#### ARTICLE

Crop Economics, Production, & Management

## Defining optimal soybean seeding rates and associated risk across North America

 Adam P. Gaspar<sup>1</sup>
 Spyridon Mourtzinis<sup>2</sup>
 Don Kyle<sup>1</sup>
 Eric Galdi<sup>1</sup>

 Laura E. Lindsey<sup>3</sup>
 William P. Hamman<sup>3</sup>
 Emma G Matcham<sup>2</sup>
 Hans J. Kandel<sup>4</sup>

 Peder Schmitz<sup>4</sup>
 Jordan D. Stanley<sup>4</sup>
 John P. Schmidt<sup>1</sup>
 Daren S. Mueller<sup>5</sup>

 Emerson D. Nafziger<sup>6</sup>
 Jeremy Ross<sup>7</sup>
 Paul R. Carter<sup>1</sup>
 Adam J. Varenhorst<sup>8</sup>

 Kiersten A. Wise<sup>9</sup>
 Ignacio A. Ciampitti<sup>10</sup>
 Walter D. Carciochi<sup>10</sup>
 Martin I. Chilvers<sup>11</sup>

 Brady Hauswedell<sup>8</sup>
 Albert U. Tenuta<sup>12</sup>
 Shawn P. Conley<sup>2</sup>

<sup>1</sup>Corteva Agriscience, 7100 NW 62<sup>nd</sup> Ave., Johnston, IA 50131, USA

<sup>3</sup>Department of Horticulture and Crop Science, Ohio State University, 2021 Coffey Rd., Columbus, OH 43210, USA

<sup>4</sup>Department of Plant Sciences, North Dakota State University, Department 7670 PO Box 6050, Fargo, ND 58108, USA

<sup>5</sup>Department of Plant Pathology and Microbiology, Iowa State University, 2213 Pammel Dr., Ames, IA 50011, USA

<sup>6</sup>Department of Crop Sciences, University of Illinois, 1102 S. Goodwin Ave., Urbana, IL 61801, USA

<sup>7</sup>Crop, Soil, and Environmental Sciences, University of Arkansas, 2301 S. University Ave., Little Rock, AR 72204, USA

<sup>8</sup>Agronomy, Horticulture, and Plant Science Department, South Dakota State University, 308 Berg Ag Hall, Box 2170, Brookings, SD 57007, USA

<sup>9</sup>Department of Plant Pathology, University of Kentucky, 1205 Hopkinsville St. P.O. 469, Princeton, KY 42445, USA

<sup>10</sup>Department of Agronomy, Kansas State University, 1712 Claflin Rd., Manhattan, KS 66506, USA

<sup>11</sup>Department of Plant, Soil, and Microbial Sciences, Michigan State University, 1066 Bogue St., East Lansing, MI 48824, USA

<sup>12</sup>Ontario Ministry of Agriculture, Food, and Rural Affairs, University of Guelph, 120 Main Street E., Ridgetown, ON NOP2CO, Canada

#### Correspondence

Adam P. Gaspar, Corteva Agriscience, 7100 NW 62<sup>nd</sup> Ave., Johnston, IA 50131, USA. Email: adam.gaspar@corteva.com

#### **Funding information**

Foundational and Applied Science Program, Grant/Award Number: 20186800828356; South Dakota Soybean Research and Promotion Council, Grant/Award Number: SD00H610-16; Kansas State Research and Extension, Grant/Award Number: IOWA3908

#### Abstract

Soybean [*Glycine max* (L.) Merr.] seeding rate research across North America is typically conducted in small geo-political regions where environmental effects on the seeding rate × yield relationship are minimized. Data from 211 individual field studies (~21,000 data points, 2007–2017) were combined from across North America ranging in yield from 1,000– 7,500 kg ha<sup>-1</sup>. Cluster analysis was used to stratify each individual field study into similar environmental (soil × climate) clusters and into high (HYL), medium (MYL), and low (LYL) yield levels. Agronomically optimal seeding rates (AOSR) were calculated and Monte Carlo risk analysis was implemented. Within the two northern most clusters the AOSR was higher in the LYL followed by the MYL and then HYL. Within the farthest south cluster, a relatively

**Abbreviations:** AOSR, agronomically optimal seeding rate; CIPAR, cumulatively intercepted photosynthetically active radiation; HYL, high yield level; LYL, low yield level; MYL, medium yield level; NCCPI, national commodity crop productivity index; PAR, photosynthetically active radiation; VRS, variable rate seeding.

This is an open access article under the terms of the Creative Commons Attribution-NonCommercial-NoDerivs License, which permits use and distribution in any medium, provided the original work is properly cited, the use is non-commercial and no modifications or adaptations are made. © 2020 The Authors. *Agronomy Journal* published by Wiley Periodicals, Inc. on behalf of American Society of Agronomy

<sup>&</sup>lt;sup>2</sup>Department of Agronomy, University of Wisconsin-Madison, 1575 Linden Drive, Madison, WI 53706, USA

small ( $\pm 15,000$  seeds ha<sup>-1</sup>) change in seeding rate from the MYL was required to reach the AOSR of the LYL and HYL, respectively. The increase in seeding rate to reach the LYL AOSR was relatively greater (5x) than the decrease to reach the HYL AOSR within the northern most cluster. Regardless, seeding rates below the AOSR presented substantial risk and potential yield loss, while seeding rates above provided slight risk reduction and yield increases. Specific to LYLs and MYLs, establishing and maintaining an adequate plant stand until harvest maximized yield regardless of the seeding rate, while maximizing seed number was important with lower seeding rates. These findings will help growers manage their soybean seed investment by adjusting seeding rates based upon the productivity of the environment.

#### **1 | INTRODUCTION**

Soybean [*Glycine max* (L.) Merr.] seeding rate or plant stand and its relationship with seed yield has been intensively studied in the major soybean producing regions across North America. The goal of these studies, like those focused on management of most agricultural inputs, is to determine an agronomically (optimize yield) and/or economically (optimize profit) optimal seeding rate (Jaynes, 2010). While many of these studies succeed in identifying optimal soybean seeding rates or plant stands and quantifying variability between fields, they typically are only conducted within one geo-political region (state or providence), limiting the range of environments evaluated in these relationships. Ultimately, this limits the ability to robustly characterize the environmental effects on the seeding rate or plant stand × seed yield relationship.

