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Using On-the-Go Soil Sensors to Assess Spatial Variability within the KS Wheat Breeding Program

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Abstract.
In plant breeding the impacts of genotype by environment interactions and the challenges to quantify these interactions has long been recognized. Both macro and microenvironment variations of soil physical and chemical properties have been shown to impact breeder selections. However, traditional soil sampling techniques are restricted by cost and labor. Therefore, on-the-go and high throughput soil sensor platforms provide a potential solution for plant breeders to quantify spatial variation, particularly for early generation testing. These sensor platforms have the capability to collect data without significantly adding time or increasing cost through laboratory soil analysis. The objective of this study was to evaluate multiple soil sensor platforms and their ability to capture the soil spatial variability of experiments within the Kansas State Wheat Breeding (KSWB) program. The Veris MSP3, Veris P4000 and lab analyzed soil cores were collected at seven site years across diverse environments in Kansas. Data collected from all three methods were analyzed and ordinary kriging was performed to extrapolate soil values for the entire experiment area. In addition to individually kriged grid points the interpolated kriged data was partitioned into zones based on the K-means algorithm to determine zonal effects on genotype yield. All assessed breeding populations were grown in a modified augmented design type 2 (MAD2) to make spatial corrections based on the experimental design. Spatial adjustments by sensor were made through a multivariate model where each soil parameter was a fixed effect covariate. Spatial zones had a significant effect on population yield for many collected soil parameters ranging from 0.02 to 1.44 tons ha^{-1}. Furthermore, individual kriged values demonstrated correlation with to grain yield and the spatial adjusted yield values improved coefficient of variation (CV) over the raw yield data by an average of 5.3% and improve CV over experimental design corrections by an average of 3.2%. However, the CV's between sensor platforms were not significantly different. These results indicate that soil spatial variability exist within the KSWB program, and that on-the-go soil sensors can aid in accounting for spatial correction in plant breeding.

Keywords.
spatial variability, on-the-go soil sensor, soil, wheat

Introduction

Environmental impacts on wheat yield are well documented and mostly modulated by heat and drought stress (Lollato et al., 2017). However, variations in soil physical and chemical properties can greatly affect genotype performance both at micro and macro levels. Despite the significant impacts of soil variation on germplasm testing is a twofold limitation of cost and time that restricts the application of sampling for spatial variability within a breeding program.

To mitigate spatial variability breeding programs commonly use a variety of experimental designs and statistical analyses to account for spatial variability. However, in early generation studies where field space and seed availability are limited, single rep experiments are usually implemented, and spatial corrections are dependent on strategically placed commercial checks. Having the ability to characterize soil parameters has the potential to make spatial corrections that can out preform the experimental design. The novelty of collecting sensor-based soil parameters is that the sample size can be significantly increased without added time in the field or the added cost and time of laboratory soil analysis. Therefore, many on-the-go sensor platforms have been commercially developed for precision spatial quantification (Lund et al., 1999).

Materials and Methods

To evaluate spatial variability within the Kansas State Wheat Breeding program early generation experimental populations were grown at two locations, Reno (RN) and Thomas (TH) Counties for the 2020 and 2021 growing seasons. All experiments were conducted in a modified augmented type 2 (MAD-2) with a three-way blend commercially adapted primary check.

Prior to planting indirect measurements of soil properties were collected using two sensor platforms. The Veris MSP-3 mobile sensor cart platform (Veris Technologies, USA) was used on a 10-meter grid pattern to collect apparent electric conductivity (ECa) at the 0-30 and 0-90 cm depth and spectral reflectance at the 5 cm depth. Whereas the Veris P4000 DW-EC-Force Probe was used on a 30-meter grid pattern to collect ECa, spectral reflectance and force for the 0-20, 20-60 and 60-100cm depths. Physical soil cores were also obtained with the Veris P4000 using the core attachment on a 60-meter grid pattern. The cores were split into three depths 0-20, 20-60 and 60-100 cm and analyzed for soil physical and chemical properties, including volumetric water content, soil texture, bulk density, pH and primary macro and micronutrients.

