12-9-2022

Reassessing nitrogen management for maize production in Mississippi

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A Thesis
Submitted to the Faculty of
Mississippi State University
in Partial Fulfillment of the Requirements
for the Degree of Master of Science
in Agronomy
in the Department of Plant and Soil Sciences

Mississippi State, Mississippi

December 2022

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Date of Degree: December 9, 2022

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Title of Study: Reassessing nitrogen management for maize production in Mississippi

Pages in Study: 48

Candidate for Degree of Master of Science

12 N treatments in 2020 and 11 in 2021 were replicated four times over four locations in a randomized complete block design. The first research tested the efficacy of CYG for Mississippi corn (*Zea mays* L.) production. The optimum N rates were calculated by fitting four models. Differences between the CYG rate and AONR were compared. AONR varied from 134 to 301 kg N ha^{-1} at different management levels. When we compared the AONR to the CYG rate, the CYG rate over-recommended N in 12 of the 14 possible comparisons. The second study compared different VIs, methods, and sensors at various corn stages to predict in-season yield potential. Relative VI measurements were superior for grain yield prediction. MicaSense best predicted yield at the VT-R1 stages, Crop Circle and SPAD at VT, and GreenSeeker at V10. When VIs were compared, SCCCI outperformed other VIs.

DEDICATION

To Caitlin, for supporting me in each and every step.

ACKNOWLEDGEMENTS

I am incredibly thankful for the guidance from Dr. Amelia Fox, Dr. Gurbir Singh, Dr. Connor Ferguson, and particularly Dr. Jagmandeep Dhillon. Through their support I was able to become a better speaker, writer, flyer, and person.

I would also like to thank James Dew, Ramandeep Sharma, Praveen Gajula, Namita Sinha, and Joey Williams. My research would have never succeeded without their help.

Lastly, I would like to thank Mom, Jeff, Dad, Erica, and my grandparents for their support and encouragement throughout graduate school. Furthermore, I would like to thank my fiancé Caitlin for her love and support each day and for always pushing me towards excellence.

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CHAPTER I

DISCREPANCY BETWEEN THE CROP YIELD GOAL RATE AND OPTIMUM NITROGEN RATES FOR MAIZE PRODUCTION IN MISSISSIPPI

Article published in Agronomy Journal: Oglesby, C., Dhillon, J., Fox, A.A.A., Singh, G., Ferguson, C., Li, X., Kumar, R., Dew, J., & Varco, J. (2022). Discrepancy between the crop yield goal rate and optimum nitrogen rates for maize production in Mississippi. *Agronomy Journal*. https://doi.org/10.1002/agj2.21179

1.1 Abstract

The varying influence of the environment on N supply and demand dictates the need for annually updated fertilizer N recommendations. Currently, crop yield goal (CYG) methods are used by 34 land grant universities, including Mississippi State University, which do not consider environmental variations. This research tested the efficacy of CYG by determining the agronomic optimum N rate (AONR) and the economic optimum N rate for Mississippi corn (*Zea mays* L.) production. In total, 12 treatments in 2020 and 11 in 2021 were replicated four times over four locations in a randomized complete block design. The optimum N rates were calculated by fitting linear, quadratic, linear plateau, and quadratic plateau models by means of three different goodness of fit measures. Furthermore, differences between the CYG rate calculated from the Mississippi yield goal equation and AONR were compared at different management levels (14 comparisons) (all data combined, both years combined, sites combined by year, and individual sites). Overall, AONR varied from 134 to 301 kg N ha^{-1} at different management levels. When we compared the AONR to the CYG rate, the CYG rate over-recommended N in 12 of the 14 possible comparisons, with differences ranging from 69 kg N

ha^{-1} less to 110 kg N ha^{-1} greater than the AONR. These differences between AONR values highlight variability caused by factors such as the soil, environment, and their interaction with N supply and demand, which are unaccounted for by the CYG method.

1.2 Introduction

Inefficient N use leads to significant economic losses, considering the cost of N fertilizer within an agricultural budget (Dhakal & Lange, 2021). Fertilizer input constraints are particularly evident when coupled with a sharp upward trend in N fertilizer prices in the United States (USDA Economic Research Service, 2022). Environmental perturbations accruing from the misuse of fertilizer N as runoff to the Gulf of Mexico have caused the death of organisms at the lowest depths of the water body (Mee, 2006). Conversely, the underapplication of N leads to below-optimum production with reduced profitability (Pagani et al., 2012; Cassman & Dobermann, 2021).

The agronomic optimum N rate (AONR) constitutes the total quantity of fertilizer N necessary to maximize yield, with the extent of the yield response diminishing beyond the optimal rate (Camberrato & Nielsen, 2014). Applying the AONR curtails the overapplication of N beyond a yield response, limiting the readily available N in the soil that is susceptible to losses. The economic optimum N rate (EONR) is defined as the N rate that makes the most effective use of N on a monetary basis. The N rates described by AONR and EONR are similar (Lindsey et al., 2015; Maharjan et al., 2016) but have an inherent difference.

The dissimilarity between AONR and EONR originates from EONR being dependent on the economic environment. For example, EONR can increase with an increase in the grain price, decrease with an escalation in the fertilizer N price, or remain unchanged if the ratio of fertilizer N costs to grain prices remain the same (Camberato et al., 2017).

Determining the optimal fertilization rate of either AONR or EONR involves obtaining the yield data from fields with multiple fertilizer N rates and then fitting the yield data to a specific yield response model. The quadratic model is the most commonly used model (Cerrato & Blackmer, 1990) but does not always produce the maximum profit for all crops, despite being the most frequently used (Bullock & Bullock, 1994). Taking care to accurately evaluate the best fitting model is necessary because of the economic and environmental importance of optimizing fertilizer N rates (Cerrato & Blackmer, 1990).

Crop yield goal (CYG) nutrient management has been a widespread practice in agriculture for farmers for nearly 50 yrs. (Rodriguez et al., 2019). Yield-based strategies continue to be recommended by 34 states at Land Grant universities, including Mississippi State University, to determine the seasonal N demand of a crop (Morris et al., 2018). Stanford (1973), who established the CYG method, created the multiplicative calculation of 1.2× the realistic yield goal to achieve an optimal fertilizer N rate for corn (*Zea mays* L.). Although their study used whole-plant N to derive this 1.2 value, it is currently multiplied solely by the expected grain yield to predict the optimal rate. For this equation to be effective, Stanford (1973) noted that reliable fertilizer prediction needs "realistic estimates of attainable yield, efficiency, and the residual mineral N supply". Despite its popularity because of its ease of use (Morris et al., 2018), there are problems with the practical application of the CYG method. For example, historical yield is not an adequate predictor of future yield (Raun et al., 2017). The discrepancy between the historical and predicted yield derives from the marked differences in corn genetics, environment, and management between locations and years (Puntel et al., 2018). Without accurate yield predictions, the ability to subsequently recommend an optimal N rate is negated (Raun et al., 2017). The discrepancy between the CYG and the optimal rate is compounded by the CYG's failure to consider the N cost (Rodriguez et al., 2019). Additionally, the alteration of the original 1.2 value to a larger number such as Mississippi's 1.3 recommendation increases the amount of N applied despite the lack of published papers justifying this modification. Evidence also suggests that even if all the necessary factors could be accurately predicted, the 1.2 nitrogen/crop ratio was created via an inadequate methodology that would still not support an optimal N rate calculation (Rodriguez et al., 2019).

If the nutritional management of crops is not improved, excessive fertilizer N applications will continue to exacerbate already problematic environmental conditions and compound economic losses (Schröder et al., 2000; Stevens et al., 2005; Cassman & Dobermann, 2021). Conversely, insufficient fertilizer N applications will negatively influence the target production demands of the ever-expanding population (Chardon et al., 2012).

Thus, the overarching purpose of this study was to evaluate the efficacy of the CYG method for fertilizer N recommendations for corn in Mississippi. This study was limited to corn in 2020 and 2021 in the general vicinity of central Mississippi.

1.3 Materials and Methods

The research was conducted in 2020 and 2021 in Mississippi across four locations: (a) Black Belt Experiment Station in Noxubee County in Brooksville, (b) the R. R. Foil Plant Science Research Center in Oktibbeha County in Starkville, (c) Delta Research Extension Center in Washington County in Stoneville, and (d) Northeast Mississippi Branch Experiment Station in Lee County in Verona. Location-specific soil information is noted in Table 1.1. The study locations are indicated in Figure 1.1.

The experiments were established in a randomized complete block design with four replications. In 2020, there were 12 treatments including a no-N control; in 2021, there were 11 treatments including the control. The complete treatment structure is found in Table 1.2. The first and second N applications consisted of a 32% urea ammonium nitrate solution knifed into the soil with a LM 1255 four-row liquid fertilizer applicator (KBH Corp., Clarksdale, MS, USA) equipped with coulter knives spaced at approximately 20 cm from the row at a 7.5-cm depth.

The Brooksville and Starkville experimental units were 3.9 m wide by 9.1 m long, planted in raised beds 96 cm high. At Stoneville, the experimental units were 4.2 m wide by 9.1 m long, planted in raised beds 101 cm high. Verona's experimental units were 3.9 m wide by 10.7 m long, planted on raised beds 96 cm high. In 2020 and 2021, soil sample data were collected at all locations on a per-replication basis, with 16 cores collected per replication at a 15-cm depth. Fertility for each location was modified on the basis of the soil test results as per Mississippi State University recommendations (Table 1.3).