There are numerous reasons for the steady decline in soybean seeding rates over the past two decades in North America. A key factor is the large switch from drills to row crop planting (> 80%), encouraged by reductions in cereal rotations (Jeschke & Lutt, 2016) which has resulted in more accurate soybean planting. Also, seed treatment adoption has reached > 80% allowing for more successful stand establishment (Gaspar, Marburger, Mourtzinis, & Conley, 2014). Seed quality and vigor has dramatically improved with adoption of better seed handling and cleaning equipment (Shelar, 2008). The adoption of soybean cultivars with herbicide resistance traits has shifted the focus away from using cultural control practices such as higher seeding rates for weed management (Bertram & Pedersen, 2004). However, there are two primary drivers. First, the 295% increase in seed costs per hectare since 1997 (USDA-ERS, 2018), justified due to increased genetic yield potential and improved pest tolerance (Rincker et al., 2014) and new technology options (e.g. herbicide traits) (Shi et al., 2009). Secondly, various studies have determined that 247,000 plants ha<sup>-1</sup> at harvest are required to maximize yield (Epler & Staggenborg, 2008; Gaspar & Conley, 2015; Lee, Egli, & TeKrony, 2008) while others have determined that 185,000 seeds  $ha^{-1}$  maximize profit (De Bruin & Pedersen, 2008a). However, these studies are typically conducted on uniform, well drained, highly productive, and intensely managed areas within a field in an effort to minimize environmental effects and variability. The same has typically been the case where on-farm trials use strips across an entire field length, which moderates the impact of high and low productivity areas of that strip. In comparison to the aforementioned studies, others have suggested plant stands as high as 600,000 plants  $ha^{-1}$  are needed in droughtprone environments (Holshouser & Whittaker, 2002) while economically optimal seeding rates can be as high as 320,000 seeds ha<sup>-1</sup> (Cox, Cherney, & Shields, 2010; Gaspar, Conley, & Mitchell, 2015; Gaspar et al., 2017). Thus, there is clearly a wide range of agronomically and economically optimal seeding rates and plant stands driven by variation in seed costs, grain prices, seed treatment use, and most importantly, the productivity of the environment. Corassa, Amado, Schwalbert, Carter, and Ciampitti (2018) and Carciochi et al. (2019) demonstrated how the overall productivity of the environment affected the agronomically optimal seeding rate (AOSR) and plant density by segregating their data by yield level. However, it was not determined what soil and climatic factors were associated with their high, medium, and low yielding environments, which was suggested as an area needing further investigation (Carciochi et al., 2019).

When holding seeding rate constant, breeding efforts have increased the yield potential per plant (Suhre et al., 2014) thereby increasing the plants compensatory ability in situations of reduced plant stands, leading to a wide range of optimal seeding rates (Carpenter & Board, 1997). However, when plant density is too low, limited light interception and crop growth rate will reduce yield potential (Board, 2000; Gaspar & Conley, 2015; Wells, 1991). This density driven reduction may be exacerbated in low yielding (Carciochi et al., 2019) and stressful (e.g. drought) (Holshouser & Whittaker, 2002) environments or in northern latitudes where cumulative intercepted photosynthetically active radiation (CIPAR) is limited (Edwards, Purcell, & Karcher, 2005; Gaspar & Conley, 2015). Ultimately, in the plant density by environment spectrum, final yield is determined by two interactive yield components, seed number and seed mass. On an area basis, seed number is strongly related to yield, while seed mass is not (Gaspar & Conley, 2015; Mourtzinis, Gaska, Pedersen, & Conley, 2015). However, the interactive effects of environment and seeding rate have been shown to significantly alter seed mass (Gaspar et al., 2015). Corassa et al. (2018) suggested that a better understanding of how these yield components on an area basis are affected by seeding rate across differential levels of productivity may identify areas for further yield improvement.

To build upon Carciochi et al., 2019, we look to expand the range of evaluation in terms of geographical footprint, database size, and yield range while also assessing environmental parameters and additional factors. . The main objective of this study was to quantify the production risk associated with soybean seed yield response to seeding rate and plant density across a range of environments varying in levels of productivity across North America. Secondary objectives were to (i) identify and quantify the subsequent yield components driving these different responses and (ii) quantify natural in-season plant attrition. With the rapid adoption of geo-spatial tools such as yield maps and variable rate seeding (VRS) over the past decade, these findings will help growers better manage (agronomically and economically) their annual seed investment by spatially adjusting seeding rates based upon the productivity of the environment and its underlying environmental factors (Smidt, Conley, Zhu, & Arriaga, 2016). This is applicable at both within- and between-field levels.

#### **2 | MATERIALS AND METHODS**

#### 2.1 | Database components

Soybean seed yield data and complementary yield component data were assembled for this study from 211 randomized and replicated field studies, which were conducted specifically to evaluate the effect of seeding rate on soybean seed yield at sites within each of 12 states (Arkansas, Iowa, Illinois, Indiana, Kansas, Michigan, Minnesota, Missouri, North Dakota, Ohio, South Dakota, and Wisconsin) and Ontario Canada from 2005 to 2007 and 2012 through 2017 (Figure 1). Data outliers (below 1,000 and above 7,500 kg ha<sup>-1</sup>) were excluded and the final database included 20,926 plot-specific soybean seed yields. For all experiments, soil pH, organic matter (OM), National Commodity Crop Productivity Index (NCCPI) (Dobos, Sinclair, & Hipple, 2008), and water holding capacity (WHC) were recorded (Soil Survey Staff, 2018). For each study, weather data were obtained from Daymet (Daily Surface Weather Data on a 1-km Grid for North America) (Thornton et al., 2014), which was chosen due to its superior accuracy when compared to other weather data sources (Mourtzinis, Rattalino Edreira, Conley, & Grassini, 2017). Weather variables included daily minimum and maximum temperatures (Tmin and Tmax, respectively), precipitation, and vapor pressure deficit (VPD). In all studies, season-wide average Tmin, Tmax, and VPD and season-wide cumulative precipitation (May to September) were calculated.

#### 2.2 | Environmental clusters

Individual field studies were in different regions, thus the effect of environment (location  $\times$  year) on soybean yield was assumed to be significant. To account for non-managementrelated effects on yield, cluster analysis was used to stratify field studies into similar growing environments based on GPS coordinates, soil pH, OM, NCCPI, WHC, and the previously outlined weather variables. Additionally, to enhance the clustering model, use of irrigation inputs were included as independent variables. Variables were then standardized to mean = 0 and standard deviation = 1 and clusters were created using PROC FASTCLUS in SAS 9.4 (SAS Institute Inc., 2016). In this method, the iterative algorithm minimizes the sum of squared distances from the cluster means. The clustering is done using Euclidean distances computed from numeric variables. This kind of clustering method is often called a k-means model, since the cluster centers are the means of the observations assigned to each cluster. In each iteration, the least-squares criterion is reduced until convergence is achieved. We used adaptive training by using the DRIFT option in which the cluster seed is updated as the current mean of the cluster each time an observation is added. We specified LEAST = 2 which minimizes the root mean square difference between the data and the corresponding cluster means. Using canonical analysis, visual evaluation of the clusters showed a high degree of separation and small overlap among the clusters (Supplemental Figure S1).

# **2.3** | Agronomically optimum seeding rate estimation

Individual field studies were grouped into three yield levels based on their average yield. The lower 30% were considered low yield levels, the middle 30–70% were considered medium, and the upper 30% were considered as high yield levels. This methodology helps account for the inherent variation present in the response of yield to seeding rate (Supplemental Figure S2). Summary details are provided in Table 1. Yield was modeled separately with the independent



