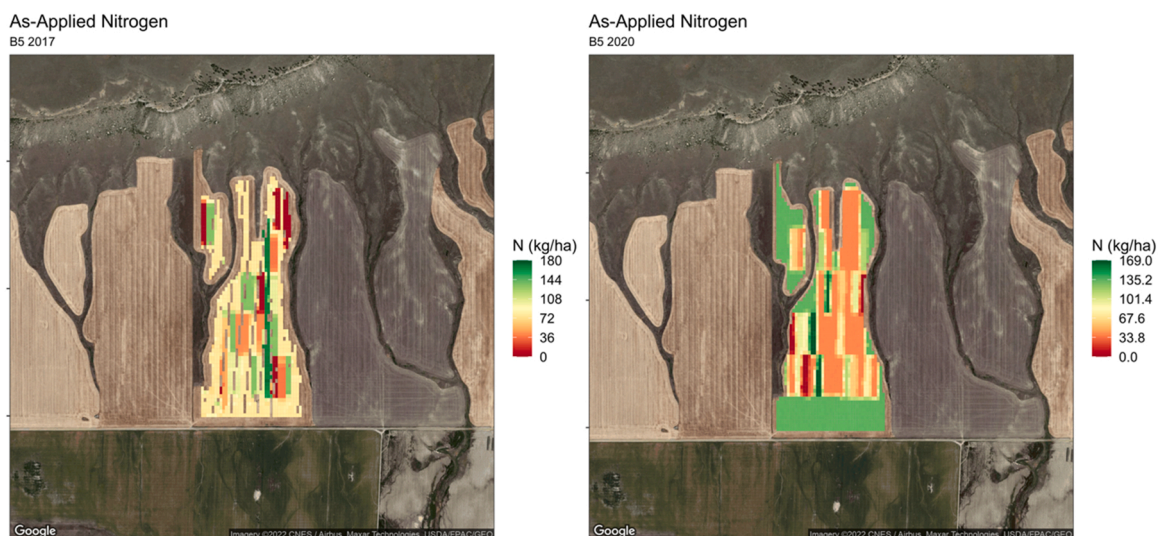


Fig. 6. As-applied N fertilizer experiments in field B5, plotted from data gathered from farmer's equipment.

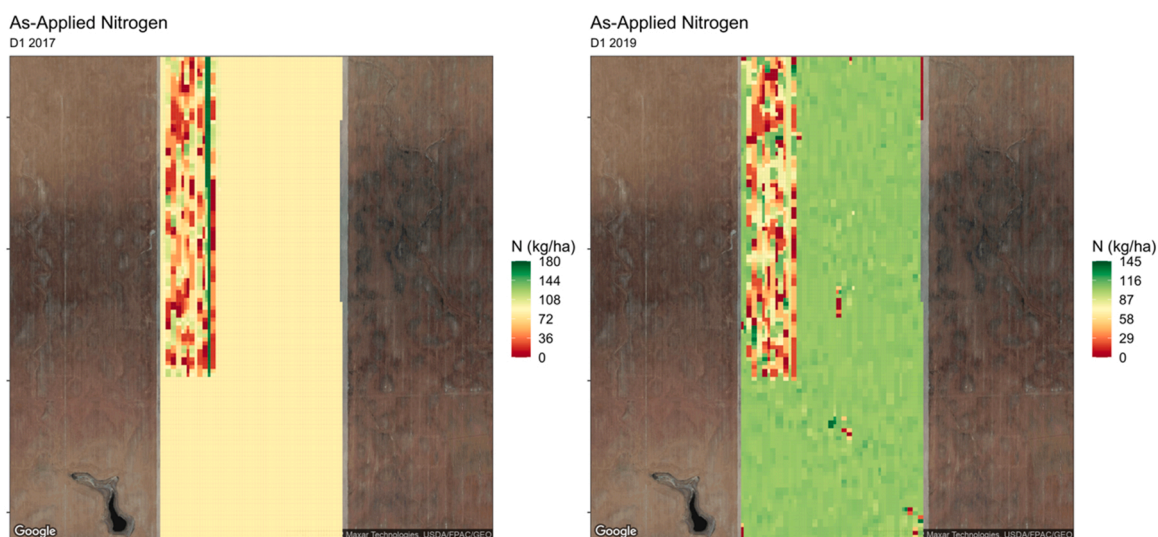


Fig. 7. As-applied N fertilizer experiments in field D1, plotted from data gathered from farmer's equipment.

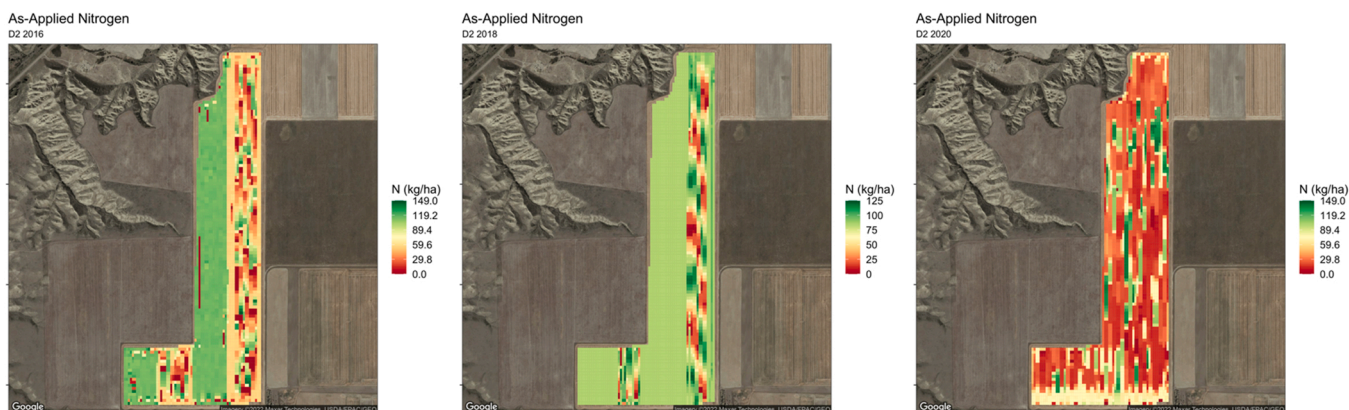


Fig. 8. As-applied N fertilizer experiments in field D2, plotted from data gathered from farmer's equipment.

years were not consistently normally distributed, and second, we have data on the actual observed distributions for each field and year and can avoid assumptions of normality and central tendency in our compar-

isons. To our knowledge this is a novel approach of assessing field specificity of crop responses as it does not reflect the traditional frequentist statistical approach to comparisons. Additionally, because

