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A Framework for Visualization and Analysis of Agronomic Field Trials from On-Farm Research Networks

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ABSTRACT

An on-farm research network is an organization of farmers that conducts agronomic experiments under local conditions. It is common that an elementary statistical analysis be conducted for individual studies. However, there is unexplored potential in detecting yield response variability patterns for better decision making. We developed a data-analytics framework and web-application program that allows users to analyze multiple studies that use a common protocol and can identify the conditions where an imposed treatment may or may not be effective. The development of this data-analytics framework is needed to improve predictions at the farm level that can lead to more cost-effective, sustainable and environmentally sound agricultural production. Data visualization is an important part of data-analytics. In this paper, we have developed and tested a Bayesian hierarchical model that can be used to assess the general agronomic performance of different management practices. Decision making related to new management practices should be based on the complete evidence, local conditions and economic considerations. The web-application includes dynamic data visualization features to enhance communication and sharing of information with the goal to reach a broader audience.

Core Ideas

- We develop a data-analytics framework and web-application for on-farm research trials.
- A Bayesian hierarchical model quantifies the uncertainty in yield response.
- The model helps assess alternative practices, products, and technologies among trial locations.
- The framework provides a reactive break-even economic analysis of alternative management practices.

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AN INTRODUCTION TO ON-FARM RESEARCH NETWORK

A farmer network is an organization of farmers who exchange experiences, share their knowledge, and test important questions using common protocols and commercially available field equipment (Matthewson et al., 2013). There is increasing interest in On-Farm Research Networks (OFRNs) because they provide the infrastructure needed to test new products and management practices in farmers' fields (Kyveryga et al., 2018). In addition, data from these experiments can be used to validate simulation models and determine the economic profitability of new technologies. Within this infrastructure, the most common design is to compare a new management practice (e.g., seeding rate, row spacing, new pest and disease treatments) to a standard farmer practice. This new generation of OFRNs can help farmers improve their productivity, efficiency and profitability (Pruss et al., 2005; Moayedi and Azizi, 2012) and, create a novel communication platform between farmers, agronomists, and scientists.

DEVELOPING RESEARCH NETWORKS

Farmer networks can arise from diverse motivations and they can start by recruiting cooperating farmers and defining the network's missions. Once a group of farmers is identified, the next important step is to define a problem and research question (Kyveryga et al., 2018). The question should be simple enough to be approached through standard experimental designs and executed using farmers' available equipment. The collaboration among farmers, researchers, local agronomists or crop consultants makes the implementation of common experiments and protocols possible by defining the number of treatments, the variables to be measured (e.g., crop yield, grain moisture and protein content), and the experimental design. Usually, scientists or research agronomists assist farmers with data collection, data analysis, interpretation and communication of results to the general public.

Analyzing Data Across Experiments

Increasingly, scientists and farmers are using on-farm testing as an approach to build locally adapted recommendations. However, the scientific community is challenged with combining results from studies conducted on different soils and climatic

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Abbreviations: OFRN, on-farm research network.

conditions. Integrating yield and climatic data has the potential to improve recommendations. For example, Kyveryga et al. (2013a) combined on-farm, weather and soil data to analyze the risk of yield losses resulting from a reduction of farmer normal N fertilizer rates applied to corn (*Zea mays* L.). Bissonnette et al. (2018) used on-farm data from 18 strip-trial experiments located in the northern half of Iowa over 3 yr to study the effect of nematicide seed treatment, Clariva Complete Beans (CCB) (*Pasteuria nishizawae*, *sedaxane*, *thiamethoxam*, *fludioxonil* and *mefenoxam* as active ingredients) compared with CruiserMaxx Advanced plus Vibrance (CMV) (*thiamethoxam*, *mefenoxam*, *fludioxonil* and *sedaxane* as active ingredients), on soybean cyst nematode (*Heterodera glycines*) reproduction and soybean [*Glycine max* (L.) Merr.] yield. They found that CCB seed treatment had a variable effect on soybean cyst nematode reproduction and soybean yield. Kyveryga et al. (2013b) analyzed data from 282 on-farm strip-trial experiments across Iowa over 5 yr of experimentation to identify when a foliar application of *pyraclostrobin* fungicide produced profitable soybean yield responses. They found that greater yield responses were observed for trials that received more than 30.5 cm of cumulative March through May rainfall.

To our knowledge, most of the existing OFRNs are based in the United States and led by public institutions such as universities or extension services (Table 1). Private companies also manage their own OFRNs, but access to data and results summaries are limited. Some ORFNs have been implemented for decades, such as the Practical Farmers of Iowa led by Cooperators' Program since 1987, and the Nebraska On-Farm Research Network led by the University of Nebraska (2018) since 1990. Most of them have similarities regarding the crops of interest, the experimental design and the topics of research. Current large-scale equipment makes some experimental designs such as replicated strip trial design with two treatments (the new management practice and the control) more practical than others. The implementation of this experimental design was made easier in recent years due to wide adoption of precision agriculture technologies that enable farmers to measure yield with mass flow sensors and GPS technology, which generally produced similar results as weigh wagons (Nelson et al., 2015). The management practices tested typically involve crop management (e.g., planting date, seeding rate, tillage, row spacing), crop protection (e.g., pesticide, genetically modified resistant cultivars), plant nutrition (e.g., fertilizer, manure, lime) and plant growth regulators (e.g., auxin, gibberellic acid, cytokinin). In some cases, OFRNs are crop-specific (e.g., Minnesota Wheat's On-Farm Research Network and On-Farm Soybean Management Network) or management practice-specific (e.g., the Indiana Infield Advantage focuses on nutrients in corn).

Results of on-farm trials are usually presented as individual field reports (i.e., a report summarizing the outcome for one trial) showing replicate yield values and treatment averages in the form of tables or histograms. Some other basic information (e.g., planting date, variety, soil texture, weather data, location) are also typically provided. In an effort to develop more practical communication methods, some OFRNs such as the Minnesota Association of Wheat Growers (2018) On-Farm Research Network, Nebraska On-Farm Research Network and Pennsylvania On-Farm Soybean Network (2018) have compiled all trial reports into an annual report format. An example from Dupont Pioneer (Jeschke and Ahlers, 2018) studied the effect of foliar fungicides (alone or combined with an insecticide) on soybean across 279 on-farm trials and shared the trials' average yield differences through a histogram and ranking of trials by decreasing yield response values. Despite the number of trials involved, only the average yield response per trial was reported and without explanations of variability in yield response. In another example, the South Dakota On-Farm Research program allows for sorting experiments into different categories. The Nebraska On-Farm Research Network and the Iowa Soybean Association On-Farm Network have online searchable databases which allow users to query individual summary trial data by year, crop and, management practice, but this is not sufficient to understand general patterns in treatment effects and gain novel insights from the data.