FIGURE 1 Location of 211 trial site-years that are included in the database and their respective environmental cluster classifications

|         |             |          |        |               | Soil               |                 |     | Climate                 |                      |      |      |                         |
|---------|-------------|----------|--------|---------------|--------------------|-----------------|-----|-------------------------|----------------------|------|------|-------------------------|
| Cluster | Yield level |          | N obs. | Yield         | NCCPI <sup>a</sup> | OM <sup>b</sup> | pН  | <b>WHC</b> <sup>b</sup> | Precip. <sup>b</sup> | Tmax | Tmin | <b>VPD</b> <sup>b</sup> |
|         |             |          |        | kg ha $^{-1}$ |                    | $g kg^{-1}$     |     | ${ m mm}~{ m m}^{-1}$   | mm                   | °C   | °C   | kPa                     |
|         | High        | Mean     | 1,040  | 5,125         | 0.29               | 23              | 6.3 | 1.7                     | 556                  | 25.1 | 12.7 | 1.76                    |
|         |             | Std Dev. |        | 602           | 0.13               | 10              | 0.8 | 0.6                     | 103                  | 0.6  | 0.5  | 0.13                    |
| 1       | Medium      | Mean     | 2,810  | 4,243         | 0.42               | 32              | 6.5 | 1.8                     | 521                  | 24.8 | 12.3 | 1.75                    |
|         |             | Std Dev. |        | 648           | 0.10               | 15              | 0.6 | 0.5                     | 89                   | 0.8  | 0.7  | 0.1                     |
|         | Low         | Mean     | 1,017  | 2,893         | 0.37               | 37              | 6.8 | 1.9                     | 408                  | 24.7 | 11.7 | 1.79                    |
|         |             | Std Dev. |        | 723           | 0.18               | 11              | 0.7 | 0.2                     | 88                   | 0.8  | 0.6  | 0.15                    |
|         | High        | Mean     | 2,471  | 5,165         | 0.76               | 35              | 6.6 | 2.2                     | 605                  | 25.3 | 13.6 | 1.7                     |
|         |             | Std Dev. |        | 574           | 0.13               | 7               | 0.3 | 0.1                     | 113                  | 0.5  | 0.7  | 0.06                    |
| 2       | Medium      | Mean     | 3,314  | 4,266         | 0.77               | 41              | 6.6 | 2.2                     | 556                  | 25.0 | 13.4 | 1.67                    |
|         |             | Std Dev. |        | 553           | 0.13               | 12              | 0.3 | 0.2                     | 99                   | 0.9  | 0.9  | 0.17                    |
|         | Low         | Mean     | 1,201  | 3,412         | 0.74               | 49              | 6.7 | 2.1                     | 498                  | 24.9 | 13.3 | 1.67                    |
|         |             | Std Dev. |        | 665           | 0.08               | 19              | 0.5 | 0.2                     | 98                   | 1.1  | 0.9  | 0.18                    |
|         | High        | Mean     | 1,734  | 5,138         | 0.80               | 36              | 6.4 | 2.2                     | 512                  | 27.7 | 14.9 | 2.06                    |
|         |             | Std Dev. |        | 698           | 0.13               | 9               | 0.5 | 0.2                     | 167                  | 1.1  | 2.0  | 0.19                    |
| 3       | Medium      | Mean     | 4,598  | 4,411         | 0.81               | 39              | 6.3 | 2.1                     | 603                  | 26.9 | 15.0 | 1.89                    |
|         |             | Std Dev. |        | 595           | 0.15               | 10              | 0.3 | 0.2                     | 118                  | 0.7  | 0.8  | 0.12                    |
|         | Low         | Mean     | 2,741  | 3,459         | 0.77               | 41              | 6.5 | 2.0                     | 498                  | 27.5 | 15.0 | 2.0                     |
|         |             | Std Dev. |        | 623           | 0.11               | 16              | 0.4 | 0.2                     | 177                  | 1.2  | 1.0  | 0.22                    |

TABLE 1 Mean yield, soil, and climatic characteristics of the low, medium, and high yield levels within the three environmental clusters

<sup>a</sup>NCCPI, National Commodity Crop Productivity Index.

<sup>b</sup>OM = organic matter; WHC = water holding capacity; Precip. = precipitation; VPD = vapor pressure deficit.

<sup>c</sup>Climatic characteristics are growing season averages from May 1 through Oct 31.

variable of seeding rate (SR) for the nine cluster  $\times$  yield levels combinations using a negative exponential model:

$$Yield = Y_{max} \times (1 - e^{-\beta \times SR})$$
(1)

This model has been used in previous studies for its meaningful biological parameters explaining soybean seeding rate relations with yield (Edwards & Purcell, 2005; Gaspar et al., 2015). The nonlinear least squares (NLS) function in R (R Development Core Team, 2016) was used to estimate the parameters  $Y_{max}$  and  $\beta$  for each cluster  $\times$  yield level combination. In Equation (1),  $Y_{max}$  is the estimated asymptotic yield maximum, and  $\beta$  determines the responsiveness of yield as seeding rate increases. The AOSR was calculated as 99% of the  $Y_{max}$  parameter for each cluster  $\times$  yield level combination to accurately reflect the current economics (De Bruin & Pedersen, 2008a; Gaspar et al., 2015; Gaspar et al., 2017) and agronomics (Arce, Pedersen, & Hartzler, 2009; Mueller et al., 2002; Wunsch et al., 2014) of soybean production in the U.S. and Canada.

#### 2.4 | Plant stand

Yield response due to plant stand, which was analyzed as a percentage of seeding rate (plants/seeding rate), was examined among the three previously defined yield levels (LYL, MYL, HYL) across the examined region (across clusters). The analysis was repeated using early and late plant stand as independent variables in two separate models. Each plant stand variable was used in mixed effect analysis of covariance (ANCOVA) with yield level, seeding rate and their interaction as a fixed effects in PROC GLIMMIX in SAS 9.4 (SAS Institute Inc., 2016). Random effects were: cluster, experiment, row spacing, and replication. The yield slopes due to plant stand were allowed to vary among the levels of random effects. Degrees of freedom were calculated using the Satterthwaite approximation and confidence level was set to 95% (alpha = .05).

#### **2.5** | Yield components

Yield response due to seed number (seeds  $m^{-2}$ ) and seed mass (g 100 seeds<sup>-1</sup>) was examined among the three clusters. Each yield component was analyzed separately in mixed ANCOVA with cluster, seeding rate, yield component, and their interaction as a fixed effects in PROC GLIMMIX in SAS 9.4 (SAS Institute Inc., 2016). Random effects were experiment, row spacing and replication. The yield slopes were allowed to vary among the levels of random effects. Degrees of freedom were calculated using the Satterthwaite approximation and confidence level was set to 95% (alpha = .05). Seed mass and seed number (seed  $m^{-2}$ ) data were present in a majority of the studies which were all well distributed across the entire region and within each cluster. Thus, we consider our results representative of the entire region.

#### 2.6 | Seeding rate risk analysis

For the yield risk analysis, the method as described in Gaspar et al. (2015) was followed to assess the agronomic risk of seeding rates that differ both above and below the AOSR within each cluster  $\times$  yield level combination. Specifically, analysis was conducted at six preset seeding rates  $(\pm 10, 20,$ and 30% from the AOSR) and probabilities to increase yield compared to AOSR for each seeding rate were calculated. To determine the probability of increasing yield, a two-step process was performed using Monte Carlo simulation in R (R Development Core Team, 2016). In the first step, seed yield based on variation in the estimated model parameters for each seeding rate was calculated within each cluster  $\times$  yield level combination. This process involved simulating 10,000 random draws of the parameters  $Y_{\text{max}}$  and  $\beta$  from a bivariate normal distribution, using the estimated parameters (Ymax and  $\beta$ ) for the mean and the variance-covariance matrix from estimating Equation (1). The MU, VCOV, and RMULTNORM functions were used to implement this process. The second step involved subtracting the AOSR yield from the yield of each seeding rate for each of the 10,000 random draws. This process gave 10,000 delta (the average yield increase or decrease compared to the AOSR) yield values for each preset seeding rate in each cluster  $\times$  yield level combination. The proportion of these differences that were positive is a Monte Carlo estimate of the yield increase probability for that seeding rate, that is, the probability that a seeding rate will generate increased yield over the AOSR. Finally, the average of all positive differences (or negative differences) is the Monte Carlo estimate of the expected increase (or decrease) in yield for that seeding rate relative to the AOSR. This process was repeated for each preset seeding rate, giving six different comparisons to the AOSR within each cluster  $\times$  yield level combination.