Corn was planted at a seeding rate of 74,000 seeds ha^{-1} in 2020 and 79,000 seeds ha^{-1} at all locations in 2021. In 2020, planting was completed from 6 to 29 April and harvested between 3 and 17 September. In 2021, planting was completed from 12 March to 21 April and harvested between 24 August and 14 September. In 2020, Brooksville and Starkville were planted to the corn hybrid 'DKC 67-44', whereas 'DKC 68-69' was planted in Verona and 'DKC 70-27' was planted in Stoneville. In 2021, all locations were planted to DKC 67-44. Each trial was established where the previous crop was soybean [*Glycine max* (L.) Merr.]. For both 2020 and 2021, the first N applications were applied during the V1–V2 growth stage followed by the second applications at the V5–V6 growth stage. In 2020 and 2021, Stoneville and Starkville were furrow-irrigated twice per year, with no irrigation used at Brooksville and Verona. Weeds at all sites were managed with a pre-emergence application of glyphosate at 0.33 kg acid equivalent ha^{-1} and an application at the V3–V4 growth stage of atrazine at 1.47 kg a.i. ha^{-1}, *S*-metolachlor at 1.47 kg a.i. ha^{-1}, and mesotrione at 0.19 kg a.i. ha^{-1}.

Weather data were collected from NOAA's monthly US Climate Division Database (NOAA, 2022). For 2020 and 2021, average temperature and precipitation data were collected from March through to September from the county weather data. The 2020 and 2021 data were then compared with the average historical weather data from the past 30 yr.

The AONR data for the combined years, by year, and by location per year data calculated by fitting the yield to the applied total N rates in linear, quadratic, linear plateau, and quadratic plateau models in R version 4.0.2 statistical software (R Core Team, 2021) with the 'easynls' (Arnhold, 2017) and 'Agroreg' packages (Shimizu & Goncalves, 2022). The Tidyverse package was used for data handling, manipulation, and visualization (Wickham et al., 2019). The best model was selected on the basis of three criteria: the coefficient of determination (R^2), the Akaike information criterion, and the root means square error (RMSE). The models that could not be fitted by all three goodness of fit measurements were not accounted for when deciding the final best model. The EONR was subsequently calculated from the best yield response model via the following equation

$$(\mathrm{CP} \times Y) - (\mathrm{Price} \times \mathrm{Rate}) \qquad 1.1$$

where CP is the corn price, Y is the yield, Price is the N price, and Rate is the total N rate. The price of corn for this equation was fixed as \$0.202 kg^{-1} and the total fertilizer N price as \$1.38 kg^{-1}.

The CYG was calculated by multiplying the yield at AONR for each level by the recommended value of 1.3 (Oldham, 2012). This approach differed from the practice of calculating CYG from an average of 3 to 5 yr plus 10% (Morris et al., 2018). There were two reasons for the deviation from the established method, (a) realistic yield goals were not calculable (Raun et al., 2017); (b) we wished to use the most accurate targeted yield for an unbiased comparison between CYG and AONR. Possible N credits were not accounted for as these are not considered in the Mississippi-based CYG recommendations. Comparisons between the AONR and CYG-recommended rate were then conducted to evaluate the efficacy of the CYG method for N recommendations.

1.4 Results

In both 2020 and 2021, the combined experiments experienced greater than average precipitation than the 30-yr average (Table 1.4). In 2020, temperatures were warmer than the average for the combined data but were less than average in 2021 when compared with the 30-yr average (Table 1.4). In 2020, when compared with the 30-year average, Brooksville was characterized by higher than average precipitation in April and June, which was also the case for Starkville in April, Stoneville in September, and Verona in August (Table 1.4). In 2021, Brooksville and Starkville's precipitation was above average in June, July, and August; the highest for Stoneville was in March and June; and the highest for Verona was in June and August (Table 1.4). Furthermore, Stoneville in March of 2021 experienced warmer temperatures compared to the average (Table 1.4).

Consistent with our objective, we examined the differences in the optimum N requirements at different levels. At the first level, all eight site-years were analyzed individually.

The second-level data were combined by location over both years. For the third level, the data were combined by years, where four sites per year were combined separately, resulting in two datasets. Finally, the data from all eight site-years were combined. The results of the three criteria used to establish the best model by year, by location, combined by location, and for the fully combined data are noted in Table 1.5.

The Brooksville site in 2020 was described by the quadratic plateau model, with an AONR of 134 kg ha^{-1} at a maximum yield of 9.8 Mg ha^{-1} (Figure 1.2a). In 2021, the Brooksville site's relationship changed and was quadratic, with an AONR of 205 kg ha^{-1} at a maximum yield of 10.5 Mg ha^{-1} (Figure 1.2e). The Starkville site in 2020 showed a similar relationship for both the quadratic and quadratic plateau model, with an AONR of 252 kg ha^{-1} at a maximum yield of 12.6 Mg ha^{-1} (Figure 1.2b). In 2021, the relationship was quadratic at Starkville and had the best fit at an AONR of 251 kg ha^{-1} at a maximum yield of 11.2 Mg ha^{-1} (Figure 1.2f). At Stoneville in 2020, the quadratic plateau model best described the yields, plateauing at an AONR of 194 kg ha^{-1}, resulting in a maximum yield of 10.9 Mg ha^{-1} (Figure 1.2c). In 2021, the relationship was quadratic when yield decreased beyond an AONR of 228 kg ha^{-1} after reaching a maximum yield of 10.0 Mg ha^{-1} (Figure 1.2g). In 2020, Verona had a linear relationship for yield as N application increased, never reaching a plateau (Figure 1.2d). However, in 2021, the relationship between yield and fertilizer N was quadratic and the yield plateaued at 11.9 Mg ha^{-1}, with an AONR of 192 kg ha^{-1} (Figure 1.2h).

When we combined the Brooksville location data over both years, the location was best fitted by the linear plateau model, with an AONR of 134 kg ha^{-1} at a maximum yield of 10.1 Mg ha^{-1} (Figure 1.3a). For the combined Starkville data, the best fitting model was also the linear plateau model, with an AONR of 156 kg ha^{-1} at a maximum yield of 11.5 Mg ha^{-1} (Figure 1.3b). The Stoneville combined data were best fitted with the quadratic model with an AONR of 201 kg ha^{-1} at a maximum yield of 10.5 Mg ha^{-1} (Figure 1.3c). Lastly, the combined Verona data were best fitted by both the quadratic and the quadratic plateau models, with an AONR of 301 kg ha^{-1} at a maximum yield of 10.0 Mg ha^{-1} (Figure 1.3d).

The combined data for all locations in both years were best fitted by the quadratic model, with an AONR of 237 kg ha^{-1} at a maximum yield of 10.5 Mg ha^{-1} (Figure 1.4a). When the years were separated the 2020 data for all locations was again best fitted by the quadratic model, with an AONR of 265 kg ha^{-1} at a maximum yield of 10.2 Mg ha^{-1} (Figure 1.4b). Alternatively, the linear plateau model best represented the 2021 data for all locations, with an AONR of 144 kg ha^{-1} at a maximum yield of 10.7 Mg ha^{-1} (Figure 1.4c). Irrigated and non-irrigated sites were combined to mimic the lack of differentiation between the two conditions by the CYG method, which does not account for the effect of weather, soil conditions, irrigation, etc.

In 12 of the 14 possible comparisons between CYG and AONR, the CYG-recommended rate exceeded the AONR. The excess in the recommended rate was exacerbated when the CYG rate was compared with the EONR, which, when averaged across all levels, recommended approximately 12% less N than the AONR (Figures 1.2–4). When the data were separated by location and year, substantial variations were observed between the AONR and the CYG rates. In Brooksville in 2020, the CYG rate was 93 kg ha^{-1} greater than the AONR. This declined to a 38 kg ha^{-1} difference in 2021. In 2020, Starkville's CYG rate was 40 kg ha^{-1} greater than the AONR, decreasing to a 9 kg ha^{-1} difference in 2021. Stoneville's CYG rate in 2020 was 59 kg ha^{-1} greater than the AONR, reducing to a 4 kg ha^{-1} difference in 2021. In contrast to 2020, when a plateau was never achieved and the AONR was not calculable, the CYG rate was 84 kg ha^{-1} greater than the AONR in Verona in 2021. For the combined Brooksville data, the CYG rate was 100 kg ha^{-1} greater than the AONR. Similar to Brooksville, the combined Starkville CYG rate was 110 kg ha^{-1} greater than the AONR. The CYG rate of combined data of Stoneville was 42 kg ha^{-1} compared with the corresponding AONR. In contrast to the other three locations, the CYG rate of the combined data of Verona was 69 kg ha^{-1} less than the AONR. In 2020, the CYG rate was 29 kg ha^{-1} less than the AONR. This contrasts with 2021, when the CYG rate was 104 kg ha^{-1} greater than the AONR. When we examined the fully combined data, the CYG method recommended a higher fertilizer N rate than the AONR by 6 kg ha^{-1} (Figure 1.5).

1.5 Discussion

The variance observed among sites in this experiment are similar to studies within similar regions (Scharf et al., 2005), as well as those in dissimilar regions and across longer time periods (Dhital & Raun, 2016). Differences in variation were omitted when the data were combined by year or completely. The variation in individual site years was overlooked when estimating an average response curve with pooled data.

Extensive differences were observed in AONR among the models, particularly when we compared the rates recommended by the linear plateau model with the other models (Table 1.5). The widespread differences raise the question as to what degree the model recommendations should be based on statistical rather than agronomic thresholds, considering that the yields at AONR are similar. The lack of a single model with the best fit across all data (Table 1.5) indicates that a single model cannot be assumed for determining the AONR and EONR. The quadratic plateau model is the most commonly used (Bullock & Bullock, 1994; Cerrato &

Blackmer, 1990; Lindsey et al., 2015; Scharf et al., 2005), and our experiment validates this choice. Although the quadratic plateau model may accurately explain the data, there is the disadvantage of possibly over-recommending N, as models such as the linear plateau recommended lower N without any yield differences. Observed differences that may have led to AONR and EONR variations include the above-average precipitation during the second N application (Tremblay et al., 2012)(Table 1.4) as well as the different soil characteristics among the sites (Camberrato & Nielsen, 2014)(Tables 1.1 and 1.3). Only limited variability may be adequately accounted for by the CYG-based recommendation, thus highlighting the inadequacy of using the CYG method for fertilizer N recommendations in Mississippi (Figure 1.5). The results of this study suggest that locations should be individually examined for fertilizer N recommendations, as failure to practice site-specific management may lead to an over- or under-application of fertilizer N (Raun et al., 2017). Ransom et al. (2020) compared 31 corn N recommendation tools and tested them across a wide geographic area and found only 10 to be weakly reliable, with CYG methods incurring the highest environmental costs. Despite some states transitioning to alternate nutrient management strategies, such as a maximum return to N approach, no one tool can deliver an optimum N across all areas (Ransom et al., 2020). Strategies incorporating location-specific models that can account for the plants' morphological features, vegetation indices, and climatological data might lead to improved N rate recommendations in Mississippi (Raun et al., 2019; Dhillon et al., 2020).