Currently, for most OFRNs, individual trial summaries provide descriptive information and elementary statistical analysis. Even though this information is highly valuable, it does not directly lead to a better understanding of the overall agronomic performance of the treatment or product. Also, they do not allow for the detection of patterns that can explain the yield response variability for different soil textures, rainfall amounts, planting dates or seed varieties. Finally, individual trial summaries cannot provide an estimate of the probability that a new management practice will or will not outperform standard practices in following growing seasons or in new environments. To overcome these limitations, a new framework for the analysis of OFRN data is needed which is not simply limited to a multi-location analysis (Moore and Dixon, 2015), although it should contain common elements found in mixed-effect models and meta-analyses (Pinheiro and Bates, 2000; Philibert et al., 2012).

The evolution and recent expansion of OFRNs (Table 1) present a unique opportunity to fill this gap by developing a data-analytics framework and an easy-to-use tool for decision making which would allow effective and simultaneous summarization, analyses, interpretation and communication of the results. The development of such a data-analytics framework is necessary to improve predictions at the farm level that can ultimately lead to more cost-effective, sustainable and environmentally sound agricultural production. Data visualization is an important element of the data-analytics framework, useful for identifying trends and clusters, spotting patterns, evaluating model outputs, and communicating results (Unwin et al., 2006). Visualization tools are needed to allow farmers and agronomists to detect patterns across sites and years. Data visualization has the potential to revolutionize sharing and communication of analysis (Wojciechowski et al., 2015) and is more convenient and informative than individual summaries. So far, this approach has not been used in the context of OFRN.

CREATING A DATA-ANALYTICS FRAMEWORK

The main goals of our data-analytics framework called Interactive Summaries of On-Farm Strip Trials (ISOFAST) are: (i) assess the general agronomic performance of different practices, (ii) explain yield response variability using field-level covariates, and (iii) use interactive and dynamic visualization to enhance communication and decision making by farmers. The utility of this framework is illustrated using three case studies testing specific agronomic questions about a foliar fungicide on

Table 1. Examples of on-farm research networks.

Name	Managing organization	Experimental design†	Starting date	Crop
On-Farm Network	Iowa Soybean Association	RST	2005	Soybean; corn
Pennsylvania On-Farm Soybean Network	Pennsylvania Soybean Board.	RST	2009	Soybean
Nebraska On-Farm Research Network	University of Nebraska	RST RCBD	1990	Soybean; corn wheat; pea sorghum; beans
Minnesota Wheat's On-Farm Research Network	Minnesota Association of Wheat Growers	RST	2014	Wheat
Practical Farmers of Iowa	Cooperators' Program	RST RRST	1987	Corn; soybean; oat Winter rye; horticulture
Purdue Collaborative On-Farm Research	Indiana Certified Crop Advisers (CCAs) and Purdue Extension	RRST	2006	Soybean; corn
South Dakota Soybean On-Farm Research Program	South Dakota Soybean Research and Promotion Council	RST	2014	Soybean
California Collaborative Research and Extension network	University of California Santa Cruz	Split-plot	2014	Vegetables; strawberry
DuPont Pioneer Soybean Fungicide Research	Dupont Pioneer	NA	2007–2014	Soybean

† RST, replicated strip trial design; RRST, randomized replicated strip trial design; RCBD, randomized complete block design.

soybean, row spacing on soybean and a soil-applied insecticide on corn. Our framework is implemented through a web-application accessible to a broad audience to improve accessibility to on-farm research insights.

Preliminary Analysis

The data-analytics framework starts by providing a brief summarization of background information and rationale for testing a new management practice under on-farm conditions. Specific agronomic objectives, details about management practices, product chemistry, application rates, timing of applications and number of locations are also included. Our data-analytics framework provides a map which displays the trial locations and general attributes (Fig. 1a).

Because precipitation and temperature are important to understanding yield responses, the data-analytics framework allows for the simultaneous display of in-season monthly rainfall and growing degree day observation for each trial. Growing degree day (GDD) is a common temperature index used to estimate plant development, and accumulation of GDD values determines the maturity of crop, yield, and yield components (Qadir et al., 2007). Reference rainfall (average over the duration of all the trials) is included which help to identify wet, dry and average seasons (Fig. 1b, left). The cumulative GDD over the growing season with reference values are shown the same way (Fig. 1b, right).

Defining Yield Responses

The main objective of our framework is to quantify the effect of a new management practice on yield compared to a control (i.e., a control corresponding to a common cropping practice or a product normally used by a farmer). Two different metrics are proposed to measure yield response; the yield ratio (a ratio of yield obtained with new management practice to yield at the control) and the yield difference (yield obtained with the new management practice minus yield at the control).

The yield difference measures the effect of the new management practice in absolute yield units. It can be easily expressed as the economic gain or loss (in dollars per hectare), but it is unit-dependent. The yield ratio measures the effect of the management practice relative to the yield obtained at the control. It is unitless and thus it does not depend on yield units or a moisture content adjustment or other similar factors. Its value can be used in different contexts characterized by different productivity levels. It is thus possible to multiply the estimated yield ratio by low to high reference yield values to obtain the range of yield gains or losses. A yield ratio higher than 1, or a yield difference higher than 0, means a yield gain using the new product or management practice. A yield ratio lower than 1, or a yield difference lower that 0, means a yield loss using the new management practice. The main consideration for favoring one metric over the other is whether the management practice scales with yield (yield change) or if it is invariant to yield levels (absolute yield difference). For this reason, our data-analytics framework provides both metrics.

Importance of Replication

It is very common in agronomic experiments to have replicates (i.e., multiple measurements for a single variable or multiple experimental units) to reduce variability and increase the statistical power of experiments. Also, replicates are important to quantify variability within each experiment (i.e., within a trial) and between experiments (i.e., between trials). Sometimes, an observation can be judged far from its group average and thus be considered as an outlier (Ramsey and Schafer, 2013). Outliers may be due to natural variation, equipment problems, human error, or can be caused by hail, flooding or extreme heat. Graphics display all replicate values and describe yield response variability between and within trials (Fig. 1c). Additionally, trials are ranked by increasing mean yield responses. Displaying the means helps to summarize data and identify replicates that deviate from the overall mean or general trend. Ranking trials by decreasing average yield response provides a first impression of the effectiveness of the treatment. Our framework does not remove outliers if they can be explained by natural, physiological or agronomic mechanisms. We consider all outliers because they often show important source of yield variability.