#### **3 | RESULTS AND DISCUSSION**

## **3.1** | Environmental cluster × yield level characteristics

The density of testing (~21,000 data points) and the ability to cluster environments by their soil and climatic characteristics and then their productivity (yield level) provided an opportunity to comprehensively evaluate the soybean seeding rate  $\times$  yield relationship (Table 1; Figure 1). The cluster analysis was useful with this data set as it allowed environmental

classification that spans across geo-political lines to evaluate the seeding rate by yield relationship with similar soil and climatic properties. Interestingly, there was a clear latitudinal separation of clusters. Cluster 1 mainly represented the northern corn belt, while cluster 3 represented the Midwest and south. Cluster 2 was primarily intermixed between both clusters 1 and 2. Cluster 1 was the lowest average yielding environment (4,087 kg ha<sup>-1</sup>), which can be attributed to lower water holding capacity (1.7-1.9 mm m<sup>-1</sup>), organic matter levels  $(23-37 \text{ g kg}^{-1})$ , total growing season precipitation (408-556 mm), and NCCPI values (0.29-0.42) compared to cluster 2 and 3. Average yields for clusters 2 and 3 were higher  $(4,281 \text{ and } 4,336 \text{ kg ha}^{-1}, \text{ respectively})$  than cluster 1 due to improved soil characteristics (NCCPI, OM, and WHC) and greater precipitation and temperature. The small separation in yield between clusters 2 and 3 is likely due to similar soil and climatic characteristics. The wide yield range present in this data set allowed separation of testing environments within each cluster into high (HYL), medium (MYL), and low (LYL) yield levels, which is a key enhancement and complement to previous research in this area (Carciochi et al., 2019; Corassa et al., 2018). For instance, approximately 2,000 kg ha<sup>-1</sup> separated the HYL and LYL within each cluster. However, all the soil and climatic characteristics did not provide a clear direction explaining these yield differences, except for total growing season precipitation differing between the HYLs and LYLs within clusters 1 and 2, in which the HYLs experienced greater precipitation. Site and trial specific management practices, such as cultivar, and soil fertility are likely key drivers explaining the yield differences between each yield level and each individual trial. However, seeding rate does not consistently interact with cultivar (Suhre et al., 2014) or row spacing (Cox & Cherney, 2011; De Bruin & Pedersen, 2008b) and a seeding rate  $\times$  soil fertility interaction has not been documented to date. Our analysis of seeding rate across North America provides guidance on overarching trends. Local or regional based studies would be better suited to identify and draw inferences on the interaction of these factors with seeding rate or plant stand.

### 3.2 | Agronomically optimal seeding rate

The AOSR varied between clusters and yield levels (Table 2). When averaged across yield levels, the AOSR for clusters 1, 2 and 3 were 460,000, 365,000, and 335,000 seeds ha<sup>-1</sup>, respectively. When averaged across all clusters, and therefore representing the entire Midwest and Canada, the AOSR was greatest for the LYL (441,000 seeds ha<sup>-1</sup>) and lowest for the HYL (348,000 seeds ha<sup>-1</sup>). Compared to the MYL's AOSR (370,000 seeds ha<sup>-1</sup>), AOSR was 19% higher for the LYL, but 6% lower for the HYL. The average yields representing the HYL, MYL, and LYL were 5,143, 4,307, and

 $3.254 \text{ kg ha}^{-1}$ , respectively (Table 1). This result is consistent with previous research from Brazil in which higher seeding rates were needed in environments of lower productivity to maximize yield while lower seeding rates maximized yield in higher productivity environments (Corassa et al., 2018). In the Midwest and Canada, Carciochi et al. (2019) also found that higher plant densities were needed in environments of lower productivity to maximize yield, but in contrast found a very small increase in plant density  $(4,000 \text{ plants } ha^{-1})$ was required in their HYL compared to MYL to maximize vield. This may be due to a smaller data set and relatively small separation between their high (> 4,300 kg ha<sup>-1</sup>), medium (4,000–4,300 kg ha<sup>-1</sup>), and low (< 4,000 kg ha<sup>-1</sup>) yield levels compared to our separation of approximately  $1,000 \text{ kg ha}^{-1}$  between the mean yields of the MYL-LYL and MYL-HYL. These findings are inversely related to maize (Zea mays L.) seeding rate recommendations (Assefa et al., 2016; Assefa et al., 2017; Bullock et al., 1998). Furthermore, our North America perspective suggested that in relation to the MYL, the increase in seeding rate within LYLs should be approximately 3x the decrease in seeding rate within HYLs, on average. This again, contrasts with maize seeding rate recommendation, which follow a more linear relationship with the productivity of the environment. This nonlinear trend for soybean was largely driven by cluster 1, which represents the northern corn belt (Figure 1). Relative to the MYL  $(415,000 \text{ seeds } ha^{-1})$ , the increase in seeding rate to reach the AOSR of the LYL (+41%) was approximately 5x the decrease in seeding rate for the HYL (-8%) or a separation of 205,000 seeds  $ha^{-1}$ . Relative to the AOSR of the MYL  $(360,000 \text{ seeds ha}^{-1})$  within cluster 2, there was not a large absolute difference in the seeding rate increase (+17%) or decrease (-13%) required to reach the AOSR of the LYL and HYL, respectively. Yet, both clusters 1 and 2 demonstrated the same trend of higher AOSRs in LYLs and lower AOSRs in HYLs compared to the MYLs. This was reversed in cluster 3 with higher AOSRs in HYLs and lower AOSRs in LYLs compared to the MYL. However, the separation between these yield levels was much smaller with only a  $\pm 4\%$  increase ( $\pm 15,000$  seeds ha<sup>-1</sup>) and decrease from the AOSR of the MYL. In summary, based on the results of this analysis, growers should increase seeding rates in lower productivity environments and decrease seeding rates in higher productivity environments. Moreover, these adjustments in soybean seeding rates are likely to be more effective in the northern corn belt compared to more southern environments.

From a physiological perspective soybean yield is linearly related to CIPAR, and this relationship is typically stronger in the Northern U.S. versus more southern environments, (Edwards et al., 2005; Gaspar & Conley, 2015), which may explain the differential results of cluster 3 compared to clusters 1 and 2. Simply put, more CIPAR increases yield, particularly in more northern environments. Specific to clusters 1

