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Harper Adams University

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Evaluating the use of electrical conductivity for defining variable-rate management of nitrogen and seed for corn production

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Abstract

This paper uses data from thirty-three on-farm experiments to explore the use of electrical conductivity (EC) for defining seeding and nitrogen rates for corn production. We estimate the yield response to nitrogen and seeding rates, including an interaction term with EC for each of the trial years. We then determine the optimal uniform and variables rates and compare the profits. If EC can be used on different fields and years, then the correlation between EC and the optimal rates should be consistent across fields and years. We find that the optimal variables rates do not produce profits above $5 an acre for the majority of the fields. Additionally, in different years on the same field, the high EC areas may require more or less of the inputs. The inconsistency of the relationship between EC and the optimal rates does not enable EC to be accurately used for variable rate applications across different growing years. While EC will continue to be important in detecting salt affected soils and can be calibrated for detection of specific soil elements, the use of EC for variable-rate input management is not recommended.

Keywords

Variable rate, Electrical conductivity, On-farm experimentation

Presenter Profiles

Brittani Edge is a doctoral candidate at the University of Illinois Urbana-Champaign. Her work focuses on precision agriculture and on-farm experiments. Particularly, she is interested in the economic benefits to farmers who participate in the experiments and how researchers can further improve the benefits of this line of research.

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Introduction

Today precision agriculture technology (PAT) and variable-rate technology (VRT) are widely available, and many commercial algorithms or crop consultants will provide prescriptions to farmers. However, there is not sufficient evidence that the prescriptions are profitable (Sozzi et al 2021; Colaco and Bramley 2018). Consequently, producers do not have confidence in the quality of commercial prescriptions (Bullock et al. 2020; Gardner et al. 2021). The methodologies to produce these prescriptions are also trying to replace or reduce the need for expensive data collection, such as soil sampling, with remote sensing, yield potential, or electrical conductivity. The methods used to collect soil characteristics are labour intensive, resulting in high costs for producers. Thus, farmers collect this data every few years rather than annually and a scale of one sample per acre. Electrical conductivity (EC) is a more reasonably priced alternative to soil sampling, is measured on a finer scale, and is related to soil characteristics that describe soil texture and are known to affect nitrogen response, such as clay content and organic matter (Heege 2013).

EC measures the soil's ability to conduct electrical current measured in miliseimens per meter and can be used for a variety of purposes depending on the collection area and calibration. EC can locate permafrost, gravel deposits, pollution plumes in groundwater, pipes, and other features. The many uses of EC highlight the importance of knowing what EC is being used for in a specific area before data collection. In agronomy and soil science, EC is used to locate salt affected soils and for soil mapping (McNeill 1980). While there is an existing literature the relationship between EC and crop yield, it is not clear if and how EC can be used in crop management decisions. For EC to impact the optimal management, it must be shown that EC changes the marginal response of yield to seed or nitrogen applications. If a consistent relationship can be defined between the yield response to nitrogen or seed and EC, this would be an important contribution in the PA literature. Specifically, this knowledge benefits small farmers who are unable to conduct on-farm experiments or those who are deciding whether to invest in VR equipment.

This paper investigates: (1) the suitability of EC as a characteristic for VR management of seed and nitrogen application and (2) the relationship between EC and field characteristics such as soil type and topography. In order for EC to be a suitable characteristic for defining VR management, there are two criteria. First, the estimated VR economically optimal input rates (EOIR) from EC result in profit increases over the uniform EOIR. Second, the relationship between EC and the EONR can be consistently explained so that the results can be used on different fields.

We use data from 33 maize trials to estimate the yield response functions using a shape-constrained additive model (SCAM) with smoothing functions for the nitrogen and seed treatments and interaction terms between seed, nitrogen, and EC. For each field trial, we present the profits from VR application using EC and the relationship between the estimated optimal input rates (EOIR) and EC. The results from this research show that using EC to define VR management does not increase profits in most of the fields. Further, the relationship between EC and the EOIR is not consistent across the different fields. Therefore, for most fields, EC maps are not sufficient for defining VR management of seed or nitrogen. Additionally, future literature may want to move away from VR application on homogenous fields such as these. On fields with more variation in the soil and topology, EC may describe nitrogen or seed response where we are unable to capture it in this research.