Yield variability can also be explained by environmental and management variables. Since trials are generally located across the state and farmers apply their own management preferences, some characteristics such soil texture, seed variety, and crop

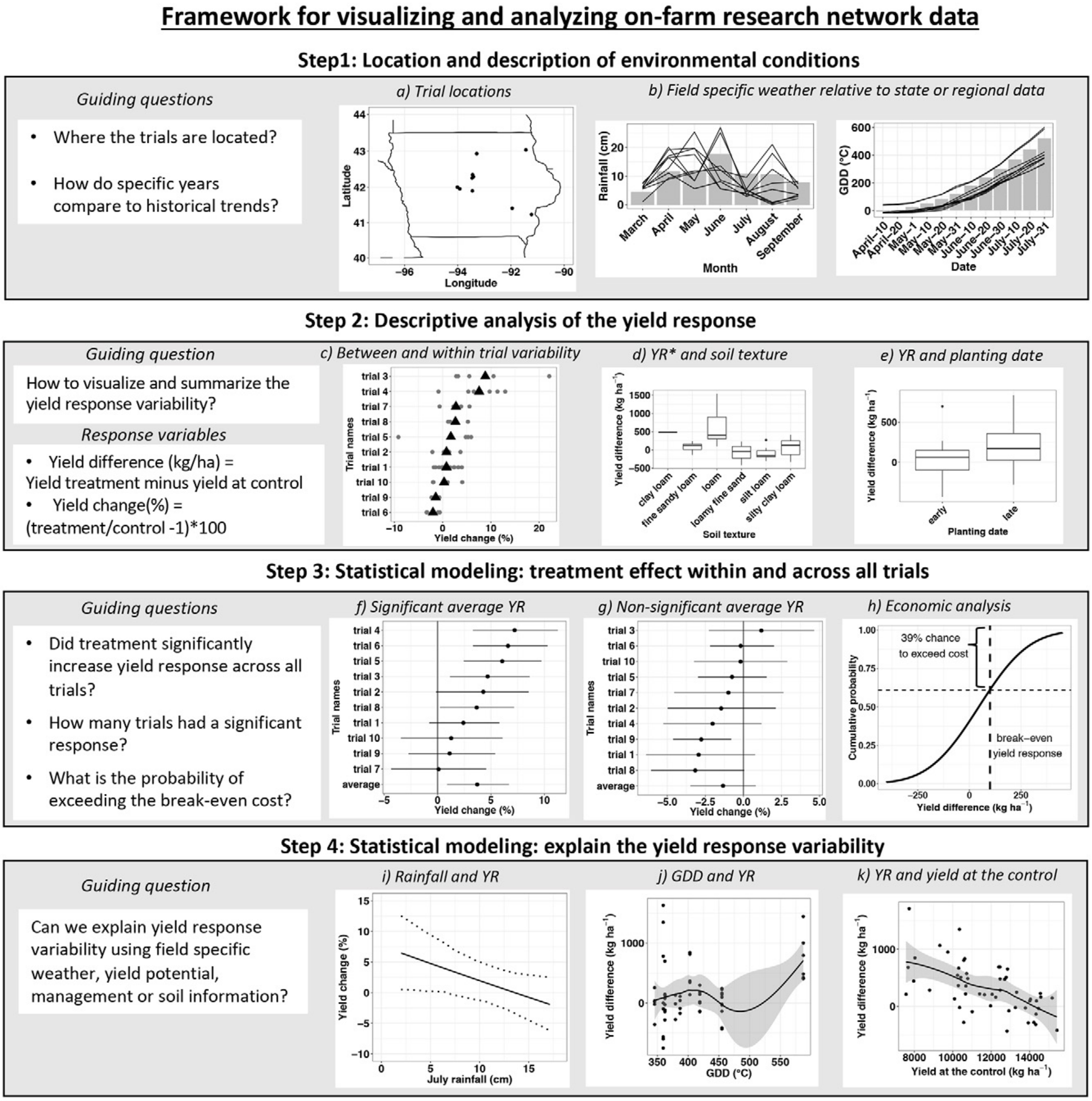

Fig. 1. Example of visualization of trial results from on-farm research networks. (a) dots represent trial locations; (b) a trial is represented by a black line, and the reference values (using historical data or climatology) are represented by grey bars; (c) dots represent individual replicates or experimental units and the black triangle represents the trial mean; (d and e) boxplots of the yield response (YR) for the soil textures and the planting dates; (f and g) estimated mean YR and the associated 95% credible intervals for the individual trials and the overall yield response at the bottom (posterior means from Bayesian analysis); (h) the dashed line represents the break-even yield response, the vertical bar represents the probability to exceed breakeven cost, and the curve represents the cumulative distribution of yield response; (i) the black line represents the estimated yield response and the dashed lines represent the 95% credible intervals (from Bayesian analysis); (j and k) the dots represent trial means; the black line, the estimated yield response; and the grey shade represents the 95% confidence intervals from the local regression.

planting dates can vary substantially. In our framework, yield responses are also presented for different soil texture and planting date categories (early and late planting date) using a boxplot (Fig. 1d-e). The planting date threshold corresponds to the midpoint between the earliest and latest planting dates related to a specific management practice.

Yield Limiting Factors and Yield Response

Yield limiting factors (e.g., weather stress, pest pressure, soil characteristics) can influence crop yields directly or by interacting with each other. When crop damage by pests is not observed, then yield at the control can be used as a proxy of yield limiting stress factors. If yield is low in the control strips, this might indicate that a limiting factor or pest pressure has prevented the crop from reaching its potential. A consistent negative relationship between yield response and yield in the control strips would suggest that the product or practice studied has directly addressed a yield limiting factor (Fig. 1k). For example, Salvagiotti et al. (2008) used yield measurements from fertilized plots (N application) and unfertilized control plot and demonstrated that yield response to N fertilization was positive when the yield potential was low. The reason behind the lower yield potential was different for each specific site-year, such as low soil pH or fertility or water limitations. Another way to assess pest pressure or other major limiting factors in on-farm trials is to use crop scouting data. This requires rigorous knowledge of pest and crop biology, pest identification and sampling methods. Consequently, at the moment, our framework does not uniformly provide a specific analysis and visualization of scouting data. After a descriptive step to visualize and describe yield response variability, statistical modeling can be used to help to explain the heterogeneity, improve the understanding of the data and quantify the uncertainty of the treatment effects.

Statistical Modeling

Appropriate statistical analyses should focus on different but related questions: What is the performance of a specific treatment in an individual trial or location? And what is performance across all trials or the overall mean yield response? Answering these questions will be beneficial (i) to understand the effectiveness of management practices at the network level, (ii) to clarify the specific questions that farmers have about their own farm, and (iii) to help make future management decisions.

Since data are collected for several individual trials, we used a hierarchical model to estimate the mean effect size at the network level, the individual effect sizes for all trials, and their credible intervals through a Bayesian approach. The network level represents the whole group of on-farm trials testing the same management practice. The Bayesian analysis has an advantage over classical statistical analyses because it can use prior information derived from literature or expert knowledge. The Bayesian approach integrates the observed data with priors and returns a posterior distribution of the parameters of interest. Another advantage of the Bayesian approach is that it allows incorporation of full uncertainty in all parameters. The uncertainty in parameter estimates is quantified by using credible intervals.

The hierarchical model uses yield ratios or yield differences as the response variable. The yield ratio generally benefits from log transformation for normality and stabilization of variances. The results are then back-transformed for interpretation as percent change; that is, yield change (%) = (yield ratio − 1) × 100. Trials are represented by site-years as they are rarely repeated at the same location over time. The Bayesian hierarchical model was implemented using the R package, *MCMCglmm*, through RStudio (Hadfield, 2010; RStudio Team, 2015).