1.6 Conclusion

This research elucidated the prevalence of temporal and spatial variability resulting from sources such as weather volatility and diverse soil characteristics, which will, in turn require dynamic N recommendations. Despite its highly normalized deployment and practice, the CYG method cannot account for site variability and is inadequate for providing accurate fertilizer N recommendations. In the future, methods that can account for in-season conditions and subsequently create a fertilizer rate that is specific to highly variable conditions may improve fertilizer N management in Mississippi. If the CYG system continues to be used, over-application of fertilizer N may continue to worsen the current environmental and economic concerns.

Table 1.1 Location, soil series, and taxonomic class of the Brooksville, Starkville, Stoneville, and Verona research locations in 2020 and 2021

Location	Coordinates	Year	Soil series	Taxonomic class
Brooksville	33°15′23.843″ N 88°33′26.208″ W	2020	Brooksville silty clay	Fine, smectitic, thermic Aquic Hapluderts
	33°15′33.307″ N 88°32′22.927″ W	2021	Okolona silty clay	Fine, smectitic, thermic Oxyaquic Hapluderts
Starkville	33°28′44.573″N 88°47′15.382″ W	2020	Leeper silty clay loam	Fine, smectitic, nonacid, thermic Vertic Epiaquepts
	33°28′42.150″ N 88°47′13.146″ W	2021	Catalpa silty clay loam	Fine, smectitic, thermic Fluvaquentic Hapludolls
Stoneville	33°25′37.333″ N 90°57′24.599″ W	2020	Bosket very fine sandy loam	Fine-loamy, mixed, active, thermic Mollic Hapludalfs
	33°25′39.313″ N 90°54′35.320″ W	2021	Bosket very fine sandy loam	Fine-loamy, mixed, active, thermic Mollic Hapludalfs
Verona	34°09′53.330″ N 88°44′30.714″ W	2020	Catalpa silty clay loam	Fine, smectitic, thermic Fluvaquentic Hapludolls
	34°10′05.135″ N 88°44′29.306″ W	2021	Tuscumbia silty clay loam	Fine, mixed, active, nonacid, thermic Vertic Epiaquepts

Table 1.2 Treatments, first and second application rates, and total nitrogen (N) rate applied at Brooksville, Starkville, Stoneville, and Verona, MS, in 2020 and 2021

Treatment	2020			2021		
	Application 1	**Application 2**	**Total N rate**	**Application 1**	**Application 2**	**Total N rate**
	—kg N ha^{-1}—					
1	0	0	0	0	0	0
2	45	0	45	90	0	90
3	45	35	80	45	45	90
4	90	0	90	135	0	135
5	45	70	115	45	90	135
6	135	0	135	180	0	180
7	45	100	145	45	135	180
8	180	0	180	225	0	225
9	45	135	180	45	180	225
10	45	170	215	270	0	270
11	225	0	225	45	225	270
12	45	200	245	–	–	–

Table 1.3 Phosphorus, K, and Mg soil test results and soil pH at 0 to 15 cm for Brooksville, Starkville, Stoneville, and Verona in 2020 and 2021 before nutrient amendments

Location	**Year**	**P**	**K**	**Mg**	**pH**
		—kg ha^{-1}—			
Brooksville	2020	59	237	74	6.7
	2021	18	268	189	6.6
Starkville	2020	129	294	105	8.3
	2021	151	268	166	8.2
Stoneville	2020	26	233	453	6.4
	2021	82	286	851	6.3
Verona	2020	79	301	115	6.5
	2021	66	228	168	8.1

Table 1.4 Average temperature and precipitation in 2020 and 2021 per month compared with the 30-yr average for Noxubee (Brooksville), Oktibbeha (Starkville), Washington (Stoneville), and Lee (Verona) Counties

Month	Location	30-yr average		2020		2021	
		Temp.	Precip.	Average temp.	Total precip.	Average temp.	Total precip.
		°C	cm	°C	cm	°C	cm
Mar.	Brooksville	13.2	13.3	17.6	18.6	14.9	20.1
	Starkville	12.9	13.5	16.6	21.2	14.8	21.5
	Stoneville	13.3	13.6	16.2	19.9	15.6	20.6
	Verona	12	13.4	15.7	16.1	14.6	21.1
Apr.	Brooksville	17.3	14	16.2	25	16.4	14.2
	Starkville	17	14.4	15.6	20.2	15.6	12.2
	Stoneville	18	14.6	17.4	17.7	16.7	10.5
	Verona	16.5	14.2	15.1	16	15.3	13.6
May	Brooksville	21.9	9.8	20.6	10.8	20.9	10.2
	Starkville	21.7	11.1	20.3	8	20.3	9.6
	Stoneville	22.7	12.3	21.9	5.6	21.5	9.2
	Verona	21.2	13.4	19.8	12.2	19.9	11.5
June	Brooksville	25.8	10.5	25.4	15.5	25.3	30
	Starkville	25.6	10.7	25.4	13.1	25.1	32.3
	Stoneville	26.5	9.8	26.1	13.4	25.9	20.2
	Verona	25.2	11.9	25	14.5	24.9	34.2
July	Brooksville	27.3	11.3	27.9	14	26.6	18
	Starkville	27.1	11.6	27.9	13.3	26.7	18.5
	Stoneville	27.9	10.2	28.5	12.4	27.7	12.6
	Verona	26.8	11.1	27.6	10.4	26.5	15.8
Aug.	Brooksville	26.9	10.3	26.8	10.4	27.1	21
	Starkville	26.8	10	26.2	8.5	27.1	21.4
	Stoneville	27.5	8.9	26.8	10.8	27.5	13.2
	Verona	26.5	9.8	25.8	16.4	27.2	16.5
Sept.	Brooksville	24.1	9.3	23.7	6.4	23.6	12.4
	Starkville	23.9	9.7	23.3	6.9	23.9	8.6
	Stoneville	24.6	8.1	24.2	13.1	24.4	6.6
	Verona	23.4	9.4	22.8	9.6	23.7	6.1

Table 1.5 Year, location, model, R^2, Akaike information criterion (AIC), RMSE, crop yield goal (CYG) rate, economically optimum nitrogen rate (EONR), agronomic optimal nitrogen rate (AONR), and yield at AONR (YAONR) for all possible models

Location	Year	Model	R^2	AIC	RMSE	CYG rate	EONR	AONR	YAONR
						—kg N ha^{-1}—			Mg ha^{-1}
Brooksville	2020	Linear	.56	137.77	0.95	–	–	–	–
		Quadratic	.75	113.71	0.73	234	163	192	10.1
		Linear plateau	.79	104.98	0.66	227	97	97	9.8
		Quadratic plateau	**.80**	**103.32**	**0.65**	**227**	**120**	**134**	**9.8**
	2021	Linear	.24	207.62	2.67	–	–	–	–
		Quadratic	**.37**	**201.89**	**2.43**	**243**	**183**	**205**	**10.5**
Starkville	2020	Linear	.83	155.72	1.15	–	–	–	–
		Quadratic	**.90**	**131.35**	**0.87**	**292**	**228**	**252**	**12.6**
		Quadratic plateau	**.90**	**131.35**	**0.87**	**292**	**228**	**252**	**12.6**
	2021	Linear	.59	161.39	1.47	–	–	–	–
		Quadratic	**.69**	**151.12**	**1.28**	**260**	**218**	**251**	**11.2**
		Linear plateau	.69	151.82	1.28	257	168	167	11.1
Stoneville	2020	Linear	.38	133.09	0.91	–	–	–	–
		Quadratic	.47	127	0.84	255	150	201	11
		Quadratic plateau	**.47**	**126.98**	**0.84**	**253**	**146**	**194**	**10.9**
	2021	Linear	.51	159.37	1.38	–	–	–	–
		Quadratic	**.65**	**146.15**	**1.16**	**232**	**196**	**228**	**10**
		Linear plateau	.62	149.30	1.21	227	147	147	9.8
Verona	2020	**Linear**	**.86**	**123.96**	**0.83**	**–**	**–**	**–**	**–**
	2021	Linear	.17	140.91	1.31	–	–	–	–
		Quadratic	**.54**	**119.14**	**0.97**	**276**	**171**	**192**	**11.9**
		Linear plateau	.53	120.41	0.98	264	105	105	11.4
Brooksville	All	Linear	.30	382.97	1.96	–	–	–	–
		Quadratic	.42	367.12	1.78	239	175	200	10.3
		Linear plateau	**.44**	**364.68**	**1.76**	**234**	**134**	**134**	**10.1**
Starkville	All	Linear	.67	335.77	1.48	–	–	–	–
		Quadratic	.79	297.62	1.19	271	212	236	11.7
		Linear plateau	**.79**	**295.85**	**1.18**	**266**	**157**	**156**	**11.5**
		Quadratic plateau	.78	298.57	1.19	273	216	242	11.8

Table 1.5 (continued)

Location	Year	Model	R^2	AIC	RMSE	CYG rate	EONR	AONR	YAONR
Stoneville	All	Linear	.27	342.38	1.51	–	–	–	–
		Quadratic	**.39**	**328.15**	**1.38**	**243**	**165**	**201**	**10.5**
		Linear plateau	.36	332.86	1.41	239	141	141	10.3
Verona	All	Linear	.34	451.20	3.04	–	–	–	–
		Quadratic	**.36**	**450.12**	**2.98**	**232**	**265**	**301**	**10**
		Quadratic plateau	**.36**	**450.12**	**2.98**	**232**	**265**	**301**	**10**
All	2020	Linear	.27	921.37	2.62	–	–	–	–
		Quadratic	**.29**	**918.22**	**2.59**	**236**	**222**	**265**	**10.2**
All	2021	Linear	.34	713.98	1.97	–	–	–	–
		Quadratic	.49	671.95	1.73	253	189	214	10.9
		Linear plateau	**.49**	**670.61**	**1.72**	**248**	**145**	**144**	**10.7**
All	All	Linear	.31	1,651.26	2.36	–	–	–	–
		Quadratic	**.36**	**1,623.16**	**2.27**	**243**	**205**	**237**	**10.5**
		Linear plateau	.36	1,623.91	2.27	239	156	156	10.3

*Note*s. The best fitting model for all data combined, both years combined, sites combined by year, and individual sites is shown in bold. A dash indicates the value is incalculable.