Electrical Conductivity and Management Zones

There are two types of EC sensors used in the agronomic literature. Direct sensing is the older method which uses four or more electrodes that maintain contact with the soil. Originally, these sensors were made to be carried across the field; today, this is the method used by the Veris machine that can be driven across a field rather than carried. The second is the electromagnetic method which uses two coils, one sending and one receiving, to measure resistivity of the soil without contact; the sensor is a bar that needs to be made portable through a sled and vehicle for transportation. Figure 1 contains two pictures from Sudduth et al. (2003) depicting the two EC sensors being implemented in the field. This is the method employed by the EM38 machine. Early trials in the DIFM project used an EM38 measurement, and later trials used a Veris machine. Thus, it is important to understand differences between these measurement methods.

Figure 1 Comparison of the electromagnetic and contact-based EC sensors in the field. (Left) Electromagnetic Geonics EM38 sensor (Right) Veris 3100 contact EC sensor. Source: (Sudduth et al., 2003).

Sudduth et al. 2003 give an extended theoretical description and empirical comparison of the two EC sensors. Their analysis discusses the benefits of each of the sensors and also the differences between the EC reported. For example, the Veris sensor is not prone to interference from humidity and temperature and does not need to be calibrated at each use. However, on rocky soils, the Veris machine can lose contact with the soil, resulting in clear outliers in the measurements. Apparent electrical conductivity is a weighted average of the conductivity over the soil profiles reached by the sensors. The weights for the different soil depths are described in figure 2 from Sudduth et al. 2003. Intuitively, comparing the shallow and deep readings from the Veris machine shows that the deep reading is more responsive to deeper soils than the shallow reading. On the other hand, the EM38 vertical mode is more responsive to deeper soils than Veris shallow or deep readings. Consequently, while Sudduth et al. (2003) find that EC maps taken with different sensors are similar, the differences between the sensors are more apparent with more layered soils where variation in EC may be better measured by one sensor than another. But overall, the EC reading correlated well with the clay content and CEC from analysed soil samples on the four fields included in their research (Sudduth et al. 2003). The authors emphasize that choosing the right sensor will depend on the intended use and location.

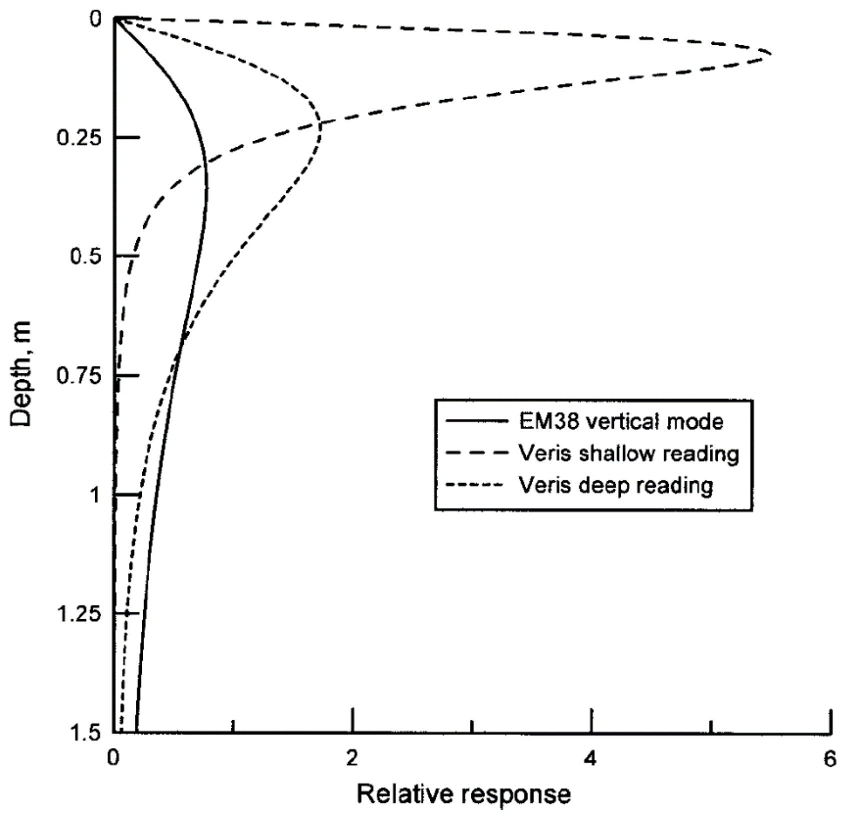

Figure 2 Response of electrical conductivity sensors as a function of soil depth Source: (Sudduth et al., 2003).