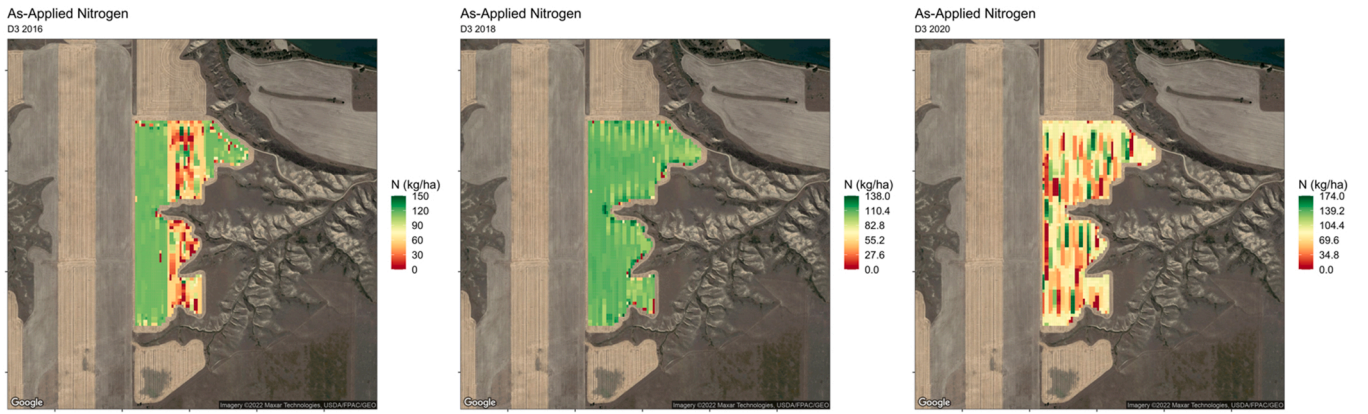


Fig. 9. As-applied N fertilizer experiments in field D3, plotted from data gathered from farmer's equipment.

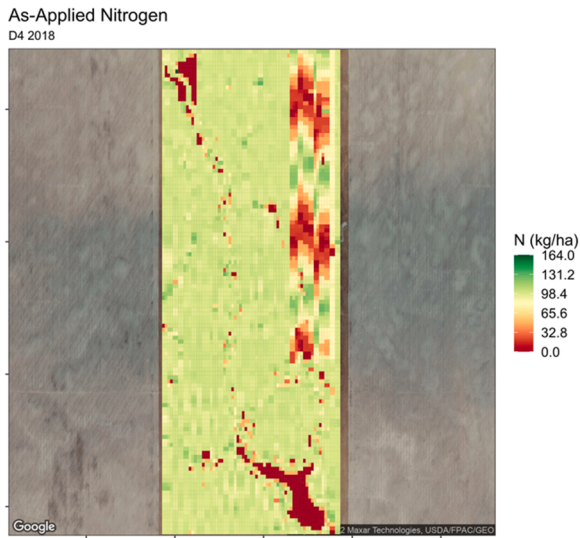


Fig. 10. As-applied N fertilizer experiments in field D4, plotted from data gathered from farmer's equipment.

different N fertilizer rates were experimentally varied across a field in each year, we are comparing the distribution of crop responses between years rather than simply whether the response in one year is different to another year. We assessed the probability that crop responses were greater for a given field and year compared to crop responses in (1) each of the other years for the given field, and (2) each of the other OFPE fields for the same year. For comparisons across years for a given field, we used spatially explicit sampling across the field to be inclusive of in-field response variation. We compared the crop response values from a target field and year of interest to the nearest measurement in the comparison year for the same field, with a maximum sampling distance of 10 m to assess the probability of difference between crop responses. For a given field, the target year was the most recent year for which data was available, while comparison years corresponded to all previous years' data. If the crop response for a given measurement within the target field and year was greater in the year of interest compared to the closest measurement in the comparison year, a value of 1 was assigned to the test in the year of interest. All values across the field for the year of interest were summed and divided by the total number of measurement locations in the year of interest to derive the probability that the crop responses were higher in the year of interest compared to the comparison year for a given field.

$$\Pr(A > B) = \frac{\sum_{i=1}^{n_A} \begin{cases} 1 & A_i > B_i \\ 0 & A_i < B_i \end{cases}}{n_A} \quad (1)$$

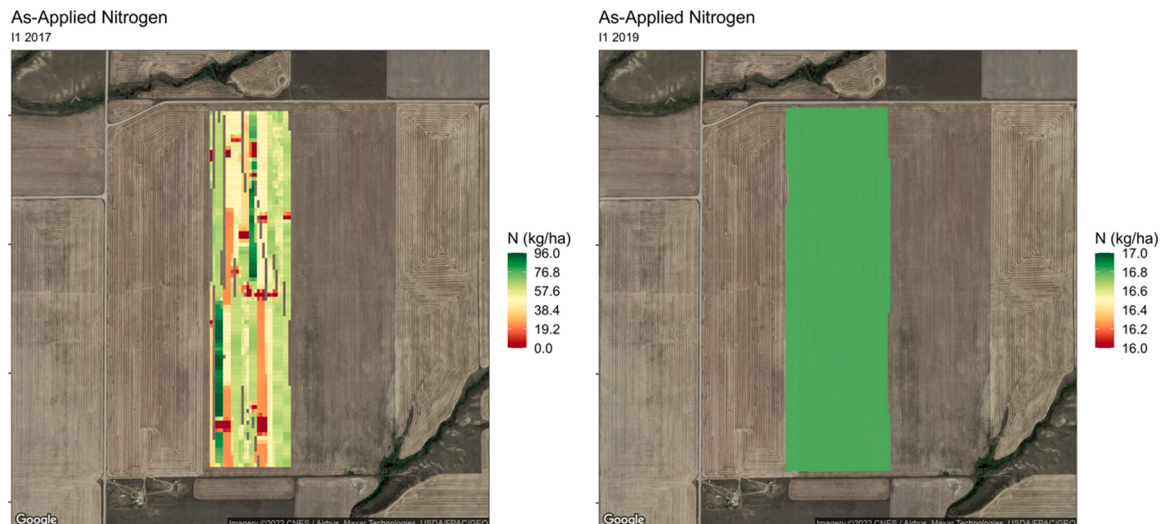


Fig. 11. As-applied N fertilizer experiments in field I1, plotted from data gathered from farmer's equipment.

