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Indirect Estimates of Soil Electrical Conductivity for Improved Prediction of Wheat Grain Yield

M. T. Humphreys, W. R. Raun,* K. L. Martin, K. W. Freeman, G. V. Johnson, and M. L. Stone

Department of Plant and Soil Sciences, Oklahoma State University, Stillwater, Oklahoma, USA

ABSTRACT

A system of midseason prediction of winter wheat grain yield based on sensed plant growth properties has been established. However, little research has been conducted to determine the relationship of grain yield, sensed plant data, and soil electrical conductivity (EC). This study was carried out to determine if soil EC could be useful in better predicting wheat grain yield. During 2001 and 2002, measurements of soil EC, normalized difference vegetative index (NDVI), and grain yield were taken on five long-term soil fertility experiments across Oklahoma. Results indicated that soil EC was not better than mid-season NDVI readings at predicting grain yield at

*Correspondence: W. R. Raun, Department of Plant and Soil Sciences, 368 Agricultural Hall, Oklahoma State University, Stillwater, OK 74078, USA; Fax: 405-744-5269; E-mail: wrr@mail.pss.okstate.edu.

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any location or year. A combination of soil EC and NDVI was also less correlated with grain yield than NDVI alone. This study showed that pseudostatic soil EC measurements did not improve upon the in-season prediction of winter wheat grain yields that could be successfully accomplished by using NDVI alone.

INTRODUCTION

Applications of variable rate technologies (VRT) for agricultural production are becoming more apparent. Increased fertilizer costs, growing environmental concerns, and pressure to increase production on less land have resulted in a need for alternatives to current management schemes. Identification of yield level and fertilization based on this expected yield is an important aspect of nutrient management, which should result in higher use efficiencies and less environmental impact.

Methods for obtaining representative soil samples have been developed over many years. The most widely used method involves obtaining 15–20 soil samples that are then mixed together to obtain a representative sample for the field. One common example of this method is provided by Zhang and Johnson.[1] This method assumes field-level heterogeneity. This assumption is validated by a visual observation of a field of wheat with some degree of soil nitrogen (N) heterogeneity, which shows that the response to soil variables (in this case, nitrogen) is very different from one section of the field to another. However, according to Solie et al.,[2] the variability of selected parameters, such as total soil N, extractable phosphorus (P) and potassium (K), organic carbon (C), and pH, was found to be significant at the meter to submeter level. This leads one to the conclusion that the most common methods of treating soil variability, while better than nothing, may need refinement.

Current work evaluating N use in winter wheat uses canopy reflectance to estimate final grain yield.[3] It has been shown that NDVI is strongly correlated with N uptake when determined at Feekes growth stage 5 in winter wheat. The NDVI is calculated as follows: $\mathrm{NDVI} = [(\mathrm{NIR_{ref}}/\mathrm{NIR_{inc}}) - (\mathrm{Red_{ref}}/\mathrm{Red_{inc}})]/[(\mathrm{NIR_{ref}}/\mathrm{NIR_{inc}}) + (\mathrm{Red_{ref}}/\mathrm{Red_{inc}})]$, where $\mathrm{NIR_{ref}}$ and $\mathrm{Red_{ref}}$ = magnitude of reflected light, and $\mathrm{NIR_{inc}}$ and $\mathrm{Red_{inc}}$ = magnitude of the incident light. This, combined with the environmental conditions conducive to plant growth measured as days from planting to sensing where growing degree days (GDD) are >0, results in reliable estimation of final grain yield where

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$GDD = [(T_{min} + T_{max})/2–4.4°C]$ (T_{min} and T_{max} being recorded from daily data). In-season estimate of yield (INSEY) is calculated as follows:

$$\text{INSEY} = (\text{NDVI}/\text{days from planting to sensing where GDD} > 0)$$

The equation, however, can be improved upon. Identification of soil parameters, such as soil moisture capacity and soil texture, could be added to the existing INSEY equation to improve yield prediction, provided that this kind of data can be collected at the same resolution.

Kachanoski et al.[4] have shown that field scale measurements of EC are strongly correlated with soil moisture holding capacity, and Williams and Hoey[5] demonstrated the correlation of EC with soil textural properties.

