Determining Site-Specific Soybean Optimal Seeding Rate Using On-Farm Precision Experimentation

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Abstract

Eleven on-farm precision experiments were conducted in Nebraska during 2018 – 2022 to address the following: i) determine the Economic Optimal Seeding Rates (EOSR) ii) identify the most important site-specific variables influencing the optimal seeding rates for soybeans.

Seeding rates ranged from 175,000 to 425,000 seeds/ha, and treatments were randomized and replicated in blocks across the entire field. The study was implemented using a variable rate prescription. Yield monitor data was obtained and post-processed to remove errors with Yield Editor Software. As-planted data was also evaluated, and blocks that did not achieve 10% of the target seeding rate were not used. Analysis of variance using RStudio was performed to evaluate the seeding rate effect on yield at each site (p<0.05). In addition, linear and non-linear models were fitted. EOSR was derived from the model fittings using 0.513 $/kg soybean price and $70/bag seed cost.

In 64% of the sites, there was no soybean yield response to seeding rate and EOSR was determined as the lowest seeding rate treatment of the field. In 18%, there was a negative linear effect of seeding rate on soybean yield and again the EOSR was determined as the lowest seeding rate treatment of the field. This is a clear indication that for these fields, growers could reduce seeding rate with no yield penalty. In 18% of the sites, soybean yield response to the seeding rate follows a quadratic model and the EOSR for these ranged from 317,536 to 350,792 *seeds/ha. Spatial analysis showed that areas with higher elevation or lower TPI within the fields may require higher seeding rates to reach the Economically Optimum Seeding Rate in wet years. Higher soil OM will require lower seeding rates than lower soil OM to reach the Economically Optimum Seeding Rate due to this property correlation with yield. Clay content was negatively correlated with yield when a site received above normal amount of rainfall. There were no consistent correlations between yield and elevation, TWI, slope, aspect, TPI, Silt content, AWC and EC. Fields with high variability in elevation, TPI, OM, clay content, pH, and CEC will benefit from adoption of VRA given that changes in these properties are strongly correlated with yield.*

Keywords.
Soybean, Seeding Rate, Variable Rate Application, EOSR, soil properties.

Introduction

Current information on soybean seeding rate needed to optimize seed yield may not be optimal for economic return. The Data Intensive Farm Management (DIFM) is an example of an integrative project where the use of On-Farm Precision Experimentation (OFPE) helps to examine yield responses to seeding rate in soybeans (Bullock et al., 2019). Still, within field characteristics such as elevation, slope, and soil organic matter have been identified as being important in delineating variable seeding rate management zones. These characteristics exhibit a correlation with yield, making them valuable indicators in the context of crop productivity (Licht et al., 2016; Hamman et al., 2021). However, the use of OFPE to quantify the economic optimal seeding rate (EOSR) with spatial analysis that contemplates soil characteristics variability has not yet been investigated. Large-scale OFPE provides the opportunity to collect large amounts of data to estimate the EOSR for soybeans with little or no cost at a site-specific level. The DIFM has expanded early efforts by conducting hundreds of OFPEs in the US and South America confirming that precision technology can be used to conduct OFPEs on very large fields at very low costs (Bullock et al.,2020). DIFM presents its OFPE methods as an alternative to or enhancement of small-plot trials. In this methodology, application rates are changed by a computer program and GPS-linked variable rate equipment, making the implementation of the trial require little extra work from the farmer (Bullock et al., 2019). Variable rate seeding was first established when farmers recognized that varying seeding rates could result in different yields (Bullock et al., 1998; Hamman et al., 2021). To make Variable-Rate seeding possible, it is necessary to create homogenous management zones within the field. These management zones represent spatial patterns that are stable over time (Maestrini & Basso, 2018; Hamman et al., 2021). Soil characteristics such as map unit, phosphorus, and organic matter were identified as important factors when creating management zones for soybean (Smidt et al., 2016; Hamman et al., 2021). Landscape properties, such as valley depth and general curvature, could also be used to create seeding rate management zones within fields (Matcham et al., 2020; Hamman et al., 2021).