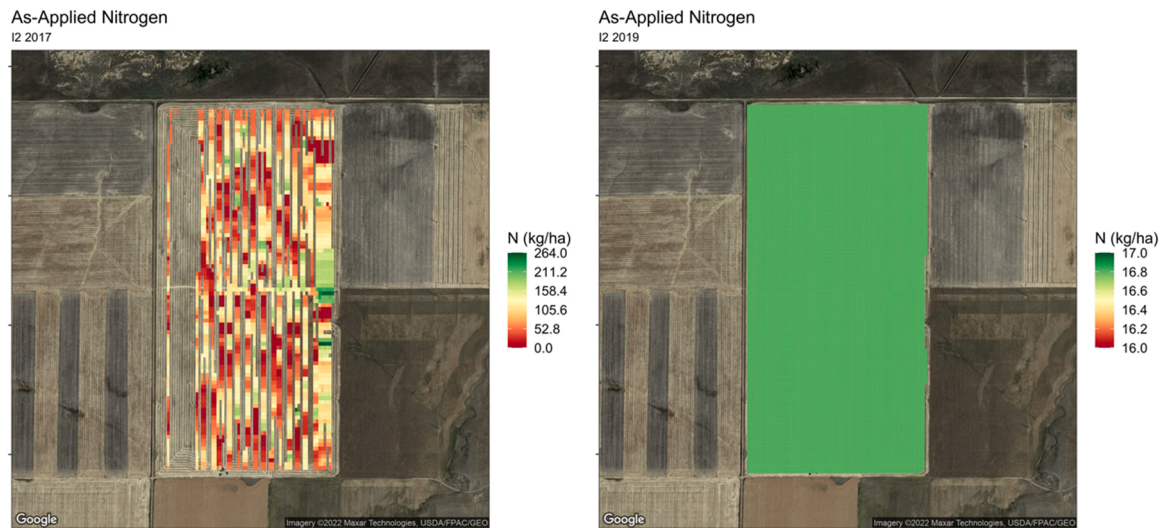


Fig. 12. As-applied N fertilizer experiments in field I2, plotted from data gathered from farmer's equipment.

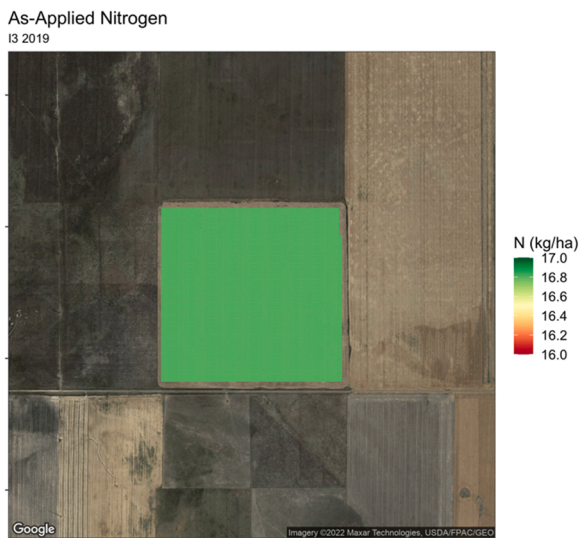


Fig. 13. As-applied N fertilizer experiments in field I3, plotted from data gathered from farmer's equipment.

Where $Pr(A > B)$ was the probability that the crop response (yield or protein) in a given target field and year (A) was greater than the crop response (yield or protein) in the same field and comparison year (B) is the response. Every observation in A was compared to the nearest neighbor within 10 m from B, and if the crop response in A was greater than B, the observation was given a value of 1. The probability was derived as the number of observations where the crop response in A was greater than in B divided by the total number of observations in A (n_a).

We used Monte Carlo sampling to compare crop responses between different fields of the same farm for a given year. For each target field for a given year, we took a random set of n samples with replacement from each crop response distribution and compared it to a random set of n samples with replacement taken from the distribution from the comparison field. If the crop response value from the field and year of interest were greater than a random draw from the distribution of the comparison field then the test was scored a 1, else scored 0. The scores from tests were added and divided by n to obtain the probability of difference. The number of tests (n) were equal to the number of crop response observations multiplied by 100 if the crop response was yield and 1000 if the crop response was protein. The calculation of the probability followed similar logic as in Eq. (1), except that tests (n) with replacement were randomly drawn from the target field and year (A) and the comparison field for the given year (B) and compared without being spatially explicit because A and B correspond to different fields cropped in the same year (Eq. 2);

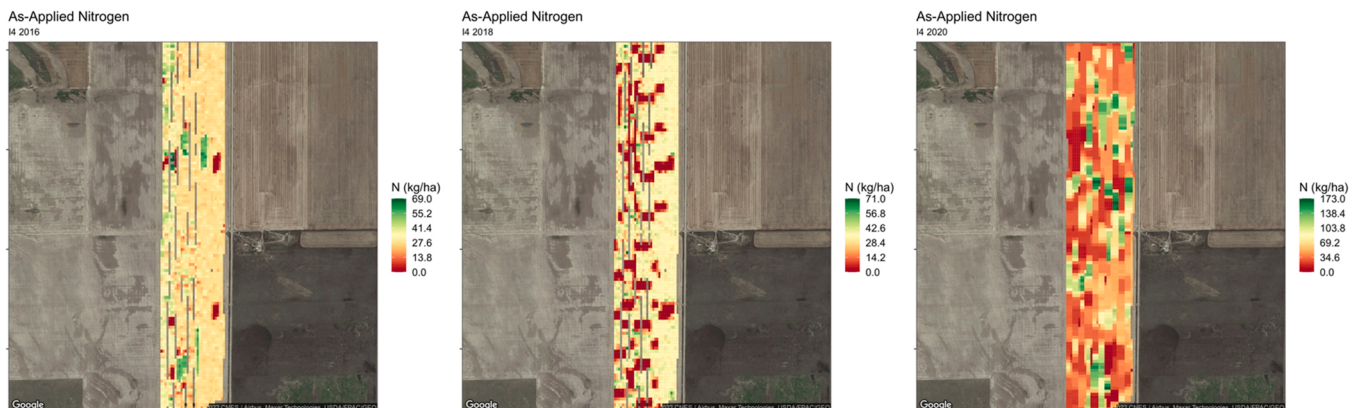


Fig. 14. As-applied N fertilizer experiments in field I4, plotted from data gathered from farmer's equipment.

Table 2

Table of covariates gathered from Google Earth Engine to enrich the crop yield and protein datasets gathered from on-farms. In some cases, multiple sources are used, however only one data source is used when aggregating to yield and protein.