For a continuous explanatory variable, the statistical model is:

$$\log(R_{ij}) = \mu + \beta X_{ij} + \alpha_i + \varepsilon_{ij}$$

where $\log(R_{ij})$ represents the natural log of the jth replicate of the yield ratio (or yield difference without log transformation) in the ith site-year; μ represents the intercept of the log transformed ratio; β represents the regression parameter (equal to zero if there is no explanatory variable such as rainfall); α_i represents the random effect of the site-year; and ε_{ij} represents the residual error. Both α_i and ε_{ij} are assumed to follow independent Gaussian distributions with mean zero and constant variances,

$\alpha_i : N(0,\sigma^2_\alpha)$, $\varepsilon_{ij} : N(0,\sigma^2_\varepsilon)$.

We defined priors for the three parameters of the model (i.e., μ, σ^2_α and σ^2_ε). The priors for the intercept μ and for the regression parameter β represent the distribution of the mean of the log ratio (or the yield difference) and the distribution of the effect of the explanatory variable X, respectively. These priors are independent Gaussian distributions with a mean of zero and a variance of 2. With a variance of 2, the log ratio and the regression parameter can take either a high positive or a low negative value depending on the dataset.

The priors of the variances of the random effect, σ^2_α, and of the residual error, σ^2_ε, are independent inverse Gamma distributions with parameters ν/2 and ν/2, where the degree of belief ν is equal to 0.002. The parametrization of the priors is specific to the R package *MCMCglmm* (Hadfield, 2010).

For a categorical variable (such as the soil texture), the statistical model is:

$$\log(R_{ij}) = \mu + \sum_{k=2}^{K} \beta_k X_{ij}^{(k)} + \alpha_i + \varepsilon_{ij}$$

where $X_{ij}^{(k)}$ is equal to 1 (an indicator variable) if R_{ij} belongs to the kth category, zero otherwise; β_k represents parameter for the kth category; and μ represents the mean log ratio of the first category.

We used the same visual approach as in meta-analysis (i.e., forest plot) to show estimated posterior yield responses from individual trials. The forest plots show variation between and within trials, as well as overall posterior means (Fig. 1f-g). Individual trial posterior means are statistically significant if their credible intervals do not cross the vertical line (i.e., yield change or yield difference equal to zero) corresponding to a threshold between yield increase and yield loss from a new management practice or treatment in question. Trials are ranked in increasing order to easily distinguish potential groups of trials with similar positive or negative yield response. Different credible interval levels (i.e., 0.80, 0.90, or 0.95) are available to satisfy farmers' and scientists' expectations and risk preferences.

Cumulative probabilities of yield response at the regional level can be calculated from the posterior distributions of yield response or yield change provided by the Bayesian model. The cumulative distribution function represents the probability that the yield response is less than or equal to a certain value (Fig. 1h). For example, if the probability of having a 4% yield increase is equal to 70% it means than there is a 70% chance of reaching a 4% yield increase or less. Cumulative distribution of yield response can be useful for decision making for farmers.

Our data-analytics framework provides two different ways to attribute yield response variability using explanatory variables. The first approach is for continuous or categorical variables in the Bayesian hierarchical model (see equations above) (Fig. 1i) and the second approach is to use a local polynomial regression (Fig. 1j) (Cleveland, 1979). For each method, 95% credible intervals or 95% confidence intervals, respectively, are displayed to describe the uncertainty in yield response.

Calculating Economic Responses

Economic analysis is important to decide if a new practice or product should be adopted. Cumulative distribution functions of yield response are used to conduct a break-even economic analysis (Fig. 1h). The on-line tool, allows users to enter grain price and treatment cost (i.e., cost of product and application). Based

Fig. 2. Interface of the web application, on the left side bar is a menu with different studies and description of the components available for that study. On the right is the main panel, displaying components which have been selected for review and interaction.

on this information, a break-even yield response and expected profit are calculated. The break-even line is plotted on the graph and the probability of exceeding the break-even cost is estimated as the distance on the y-axis between 1 and the intersection of the cumulative distribution curve with the break-even line. The range in expected average profit is calculated using 25th and 75th percentiles from the cumulative distribution function.

Visualization

The graphical features are implemented through an interactive and dynamic graphical web-tool. We used Shiny, an R package from RStudio (RStudio Team, 2015; Chang et al., 2016) that combines numerous extension packages. The web-application has a user interface divided in two parts: the sidebar menu on the left and the main panel on the right (Fig. 2). On the sidebar menu, the user can select the crop and then a specific management practice. Then, the user has access to different components organized into a list on the sidebar menu.

The main panel, located on the right side of the interface, returns visuals described in Fig. 1. The main panel has interactive features such as zoom-in, zoom-out, filter, select and pointer-hovering to interact with data and graphical information. Zoom-in and zoom-out are interactive features available for all the visual graphics but are most useful for the trial locations maps if users want more precision regarding trial location. The tool blocks identifying exact trial location due to data privacy issues. Because of the large amount of data for some management practices, it can be inconvenient to observe summaries of all data at once.

To overcome this visualization issue, data can be filtered by year to allow users to focus on a specific data subset. Selection is another important visualization process in our web-application. When a graphic represents the yield response, users can choose between the yield change and the yield difference. For the relationship between yield response and monthly rainfall, users can select a specific month or cumulative months by start, middle or end of crop season. By hovering the pointer over the dot on a visual graphic, a label reports extra information such as the exact numerical value of the dot. For example, for the visual graphic representing the overall and trial yield responses (Fig. 1f), a label reports the exact numerical value of the point estimate and the boundaries of the credible interval for yield difference or yield change.

The web-application also provides interactive boxes located below each graphic to report extra information, results of statistical analyses and key messages. Some boxes are updated in real time after users' action. For example, the number of trials that had a significant positive yield response is updated after the selection of a significant level for the credible interval. The web-tool is comprehensive and intuitive enough to be easily used by a broader audience that will include farmers and non-specialists. More detail about the structure of our web-application and how to use it are available in the supplemental material.

Our data-analytics framework was implemented for a total of 34 different management practices tested by the Iowa Soybean Association. The data related to the different management practices are stored in different datasets (one dataset per management practice) and differed by number of trials, yield value and years of experiments (Table 2).

The following section provides examples of the implementation of the data-analytics framework for three case studies: foliar fungicide on soybean, row spacing on soybean and soil-applied insecticide on corn.

Case Studies

Foliar Fungicide Impact on Soybean Yield

Hypothesis: foliar fungicides increase soybean yields.

