



A yield comparison between small-plot and on-farm foliar fungicide trials in soybean and maize

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Abstract

Agronomic research provides management recommendations based on small-plot trials (SPTs) and on-farm trials (OFTs) with very different characteristics. SPTs are traditionally conducted at agricultural experiment stations by research institutes or universities, while OFTs are conducted under commercial-scale conditions and managed by farmers using their own equipment. Several researchers claimed that discrepancies could occur between these two types of trials, which can make the extrapolation of results from SPTs to the farm level difficult. In our study, we conducted an extensive comparison of small-plot and on-farm trials to analyze the effect of foliar fungicide application on maize and soybean yields. We collected data on maize and soybean from five US states. Analysis of the soybean data showed similar mean yield responses and within-trial standard deviation to fungicide application between 479 OFTs and 83 SPTs. For maize, our comparison of 300 OFTs and 114 SPTs showed similar mean yield response in both. Nevertheless, the within-trial standard deviation was three times smaller in on-farm compared to small-plot trials. On the other hand, the between-trial standard deviation (measuring the variability of the effects of fungicide application across different environments) was almost twice as large in SPTs than in OFTs for both crops. Hence, the differences in the effects of fungicide on yield were similar whether they were estimated using OFTs or SPTs for both crops. This implies that OFTs can potentially detect significant yield differences with fewer replicates and thus reduce the cost of data generation. We argue that SPTs can be seen as a preliminary step before scaling up to OFTs to facilitate technology transfer and extrapolate the results in real farming conditions.

Keywords Bayesian multilevel · Crop yield · Foliar fungicide · On-farm trial · Scaling

1 Introduction

Agronomic research commonly produces knowledge of production-system performance and provides valuable management recommendations based on field experiments (Kravchenko et al., 2017). Agronomists carry out different types of field, and these involve experimental plots with very different characteristics. For example, small-plot research trials (SPTs), based on experimental plots of 0.005 to 0.01 ha,

are the most widely used to provide management recommendations (Kravchenko et al., 2017). They are traditionally conducted at agricultural experiment stations by research institutes or universities and are better suited for advanced or complex experimental designs (i.e., randomized complete block or split-plot). While SPTs might not always represent local or conventional farming systems and farming practices (Marchant et al., 2019), they are easier to manage for evaluating several treatments in the same experiment (Kandel et al.,

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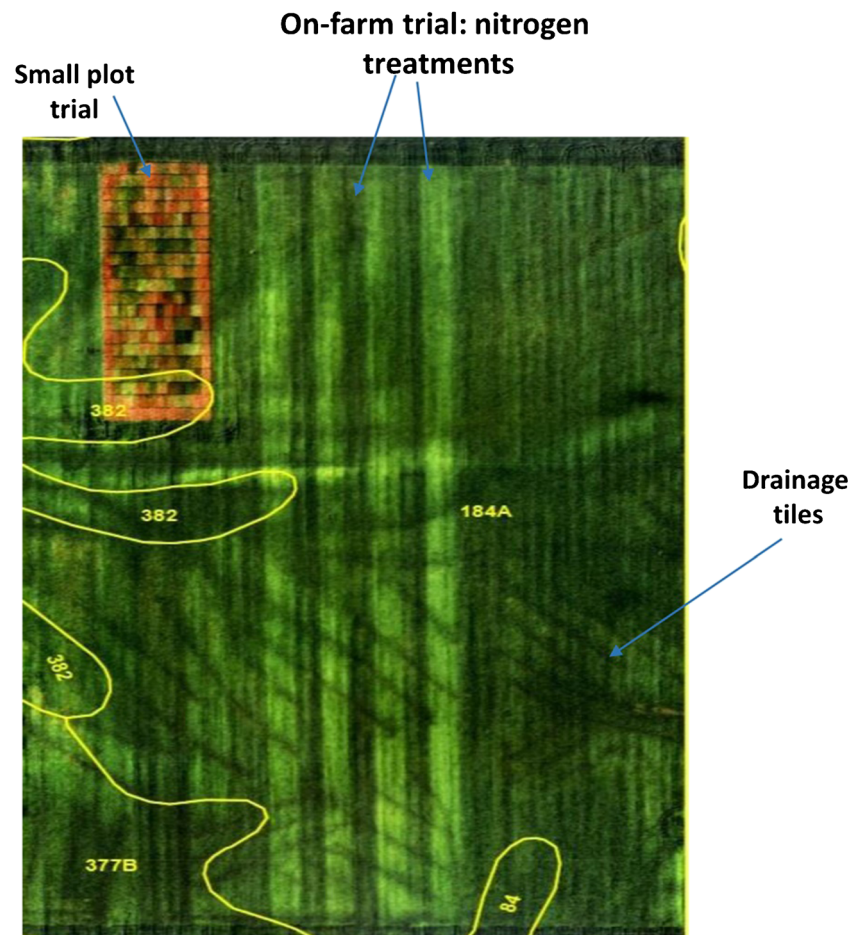
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2018). By contrast, on-farm research trials (OFTs) are experiments conducted on considerably larger areas (1.9–11 ha, see Laurent et al., 2019), usually on a commercial farm, and managed by farmers using their own equipment to answer field-level questions (Robertson et al., 2007). The most common experimental design for OFT is the replicated strip (several long strips laid out side-by-side in a field) where a new management practice, or product, is compared to a standard farmer practice (Kyveryga et al., 2018; Laurent et al., 2019). Precision agriculture technologies facilitate more advanced experimental designs such as randomized complete block designs. OFTs are becoming more widespread due to a growing interest among farmers and the research community regarding the usefulness of SPTs to predict on-farm outcomes (Kyveryga, 2019).

The difference between the two experimental scales is illustrated in Figure 1, where one SPT and one OFT were implemented in the same field located in Iowa. For an OFT, the width of an individual strip depends on the size of available equipment and can range from 5 to 20 m. The length of a strip (considered an experimental unit) depends on the field size. For example, a typical field in central Iowa, USA, is about 32

ha, approximately 457 m by 701 m (Laurent et al., 2019). Because of the plot size, localized variability, such as that caused by soil type, past management or subsurface drainage pipes, may result in greater yield variability in SPT than OFT. One advantage of SPT is that inter- and intra-plot variability tends to be minimized by blocking factors, judicious plot layouts, and location on favorable soils (Kravchenko et al., 2017). Thus, detecting a treatment effect is arguably easier. A recent power analysis also showed that more replications were required in SPTs than OFTs to detect the same overall treatment differences (Kandel et al. 2018). Crop yields can be highly variable across a field as a result of the interaction between topography (e.g., terrain slope), soil properties (e.g., soil fertility and moisture), weather conditions, and management practices (Kravchenko and Bullock, 2000; Kravchenko et al., 2005; Terra et al., 2006). However, OFTs represent a more relevant commercial scale regarding farming systems, farming skills, soil properties, topography, and hydrological conditions (Kravchenko et al., 2005, 2017; Terra et al., 2006; Marchant et al., 2019). Nevertheless, farmers may face logistical constraints (e.g., equipment problems), experience yield losses due to poor management, or be forced to follow

Fig. 1 Small-plot trial (randomized complete block design) and on-farm trial (replicated strip trial design) in the same field with nitrogen fertilizer rate treatments. The dark angled lines indicate the location of drainage tiles, and the yellow lines indicate soil map units. The dark vertical strips are side-dressed applications of nitrogen. Source: Kyveryga et al. (2018).



suboptimal management practices, resulting in increased yield variability. Overall, this can reduce statistical power and make the treatment effect more difficult to detect.

