Field Crops Research 301 (2023) 109012

Contents lists available at ScienceDirect

Field Crops Research

journal homepage: www.elsevier.com/locate/fcr

Field-level yield benefits and risk effects of intensive soybean management across the US

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ARTICLE INFO

Keywords:
Soybean
Risk
Input system

ABSTRACT

Context or Problem: High commodity prices reflecting increased global demand have encouraged the development of high-input management systems for soybean production in the US. Such systems are promoted as high-yield low-risk that can secure food production and enhance farmers' income.
Objective or Research Question: The objective of this work was to assess the performance and downside yield risk of high- and low-input soybean management systems across the US.
Methods: The high-input cropping system included fungicide, insecticide and biological seed treatments, soil and foliar fertilizer and foliar fungicide and insecticide applications. None of these inputs were applied in the low input system. Data were analyzed using a moment-based approach by evaluating the mean, variance, skewness, and kurtosis of soybean yield conditional on state (average of all locations in a state) and cropping system.
Results: We found that the field-level yield effect of high-input systems was inconsistent (−4.9 to 12.7% of average yield) and state-specific. Although high-input management may increase mean soybean yield across the US, it likely increases the variance (risk) of soybean yields as well. Our analysis shows that the average cost of yield risk decreased minimally (<3% of average yield) in each state when switching from a low-input system to a high-input system.
Conclusions: We conclude that high-input systems do not consistently and significantly protect soybean yield from downside yield risk or risk of extreme yields at the field level and should not necessarily be considered a broad-scale profitable and sustainable food-securing practice.
Implications or Significance: These results further support the use of integrated pest management (IPM) for making input decisions instead of relying on prophylactic input applications as insurance against yield-limiting factors. We argue that future studies of food security and crop production should be region-specific and focus on identifying management practices with the greatest yield potential based on IPM practices rather than recommending broad-scale intensive management systems as insurance practice.

1. Introduction

Average crop yields will need to increase during the next three decades to meet expected increases in food demand without a massive cropland area expansion (Tilman et al., 2011; Alexandratos and Bruinsma, 2012; Grassini et al., 2013). Soybean (*Glycine max* L.) is one of the most important oil seed crops in the world, with the United States (US) accounting for 31% of global production (FAOSTAT, 2021). By the end of this decade, global soybean production needs to increase by *ca*. 15% to meet the projected demand (OECD-FAO, 2019). This challenge can be met by identifying and adopting best management practices for major production environments.

Best management practices are those that, for a given environment, consistently result in high yields with reduced downside yield risk from issues such as adverse weather and pest damage. Farm economic realities also require that these practices be profitable. Hence, farmers

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https://doi.org/10.1016/j.fcr.2023.109012
Received 22 March 2023; Received in revised form 12 June 2023; Accepted 14 June 2023
Available online 1 July 2023
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regularly explore opportunities to increase yield and profit and to minimize production risks. Furthermore, at planting time, weather and pest pressure during the growing season are unknown and so uncertainty exists about which specific management practices and inputs will be needed and at what amounts. This uncertainty, coupled with increased soybean prices and commercial marketing, have encouraged soybean farmers to adopt high-input management systems to protect and maximize yield and profitability (Marburger et al., 2016; Orlowski et al., 2016). Such systems involve prophylactic application of multiple inputs such as biological and pesticidal seed treatments, soil and foliar fertilizers, and foliar pesticides regardless of the soil nutrient status or anticipated disease pressure.

Although high crop yields are important, one of the main dimensions of food security is production stability across regions and over time. Yield variance is a symmetric measure of variability around the mean, and an important measure of production stability, but unusually low yields are often more problematic than unusually high yields. Hence, a key question is whether the prophylactic application of multiple inputs in high-input management systems enhances food security compared with low-input management systems by better protecting from yield losses, i.e., does it lower downside yield risk? Several recent studies in different regions across the US compared intensive and low-input management systems (Bluck et al., 2015; Gregg et al., 2015; Mourtzinis et al., 2016; Marburger et al., 2016; Orlowski et al., 2016; Quinn and Steinke, 2019). In the absence of adverse environmental conditions, inconsistent or nonsignificant yield benefits were observed from intensive management. However, these studies did not report information about the degree high-input management systems reduced downside yield loss risk and therefore, contribute to stable production and food security.