Soil and plant laboratory testing has been agricultural scientists' main tool for determining nutrient availability. Whether it be pH, cation exchange capacity (CEC), NH_4-N, NO_3-N, P, K, micronutrients, or a number of other factors, soil and plant laboratory testing has been and will continue to be useful. Until recently, variability of soil parameters, such as NO_3-N, organic carbon, PO_4-P, soil water content, and K, have been unknown. Several studies have been conducted within the past 10 years to determine the resolution at which there is significant difference in soil test parameters.

However, advancements in technology and the skill to interpret the data that certain technologies will yield has opened a whole new science of nondestructive, nonintrusive diagnostic tools. Of those tools, the one of interest here is the spectral reflectance readings on plants and their correlation with grain yield data. Lukina et al.[3] made substantial progress in this area by reporting on a method to determine fertilizer N rates by using estimates of early-season plant N uptake and potential yield determined from in-season spectral reflectance measurements collected between January and April. The red (671 ± 6 nm) and near infrared (780 ± 6 nm) reflectance readings were collected from nine winter wheat experiments that were used to refine estimates of early-season plant N uptake at or near Feekes growth stage 5. For the early season plant N uptake experiments, 1-m^2 plots were immediately hand clipped after sensing and were analyzed for total N. Potential grain yield experiments were sensed in 4-m^2 areas during the growing season. Then, grain was harvested and was recorded from the same area. The results of this study indicated that NDVI was an excellent predictor of early season N uptake and that NDVI mid-season readings were also positively correlated with final grain yield. The ability to predict potential grain yield was then used in the nitrogen fertilization optimization algorithm (NFOA), which would result in an N fertilization rate based on predicted need.

The basis for treating the soil at such a small scale is found in the fact that many soil parameters vary greatly at the meter and submeter level.[2,6] In these studies, soils were sampled at a very minute scale (0.3 by 0.3 m) over a 2.13 by 21.33-m area. The resulting soil test parameters, such as total soil N, extractable P and K, organic C, and pH, were found to have large differences over small distances (<0.3 m).

Geologists and other scientists have been using soil electrical conductivity (EC) measurements during the twentieth century for finding archeological sites, pollution borders, and bedrock locations and types. However, the literature for agricultural use of soil EC measurements is quite recent (1970s), meaning that scientists are just beginning to learn about and correlate the EC data they record. Most recent articles on agricultural soil EC have referenced Williams and Hoey,[5] where it was discovered that both total soluble salts and $<2\,\mu$m clay material were correlated with apparent EC values. Since then, other soil properties have been measured, including depth to claypan,[7] soil water storage capacity,[4] saline-seep areas,[8] cation exchange capacity,[9] and herbicide behavior in the soil.[10] Kitchen et al.[11] investigated the soil EC/claypan/yield relationship. This study noted that topsoil thickness was related to a transformed EC ($1/EC_a$) and that there was a significant relationship between EC_a (apparent EC) and grain yield. However, they noted that climate, crop type, and specific field information was also needed to explain the interaction between EC_a and potential yield.

The reproducibility of Veris 3100 EC readings over multiple years is very important. In a paper presented at the Wisconsin Fertilizer, Aglime and Pest Management Conference in 2001, Tom Doerge[12] reported that the soil EC patterns obtained from a field can be stable over time. Doerge[12] goes on to note that relative accuracy is maintained unless some major soil movement by man or nature occurs. The usefulness of the Veris 3100 EC instrument is built on the ability of the system to reproduce similar results (field patterns, maps, etc.) from year to year. This is also important to the farmer in that if he obtains an EC map with the Veris instrument and is told that the data he receives is fairly accurate for a number of years, he will most likely make management decisions based on that data. Should the data prove to be unreliable from year to year, the farmer will be faced with having to obtain a new set of Veris data or continue making management decisions with the inaccurate measurements. However, if the Veris instrument data (and their patterns) are found to be statistically the same from year to year, the return on investment to the farmer could be very good.