Even though OFTs can be used to validate SPTs at a larger field-scale (Licht and Witt, 2019), several authors have mentioned discrepancies between these two types of trials (Table 1), especially regarding crop yield. Therefore, extrapolating the results from SPTs to a larger scale can be challenging or misleading. Thus, there is a need to better understand the effect of experimental scale on data, results, and conclusions. In their study, Tedford et al. (2017) analyzed the yield benefits from foliar fungicides on maize at different scales. They reported a yield difference between fungicide application and untreated control equal to 1132 kg/ha at the field-scale (8.1 ha) while at the small-plot scale (14 to 45 m²),

the yield difference was equal to 378 kg/ha. They suggested that yields are higher near the alley and edge of the plots, than towards the center of the plot because plants experience less competition and have better light interception. In contrast, Vincelli and Lee (2015) demonstrated that open alleys did not impact the effect of foliar fungicide on maize yields in field trials (Table 1). Schmer et al. (2008) compared inputs to bioenergy crop OFTs (6.7 ha on average) with those to SPTs (<5m²). They found that agricultural energy inputs (i.e., fertilizer, herbicide, seed, diesel, and other) were lower at the field scale than thought from previous studies based on SPTs. Moreover, switchgrass from OFTs (managed for biomass yield with moderate levels of N fertilizer) produced 471% more ethanol per hectare than low agricultural input switchgrass on SPTs. Conversely, Kandel et al. (2018)

Table 1 Main differences between small plot and on-farm trials.

Characteristic	Small plot trial (SPT)	On-farm trial (OFT)
Plot size	- From 0.005 to 0.01 ha (Kravchenko et al., 2017)	- From 1.9 to 11 ha depending on the size of application equipment (Laurent et al., 2019)
Experimental design	- Usually randomized completely block design with multiple treatments tested simultaneously - Split-plot design is also frequently used - Implemented by agricultural scientists in agricultural experimental stations located in research institutes or universities - Variability is minimized by blocking, contiguous designs, judicious plot layouts and location on favorable soil (Kravchenko et al., 2017) - Treatments are randomized within blocks - Monitor and control pest - Management practices are consistent across the trial and the treatment is the only management factor to change	- Replicated strip trial design with two treatments (the new management practice and the control) is the most popular and practical design - Randomized complete block design or paired comparison are two design sometimes used (Varner, 2009) - Implemented by farmers with their own equipment - Variability in soil properties is not minimized (Kyveryga et al., 2018) - Replicated strip design usually presents a lack of randomization (Laurent et al., 2019). Thus, bias from unknown factors that could affect yield is not minimized - Rarely monitored or scouted for pest control - Management practices are consistent across the trial and the treatment is the only management factor to change
Harvest	- Small-plot combine	- Farmers measure yield with mass flow sensors and GPS technology. For many years, farmers used weigh wagons (Nelson et al., 2015)
Soil	- Greater noise (yield variability) in SPT could be explained by larger soil variation (Kandel et al., 2018) - SPTs are usually located on favorable soils (Kravchenko et al., 2017)	- Soil and topographic diversity leads to spatial variability in plant growth and diminishes effects on crop yield (Kravchenko et al., 2005)
Alleys and edges	- Yield of plants near alley are higher than plants towards the center of the plot (less competition and/or better light interception) (Tedford et al., 2017). Thus, fungicides have limited benefit. - Edge and alley effects may influence yields (Kleczewski, 2017). Plants on the edges of plots experience a slightly different environment than those inside the plot. - With fungicide treatment, alleys and edge effect do not influence yield (Vincelli and Lee, 2015)	- Within OFT, yield of plants are lower within strips (more competition for light and nutrients), therefore yield improvement is more likely with products that can mitigate plant stresses like fungicides (Tedford et al., 2017) - Edge effect relative to the overall treatment area is small (Kleczewski, 2017)
Weed control	- Mechanical weed control can generally be conducted at optimal times (Kravchenko et al., 2017) - SPT can, sometimes, represent an artificial system (hand-seeded, hand-weeded, and irrigated during establishment) (Schmer et al., 2008)	- Weed control practices are representative of the local farming system and technologies (Marchant et al., 2019)

reported similar yield responses between SPTs and OFTs to foliar fungicide applications on soybean over a control to which no fungicide was applied. On average, yield responses were identical, while the within-trial variance was smaller in OFTs than in SPTs. Kravchenko et al. (2017) showed that small-plot scale yields well-matched field-scale yields for conventional management systems but not for alternative systems (reduced-input and organic). Alternative farming systems depend more on timely management interventions, such as weed control, which is the greatest management challenge for farmers at the field-scale. In contrast, mechanical weed control can generally be conducted at an optimal time at a small-plot scale.

Field surveys can be used to understand to which extent results from SPTs can translate to those in producers fields. Andrade et al. (2019) compared the yield difference between narrow (38 cm) row and wide (76 cm) row spacing on soybean yield using field survey data and SPTs data in different US soybean regions. They reported consistent yield differences in producer fields and small plots within the Central US region, but not for the North US region. Beyond small-plot trials and on-farm trials, Andrade et al. (2019) suggested analyzing data collected from producer field surveys to better understand the discrepancy between experimental scales.

In our study, we quantify the impact of experimental scale on the effect of foliar fungicide application on crop yield and investigate potential causes for discrepancies. Foliar fungicide application has been widely reported in the literature, and a substantial amount of data have been generated to allow us to test the discrepancies between the two experimental scales. To do so, we collected data from published reports (in which data were averaged across replications) and raw data from SPTs and OFTs looking at the foliar fungicides' effect on yield. Data were collected from five states across the USA on maize and soybean, including 53 active ingredients (alone and in combination) present in commercial foliar fungicides. Thus, our results should cover broader conditions than the ones already published. Understanding the causes of yield gaps between SPT and OFT is crucial to better inform on-farm decision-making and interpret results at appropriate spatial scales.

2 Materials and methods

2.1 Data description

The data were extracted from foliar fungicide reports published in Fungicide and Nematicide Tests (F&N Tests) and Plant Disease Management Reports (PDMR), Iowa State Research Farm Progress Reports, Nebraska On-Farm Research Network (OFRN), Iowa Soybean Association OFRN, Ohio OFRN, South Dakota OFRN, Pennsylvania

OFRN, and peer-reviewed papers. The keywords *maize*, *soybean*, and *foliar fungicide* were used to find the published reports or peer-reviewed articles. More information about the search strategy can be found in supplemental materials (Supplemental Section 1).

We considered a trial as a unique combination of year and location. Published reports and raw data were collected from 978 trials conducted from 1999 to 2019, and 6280 observations met our criteria for inclusion in the data set. Data were shared as raw data (i.e., they had not been processed) or averaged across repetitions (in the case of published reports from F&N Tests, PDMR, and Iowa State Research Farm Progress Reports). One observation represented data from a pair of treatments: fungicide applied and control (no fungicide applied). Most of the time, a published report included a single trial from one location. In some cases, published reports included data from nearby locations or at the same research station but testing, for example, different hybrids. In that case, we considered each experiment as a separate trial. To be selected, the experimental design must have included a minimum of two replicates, an untreated control, and a treatment(s) defined as the application of a single foliar fungicide on maize or soybean, which were the crops of interest. Studies must have reported the grain yield (raw data or summaries in weight or volume per unit area) for the untreated control and the treatment(s). Treatment with seed-applied fungicide and combinations of different foliar fungicides products were not included in the data set. Other variables were included in the data set if available (e.g., hybrid, plot length, plot width, rate of application, and application timing; see Supplementary Table S1 for more information) but were not considered for inclusion in the analysis because they were not systematically reported.

