Modeling the Effect of Varied and Fixed Seeding Rates at a Small-Plot Scale

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ABSTRACT

The optimum corn (Zea mays L.) seeding rate which maximizes profitability can vary with small differences in environmental characteristics. Because environmental characteristics can vary at small spatial scales, the optimum seeding rate might vary similarly. The objectives of this study were to use data from 125 small-plot field trials in Ohio (93) and Illinois (32) to model the effects of varied and fixed seeding rates on corn yield production, return to seed (RTS), and determine if optimal seeding rate changed with yield potential. The mathematical relationship between yield and seeding rate was used to determine the economic optimum seeding rate (EOSR) for each trial (assuming a seed cost of US$3.00 per thousand seeds and grain price of $0.148 kg⁻¹) and model the uniform optimum seeding rate (UOSR) for each state that would result in greatest overall profitability if used in every trial. Estimated RTS was determined by subtracting the averaged value from implementing the UOSR in every trial from the averaged EOSRs from each trial. The EOSR (varied seeding rate) provided greater RTS when compared to the UOSR (fixed seeding rate) in each state, but the potential was greater in Ohio ($30.98 ha⁻¹) than in Illinois ($7.76 ha⁻¹). However, relatively flat population curves suggest that deviation from the optimum seeding rate may have little consequence for yield (<1.5% loss at the UOSR compared to EOSR). This suggests accurate characterization of responses may be difficult to attain for use in variable rate seeding applications.

Core Ideas

- Quadratic and quadratic-plateau responses were most common in Ohio and Illinois, respectively.
- Optimizing seeding rates in Ohio resulted in greater return to seed than in Illinois.
- Factors other than yield potential contribute toward yield response to seeding rate.

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may have altered this conclusion. For example, in Ohio and Illinois the state grain yield average has increased by approximately 2500 kg ha\(^{-1}\) in 20 yr since 1997, and price received has increased by $0.007 kg\(^{-1}\) per year (USDA–NASS, 2017). The increased use of transgenic hybrids (some with multiple transgenes or events), increased seeding rates, value-added products, and products containing refuge in the bag have all impacted the cost of seed over the last 20 yr as well, especially since 2006 (Schnitkey and Sellars, 2016). The objectives of this analysis were to (i) model the use of optimized (varied) seeding rates compared to a uniform (fixed) seeding rate in different environments; (ii) determine if optimum population changes with yield potential; and (iii) evaluate the economic RTS of optimizing seeding rate for corn in Ohio and Illinois by examining change in yield and cost of seed.

**METHODS**

Data from trials conducted from 2012 through 2016 at multiple locations evaluating corn yield response to seeding rate were collected from Ohio (93 trials, Supplemental Table S1) and Illinois (32 trials, Supplemental Table S2). All trials were rainfed, and were managed such that pests and soil nutrients were non-limiting. Soil type, planting date, previous crop, and tillage information is given in Tables S1 and S2. Each trial consisted of four to six seeding rates ranging from 44,480 to 123,550 seeds ha\(^{-1}\), planted in small plots (3.04 m × 7.30 or 12.18 m long; four rows in 76-cm rows) with three or four replications. For studies thinned to final stands within this population range, final stands were divided by 0.95 prior to analysis to emulate planting to establish a stand equal to 95% of the seeding rate. This rate was selected based on analysis of the percent emergence data as reported in the Ohio Corn Performance Trials during the same period (Minyo et al., 2012, 2013, 2014, 2015, 2016), and has been supported by other researchers (Elmore, 2013). For studies with multiple hybrids at each seeding rate, yield was averaged across hybrids within each seeding rate prior to analysis. This was done to describe the average corn response to seeding rate within the specific study environment. Planting dates ranged from 12 April to 16 June, but most studies in Ohio were planted between early May and early June and between mid-April and early May in Illinois (Supplemental Tables S1 and S2). Because seeding rate responses may be influenced by planting date within a location, each trial with a unique planting date was analyzed independently. Yield and harvest moisture was collected from the center two rows after maturity, and yields were adjusted to 155 g kg\(^{-1}\) moisture prior to analysis.