The primary objective of this study was to improve the INSEY equation by use of EC data obtained from the fields. Raun et al.[6] have shown that there is significant soil test variability among <1-m^2 areas. The work noted before has correlated EC with various soil parameters, including depth to claypan, soil water storage capacity, saline-seep areas, and CEC. Therefore, the EC data gathered by using the Veris instrument should yield a set of data for each field that indirectly integrates differences in several soil parameters. This would, in turn, explain potential problems encountered by making fertilizer recommendations by plant sensing only, without direct reference to various soil parameters.

MATERIALS AND METHODS

This study was conducted on 5 long-term soil fertility experiments at Stillwater 222, Efaw 301, Efaw AA, Perkins N & P, and Haskell 801 (see Table 1 for soil characteristics at these locations). At each of these sites, soil EC readings were taken with a Veris 3100 EC Soil Mapping instrument during the summers of 2001 and 2002. Before the 2002 readings were taken, the instrument was tested with an instrument test load and implement test box to ensure that it was functioning properly. The Veris instrument uses 6 rotating soil-contacting discs placed

Table 1. Initial surface (0–15) soil test results for the Efaw AA, Efaw 301, Haskell 801, Perkins N & P, and Stillwater 222 sites, 2001.

			NH_4-N	NO_3-N	P	K	Total N	Organic C
Location	N-P-K	PH	(mg kg^{-1})				(g kg^{-1})	
Efaw AA	Check	6.0	2.5	11.3	19.9	197	0.94	10.4
Classification: Easpur loam (fine-loamy, mixed, superactive, thermic Fluventic Haplustoll)								
Efaw 301	Check	5.8	6.9	5.0	30.2	16.8	1.06	11.9
Classification: Norge loam (fine mixed, thermic Udertic Paleustoll)								
Perkins N & P	Check	5.4	2.6	9.1	16.5	132	0.79	7.0
Classification: Teller sandy loam (fine-loamy, mixed, thermic Udic Argiustoll)								
Stillwater 222	Check	5.9	12.0	8.6	31.8	462	0.86	7.9
Classification: Kirkland silt loam (fine-loamy, mixed, thermic Pachic Argiustoll)								
Haskell 801	Check	5.6	19.3	14.5	95.6	558	1.05	11.9
Classification: Shellabarger sandy loam (fine-loamy, mixed, thermic Udic Argiustoll)								

approximately 6 cm in the soil. One pair of discs (discs 2 and 5) passes an AC current (at 150 Hz, open circuit, voltage of 25 volts) into the soil, while the other two pairs measure the drop of the current. The Veris 3100 is capable of measuring both a shallow EC (0–30.5 cm) and a deep EC (0–91.4 cm). The EC data taken from the readout is in $mS\,m^{-1}$, with no need for any calculation. The data were georeferenced by using a Trimble (AgGPS) with differential correction (DGPS). Speed across the field was approximately 4.8 kph, giving 1 sample for every 1.5 m, and swaths were the width of the Veris cart (2.3 m).

These data were integrated into a field map for visual and statistical comparisons with plot plans by using SSToolbox programs. The various DGPS referenced points and EC data were converted into a surface grid of 4 by 4 m over the whole of each site by using the inverse distance function. A surface grid was made for shallow 2001, deep 2001, shallow 2002, and deep 2002 readings at each site by using an inverse distance function. The EC data used in statistical analysis were obtained by several steps. First, GPS readings were taken to determine the exact place of the yield potential (YP) plots since the data were taken over the whole field with no reference to a plot map. Once the YP plots were accounted for, the Veris readings were selected within the YP area to obtain an average value for either the surface grids or the specific data points. Contour maps for visual and statistical comparison of 2001 and 2002 Veris readings were also produced and analyzed.

Soil samples of each yield potential plot within each different experiment were taken before fertilization in the fall of 2001 and were analyzed for organic C, pH, EC, NH_4-N, NO_3-N, P, K, and total N. Following harvest, stepwise regression was used with these variables to identify the best predictor of yield with either single variables or a set of variables.

