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Abstract.

Soil health influences grain quality and yield. Within-field mapping of soil health index and grain quality can help farmers and managers to adjust site-specific farm management decisions for economic benefits. A study was conducted to map within-field soil health and grain protein and oil content variations using apparent electrical conductivity (ECa) and terrain attributes as their predictors. Two hundred and two topsoil samples were analyzed to determine soil health index based on the Haney Soil Health Tool. Grain protein and oil content were measured using CropScan monitor and ECa with DualEM sensor. Soil health index, protein and oil content were predicted using ECa and 14 terrain attributes derived from the digital elevation model. We found ECa a good predictor of soil health index and protein content, terrain attributes such as wetness index and elevation were also important. We found the field had a good soil health status and, areas with higher soil health index had higher protein content. Soil types also influenced soil health index and grain protein and oil content across the field.

Keywords.
Soil health, grain quality, geostatistics, machine learning

Mapping soil health and grain quality variations across a corn field in Texas

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Introduciton

Soil is a foundation of agriculture (Parikh & James, 2012) and its quality or health determines the yield and nutritive value of crops we grow in soils. Soil health indicates 'the capacity of soil to function as a vital living system to sustain biological productivity, promote environmental quality, and maintain plant and animal health' (Doran & Zeiss, 2000). Several physical-chemical and biological soil properties such as texture, pH, soil organic matter, moisture content, and soil organisms influence the status of soil health (Kibblewhite, Ritz, & Swift, 2008). These properties are known as soil health indicators (Soil Health Institute, 2018). Soil health indicators are used to assess soil health status, and two soil health indices common in US are the Haney Soil Health Tool (Haney, Haney, Smith, Harmel, & White, 2018) and Cornell's Comprehensive Soil Health Assessment (Moebius-Clune et al., 2016). Studies suggested that improving soil health status increased crop yield and grain quality (Brevik, 2010; van Es & Karlen, 2019), and spatial assessment of those properties at within-field scale could be useful in precision agriculture applications. Our objective was to predict and map within-field variations of HSHT, and grain protein and oil content across a corn field in Texas using apparent electrical conductivity (ECa), and topography as potential predictors.

Materials and Methods

Soil samples (*n*=202) from the topsoil (0-15 cm) were collected following a 35-m grid design and were used to determine HSHT as described in Haney et al. (2018). ECa and topographic data were used as predictors of soil health index, grain protein and oil content in the study area. ECa data were collected using a DualEM sensor, and topographic data (14 terrain attributes including slope, wetness index etc.) were derived from a digital elevation model (Adhikari et al., 2022). Corn grain quality data represented protein and oil content (%) measured on-the-go using CropScan 3300h grain quality monitor (Next Instruments, NSW, Australia) mounted to the combine (Long et al, 2005). Figure 1 shows the HSHT and grain quality measurement locations, ECa map derived from kriging using point measurement of the DualEM sensor, and an elevation map of the investigated field.

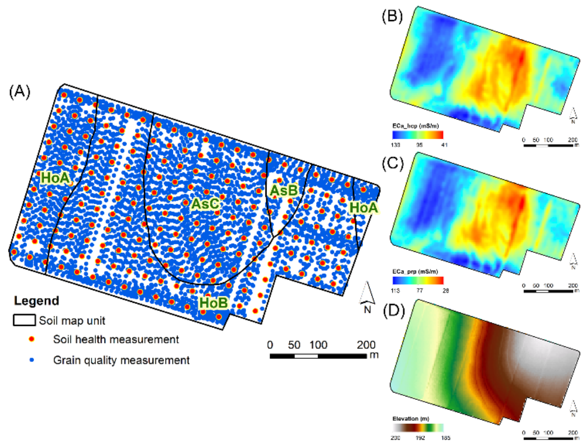

Figure 1. (A) Soil health and grain quality measurement locations; (B, C) apparent electrical conductivity measurements, and (D) elevation of the study area. [AsB: Austin silty clay, 1-3% slope; AsC: Austin silty clay, 2-5% slope; HoA: Houston Black clay, 0-1 % slope; HoB: Houston Black clay, 1-3% slope].

The model to predict soil health, protein, and oil content was built with random forest (RF) algorithms using 'randomForest' package in R program (R Development Core Team, 2008). Among the 16 predictors used (14 terrain attributes and 2 ECa), only those predictors that were significant at α=0.05 for each property were used in the prediction. The model was calibrated on 70% randomly divided observations and was evaluated on the remaining 30% using coefficient of determination (R^2), root mean square error (RMSE), and mean error (ME) indices.

Results and Discussion

The field had an average soil health index of 8.5, protein content of nearly 8%, and oil content of 3.85%. Protein content ranged between 5.81 and 10.7%, and oil content ranged between 2.13 and 6.40%. Soil health index had the highest CV (26.7%) and protein content had the lowest CV (9.3%) of all. Based on the predicted maps (Figure 2), average soil health index was 8.7, and that of protein and oil content were 8.03 and 3.75, respectively. Overall, the field had a healthy soil status. As reported in Haney et al. (2018), soil health index higher than 7.0 are generally considered good for many agricultural systems.