Literature on EC highlights the ambiguity of this measure; EC is correlated with clay, water, organic matter, salts, and the interactions between these variables (Heege 2013). While salt detection is not as likely in humid climates, the other variables play important roles, particularly clay and water (Heege 2013). EC and clay are highly correlated, and clay impacts yield response to nitrogen application through organic matter. Clay content and organic matter both increase yield potential; however, heavy rainfall may alter the nature of the relationship between EC and the marginal response to nitrogen. While increased organic matter can reduce the economically optimal nitrogen rate, heavy rainfall can also lead to nitrogen losses. The nitrogen losses will be higher in clay soils, which will likely have a higher EONR. These two scenarios make the relationship between EC harder to establish. As noted by Heege (2013), there is a level of clay content where the yields may decrease due to waterlogging or dense soil texture.

As expected, past research indicates both positive and negative relationships between the variable and yield (Kitchen et al. 2003; Kravchenko et al. 2003). Kravchenko et al. find that EC had a negative effect on yield when there was high March precipitation; this result is consistent with high EC values in Illinois being associated with high levels of clay, water content, and poor drainage. Soil type can also explain the relationship between EC and yield because soils contain different types of salts with different relationships to crop yield (King et al. 2005). Miao et al. (2018) compare using EC zones to soil zones for one field, finding EC zones perform better, but zones combining soil and EC perform best in terms of profits. Most recently, da Silva et al. conducted experiments on three fields in two years, finding EC and clay content to best describe yield response to seeing rate (2022). However, the derived seeding maps were designed to maximize yield rather than profits, and the second-year analysis was performed by applying the prescription, not a trial, to confirm the previous year results (da Silva et al. 2022).

This research contributes to a large literature on VR management of nitrogen and seeding rates and literature on the use of EC for VR management. Early work used soil tests to measure soil properties such as organic matter, phosphorous, and in-soil nitrogen (Carr et al. 1991; Ferguson et al. 1996; Mausbach et al. 1993). The cost of soil sampling is high due to the physical labor of taking the samples and the lab analysis; thus, early research tried to understand how much the sampling density could be reduced while maintaining profitable management zones. Ferguson et al. (2016) found low density soils maps could produce VR applications resulting resulted in higher profits than a single-rate application. (Ferguson et al. 1996). However, homogenous Midwest fields may not benefit from VR application of inputs as noted by Bullock et al. 1998 and Bullock et al. 2020.

Yield maps are a low-cost alternative to soil zones, and as stated previously, many researchers believe that yield potential is essential for determining EOIR. Unlike a soil map that may be used for a few years, one year of yield will not be representative due to weather fluctuations. Thus, research evaluating yield zones use multiple years of past yield data to delineate management zones (Ferguson et al. 1996; King et al. 2005; Hörbe et al. 2013;). The zones attempt to identify areas of the field with consistently high yield, low yield, or mixed yields. Some studies have shown profits from yield zones (Hörbe et al. 2013), but generally the relationship between yield level and EOIR appears to be weak (Bachmeir et al. 2009; Scharf et al. 2006). However, this has not dissuaded the use of yield zones or the evaluation of management zones by looking at their yield prediction. Beyond defining management zones, King identifies yield maps as a way to assess field variability and, thus, suitability for VR application (King et al. 2005). Rather than soil zones or yield zones, this paper focuses on EC; the collection of EC is cheaper than soil sampling and captures underlying soil properties and texture more directly than yield maps. The use of EC in zoning does not require multiple years of data, although it can help remove the variation due to weather.

There are several limitations and gaps in the existing literature. First, the previous literature on EC and management zones lacks economic evaluation. Many of the papers delineate management zones without assigning optimal input rates and evaluating the profits compared to an optimal uniform rate (Cillis et al. 2018; Colaco and Bramley 2018; Velasco 2020; Kayad 2021; da Silva et al. 2022). Much of the literature evaluates management zones based on yield prediction or profit comparison to the farmer's chosen rate, which may be far from the optimal uniform rate. Given recent work by Bullock et al. (2020) which indicates that the largest profit gains from agronomic trials may be from a better estimation of the optimal uniform rate, these studies are likely overestimating the profitability of the management zones. Second, the papers evaluating the use of EC for nitrogen management have limited data, from one to four fields (Cillis et al. 2018; Miao 2018; da Silva et al. 2022). This paper is unique in its access to trial data from 33 different whole-field randomized trials where EC maps are available.