Most OFTs (90%) were conducted using a replicated strip design. The majority of SPT was conducted using completely randomized designs (93%). The number of replicate blocks ranged from 2 to 20 for the OFTs and 3 to 8 for the SPTs (Table 2). The median number of replicates was 4 or 5 for both OFTs and SPTs (Figure 2). For the OFTs, the experimental units were 76 to 762 m long by 3 to 36 m wide, while for the SPTs, the experimental units were 1.8 to 35 m long by 1.2 to 12 m wide (Table 2). In most cases, a nonionic surfactant was used with the foliar fungicide application. Data were collected from 1999 to 2019 from 5 states (Iowa, Nebraska, Pennsylvania, South Dakota, and Ohio). For maize, 31%, 26%, and 12% of the trials included pyraclostrobin, prothioconazole + trifloxystrobin, and azoxystrobin + propiconazole as a treatment, respectively. For soybean, 32%, 16%, and 11% of the trials included pyraclostrobin, prothioconazole + trifloxystrobin, and pyraclostrobin + fluxapyroxad as a treatment, respectively. Active ingredients present in the foliar fungicides used in the trials belonged to three Fungicide Resistance Action Committee (FRAC) code

Table 2 Description of the two experimental scales, small-plot trial and on-farm trial, available in our dataset.

Variables	On-farm trials	Small-plot trials
Number of trials for maize	300	114
Number of trials for soybean	481	83
Range plot length (m)	76 to 762	1.8 to 35
Range plot width (m)	3 to 36	1.2 to 12
Mean number of replicate (min-max)	5 (2-20)	5 (3-8)
Number of trials in IA	640	64
Number of trials in NE	24	55
Number of trials in OH	55	62
Number of trials in PA	18	3
Number of trials in SD	44	13
Number of maize trials with a fungicide product belonging to one FRAC Code Group	297	15
Number of soybean trials with a fungicide product belonging to one FRAC Code Group	465	39
Number of maize trials with a fungicide product belonging to at least two FRAC Code Group	3	99
Number of soybean trials with a fungicide product belonging to at least two FRAC Code Group	16	44

groups (FRAC, 2020); FRAC Code 3, demethylation inhibitors (DMI), FRAC Code 7, succinate-dehydrogenase inhibitors (SDHI), and FRAC Code 11, the quinone outside inhibitors (QoI). Most commercial fungicide products contain active ingredients from at least two FRAC Code groups. Thus, fungicide treatments were grouped according to the FRAC

groups to that their active ingredient(s) belonged to. For products that contained active ingredients belonging to more than one FRAC group, groups were separated by an underscore (e.g., QoI_DMI). A larger proportion of fungicides with at least two FRAC groups were compared in SPT than OFTs (Table 2).

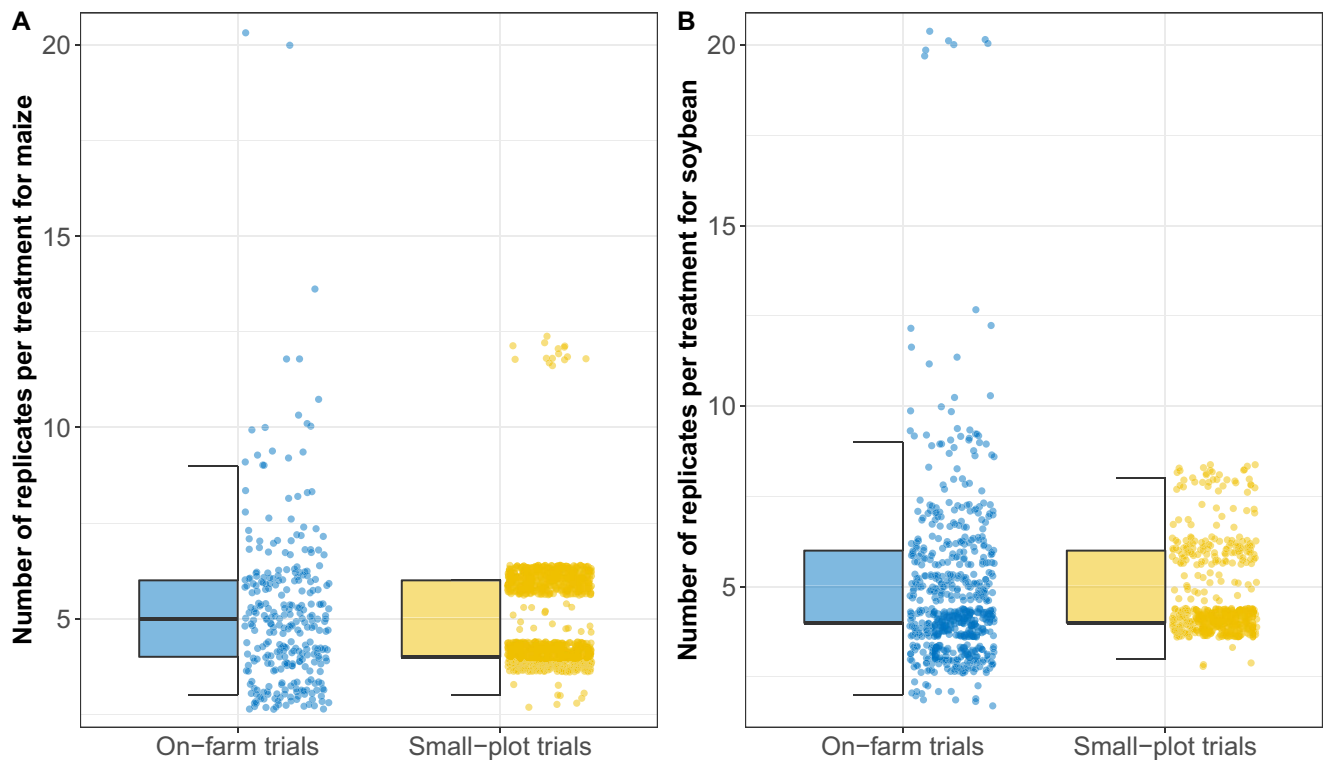


Fig. 2 Boxplots of the number of replicates for maize (a) and soybean (b) for the different experimental scales. On-farm trials (OFTs) are represented in blue and small plot trials (SPTs) in yellow. One dot represents the number of replicates for one combination trial and treatment.

2.2 Data analysis

Mean log yield ratio (yield with fungicide treatment over yield in untreated control) was calculated for each trial by averaging raw data when available or from aggregated data otherwise (i.e., yield data averaged over all repetitions reported in published reports). Log yield ratio was used instead of yield ratio to obtain a more symmetrical distribution and facilitate the statistical analysis. When several foliar fungicide product treatments per trial were available, one mean log yield ratio was calculated for each fungicide product.