Data Type	Data Sources	Resolution	Years Collected	Description
Normalized Difference Vegetation Index (NDVI)	Sentinel 2, Landsat 5/7/8	10 m, 30 m	S2: 2016-present L5: 1999–2011 L7: 2012–2013 L8: 2014 - present	Sentinel 2 is from the European Space Agency as part of the Copernicus program. Landsat is an ongoing USGS and NASA collaboration. <u>Bands (NIR, red)</u> S2: B8 and B4 L5/L7: B4 and B3 L8: B5 and B4 Bands B5 and B6
Normalized Difference Red Edge (NDRE)	Sentinel 2	20 m	S2: 2016-present	
Red Edge Chlorophyll Index (CI _{RE})	Sentinel 2	20 m	S2: 2016-present	Bands B7 and B5
Elevation	USGS NED	~10 m (1/3"), ~23 m (3/4")	1999-present	USGS National Elevation Dataset. Measured in meters.
Aspect	USGS NED	~10 m (1/3"), 30 m	1999-present	Direction the surface faces, function of neighboring elevations, in radians. Also calculated for each E/W and N/S direction as cosine and sine.
Slope	USGS NED	~10 m (1/3"), 30 m	1999-present	Rate of change of height from neighboring cells, in degrees. Measured in degrees.
Topographic Position Index (TPI)	USGS NED	~10 m (1/3"), 30 m	1999-present	Measure of divots and low spots as a function of neighboring elevation.
Precipitation	DaymetV3	1 km	1999-present	Estimates from the NASA Oak Ridge National Laboratory (ORNL). Measured in mm.
GDD	DaymetV3	1 km	1999-present	Estimates from the NASA Oak Ridge National Laboratory (ORNL).
susm	SMAP	10 km	2016-present	Surface (0–5 cm) and sub-surface (5–100 cm) soil moisture content.

Table 2 (continued)

Data Type	Data Sources	Resolution	Years Collected	Description
grtgroup	OpenLandMap	250 m	1999–2018	Predicted USDA soil taxonomy great group probabilities.
texture	OpenLandMap	250 m	1999–2018	Soil texture classes (USDA system) averaged over 6 soil depths (0, 10, 30, 60, 100 and 200 cm).
bulkdensity	OpenLandMap	250 m	1999–2018	Soil bulk density (fine earth) 10 x kg / m3 averaged over 6 standard depths (0, 10, 30, 60, 100 and 200 cm).
claycontent	OpenLandMap	250 m	1999–2018	Clay content in % (kg / kg) averaged over 6 standard depths (0, 10, 30, 60, 100 and 200 cm).
sandcontent	OpenLandMap	250 m	1999–2018	Sand content in % (kg / kg) averaged over 6 standard depths (0, 10, 30, 60, 100 and 200 cm).
pH (phw)	OpenLandMap	250 m	1999–2018	Soil pH in H ₂ O averaged over 6 standard depths (0, 10, 30, 60, 100 and 200 cm).
watercontent	OpenLandMap	250 m	1999–2018	Soil water content (volumetric %) for 33kPa and 1500kPa suctions predicted and averaged over 6 standard depths (0, 10, 30, 60, 100 and 200 cm).
carboncontent	OpenLandMap	250 m	1999–2018	Soil organic carbon content in x 5 g / kg averaged over 6 standard depths (0, 10, 30, 60, 100 and 200 cm).

$$\Pr(A > B) = \frac{\sum_{i=1}^n \left\{ \begin{matrix} 1 \\ 0 \end{matrix} \right\}_{\substack{A_i > B_i \\ A_i < B_i}}}{n} \quad (2)$$

Where $\Pr(A > B)$ was the probability that the crop response (yield or protein) in a given target field and year (A) was greater than the crop response (yield or protein) in a comparison field from the same year (B). Random samples with replacement were drawn from the crop response distribution from A, and compared to a randomly drawn crop response from the distribution of B. If the crop response in A was greater than B the test was given a value of 1. The probability is derived as the number of draws where the crop response in A was greater than in B divided by

the total number of random samples taken with replacement from the data (n).

Probability of difference provided a continuous scale to judge field and yearly differences in crop response. Thus, the closer the probability was to 1.0 (target field was always greater than compared field or time) or 0 (target field was always less than compared field or time) indicated high confidence in difference between fields or years, versus probabilities near 0.5 indicated that there was no discernable difference between crop responses between the target and comparison field.

2.3. Sensitivity analysis

For every field, a generalized additive model (GAM) using thin plate shrinkage splines was fit individually to observed yield and protein data from all years (Wood et al., 2016; Wood, 2003). We pooled field data across years to fit one model for each field for each crop response and used these models to perform the sensitivity analysis on each crop response in each year for the field. Bidirectional AIC based model selection was performed from the initial full model for both yield and protein (Eq. 3). Covariates included in the initial model were limited to those that did not show any correlation with other predictors and had no singularities across fields and years. Diagnostics were evaluated for each model before settling on a final form and all predictors were centered, defined as subtracting the value of the variable from the mean value of the variable, prior to model fitting to limit the influence of scale differences. As crop responses differed across fields, not all fit GAMs for yield and protein for a given field had the same predictors. All final models for each field were selected from the following initial full model;

$$\begin{aligned} R \sim & f_1(x, y) + f_2(N) + f_3(\text{aspectCos}, \text{aspectSin}) + f_4(\text{slope}) \\ & + f_5(\text{elev}) + f_6(\text{tpi}) + f_7(\text{prec}_{cy}) + f_8(\text{prec}_{py}) + f_9(\text{gdd}_{cy}) + f_{10}(\text{gdd}_{py}) \\ & + f_{11}(\text{ndvi}_{cy}) + f_{12}(\text{ndvi}_{py}) + f_{13}(\text{ndvi}_{2py}) + f_{14}(\text{bulkdensity}) \\ & + f_{15}(\text{claycontent}) + f_{16}(\text{sandcontent}) + f_{17}(\text{phw}) \\ & + f_{18}(\text{watercontent}) + \epsilon \end{aligned} \quad (3)$$