Appropriate regression functions (linear, quadratic, or quadratic-plateau) were fit to the mean yields of each trial to model grain yield response to seeding rate (Tables S1 and S2). Regression procedures in SAS 9.4 were utilized to determine the model of best fit (REG and NLIN procedures). Actual seeding rates were divided by 1000 for better resolution in the model coefficients, and the model that best fit the data was selected based on the lowest Second-Order Information Criterion (AICc) value (reported in Tables S1 and S2) (Snipes and Taylor, 2014; Maestri and Basso, 2018).

The EOSRs from the regression functions were calculated assuming a seed cost of $3.00 per thousand seeds and grain price of $0.148 kg\(^{-1}\) ($3.75 bu\(^{-1}\)) (ratio of $3/$0.148 = 20.32). The grain price was obtained using The Ohio State University 2016 Corn Production Enterprise budget (Ward et al., 2016). The seed cost was generated using the base price from the enterprise budget ($3.44 per 1000 seeds) and subtracting a 12.7% cash discount, which is commonly provided to seed purchasers. No other costs were included in this analysis because it was assumed that most other crop inputs or costs would not change with altered seeding rate.

For each trial with a quadratic or quadratic-plateau curve with a negative coefficient for the second-degree term, the EOSR was determined by solving for the independent variable after setting the first order derivative equal to the ratio of seed cost to grain price (20.32). In cases where this practice lowered the EOSR below the tested seeding rates, the lowest tested seeding rate was set as the EOSR for that trial. Three Ohio trials produced quadratic responses with a positive coefficient for the second-degree term; in these, the EOSR was determined as the seeding rate within the tested range that resulted in the greatest economic return. The EOSR for linear responses was determined from the slope magnitude; a slope less than the seed cost to grain price ratio resulted in an EOSR equivalent to the lowest tested seeding rate and a slope greater than the ratio resulted in an EOSR equivalent to the highest tested seeding rate. Yield at the EOSR was calculated by using the EOSR as the independent variable in each trial’s regression equation. The estimate of RTS was calculated by multiplying the yield at the EOSR by the grain price, and then subtracting the seed cost ($3.00 × EOSR in thousands).

To determine the UOSR (or the seeding rate that maximized RTS averaged across all trials) in each state, the seeding rate response model for each trial was run initially using a seeding rate range of 44,480 to 123,550 seeds ha\(^{-1}\) in increments of 4940 seeds ha\(^{-1}\) planted in small plots (3.04 m × 7.30 or 12.18 m long; four rows in 76-cm rows) with three or four replications. For studies thinned to final stands within this population range, final stands were divided by 0.95 prior to analysis to emulate planting to establish a stand equal to 95% of the seeding rate. This rate was selected based on analysis of the percent emergence data as reported in the Ohio Corn Performance Trials during the same period (Minyo et al., 2012, 2013, 2014, 2015, 2016), and has been supported by other researchers (Elmore, 2013). For studies with multiple hybrids at each seeding rate, yield was averaged across hybrids within each seeding rate prior to analysis. This was done to describe the average corn response to seeding rate within the specific study environment. Planting dates ranged from 12 April to 16 June, but most studies in Ohio were planted between early May and early June and between mid-April and early May in Illinois (Supplemental Tables S1 and S2). Because seeding rate responses may be influenced by planting date within a location, each trial with a unique planting date was analyzed independently. Yield and harvest moisture was collected from the center two rows after maturity, and yields were adjusted to 155 g kg\(^{-1}\) moisture prior to analysis.