Background. Foliar fungicides help to manage several common foliar diseases in soybean such as anthracnose, Septoria brown spot, Cercospora leaf blight, frogeye leaf spot, pod and stem blight, and soybean rust. Foliar pathogens reduce green leaf area causing a reduction of photosynthetic activity which can affect crop growth and yield (Bassanezi et al., 2001). In Iowa, foliar diseases typically result in minor yield losses which explains why applying foliar fungicide has not been a common practice (Swoboda and Pedersen, 2009; Wrather and Koenning, 2006). However, the use of foliar fungicide has increased since 2004, especially during periods of high market grain prices. As a consequence, better information was needed about fungicides in managing Septoria brown spot or frogeye leaf spot (Kyveryga et al., 2013b). The objective of these trials was to study the effect of a foliar fungicide (Headline) on soybean compared to a control by quantifying the yield response across a wide range of environmental and management practices.

Materials and Methods. The foliar fungicide Headline was tested in 206 trials (Fig. 3, left) over 9 yr (2006–2013, 2015) and compared to a control (untreated). These experiments used yield data collected on combines equipped with GPS. The active ingredient of Headline is *pyraclostrobin*. Most of the applications were done by farmers using ground sprayers, but in ~20% trials the foliar fungicide was applied by airplanes. The time of application varied between trials but most of them were done at the crop stage R3 (beginning pod development).

The experimental design was the replicated strip, where the two treatments are applied in strips without randomization (Fig. 3, right). A pair of strips (foliar fungicide and the control) constitutes a replicate. Each trial which was part of the network had a minimum of three replicates. Some trials required more than three replicates to capture the entire field for spatial analysis of yield responses. The width of the individual strip depends on the size of application equipment and can range from 4.6 to 27.4 m. The length of the strips depends on the

Table 2. Description of different on-farm trial categories included in our framework. Chemical names for registered commercial products are given in parentheses.

Treated	Control	Crop	No. trials	No. experimental units per treatment	No. years
Nematicide Clariva Complete Beans† (*Pasteuria nishizawae*)	Cruiser Maxx Advanced + Vibrance (*thiamethoxam, mefenoxam, fludioxonil* and *sedaxane*)	Soybean	32	223	3
Seed treatment Ilevo† (*fluoryram*) + Acceleron†	Acceleron (*pyraclotrobin* and *imidacloprid*)	Soybean	26	353	2
Row spacing 15 inches	30 inches	Soybean	18	120	4
Foliar fungicide Headline† (*pyraclostrobin*)	Untreated	Soybean	206	1088	9
Foliar fungicide Stratego† (*prothioconazole* and *trifloxystrobin*)	Untreated	Soybean	29	328	5
Foliar fungicide Stratego YLD† (*prothioconazole* and *trifloxystrobin*)	Untreated	Soybean	37	200	3
Foliar fungicide Priaxor† (*pyraclostrobin* and *fluxapyroxad*)	Untreated	Soybean	43	191	6
Foliar fungicide Priaxor and Fastac† (*alpha-cypermethrin*)	Untreated	Soybean	22	97	5
Foliar fungicide Quadris† (*azoxystrobin*)	Untreated	Soybean	18	93	1
Hero† pyrethroid insecticide (*bifenthrin* and *zeta-cypermethrin*)	Untreated	Soybean	7	43	1
Inoculant Terramax†	Untreated	Soybean	15	99	1
Biostimulant Vitazyme† (1-*triacontanol* and *brassinosteroids*)	Untreated	Soybean	10	44	2
Biological co-product Tryptophan†	Untreated	Soybean	16	89	2
Seed treatment Nemastrike† (*tioxazafen*) + Acceleron	Acceleron (*pyraclotrobin* and *imidacloprid*)	Soybean	6	34	1
High density seeding (normal rate + 30,000)	Normal rate between 140,000 and 170,000 (rate commonly used in Iowa)	Soybean	20	12	4
Low yield density (normal rate 30,000)	Normal rate between 140,000 and 170,000 (rate commonly used in Iowa)	Soybean	21	140	4
Winter rye cover crop	Untreated	Soybean	32	166	6
Oats cover crop	Untreated	Soybean	12	50	2
Sulfur SuperCal SO4	Untreated	Soybean	15	75	1
Residual sulfur SuperCal SO4	Untreated	Soybean	6	27	1
Soil-applied insecticide Aztec† (*tebupirimphos* and *cyfluthrin)*	Untreated	Corn	36	195	8
Fertilizer anhydrous ammonia	UAN	Corn	26	127	4
Fall-applied anhydrous ammonia	Spring-applied anhydrous ammonia	Corn	66	360	6
Nitrification inhibitor (Instinct†) on manure	Untreated	Corn	29	115	4
Nitrification inhibitor (Instinct) on UAN	Untreated	Corn	19	96	3
Foliar fungicide Headline (*pyraclostrobin)*	Untreated	Corn	143	703	9
Foliar fungicide Stratego (*propiconazole* and *trifloxystrobin*)	Untreated	Corn	32	153	2
Foliar fungicide Stratego YLD (*propiconazole* and *trifloxystrobin*)	Untreated	Corn	82	444	6
Foliar fungicide Quilt† (azoxystrobin and propiconazole)	Untreated	Corn	28	144	3
Biological co-product Tryptophan†	Untreated	Corn	14	68	2
Seed treatment Nemastrike (*tioxazafen*) + Acceleron	Acceleron (*pyraclotrobin* and *imidacloprid*)	Corn	8	53	1
Mycorrhizal fungi Endoprime†	Untreated	Corn	17	148	2
Sulfur SuperCal SO4	Untreated	Corn	48	214	4
Residual sulfur SuperCal SO4	Untreated	Corn	16	77	2

† Commercial products are trademarks of the respective companies.

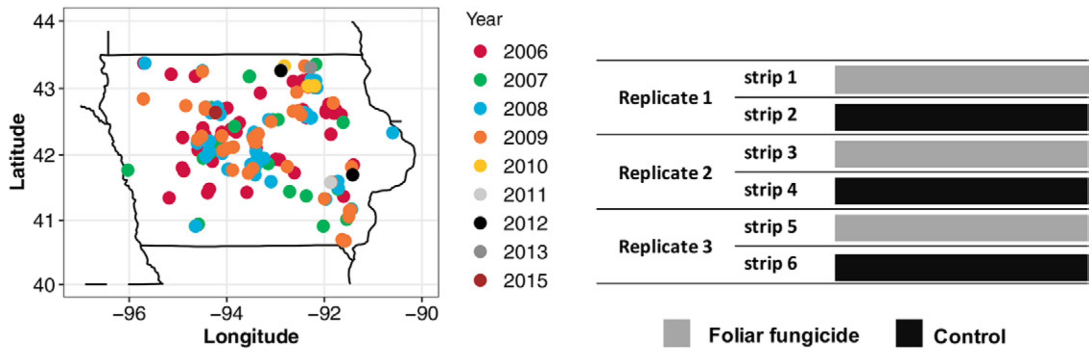

Fig. 3. Schematic illustration of an on-farm research network where foliar fungicide applications on soybean were compared to an untreated control. Each trial is represented by a dot (described on the left) on the map where the year of measurement is distinguished by color. All the trials follow a replicated strip trial design (described on the right) and have at least three replicates.

field size. For example, a typical field in Central Iowa is ~32 ha, which would have a dimension of approximately 457 by 701 m.