For the statistical analysis, the mean log yield ratio was used as the effect size. The model was:

$$\log(R_{ijk}) = \mu_{OFT} + \delta_{SPT}X_i + \alpha_{ij} + \varepsilon_{ijk} \quad (1)$$

$$\begin{aligned} \alpha_{ij} &\sim N(0, \sigma_{\alpha_i}^2) \\ \varepsilon_{ijk} &\sim N(0, \sigma_{\varepsilon_i}^2) \end{aligned}$$

where $\log(R_{ijk})$ represents the natural log of the j th trial of category i ($i=SPT$ or $i=OFT$) for the k th yield ratio.

μ_{OFT} represents the mean value of the log ratio for the OFT category.

δ_{SPT} represents the mean effect of the SPT category on the log ratio compared to OFT.

X_i is a dummy variable equal to 1 if R_{ijk} belongs to the SPT category; zero if R_{ijk} belongs to the OFT category.

α_{ij} represents the random effect of the j th trial for the i th category of trials.

ε_{ijk} represents the residual error.

α_{ij} is assumed to follow independent Gaussian distributions with mean zero and unequal between-trial variance $\sigma_{\alpha_i}^2$ for the $i=SPT$ and $i=OFT$ categories.

ε_{ijk} is assumed to follow independent Gaussian distributions with zero mean and unequal within-trial variance $\sigma_{\varepsilon_i}^2$ for the $i=SPT$ and $i=OFT$ categories.

Model (1) includes five parameters, δ_{SPT} , μ_{OFT} , $\sigma_{\alpha_i}^2$ and $\sigma_{\varepsilon_i}^2$. The variance $\sigma_{\alpha_i}^2$ and $\sigma_{\varepsilon_i}^2$ quantifies the between- and within-trial variabilities, respectively. Separate variances are considered for OFT and SPT.

To take categorical variables (i.e., fungicide Group Name) into account, we use the following statistical model:

$$\log(R_{ijk}) = \mu_{OFT} + \delta_{SPT}X_i + \sum_{g=2}^G (\beta_g + \theta_{SPTg}X_i)Z_{ijk}^{(g)} + \alpha_{ij} + \varepsilon_{ijk} \quad (2)$$

The model (2) remains the same as (1) except for β_g representing the parameter for the g th fungicide Group Name, θ_{SPTg} representing the interaction between the fungicide Group Name and the SPT category, and the $Z_{ijk}^{(g)}$ representing a binary variable equal to 1 if R_{ijk} belongs to the g th fungicide Group

Name; zero otherwise. G represents the total number of distinct fungicide Group Name in our analysis.

Models (1) and (2) were fitted using a Bayesian approach with the R package *brms* (Bürkner, 2017). The priors for $\log(\sigma_{\alpha_i})$ were defined as a truncated Student's t distribution with 10 degrees of freedom, a mean of zero and a scale parameter of 0.1. The prior for $\log(\sigma_{\varepsilon_{OFT}})$ was defined as a truncated Student's t distribution with 10 degrees of freedom, a mean of -4.4 , and a scale parameter of 0.1. The prior for $\log(\sigma_{\varepsilon_{SPT}})$ was defined as a truncated Student's t distribution with 5 degrees of freedom, a mean of -3.2 , and a scale parameter of 0.5. These priors were based on Laurent et al. (2019). Priors for μ_{SPT} and μ_{OFT} were defined as a normal distribution centered on zero with a variance of 0.2.

With a variance of 0.2, the log ratio can take either a high positive or a low negative value. Posterior distributions for β_g and θ_{SPTg} were computed using the No-U-Turn Samplers (Hoffmann and Gelman, 2014) as implemented in the Stan software (Stan Development Team, 2018). The convergence of the MCMC chains was checked by running three independent chains for 3,000 iterations and the metric *Rhat*, which compares the between- and within-chain estimates for model parameters, were between 1 and 1.02, indicating convergence. Three variants of the model (1) were fitted and evaluated using the Widely Applicable Information Criterion (WAIC) values. The WAIC is a more general criterion than Akaike Information Criteria (Watanabe, 2013) and is appropriate for Bayesian models. Indeed, a first candidate model included equal between and within-trial variances, a second candidate model included unequal within-trial variance only, and the third candidate model considered unequal between-trial variances only for the plot-scale factor. Model (1) and the model with unequal within-trial variance only performed better, but considering the unbalanced structure of the data, we selected model (1). We considered other models, but they resulted in higher WAIC values, so we did not select them. We performed a Pareto-Smoothed Importance Sampling cross-validation (PSIS) (Vehtari et al., 2017; McElreath, 2020) to detect highly influential observations on the WAIC. Two yield observations for both maize and soybean had high values of k , the Pareto shape parameter, which indicates potentially influential observations, and were discarded from the data set. These four observations were each from Ohio OFRN, South Dakota OFRN, Iowa State Research Farm Progress Reports, and Plant Disease Management Reports.

The four moments for the log ratio of maize and soybean and for each experimental scale were computed using the R package *moments* (Komsta and Novomestky, 2015).

We also computed 95% prediction intervals describing a plausible range of values of yield ratio for a new OFT and SPT, similar to those included in our database assuming similar conditions (Higgins et al., 2009; Int'Hout et al., 2016).

3 Results

3.1 Descriptive analysis

For maize, the mean yield ratio for the two experimental scales was similar (1.018 and 1.020 for OFT and SPT, respectively) while the variance was three times higher for SPT compared to OFT (Table 3). The shapes of data distribution were relatively symmetrical for OFT and SPT (Table 3 and Figure 3.A), and the kurtosis was 5.6 and 10.6 for OFT and SPT, respectively. The distribution had a high and sharp peak. The peak was higher for OFT than for SPT (Figure 3.A). Distributions of the data were fairly symmetrical for SPT and slightly skewed to the left for OFT (Figure 3.B). The kurtosis was 7.2 and 3.9 for OFT and SPT, respectively, so the distribution was Leptokurtic (peak is high and sharp) for OFT and Mesokurtic (similar to a normal distribution) for SPT.

Across all FRAC Groups, the median log-ratio was positive for SPT and OFT (Figure 4), indicating that fungicide application increased yield across all groups. For the maize in OFTs, the DMI and QoI were not represented, and QoI_DMI_SDHI was poorly represented. For maize, QoI_DMI and SDHI, the median log-ratio for maize were similar, but the data were more dispersed for SPT. Across all the fungicide Group Names, maize mean yield ratios were less dispersed around the median for OFTs than SPTs while soybean mean yield ratios were as dispersed for OFTs as for SPTs. For soybean, OFTs and SPTs were represented across all FRAC Groups but with less data for QoI_DMI_SDHI.

A large proportion of the soybean data came from OFTs conducted in Iowa and SPTs from Iowa and Ohio (Figure 5, Table 2). For maize, most of the data came from OFTs in Iowa and SPTs trials from Iowa and Nebraska. In Iowa, the quantile ranges for OFTs were shorter than SPTs for maize and soybean. For soybean, most of the data came from Iowa and Ohio for both experimental scales.

Other boxplots comparing foliar fungicide application timings and year of harvest are available (Supplemental Material, Figures S1-2), along with the relationship between the yield difference and yield of the control in maize and soybean for both experimental scales (Supplemental Material, Figure S3).

Table 3 Description of the four moments (mean, variance, skewness, and kurtosis) for the log yield ratio of maize and soybean for on-farm trial (OFT) and small-plot trial (SPT). Moments for the yield ratio are indicated in parentheses.