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The RTS at the UOSR was calculated for each trial’s response curve, and these values were averaged to produce the estimated RTS had the UOSR been used in each trial. To determine the increase from using calculated EOSR values in each trial compared to the UOSR in each trial, a partial budget analysis (Tigner, 2006) was conducted by subtracting the RTS at the UOSR from the averaged RTS values calculated at the EOSR for each trial. Additionally, yield and seeding rate differences between the EOSR and UOSR were used to separate contributions of seed cost savings and grain yield increases to the RTS from using EOSR values for each trial. The differences between EOSR and UOSR in optimum seeding rate, grain yield at the optimum, and RTS were evaluated for significance using a paired t test (α = 0.05).

**RESULTS AND DISCUSSION**

The EOSR values in Ohio trials ranged from 44,480 to 109,568 seeds ha\(^{-1}\), with an overall average of 79,391 seeds ha\(^{-1}\) and a standard deviation of 15,032 seeds ha\(^{-1}\). Yield at the EOSR ranged from 7335 to 16,997 kg ha\(^{-1}\) (12,886 kg
ha^{-1} average), which resulted in a RTS range of $890.13 to $2223.61 ha^{-1} with an average RTS of $1664.28 ha^{-1} (Fig. 1). The function to describe the UOSR for Ohio trials (Fig. 2) was determined to be as follows:

\[
\text{if } x \leq 80.854 \text{ 1000 seeds ha}^{-1} \text{ then } y = -0.1219x^2 + 19.662x + 841.16; \text{ and}
\]

\[
\text{if } x > 80.854 \text{ 1000 seeds ha}^{-1} \text{ then } y = -0.1033x^2 + 16.531x + 973.01.
\]

The UOSR and yield at the UOSR of the Ohio trials were determined to be 80,854 seeds ha\(^{-1}\) and 12,706 kg ha\(^{-1}\), respectively, with an estimated RTS of $1633.30 ha\(^{-1}\). While the difference between the average EOSR and the average UOSR was not significant \((P = 0.351)\), the yield as a result of using the EOSR was greater than when using the UOSR \((P < 0.01)\) (Table 1). Based on this analysis, the estimated RTS advantage from using the EOSR in each trial was $30.98 ha\(^{-1}\), with 86\% of the greater return coming from greater yield and 14\% coming from lower seed cost (Table 1).

Sixty-one percent (57 out of 93) of the trials included in the Ohio analysis above exhibited model \(P\)-values less than 0.2 (Supplemental Table S1). In a separate analysis, the 36 models that exceeded a \(P\)-value of 0.2 were excluded and the same process was conducted using only the remaining models. This resulted in an EOSR of 84,778 seeds ha\(^{-1}\) with an average RTS of $1748.01 ha\(^{-1}\), and an UOSR of 84,268 seeds ha\(^{-1}\) with an average RTS of $1715.92 ha\(^{-1}\) (RTS advantage of $32.09 ha\(^{-1}\) from EOSR compared to using the UOSR). The advantage of RTS was a result of increased yield (worth $33.62) despite increased seed cost ($1.53).

The exclusion of the models in Ohio resulted in greater overall optimum seeding rates by approximately 4000 seeds ha\(^{-1}\) and greater RTS values by $80 ha\(^{-1}\), but only increased overall RTS by $1.12 ha\(^{-1}\) compared to the results when all models were included (Table 1). The differences in results in Ohio may have been partially due to many of the removed sites exhibiting small responses to increased seeding rate, and partially due to some of the models exhibiting the modeled relationship but having a high \(P\)-value due to few degrees of freedom. Additionally, consultants and producers may rely on nonsignificant but accurate regression analysis to characterize environmental response to seeding rate so it is important to evaluate the results with their inclusion and exclusion.

