Can Soil Health Measurements Improve Corn Potassium Fertilizer Recommendations?

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Corn Ideas

- The most consistent soil test parameters related to corn yield response to K fertilization included soil test K, soil organic matter, total C, and the arylsulphatase enzyme.
- Explained variability in response to K fertilization by soil test K alone was 11%
- Including additional soil health measurements improved explained variability in K response by only 7 to 10%.
- Including soil health variables measured in this study to improve K recommendations is not recommended.
- Including soil variables of soil test K, pH, soil organic matter, and total C best explained the variability in the response of corn to K fertilization. However, the overall explained variability of 23% is still low and more research is needed before the addition of more variables into the K recommendation will be completed.

INTRODUCTION

The amount of K available to plants determined through soil testing is often the only soil measurement used to make the decision of whether to apply additional K to the soil. However, there are other soil measurements that influence soil K's plant availability like pH, organic matter, and apparent cation exchange capacity that could be used to improve the accuracy of predicting whether corn will respond to additional K fertilization. This study evaluated if additional soil physical, biological, or chemical properties could be used to improve K fertilizer recommendations. The objective of this research was to determine if yield response to K fertilization predictability is improved when including selected soil fertility and soil health measurements.

MATERIALS AND METHODS

Research Sites and Experimental Design

Research trials were conducted at 28 farmer fields across central and eastern South Dakota from 2019 to 2022 (Figure 1). Locations varied in soil conditions and by management practices. The experimental design had three to five K fertilizer response trials (i.e., monitoring sites) completed in each field based on the topography of the field. The monitoring site placements were chosen with the goal of finding areas that would vary in soil test K. In total, there were 97 K fertilizer response monitoring sites. The K fertilizer treatments consisted of 0 lbs K_2O/ac (control) and one with 100 lbs K_2O/ac broadcast applied as potash (0-0-60). This rate was considered sufficient to maximize the probability of a yield response to K application and current South Dakota State K recommendations with a yield goal of 200 bu/ac. All other fertilizers (nitrogen, phosphorus, and sulfur) were broadcast applied based on the farmer's normal rate practices.

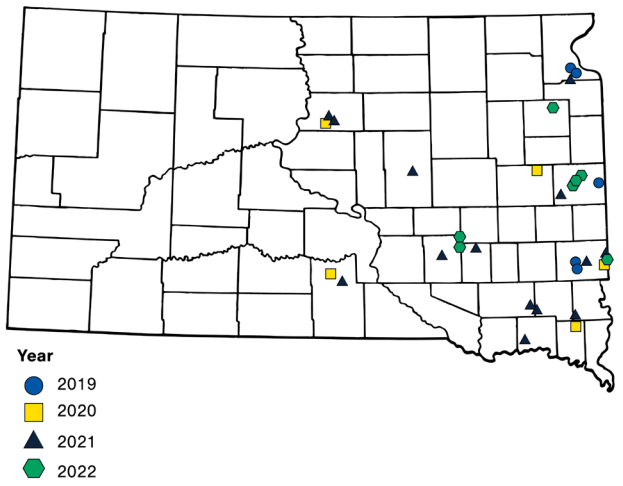

Figure 1. Research locations from the 2019-2022 growing seasons.

Sampling and Laboratory Analyses

Soil samples were obtained at each monitoring site in the spring before planting or fertilization at the 0-2 and 2-6 in. depths. These samples were analyzed for soil health (β-glucosidase, acid-phosphatase, arylsulfatase, and soil respiration), soil fertility, pH, soil organic matter, soil test K, and apparent cation exchange capacity), and C measurements (permanganate oxidizable C and total C). Grain weight from hand and combine harvesting methods were adjusted to 15.5% moisture. Relative yield was calculated by dividing the control area by the K-fertilized area and multiplying by 100.

Data Analyses

Random forest models were used to determine variables that were the most to least influential for relative yield predictions using soil fertility, soil C, and soil health measurements. The following models were evaluated in their predictability of relative yield: (1) soil test K alone; (2) common soil fertility measurements with soil test K; (3) soil fertility plus soil C (total C and POX-C); (4) soil fertility plus soil health measurements; and (5) soil fertility plus soil C plus soil health measurements. Each of the models tested were evaluated based on the calibration and validation datasets using R^2 and root-mean-square error (RMSE) values. The R^2 measures prediction error in random forest modeling. Node purity and increase in mean square error (MSE) were used to identify the most influential variables for predicting relative yield. Node purity is determined by summing the decrease in the residual sum of squares achieved at every random forest node split, across all splits and trees. The percentage increase in MSE was calculated as each variable was randomly selected and permutated over the dataset while all other explanatory variables were held constant. Greater increases in node purity and MSE provide evidence that a variable was more important to the model (Genuer et al., 2010; Hastie et al., 2009).

RESULTS AND DISCUSSION

The 0-6 in. pre-plant soil test K levels across all experimental areas ranged from 99 to 613 ppm with the average being 284 ppm. Thirty-two of the 97 experimental areas were below the current SD critical value for K recommendations of ammonium-acetate K (160 ppm). When split into thresholds according to the South Dakota Fertilizer Recommendation Guide, the 32 insufficient areas were considered medium (6 areas, 80-119 ppm) or high (26 areas, 120-159 ppm). No areas were located on soils testing in the “very low” (0-39 ppm) or “low” (40-79 ppm) categories. Corn yield from the control areas ranged between 35 and 249 bu/ac with a mean of 148 bu/ac. Once K fertilizer was applied corn yield ranged between 27 and 257 bu/ac with a mean of 144 bu/ac.