Trials were well distributed throughout Iowa, with a majority located in the Des Moines Lobe (Fig. 3, left). Therefore, our data cover a broad set of environmental conditions and field management across Iowa.

Disease development in soybean fields can be affected by different environmental conditions or management practices. The tool provides the ability to display the effect of planting date and soil texture on yield response to fungicide. In this case, yield difference was not significantly affected by planting date or soil texture (Fig. 4). However, the mean yield difference was higher for the early planting date than for the late planting date, at 246 kg ha^{-1} (se = 28) and 195 kg ha^{-1} (se = 24), respectively.

The average yield change was statistically significant and equal to 4.5% (3.9; 5.1) indicating a 95% probability that the posterior yield response would fall in a range from 3.9 to 5.1% of yield increase (Fig. 5). Considering all years, 54% of the trials (112 of 206 trials) had a significant positive yield response to the foliar fungicide Headline. These results confirm that this management practice provided consistent yield benefits under the evaluated conditions.

Our results are in general agreement with previous studies looking at the difference between Headline and an untreated control. For example, results from small plot research trials over 5 yr managed by Dupont Pioneer (Jeschke and Ahlers, 2018) showed an average yield response of 249 kg ha^{-1} when Headline was applied at the R3 growth stage and a total of 78% of the trials presented a positive yield response. Bestor et al. (2014) had similar results and reported that Headline had a higher yield (276 kg ha^{-1}) than the untreated control. The average yield difference, based on seven locations, was equal to 276 kg ha^{-1}. Wise and Buechley (2010) and Mahoney et al. (2015) reported a yield for Headline and untreated control of 202 kg ha^{-1} and 180 kg ha^{-1}, respectively.

Row Spacing Impact on Soybean Yield

Hypothesis 1: Narrow row spacing produce higher yields than wide row spacing on soybean.

Hypothesis 2: Wet conditions increase diseases in narrow row spacing on soybean.

Background. A common soybean row width spacing is equal to 76 cm, however many farmers have been testing whether yield will increase by planting narrower rows (De Bruin and Pedersen, 2008). Soybean often yields higher when planted in narrow versus wide row spacing. For example, De Bruin and Pedersen (2008) advocate the adoption of 38-cm row spacing based on a 5.6% yield increase in a 38-cm vs. 76-cm spacing in a 3-yr study at five locations in Iowa. Iowa State University Extension and Outreach showed a 309 kg ha^{-1} advantage of 38-cm over 76-cm in a 2-yr study at 17 locations. However, many farmers are still hesitant to switch to narrow row spacing due to the required investment in new planters and the higher risk of soybean diseases in narrow

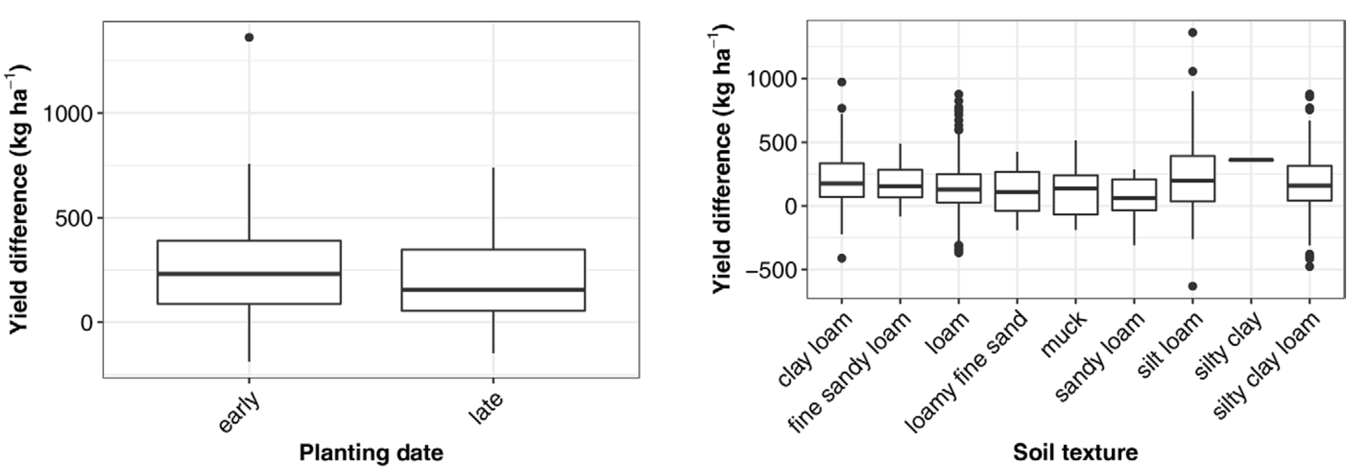

Fig. 4. Yield difference by planting date (on left) and soil texture (on right) for the foliar fungicide on soybean dataset. A planting date before 20 May is considered as early; after as late.

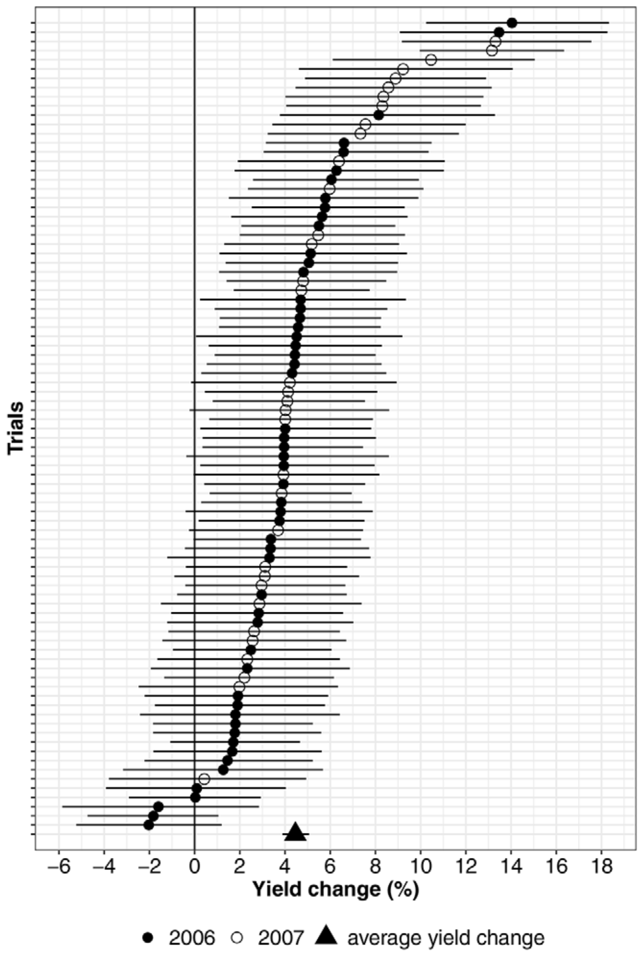

Fig. 5. Estimated posterior mean yield change for individual trials and their 95% credible intervals for data collected in 2006 to 2007 for the foliar fungicide on soybean dataset. The average yield change is estimated using the whole data set. For simplicity, only 2 yr of measurements are displayed in this figure.

rows. In fact, narrow spacing increases the canopy area development, light interception, growth rate, dry matter accumulation and seed yield but also results in higher soil moisture or relative humidity which may create favorable conditions for the development of white mold (Sclerotinia stem rot). The objectives were (i) to study the impact of narrow row spacing compared to wide row spacing by quantifying the yield response, and (ii) to study the effect of rainfall amounts on yield differences.