The results in Illinois differed from those in Ohio, primarily due to the dominance of quadratic-plateau responses compared to mostly quadratic responses in Ohio. The EOSR in the Illinois trials ranged from 59,357 to 100,420 seeds ha\(^{-1}\) with an average optimum of 83,472 seeds ha\(^{-1}\) and a standard deviation of 3303 seeds ha\(^{-1}\). Yield at the EOSR ranged from 8292 to 16,814 kg ha\(^{-1}\) (14,210 kg ha\(^{-1}\) average), with an estimated RTS range of $1046.04 to $2251.43 ha\(^{-1}\) ($18,477.37 ha\(^{-1}\) average) (Fig. 3). The function to describe the UOSR for Illinois trials was determined to be as follows (Fig. 4):

\[
\text{if } x \leq 80.854 \text{ 1000 seeds ha}^{-1} \text{ then } y = -0.1864x^2 + 30.760x + 570.27; \text{ and}
\]

\[
\text{if } x > 80.854 \text{ 1000 seeds ha}^{-1} \text{ then } y = -0.0746x^2 + 11.689x + 1384.10.
\]

The UOSR for Illinois trials was determined to be 83,283 seeds ha\(^{-1}\), with the average yield across trials each at the UOSR.
Table 2. Average economic optimum seeding rate (EOSR) and uniform optimum seeding rate (UOSR) for the Illinois trials. The column ‘Difference’ shows the UOSR subtracted from the EOSR value for each row.

<table>
<thead>
<tr>
<th>Seeding rate (kg ha(^{-1}))</th>
<th>EOSR</th>
<th>UOSR</th>
<th>Difference†</th>
</tr>
</thead>
<tbody>
<tr>
<td>83.472</td>
<td>83.283</td>
<td>189 ns</td>
<td></td>
</tr>
<tr>
<td>14,210</td>
<td>14,153</td>
<td>57 ns</td>
<td></td>
</tr>
<tr>
<td>Return from seed ($ ha(^{-1}))</td>
<td>$250.42</td>
<td>$249.85</td>
<td>$0.57 ns</td>
</tr>
<tr>
<td>Return from yield ($ ha(^{-1}))</td>
<td>$2,097.79</td>
<td>$2,089.46</td>
<td>$8.33 ns</td>
</tr>
<tr>
<td>Return to seed ($ ha(^{-1}))</td>
<td>$1,847.37</td>
<td>$1,839.61</td>
<td>$7.76 **</td>
</tr>
</tbody>
</table>

† ns indicates paired t-test is significant at \(P < 0.01\).
†† indicates paired t-test is significant at \(P < 0.05\).

Fig. 3. Estimated return to seed (lines) for each Illinois trial (32 trials conducted from 2012–2016) calculated using the seeding rate response curves in Supplemental Table S2. White circles represent the economic optimum seeding rate for each trial.

of 14,153 kg ha\(^{-1}\) and an estimated RTS of $1839.61 ha\(^{-1}\) (Table 2). Neither seeding rate nor grain yield difference for the EOSR compared to the UOSR was significant (\(P = 0.955\) and 0.120, respectively; Table 2), but the combination of increased seeding rate and grain yield for the EOSR compared to the UOSR resulted in a significant RTS advantage of $7.76 ha\(^{-1}\). The advantage came as a yield increase for the EOSR (worth $8.33) but requiring 189 more seeds (worth $0.57 ha\(^{-1}\)).

These results show that the process of implementing optimized seeding rates was more profitable for the Ohio sites compared to the Illinois sites used in these calculations. This finding is intuitive when contrasting the spread of seeding rate optima between the two states (Fig. 1 and 3). The optima in Ohio ranged more widely (more points at the higher and lower ends of the range), which increased the penalty from using a seeding rate in the middle. Additionally, 80% of the Ohio trials were quadratic (or linear with a slope less than the seed cost to grain price ratio) meaning there was a greater penalty from using a seeding rate above the EOSR compared to sites with a quadratic-plateau response (53% of the Illinois trials exhibited a quadratic-plateau response). These results suggest Ohio environments may benefit from practices such as variable rate seeding.

Fig. 4. Average return to seed (triangles) across all Illinois trials at 4940 seeds ha\(^{-1}\) (2000 seeds ac\(^{-1}\)) increments. The lines correspond to the two-part quadratic response to increasing seeding rate across all trials, and are divided at the uniform optimum seeding rate.

where the differences in optimum seeding rates should vary by at least 9880 plants ha\(^{-1}\) (Jeschke et al., 2015).