Studies have shown that increasing seeding rates after a certain point will result in minimal yield responses, and since seed costs increase, the focus must be placed on economic return rather than yield maximization (De Bruin & Pedersen, 2008). The optimum seeding rate for soybean production can be identified as the agronomic optimum seeding rate, where yield is maximized. The EOSR, instead, is identified as the point at which the additional seed costs equal the net return of the additional yield (Lindsey et al., 2018). The EOSR, which maximizes profitability and production, can vary with small differences in environmental characteristics. Factors such as planting date, soil type, depth, drainage, soil fertility, pest pressure, and growing season conditions can impact plant growth and yield. Since field variability can occur at small spatial scales, the optimum seeding rate may also vary on a similar scale. Additionally, the response function to describe yield response to the seeding rate has spatial and temporal variation (Lindsey et al., 2018). Correlating soil characteristics with the EOSR would help to understand variability within fields and enable producers to use variable rate seeding practices to maximize their profits. As current information may be overestimating soybean seeding rates, we hypothesize that growers might be using higher numbers than the ones necessary to maximize profit. Moreover, yield response to seeding rates can vary within the field. Therefore, the EOSR may have site-specific variations depending on site characteristics.

The objectives of this work are I) Determine the EOSR for each site II) Determine the most important site-specific variables influencing the optimal seeding rate for soybeans.

Materials and Methods

Eleven OFPE trials were conducted from 2018 – 2022 in Nebraska (Figure 1). The method followed to conduct trials was the same as the DIFM project used to design and run randomized agronomic field trials on whole commercial farm fields, proceedings described in Bullock et al., 2019. Seeding rates ranged from 175,000 to 425,000 seeds/ha, with 4 or 3 seeding rates tested depending on the site. The different seeding rates were randomized and replicated in blocks across the entire field, with plot sizes ranging from 1,986 to 5,759 m², and the study was implemented using a variable rate prescription. Yield monitor data was obtained and post-processed to remove errors with Yield Editor Software (Sudduth & Drummond, 2007; Sudduth et al., 2012) As-planted data was also evaluated, and blocks where the seeding rate varied more than 10% of the target seeding rate were removed from the analysis.

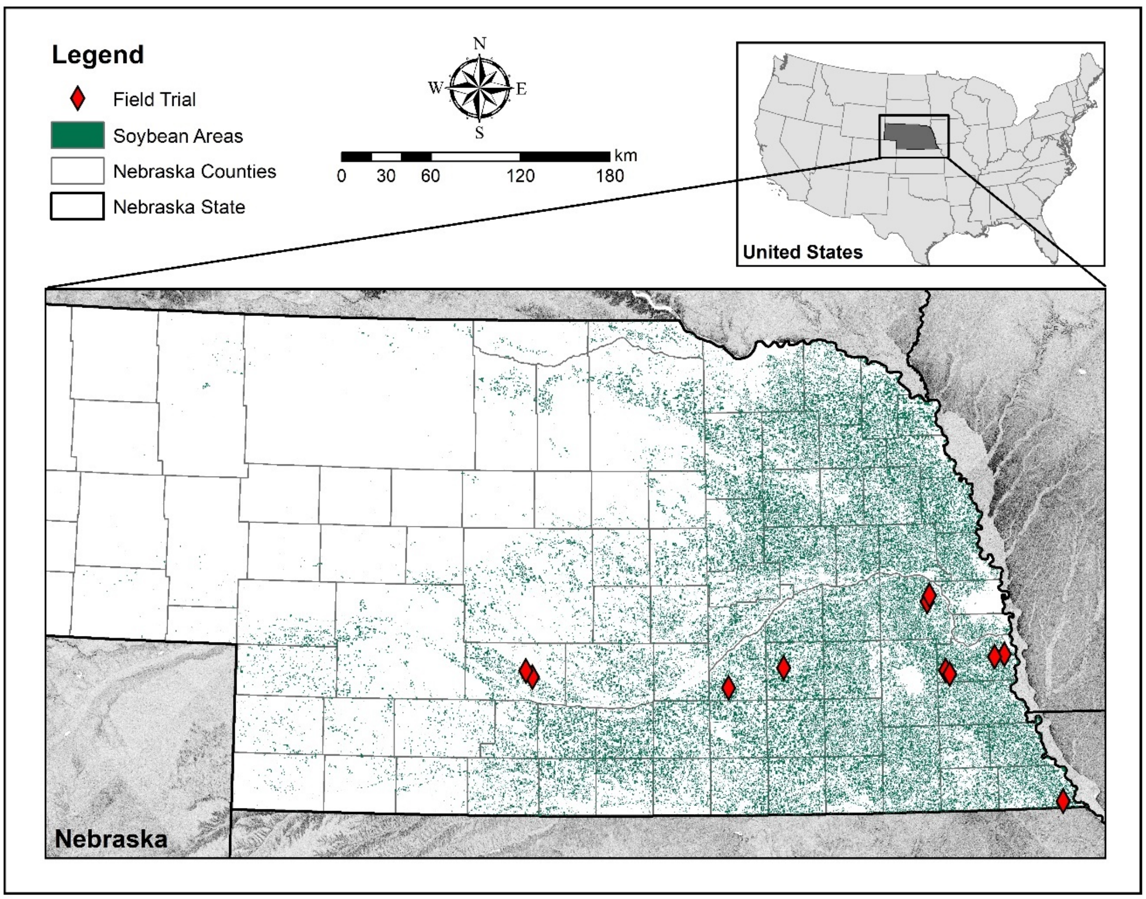


Figure 1. Location of 11 on-farm trials conducted from 2018 to 2022 in Nebraska.