Materials and Methods. Wide row spacing (76 cm) and narrow row spacing (38 cm) were tested in 18 trials in Iowa conducted during 4 yr (2010, 2014–2016). Wide row spacing is considered as the control treatment since it is used more commonly. To achieve the narrow, 38-cm, row spacing treatment a 76-cm row planter was used twice in the same treatment using autosteering or GPS guidance systems. This is feasible for research trials, but not practical for typical commercial use. The experimental design is the same as the one described on Fig. 3.

Results and Discussion. The overall mean yield change as a result of switching from wide to narrow row spacing was estimated at 1.4% (–2.1; 4.6). The treatment difference is not significant as the low boundary of the credible intervals is negative (Fig. 6). The trial 2014-012A at the top of Fig. 6 reached the highest estimated yield change and deviated substantially from other trial results. A plausible explanation is that this trial was

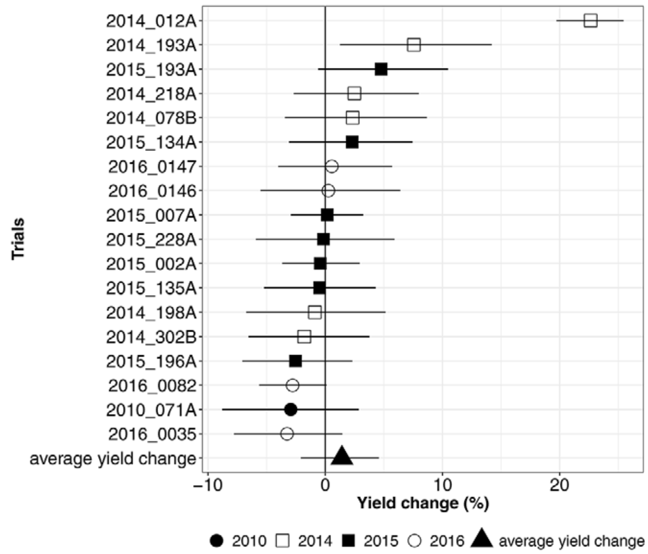

Fig. 6. Estimated posterior mean yield changes for on farm trials comparing narrow to wide soybean row spacing and their 95% credible intervals for row spacing on soybean dataset. The codes on the *y* axis are the identifiers for different strip trials (fields). All trials were conducted in Iowa.

affected by hail in early July and these conditions favored the ability of plants in the 38-cm row spacing to recover over that of plants in 76-cm row spacing. Only 2 of the 18 trials had a significant positive yield response which favored the 38-cm row spacing compared to the 76-cm row spacing.

Our results do not agree with the findings of De Bruin and Pedersen (2008) as they found that 38-cm row spacing yielded 248 kg ha^{-1} higher than 76-cm row spacing in Iowa. They advocated the adoption of 38-cm row spacing based on a 5.6% yield increase in a 38-cm vs. 76-cm spacing in a 3-yr study at five locations in Iowa. Another study led by the ISU Extension and Outreach (2019) including more than 30 experiments found that the average yield response for narrow rows was higher than 303 kg ha^{-1} compared with wide row spacing. Differences between studies were attributed to soil dryness. For example, the relationship between yield response and rainfall in July (Fig. 7) suggests that there is an advantage of using 76-cm

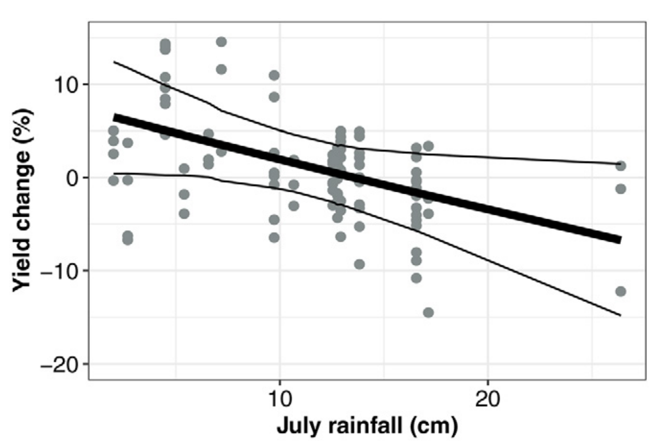

Fig. 7. Yield change for all the trials as a function of July rainfall and 95% credible intervals (thinner lines) for the mean change for the row spacing on soybean dataset. Grey dots represent the data points (for all the trials) used to adjust the Bayesian hierarchical model with July rainfall as a continuous variable.