To assess spatial patterns ordinary kriging (OK) was applied to the observed soil properties from all platforms using the 'gstat' R package (Pebesma & Graeler, 2015). Furthermore, the interpolated kriged data was partitioned into zones based on the k-means algorithm and optimized with the silhouette method. Each plot was then assigned a kriged value and cluster group through the join attributes by nearest distance function in Quantum GIS.

To test spatial zone effects on yield, a Wilcoxon test was performed on each individual zone at the 0.95 significance level. To make to make spatial corrections with plot level kriged values, a mixed multivariate model was used within the 'ASReml-R' package (Butler et al., 2009)

Results

In most cases, field experiments covered multiple k-means cluster groups (Fig 1). However, in some cases not all cluster groups were represented which could present an opportunity for cluster avoidance or cluster blocking. In cases where more than one cluster was present a significant yield differential was observed and ranged from 0.02 to 1.44 tons ha^{-1}.

Soil geo-spatial corrections improved the coefficient of variation (CV) over the raw yield data by an average of 5.3% and improve CV over experimental design corrections by an average of 3.2% (Table 1). Additionally, the MSP3 sensor had the best CV in 4 of the 7 experiments (57.1%), while the soil cores were best in 2 of the 7 experiments (28.6%) and the experimental design was best once. However, the CV differences between the soil platforms was not significant and were never greater than 1.7%.

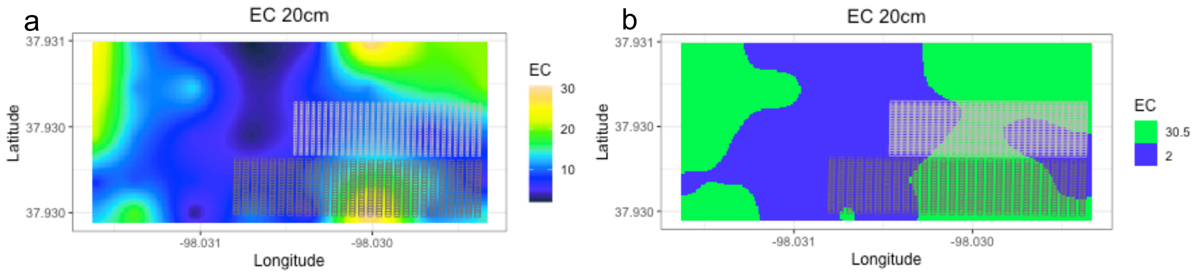

Fig 1. Kriged (a) and k-means cluster contour (b) maps for 0-20cm depth EC from the P4000 at 21RNS with PYN and YT plot map overlays. Number of color clusters in the cluster map were determined by k-means clusters and the values for the cluster color represent the median value of the cluster for ECa.

Table 1. Coefficient of Variation (CV%) of yield data from seven trial across two years. Values are obtained from the raw yields, the experimental design spatial corrections, and spatial corrections from soil core, MSP3 and P4000 data.

Year	Loc	Exp.	Raw Yield	MAD-2 Corrections	Soil Core Corrections	MSP3 Corrections	P4000 Corrections
2020	THD	AeTa	18.9%	16.6%	16.9%	17.0%	17.5%
2020	THI	DPYNA	26.7%	18.9%	14.1%	14.0%	15.7%
2021	RNN	F4	13.7%	12.7%	9.7%	9.7%	9.7%
2021	RNS	PYN	9.3%	9.1%	6.7 %	6.9%	6.8%
2021	RNS	YT	14.12%	13.7%	9.5%	9.2%	9.7%
2021	THD	PYNA	16.7%	15.3%	11.2%	11.0%	11.1%
2021	THI	DPYNA	23.9%	22.7%	17.4%	17.0%	17.4%

Conclusion

This experiment confirms that soil spatial variation within breeding experiments exist and that it has significant impacts on genotype performance. Additionally, there is support that on-the-go precision soil sensors have the capability to capture this variation similarly to traditional soil sampling methods likely due to the ability to increase sample density. However, it is unknown if these platforms would need to be used on every field for every growing season, or if more stable soil properties such as soil texture can be quantified once and used across multiple years. Furthermore, the cost of equipment and operation need to be explored prior to implementation of this technology into a breeding program.

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