Analysis of variance (ANOVA) was performed to evaluate the seeding rate effect on yield at each site ($p<0.05$). In addition, linear, quadratic, and non-linear regressions were fitted for each field and each block to obtain the AOSR. These models were chosen since many studies show that they are the most common models to describe the relationship between yield and seeding rates (Chen & Wiatrak, 2011). For each trial and block, the model with a higher R-squared was selected.

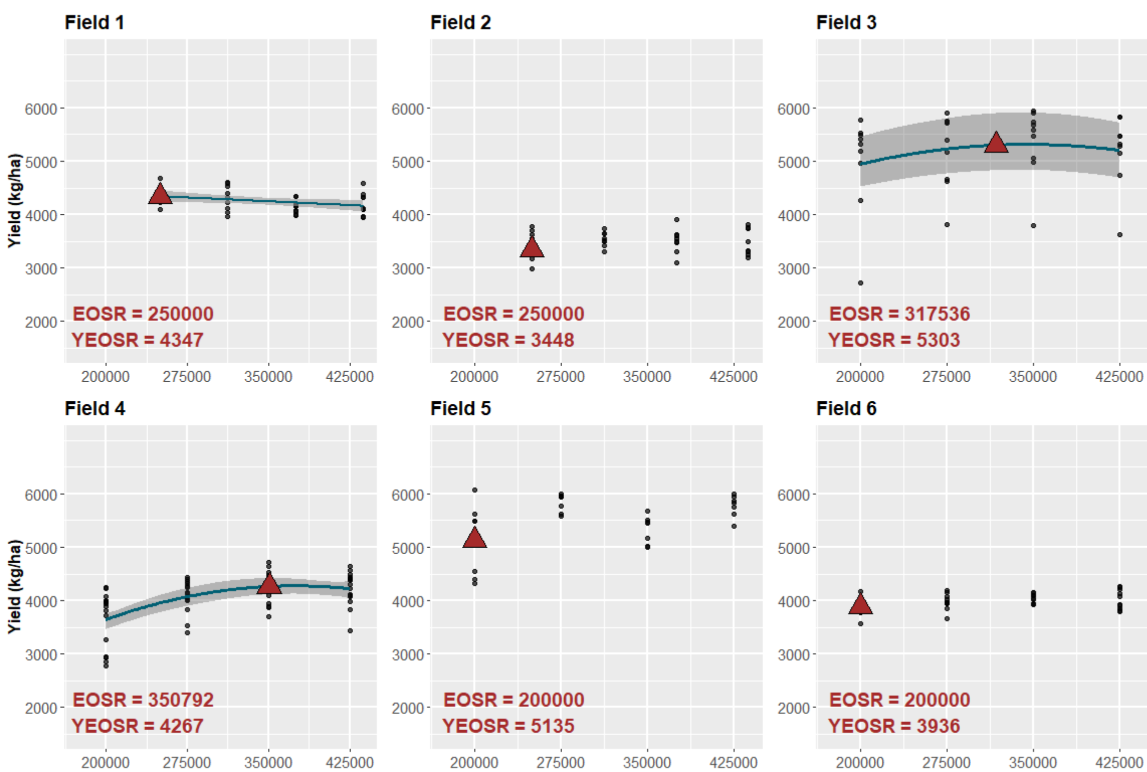
EOSR derived from the maximum profit resulting from the models fitted using 0.513 $/kg soybean price and $70/unit of 140,000 seed cost (Eq. (1)). Models were fitted in R (R Core Team, 2022).

$$Profit = Price\ of\ soybean * \ yield - Price\ of\ seed * \ seed\ rate \qquad (1)$$

Spatial variability in soils was evaluated following a specific protocol. Digital Elevation Models (DEM) were downloaded using the *elevatr* package in R (Hollister et al., 2023). Terrain properties such as slope, aspect, Topographic Position Index (TPI), and Topographic Wetness Index (TWI) were then extracted from the DEM. Soil properties are derived from the Soil Survey Geographic Database (SSURGO) using the soilDB package (Beaudette et al., 2024). The following soil properties were obtained from SSURGO: sand, silt, and clay content, Available Water Capacity (AWC), pH, Electrical Conductivity, Organic Matter (OM), and Cation Exchange Capacity (CEC). Topographic and soil properties were extracted per block and finally were associated with the EOSR in R to understand whether within-field changes in EOSR are related to soil characteristics.