|             |                 | Cluster 1                                     |                                  |              | Cluster 2                        |                       |              | Cluster 3                        |                     |              |
|-------------|-----------------|---|----------------------------------|--------------|----------------------------------|-----------------------|--------------|----------------------------------|---------------------|--------------|
| Yield level | Seeding<br>rate | Yield<br>increase<br>probability <sup>ª</sup> | Avg. delta<br>yield <sup>b</sup> | Std.<br>Dev. | Yield<br>increase<br>probability | Avg. delta<br>yield   | Std.<br>Dev. | Yield<br>increase<br>probability | Avg. delta<br>yield | Std.<br>Dev. |
|             | Seeds $ha^{-1}$ |   | ——kg ha <sup>_</sup>             | 1            |                                  | ——kg ha <sup>-1</sup> | 1            |                                  | kg ha <sup>-1</sup> |              |
|             | +30%            | 0.53  | 2.6                              | 32.7         | 0.56                             | 3.0                   | 21.3         | 0.60                             | 3.3                 | 12.9         |
|             | +20%            | 0.53  | 2.1                              | 32.5         | 0.55                             | 2.5                   | 21.1         | 0.60                             | 3.2                 | 12.8         |
|             | +10%            | 0.52  | 1.3                              | 32.2         | 0.53                             | 1.6                   | 21.0         | 0.59                             | 2.8                 | 12.8         |
| Low         | AOSR            | (585,000) <sup>°</sup>                        |                                  |              | (420,000)                        |                       |              | (320,000)                        |                     |              |
|             | -10%            | 0.46  | -3.6                             | 31.0         | 0.43                             | -3.9                  | 20.2         | 0.46                             | -0.3                | 12.4         |
|             | -20%            | 0.37  | -10.0                            | 29.6         | 0.29                             | -11.1                 | 19.5         | 0.39                             | -3.4                | 12.1         |
|             | -30%            | 0.21  | -22.5                            | 27.6         | 0.09                             | -25.2                 | 18.9         | 0.18                             | -11.4               | 12.1         |
|             | +30%            | 0.60  | 3.8                              | 15.6         | 0.59                             | 2.6                   | 10.9         | 0.68                             | 4.2                 | 9.4          |
|             | +20%            | 0.58  | 3.3                              | 15.5         | 0.55                             | 1.2                   | 10.8         | 0.67                             | 4.0                 | 9.3          |
|             | +10%            | 0.56  | 2.2                              | 15.4         | 0.52                             | 0.2                   | 10.6         | 0.65                             | 3.6                 | 9.3          |
| Medium      | AOSR            | (415,000)                                     |                                  |              | (360,000)                        |                       |              | (335,000)                        |                     |              |
|             | -10%            | 0.39  | -4.4                             | 14.7         | 0.06                             | -14.9                 | 9.8          | 0.42                             | -0.6                | 9.0          |
|             | -20%            | 0.18  | -13.1                            | 14.0         | 0.00                             | -30.9                 | 9.4          | 0.33                             | -3.9                | 8.8          |
|             | -30%            | 0.01  | -30.5                            | 13.0         | 0.00                             | -60.0                 | 9.1          | 0.06                             | -13.6               | 8.9          |
|             | +30%            | 0.58  | 4.6                              | 23.2         | 0.64                             | 4.6                   | 13.0         | 0.59                             | 4.6                 | 19.5         |
|             | +20%            | 0.57  | 3.9                              | 23.1         | 0.62                             | 3.9                   | 12.9         | 0.58                             | 3.9                 | 19.4         |
|             | +10%            | 0.54  | 2.6                              | 22.9         | 0.58                             | 2.7                   | 12.8         | 0.55                             | 2.5                 | 19.2         |
| High        | AOSR            | (380,000)                                     |                                  |              | (315,000)                        |                       |              | (350,000)                        |                     |              |
|             | -10%            | 0.40  | -5.5                             | 21.9         | 0.34                             | -4.9                  | 12.2         | 0.38                             | -5.9                | 18.4         |
|             | -20%            | 0.22  | -16.1                            | 20.9         | 0.10                             | -15.0                 | 11.7         | 0.17                             | -16.9               | 17.6         |
|             | -30%            | 0.03  | -37.3                            | 19.4         | 0.00                             | -35.2                 | 11.3         | 0.01                             | -38.6               | 16.7         |

**TABLE 2** Agronomically optimal seeding rates (AOSR) for each cluster by yield level combination (9) with the resulting yield increase probabilities and average delta yields from the agronomic risk analysis at seeding rates surrounding each AOSR

<sup>a</sup>Yield increase probability is the probability that a seeding rate will at least provide the same yield as the agronomically optimal seeding rate (AOSR) within each cluster by yield level combination.

<sup>b</sup>Average delta yield compared to the agronomically optimal seeding rate (AOSR) within each cluster by yield level combination.

<sup>c</sup>The agronomically optimal seeding rate (seeds ha<sup>-1</sup>) for each cluster by yield level combination is displayed in parenthesis.

and 2, a plausible hypothesis is that in highly productive environments, current cultivars can maintain yield with slightly reduced seeding rates because the individual plant growth rate is not limited, maximum CIPAR is realized, and therefore yield is still maximized. It has been demonstrated that breeding efforts have increased the yield produced per plant and specifically, this increase is attributed to the branches, not the main stem of the plant (Suhre et al., 2014). This complements lower stands by increasing the plant's compensatory ability where stands are lower within high yield levels (Carpenter & Board, 1997). However, in the inverse direction, breeding efforts have also been shown to make current soybean cultivars more responsive to higher seeding rates. This corroborates the increased seeding rate required in areas of lower productivity (Table 2), where the plants growth rate and branching can be limited due to many potential factors, such as precipitation amount, soil WHC, nutrient supply, rooting depth, etc. Specific to this study, our low yield levels within

clusters 1 and 2 experienced lower precipitation amounts and a higher VPD (Table 1). These factors, often limited in low productivity areas, can challenge the ability of soybean plants to maximize CIPAR. Increased plant density from higher seeding rates could help maximize CIPAR and yield in these lower yield environments (Gaspar & Conley, 2015). Similarly, total available photosynthetically active radiation (PAR) is typically more limited in northern latitudes, and thus an increase in seeding rate to reach the AOSR within the low yield level is particularly effective in northern (cluster 1) environments vs. more southern (cluster 3) environments (De Bruin and Pedersen, 2009; Gaspar & Conley, 2015; Seversike, Purcell, Gbur, Chen, & Scott, 2009). Specific to cluster 3, seasonal PAR is typically not the most yieldlimiting factor and seeding rate does not heavily affect CIPAR regardless of the environments productivity. Therefore, these conditions are likely diluting the effects of seeding rate within all yield levels, helping explain our non-differentiated

**TABLE 3** Analysis of covariance for early (V2) and late season plant stand (R8)

| Source            | df | Early season stand <sup>a</sup> | Late season stand <sup>a</sup> |  |  |  |
|-------------------|----|---------------------------------|--------------------------------|--|--|--|
|                   |    | P > F                           |                                |  |  |  |
| Seeding rate (SR) | 1  | 0.627                           | < 0.001                        |  |  |  |
| Yield level (YL)  | 2  | 0.976                           | 0.607                          |  |  |  |
| $SR \times YL$    | 2  | 0.263                           | 0.334                          |  |  |  |

<sup>a</sup>Early season stand and late season stand were analyzed as a percentage of seeding rate (plants/seeding rate).

AOSRs within cluster 3 (De Bruin and Pedersen, 2009; Edwards et al., 2005).

### 3.3 | Plant stand

Early and late season stand was evaluated with yield levels combined across clusters and as a percentage (%) of seeding rate, not an absolute value of stand (plants ha<sup>-1</sup>) (Table 3; Figure 2). Seeding rate, yield level, and their interaction did not affect early season stand (V2). Late season stand (R8) was affected by seeding rate (P < .001) but not by yield level or the seeding rate by yield level interaction (Table 3). As seeding rate increased, percent late season stand decreased (data not shown). Therefore, because early season stand was not affected by seeding rate (P = 0.627), but late season stand was (P < .001), one can conclude that in season plant attrition increased as seeding rate increased.

The early and late season stand covariates both interacted with yield (productivity) level, meaning their relationship with yield differed between yield levels (P < .05) (Figure 2). The slope coefficients describing this relationship as the increase in yield (kg ha<sup>-1</sup>) per unit increase in stand (%) were similar for both early and late season stand within the LYL and MYL. The HYL displayed non-significant slope coefficients for both early and late season stand, suggesting that maintaining stand through the whole growing season had no effect on yield within this yield level, as this is likely the environment where soybean plant compensatory ability is maximized.