Our objective was to measure the effect of high-input management systems on soybean yield and risk by analyzing yield data from field experiments over the period 2009–2014 across the US (Fig. 1). The high-input cropping system included fungicide, insecticide and biological seed treatments, soil and foliar fertilizer and foliar fungicide and insecticide applications (Table S1). None of these inputs were applied in the low input system. We examined two hypotheses: (i) high-input management systems consistently increase soybean productivity across the US and (ii) high-input management systems are associated with lower yield risk as measured by the variance, skewness, and kurtosis of soybean yield. Reduced variance and increased skewness are desirable as they lead to lower risk exposure (from a lower variance) and lower exposure to unfavorable events implied by the lower tail of the yield distribution (higher skewness). Decreased kurtosis means a lower exposure to rare events in the tails of the yield distribution which is desirable. Our analysis documents the extent to which intensive soybean management contributes to high yield by reducing yield loss and risk exposure.

2. Methods

2.1. Data description

We used yield data from replicated field experiments over the period 2009–2014 within 10 states (Fig. 1). Within each experiment, two cropping systems were applied. The high-input cropping system included fungicide, insecticide and biological seed treatments, soil and foliar fertilizer and foliar fungicide and insecticide applications (Table S1). None of these inputs were applied in the low input system. All experiments were non-irrigated and the same background management practices (e.g., tillage, previous crop, row spacing, seeding rate) were used for both systems.

2.2. Evaluating mean effects and risk exposure

Our analysis relies on a moment-based approach by evaluating the mean, variance, skewness, and kurtosis of soybean yield conditional on state (average of all locations in a state) and cropping system (Shi et al., 2013). Mean yield reflects average productivity of each cropping system in each state. The variance captures the variability of soybean yield around its mean. The skewness measures the asymmetry of the yield distribution, with a negative skewness capturing exposure to losses located in the lower tail of the distribution (downside risk). The kurtosis measures the thickness in the tails of the distribution of soybean yield. A large kurtosis is associated with a high risk because it indicates high probabilities of extreme yields (low and high).

We specified a multilevel model for mean yield as function of state and cropping system using individual site-years within states as a random sample of all possible growing environments in the region. The effects of year and the interactions of location, replication, cropping system, within each year were treated as random factors. The error term was then used to estimate the variance, skewness and kurtosis by regressing the second, third, and fourth power of the error term, respectively, against state and cropping system (Shi et al., 2013).

To analyze the variance, skewness and kurtosis, the analysis used a frequentist approach in PROC GLIMMIX SAS 9.4 using robust standard

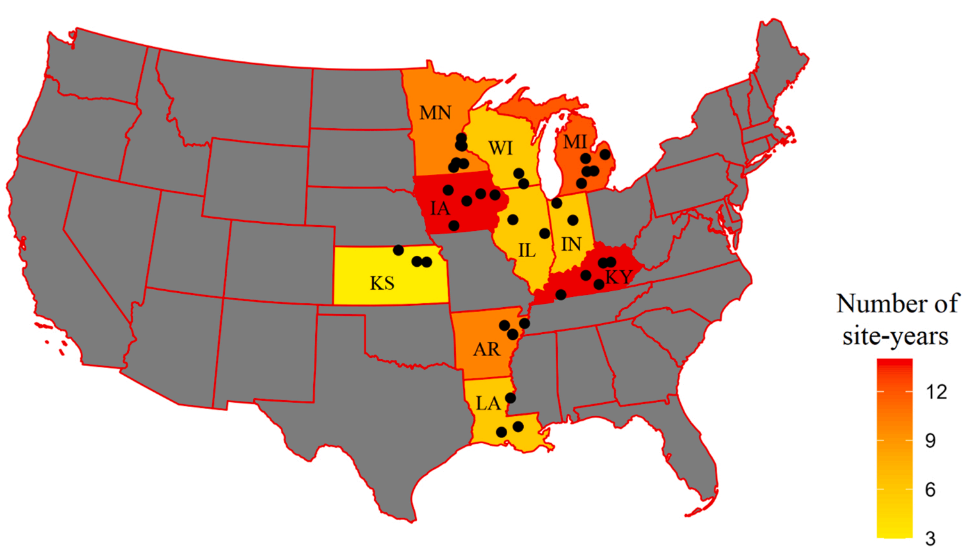

Fig. 1. Locations and number of site-years within each state between 2009 and 2014.

errors (EMPIRICAL=classical) and Bayesian approach in PROC BGLIMM. The Bayesian approach used 510,000 iterations (excluding 10,000 burn-in iterations) and a thinning rate of 100. Constant non-informative priors were used for fixed effects and Inverse Gamma (Shape=2, Scale=2) priors were used for random effects. Fit statistics such as effective sample size and autocorrelation plots were used to assess the fit of the Bayesian models.