Results and Discussion

Across the 11 fields, seed yield responses to seeding rate were explained by quadratic (two fields) and linear (two fields) models, and no seed yield response was found in the remaining seven fields. In fields where no model was fitted, the EOSR was assumed to be the lowest seeding rate tested (Figure 2). The Economic Optimum Seeding Rate ranged from 175,000 to 350,792 seeds/ha with an average of 258,665 seeds/ac. Yields per field ranged from 3,498 to 5,820 kg/ha with an average of 4,650.



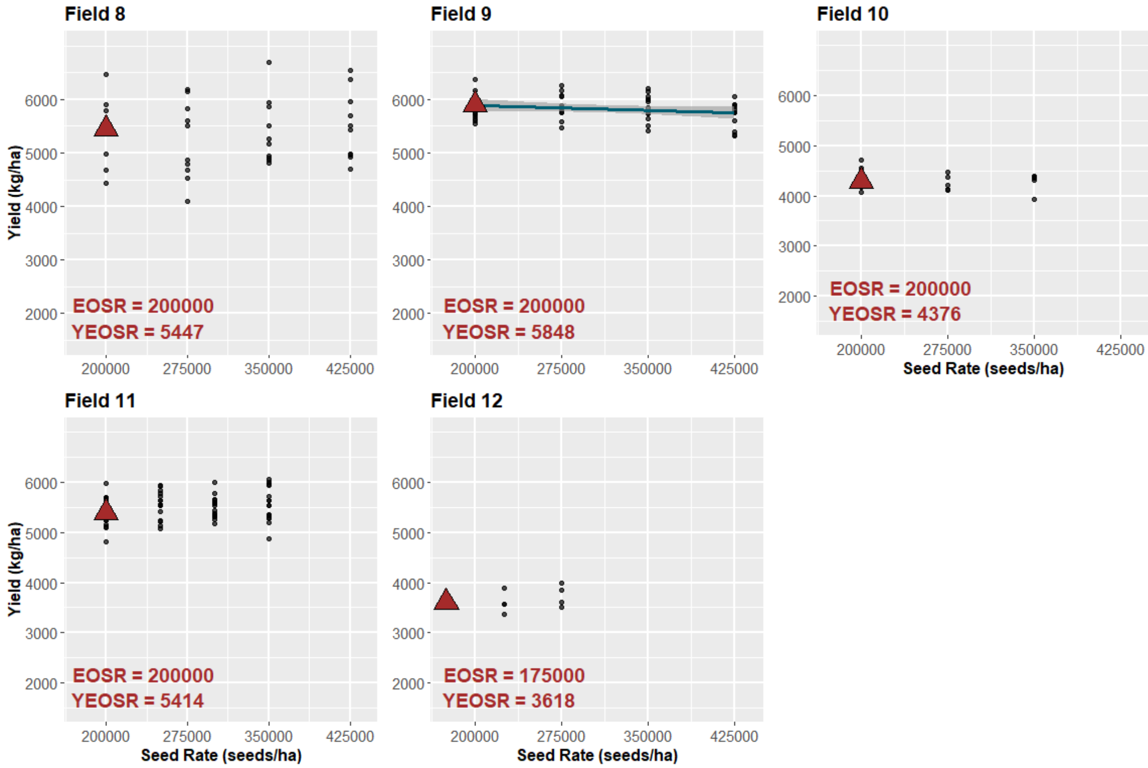


Figure 2. Relationship between soybean yield and seeding rate. The Economic Optimal Seeding Rate (EOSR) in units of seeds/ha is represented by red triangles. EOSR was calculated based on 0.513 $/kg soybean price and $ 70/bag (140,000 seeds) seed cost. Black points indicate the average yield seeding rate in each replication. YEOSR represents the yield at the EOSR.

Soybean seed yield did not respond to an increase in seeding rate in 64% of the sites and had a negative linear response for the other 18% of the sites. This indicates that growers could reduce the seeding rate with no yield penalty for these sites. In the remaining 18% of the sites, EOSR ranged from 317,536 to 350,792 seeds/ha.

When looking at the within-field variability on yield response to seeding rates, a total of 105 blocks were tested across the 11 fields, and the result was 37 blocks where the seed rate was significant. Of the 37 yield responsive blocks, 32% (12) fitted a linear model, 35% (13) fitted a quadratic model, 32% (12) fitted a linear plateau model (Figure 3), and none fitted a quadratic plateau. Two blocks performed a quadratic plateau, but when this model was compared to the linear plateau, the second showed better results for the goodness of fit in terms of R^2 and, therefore, was selected.