[a] CYG was calculated as 10.1 Mg ha^{-1} = $\frac{10.1 \times 1{,}000}{62.77}$ = 161 bu acre^{-1}; 161 × 1.3 = 209.17 lb N acre^{-1}; 209 × 1.12 = 234 kg N ha^{-1}. Conversions: 1Mg = 1,000 kg, 1 bu acre^{-1} = 62.77 kg ha^{-1}, 1 lb acre^{-1} = 1.12 kg ha^{-1}.

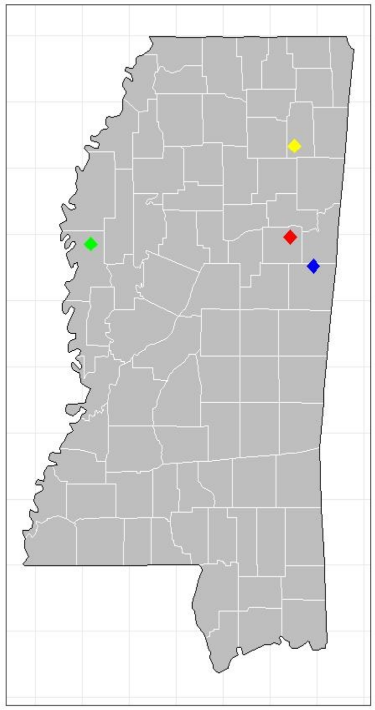

Figure 1.1 Locations of four experimental sites within the state of Mississippi: Brooksville (blue), Starkville (red), Stoneville (green), and Verona (yellow)

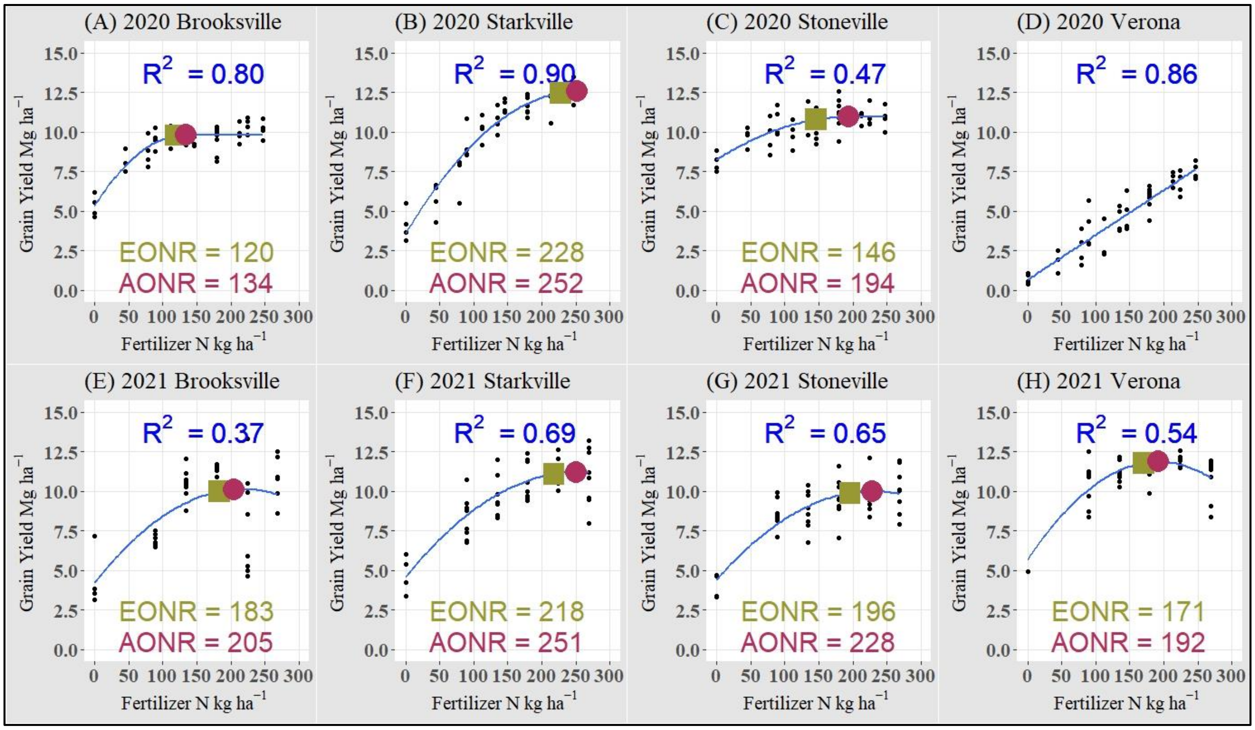

Figure 1.2 The effect of the total N application rate on grain yield in 2020 and 2021 by site for (a) 2020 in Brooksville, (b) 2020 in Starkville, (c) 2020 in Stoneville, (d) 2020 in Verona, (e) 2021 in Brooksville, (f) 2021 in Starkville, (g) 2021 in Stoneville, and (h) 2021 in Verona. Black dots indicate yield at each fertilizer nitrogen (N) application rate, the agronomic optimum nitrogen rate (AONR) is represented by the maroon dot, and the economic optimum nitrogen rate (EONR) is represented by the green square

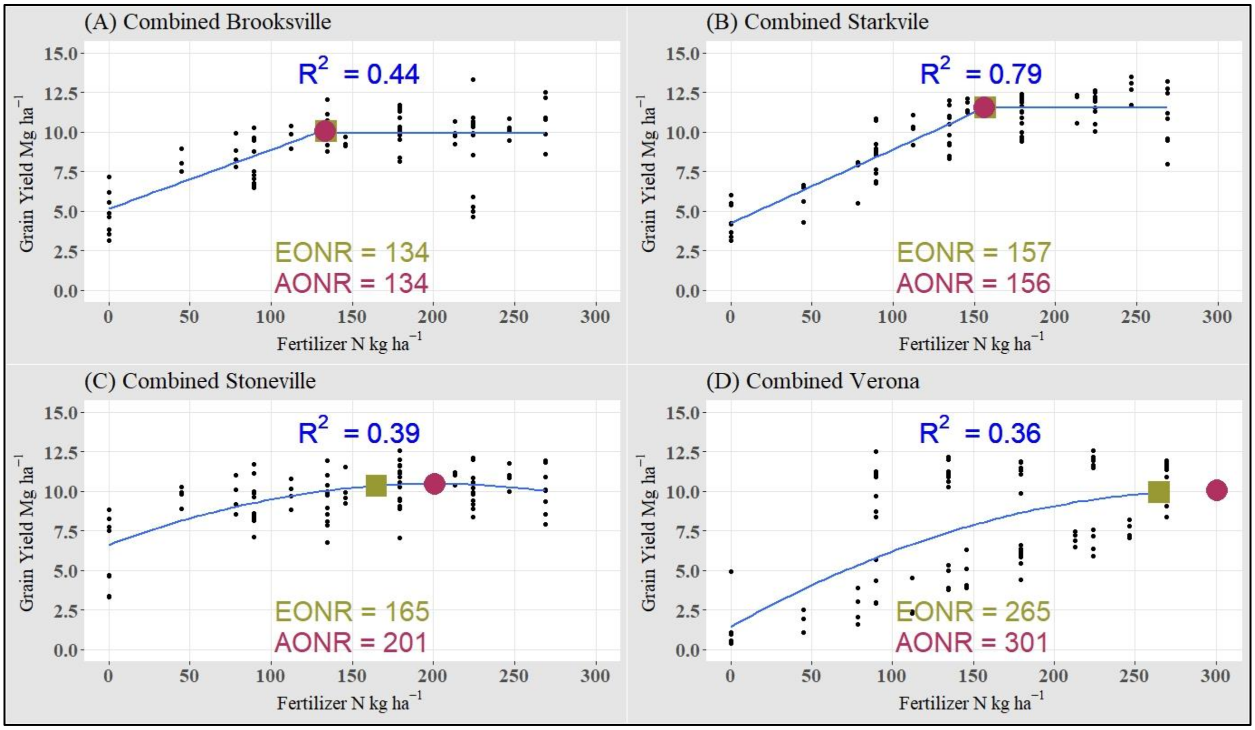

Figure 1.3 The effect of total nitrogen application rate on grain yield in 2020 and 2021 for the sites combined over both years for (a) Brooksville, (b) Starkville, (c) Stoneville, and (d) Verona. The goodness of fit is indicated by the coefficient of determination (R^2) in blue. Black dots indicate the yield at each N rate, the agronomic optimum nitrogen rate (AONR) is represented by the maroon dot, and the economic optimum nitrogen rate (EONR) is represented by the green square