2.3. Evaluating the cost of risk

We consider the case where the farmer's risk preferences are described by a constant relative risk aversion utility function, a common form of risk preferences used for farmers (Shi et al., 2013):

$$U(y) = \frac{y^{(1-r)}}{1-r}$$

where $r \geq 0$ is the Arrow-Pratt relative risk aversion coefficient (Pratt, 1964). The cost of risk becomes:

$$R_r(x) \approx \frac{r}{2} \times \frac{M_2(x)}{M_1(x)} - \frac{r(r+1)}{6} \times \frac{M_3(x)}{M_1(x)^2} + \frac{r(r+1)(r+2)}{24} \times \frac{M_4(x)}{M_1(x)^3}$$

where $M_1(x)$ is mean soybean yield, $M_2(x)$ is the yield variance (squared residuals), $M_3(x)$ is the yield skewness (residuals to the third power) and $M_4(x)$ is the yield kurtosis (residuals to the fourth power) (Shi et al., 2013). The risk aversion parameter typically ranges between 1 and 5 for a low to high degree of risk aversion, respectively. We estimated the cost of risk for a moderately risk averse farmer (r=3) and for a highly risk averse farmer (r=5).

3. Results

3.1. Level of management intensity affects soybean yield

High-input management systems increased soybean yield compared to low-input systems within each of the examined states, apart from KS (Fig. 2). In these states, the estimated probability of a positive yield difference (high- minus low-input management systems) was ≥ 97%. The realized yield increases ranged between 6.3% and 12.7% of average yield (Table S2), with the largest yield benefits observed in northern states (MN and WI). The only state where high-input management did not increase yield compared to low-input management was KS.

3.2. Risk effects relative to management intensity

Our analysis shows that high-input management had effects on yield variance that varied by state (Fig. 3, Table S3). In AR, MN, and LA, low-input systems had a greater yield variance than high-input systems, while the opposite was observed in the other states, apart from KS where the two systems exhibited similar yield variance. The 95% credible intervals for all states include zero, suggesting that differences were not significant, except for KY, where the variance for low-input system was decreased. These results show that intensive soybean management does not consistently reduce yield risk across the examined growing environments.

Next, we examine differences in the yield skewness and kurtosis between systems. For yield skewness, high-input systems slightly increased yield skewness in IA, IL, IN and KS (Fig. 4, Table S4), implying lower risk of unusually low yields, while in AR, LA and WI, the yield skewness decreased. However, the 95% credible intervals in every state included zero, suggesting little empirical support that yield skewness changes significantly when using high-input management systems. For yield kurtosis, high-input systems exhibited lower kurtosis than low-input systems in AR, KS, LA and MN, suggesting lower risk exposure to the tails of the distribution (Fig. 5, Table S5). The opposite was observed in IA, IL, IN, KY and MI and no clear evidence of kurtosis differences were observed in the remaining states. Again, apart from AR, IA, KY and low-input system in MN, the 95% credible intervals in every other state included zero, providing little empirical support that yield kurtosis changes significantly when using high-input management systems. Overall, results suggest that soybean management contributions to reducing low yields or rare yield events depends on the growing environment.