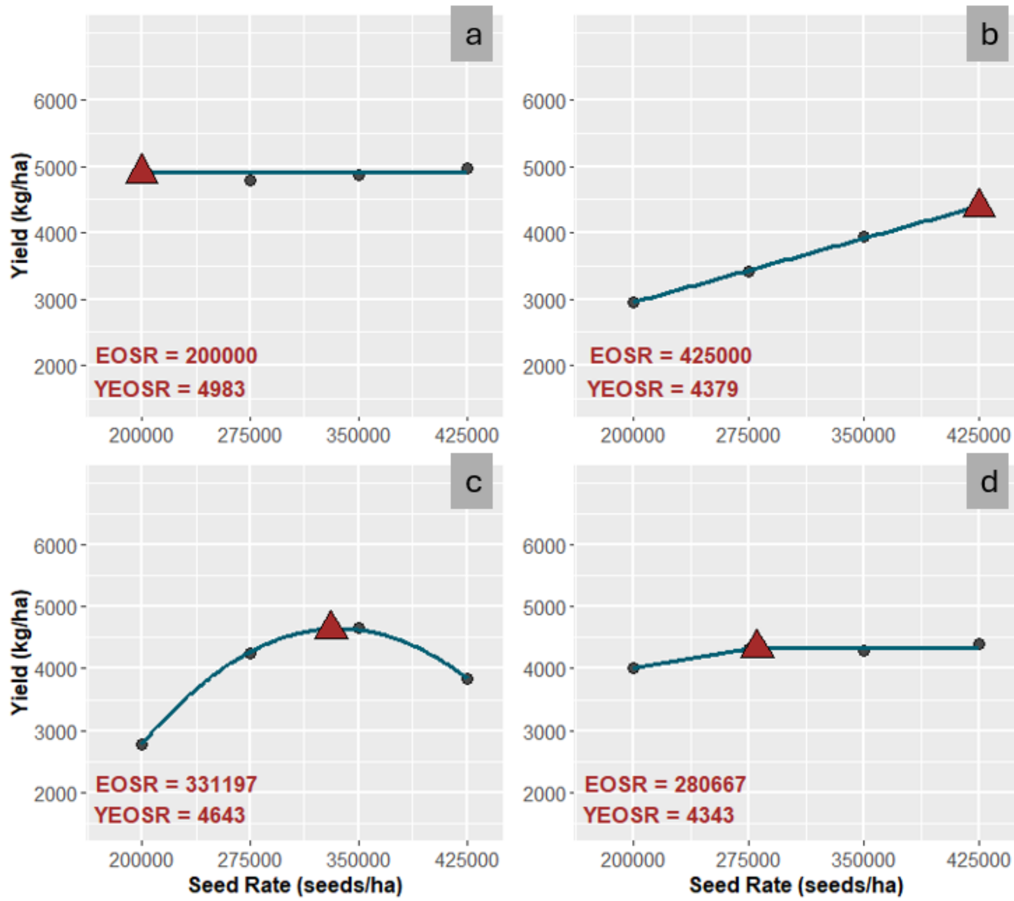


Figure 3. Relationship between soybean Seed rate and yield. The continuous line is the statistical model fit to each block. 3a indicates an intercept model fitted for field 8 block 13, 3b indicates a linear model fitted for field 4 block 3, 3c indicates a quadratic model fitted for field 4 block 15, and 3d indicates a linear plateau fitted for field 4 block 2.

Within fields, variability in EOSR ranged from 0% to 33%, with an average of 13% (Table 1). These results consider all the block's data sets, including the ones where no model was fitted, and the lowest seeding rate was considered as being the EOSR. Variability in EOSR higher than zero means that would be beneficial to adopt VRA technology in their fields. According to these results, six out of the 11 fields presented variability different from zero (2, 3, 4, 6, 8, and 11).

Field	# blocks	Mean	SD	CV (%)
1	9	250000	0	0
2	7	263033	34481	13
3	9	267515	78055	29
4	14	264233	70538	27
5	6	200000	0	0
6	10	227113	60227	27
8	10	247007	81695	33
9	11	200000	0	0
10	5	200000	0	0
11	15	210000	28031	13
12	4	200000	50000	0

Table 1. Statistics for each field study and variability on EOSR within fields represented by the CV (%).

Given that within-field variability is associated with the grower's decision-making, understanding how spatial soil types and properties influence variability in EOSR should be considered. Figure 5 illustrates how different portions of the field can cause different yield responses, and, consequently, number of seeds should be varied within a field to reach optimum net return per field. Fields 3 and 8 were selected due to the 2 highest variability among the 11 fields.