Data

These data come from thirty-three completely randomized seed and nitrogen trials from 2016 to 2021 with the Data Intensive Farm Management project at the University of Illinois in Urbana-Champaign. Most trials had four nitrogen rates and four seed rates for 16 treatments. The fields differ in the nitrogen types, including UAN32, UAN28, and urea. Some fields included a base application in the fall or a preplant application. The treatment rates for nitrogen and seed are designed around the farms' status quo rates for each field; thus, the rates are not centred around the same values in each trial, nor is the range of rates the same across fields.

The trial plot dimensions are also different across fields based on the farms' equipment size. The trial plot width ensures accurate application of inputs and collection of yield in each plot. Many of these farms have a 30-foot harvester and 60-foot applicators; thus, the most common plot width is 60 feet. Additionally, the plot length is designed for enough data after eliminating the observations around the transition zone from one plot to the next, where the yield monitor is likely to have errors as it moves across plots with different treatments and mean yields. The exact length needed for accurate yield is not known and depends on the field's yield response and the yield monitor used. This is a difficult area of research due to ongoing improvements in the technology, making old results inapplicable to new yield monitors. However, recent research by Gauci et al. (2022) suggests that at a length of 200 feet the yield monitor is able to identify a change in harvest level; however, they say that a length of 397 feet may be necessary if the yield monitor is not properly calibrated. The plot length for the trials was around 280 feet given the constraints mentioned.

The trial is designed assuming the operator will drive through the middle each plot, maintaining a steady speed. However, in practice, they will take breaks, slow down and speed up, and will likely veer from the centre of the plot. All of these events cause errors in the data reported and points where they occur are removed from the final datasets. The first step in data processing is removing the headlands and sidelands of each trial. When the trials are designed, plots on the edges of the field and partial plots are assigned the rate the farmer would normally use, and these plots are not included in the analysis. There are too few observations in small plots, and the driving patterns and sun or wind exposure on the edge of the field result in unreliable data. After removing the bordering plots on the field, the yield and as applied data are cleaned removing observations outside of three standard deviations from the mean.

Rather than using the original trial plots, the yield observations are the "building blocks" for the final units of observation, where they are aggregated into groups after going through a screening to identify treatment mixing. The general steps are as follows:

1. Polygonise the yield and treatment points and intersect all polygons
2. Calculate the area-weighted deviation from the mean of the treatment rates inside each yield polygon
3. Remove yield polygons with an area-weighted deviation greater than 40 pounds of nitrogen or 20 thousand seed per acre
4. Group the yield polygons sequentially, allowing a group to continue if the treatment does not change by an amount greater than 20 pounds of nitrogen or 10 thousand seed
5. Define subgroups for each group to reach a length of at least 30 feet
6. Define polygon around each subgroup and aggregate all data into this new unit of observation

Table 1 reports the soil and field characteristics of each field. Fields 1 and 2 have low yields for multiple trial years, with average yield as low as 138 and 148 bushels per acre. Field 14 has consistently high average yields, ranging from 220 to 254 bushels per acre. In general, the high yield fields tend to have low variation while the low yielding fields have high variation in yields.

The high variation in Fields 1 and 2 may be a result of distinct but generally poor growing conditions, driven by texture or rooting depth. On the other hand, Field 14 appears to have homogenously good growing conditions across the field. As is common in Central and Northern Illinois, these fields have low variation in elevation. This may lead to results similar to those found in the past literature indicating VR applications are not profitable for this field type (Bullock et al. 1998, Thrikwala et al. 1999, Isik et al. 2001). There are differences in the soil texture due to weathering, specifically Fields 2 and 9 are on highly weathered soils.