3.3. Quantifying the cost of risk

To evaluate the importance of the observed effects of management intensity on the yield distribution, we calculated the cost of risk (measured as kg/ha of soybean yield) by assuming a moderately risk averse and a highly risk averse farmer (see methods). For a moderately risk averse farmer (r=3), the change in the total cost of risk between the high- and low-input systems was minimal, varying between – 21 to 30 kg/ha (Fig. 6, Table S6) with no evidence that these differences were significant (95% credible intervals included zero). The estimated mean costs of risk were less than 3% of their respective system-state-average yield (Fig. S1). Yield variance accounted for more than 80% of the cost of risk and varied by input system and state. Skewness and kurtosis accounted for a much lower percentage of the cost of risk and a

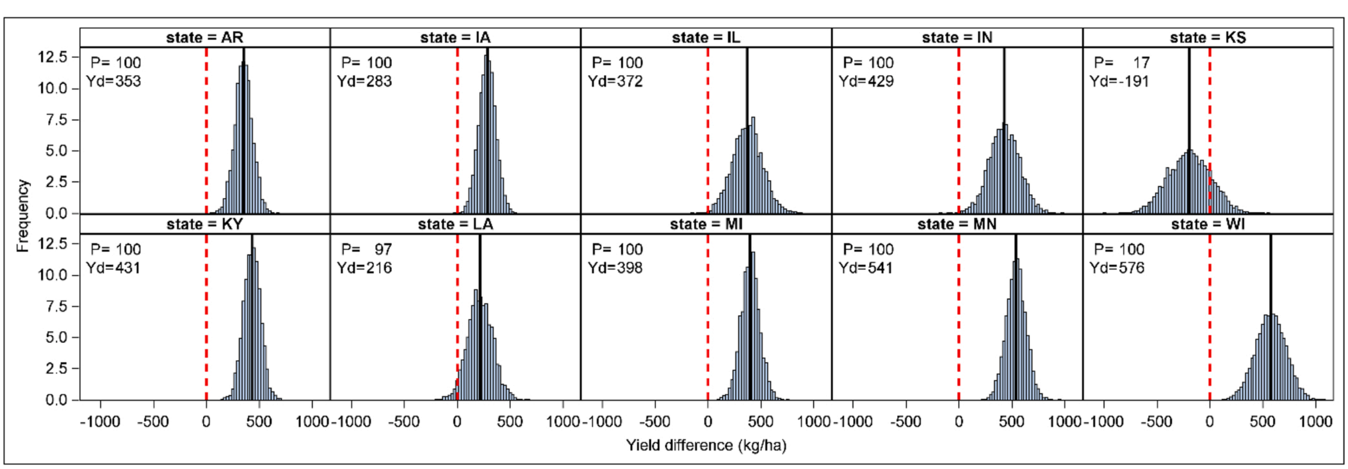

Fig. 2. Distribution of the yield difference (kg/ha) between high- and low-input cropping systems in each state and the probability (P) as a percentage that the yield difference > 0 in the posterior sample distribution (n = 5100). Within each state, the red dashed line shows the zero yield difference, and the black line indicates the mean yield difference (Yd).