This simulated approach comparing EOSR to UOSR using actual small-plot scale data from a wide range of sites may provide an estimated potential of a variable rate seeding plan to increase net returns, but the determination of site-specific seeding rate optima for each part of a field remains a challenge.

Delineation of specific management zones may be possible using various soil characteristics (Licht et al., 2017; Smidt et al., 2016), but it may take time to identify consistent patterns under different crop rotations or tillage regimes (Bunselmeyer and Lauer 2015). Modern techniques that utilize yield map history and in-season thermal imagery have been able to predict or identify areas of consistent yield levels (high, medium, low) and stability (stable vs. unstable), which should improve the accuracy of the process (Maestrini and Basso, 2018). However, weather variability in-season will constitute an ongoing impediment.

In both Ohio and Illinois, the linear relationship between EOSR and yield (Fig. 5a and 5c) or RTS (Fig. 5b and 5d) indicated possible utility of using yield potential to set seeding rates within a field. However, these relationships were relatively weak and it is noted that the medium- to high-yielding environments tended to show relatively flat yield responses to increased seeding rate (Fig. 1 and 3). This hints at the difficulty of accurately predicting site-specific optima needed for fully efficient variable rate seeding practices. These results are similar to those recorded in Indiana, where population responses generated in field-scale trials were also relatively flat (Nielsen et al., 2017).

Because most environments in these studies had medium to high yield potential (>11,300 kg yield ha\(^{-1}\)), these results suggest that targeted increases in seeding rate can improve profitability as has been shown in southern Brazil (Hörbe et al., 2013). While Ping et al. (2008) found no interactions of seeding rate and yield in high-yielding irrigated corn in Nebraska, rain-fed environments in the eastern US Corn Belt have been shown to exhibit yield responses in high-yield environments due to seeding rate (Lindsey and Thomison, 2016). These data also suggest that gains from optimization may still be achieved on land that exhibits high yield potential, which differs from the conclusions.
presented by Lowenberg-DeBoer (1999) who suggested that areas of low productivity (less than 6300 kg yield ha\(^{-1}\)) may be necessary to make variable rate seeding profitable. The returns in this study were also less than those reported in popular press articles ($21.76–85.30 ha\(^{-1}\) returns from using variable rate seeding) [Hest, 2011], which may be a consequence of site selection of differences in growing conditions.

**Conclusions**

These results indicate that there may be potential for modest increases in profitability from optimization of corn seeding rate in states like Ohio and Illinois. However, predictions of optimal seeding rates within a field and year will need to improve beyond current levels before estimated RTS of this level will be approached. Additionally, these results suggest improved RTS may be realized at medium and high yield levels. These results also suggest small changes in seeding rates may be needed to impact profitability, but obtaining this resolution on small spatial scales is a challenge that will need to be addressed in future research.

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**Supplemental Material**

Table S1. Study characteristics and regression analysis output for each trial in Ohio from 2012–2016. A previous crop of S is soybeans [Glycine max (L.) Merr.], C is corn, and W is winter wheat [Triticum aestivum L.]. Regression used seeding rate (1000 seeds ha\(^{-1}\)) as the
independent variable \( (x) \), and grain yield in kg ha\(^{-1} \) as the dependent variable \( (y) \). The type of curve is denoted as linear (L), quadratic (Q), or quadratic-plateau (QP). The Second-Order Information Criterion (AICc) value and overall \( P \)-value for each model is also provided.

Table S2. Study characteristics and regression analysis output for each trial in Illinois from 2012–2016. For all trials, the previous crop was soybeans. Regression used seeding rate (1000 seeds ha\(^{-1} \)) as the independent variable \( (x) \), and grain yield in kg ha\(^{-1} \) as the dependent variable \( (y) \). The type of curve is denoted as linear (L), quadratic (Q), or quadratic-plateau (QP). The Second-Order Information Criterion (AICc) value and overall \( P \)-value for each model is also provided.

REFERENCES