Crop	Experimental scale	Mean	Variance	Skewness	Kurtosis
Maize	OFT	0.017 (1.018)	0.001	0.66 (0.83)	5.6 (5.8)
	SPT	0.019 (1.020)	0.003	-0.008 (0.73)	10.6 (11.2)
Soybean	OFT	0.036 (1.038)	0.003	-0.47 (-0.05)	7.2 (6.2)
	SPT	0.027 (1.029)	0.003	0.18 (0.44)	3.9 (4.2)

3.2 Results obtained with the Bayesian approach

The between-trial standard deviation was almost twice as large for SPT than for OFT for both maize and soybean (Table 4). For soybean, the within-trial standard deviation was similar between OFT and SPT, but for maize, the within-trial standard deviation was thrice larger for SPT than OFT (Table 4). For model (2), the within and the between-trial standard deviation was thrice and twice as large for SPT than for OFT, respectively, for maize (Table 5). For model (2), the between-trial standard deviation was as twice as large for SPT than for OFT, for soybean. The credibility intervals for the population estimates were similar between the two experimental scales and for both crops (Table 5).

For maize and soybean, the range of plausible yield ratios was larger for a new SPT than for a new OFT (Figure 6). Indeed, the 95% prediction interval for a new SPT was 1.6 and 1.5 times larger than the 95% prediction for a new OFT, for maize and soybean, respectively, and this is a result of the additional uncertainty considered for trials in new situations.

Regardless of the foliar fungicide FRAC Group, the 95% prediction intervals were always larger for a new SPT than a new OFT (Figure 7) for maize and soybean as the between-trial variance is larger for SPT than OFT. Only the FRAC Groups having at least 20 trials in both experimental scales were included in the analysis. In the maize trials, only the SDHI and QoI_DMI fungicide Group Names were included in the analysis (Figure 7.A), while for soybean, five fungicide Group Names were included (Figure 7.B).

4 Discussion

Management recommendations are often made using data from SPTs that may not be representative of commercial fields. In the present study, we assessed the impact of experimental scale (i.e., OFTs vs SPTs) on the effect of foliar fungicide applications on maize and soybean yields compared to an untreated (no fungicide) control. We compared 300 OFTs and 114 SPTs for maize and found similar mean yield responses between experimental scales; however, the within-trial standard deviation for OFT was three times smaller than the standard deviation for SPT. It is important to mention that in our dataset, 99% of the OFTs on maize included fungicides

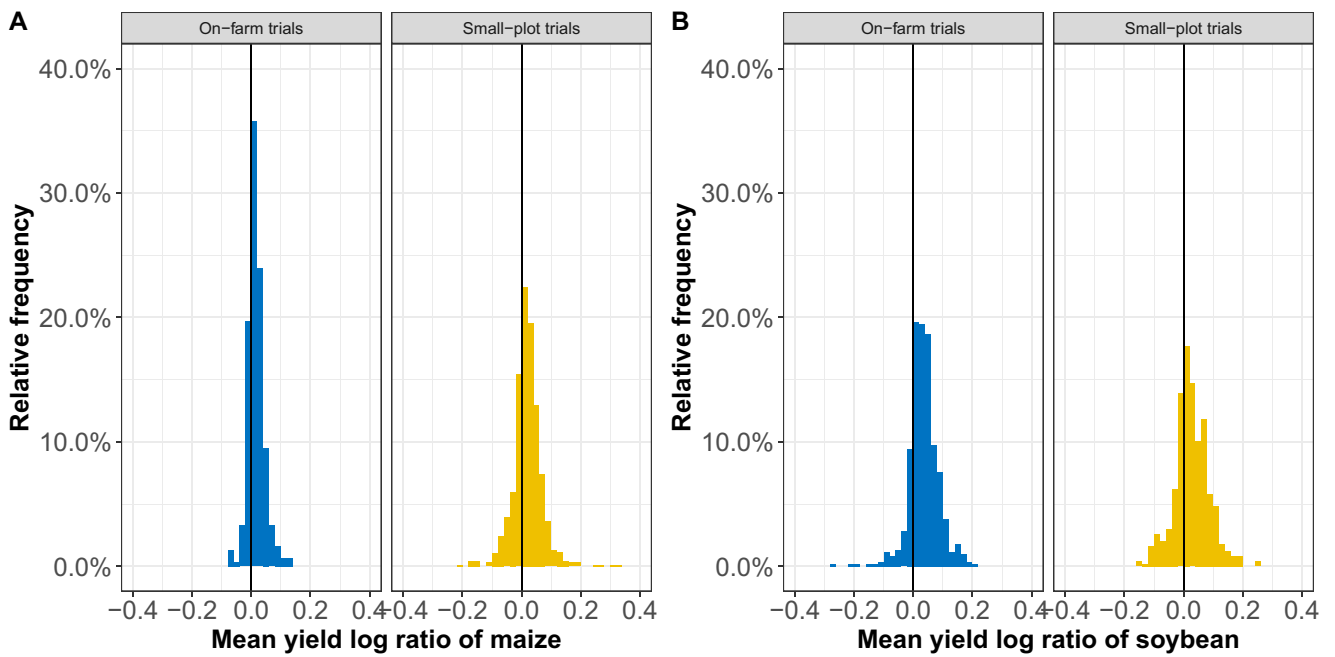


Fig. 3 The mean log yield ratio distribution for maize (a) and soybean (b). On-farm trials are represented in blue and small plot trials in yellow. One count represents one replicate from the raw data or the mean yield difference from the report summaries.