In field 3, soil type 8840 had an EOSR of 275,000 seeds/ha; soil type 8815 ranged the EOSR from 2833,668 to 338,760 seeds/ha; and in soil type 8869, the EOSR was 425,000 seeds/ha. In field 8, soil type 8815 ranged from 200,000 to 295,068 seeds/ha, while soil type 8869 ranged from 200,000 to 350,000 seeds/ha.

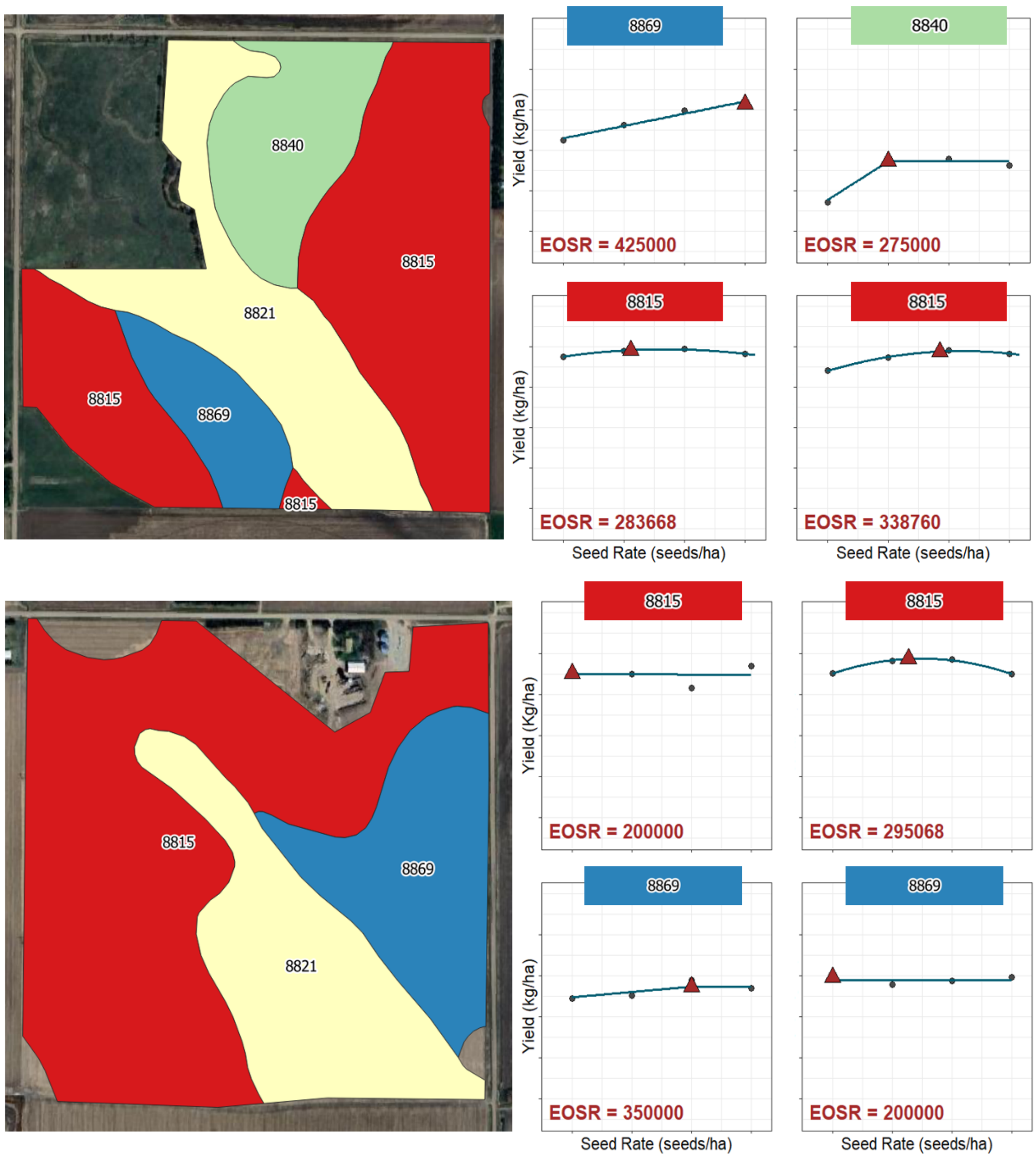


Figure 5. Yield response curves and economically optimal seeding rate in different portions of fields 3 and 8 with SSURGO soil types.