Winter wheat (*Triticum aestivum* L.) was planted in these fields at 78 $kg\,ha^{-1}$ with 0.19-m row spacing; NDVI readings were taken at Feekes 4, 5, and between 6 and 7. These spectral measurements were taken from the YP plots in each experiment. The YP plots were 2×2 m within larger existing long-term experimental plots. Separate NDVI readings were taken on these plots and were harvested separate from the larger plots. The reflectance measurements were taken in two bands, RED (671 ± 6 nm) and near infrared (NIR; 780 ± 6 nm) bandwidths.[13] To obtain the INSEY, NDVI (Feekes 4 to 6) was divided by the number of days from planting, where, GDD > 0.[14] Statistical analysis by using NDVI, INSEY, and yield with EC were used to evaluate the use of Veris EC data in improving the prediction of yield.[15] Weather data was also collected in 2002 for the week prior to taking the EC measurements (Table 2).

Table 2. Weather data for the week prior to taking Veris EC readings at all locations, 2002.

		Air temperature (F)				Air humidity (%)			Rain	4″ Soil temperatures			
Site	Period	Max	Min	Avg	Dewpt	Max	Min	Avg	(in)	Sod	Bare	Max	Min
Stillwater 222 unt	6/25/2002–7/5/2002	85.29	69.14	76.54	69.61	96.29	59.29	81.14	0.12	78.60	79.69	84.57	75.29
Perkins N&P unt	7/9/2002–7/15/2002	90.71	69.71	79.39	68.87	94.14	46.86	72.57	0.01	79.30	79.09	81.57	76.57
Efaw AA unt	7/10/2002–7/16/2002	89.43	67.71	78.26	68.34	96.14	47.43	73.71	0.00	80.19	83.66	89.00	78.57
Efaw 301 unt	7/10/2002–7/16/2002	89.43	67.71	78.26	68.34	96.14	47.43	73.71	0.00	80.19	83.66	89.00	78.57
Magruder till	7/20/2002–7/26/2002	97.57	72.86	84.77	69.71	87.57	39.57	63.29	0.00	83.24	88.19	94.71	82.14
Efaw AA till	9/19/2002–9/25/2002	78.43	51.14	64.69	53.94	97.86	41.14	73.00	0.05	71.31	70.67	78.00	64.14
Stillwater 222 till	9/19/2002–9/25/2002	78.43	51.14	64.69	53.94	97.86	41.14	73.00	0.05	71.31	70.67	78.00	64.14
Efaw 301 till	9/19/2002–9/25/2002	78.43	51.14	64.69	53.94	97.86	41.14	73.00	0.05	71.31	70.67	78.00	64.14

unt, untilled; till, tilled.

RESULTS AND DISCUSSION

Veris Reproducibility

The collection of data from the Veris EC instrument was completed in 2002. One of the first things observed with this data was that patterns seen in the experiment in one year were also observed in the next, though at differing intensities. Although patterns were similar, definite differences were present when studied at a small scale. Though the year-to-year likeness was the case in most of the experiments, there were exceptions.

To determine whether the patterns were significantly different, statistical analysis was performed on four of the experiment sites. The data from these sites was made into a surface of 4 by 4-m grids by using an inverse distance function. The resulting sets of data for both shallow and deep were graphed, regressed on one another, and analyzed to determine if the slope was equal to one. If it did not equal one, that would infer that from one year to the next, the data were not static but only represented significant patterns in the field. The results from this analysis can be seen in Figs. 1 and 2. Although the graphs definitely display a year-to-year trend, the statistical analysis shows that the slope of both lines was significantly different from 1 (PR > t, 0.01), especially for the Veris shallow readings. This suggests that from 2001 to 2002, the Veris