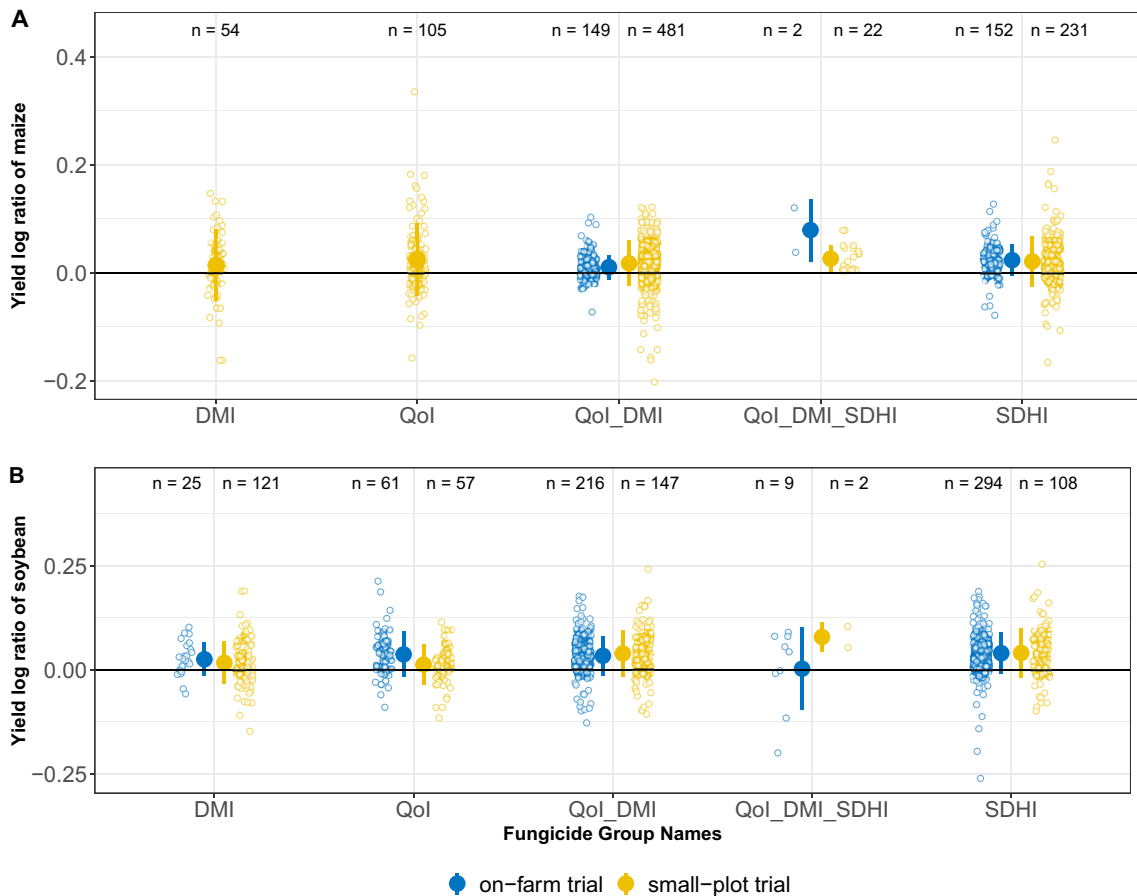


Fig. 4 Boxplots of the mean yield log ratio of maize (a) and soybean (b) to which fungicide products containing specific FRAC Code Groups were applied. On-farm trials are represented in blue, and small plot

trials are in yellow. One dot represents the mean yield difference for one trial. A vertical line represents a 95% confidence interval. The numbers of trials are displayed at the top of each figure (n).

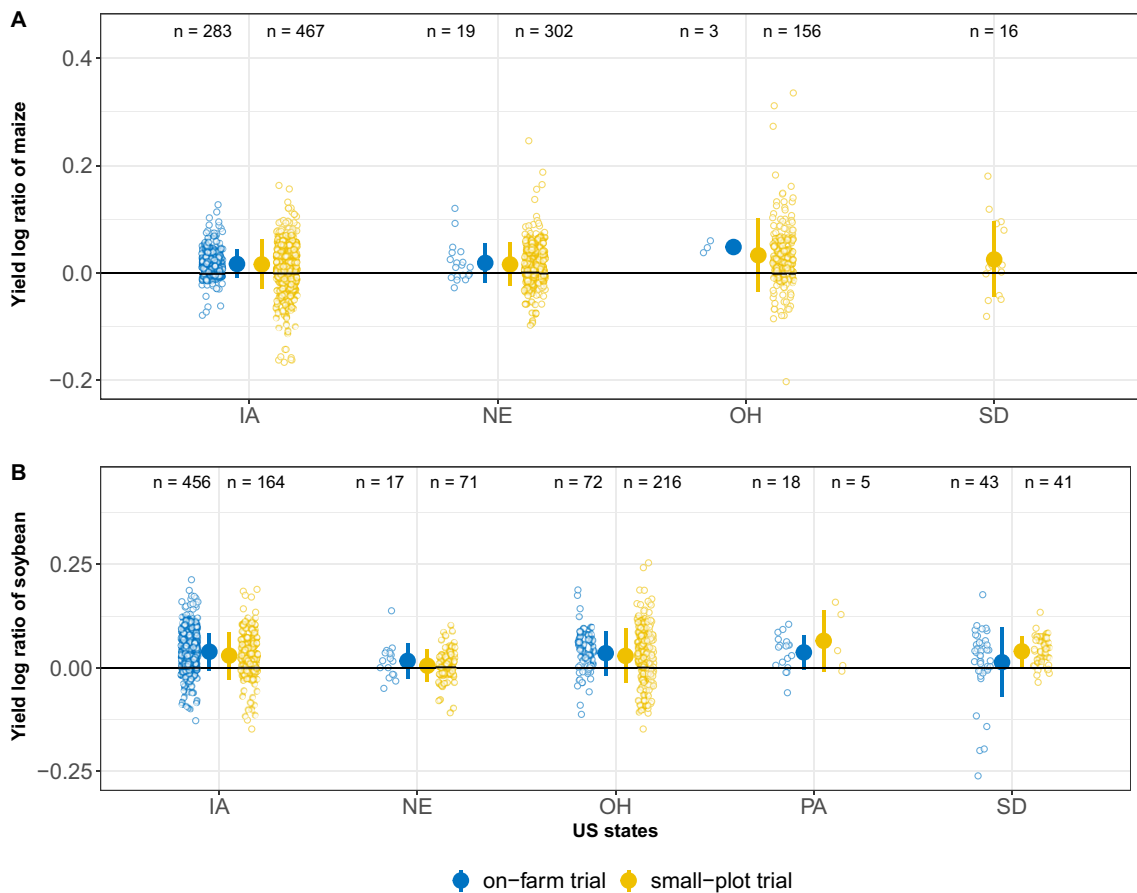


Fig. 5 Boxplots of the mean yield log ratio of maize (a) and soybean (b) by fungicide application for each state. On-farm trials are represented in blue, and small plot trials are in yellow. One dot represents the mean yield

difference for one combination of trial and foliar fungicide. A vertical line represents a 95% confidence interval. The number of combinations is displayed at the top of each figure.

containing active ingredients belonging to only one fungicide FRAC Group (Table 2), which can explain the smaller credible interval in OFTs. Similarly, our comparison of 479 OFTs and 83 SPTs for soybean showed no statistical difference between mean yield responses, and, unlike the maize data, we found no statistical difference between within-trial standard deviations. We also examined yield responses among

Table 5 Parameter estimates of response ratios and 95% credible intervals (in brackets) for model (2) for soybean and maize. μ are population estimates (means) and σ are standard deviations. For maize, some parameters could not be estimated because the corresponding foliar fungicide Group Names were not represented in the database (referred as “not applicable”). OFT = on-farm trial; SPT = small-plot trial; QoI = quinone outside inhibitors; DMI = demethylation inhibitors; SDHI = succinate-dehydrogenase inhibitors. For SPT, the mean values were estimated as $\mu_{SPT} = \mu_{OFT} + \delta_{SPT}$.

Table 4 Parameter estimates of response ratios and 95% credible intervals (in brackets) for model (1) for soybean and maize. μ are population estimates (means) and σ are standard deviations. OFT stands for on-farm trial and SPT for small-plot trial. For SPT, the mean values were estimated as $\mu_{SPT} = \mu_{OFT} + \delta_{SPT}$.