It has been hypothesized that early and late season stand (measured as a percentage of seeding rate) in areas of lower productivity is often reduced to a greater extent than in higher productivity areas. Therefore, one could conclude that reduced stand is a driving principal of why seeding rates should be increased in low yield levels. However, we found that early and late season stand was not affected by yield level, regardless of geographical location in the U.S. (Table 3). Thus, yield level and stand are mutually exclusive and early and late season stand are not driving factors behind the relatively higher seeding rates required in lower productivity environments. A similar conclusion was reached by (Carciochi et al., 2019). However, within each yield (productivity) level there was a differential effect of early and late season stand on yield (Figure 2). Greater early and late season stand positively affected yield similarly within the MYL and LYL. In contrast, yield within the HYL was not affected by early or late season stand. However, regardless of yield level we did find that higher seeding rates resulted in greater amounts of in season plant attrition. Therefore, within MYLs and to an even greater extent LYLs (which displayed higher AOSRs), establishing an adequate stand at planting and maintaining this increased stand until harvest is critical to maximize yield within these yield levels. In contrast, HYLs can maximize yield across a much wider range of plant stands and attrition rates, likely due to a higher plant growth rate and ability to intercept more PAR as previously hypothesized. The use of seed treatments (Gaspar et al., 2014), appropriate tillage and planting practices (Oplinger and Philbrook, 1992), narrow rows (Andrade et al., 2019; De Bruin & Pedersen, 2008b), and adequate fertility are all components which can maximize early season stand and minimize in season plant attrition to ensure adequate late season stands are achieved which is particularly important in medium and low yield levels. Yet, growers will continually encounter greater attrition rates as seeding rate increases, further supporting the limited yield and risk benefits from increasing seeding rates above the AOSR.

#### 3.4 | Seed mass and seed number

The three-way interaction between cluster, seeding rate and seed number is displayed in Figure 3. When using seed mass as a covariate, the two-way interaction between cluster and seed mass was significant (Figure 4). These results suggest that seed number and seed yield have a stronger correlation than seed yield and seed mass. Others have also demonstrated the importance of seed number and its strong relationship with yield (Board, Kang, & Harville, 1999; Gaspar & Conley, 2015; Gaspar et al., 2015; Wells, 1991). The modeled effect of seed number on yield was always positive regardless of the cluster or seeding rate group. However, this study also suggests that there are differential environments where seed number may be increasingly important depending upon the seeding rate. At relatively higher seeding rates (> 400,000 seeds  $ha^{-1}$ ) the effect of seed number on yield was similar across the three clusters. In contrast, as seeding rate moved to 300,000 seeds ha<sup>-1</sup> and below, yield was more sensitive to seed number in cluster 3 compared to clusters 1 and 2. This sensitivity could be explained by a longer seed fill period in more southern locations represented by cluster 3 resulting in greater seed mass, thus magnifying impact of a change in seed number on yield with lower seeding rates as suggested by Egli (1988). In contrast, within the two-way interaction of seed mass and cluster, yield was the most sensitive to seed mass within cluster 1, which represents more northern environments. These



**FIGURE 2** Relationship between percentage early (V2) and late (R8) season stand with yield derived from an analysis of covariance. Clusters were combined within each yield level. Percent early and late season stand were calculated by dividing the plant stand at each time by seeding rate. Slope coefficients are reported for each line followed by the standard error of the slope (in parenthesis). Different letters signify statistically different slopes at the .05 confidence level within each separate graph whereas, ns denotes that the slope was not significantly different from zero



**FIGURE 3** Modeled effect of seed number (seeds  $m^{-2}$ ) on yield at 6 different predetermined seeding rates (SR) reported as  $\times 1,000$  seeds ha<sup>-1</sup> with 95% confidence intervals

northern environments typically have a condensed seed fill period and thus, the opportunity for the greatest improvement or effect on seed mass. However due to the large 95% confidence intervals there is limited inference to be made (Figure 4). In summary, emphasis should be placed on increasing seed number where low to moderate seeding rates are planted within southern environments, while seed mass may deserve more attention in more northern environments. Ultimately, further testing is needed to better understand the differential effects of seeding rate within various environments on these two key yield components as identified by this study.

#### 3.5 | Seeding rate risk analysis

The Monte Carlo analysis of risk provided a yield increase probability (the probability that a seeding rate will at least provide either the same yield or a higher yield than the AOSR) and average delta yield (the average yield increase or decrease compared to the AOSR) (Table 2). For example, within the MYL of cluster 1, a 20% decrease in seeding rate from the AOSR had a 0.18 (18% chance) probability of either maintaining or increasing yield over the AOSR and on average decreased yield by 13.1 kg ha<sup>-1</sup> with a standard deviation



**FIGURE 4** Modeled effect of seed mass (g 100 seeds<sup>-1</sup>) on yield between each cluster with 95% confidence intervals

of 14 kg ha<sup>-1</sup>. In comparison, a 20% increase in seeding rate over the AOSR displayed a 0.58 probability of either maintaining or increasing yield over the AOSR with an average yield increase of 3.3 kg ha<sup>-1</sup> and standard deviation of 15.5 kg ha<sup>-1</sup>.

Risk aversion is a common component in farm level soybean seeding rate decisions and many times results in growers inflating seeding rates. Across all nine cluster × yield level combinations, seeding rates above the AOSR always resulted in a yield increase probability above 0.5 (0.52–0.68), while decreasing the seeding rate below the AOSR resulted in exponentially greater risk (0-0.46). Thus, decreasing the seeding rate below the AOSR resulted in a change in the yield increase probability of greater magnitude compared to a seeding rate increase above the AOSR. For instance, within the HYL of cluster 1, a 30% increase in seeding rate above the AOSR resulted in a yield increase probability of 0.58, which is a rise in probability of 0.08, compared to a probability decline of 0.47 from a 30% decrease in seeding rate from the AOSR (380,000 seeds  $ha^{-1}$ ). A similar trend was observed for the average delta yield, where increasing the seeding rate above the AOSR resulted in small yield increases of 1.3-4.6 kg ha<sup>-1</sup>. In comparison, larger decreases in yield were observed with seeding rates below the AOSR, which in some cases reached an average delta yield of  $-60 \text{ kg ha}^{-1}$ . Therefore, the magnitude of change in the average delta yield was greater when seeding rates were below, not above, the AOSR. However, for both the yield increase probability and average delta yield, the magnitude of change due to seeding rate was cluster  $\times$  yield level dependent.

Ultimately, risk-averse growers may choose to increase seeding rates slightly above the AOSR to ensure yield is maximized, but should not expect substantial yield increases, while growers who are comfortable with additional risk may choose to decrease seeding rates below the AOSR. However, there was considerably more downside risk and potential yield loss with a decrease in seeding rate below the AOSR than upside potential with an equivalent increase above the AOSR. Furthermore, the balance of risk vs. yield stability was different within each cluster  $\times$  yield level combination, meaning growers must understand this dynamic specific to their geography and risk tolerance in combination with farm level economics (Gaspar et al., 2017).