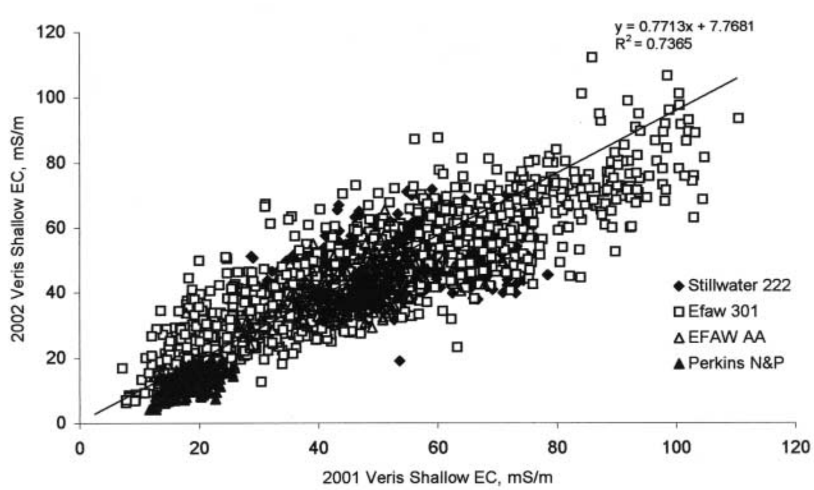

Figure 1. The relationship between 2001 and 2002 Veris shallow readings at Stillwater 222, Efaw 301, Efaw AA, and Perkins N & P, Oklahoma.

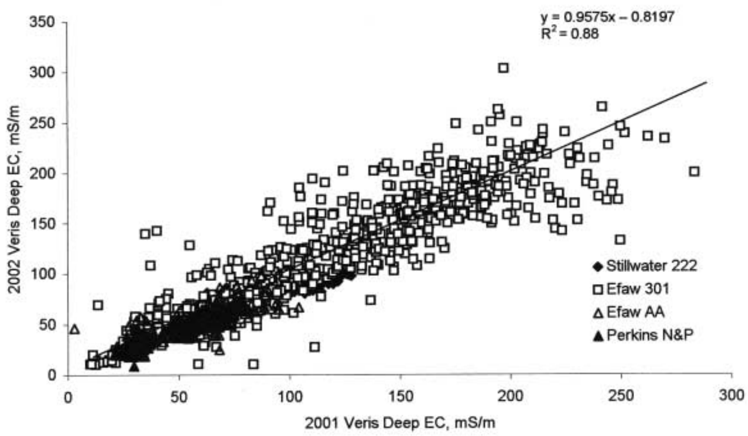

Figure 2. The relationship between 2001 and 2002 Veris deep readings at Stillwater 222, Efaw 301, Efaw AA, and Perkins N & P, Oklahoma.

readings changed relative to each other. This would perhaps lead one to call into question the reproducibility of the Veris EC readings over a long period of time. If a static variable is to be used over a period of say 10 years for managing inputs, it needs to be unaffected by time. These results clearly show that the Veris readings were significantly altered from one year to the next, even though the readings remained highly correlated with each other.

The Veris data were also tested for normality, and the results indicate that over locations and years, not one location or year was normally distributed. Several of the sites had left skewed distributions, and one site (Efaw 301, 2001, deep EC) had a bimodal distribution.

Soil Test Data Relationships

Initial 15-cm deep soil test data and laboratory results from 2001 are represented in Table 1. Simple linear regression analysis was performed on organic C, pH, lab EC (μS/m), NH_4-N, NO_3-N, P, K, total N, Veris shallow, Veris deep, and grain yield (Table 3). One interesting observation was that the EC readings obtained from the laboratory (via saturated paste extract) were not related to grain yield. It is important to note that the Veris EC instrument integrates combined effects of soil parameters, such as water content, clay content, and salts in

Table 3. Correlation coefficients (r) of soil test data with grain yield and Veris shallow and deep EC readings.

	Grain yield	Veris shallow EC	Veris deep EC	Lab EC
NH_4-N	0.349[c]	−0.289[b]	−0.359[c]	0.415[c]
NO_3-N	NS	0.557[c]	NS	0.936[c]
P	NS	NS	NS	NS
K	−0.499[c]	NS	0.486[c]	NS
pH	0.279[b]	NS	NS	0.414[c]
OC	NS	NS	NS	NS
TN	NS	NS	NS	NS
Lab EC	NS	0.479[c]	NS	—

[a,b,c]Significant at the 0.05, 0.01, 0.001 probability levels, respectively.
P, Mehlich III extractable phosphorus.
K, Mehlich III extractable potassium.
OC, soil organic carbon.
TN, total soil nitrogen.
Lab EC, saturated paste extract.
$n = 99$.

solution, whereas the lab EC reading is strictly a measurement of dissolved salts or salinity. Lab EC itself was not significantly related to yield. However, the Veris shallow reading was correlated with the lab EC with simple correlation of $r = 0.48$. Also, the Veris deep reading was not related to lab EC. Soil test NO_3-N was negatively correlated with yield due to the application of high N rates in the Haskell 801 long-term fertility experiment. At this site, plots receiving high N rates have severely reduced yields and where NO_3-N has accumulated proportionately as a function of the N rate. It was also noted that significant correlations existed between yield and NH_4-N, K, and pH.