Where R was yield (kg/ha) or grain protein content (%) observations, $f_1 - f_{18}$ were smoothing functions fit with maximum likelihood on the tensor product of the x and y coordinate (x, y) and the rest of the parameters. The main explanatory variable was as-applied nitrogen (N), along with topographic variables including the tensor product of aspect in the E/W direction (aspectCos) and aspect in the N/S direction (aspectSin). Additional topographic parameters were slope in degrees (slope), elevation in meters (elev), and topographic position index (tpi). Precipitation accumulated from November 1st of the year prior to the observation year to March 31st of the observation year (prec_{cy}) was also used, along with precipitation accumulated from November 1st of two years prior to the observation year to October 31st of the year prior to the observation year (prec_{py}). Additional weather variables included growing degree days accumulated from January 1st to March 31st of the observation year (gdd_{cy}), and growing degree days accumulated from January 1st to December 31st of the year prior to the observation year (gdd_{py}). To provide information on crop productivity of the current year up to the decision point, normalized difference vegetation index (NDVI) data aggregated from January 1st to March 31st of the observation year (ndvi_{cy}) was used. To provide information on past crop productivity, NDVI aggregated from January 1st to December 31st of the year prior to the observation year (ndvi_{py}) and NDVI aggregated from January 1st to December 31st two years prior to the observation year (ndvi_{2py}) were used. Soil characteristics including bulk density in $10 \times \text{kg/m}^3$ (bulkdensity), percent clay averaged over 0 – 200 cm (claycontent), percent sand averaged over 0 – 200 cm (sandcontent), the pH ($\times 10$) of soil water averaged over 0 – 200 cm (phw), and the volumetric water content averaged across field capacity and wilting point and over 0 – 200 cm (watercontent) were used. Finally, random error (ϵ) was incorporated.

Generalized additive models were chosen due to their flexibility and

ability to fit highly scattered observed crop response data. Thin plate shrinkage splines were used for all variables to allow the estimated degrees of freedom (EDF's) of parameters to shrink to zero, combining the process of model fitting and selection. The parameter exceptions to thin plate shrinkage splines were the use of a gaussian process for the interaction of latitude and longitude to account for spatial autocorrelation between observed points within the field.

To determine the site-to-site and annual differences in covariates with high relative impact on crop responses and net-return, sensitivity/elasticity analyses were performed on each of the covariates in GAM's developed on a field-specific basis. Sensitivity analyses were performed for each fit predictor variable by systematically increasing and decreasing the fit parameter value for each parameter by 10 % while holding all other variables with default fit values. The change in estimated response for each point was recorded for the comparison of each change to the observed values to determine which variable contributed to the largest change in observed crop response. This was repeated for every field and year combination. The sensitivity of responses for each field was evaluated by calculating the elasticity compared to the default observed conditions. Elasticity is defined as the absolute value of the difference between the average crop response in the default condition to the average crop response in the altered condition (with a covariate increased or decreased by 10 %). The most elastic variables were grouped for each field across years and between fields by farms to assess spatiotemporal trends in drivers of crop productivity and quality.

To perform a sensitivity/elasticity analysis on net-return, protein and yield were combined by using kriging to spatially interpolate protein observations to coincide with the locations of yield. Correlation coefficients were created for each field and year to quantify the direction and magnitude of the relationship between yield and grain protein. Net-return was calculated as a function of yield, protein, the cost of N , and other fixed costs associated with producing the crop (Eq. 4) for each point in the field.

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

$$NR = \text{yield} * P - CA * AA - FC - ssAC \quad (4)$$

Where P was the final price received (\$/bushel), Bp was the base price received (\$/bushel), $B0pd$ was the intercept of the protein premium/dockage function set by the grain elevator, $B1pd$ was the coefficient on the grain protein content (protein , %) and $B2pd$ was the coefficient on the squared protein term. NR was the net-return received and a function of the product of the yield (kg/ha) and P , minus the cost of the applied input (CA) multiplied by the as-applied rate of the input (AA), the fixed costs (FC) associated with production (\$/ac) that do not include the input, and the cost per hectare of the site-specific application ($ssAC$).

The protein premium/dockage equation was fit using the data from one elevator in 2016. Base prices were gathered from Montana State University Extension Service (https://econtools.msuextension.org/mt_ag_prices/GrainPrices.html) and the cost of the N fertilizer, the fixed costs, and the cost of site-specific application were obtained from each farmer. As with yield and protein, sensitivity analysis for net-return was performed over all distinct fields and years, where all variables in Eq. 4 were increased or decreased by 10 %. Results of the most elastic parameter were compiled to assess variation in drivers of net-return across fields and years.

3. Results

3.1. Assessment of spatiotemporal differences in crop responses

We observed a large spread across field and year combinations in the probability of the difference between crop responses for the same field across years. While we saw a trend that the probability that yields tended to be greater in more recent years for given fields compared to prior

years across all farms, some fields showed no discernable difference in yields between a given target year and a comparison year (e.g., comparing B4 yields in 2020–2016), while other fields showed that yields were greater in prior years compared to the target (the most recent) years (Table 3). Trends of the probability that grain protein content in target years were greater than prior comparison years were less clear, indicating that there is variability between fields in the similarity of protein responses across years for a given field (Table 4). While in most fields there is a chance that grain protein content varies across years, only B4 showed a consistent lack of differentiation between protein across time (Table 4).

The results also provide evidence that crop responses differ among other fields on a farm during a given year. When comparing the yields of a field and year of interest to yields of different fields on the same farm for the same year, we did not detect a clear pattern across time that the probability that yields for fields of the same farm were more similar than yields between fields of the same farm in other years. In 2020 and 2019 there was little evidence that yields were similar between fields on the same farm (Table 5). In some years there was evidence that some fields on the same farm were more similar than other fields on the same farm. For example, in 2018 there was little evidence that the yield response was similar between fields D2 and D3 but more evidence that fields D2 and D3 and D3 and D4 had different yield responses (Table 5). Additionally, in 2016 we observed that field B2 and B3 had similar yield responses while B2 and B4 and B3 and B4 differed (Table 5). Similarities between protein responses of different fields on the same farm were less common, where only fields D2 and D3 in 2018 and B2 and B4 in 2016 indicated similar protein responses (Table 6). The only trend is the high degree of variation across time, as there were no years where protein seemed more similar between fields than in other years. These results indicate that not only do crop responses for a given field vary across time, but crop responses also vary across fields within farms.

3.2. Sensitivity analysis for drivers of crop responses and net-return

The resolution of measurements for precipitation and growing degree days were coarser than the size of the field, so the influence of these parameters on the response for a given field and year shrunk to zero during fitting of the GAM's due to the lack of variation in these parameters across the field. However, we maintain the assumption that weather influences rainfed crop responses. Nitrogen fertilizer rate was not as influential as we expected, even though it was experimentally varied. We had yield data from 28 field and year combinations, protein data from 27 field and year combinations, and 28 field and year combinations for net-return, albeit omitting protein as a parameter in Eq. 4 for I2 in 2017.