Results presented in Table 2 show the strength of the correlation between soil characteristics by block and EOSR. Overall, **elevation** showed a negative correlation with within-field EOSR. The **TPI** showed a consistent negative correlation with EOSR for all the fields. The **clay content** showed a positive correlation with EOSR. Finally, the **OM** showed a negative correlation with EOSR, while TWI, aspect, slope, sand content, silt, AWC, pH, and CEC had no consistent correlation with EOSR, showing positive and negative correlations across the fields.

The negative correlation between elevation and EOSR suggests that higher areas within the fields analyzed required lower seeding rates to maximize profit compared to lower areas of the field. Usually, higher yields are reported in lower areas and are related to water availability. Therefore, yields might be higher in lower areas, but in these areas, more seeds will be required to reach EOSR than in the higher areas.

The consistently negative correlation between TPI and EOSR suggests that areas within a field located at the bottom of a valley will need more seeds to reach the EOSR. Years with above average precipitation, which is the case here, can result in excessive soil moisture conditions which may cause waterlogging in the deposition areas. The anaerobic soil conditions caused by the waterlogged soils result in poor plant stand establishment and growth (Singh et al., 2016). Given the situation, it is a consequence that these areas will demand a higher number of seeds to be able to reach the EOSR.

Soils with high OM will naturally reach optimum rates before soils with low OM. Given that OM is correlated with yield, higher OM soils will yield more and therefore reach an economical optimum rate demanding less seeds compared to a lower OM soil.

Table 2. Correlation analysis of EOSR performed based on terrain and soil variables. Pearson's Correlation at 0.05 significance level. Darker colors indicate a high correlation between the parameter and EOSR, while lighter colors indicate a low correlation between the parameter and EOSR. Grey boxes indicate parameters where correlation was unable to be calculated due to no field variability or insufficient count of EOSR per field. White boxes indicate no correlation between EOSR and parameters.

Variable	Field										
	1	2	3	4	5	6	8	9	10	11	12
Elevation		-0.35	-0.03	-0.13	0.11	-0.34	-0.68	0.09		-0.44	-0.41
TWI		0.17	-0.3	0.04	0.33	0.13	-0.29	-0.07			0.31
Slope		0.03	0.31	0.02	-0.37	0	-0.45	-0.09		-0.39	-0.52
Aspect		-0.06	0.24	-0.1	0.35	-0.31	0.41	-0.06		-0.21	0.27
TPI		-0.04	-0.12	-0.32	-0.31	-0.51	-0.25	-0.43		-0.04	-0.02
Sand Content		0.06	-0.14	0.18	-0.15	-0.52	-0.74	-0.02		-0.49	
Silt Content		0.06	0.1	-0.19	-0.37	-0.55	0.69	-0.02		0.49	
Clay Content		-0.06	0.62	0.01	0.38	0.54	0.77	0.02		0.49	
AWC		0.06	0.13	0.14	-0.35	-0.52	0.77	0.03			
pH		-0.06	0	-0.1	0.43	0.47	0.62	-0.01		0.49	
EC			-0.04	-0.31	0.19	0.16	0.62			0.49	
OM		0.06	0.04	-0.15	-0.38	-0.53		0		-0.49	
CEC		-0.06	0.53	0.08	0.37	0.53	0.7	0.02		-0.49	

Correlation
weak
moderate
strong

In general, yields at the EOSR had higher correlations with the variables than the EOSR (Table 3). Overall, **sand c**ontent showed a positive correlation with yield. Six out of 9 fields showed a positive correlation. On the other hand, **clay content** showed a negative correlation with yield. Seven out of 9 fields showed a negative correlation. Similarly, **pH** showed a negative correlation with yield. Six out of 9 fields showed a negative correlation. Finally, **CEC** showed a negative correlation with yield. Eight out of nine fields showed a negative correlation. Elevation, TWI, Slope, Aspect, TPI, Silt content, AWC, and EC had no consistent correlation with yield, showing mixed strong positive and negative correlations.

Table 3. Correlation analysis of yield at the EOSR performed based on terrain and soil parameters. Pearson's Correlation at 0.95 significance (p-value < 0.05). Darker colors indicate a high correlation between the parameter and EOSR, while lighter colors indicate a low correlation between the parameter and EOSR. Grey boxes indicate parameters where correlation could not be calculated due to no field variability or insufficient count of EOSR per field. White boxes indicate no correlation between EOSR and parameters.