Grain Yield and Veris Readings

The relationship between Veris readings and grain yield could be important, even though many other independent variables may be helpful in refining yield prediction models. In the beginning steps of this research, the relationship between simple Veris shallow or deep readings was observed graphically and statistically. The linear relationship between Veris shallow and deep readings with grain yield are illustrated for all

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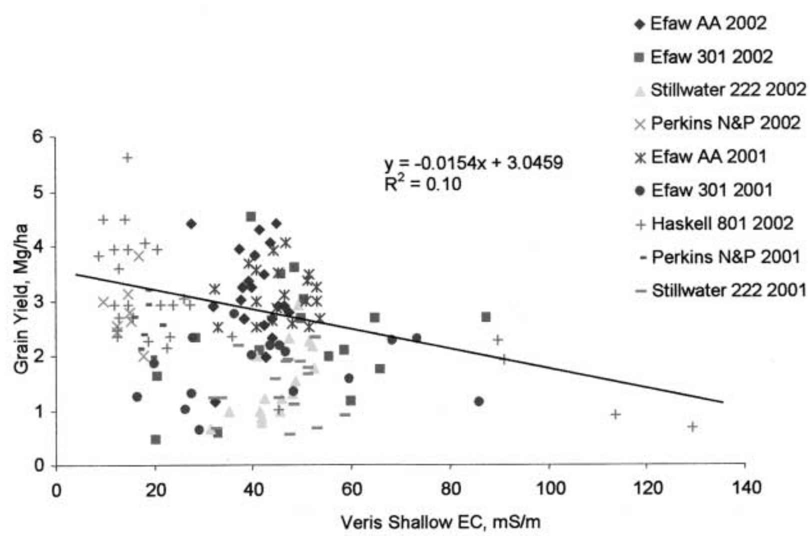

Figure 3. Relationship between Veris shallow EC and grain yield at Perkins N & P, Stillwater 222, Efaw 301, Efaw AA, and Haskell 801, Oklahoma, 2001–2002.

years in Figs. 3 and 4. Neither Veris shallow nor deep readings were correlated with grain yield. However, though there was no consistent correlation over sites, there were two site-years that were significant: Stillwater 222 shallow Veris EC with Grain Yield, and Haskell 801 both shallow and deep Veris EC with Grain Yield (Table 4). Regarding the Haskell 801 site in Haskell, OK, with an increase in Veris EC, there was a decrease in yield. This was due to the high rates of applied N on several plots in the experiment that caused dramatic yield reductions due to excessive salt accumulation.

Surface Response Models

The response in grain yield to changes in NDVI and Veris shallow was altered from one year to the next, thus restricting the temporal use of surface response models. The other independent variables evaluated in surface response models were Veris deep, Veris shallow $\times$ Veris deep, Veris shallow/Veris deep, Veris deep/Veris shallow, Relative Veris shallow/Relative Veris deep. Relative Veris shallow and Relative Veris