Table 1: Table of Field Characteristics

Field	*Year*	*Yield (bu/ac) (Mean/SD)*	*ECS (Mean/SD)*	*Elevation (Mean/SD)*	*N (lbs/ac) (Mean/SD)*	*S (k/ac) (Mean/SD)*	*EC Clay Correlation (Mean/SD)*
1	2016	138.11 36.52	28.06 7.53	175.03 0.35	180 0	33.3 4.06	0.16***
	2018	173.96 36.31	27.55 7.45	175.04 0.3	156.89 0	31.33 2.7	0.17***
	2020	143.6 40.35	27.66 7.48	175.08 0.31	185.92 0	27.63 6.23	0.21***
2	2016	128.97 34.12	31.65 6.7	175.37 0.17	198.47 0	33.18 4.06	-0.25***
	2018	205.27 25.12	32.32 8.34	175.18 0.36	170.98 0	31.15 2.6	-0.45***
	2020	143.81 39.21	31.94 7.86	175.33 0.24	193.18 0	26.47 6.26	-0.35***
3	2017	172.56 29.5	21.5 6.81	174.86 0.57	199.71 0	33.05 3.84	-0.1***
4	2018	249.61 9.15	45.17 7.22	204.44 0.41	200.94 0	32.45 2.79	-0.04*
5	2017	234.88 13.39	27.48 6.36	210.14 0.58	223.46 0	35.22 2.8	0.64***
	2019	206.78 11.12	27.2 6.53	688.49 2.52	236.55 0	32.69 5.4	0.69***
6	2017	233.4 14.22	10.69 5.07	309.03 1.15	199.76 0	34.06 2.29	0.52***
	2019	185.52 16.66	10.22 4.55	309.06 1.07	183.28 0	34.8 2.51	0.38***
	2021	213.84 22.61	10.42 4.85	309 1.05	194.39 0	33.14 5.91	0.17***
7	2017	345.36 25.31	11.35 6.19	265.72 0.86	194.87 0	34.5 3.33	0.15***
	2019	200.47 17.49	10.94 6.29	265.78 0.93	NA	35.38 3.78	0.2***
8	2018	239.96 29.57	37.94 8.8	NA	229.95 0	33.54 4.05	0.37***
	2021	220.97 26.62	37.92 8.49	NA	NA	35.5 5.3	0.39***
9	2017	261.99 20.91	27.1 7.52	205.53 4.17	209.91 0	33.66 2.55	0.44***
	2021	223.72 23.24	28.29 7.22	204.04 0.27	123.9 0	30.6 3.96	0.65***
10	2018	240.07 16.23	34.12 10.36	209.66 4.28	108.27 0	32.58 2.9	0.43***

	2020	222.49	34.43	209.8	187.22	26.64	0.5***
		21.32	10.8	4.46	0	4.38	
11	2017	229.17	82.73	233.3	153.13	33.88	0.12***
		11.89	6.3	0.85	0	2.59	
12	2018	217.35	48.88	204.25	209.23	36.2	-0.66***
		30.17	6.5	0.7	0	0.09	
13	2016	228.91	27.05	205.81	198.45	34.33	0.24***
		12.67	5.98	0.53	0	3.79	
14	2016	220.5	31.59	193.43	160	33.95	-0.03
		16.73	8.39	0.75	0	4.13	
	2018	254.42	31.42	193.48	209.89	32.82	-0.06***
		19.49	8.46	0.78	0	2.46	
	2020	244.96	23.69	194.19	188.19	32.55	-0.34***
		11.32	9.12	0.62	0	6.11	
15	2017	224.67	54.18	192.23	252.97	33.74	-0.39***
		13.69	9.6	0.61	0	3.23	
	2021	237.54	54.44	192.25	139.81	33.04	-0.05***
		25.72	10.34	0.83	0	5.25	
16	2017	230.3	29.36	191.48	218.31	32.19	0.04
		15.09	5.75	0.38	0	3.5	
	2019	205.29	28.93	191.47	237.58	33.31	0.06**
		28.91	5.33	0.41	0	4.14	
17	2018	235.77	31.12	191.37	160.37	32.36	0.04
		21.96	8.32	0.6	0	3.72	

Because EC is not a direct measure of a particular soil property, the literature has emphasized the importance of understanding what EC is capturing on a field before defining a management strategy. Past research focused on this question of what soil characteristics are being captured by EC, finding clay, CEC, and Ca to be common elements associated with high EC measurements (King et al. 2005). The fields in this research do not have soil testing; thus, the SSURGO database is utilized to look at EC measurements within the different soil types and characteristics such as the drainage class. Box plots compare the EC data in each of the map units and drainage classes. For most fields, the poorly drained areas of the fields had higher EC values than well-drained or moderately drained soils. This result follows from the fact that EC increases with soil moisture and clay content. If EC is a profitable investment, it should provide more information than the publicly available SSURGO maps; thus, the fields where the SSURGO information does not explain EC are of particular interest.