We observed that across fields, varying the elevation parameter had

Table 3

Probabilities that the yields for the given field in the target year (corresponding to A in Eq. 1) were greater than yields for the given field in the comparison year (corresponding to B in Eq. 1). D4 and I3 had only one year of data so no comparisons were possible.

Target (A)		Comparison Year (B)		
Field	Year	2018	2017	2016
B1	2019		0.687	
B2	2019			0.875
B3	2018			0.899
B4	2020	0.208		0.502
B5	2020		0.399	
D1	2019		0.885	
D2	2020	0.233		0.761
D3	2020	0.445		0.842
I1	2019		0.728	
I2	2019		0.749	
I4	2020	0.6		0.594

Table 4

Probabilities that the grain protein content for the given field in the target year (corresponding to A in Eq. 1) were greater than grain protein content for the given field in the comparison year (corresponding to B in Eq. 1). D4 and I3 had only one year of data so no comparisons were possible. No comparisons were made for I2 because of a lack of protein data.

Target (A)		Comparison Year (B)		
Field	Year	2018	2017	2016
B1	2019		0.857	
B2	2019			0.403
B3	2018			0.025
B4	2020	0.532		0.527
B5	2020		0.386	
D1	2019		0.355	
D2	2020	0.284		0.355
D3	2020	0.369		0.781
I1	2019		0.033	
I4	2020	0.402		0.073

Table 5

probabilities that the yields of the target field for a given year (corresponding to A in Eq. 2) are greater than yields from comparison fields of the same farm for the given year (corresponding to B in Eq. 2). If multiple fields from the same farm were not experimented in during the same year no comparison was made.

Target Field (A)	Comparison Field (B)	Probability A > B
	2020	
B4	B5	0.364
D2	D3	0.285
2019		
B1	B2	0.623
I1	I2	0.971
I1	I3	0.988
I2	I3	0.835
2018		
B3	B4	0.575
D2	D3	0.458
D2	D4	0.620
D3	D4	0.670
2017		
B1	B5	0.540
I1	I2	0.982
2016		
B2	B3	0.517
B2	B4	0.397
B3	B4	0.369
D2	D3	0.476

the greatest influence on variation in predicted yields across years, with only B1 indicating that aspect had a higher influence on yield than elevation. This is important to note because it differed with the adjacent field B2, which has similar geography (Fig. 15). There was much more variability in the most influential parameter on predictions of grain protein content across fields and years (Fig. 16). While *elevation* was the most common driver of protein, we saw that in some fields and years N, pH of soil water, sand content, and the *watercontent* parameter had the most influence on protein in some fields and years (Fig. 16). Drivers of grain protein content were relatively consistent over time, with only I4 and I1 showing any variation in the most influential parameter on protein across years where, in some years for these fields, protein was most influenced by N, while in other years, protein was most influenced by elevation or the pH of soil water.

There was also variability in the most influential parameter on net-returns (Fig. 17). The most common parameter that influenced net-returns was the protein concentration in the field. Farmers either receive a premium or dockage on their base price received above or below a protein concentration that varies annually. As expected, yield also had a large influence on net-returns. The third most common driver of net-return for a farmer in a given field and year was crop base price, a

Table 6

Probabilities that the grain protein content of the target field for a given year (corresponding to A in Eq. 2) are greater than protein contents from comparison fields of the same farm for the given year (corresponding to B in Eq. 2). If multiple fields from the same farm were not experimented in during the same year no comparison was made.

Target Field (A)	Comparison Field (B)	Probability A > B
	2020	
B4	B5	0.813
D2	D3	0.341
2019		
B1	B2	0.317
I1	I2	0.014
I1	I3	0.347
I2	I3	0.982
2018		
B3	B4	0.278
D2	D3	0.449
D2	D4	0.048
D3	D4	0.044
2017		
B1	B5	0.347
2016		
B2	B3	0.229
B2	B4	0.507
B3	B4	0.855
D2	D3	0.758

factor set by the grain elevators that farmers sell to. Drivers of net-returns not only showed variation across space, but time as well, with some fields experiencing different drivers of net-return in different years. In D2, D3, and I4 some years were most influenced by base price, while in others it was most influenced by grain protein concentration. Considering these cases individually indicated commonality across space, as base price was the biggest driver in each of these fields in 2018. On Farm B, the major driver of net-return in B2, B3, and B4 varied between yield and protein. In 2019 we see variation across space in terms of the major drivers of net-return in adjacent fields of B1 and B2, where yield had the most influence on net-return in B1, while protein had the most influence on net-return in B2 that year. These results indicate that drivers of net-return are also not consistent across time and space, and that the metric most directly applicable to farmer's livelihoods (net-return) is not always a factor that they can manage (i.e. base price or protein price premium/dockage are largely out of their control).

4. Discussion

The fields and farms we analyzed for spatial and temporal agroecosystem variability are typical of conventional dryland small grain farms in practices and management approaches, and therefore our results are likely indicative across rainfed cropland farms elsewhere in the industrialized Northern Great Plains of North America where winter wheat is a commonly grown crop. Our analysis provides evidence that crop responses in fields are variable across time and space, expanding on literature that has assessed only spatial variability in crop responses

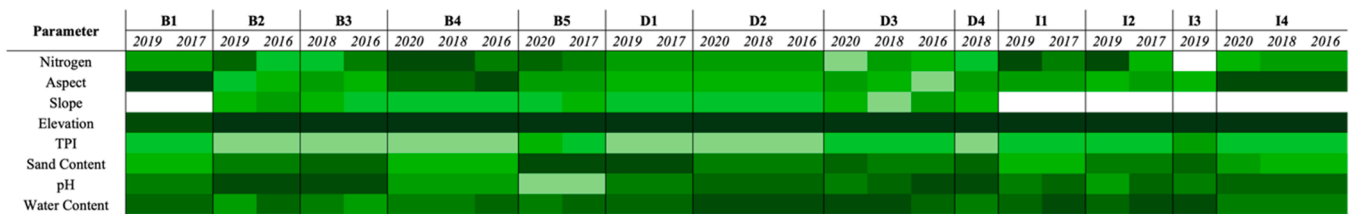


Fig. 15. Results for sensitivity analyses of yield performed based on parameters of Eq. (3) for each field and year. The darkest color represents the parameter with the most influence on yields with increasingly lighter colors corresponding to less influence on yields. Boxes left white indicate parameters that did not come into the model. For all models for all fields and years, precipitation, GDD, NDVI, bulk density, and clay content were all omitted due to model selection.