Variable Importance

The random forest machine learning technique was used to identify the importance of variables in our dataset to predict corn grain yield response to K fertilization (relative yield). The variables that were consistently in the top five of most influential variables were soil test K, soil organic matter, arylsulphatase, and total C. Of the soil health variables evaluated in this study, arylsulphatase was the only one to be listed in the top five influential variables in both variable importance methods used.

Combining Soil Fertility, C, and Soil Health Variables

Using soil test K alone to predict relative yield resulted in an R^2 value of 0.11 (Table 1). Including additional soil fertility, C, and soil health variables increased relative yield prediction by an R^2 of 0.07 to 0.10. Specifically, including additional soil fertility variables of pH, soil organic matter, and cation exchange capacity improved the relative yield prediction by an R^2 of 0.07. Beyond including soil fertility variables, including soil C variables improved the R^2 value by 0.03 while including soil health variables improved the R^2 value by 0.02. A full model including soil fertility, soil C, and soil health variables only improved the R^2 value by 0.10, which was the same as the soil fertility plus soil C model. These results indicate that including additional soil fertility variables (pH, soil organic matter, and cation exchange capacity) with soil

test K can be used to improve the prediction of relative yield. Further small improvements can be found by also including additional soil C or soil health variables. However, the improved predictability of relative yield was similar (within R^2 of 0.01) by including the evaluated soil C or soil health variables. Due to the greater cost of the soil health variables, the addition of the soil C measurements would be the best economic choice. Therefore, the use of typical soil fertility measurements and soil C without soil health measurements was the best economical option for improving the prediction of increasing corn yield from K fertilization in South Dakota.

Table 1. Model statistics for random forest algorithms predicting corn yield response to K fertilization using soil test K alone and soil fertility, soil texture, soil C, and soil health variables.

Model Input Categories	Calibration		Validation	
	R^2	RMSE	R^2	RMSE
Soil test K only	0.11	6%	0.04	10%
Soil fertility	0.18	5%	0.19	8%
Soil fertility + soil C	0.21	5%	0.16	7%
Soil fertility + soil health	0.20	5%	0.26	7%
Soil fertility + soil C + soil health	0.21	5%	0.17	7%

Soil testing costs increase with the addition of each test used in the model predicting corn yield responses to K fertilization. Therefore, we took the model with the best R^2 (Soil fertility + Soil C) and removed variables in order of lowest to highest importance. Removing POX-C from the model increased the R^2 by 0.02 and did not change RMSE (Table 2). When pH was removed from the model, the R^2 decreased and RMSE increased so we reintroduced it into the model and took out the next lowest increase in MSE variable of cation exchange capacity, which increased the R^2 back to 0.23. Removing the remaining variables of total C and soil organic matter reduced the R^2 value by 0.40 and 0.10, respectively. These results indicate the Random Forest model predicting corn yield response to K fertilization that had the best R^2 value, lowest RMSE, and contained the least number of soil tests included the variables of soil test K, pH, soil organic matter, and total C.

It is important to note that including pH, soil organic matter, and total C did improve the predictability of K response by an R^2 of 0.12 but that the overall predictability of 0.23 is still low, indicating further research is needed to improve the explained variability. Costs of additional soil testing should also be considered as adding pH, soil organic matter, and total C would increase soil testing costs.

Table 2. Model statistics for random forest algorithms predicting corn yield response to K fertilization starting with the full model containing all the soil fertility and soil C variables and then the successive models after removing variables in order of lowest to highest increase in MSE.

Change in Model		Calibration		Validation	
Input Categories[a]	Model Input Categories[a]	R^2	RMSE	R^2	RMSE
Soil fertility + soil C	STK + pH + SOM + CECa + POX-C + TC	0.21	5.3%	0.16	7.4%
-POX-C	STK + pH + SOM + CECa + TC	0.23	5.3%	0.17	7.4%
-pH	STK + SOM + CECa + TC	0.22	5.3%	0.08	7.8%
+pH, -CECa	STK + pH + SOM + TC	0.23	5.3%	0.17	7.4%
-TC	STK + pH + SOM	0.19	5.7%	0.21	7.4%
-SOM	STK + pH	0.13	6.1%	0.12	7.5%

[a]STK, Soil test K; SOM, Soil organic matter; CECa, Apparent cation exchange capacity; POXC, Permanganate oxidizable C; TC, Total C

CONCLUSIONS

The inclusion of additional soil fertility and soil C measurements improved the predictability of the models (R^2 improvement of 0.12), but the addition of the evaluated soil health variables did not further improve predictability. The simplest model with the best R^2 included the basic soil fertility variables of soil test K, pH, soil organic matter and the C measurement of total C. The lack of impact of the measured soil health variables on the R^2 values was attributed to the soil fertility and soil health testing being designed for different purposes. Therefore, the use of adding soil health measurements to improve K fertilizer decisions is not warranted but rather adding total C to basic soil fertility measurements (soil test K, pH, and soil organic matter) are the best tools for K fertilization prediction in South Dakota. It is also important to note that the best model did improve predictability by an R^2 of 0.12 but that the overall predictability of 0.23 is low, indicating further research is needed to further improve the explained variability.

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