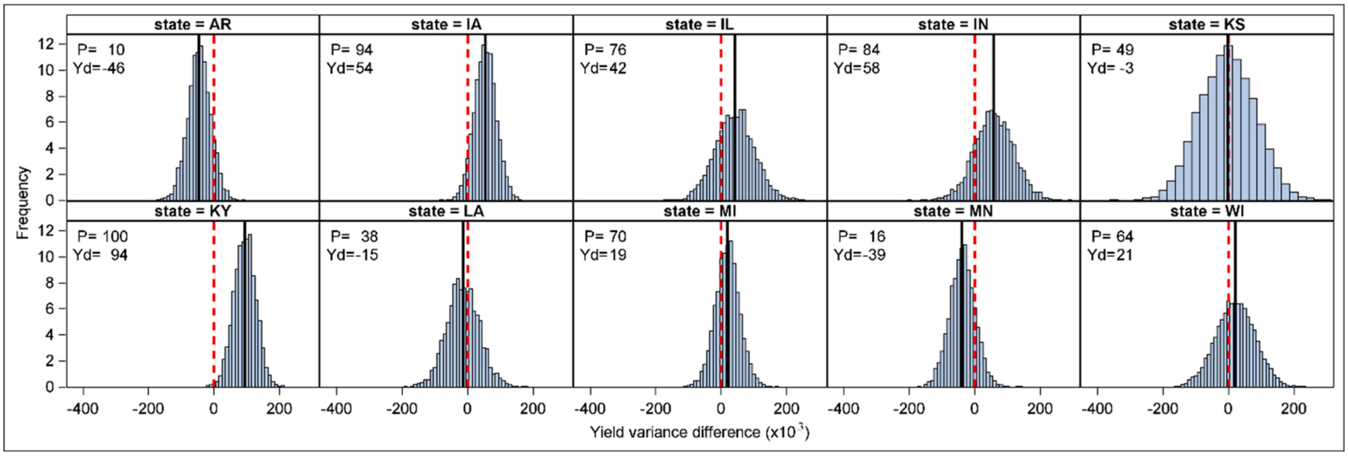

Fig. 3. Distribution of yield variance difference between high- and low-input cropping systems in each state and probability (P) as a percentage that the yield variance difference > 0 in the posterior sample distribution (n = 5100). Within each state, the red dashed line shows the zero variance difference, and the black line indicates the mean variance difference (Yd).

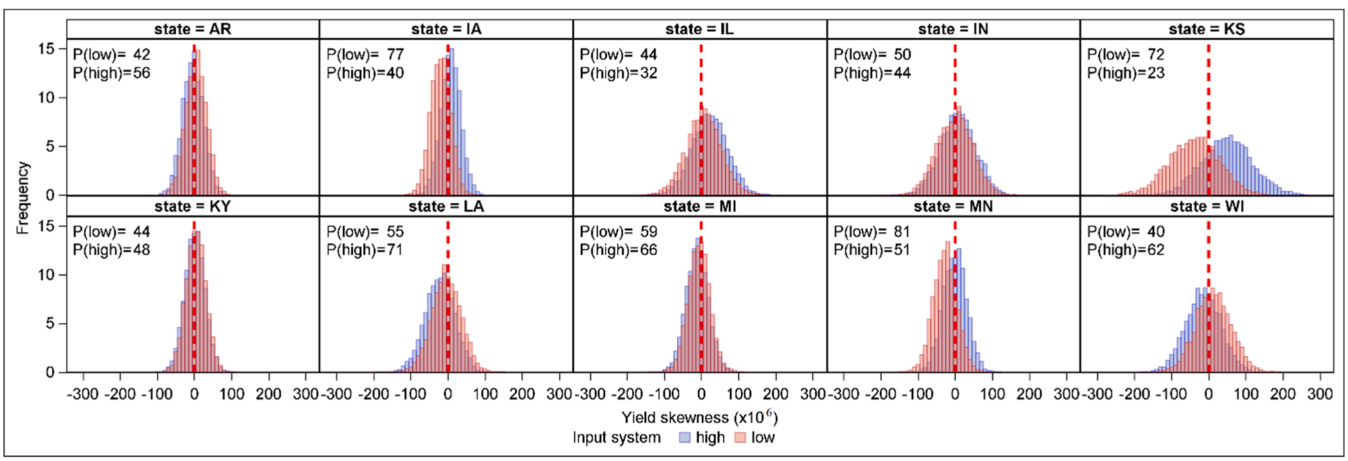

Fig. 4. Distribution of yield skewness and the probability as a percentage that yield skewness < 0 in the posterior sample distribution (n = 5100) in high (blue histogram P(high)) and low (red histogram P(low)) input cropping systems in each state. Within each state, the red dashed line shows the zero-yield skewness.