Weather data is collected from the Daymet database by ORNL, and key weather measures are calculated for each field trial. Past research highlights the importance of weather not just impacting yield but also the nitrogen dynamics on the field that influence the yield response to nitrogen (Bean et al 2021; King et al. 2005; Tremblay et al 2012). We calculate measures over the whole growing season and during critical periods in the maize development. The estimated growing degree days to pollination and maturity (black layer) is often found on the breeders' websites. Combining this information with the hybrid, planting date, and daily weather data from DaymetR, we estimate the date of pollination and maturity for each trial. Then, we calculate the precipitation and temperature during a two-week period around pollination and the grain fill period from pollination until maturity. Thus, we can examine how weather around the critical growth stages impacts the potential use of EC for VR management. An additional weather measure used in the literature is the Shannon Diversity Index (SDI); the index was intended for use in species diversity across locations (Bronikowski and Webb 1996). However, several papers have adapted this measure to capture the evenness of the rainfall distribution throughout a growing season (Bean et al. 2021; Bronikowski and Webb 1996; Tremblay et al. 2012). The calculation of SDI is in equation 1 where $Rain_i$ is the rainfall on day i and N is the number of days in the calculation period.

$$SDI = \left(-\sum_{i}^{N} \frac{Rain_i}{\sum Rain_i} * \ln\left(\frac{Rain_i}{\sum Rain_i}\right)\right) \Big/ \ln(N) \quad (1)$$

The SDI calculations range between 0 (completely uneven) and 1 (completely even). When the rainfall is perfectly even across the days, SDI = 1; when all rainfall occurs on one day, SDI = 0.

Table 2 reports the rainfall and temperature measures during the growing season and critical growth stages. However, we present the total season precipitation, precipitation during pollination, precipitation during gran fill, SDI, temperature during pollination, and temperature during grain fill. Eight of the fields received less than the 45 centimetres of rain in the growing season, which is ideal for the region. Fields 1 and 2 had less than an inch of rainfall during pollination combined with an average temperature of 78, resulting in an increased variation in the yields for the 2020 trial year.

Table 2: Trial Weather Data for the Season and Critical Growth Stages

Field	Year	Prec Poll (in.)	Prec GF (in.)	SDI	Season Prec (in.)	Temp Poll (F)	Temp GF (F)
1	2016	4.88	12.34	0.72	22.11	74.94	77.88
	2018	3.51	8.91	0.68	19.10	77.61	76.57
	2020	0.40	11.49	0.68	19.41	78.80	75.36
2	2016	4.88	12.34	0.72	22.11	74.94	77.88
	2018	3.51	8.91	0.68	19.10	77.61	76.57
	2020	0.40	11.49	0.68	19.41	78.80	75.36
3	2017	0.75	4.86	0.63	16.22	78.33	74.49
4	2018	1.42	6.75	0.67	14.10	77.06	74.48
5	2017	2.88	4.46	0.66	18.95	77.04	71.19
	2019	0.34	6.68	0.69	19.42	78.37	73.56
6	2017	4.53	5.34	0.72	22.89	74.59	68.89
	2019	2.19	5.02	0.70	17.37	75.55	70.89
	2021	5.58	9.58	0.74	22.59	73.97	73.07
7	2017	6.25	8.61	0.67	21.26	71.51	66.92
	2019	1.70	16.84	0.76	33.58	75.78	67.46
8	2018	1.10	8.02	0.68	23.70	73.03	71.10
	2021	1.78	3.84	0.66	13.75	69.73	72.00
9	2017	3.51	3.03	0.61	12.63	74.31	67.99
	2021	3.71	5.86	0.69	22.51	71.63	73.70
10	2018	0.72	7.09	0.69	16.46	75.74	73.65
	2020	1.10	4.64	0.70	23.35	78.50	74.30
11	2017	1.39	5.40	0.66	22.36	75.17	73.55
12	2018	1.72	7.46	0.69	19.03	76.55	74.00
13	2016	5.10	10.04	0.72	22.07	74.68	75.38
14	2016	4.50	10.69	0.70	21.36	76.83	76.19
	2018	1.62	5.23	0.67	15.08	76.64	74.39
	2020	2.25	3.57	0.60	9.18	74.81	70.40
15	2017	2.19	4.03	0.66	11.50	76.75	70.51
	2021	3.26	5.75	0.72	18.70	72.72	74.43