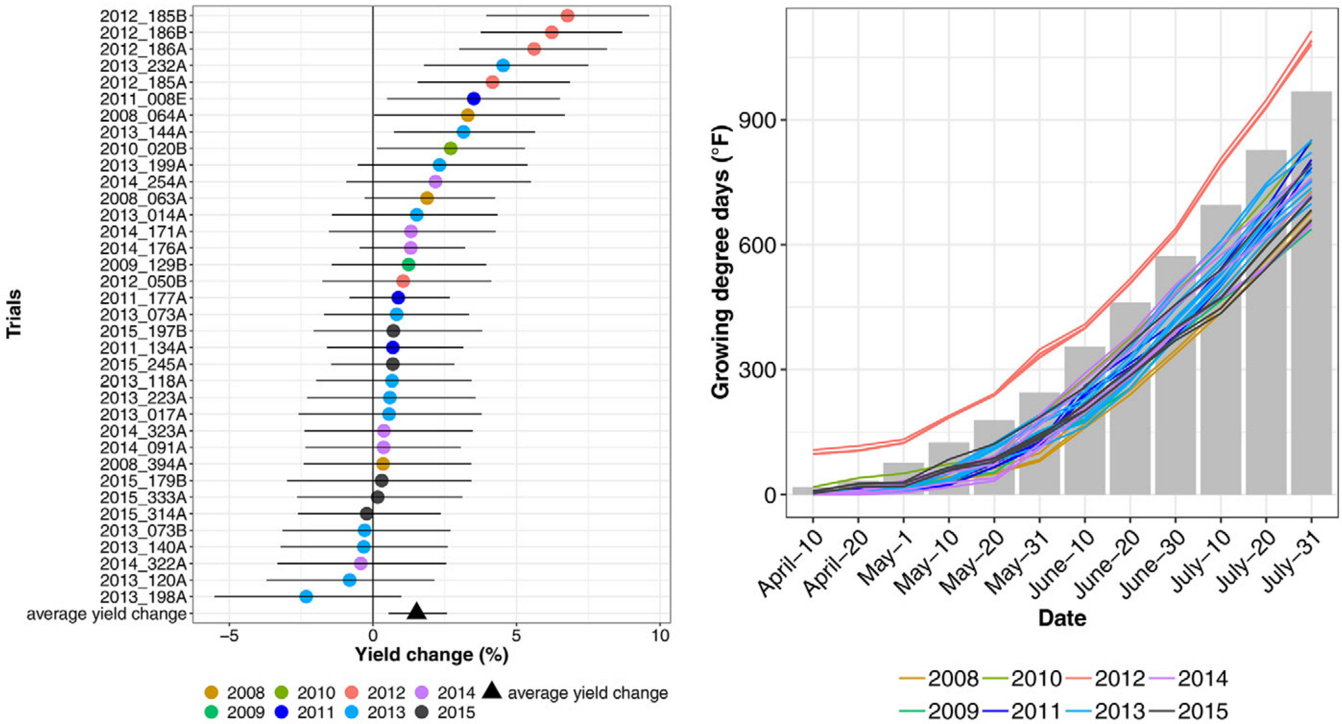

Fig. 8. Estimated yield change for individual trials and the corresponding 95% credible intervals for the soil-applied insecticide treatment (Bayesian hierarchical model outputs) (on left). Each trial is represented by a line and reference values of growing degree days in Central Iowa are represented by gray bars (on right).

row spacing when rainfall amounts exceed ~15 cm. Under wet conditions, the 38-cm row spacing results in excessive moisture build-up in the canopy favoring the development of Sclerotinia stem rot. Consistent with this result, Andrade et al. (2019) found that, in the central United States, July rainfall was higher in the experiments showing a yield advantage using wide row spacing. Soybean producers should be aware that the conclusion given by published data using small plot studies do not necessarily agree with the conclusions from OFRN. There is a need to understand why sometimes the results from OFRN and small plot research are not consistent.

Soil-Applied Insecticide Impact on Bt-Corn Yield

Hypothesis 1: Soil-applied insecticide to Bt-corn protect yield from corn rootworm (Diabrotica virgifera virgifera) damage.

Hypothesis 2: Soil-applied insecticide reduce the impact on corn root mass.

Background. The western corn rootworm is one of the most destructive corn pests in the Midwestern United States (Park and Tollefson, 2006). Corn rootworm feeds on corn roots and can drastically reduce root mass and grain yield (Oleson et al., 2005). Planting genetically modified corn, such as Bt-corn, can be a management strategy to reduce pest pressure, as they produce insecticidal proteins. In 2009, a study including 64 trials on continuous corn showed that soil insecticides could boost yields of corn rootworm hybrids with the Bt trait (Swoboda, 2009). The average yield increase was greater than 672 kg ha^{-1} for 40% of the trials. In addition, some farmers used soil-applied insecticide on Bt-corn to reinforce their protection strategy despite a significant cost.

The objectives are (i) to study the impact of a soil-applied insecticide to Bt-corn compared to an untreated control by quantifying the yield response, and (ii) to quantify root damage by measuring root injury (eaten nodes) and root weight.

Materials and Methods. The commercial soil-applied insecticide Aztec (active ingredients *tebupirimphos* and *cyfluthrin*) was compared with an untreated control in 36 trials over 8 yr (2008–2015). All the trials had corn as a previous crop. The two treatments were applied to corn rootworm resistant corn hybrids (containing the Bt trait). Aztec was applied in-furrow with farmer equipment. The experimental design was the same as the one described in Fig. 3.

Results and Discussion. The Bayesian hierarchical model estimated a yield increase across all trials equal to 1.5%, with corresponding 95% credible intervals (0.5; 2.6) (Fig. 8, left). These results were different from a study conducted by Petzold-Maxwell et al. (2013) where yield differences were not detected.

Nine out of 36 trials had a significant yield response and four of them occurred in 2012. This is likely because 2012 was dryer and warmer than normal years, leading to conditions where corn without a soil-applied insecticide suffers greater yield losses (Fig. 8, right) and the insecticide had a positive impact on corn yield. Our scouting data related to root injury did not show a clear difference between corn with or without a soil-applied insecticide. In the previous study conducted by Petzold-Maxwell et al. (2013) there was no significant difference in root injury between Bt-corn with or without a soil-applied insecticide while Gassmann (2012) found that root injury was significantly lower for Bt-corn with soil-applied insecticide compared to the control.

Limitations of the Data-Analytics Framework

Some caveats of our approach should be highlighted. Limited access to environmental and management variables prevented us from gaining a deeper understanding of yield response variability. Data collection of environmental and management variables should be a crucial step in the ORFN to improve the analysis. Since the analysis of scouting data is specific to each new management practice and research question, our data-analytic framework does not provide uniform visual graphics and statistical methods to summarize this type of data. Nevertheless, we highly recommend studying the relationship between scouting data and other variables collected through the OFRN such as growing degree days, cumulative rainfall, soil texture, and planting date.

To facilitate the adoption of the new platform, we wrote a manual guide for farmers that explains how to use the web-application and how to interpret the graphics. Next steps will be to include contextual tooltips into the web-application and to provide training to improve and facilitate the adoption of the web-application.

Our web-application will continue to evolve as needed with upgrades to existing plots, summaries, and the addition of new management practices. In the future, our web-application could be improved by interviewing users to receive their feedback and to ensure proper interpretation and understanding of the graphics and information available.

SUMMARY

In this paper, we presented an interactive data-analytics framework for analyses and visualization of data from OFRNs. The aim of our data-analytics framework is to communicate and share descriptive information and statistical summaries of on-farm research to a broader audience. Our framework is well adapted to a replicated strip trial design using two treatments with or without strip randomization. Most of the visual graphics can be applied to other experimental designs. Graphics and statistical methods were implemented for 34 different management practices tested on soybean and corn. We used statistical approaches that differed from those commonly applied to OFRN data. Trials were analyzed together and not individually, which provides a better understanding of the overall effectiveness of a new management practice. In addition, the uncertainty of the yield response was estimated to include the range of plausible values. Decision making about the new management practice should be based on combining different outputs and summaries from the data-analytics framework in a proper economic and agronomic context.

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SUPPLEMENTAL MATERIAL

Supplemental material is available with the online version of this article. The supplemental document contains screenshots of the web-application interface and examples of product outcomes.

SOFTWARE AVAILABILITY

Software name: ISOFAST

Developers: Anabelle Laurent, Xiaodan Lyu, Suzanne Fey, Samantha Tyner, Halley Jeppson, Eric Hare.

Year of release: 2018

Hardware required: PC, tablet, mobile

Software required: Web browser. Firefox, Chrome, Safari, Internet Explorer

Programming language: R

Availability: Currently hosted at https://analytics.iasoybeans.com/cool-apps/ISOFAST/

License: Free for non-commercial use

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