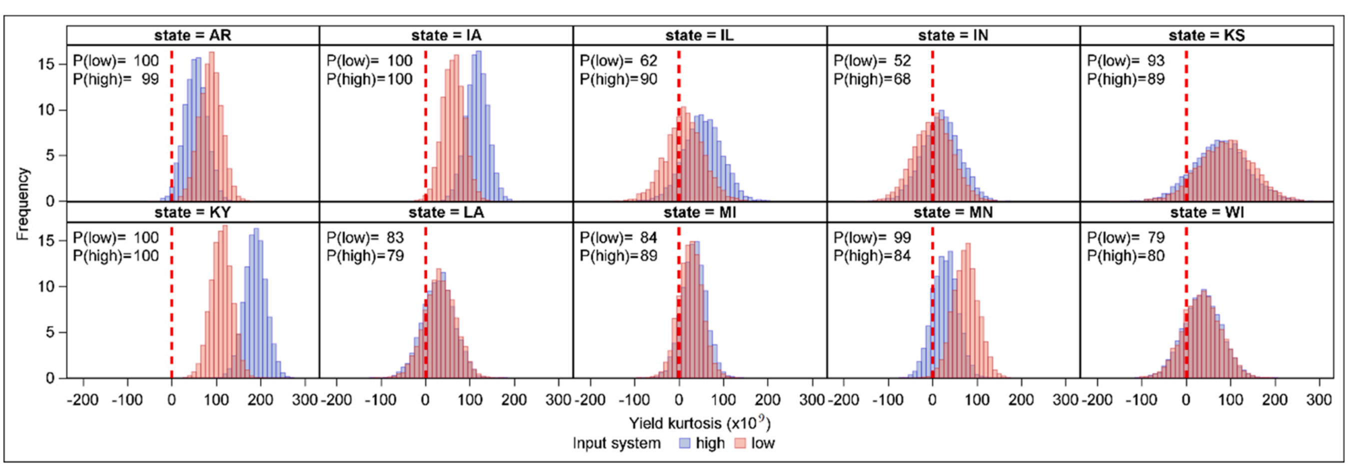

Fig. 5. Distribution of yield kurtosis and the probability as a percentage that yield kurtosis > 0 in the posterior sample distribution (n = 5100) in high (blue histogram P(high)) and low (red histogram P(low)) input cropping systems in each state. Within each state, the red dashed line shows the zero-yield kurtosis.

negligible percentage of average yield.

Repeating the analysis assuming a more risk-averse farmer (r=5), as expected, the estimated cost of risk increased, ranging between − 41 to 54 kg/ha (Fig. S2, Table S7). Again, estimates were not significant (95% credible intervals included zero) and the overall conclusions remained the same as observed for a moderately risk averse farmer. As an

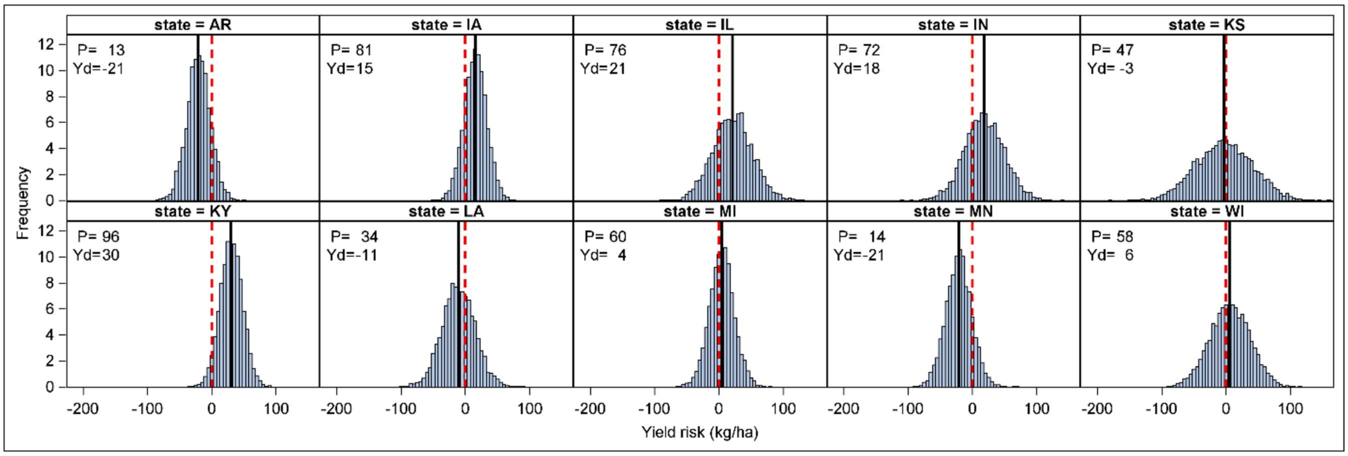

Fig. 6. Distribution of the change in the cost of yield risk (kg/ha) between high- and low-input cropping systems in each state and probability (P) as a percentage that the cost difference > 0 in the posterior sample distribution (n = 5100). Within each state, the red dashed line shows the zero cost difference, and the black line indicates the mean cost difference (Yd).

additional robustness check, we repeated the analysis using a frequentist approach with robust standard errors (see methods and Figs. S3-S5, Tables S8-S10). Again, overall results were consistent with the Bayesian analysis approach.