Field	Year	Prec Poll (in.)	Prec GF (in.)	SDI	Season Prec (in.)	Temp Poll (F)	Temp GF (F)
16	2017	1.74	4.50	0.62	22.03	77.67	73.04
	2019	0.88	9.75	0.69	24.23	79.29	74.40
17	2018	2.15	11.14	0.66	21.57	77.48	75.95

Methods

We estimate the yield response to nitrogen and seeding rate, including an interaction with EC for both inputs. There is existing literature examining potential functional forms of yield's response to inputs. Popular forms include quadratic, quadratic plateau, linear plateau, von Leibig, and the Misterlich-Baule form. The last three are nonlinear forms that allow for non-substitutability between inputs, consistent with Leibig's Law of the Minimum (Llewelyn and Featherstone 1997). Studies comparing functional forms have consistently found that the quadratic form overestimates the maximum yield, resulting in over-estimating economically optimal nitrogen rates (Llewelyn and Featherstone 1997).

Another estimation method used in the ecology literature for predicting yield is GAM (Chen, O'Leary, and Evans 2019; Estes et al. 2013; Yee and Mitchell 1991). GAM allows flexibility in the estimated yield response and less sensitivity to outliers by introducing smoothing functions. One way of thinking about the model is that it is "data driven rather than model driven"; there is no need to specify the model before estimation (Yee and Mitchell 1991). Rather than a symmetric quadratic yield response curve, GAM can estimate a quadratic plateau if the data indicate such a response. More recently, Pya and Wood (2014) proposed a shape-constrained additive model (SCAM) that allows constraints such as concavity or monotonicity on the smoothing functions; they show that SCAM results in more efficient estimations than the more flexible GAM (Gardner et al. 2021). Here we use a SCAM estimation with zone i specific smoothing functions for seed and nitrogen rates and linear functions for field characteristics. The nitrogen function is constrained to be concave and monotonically increasing while the seed function is concave but can decrease if the seeding rate is too high. Equations (2) to (4) describe this process. First, yield is estimated as a function of nitrogen (N), seed (S), and other characteristics in the field (denoted by the vector X_C), such as topography variables.

$$y = \beta_0 + s_N(N) + s_S(S) + \beta_{ec}ec + \beta_{ecN}Nec + \beta_{ecS}Sec + \beta_{SN}SN \quad (2)$$

We estimate the optimal uniform input rate ($\widehat{EOIR}$), and optimal variable input rate ($\widehat{EONR}_i$), with subscript *VR*, and compare the profits in equations 2 and 3.

$$\pi_{VR} = \max_{(n,s)} yield(n,s,ec) - \boldsymbol{p}(n,s)\ for\ each\ observation\ j\ (3)$$

$$\pi_{UR} = \max_{(n,s)} \sum_{i}^{N} yield_{i,j}(n,s,ec) - \boldsymbol{p}(n,s)\ (4)$$

Where $\boldsymbol{p}$ is the price vector, and *j* is the observation. If $\pi_{VR} > \pi_{UR}$, then the variable rate application produces additional value beyond improving the uniform management rates. Further, if there is a consistent relationship between $\widehat{EONR}$ and EC, then we should see clear differences in the change in $\widehat{EONR}_i$ between high EC and low EC zones, and any outliers should be explained by weather or observable soil characteristics. For robustness, we also include results from an estimation with a spatial error model with a quadratic functional form.

Results

Table 3 presents the results of the yield estimation for each field. The results include the estimated uniform rate, the range of estimated optimal variable rates, the correlation between EC and the optimal seed and nitrogen rates, and the estimated profit difference between VR and UR application. The profit differences are below $5 per acre for all but two of the thirty-three fields analysed. Thus, the profit differences do not cover the cost of EC collection on the majority of fields. For field 8 which has the highest profit difference of $28 per acre, EC does not appear to be related to the soil types or the drainage class as seen in the box plots, and the correlation between EC and clay content from SSURGO is 0.37. A better understanding of what soil characteristics EC is correlated with on this field is necessary for the use of EC; note that the next year VR from EC does not induce additional profits. Similarly, field 6 has modest profits of $5.89 and $3.71 in two years but no VR estimates or profits in the last trial year.