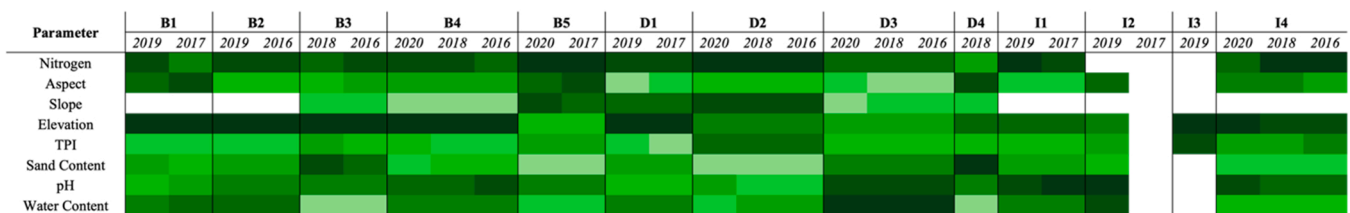


Fig. 16. Results for sensitivity analyses of grain protein content performed based on parameters of Eq. (3) for each field and year. The darkest color represents the parameter with the most influence on protein with increasingly lighter colors corresponding to less influence on protein. Boxes left white indicate parameters that did not come into the model. For all models for all fields and years, precipitation, GDD, NDVI, bulk density, and clay content were all omitted due to model selection. No sensitivity analysis was performed for I2 in 2017 because of a lack of protein data.

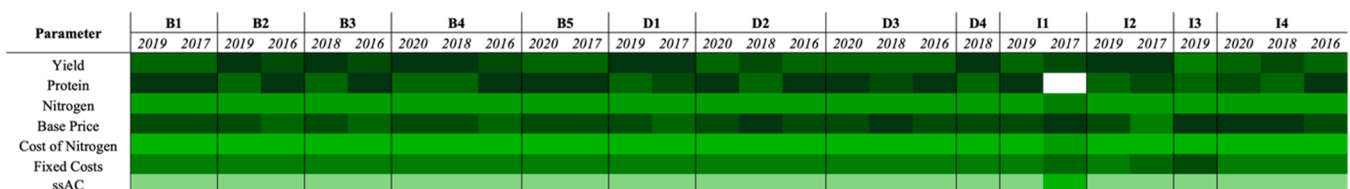


Fig. 17. Results for sensitivity analyses of net-return performed based on parameters of Eq. (4) for each field and year. The darkest color represents the parameter with the most influence on net-return with increasingly lighter colors corresponding to less influence on net-return. Boxes left white indicate parameters that did not come into the model. Grain protein content was not included in the sensitivity analysis for I2 in 2017 because of a lack of protein data.

(Trevisan et al., 2021). We did observe cases where there was little variation in crop response within a farm, thus we must acknowledge that there may be cases where fields on the same farm may not require independent experiments (Tables 5 & 6). However, one would not be able to arrive at such a conclusion without conducting field-specific experiments. Similarly, we acknowledge that although we saw evidence of differences in crop responses over years (Tables 3 & 4), the variables that logically contribute to this variation, like precipitation received, are not measured at an appropriate spatial scale to examine variation within a field. Previous research in these systems suggests that field-specific experimentation might not be required for an indefinite period and we can expect that parameterization of models will stabilize after 6–8 years of data collection (Lawrence et al., 2015). However, with uncertainty in climate change, future work will not only require accumulation of data from different weather conditions (years), but will require assessment of differences in weather patterns, such as the distribution of precipitation across years, rather than assessment of differences in total accumulation of precipitation (Whitlock et al., 2017).

There were differences in crop responses and their drivers in fields adjacent to each other, as well as differences across years for some fields (Tables 3–6). Not only did crop responses vary, but the covariates for characterizing crop responses differed in adjacent fields and for the same field across time (Figs. 15 & 16). This implies that information from small-plot research centers could be disseminated more usefully by targeting farms with matching soil and weather characteristics rather than based on geographic proximity to the research center, which have been associated with farmer distrust in recommendations (Luschei et al., 2001). The implications of the lack of consistency between crop response models parameterized from experiments in fields that share a border are an unnecessary increase in uncertainty to input management recommendations. Thus, with ease of conducting OFPE, we conclude that all fields should receive experiments to make the most accurate and subsequent efficient recommendations.

Our hypothesis that crop responses would be driven primarily by the management of variable N fertilizer rate was not supported, as elevation was the primary driver of yields and protein (Figs. 15 & 16). This indicates that variable application of fertilizer within fields must be managed with consideration of the ecological relationship between topography and crop responses. The topography of a field influences the direction and speed at which water flows, and as fertilizer and organic N are converted to highly soluble nitrate influencing availability of plant available N across fields (Sebilo et al., 2013; Trudgill et al., 1991). Aspect influences water and subsequently N in a similar fashion, as north facing slopes in the Northern Hemisphere receive less solar insolation and retain more moisture compared to south facing slopes (Weil and Brady, 2017). Weather covariates were also expected to have a high influence on crop responses, but because of the resolution at which they were collected, they had little to no variation across fields and often were singular values, and rarely were present in the final forms of GAM's used for the sensitivity analysis.

Additionally, the results of the sensitivity analysis on yield and protein imply that background soil N was high enough to mask the N response of wheat crops. This is important information for farmers because with their current N inventories that are present in the soil, they are not achieving a crop response to N fertilizer. The implications for management based on this information is that they would benefit from not applying N fertilizer until they see a response in production or quality to varying N fertilizer rates, something that would not be identified without on-farm experimentation or adaptive management (Moore, 2009; Mueller et al., 2009).

The significant covariates in crop yield and protein response models contribute to the variation across years within fields. Ecological processes are complex, local at the sub-field scale and change over time. Thus, it is imprecise to apply management with a broad stroke across farms or fields, or from recommendations taken from sources that have never considered the field-specific conditions and history (Tittone

et al., 2005, 2007; Zingore et al., 2007b, 2007a, 2009). Different N fertilizer rates need to be applied spatially across fields, let alone fields or farms with recognition of the ecological parameters that may influence crop responses more so than fertilizer. However, the time-specificity of responses indicate that the levels of rates applied in spatially distinct portions of the field need to vary over time and according to potentially varying factors like precipitation received, which can only be achieved by repeating the in-field experiment over years (Lawrence et al., 2015). Variation in the relationship between crop production and quality within fields and across years suggest that managers need to consider the competing interests of maximizing yield and protein and identify the rate that optimizes net-return and not simply yield or protein. We see further evidence for variation in relationship between crop yield and quality in the sensitivity/elasticity analysis for net-returns, where there was variability among fields in whether yield or protein contribute a greater effect on net-return (Figs. 15 – 17). In some fields and years, the base price received for the crop was the most important driver of net-return received by the farmer and is a variable that producers cannot typically control or manage apart from contracts or on-farm grain storage capability.