4. Discussion

US farmers have become more interested in using multiple inputs in their soybean systems due to increased soybean prices, coupled with hypothesized nutrient deficiencies, potential plant health benefits, perceived level of potential pest infestation, and industry promotion. As an insurance practice, farmers typically decide to apply many of these inputs well in advance of planting time when there is little to no information about the potential severity or even presence of yield limiting factors. Here we detected a yield increasing effect due to high-input systems which was inconsistent among the examined states (−191 to 576 kg/ha or −4.9 to 12.7% of average yield).

Reducing the risk of crop failure and yield loss is desirable to farmers who rely on high and stable crop yield to ensure consistent profitability and business welfare. Reducing the risk of production loss in major producing countries such as the US is also essential to food security in major soybean importing consuming countries such as China (Yao et al., 2020). Our risk analysis showed that the mean cost of the yield risk difference at the field level between high- and low-input systems in each state was minimal (< 3% of total yield) and inconsistent, suggesting that applying multiple inputs had little effect on reducing downside yield risk at the field level. Consistent with previous studies (Shi et al., 2013), we found that most of the cost of risk at the field level comes from the variance component and intensive management resulted in similar or increased variance compared to low-input systems. This result is consistent with the risk increasing effect of pest management inputs noted in previous studies (Horowitz and Lichtenberg, 1994; Salazar and Rand, 2020). The effect of management intensity on field-level yield skewness and kurtosis showed non-significant and inconsistent effects across the states. That the high-input system used multiple inputs, some protective and some productive, may have contributed to finding inconsistent effects. Our analysis shows that intensive management increased mean soybean yield and may increase the variance of yield at the field-level for many farmers, with no consistent effect on downside risk as measured by the higher moments of yield.

This analysis was at the field level for soybean production in isolation, but at the whole farm level, aggregate risk effects of high and low-input soybean systems can be different. Factors that may increase risk at the field level (such as high-input soybeans), can reduce risk in aggregate for a farm (Tack and Yu, 2021). For example, Hurley et al. (2004) showed that adopting Bt corn increased risk at the field level by increasing yield variance, but at the whole farm level, can increase or decrease farm risk depending on technology cost and how the farm adjusts the total area cropped. Also, farmers choose inputs to manage more than just yield or income risk, such as human and environmental safety or time and managerial simplicity (Hurley and Mitchell, 2020). Overall, these results suggest that the yield risk effects of intensive soybean management systems at the field level are not large and such systems should not necessarily be considered a broad-scale profitable and sustainable food-securing practice across the US to reduce downside production loss risk. This is in agreement with recent work that showed that most of the management practices in the high-input system exhibited low-to-moderate importance in predicting soybean yield in major crop producing regions in the US (Shah et al., 2021).

The greatest yield benefits from high-input systems were observed in the northern states of MN and WI (541 and 576 kg/ha, respectively). These mean yield increases accounted for a respective 12.7% and 12.1% of average yield and can be considered as substantial. The multiple applied inputs are estimated to cost *ca.* 420 $/ha which means that the soybean price would need to exceed 776 and 730 $/ton to cover the cost of application in MN and WI, respectively. Such high prices have never been observed and therefore, these results question the profitability of broad scale adoption of high-input soybean management across the US. We argue that identifying management with high potential to consistently increase yield in specific regions will be more likely to result in profitable yield increases (Andrade et al., 2022).

5. Conclusions

Overall results in this work show that when compared to low input application, intensifying soybean management is yield increasing without reducing downside yield loss risk. Additionally, the observed yield benefits indicate a negative return on investment which is consistent with previous studies (Mourtzinis et al., 2016; Orlowski et al., 2016; Quinn and Steinke, 2019). These results further support the use of integrated pest management (IPM) for making input decisions instead of relying on prophylactic input applications as insurance against yield-limiting factors. Such approach can be cost-effective and environmentally friendly since inputs are applied when and where needed. We conclude that future studies of food security and crop production should be region-specific and focus on identifying management practices with the greatest yield potential based on IPM practices rather than recommending broad-scale intensive management systems as insurance practice.

Declaration of Competing Interest

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

Data Availability

Data will be made available on request.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.fcr.2023.109012.

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