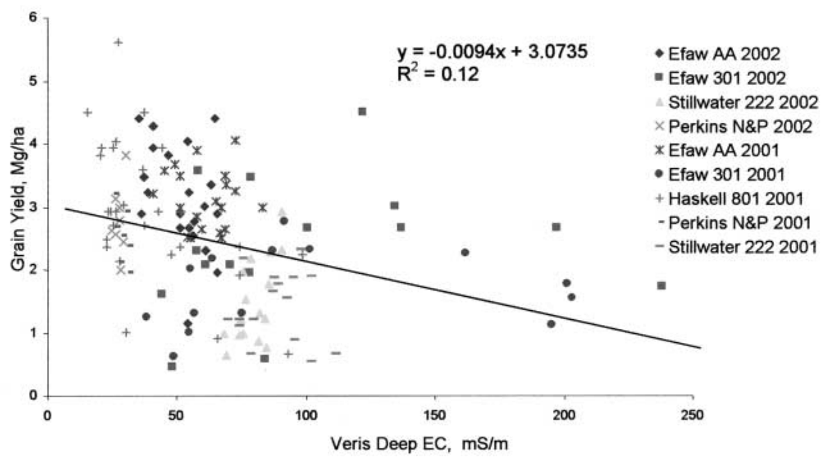

Figure 4. Relationship between Veris deep EC and grain yield at Perkins N & P, Stillwater 222, Efaw 301, Efaw AA, and Haskell 801, Oklahoma, 2001–2002.

deep consisted of the following; (1) dividing all data points at a specific site by the maximum reading; or (2) dividing all data points at a specific site by the minimum reading. The rationale behind relative Veris calculations was to provide a transformation that would take into account the differences around the mean, thus in a sense, normalizing the data. All of these transformations showed less significant trends, and none yielded a better model than Veris shallow and NDVI with grain yield.

Stepwise Regression Analysis

Soil test data, Veris EC readings, NDVI, and INSEY readings over all sites and years were all entered into a stepwise regression procedure to obtain possible variables that would improve the prediction of yield. Those variables that were found to best predict yield were NDVI, soil NO_3-N, and Veris deep EC. The following equation, using those three variables, was obtained: Yield $= -1.418 - 0.0037$ (deep EC) $- 0.0066$ (NO_3-N) $+ 6.811$ (NDVI). This equation had an R^2 of 0.71. Although it was stated before that Veris deep readings were not correlated with grain

Table 4. Correlation coefficients and associated significance for grain yield vs. the following: NDVI, INSEY, Veris readings, and Veris transformations evaluated in simple linear regression, by location over years 2001–2002.

Loc	NDVI	INSEY	Shall	Deep	Shall/ deep	Deep/ shall	RShaMx/ RDeMx	RShaMn/ RDeMn	Shall[a] ×deep	NDVI/ (Sha/De)	(NDVI + Sha)/ deep	NDVI + deep
Efaw AA	(0.544)[c]	(0.38)[b]	n	n	(0.332)[b]	(−0.35)[b]	(0.318)[b]	(0.33)[b]	n	n	(0.336)[b]	n
Efaw 301	(0.652)[c]	(0.634)[c]	n	n	n	n	n	n	n	(0.333)[a]	n	n
Stillwater 222	(0.844)[c]	(0.72)[c]	(0.352)[b]	n	n	(−0.30)[a]	n	n	n	(0.69)[c]	n	n
Perkins N & P	(0.486)[b]	(0.571)[b]	n	n	n	n	n	(−0.529)	n	n	n	n
Haskell 801	(0.645)[c]	(0.645)[c]	(−0.67)[c]	(−0.545)[c]	(−0.578)[c]	(0.453)[b]	(−0.578)[c]	(−0.578)[c]	(−0.61)[c]	(0.507)[c]	(−0.564)[c]	(−0.542)[c]

[a,b,c]Significant at the 0.1, 0.05, 0.01 levels, respectively.
RShaMx, all shallow readings divided by the maximum shallow reading, by site, by year.
RDeMx, all deep readings divided by the maximum deep reading, by site, by year.
RShaMn, all shallow readings divided by the minimum shallow reading, by site, by year.
RDeMn, all deep readings divided by the minimum deep reading, by site, by year.

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yield, it appears that the deep readings did improve multiple regression grain yield prediction a small amount.

CONCLUSIONS

Soil EC measurements were not useful for predicting grain yields in rainfed winter wheat. Although EC has been found to be correlated with grain yields in other studies, this work does not support this finding. Soil EC has been shown to be influenced by many variables, including soluble salts, depth to clay pan, soil moisture, soil texture, and surface horizon depth. Therefore, finding correlation of soil EC with yield is likely the exception rather than the rule, since the expression of each is influenced by temporal variability and spatial scale.

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