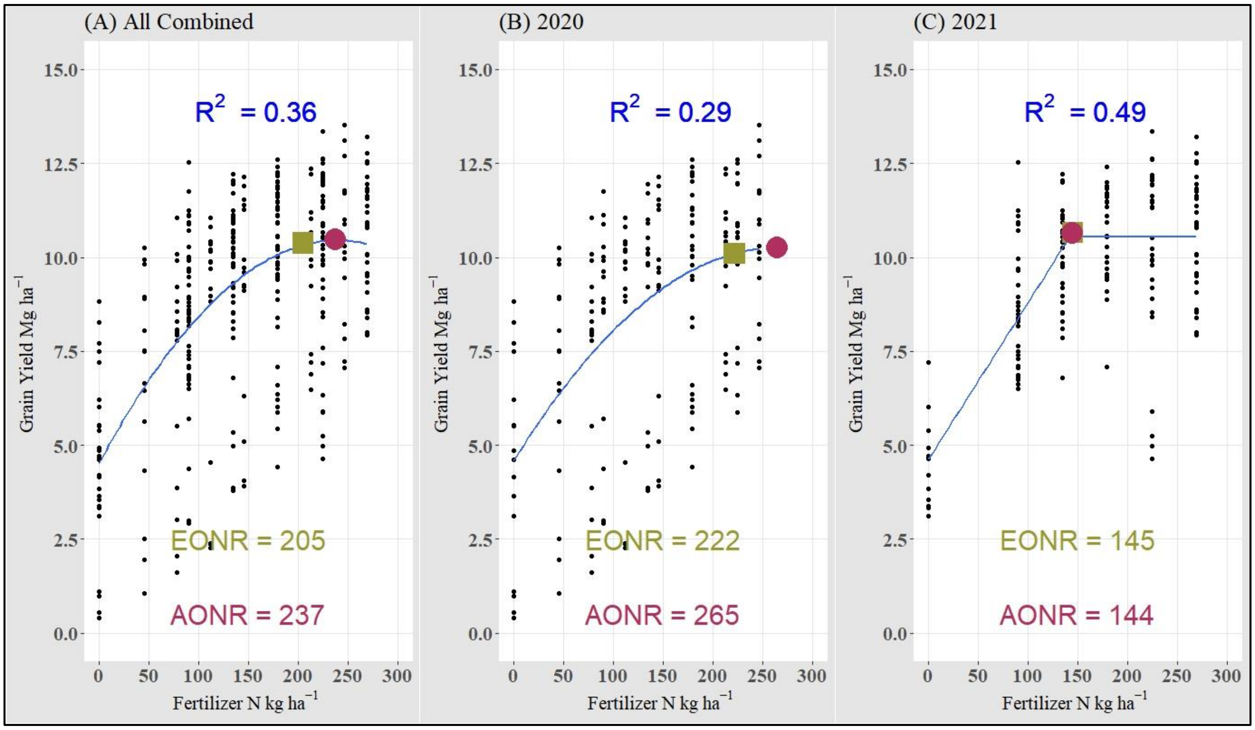

Figure 1.4 The effect of total nitrogen application rate on grain yield for (a) the fully combined data, (b) 2020 data, and (c) 2021 data. The goodness of fit was indicated by the coefficient of determination (R^2) in blue. Black dots indicate yield at each N rate, the agronomic optimum nitrogen rate (AONR) is represented by the maroon dot, and the economic optimum nitrogen rate (EONR) is represented by the green square

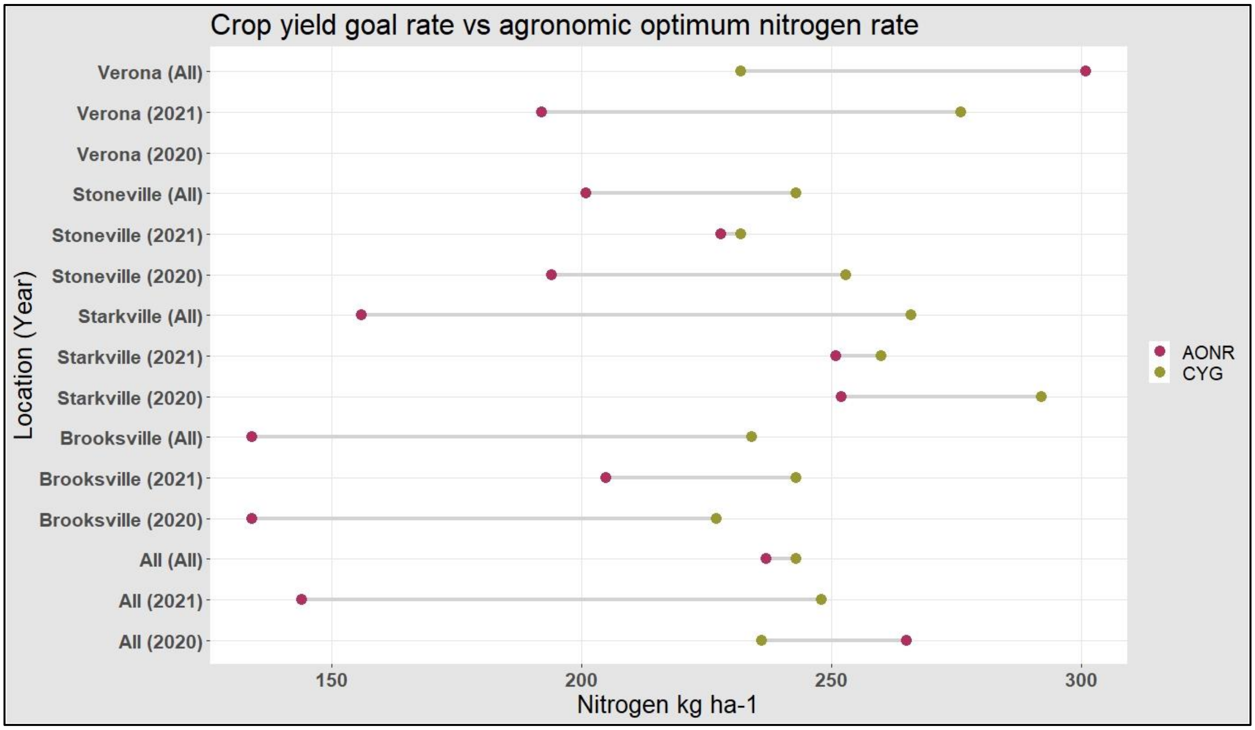

Figure 1.5 A comparison of the agronomically optimum nitrogen rate (AONR) versus the crop yield goal (CYG) rate for all data combined, both years combined, sites combined by year, and individual sites

CHAPTER II

PREDICTING IN-SEASON MAIZE GRAIN YIELD USING OPTICAL SENSORS

Article published in Agronomy: Oglesby, C., Fox, A.A.A., Singh, G., Dhillon, J. Predicting in-season corn grain yield using optical sensors. *Agronomy 2022, 12*, 2402. https://doi.org/10.3390/agronomy12102402

2.1 Abstract

In-season sensing can account for field variability and improve nitrogen (N) management, however, opportunities exist for further refinement. The purpose of this study was to compare different sensors and vegetation indices (VIs) (normalized difference vegetation index (NDVI); normalized difference red edge (NDRE); Simplified Canopy Chlorophyll Content Index (SCCCI)) at various corn stages to predict in-season yield potential. Additionally, different methods of yield prediction were evaluated where the final yield was regressed against raw or % reflectance VIs, relative VIs, and in-season yield estimates (INSEY, VI divided by growing degree days). Field experiments at eight-site years were established in Mississippi. Crop reflectance data were collected using an at-leaf SPAD sensor, two proximal sensors: GreenSeeker and Crop Circle, and a small unmanned aerial system (sUAS) equipped with a MicaSense sensor. Overall, relative VI measurements were superior for grain yield prediction. MicaSense best predicted yield at the VT-R1 stages (R^2 = 0.78-0.83), Crop Circle and SPAD at VT (R^2 = 0.57 and 0.49), and GreenSeeker at V10 (R^2 = 0.52). When VIs were compared, SCCCI (R^2 = 0.40-0.49) outperformed other VIs in terms of yield prediction. Overall, the best

grain yield prediction was achieved using the MicaSense derived SCCCI at the VT-R1 growth stages.

2.2 Introduction

Nitrogen application has increased crop yields by 30-50% (Stewart et al., 2005), promoting economic development, and supporting a larger population (Foley et al., 2011). Currently, most of the N fertilizer consumed in the US is used for corn production. Only half of the N applied is recovered with rest lost to the environment and causing agricultural N pollution (Raun & Johnson, 1999). One of the reasons for low N recovery is the use of suboptimal methods such as yield goals for N recommendation (Raun et al., 2017; Rodriguez et al., 2019). Moreover, Mississippi State also recommends the crop yield goal (CYG) method for N rate recommendation (Morris et al., 2018), which was proven ineffective in Mississippi for accounting the spatial and temporal variabilities necessary to minimize misapplication (Oglesby et al., 2022).

One proposed alternative to CYG based N management is non-destructive canopy reflectance sensing (Raun et al., 2001). Nitrogen is important for many significant processes within the plants. It is required in large quantities compared to other nutrients, and its deficiency is reflected in chemical or physical properties of plants (Morris et al., 2018). Crop canopy sensors accurately account for N deficiencies as it results in lower chlorophyll content and greenness of plants. Furthermore, various vegetation indices (VIs) were developed based on differences in crop reflectance to characterize spatial and temporal N variability.