#### 4 | CONCLUSIONS

This work suggests that there is an opportunity for growers to adjust seeding rates at both the between- and within-field level based upon the environment's historical productivity to maximize yield, particularly in more northern environments. Growers can utilize current variable rate seeding planter technology to better manage their soybean seed investment, by following the strategy of using higher seeding rates in environments of lower productivity and lower seeding rates in environments of higher productivity within a field. Furthermore, the AOSR should be targeted within each environment (cluster  $\times$  yield level). From a risk perspective, this is critical, as seeding rates increasingly below the AOSR exponentially increased risk and potential yield loss, while seeding rates above the AOSR provided slight risk reduction and potential yield increases but also increased seed cost. Particularly in northern environments, the increase in seeding rate to reach the AOSR within lower productivity environments should be relatively greater than the decrease in seeding rate to reach the AOSR within higher productivity environments. Furthermore, the absolute difference in AOSR between the HYL and LYL will likely be greater in northern vs. southern environments. Ultimately, the specific seeding rates for the varying levels of productivity across an individual field or between fields will be based upon local agronomic recommendations (e.g. weed control, white mold (Sclerotinia sclerotiorum), iron deficiency chlorosis), grower risk tolerance, and economics (e.g. seed costs), but should follow the aforementioned strategy. In this seeding rate strategy, growers should focus on maximizing seed number not seed mass, especially when lower seeding rates are used. Regardless of the seeding rate implemented, growers should strive to establish an optimal stand at planting and maintain this stand until harvest to maximize yield, specifically within low and moderate yield levels.

#### ACKNOWLEDGMENTS

The authors wish to thank Adam Roth and John Gaska of UW-Madison, Laura Wolf and Eric Egan of Corteva Agriscience, Adam Byrne and John Boyse of MSU, Jeffrey Ravellette, Nolan Anderson, and Jon Leuck of Purdue University, Yuba Kandel and Stith Wiggs of ISU, Joshua Vonk and Jason Niekamp of the University of IL, and Osler Ortez and Luiz Moro Rosso of KSU. Furthermore, the support from Joe Davlin, Matt Davis, Lynn Ault, Philip Rozeboom, and Cole Dierks as on-farm collaborators was appreciated. The technical review of Jeff Schussler was critical in the development of this manuscript. We would also like to thank the Wisconsin Soybean Marketing Board, University of Wisconsin-Madison, North Dakota State University, North Dakota Soybean Council, Ohio Soybean Council, Foundational and Applied Science Program grant no. 20186800828356 USDA-NIFA, South Dakota Soybean Research and Promotion Council, USDA-NIFA Hatch Project SD00H610-16, Michigan Soybean Promotion Committee, Indian Soybean Alliance, Kansas Soybean Commission, Kansas State Research and Extension, USDA Hatch Project IOWA3908, and Corteva Agriscience.

#### ORCID

Adam P. Gaspar (b) https://orcid.org/0000-0001-7735-1368 Spyridon Mourtzinis (b)

https://orcid.org/0000-0002-7302-5482

Laura E. Lindsey D https://orcid.org/0000-0001-7026-0949 Emma G Matcham D

https://orcid.org/0000-0002-9896-2253

*Shawn P. Conley* (b) https://orcid.org/0000-0002-8413-1088

#### REFERENCES

- Andrade, J., Rattalino Edreira, J. I., Mourtzinis, S., Conley, S., Ciampitti, I., Dunphy, J., ... Grassini, P. (2019). Assessing the influence of row spacing on soybean yield using experimental and producer survey data. *Field Crops Research*, 230, 98–106. https://doi.org/10.1016/j. fcr.2018.10.014
- Arce, G., Pedersen, P., & Hartzler, R. (2009). Soybean seeding rate effects on weed management. Weed Technology, 23(1), 17–22. https://doi.org/10.1614/WT-08-060.1
- Assefa, Y., Vara Prasad, P. V., Carter, P., Hinds, M., Bhalla, G., Schon, R., ... Ciampitti, I. A. (2016). Yield responses to planting density for US modern corn hybrids: A synthesis-analysis. *Crop Science*, 56, 2802–2817. https://doi.org/10.2135/cropsci2017.01.0066
- Assefa, Y., P.V. V. Prasad, P. Carter, M. Hinds, G. Bhalla, R. Schon, ... I.A. Ciampitti. (2017). A new insight into corn yield: Trends from 1987 through 2015. *Crop Science*, 57:2799–2811. https://doi.org/10. 2135/cropsci2016.04.0215
- Bertram, M. G., & Pedersen, P. (2004). Adjusting management practices using glyphosate-resistant soybean cultivars. *Agronomy Journal*, 96, 462–468. https://doi.org/10.2134/agronj2004.4620
- Board, J. E. (2000). Light interception efficiency and light quality affect yield compensation of soybean at low plant populations. *Crop Sci*ence, 40, 1285–1294. https://doi.org/10.2135/cropsci2000.4051285x
- Board, J. E., Kang, M. S., & Harville, B. G. (1999). Path analyses of the yield formation process for late-planted soybean. *Agronomy Journal*, 91(1), 128–135. https://doi.org/10.2134/agronj1999. 00021962009100010020x
- Boquet, D. J. (1990). Plant population density and row spacing effects on soybean at post-optimal planting dates. *Agronomy Journal*, 82, 59– 64. https://doi.org/10.2134/agronj1990.00021962008200010013x

- Bullock, D.G., D.S. Bullock, E.D. Nafziger, T.A. Doerge, S. R. Paszkiewicz, P.R. Carter, & T.A. Peterson. (1998). Does variable rate seeding of corn pay? *Agronomy Journal*, 90:830–836. https://doi.org/10.2134/agronj1998.00021962009000060019x
- Carpenter, A. C., & Board, J. E. (1997). Branch yield components controlling soybean yield stability across plant populations. *Crop Science*, 37, 885–891. https://doi.org/10.2135/cropsci1997. 0011183X003700030031x
- Carciochi, W. D., Schwalbert, R., Andrade, F. H., Corassa, G. M., Carter, P. R., Gaspar, A. P., ... Ciampitti, I. A. (2019). Soybean seed yield response to plant density by yield environment in North America. Agronomy Journal, 111, 1923–1932. https://doi.org/10.2134/ agronj2018.10.0635
- Corassa, G. M., Amado, T. J. C., Schwalbert, R., Carter, P. R., & Ciampitti, I. A. (2018). Optimum soybean seeding rates by yield environment in Southern Brazil. *Agronomy Journal*, *110*, 2430–2438. https://doi.org/10.2134/agronj2018.04.0239
- Cox, W. J., Cherney, J. H., & Shields, E. (2010). Soybeans compensate at low seeding rates but not at high thinning rates. *Agronomy Journal*, 102, 1238–1243. https://doi.org/10.2134/agronj2010.0047
- Cox, W. J., & Cherney, J. H. (2011). Growth and yield responses of soybean to row spacing and seeding rate. Agronomy Journal, 103, 123– 128. https://doi.org/10.2134/agronj2010.0316
- De Bruin, J. L., & Pedersen, P. (2008a). Soybean seed yield response to planting date and seeding rate in the upper Midwest. Agronomy Journal, 100, 696–703. https://doi.org/10.2134/agronj2007.0115
- De Bruin, J. L., & Pedersen, P. (2008b).Effect of row spacing and seeding rate on soybean yield. *Agronomy Journal*, *100*, 704–710. https://doi. org/10.2134/agronj2007.0106
- De Bruin, J. L., & Pedersen P. (2009). New and old soybean cultivar responses to plant density and intercepted light. *Crop Science*, 49:2225–2232. https://doi.org/10.2135/cropsci2009.02.0063
- Dobos, R. R., Sinclair, H. R., & Hipple, K. W. (2008). User guide national commodity crop productivity index (NCCPI) Version 1.0. Lincoln, Nebraska: Department of Agriculture, Natural Resources Conservation Service, National Soil Survey Center.
- Edwards, J. T., & Purcell, L. C. (2005). Soybean yield and biomass responses to increasing plant populations among diverse maturity groups. *Crop Science*, 45, 1770–1777. https://doi.org/10.2135/cropsci2004.0564
- Edwards, J. T., Purcell, L. C., & Karcher, D. E. (2005). Soybean yield and biomass responses to increasing plant populations among diverse maturity groups. *Crop Science*, 45, 1778–1785. https://doi.org/10. 2135/cropsci2004.0570
- Egli, D. B. (1988). Alterations in plant growth and dry matter distribution in soybean. *Agronomy Journal*, *80*, 86–90.
- Epler, M., & Staggenborg, S. (2008). Soybean yield and yield component response to plant density in narrow row systems. *Crop Management*. https://doi.org/10.1094/CM-2008-0925-01-RS
- Gaspar, A. P., & Conley, S. P. (2015). Responses of canopy reflectance, light interception, and soybean seed yield to replanting suboptimal stands. *Crop Science*, 15, 377–385. https://doi.org/10.2135/ cropsci2014.03.0200
- Gaspar, A. P., Conley, S. P., & Mitchell, P. D. (2015). Economic risk and profitability of soybean fungicide and insecticide seed treatments at reduced seeding rates. *Crop Science*, 15, 924–933. https://doi.org/10. 2135/cropsci2014.02.0114
- Gaspar, A. P., Marburger, D. A., Mourtzinis, S., & Conley, S. P. (2014). Soybean seed yield response to multiple seed treatment components