Twenty-two trials have VR seeding although some of ranges are very narrow; thirteen fields indicate that low EC areas should receive lower seeding rates. Eighteen trials have VR nitrogen, with fifteen of those trial indicating high EC areas should receive higher nitrogen rates. The relationship between EC and seeding rate appears to be less consistent, changing across fields and between years in a single field. The three trials with a negative relationship between VR N and EC are not easily explained by field characteristics or weather; fields 1 and 2 are adjacent with similar soil and weather. Field 1 has a negative relationship between VR N for two trial years while field 2 displays a positive relationship for two trial years. Field 10 received very low rainfall during pollination and also shows a negative relationship between EC and N. The boxplots of EC and soil characteristics for this field show that EC increases in poorly drained fields and decreases in the eroded areas of the field. Combining the profit results and the consistency of the estimated relationship between EC and VR application, there is not an indication that a general management strategy could be defined from an EC map.

Table 3 Estimation Results from Analysis with EC Interaction with Seed and Nitrogen

Field	Year	UR	VR S	VR N	S Corr.	N Corr.	Profit ($/ac)
1	2016	27, 192	27 - 39	140 - 196	(+)	(-)	1.49
	2018	36, 197	30 - 36	NA	(-)		0.86
	2020	17, 288	NA	194 - 288		(-)	1.61
2	2016	39, 185	NA	181 - 197		(+)	0.06
	2018	36, 199	27 - 36	151 - 199	(-)	(+)	0.45
	2020	39, 264	NA	NA			0.00
3	2017	27, 236	NA	NA			0.00
4	2018	35, 163	35 - 37	149 - 225	(+)	(+)	0.92
5	2017	31, 202	31 - 39	168 - 230	(-)	(+)	0.50
	2019	33, 196	33 - 34	160 - 238	(-)	(+)	1.50
6	2017	30, 167	30 - 38	167 - 213	(+)	(+)	5.89
	2019	30, 218	30 - 39	210 - 252	(+)	(+)	3.71
	2021	42, 281	NA	NA			0.00
7	2017	34, 211	32 - 38	NA	(-)		0.51
	2019	35	34 - 36		(-)		0.02
8	2018	32, 167	32 - 34	167 - 231	(+)	(+)	28.79
	2021	27	NA				0.00

Field	Year	UR	VR S	VR N	S Corr.	N Corr.	Profit ($/ac)
9	2017	29, 146	NA	146 - 212		(+)	0.40
	2021	25, 237	MA	183 - 239		(+)	1.22
10	2018	33, 114	32 - 33	110 - 152	(-)	(-)	0.31
	2020	29, 231	27 - 35	NA	(+)		0.78
11	2017	33, 200	32 - 35	NA	(+)		0.74
12	2018	36, 231	NA	193 - 231		(+)	1.57
13	2016	31, 216	30 - 32	160 - 216	(-)	(+)	0.35
14	2016	28, 160	NA	160 - 220		(+)	0.00
	2018	36, 219	28 - 36	NA	(+)		0.04
	2020	29, 257	28 - 29	193 - 257	(-)	(+)	1.83
15	2017	29, 218	29 - 31	NA	(-)		0.01
	2021	30, 216	29 - 32	214 - 218	(-)	(+)	0.09
16	2017	37, 228	31 - 37	NA	(-)		0.03
	2019	38, 267	37 - 38	NA	(+)		0.01
17	2018	35, 174	34 - 35	NA	(-)		0.06

Conclusion

This research highlights the difficulty when using a measure like EC that is a proxy for many unobservable soil characteristics. While data collection may be profitable in some areas with distinct growing conditions, this is not true for the majority of fields presented here. Further, the relationship between EC and the optimal variable rates is not easily established for use across fields or years. This is a challenge faced in the management zone literature and may explain the prevalence of papers that establish management zones without defining seed or nitrogen prescriptions on the zones. EC is an important tool for mapping and detecting a variety of soil conditions for use in agriculture and other industries, but we do not find it to be promising for broad use in VRA.

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