These results provide evidence that optimum management that maximizes net returns to the farmer needs to be specific to each field and growing season, with decisions being made specifically for a field based on information gathered from that field (Fig. 17). Variation occurs at spatiotemporal scales beyond a farmer's control yet understanding this variation and crop responses at the finest scale possible allow one to scale management up without a loss of information (Blöschl and Sivalan, 1995; Fritsch et al., 2020). This variation is important to consider when developing decision support systems by recognizing that most fields are different from other fields and from themselves over time (Bullock et al., 2019).

Understanding and managing based on spatiotemporal variation requires embracing technology and utilizing it as the empirical basis for adaptive management and modern objective decision making (Gebbers and Adamchuck, 2010). The automatic transfer of data from machine monitors and field sensors is becoming increasingly easy through automated transfer to cloud-based software. The data available includes as-applied maps of variable rate application (VRA) of inputs such as seeds, fertilizers, pesticides and crop production and quality (e.g., crop yield and grain protein content). The additional prevalence of open-source satellite data provides a trove of data available to understand and amend management of inputs specific to fields (Gorelick et al., 2017). Remotely sensed productivity data can be collected at 2- to 4-week intervals from open-source imagery or as often as desired with private drone flights. Increasing the number of weather stations on farms will provide spatially accurate and temporally dense measurements of variables such as precipitation and temperature. The combination of these temporally dense measurements provides information for adaptive management at a finer scale than was historically possible.

Extensive access to data enables rapid response to weeds, insects, disease, and informs site-specific recommendations of fertilizer, seeding rates, and other agricultural inputs (Basso and Antle, 2020). Resource efficiency remains limited even in areas with high technology adoption because experimentally applied inputs have not been employed with the specific purpose to improve crop response models and subsequent recommended management (Schimmelpfennig and Lowenberg-DeBoer, 2020). Greater adoption of the data returned from day-to-day farming operations can be exploited to increase resource efficiency and produce crops in a manner that reduces the environmental impacts and increase the ecological and economic resilience of agroecosystems (Bucci et al., 2018).

Industrial farms in the developed world are typically the largest, wealthiest, and the most automated, suggesting that these producers have the means to adopt new technology and tools, yet conventional input-centric farms are managed according to generalized input prescriptions (Carbonell, 2016). The farms with increasing field sizes are

primed for an automated adaptive management utilizing OFE. The principles of OFE and adaptive management contrast the recent trend of big data in agriculture by using information from a field to make decisions on a field. While big data analytics and approaches have the potential for benefitting agriculture, concerns abound about data privacy and ethics (Carbonell, 2016; Sykuta, 2016). Additionally, big data approaches use data gathered across many fields and farms to mine trends and create predictive analytics, ignoring field specificity by generating decisions based on the cumulation of massive amounts of information and have the potential to lead to inaccurate recommendations (Carolan, 2017; Kung et al., 2016; Lokers et al., 2016). We also recognize the potential for the utilization of crop growth models to making informed decisions as an alternative to OFE, however we argue that OFE is the only method to truly understand field specific responses due to assumptions and limitations associated with crop growth models, especially regarding generalizability and parameterization (Boote et al., 1996; Palosuo et al., 2011).

Adaptive management embraces field specificity and attempts to understand it through iterative experimentation, monitoring, and decision making (Haas et al., 2009; Moore, 2009; Mueller et al., 2009; Wyeth, 2009). Decision making thus remains in the hands of the farmer/field manager who is responsible for the selection of management strategies for a specific field based on the information gathered from that specific field. Adaptive management creates a new level of science-based information between the traditional research center paradigm and the field-specific knowledge of the producer. Thus, adaptive management augments the field-manager's site-specific knowledge of input management and allows understanding the result of complex interaction between, physical, biological, and economic factors that determine optimum management given multiple objectives of profit maximization, pollution minimization and ultimately resilience to factors causing variability.

5. Conclusion

Ecological principles tell us that variability and crop responses are site, time, and field history of management-specific, and thus it is inappropriate to apply management with a broad stroke across farms or fields, or from recommendations taken from sources that have never considered field specific conditions and history. Our results suggest the time-specificity of crop responses indicate that the levels of N fertilizer rates applied in spatially distinct portions of the field need to vary over time and according to potential for different weather and varying economic factors.

These results provide basic evidence justifying the use of OFE for farm management and that management needs to be specific to each field and point in time, with management prescriptions being made specifically for a field based on information gathered specifically from that field. Development of management decisions requires OFE to determine the site-specific responses of crops within farmers' fields. Variation occurs at different spatiotemporal scales, something that farmers can control most effectively with field specific knowledge. Understanding the variation in crop responses at the finest scale possible allows one to scale management up without a loss of information and reveals the uncertainty most relevant to management. Typical treatment of data is to aggregate crop responses and as-applied rates to the scale of management, averaging over spatial areas and removing observed variation within fields. Aggregation and averaging results in information loss when quantifying uncertainty in recommendations because the response of crops to variable rates of input are generalized to the management scale with no recognition of the true variation in crop response within a treatment area.

Embracing the digital age of agriculture makes adaptive management empirically based and thus directly applied. Adaptive management involves iterative application of OFE and the vast stream of data from farms to inform management decisions (Lacoste et al., 2021). Automatic

collection of data from farms and about farms is becoming increasingly easier through cloud-based software and open-source data repositories. These findings are relevant to farmers because it shows that drivers influencing crop responses and net-returns vary within farms and between adjacent fields of the same year. OFE will enable farmers to identify these drivers and understand how their inputs influence yield and protein within fields. Using information provided by OFE with decision support systems can enable farmers to make informed management decisions that maximize their profits and increase the efficiency of chemical inputs, such as N fertilizer.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Paul B. Hegedus reports financial support was provided by Montana Fertilizer Advisory Committee. Paul B. Hegedus reports a relationship with University of Illinois at Urbana-Champaign that includes: employment and travel reimbursement. Bruce D. Maxwell reports a relationship with University of Illinois at Urbana-Champaign that includes: funding grants and travel reimbursement.

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