Consistently, in-season sensing has demonstrated the capability to provide an environmentally distinct N rate that can account for temporal and spatial variability (Ali & Thind, 2015; Dhillon et al., 2020; Dhital & Raun, 2016). The development of a nutrient management strategy grounded in sensor technology is contingent upon the ability to predict in-season yield potential using an algorithm created from on-site observations (Bushong et al., 2018; Dhillon et al., 2020; Raun et al., 2017). The calculation of in-season yield potential is enabled by the ability to distinguish differences in crop N uptake by using distinctions in vegetation indices (VI) as a proxy for crop N uptake differences (Raun et al., 2002).The algorithm is created by computing a regression analysis between actual yield and a predictor such as raw or % reflectance corrected VI values, or in-season estimated yield (INSEY) expressed as a VI (such as the normalized difference vegetation index (NDVI) divided by growing degree days (GDD)), with a more robust data set generally improving yield prediction. Recently, Paiao et al. (2020) introduced relative VIs for comparison, where these values were calculated by dividing VI from each plot by VI from the highest N rate treatment. Specifically, when INSEY is used the predicted in-season yield potential is multiplied by a response index (RI), created from an N-rich strip as a proxy for unlimited N supply, to calculate whether yield may be improved by the addition of N. Finally, an N rate prescription is created specific to that site to match crop N demand (Raun et al., 2002).

2.2.1 Sensor-based Datasets and Corn Correlations

Accurate in-season yield prediction is dependent upon a range of factors including corn growth stage, VI, and sensor. Corn growth stages are generally divided into vegetative and reproductive stages, where V1 denotes 1-leaf stage until tasseling which is designated as VT. Similarly, R stages are designated as R1 based on corn kernel development and ends at R6 with a mature harvest ready crop (Ritchie et al., 1986). Martin et al. (2007) observed that NDVI was most correlated to corn grain yields at the V7 to V9 growth stages. Similarly, Tagarakis and Ketterings (2017) observed V7 as the most effective stage for grain yield prediction. Different sensors have also been compared, with Sharma et al. (2016) revealing no significant differences between the Crop Circle™ ACS-430 (Holland Scientific, Lincoln, Nebraska, USA) and GreenSeeker™ (Trimble Inc., Sunnyvale, California, USA) sensors when predicting yield using an NDVI-derived INSEY approach at the V6 stage.

Furthermore, the accuracy of in-season yield potential prediction is conditional upon the strength of the relationship between final grain yield and an in-season crop indicator. An INSEY-based prediction model is predominantly used and recommended. Tagarakis and Ketterings (2017) used an INSEY-based model, with the INSEY-derived model exhibiting superior capabilities for grain yield prediction. Paiao et al. (2020) compared Soil Plant Analysis Development (SPAD™) (Konica Minolta, Inc., Japan), NDVI, relative NDVI, normalized difference red edge (NDRE), and relative NDRE with the relative NDRE demonstrating the greatest capability for grain yield estimation.

The relationship between INSEY and yield improved when NDRE was utilized due to the red edge wavelength being less influenced by saturation effects at later growth stages (Paiao et al., 2020). There is also evidence that the simplified canopy chlorophyll content index (SCCCI), which incorporates both NDVI and NDRE, is better for grain yield prediction versus NDVI or NDRE (Barzin et al., 2020; Parker, 2022; Sumner et al., 2021) .

Considering the intertwining factors influencing in-season yield prediction, the purpose of this study was to assess the applicability of sensor-based N management comprehensively. N management assessment was accomplished by analyzing the ability to predict yield potential using various sensors and VIs at multiple growth stages. The most competent method for utilizing VI data for grain yield prediction was also evaluated. The ultimate goal of this study is to use drawn conclusions to create an algorithm capable of accurately predicting N needs in

Mississippi similar to those created for other regions (Dhillon et al., 2020; Tagarakis & Ketterings, 2017).

2.3 Materials and Methods

The research was conducted in 2020 and 2021 at four locations across Mississippi: a) Black Belt Experiment Station, in Noxubee County at Brooksville, b) R. R. Foil Plant Science Research Center, in Oktibbeha County at Starkville, c) Delta Research Extension Center, in Washington County at Stoneville d) Northeast Mississippi Branch Experiment Station, in Lee County at Verona. In both years soil sample data were collected on a per replication basis at all locations. 16 cores were collected per replication at a 15 cm depth. Fertility for each location was modified according to Mississippi State University recommendations based on soil test results (Table 2.1).

The experiment employed a randomized complete block design with four replications. In 2020, the experiment consisted of 12 treatments including a 0-N control, and in 2021, 11 treatments including a 0-N control. Treatment structure details are located in Table 2.2. Both N applications utilized 32% urea ammonium nitrate (UAN) solution knifed into the soil using a four-row liquid fertilizer applicator. In 2020, corn harvest occurred between September 3rd and September 17th. In 2021, harvest began August 24th and completed September 14th. The middle two rows of each treatment were combine harvested then the yield data was adjusted to 15.5% moisture level.

The V stage was identified each time staging was executed by the number of visible leaf collars on a random selection of three corn plants within the field. At later stages where the earliest collars had diminished, three plants were bisected, and nodes counted to gain an indication of V stage. The R1 stage was identified by the presence of visible silks and the R5 stage by denting on a majority of corn kernels.

2.3.1 Sensor Technologies

The center two rows of each plot were used for data collection. The sensors utilized in this study included the GreenSeeker hand-held, Crop Circle ACS-430, SPAD, and MicaSense™ MX RedEdge (MicaSense Inc., Seattle, WA, USA) sensors. The wavelengths measured by each sensor are noted in Table 2.3. The GreenSeeker sensor utilizes two bands, a 656 nm red band and a 774 nm NIR band, which can be used to calculate NDVI (Whelan, 2015). The Crop Circle sensor employs three bands, a 670 nm red band, a 730 nm red edge band, and a 780 nm near-infrared (NIR) band to calculate both the NDVI and NDRE (Whelan, 2015). The MicaSense camera utilizes five bands, a 668 nm red band, a 560 nm green band, a 475 nm blue band, an 840 nm NIR band, and a 717 nm red edge band (Thomson et al., 2021). The band combinations can calculate, among other VIs, NDVI, NDRE, and SCCCI (Barzin et al., 2022). Consistent sensor deployment and/or timing was not executed in either year, with sensor heterogeneity and sensing frequency concentrated within the later stages, the 2020 year, the Crop Circle sensor, and the Brooksville and Starkville locations.

Three SPAD measurements were sampled per plant on the corn leaf between the midrib and leaf margin and then averaged for three different plants for a total of three SPAD values per treatment. This averaged number was not further modified except for transformations to an INSEY and relative value in the relevant VI comparisons. In both years, SPAD measurements were collected during the VT and R1 growth stages.

In 2020 and 2021, remote and proximal sensing was conducted from the V4 to R5 growth stages, with measurements primarily taken within the V6 to VT growth stages. Proximal sensing measurements were parallel to the canopy at a 0.5 m from the canopy. The remote sensing sensor was mounted on a 650 mm class X-frame small unmanned aerial system (sUAS). Flight creation and implementation were completed using ArduPilot® Mission Planner® (Mission Planner, 2021). Flights were conducted during solar noon at 60 m above the canopy and speed of 7.6 m s^{-1}. Overlap and sidelap were set to 75% and overshoot and lead in 15 m. All images were 1280 x 960 pixels at a 16-bit resolution. Camera specifications included a 47.2° horizontal field of view (HFOV) and a 35.4° vertical field of view (VFOV). Reflectance panel imagery was taken before and after each flight for absolute reflectance referencing.

2.3.2 Data Processing

Data from the Crop Circle and GreenSeeker sensors was averaged in Microsoft® Office Excel to create a single data point per treatment per growth stage. Post-flight image processing was conducted using the Ag Multispectral workflow in Pix4DMapper® (Pix4Dmapper, 2021) to create image mosaics. Pixels were converted to % reflectance using the reflectance panel imagery at a reflectance value of 0.98. The purpose of this was to compensate for varying light conditions so that the image mosaics would be comparable across space and time. Raw Crop Circle, GreenSeeker, and SPAD values were not converted to % reflectance. VI data extraction was completed within QGIS® Desktop 3.16.6 with GRASS 7.8.5 (QGIS Development Team, 2021), ArcGIS® Desktop 10.8.1 (ESRI, 2021), and R® version 4.0.2 (R Core Team, 2021) with only the center two rows extracted and subsequently used for VI calculations.

2.3.3 Vegetation Indices

Indices including NDVI, NDRE, and SCCCI were calculated for each sensor. Table 2.4 displays the VI calculations calculated for each sensor.

2.3.4 Calculations and Statistics

Three methods were utilized for the best means of sensor-based yield prediction. Regression analysis with grain yield included comparisons with raw or % reflectance corrected VI values (Frels et al., 2018), an INSEY based comparison (Raun et al., 2002), and relative VI values (Paiao et al., 2020) for all sensors. The INSEY was calculated as VI divided by growing degree days (GDD), consisting of the sum of the number of days from sowing to sensing with an average temperature above 10 ◦C (Raun et al., 2002). Similarly, relative VI values were calculated by dividing the sensor reading in each plot by the mean reading in the highest N rate treatment (Paiao et al., 2020). Comparisons of the three methods were completed across each VI sensor combination present within this study with the entire VI dataset utilized within this segment of comparison.

Next, the VI with the greatest capability for yield prediction was evaluated. Only the MicaSense relative NDVI, NDRE, and SCCCI, and Crop Circle relative NDVI, NDRE, and SCCCI values were utilized in this comparison due to the capability of both sensors to calculate each VI evaluated within this study.

After the VI to yield comparison, the most efficient sensor for yield prediction was evaluated. The SPAD, GreenSeeker, and Crop Circle sensors were compared at the VT stage. For the GreenSeeker and Crop Circle sensors, NDVI relative values were employed for comparison. VT was chosen due to being the most prominent stage for VI data collection. NDVI was used due to the commonality between sensors. The lack of VT data for every location in 2021 led to 2021 data omission for the sensor comparison. There was an inadequate amount of MicaSense data to accurately make a yield prediction comparison to its counterparts.