Variable	Field										
	1	2	3	4	5	6	8	9	10	11	12
Elevation	-0.18	0.66	0.7	0.08	-0.71	-0.41	0.55	0.46	-0.82	-0.25	0.86
TWI	0.01	-0.51	-0.1	0.09	0.09	0.2	0.59	0.47	0		-0.78
Slope	0.13	-0.78	0.33	0.02	0.22	-0.03	-0.09	-0.43	-0.86	0	0.72
Aspect	0.33	-0.59	0.19	-0.02	-0.67	-0.56	0.39	-0.04	0.85	-0.26	0.61
TPI	-0.22	0.38	0.64	-0.15	-0.84	0.25	0.06	-0.03	0.49	-0.1	0.82
Sand Content		0.6	0.94	0.27	-0.12	-0.44	0.82	0.48	0.64	-0.08	
Silt Content		0.6	-0.95	-0.2	0.78	-0.47	-0.84	0.48	-0.2	0.08	
Clay Content		-0.6	-0.67	-0.1	-0.66	0.47	-0.38	-0.48	-0.75	0.08	
AWC		0.6	-0.88	0.29	0.74	-0.58	-0.38	0.51	0.55		
pH		-0.6	-0.66	-0.18	-0.65	0.49	-0.85	-0.49	0.39	0.08	
EC			0.52	-0.41	-0.25	-0.39	-0.85		-0.1	0.08	
OM		0.6	-0.86	-0.1	0.77	-0.5		0.49	-0.31	-0.08	
CEC		-0.6	-0.77	-0.02	-0.75	0.3	-0.38	-0.47	-0.21	-0.08	

Correlation
weak
moderate
strong

Cox et al., 2003 found that higher clay content had higher soybean yield, which was attributed to more plant-available water during dry periods of the growing season. Our results show the opposite situation with higher clay content generating yield reductions. This might be attributed to the amount of rainfall that the fields with a negative correlation between yield and clay content received during the growing season. In years with normal or above normal rainfall, the effect of the clay content can be negative on yield (Cox et al., 2003). Similarly to this study, other works also report a negative correlation between yield and pH, such as Cox et al., 2003 and Anthony et al., 2012. In these works, site areas with high pH exhibited visual symptoms of pH-related iron deficiency chlorosis (IDC). This brings to attention the magnitude of the management challenge imposed by high soil pH and IDC, which is widely well-known for the soils of the North-Central United States (Hansen et al., 2003), even though we don't have visual assessments for our study.

A negative correlation between yield and CEC has been reported in other studies, and researchers attributed this correlation to higher clay and lower fertility soil (Cox et al., 2003). Agreeing with that, another study presented both positive and negative correlations between yield and CEC (Kravchenko & Bullock., 2000). However, soil fertility was not yield-limiting in this one.

We observed no consistent correlations between yield and elevation and slope, which differs from the results of a similar experiment in Illinois reported by Kravchenko & Bullock al., 2000 where elevation had the most influence on yield, with higher yields consistently observed at lower landscape positions. TWI was another no consistent property correlating with yield, although higher yields are generally related to high TWI, which may reflect a more favorable position in the landscape in relation to crop water supply and likely better soil quality (Mourtzinis et al., 2018). Johnson et al. (2005) investigated the use of EC and found that there was no consistent relationship between EC and soybean yield, similar to what we found in this study since the two strongest correlations between yield and EC are positive and negative.

Conclusions

The EOSR varied 11% between fields and the variability within fields was 19%. Elevation, TPI and OM were strongly correlated properties with EOSR, while clay content, pH and CEC were strongly correlated properties with yield.

Areas with higher elevation or lower TPI within the fields may require higher seeding rates to reach the Economically Optimum Seeding Rate in wet years. Higher soil OM will require lower seeding rates than lower soil OM to reach the Economically Optimum Seeding Rate due to this properties correlation with yield. There were no consistent correlations between TWI, aspect, slope, sand content, silt, AWC, pH and CEC with EOSR. Fields with high variability in elevation, TPI, clay and OM, will benefit from adoption of VRA given that changes in these properties are strongly correlated with changes in the amount of seeds needed to reach the maximum profit.

Clay content was negatively correlated with yield when a site receives above normal amount of rainfall. There were no consistent correlations between yield and elevation, TWI, slope, aspect, TPI, Silt content, AWC and EC. These relationships suggest that other factors were yield-affecting. Fields with high variability in elevation, TPI, OM, clay content, pH, and CEC will benefit from adoption of VRA given that changes in these properties are strongly correlated with yield.

The strong correlation between certain field properties and EOSR suggests that tailored management practices can significantly enhance yield. Fields with high OM might need lower seeding rates leading to cost savings and better crop management in soils with varying OM levels. Areas with higher elevation or lower TPI might require higher rates during wet years. This customized approach can lead to better utilization of field potential with better planning and resource allocation.

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