across diverse environments. *Agronomy Journal*, *106*, 1955–1962. https://doi.org/10.2134/agronj14.0277

- Gaspar, A. P., Mueller, D. S., Wise, K. A., Chilvers, M. I., Tenuta, A. U., & Conley, S. P. (2017). Response of broad-spectrum and target-specific seed treatments and seeding rate on soybean yield, profitability, and economic risk. *Crop Science*, 56, 2251–2262. https://doi.org/10.2135/cropsci2016.11.0967
- Holshouser, D. L., & Whittaker, J. P. (2002). Plant population and row spacing effects on early soybean production systems in the Mid-Atlantic USA. Agronomy Journal, 94, 603–611. https://doi.org/10. 2134/agronj2002.6030
- Jaynes, D. B. (2010). Confidence bands for measuring economically optimal nitrogen rates. *Precision Agriculture*, 12, 196–213. https://doi.org/10.1007/s11119-010-9168-3
- Jeschke, M., & Lutt, N. (2016). Row width in soybean production. Crop Insights, 26, 12. Pioneer Hi-Bred.
- Lee, C. D., Egli, D. B., & TeKrony, D. M. (2008). Soybean response to plant population at early and late planting dates in the Mid-South. Agronomy Journal, 100, 971–976. https://doi.org/10.2134/ agronj2007.0210
- Mourtzinis, S., Gaska, J. M., Pedersen, P., & Conley, S. P. (2015). Effect of seed mass and emergence delay on soybean yield and quality. *Agronomy Journal*, 107, 181–186. https://doi.org/10.2134/agronj14. 0391
- Mourtzinis, S., Rattalino Edreira, J. I., Conley, S. P., & Grassini, P. (2017). From grid to field: Assessing quality of gridded weather data for agricultural applications. *European Journal of Agronomy*, 82(Part A), 163–172. https://doi.org/10.1016/j.eja.2016.10.013
- Mueller, D. S., Dorrance, A. E., Derksen, R. C., Ozkan, E., Kurle, J. E., Grau, C. R., ... Pedersen, W. L. (2002). Efficacy of fungicides on Sclerotinia sclerotiorum and their potential for control of Sclerotinia stem rot on soybean. *Plant Disease*, *86*, 26–31. https://doi.org/ 10.1094/PDIS.2002.86.1.26
- Oplinger, E. S., & Philbrook, B. D. (1992). Soybean planting date, row width, and seeding rate response in three tillage systems. *Journal of Production Agriculture*, 5, 94–99. https://doi.org/10.2134/jpa1992. 0094
- Rincker, K., Nelson, R., Specht, J., Sleper, D., Cary, T., Cianzio, S. R., ... Diers, B. (2014). Genetic improvement of U.S. soybean in maturity groups II, III, and IV. *Crop Science*, 54, 1419–1432. https://doi.org/ 10.2135/cropsci2013.10.0665
- R Development Core Team. (2016). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.
- SAS Institute. (2016). The SAS system of Windows. Cary, NC: SAS Institute.
- Seversike, T. M., Purcell, L. C., Gbur, E., Chen, P., & Scott, R. (2009). Radiation interception and yield response to increased leaflet number in early-maturing soybean genotypes. *Crop Science*, 49, 281–289. https://doi.org/10.2135/cropsci2007.08.0472

- Shelar, V. R. (2008). Role of mechanical damage in deterioration of soybean seed quality during storage: A review. *Agricultural Reviews*, 29, 177–184.
- Shi, G., Chavas, J. P., & Stiegert, K. W. (2009). Pricing of herbicidetolerant soybean seeds: A market-sturcture approach. *AgBioForum*, 12, 326–333.
- Smidt, E. R., Conley, S. P., Zhu, J., & Arriaga, F. J. (2016). Identifying field attributes that predict soybean yield using random forest analysis. *Agronomy Journal*, 108, 637–646. https://doi.org/10.2134/ agronj2015.0222
- Soil Survey Staff. (2018). Web soil survey. Washington, DC: Natural Resources Conservation Service, United States Department of Agriculture. https://websoilsurvey.sc.egov.usda.gov/ (accessed 11 Oct. 2018).
- Suhre, J. J., Weidenbenner, N. H., Rowntree, S. C., Wilson, E. W., Naeve, S. L., Conley, S. P., ... Davis, V. M. (2014). Soybean yield partitioning changes revealed by genetic gain and seeding rate interactions. *Agronomy Journal*, *106*, 1631–1642. https://doi.org/10.2134/ agronj14.0003
- Thornton, P. E., Thornton, M. M., Mayer, B. W., Wilhelmi, N., Wei, Y., Devarakonda, R., & Cook, R. B. (2014). Daymet: Daily surface weather data on a 1-km grid for North America, Version 2. ORNL DAAC, Oak Ridge, TN, USA. https://doi.org/10.3334/ORNLDAAC/ 1219.
- USDA-ERS. (2018). Recent US soybean production costs and returns. Retrieved from www.ers.usda.gov (accessed 14 Sept. 2018; confirmed 20 Oct. 2019).
- Wells, R. (1991). Soybean growth response to plant density: Relationship among canopy photosynthesis, leaf area, and light interception. *Crop Science*, 31, 755–761. https://doi.org/10.2135/cropsci1991. 0011183X003100030044x
- Wunsch, M., Kraft, B., Schaefer, M., Kallis, S., Cooper, K., Besemann, L., ... Jacobs, J. (2014). Optimizing row spacing and seeding rate for maximum soybean agronomic performance under white mold pressure. Fargo, ND: North Dakota State Cooperative Extension.

### SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

How to cite this article: Gaspar AP, Mourtzinis S, Kyle D, et al. Defining optimal soybean seeding rates and associated risk across North America. *Agronomy Journal*. 2020;112:2103–2114. https://doi.org/10.1002/agj2.20203