Lastly, the optimum stage for yield prediction was assessed. All GreenSeeker, MicaSense, and Crop Circle sensor data, differentiated by stage, were utilized for comparison. As SCCCI was most correlated to yield, MicaSense and Crop Circle sensor's relative SCCCI values were chosen for comparison. For the GreenSeeker sensor, relative NDVI was used. For the GreenSeeker sensor the V4, V6, V10, and VT stages, the Crop Circle sensor the V4, V6, V8, V10, and VT stages, and the MicaSense sensor the V6, V8, V10, VT, R1, and R5 stages were compared.

Datapoints 2.5 standard deviations or greater were removed as outliers before analysis. Comparisons were gauged by goodness of fit through coefficient of determination (R^2), Akaike Information Criterion (AIC), and Root Mean Square Error (RMSE). As this study should be considered a feasibility study, no independent validation of results was performed and will be completed in future research.

2.4 Results

2.4.1 Best method for sensor-based grain yield predictions

All collected VI data was utilized in this segment of comparison. Best results for the Crop Circle and the MicaSense sensor are illustrated in Figure 2.1. Sensor-based yield prediction employed three different methods for grain yield prediction, including raw or % reflectance corrected VI values, INSEY, and relative VI values. With the SPAD sensor, the raw values were best at explaining grain yield variations with an R^2 of 0.49, AIC of 1873, and RMSE of 1.945. Relative values were almost identical in yield prediction capabilities with an R^2 of 0.48, AIC of 1888, and RMSE of 1.976 (Table 2.5). For the GreenSeeker sensor, no method effectively predicted grain yield. The INSEY VI values were the most effective method, with a low R^2 of 0.11, AIC of 1941, and RMSE of 3.171 (Table 2.5). With the Crop Circle derived NDVI, the

INSEY method predicted yield with a low R^2 of 0.07, AIC of 5602, and RMSE of 2.955. Furthermore, for Crop Circle, the relative NDRE yield prediction resulted in an R^2 of 0.29, AIC of 5299, and RMSE of 2.582 (Figure 2.1C). Relative SCCCI was the best yield prediction method for the Crop Circle derived SCCCI, with an R^2 of 0.40, AIC of 5109, and RMSE of 2.371 (Table 2.5; Figure 2.1E). For the MicaSense sensor's NDVI, relative values predicted yield with an R^2 of 0.25, AIC of 1347, and RMSE of 1.941 (Figure 2.1B). NDRE's yield prediction capabilities for the MicaSense sensor were maximized when relative values were used, with an R^2 of 0.44, AIC of 1251, and RMSE 1.674. For SCCCI, relative values were also best for yield prediction, with an R^2 of 0.49, AIC of 1227, and RMSE of 1.611 (Table 2.5; Figure 2.1F).

2.4.2 Comparison of VIs for sensor-based yield prediction

Total MicaSense and Crop Circle sensor data was utilized in this comparison segment. For the Crop Circle sensor, the relative SCCCI values were best for grain yield prediction, with an R^2 of 0.40, AIC of 5109, and RMSE of 2.371 (Table 2.5; Figure 2.1E). Relative SCCCI was also best for yield prediction for the MicaSense sensor, with an R^2 of 0.49, AIC of 1227, and RMSE of 1.611 (Table 2.5; Figure 2.1F). For the MicaSense sensor, the relative NDRE values provided a similar capability for grain yield prediction with an R^2 of 0.44, AIC of 1251, and RMSE of 1.674 (Table 2.5; Figure 2.1D). For both the Crop Circle and MicaSense sensor, NDVI was the worst VI for grain yield prediction (Table 2.5).

2.4.3 Comparison of Sensors for sensor-based yield prediction

In this segment, the 2020 SPAD, GreenSeeker, and Crop Circle VT sensor data was compared. Between the SPAD, GreenSeeker, and Crop Circle sensors, the SPAD sensor was most effective for grain yield prediction when all sensors were compared, with an R^2 of 0.53, AIC of 647.3, and RMSE of 2.243 (Table 2.6; Figure 2.2A). The second most suitable sensor was the Crop Circle sensor with an R^2 of 0.31, AIC of 701.6, and RMSE of 2.709 (Table 2.6; Figure 2.2C). The least effective sensor for grain yield prediction was the GreenSeeker sensor with an R^2 of 0.24, AIC of 714.3, and RMSE of 2.831 (Table 2.6; Figure 2.2B).

2.4.4 Comparison of growth stages for sensor-based yield prediction

In this segment, total GreenSeeker, MicaSense, and Crop Circle sensor data, separated by stage, was compared. For the GreenSeeker sensor, the most effective stage for yield prediction was the V10 stage with an R^2 of 0.52, AIC of 359.7, and RMSE of 1.527 (Table 2.7). The most suitable stage for yield prediction for the Crop Circle sensor was the VT stage with an R^2 of 0.57, AIC of 1156, and RMSE of 1.916 (Table 2.7). For the MicaSense sensor, the superior stage for grain yield prediction within the vegetative stages was the VT stage with an R^2 of 0.78, AIC of 134.3, and RMSE of 1.075. When the reproductive stages are included, R1 was most suitable for grain yield prediction with an R^2 of 0.83, AIC of 124.7, and RMSE of 0.962 (Table 2.7).

2.5 Discussion

As opposed to Tagarakis and Ketterings (2017), where GreenSeeker INSEY values were better suited for yield prediction, we found that was not the most common optimal method overall (Table 2.5). The insufficiency of the INSEY method may be derived from the consistent GDDs present within the corn growing season relative to crops such as winter annuals. Results also correspond to the findings of Paiao et al. (2020), with five of the eight sensor VI combinations best predicting yield when the relative VI method was utilized (Table 2.5). Akin to past studies, VIs that incorporated the red-edge wavelength were better predictors of grain yield, with SCCCI superior to either NDVI or NDRE (Barzin et al., 2020; Sumner et al., 2021)(Table

2.5). This greater prediction capability is possibly due to SCCCI, which integrates NDRE and NDVI, being responsive to variance in both biomass and chlorophyll (Sumner et al., 2021). While NDVI is the most common VI utilized in yield prediction, the improved relationship between relative SCCCI and yield necessitates further research into the capabilities of relative SCCCI-derived algorithms. For sensor comparison, results were similar to Sharma et al. (2016), with the Crop Circle and GreenSeeker sensors providing proximate prediction capability when NDVI is employed (Table 2.6). The sUAS driven MicaSense sensor has the greatest potential for commercial use due to its ability for rapid data collection relative to the other sensors.

Considering this advantage, the significance of the proportion of sensor capability to applicability should be considered when the aim is for commercial employment. Also, the capability of an algorithm to accurately predict N requirements should be gauged when the data originates from a sensor type not utilized in its creation (Sumner et al., 2021). The study results are similar with findings from past studies that have analyzed the effect of stage, with VI to yield correlation strengthening as the season progresses (Martin et al., 2007; Tagarakis & Ketterings, 2017). The improved correlation between yield and relative VI as the corn matures will need to be considered in algorithm creation due to the need for specialized equipment at later stages. In total, the combination that produced the highest correlation between VI and grain yield was the MicaSense sensor with relative SCCCI at the VT or R1 growth stages.

Recently, Colaço et al. (2021) challenged the existing sensor-based N management strategies and inferred that encompassing multiple variables and using a non-mechanistic model would lead to a more accurate N rate. Furthermore, this paper is accentuating the need to account for VI methodology for algorithm creation in N management. By distinguishing the most accurate VI, sensor, and stage, and considering the best method for VI data manipulation, a more robust algorithm can be created that could enhance N rate prescription capabilities

2.6 Conclusion

In this study, four sensors and three VIs across multiple growth stages were assessed. Distinctions in the capability for grain yield prediction were observed across the different VIs, sensors, and stages. Specifically, SCCCI and later growth stages were best able to predict grain yield. While the SPAD sensor was best suited for grain yield prediction, practicality should be considered when the ultimate goal for an algorithm is commercial employment. Additionally, this study evaluated and found significant variance when VI data methodology was examined. Variance derived from methodology differences highlights the pertinence of assessing VI methodology in future yield prediction modeling. By considering each factor, more accurate yield prediction algorithms may be derived that, sequentially, could provide better N prescription capabilities.

Table 2.1 Phosphorus (P), potassium (K), and magnesium (Mg) soil test results in kg ha^{-1} and soil pH 0 to 15 cm for Brooksville, Starkville, Stoneville, and Verona in 2020 and 2021 before nutrient amendments

Location	Year	P (kg ha^{-1})	K (kg ha^{-1})	Mg (kg ha^{-1})	pH
Brooksville	2020	59	237	74	6.7
Brooksville	2021	18	268	189	6.6
Starkville	2020	129	294	105	8.3
Starkville	2021	151	268	166	8.2
Stoneville	2020	26	233	453	6.4
Stoneville	2021	82	286	851	6.3
Verona	2020	79	301	115	6.5
Verona	2021	66	228	168	8.1

Table 2.2 Treatments, first and second application rates, and total N rate applied at Brooksville, Starkville, Stoneville, and Verona, MS in 2020 and 2021

	2020			2021		
Treatment	Application 1 kg N ha^{-1}	Application 2 kg N ha^{-1}	Total N rate kg N ha^{-1}	Application 1 kg N ha^{-1}	Application 2 kg N ha^{-1}	Total N rate kg N ha^{-1}
1	0	0	0	0	0	0
2	45	0	45	90	0	90
3	45	35	80	45	45	90
4	90	0	90	135	0	135
5	45	70	115	45	90	135
6	135	0	135	180	0	180
7	45	100	145	45	135	180
8	180	0	180	225	0	225
9	45	135	180	45	180	225
10	45	170	215	270	0	270
11	225	0	225	45	225	270
12	45	200	245	-	-	-

Table 2.3 Sensor types with their respective sensed wavelengths

Sensor Name	Blue λ	Green λ	Red λ	Red Edge λ	NIR λ
Crop Circle			670	730	780
GreenSeeker			656		774
MicaSense	475	560	668	717	840
SPAD			650		940