Parameter	Soybean	Maize
μ_{SPT}	1.028 [1.017; 1.039]	1.0191 [1.011; 1.026]
μ_{OFT}	1.037 [1.032; 1.041]	1.0171 [1.014; 1.021]
$\sigma_{\alpha SPT}$	0.039 [0.031; 0.048]	0.0393 [0.034; 0.046]
$\sigma_{\alpha OFT}$	0.023 [0.016; 0.032]	0.0242 [0.022; 0.027]
$\sigma_{\epsilon SPT}$	0.046 [0.043; 0.049]	0.034 [0.033; 0.036]
$\sigma_{\epsilon OFT}$	0.0436 [0.0394; 0.0481]	0.012 [0.010; 0.015]

Parameter	Soybean	Maize
μ_{SPT}	1.015 [1.007; 1.027]	1.019 [1.011; 1.026]
μ_{OFT}	1.023 [1.004; 1.043]	1.011 [1.006; 1.015]
$\sigma_{\alpha SPT}$	0.039 [0.030; 0.049]	0.039 [0.030; 0.042]
$\sigma_{\alpha OFT}$	0.022 [0.016; 0.031]	0.023 [0.02; 0.026]
β_{QoI}	1.014 [1.011; 1.036]	not applicable
β_{QoI_DMI}	1.009 [0.991; 1.029]	not applicable
β_{SDHI}	1.017 [0.997; 1.036]	1.012 [1.006; 1.018]
$\theta_{SPT QoI}$	0.990 [0.963; 1.018]	not applicable
$\theta_{SPT QoI_DMI}$	1.005 [0.980; 1.028]	not applicable
$\theta_{SPT SDHI}$	1.007 [0.983; 1.030]	0.989 [0.981; 1.997]
$\sigma_{\epsilon SPT}$	0.043 [0.040; 0.046]	0.030 [0.028; 0.033]
$\sigma_{\epsilon OFT}$	0.043 [0.039; 0.047]	0.011 [0.010; 0.015]

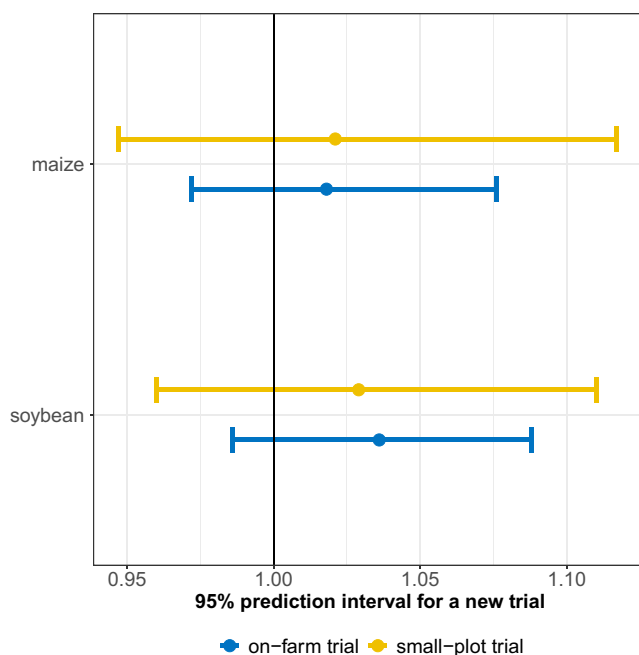


Fig. 6 95% prediction intervals of yield ratios for a new small-plot trial (in yellow) and a new on-farm trial (in blue) for response of maize and soybean to a foliar fungicide application. Computations were done using model 1.

fungicide FRAC Groups in both maize and soybean SPT and OFT and detected no differences.

We found similar credible intervals of the mean effect size (i.e., mean yield ratio) for both experimental scales, which was

interesting since we expected a narrower confidence interval for the SPTs. Indeed, experimental designs for SPTs are more complex to minimize variability by blocking, contiguous designs, and judicious plot layouts and location. The prediction interval, which represents the uncertainty around the mean yield ratio for a new environment, is relevant when the between-trial variability is large (Laurent et al., 2020b). The between-trial variance was higher for SPTs than OFTs, which suggests a larger diversity of environmental conditions and practices tested for SPTs than OFTs; thus, the prediction interval is larger for SPT than OFT. Our results are in accordance with the study of Laurent et al. (2020b) as they also reported a small between-trial variability for OFTs that were part of an on-farm research network.

Our results are consistent with Kandel et al. (2018), who compared the effect of foliar fungicides on soybean yield in 230 OFTs and 49 SPTs established in Iowa from 2008 to 2015 and found similar soybean yield responses between the two experimental scales. However, when analyzing a subset of 12 OFTs and 12 SPTs, Kandel et al. (2018) reported that the residual variance in OFTs was smaller than SPT, while our residual standard deviations in OFTs and SPTs for soybean were similar (Table 4). Kandel et al. (2018) used power analysis to demonstrate that SPTs need more treatment replicates than OFTs to detect the same overall treatment difference. They suggested that larger soil variability or increased combine operator error resulted in greater noise in SPTs. However, it is not always possible to increase the number of replicates in SPT because of limitations in land, economic, technical, and/or labor resources. A larger

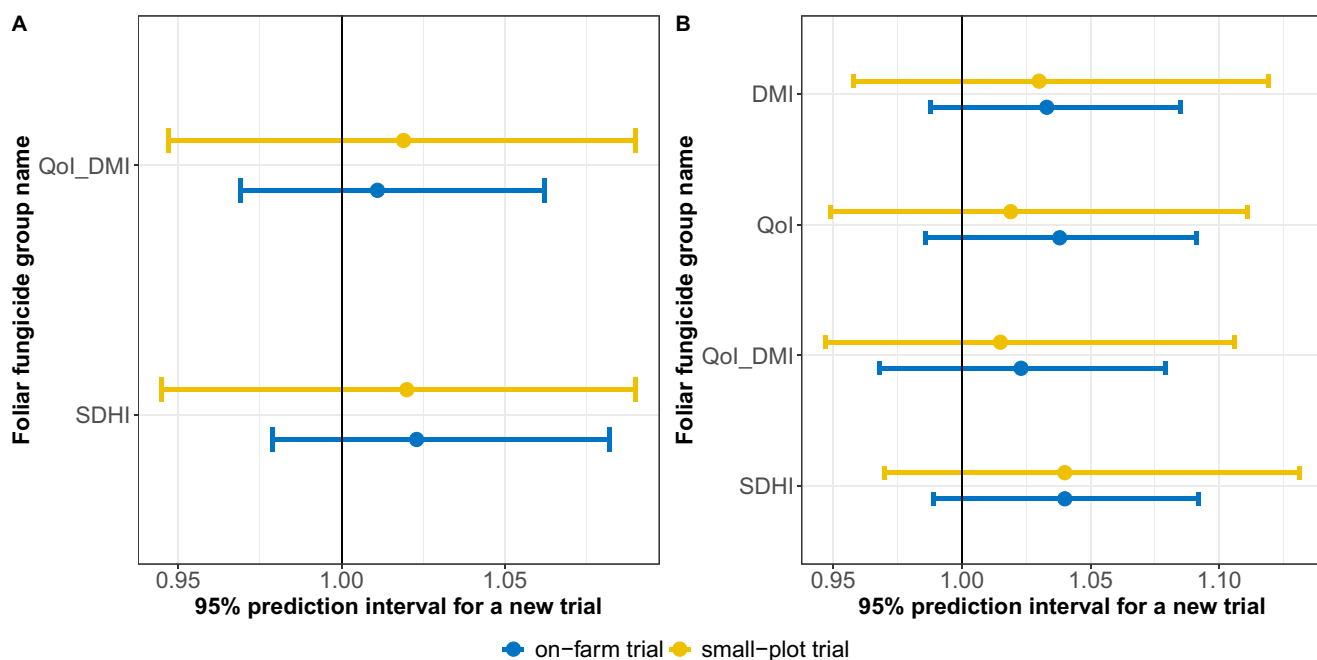


Fig. 7 95% prediction intervals per fungicide FRAC Group for a new small-plot trial (in yellow) and a new on-farm trial (in blue) for maize (on the left) and soybean (on the right). Computations were done using model

2. QoI, quinone outside inhibitors; DMI, demethylation inhibitors; SDHI, succinate-dehydrogenase inhibitors.

within-trial variability of yield response in SPTs could also be explained by a larger impact of the spatial heterogeneity in yield among plots. Work by Knörzner et al. (2013) supports this hypothesis as they showed that biomass yield has a high variance when the sampling area is small.