Table 2.4 Vegetation indices used in the study table adapted from Fox (2015)

Acronym	Name	Algorithm	Reference
NDVI	Normalized Difference Vegetation Index	(R840-R650)/(R840+R650)	Rouse et al. (1973)
NDRE	Normalized Difference Red Edge	(R780-R720)/(R780+R720)	Barnes et al. (2000) Varco et al. (2013)
SCCCI	Simplified Canopy Chlorophyll Content Index	NDRE/NDVI	Barnes et al. (2000) Varco et al. (2013) Raper and Varco (2014) Fox (2015)

Table 2.5 Comparison in yield prediction between the raw or % reflectance corrected VI, INSEY, and relative VI values for the SPAD, GreenSeeker, Crop Circle, and MicaSense sensors. The best fit method based on R^2, AIC, and RMSE for each VI by sensor is bolded

Sensor	Method	n	Y	R^2	P	AIC	RMSE
SPAD	**SPAD**	**448**	**-1.39 + 0.236 X**	**0.49**	**<0.001**	**1873**	**1.945**
	SPAD-INSEY	448	6.1 + 97.2 X	0.17	<0.001	2096	2.494
	rSPAD	448	-3.95 + 13.8 X	0.48	<0.001	1888	1.976
GreenSeeker	GS-NDVI	376	11.7 – 5.67 X	0.11	<0.001	1942	3.176
	GS-INSEY	**376**	**3.75 + 6.61 x 10^3 X**	**0.11**	**<0.001**	**1941**	**3.171**
	GS-rNDVI	376	0.259 + 8.03 X	0.08	<0.001	1954	3.228
Crop Circle	CC-NDVI	1118	9.1 – 0.786 X	< 0.01	0.095	5681	3.062
	CC-INSEY (NDVI)	**1118**	**4.91 + 5.38 x 10^3 X**	**0.07**	**<0.001**	**5602**	**2.955**
	CC-rNDVI	1118	1.18 + 7.74 X	0.07	<0.001	5607	2.962
	CC-NDRE	1118	7.84 + 2.95 X	< 0.01	0.004	5675	3.054
	CC-INSEY (NDRE)	1118	3.64 + 1.72 x 10^4 X	0.16	<0.001	5491	2.812
	CC-rNDRE	**1118**	**-3.71 + 13.2 X**	**0.29**	**<0.001**	**5299**	**2.582**
	CC-SCCCI	1118	-6.4 + 35.7 X	0.21	<0.001	5418	2.723
	CC-INSEY (SCCCI)	1118	6.62 + 3.79 x 10^3 X	0.09	<0.001	5583	2.931
	CC-rSCCCI	**1118**	**-17.1 + 26.5 X**	**0.40**	**<0.001**	**5109**	**2.371**
MicaSense	MC-NDVI	322	3.93 + 7.1 X	0.11	<0.001	1404	2.120
	MC-INSEY (NDVI)	322	7.37 + 3.27 x 10^3 X	0.06	<0.001	1421	2.178
	MC-rNDVI	**322**	**-6.6 + 16.8 X**	**0.25**	**<0.001**	**1347**	**1.941**
	MC-NDRE	322	4.05 + 10.9 X	0.24	<0.001	1354	1.962
	MC-INSEY (NDRE)	322	7.09 + 5.62 x 10^3 X	0.11	<0.001	1402	2.114
	MC-rNDRE	**322**	**-3.22 + 13.6 X**	**0.44**	**<0.001**	**1251**	**1.674**
	MC-SCCCI	322	2.66 + 10.7 X	0.17	<0.001	1381	2.048
	MC-INSEY (SCCCI)	322	8.22 + 2.33 x 10^3 X	0.04	<0.001	1428	2.202
	MC-rSCCCI	**322**	**-14.6 + 24.9 X**	**0.49**	**<0.001**	**1227**	**1.611**

Table 2.6 Sensor comparison between the relative VI values for the SPAD, GreenSeeker, and Crop Circle sensors. Data was collected at the VT stage from the Brooksville, Starkville, and Verona 2020 sites. The best fit sensor based on R^2, AIC, and RMSE is bolded

Sensor	n	Y	R^2	P	AIC	RMSE
rSPAD	**144**	**-6.31 + 15.6 X**	**0.53**	**<0.001**	**647.3**	**2.243**
GS-rNDVI	144	-31.4 + 40.2 X	0.24	<0.001	714.3	2.831
CC-rNDVI	144	-35.9 + 45 X	0.31	<0.001	701.6	2.709

Table 2.7 Stage comparison between the GreenSeeker, Crop Circle, and MicaSense sensors. The best fit stage based on R^2, AIC, and RMSE is bolded

Sensor	Stage	n	y	R^2	P	AIC	RMSE
GreenSeeker	V4	88	8.77 + 1.89 X	0.05	0.029	300.6	1.291
	V6	48	8.89 + 1.6 X	0.07	0.074	152.5	1.113
	V10	**96**	**-15.1 + 21 X**	**0.52**	**<0.001**	**359.7**	**1.527**
	VT	144	-31.4 + 40.2 X	0.24	<0.001	714.3	2.831
Crop Circle	V4	275	-23.9 + 33.2 X	0.15	<0.001	1331	2.691
	V6	192	-32.2 + 42 X	0.46	<0.001	849.6	2.177
	V8	181	-3.64 + 13.5 X	0.27	<0.001	786.6	2.091
	V10	192	-25.3 + 34.6 X	0.56	<0.001	856.9	2.219
	VT	**278**	**-16.1 + 25.9 X**	**0.57**	**<0.001**	**1156**	**1.916**
MicaSense	V6	48	-45.7 + 54.9 X	0.43	<0.001	150.7	1.092
	V8	48	-60.4 + 72.7 X	0.67	<0.001	187.3	1.599
	V10	96	-23.2 + 33.8 X	0.5	<0.001	366.9	1.585
	VT	**43**	**-19.7 + 30.1 X**	**0.78**	**<0.001**	**134.3**	**1.075**
	R1	**43**	**-14 + 24.1 X**	**0.83**	**<0.001**	**124.7**	**0.962**
	R5	44	-7.2 + 17.5 X	0.54	<0.001	156	1.331

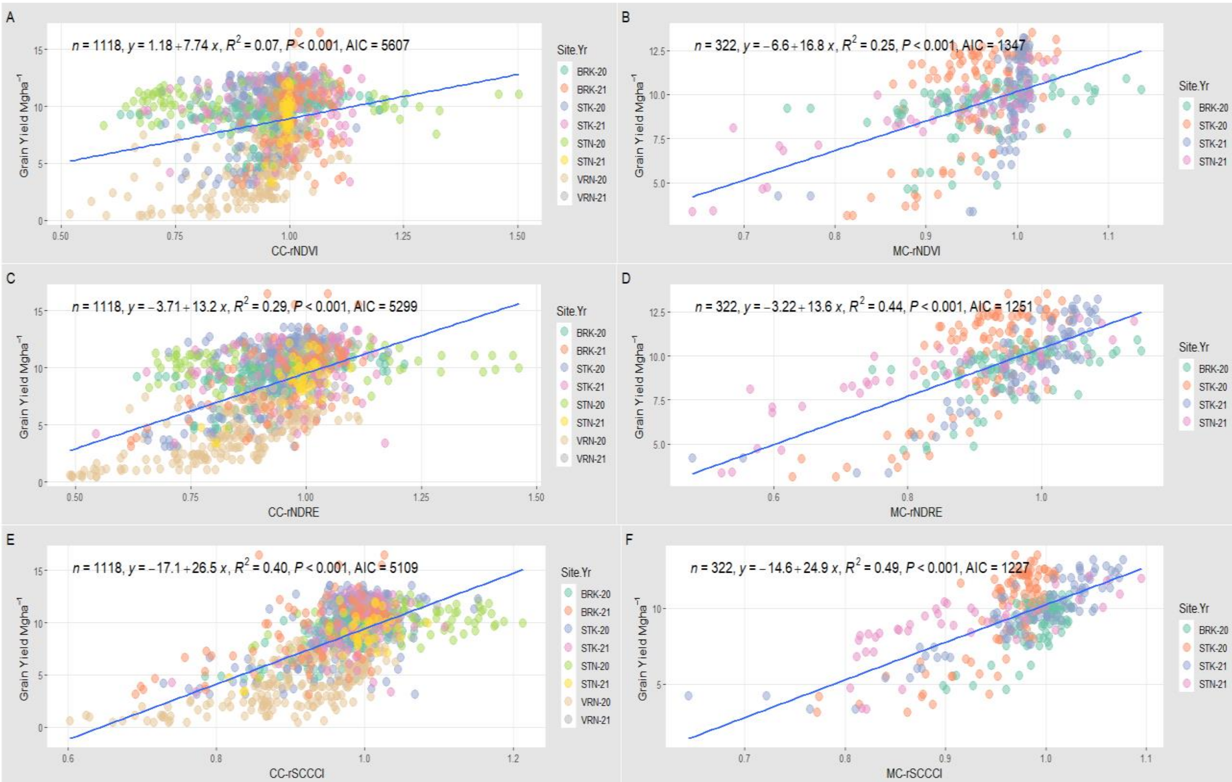

Figure 2.1 Grain yield vs. relative VI comparison when collected using Crop Circle and MicaSense sensors. Crop Circle relative VIs included NDVI (A), NDRE (C), SCCCI (E), whereas MicaSense relative VIs included NDVI (B), NDRE (D), and SCCCI (F). The number of datapoints for each equation are represented by n, the equation is represented by y, the coefficient of determination is represented by R^2, the P-value by P, and the Akaike Information Criterion by AIC

Figure 2.2 Sensor comparison between the relative VI values for the SPAD (A), GreenSeeker (B), and Crop Circle sensors (C) at the VT stage. The population for each equation is represented by n, the equation is represented by y, the coefficient of determination is represented by R2, the P-value by P, and the Akaike Information Criterion by AIC

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