In our study, a major difference between SPTs and OFTs was the number of foliar fungicide FRAC Group treatments included in the experimental design. An SPT often included several fungicide products that contained a mix of active ingredients that belonged to different FRAC Groups, while in the majority of OFTs, a single fungicide with an active ingredient belonging to a single FRAC Group was compared with an untreated control. Thus, the estimated uncertainty around the mean yield could also be explained by the variation between foliar fungicide treatments. Tedford et al. (2017) reported a greater yield response of foliar fungicides on maize in OFTs than SPTs, which contradicts our findings. Indeed, the mean yield responses in SPTs and OFTs in our study were similar, but the uncertainty around the mean yield ratio for OFTs was smaller. Tedford et al. (2017) suggested that the edge effect was primarily responsible for the differences detected among SPT and OFT because more plants in SPTs bordered alleyways with no plants and thus had less competition for water and nutrients and/or better light interception. Similarly, SPTs with alleyways could be prone to drift during foliar fungicide application, which could increase variability especially at the plot edges.

We found no difference in yield among foliar fungicide FRAC Groups. In contrast, Paul et al. (2011) reported a greater yield response when fungicides belonging to the DMI_QoI fungicide Group Name were applied to maize.

OFTs and SPTs do not share the same purposes, and neither should be discounted. SPTs are more appropriate for advanced or complex experimental designs (e.g., randomized complete block, split-plot) and enable multiple treatments with or without different levels to be tested simultaneously. Nevertheless, farmers can easily set up more advanced experimental designs with the support of GPS technology and precision agriculture, such as variable rate technologies (USDA National Agricultural Statistics Service, 2021). In addition, SPTs are suitable for testing the introduction of innovative management practices, identifying the best treatments, and increasing agronomic knowledge before an on-farm evaluation to see if the results hold true. OFTs are useful for comparing a new management practice to a standard practice using a replicated strip design (Laurent et al., 2019), they can be executed under commercial conditions and use farmers' equipment. Thus, farmers tend to place more trust in OFTs results than SPTs results (Thompson et al., 2019), and thus OFTs may facilitate the adoption of new management practices. OFTs also allow in-depth investigation across a wider variety of soils and landscape positions, which is usually limited when only research stations are used. Indeed, it is usual

for OFTs to collect spatial yield data across soils and landscapes to allow the assessment of site-specific responses. OFTs can answer specific field-level questions such as nutrient management, environmental issues (Schnepf and Cox, 2007), impact of rainfall on response to fungicide (Kyveryga et al., 2013), and investigate runoff and soil erosion (Kuhn et al., 2014). Regarding financial and land resource constraints, OFTs represent a more feasible option than SPTs, usually conducted at experimental research stations where land is usually limited or not representative of the surrounding area (Thompson et al., 2019).

Although our study compares yield response in OFTs and SPTs, it is essential to consider crop price and fungicide cost to inform better decision-making. A yield benefit is not always enough to offset the fungicide cost in case of the absence of disease (i.e., assumed here by a high yield at the control). Kandel et al. (2016) suggested that although fungicides can increase soybean yield in the apparent absence of disease, only 14% of the trials were economically profitable. A web-application, called ISOFAST, synthesizing data from replicated on-farm trials, provides break-even economic analysis of foliar fungicides on maize and soybean (Laurent et al., 2019, 2020a). Of the 19 foliar fungicide products evaluated, only six had a >50% probability of exceeding the break-even cost (considering grain market price and application cost averaged over the last 10 years). It suggests the need for reporting an economic analysis in addition to yield performance to better inform decision-making.

Some limitations of our study should be highlighted. While our goal was to compare OFTs and SPTs across different states, including different pedoclimatic conditions, this resulted in an unbalanced dataset. For example, OFTs for maize mostly came from Iowa, and some from Nebraska, which may explain the smaller uncertainty around the mean yield as most of the trials are from the same farming area. For soybean, data were also unbalanced as 82% of the trials were OFTs. A future investigation could consider accounting for covariables, such as fungicide application timing and maize hybrid, to examine their effects on yield response (Kyveryga et al., 2013; Laurent et al., 2020a). Wise et al., (2019) have shown that yield response to a fungicide is affected by the growth stage of the crop at the time of application. Unfortunately, these variables are not systematically informed in our dataset, which does not allow their inclusion in a statistical model. We suggest that systematically reporting variables such as crop stage at the time of application, application rate, and disease pressure will help further understand the effect of foliar fungicide application on crop yield.

5 Conclusion

In this paper, we compared the effect of foliar fungicide on maize and soybean yield using two types of experiments (SPT vs OFT) to better inform on-farm decision-making. SPT and OFT data

were analyzed together, which provides a better understanding of the overall effectiveness of foliar fungicides. For maize, we found similar mean yield responses with both types of experiments, but the within-trial standard deviation estimated from the OFTs was thrice smaller than the value estimated from the SPTs. For soybean, no meaningful difference between mean yield responses and between standard deviations was found in OFTs and SPTs. The approach followed here can be used for other management practices to understand how data from SPTs support (or not) those from OFTs.

Our results, and previous published studies, show that OFTs are sometimes characterized by lower within-trial variability than that obtained in SPTs. This indicates that OFTs can potentially detect significant yield differences with fewer replicates (Kandel et al., 2018) and thus reduce the cost of data generation (Bullock et al., 2020). Another advantage of OFTs is that they involve farmers more directly than SPTs and thus contribute to helping farmers change their farming practices in their own fields (Thompson et al., 2019). On the other hand, SPTs appear to be more suitable for collecting measurements requiring technical expertise and higher labor requirements to understand physical and biological processes. SPTs can be seen as a preliminary step before scaling up to OFTs to facilitate technology transfer and extrapolate the results in real farming conditions. However, to make OFTs a real pillar of agronomic research, specific technologies should be developed and widely implemented to support farmers' ability to collect data themselves.

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Authors' contributions AL: conceptualization, methodology, programming, writing—original draft preparation, visualization, writing—reviewing and editing. EH: writing—reviewing and editing. PK: investigation, writing—reviewing and editing. DM: conceptualization, methodology, writing—reviewing and editing, supervision. LP: investigation, writing—reviewing and editing. AR: investigation, writing—reviewing and editing. LT: investigation, writing—reviewing and editing. FM: conceptualization, methodology, writing—reviewing and editing, funding acquisition, supervision.

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Network were supported by the Nebraska Corn Board, Nebraska Corn Growers Association, and the Nebraska Soybean Board.

Data availability The datasets generated during and/or analyzed during the current study are not publicly available due to privacy purpose.

Code availability The code generated during the current study is not publicly available.

Declarations

Conflict of interest The authors declare no competing interests.

Ethics approval Our study did not involve human participants.

Consent to participate Not applicable

Consent for publication Not applicable

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