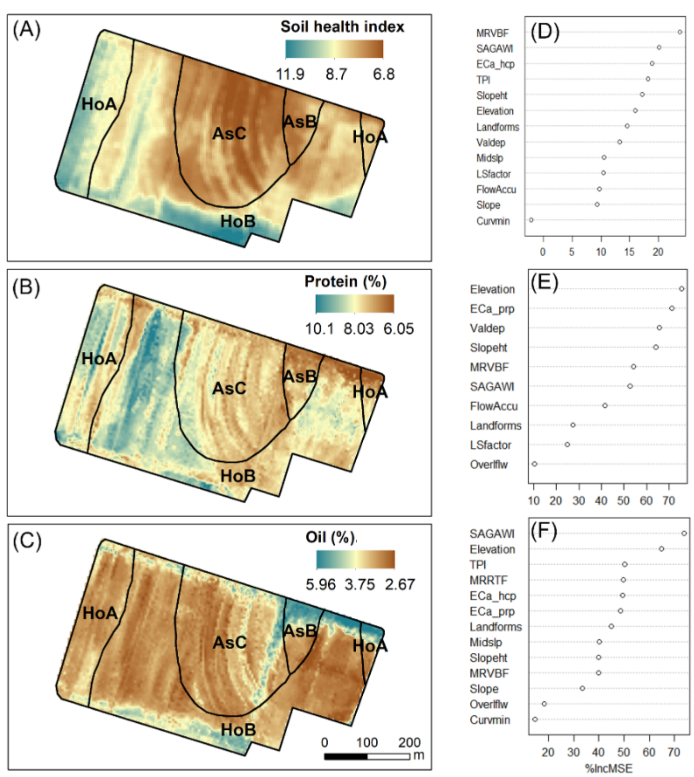

Figure 2. (A) Predicted map of soil health index, (B) protein, and (C) oil content, and their corresponding important predictors (D, E, and F). [AsB: Austin silty clay, 1-3% slope; AsC: Austin silty clay, 2-5% slope; HoA: Houston Black clay, 0-1 % slope; HoB: Houston Black clay, 1-3% slope].

Predicted map of soil health index, protein, and oil content are shown in Figure 2. Overall, the central part of the field had a lower soil health index value compared to western and southern part of the field. Protein content showed the similar spatial pattern like soil health index, most of the central and eastern part of the field had lower protein content compared to the western part of the field which had a higher protein. The map showed very low grain oil content across the field, almost all part of the field had oil content lower than the field average of 3.75%. We found that ECa had a positive correlation with soil health index and protein but a negative correlation with oil content. Similarly, terrain attributes such as wetness index, multi resolution valley button flatness index, mid slope position, and valley depth had a strong positive correlation with soil health index, whereas elevation and topographic position index had a negative correlation with the SHI. Protein content, on the other hand, was positively correlated with valley depth, wetness index, and multi resolution valley button flatness index but negatively correlated with elevation, topographic position index and multi resolution ridge top flatness index. For the oil content, all predictors including ECa were negative correlated except for elevation, topographic position index and multi resolution ridge top flatness index that were positively correlated.

While looking at the important variables in the prediction model, we found elevation, ECa, and valley depth as the top three predictors with >65% RI for grain protein content, whereas wetness index and elevation were the top predictors with RI >65% for grain oil content. For the soil health index prediction, multi resolution valley button flatness index, wetness index and ECa were the top three predictors with >20% relative importance (Figure 2d,e,f). Among the soil map units, HoA and HoB had a higher soil health index and protein content than that from soil map unit AsB and AsC. However, grain oil content was slightly higher in AsB compared to the rest of the soil map units (Figure 3).

For the model performance, grain oil content was predicted better compared to the protein prediction as the former had a higher R^2 (0.91, 0.53) and lower ME (0.00, 0.01) and RMSE (0.27%, 0.57) for both training and test datasets, respectively. For soil health index prediction, the R^2 ranged between 0.90 and 0.47 and RMSE between 0.61 and 1.38 for training and test data sets, respectively, whereas the ME for both data sets were nearly zero. We observed an influence of soil map unit in the distribution of soil health index, protein, and oil content. Soil map unit HoA and HoB had a higher soil health index and protein content compared to soil map units AsB and AsC. However, the oil content was higher AsB compared to the rest of the soil ma units (Figure 3).

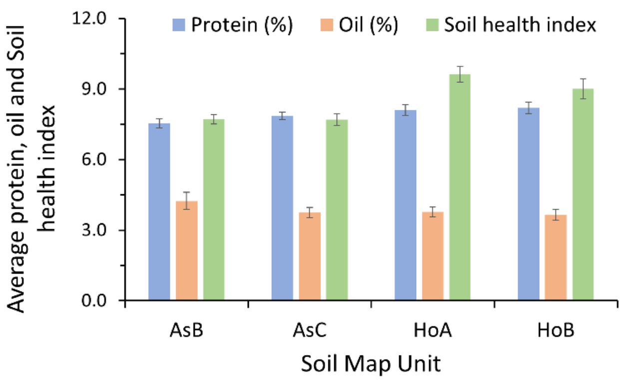

Figure 3. Protein, oil and soil health index by soil map unit based on their corresponding predicted maps. [AsB: Austin silty clay, 1-3% slope; AsC: Austin silty clay, 2-5% slope; HoA: Houston Black clay, 0-1 % slope; HoB: Houston Black clay, 1-3% slope].

Conclusion or Summary

This study investigated within-field variation of soil health and grain quality across a corn field in Texas by modeling and mapping their spatial distribution using ECa and terrain attributes as predictors. We found ECa and terrain attributes such as wetness index, multiresolution valley bottom flatness index and topographic position index were the best predictors of soil health index, and grain protein and oil content. Soil types also influenced their distribution across the field. We believe that the maps of soil health index and grain protein and oil content can be useful in precision agriculture decisions.

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References

Adhikari, Kabindra, Smith, Douglas R., Collins, Harold, Hajda, Chad, Acharya, Bharat Sharma, & Owens, Phillip R.

(2022). Mapping Within-Field Soil Health Variations Using Apparent Electrical Conductivity, Topography, and Machine Learning. *Agronomy, 12*(5), 1019.

Brevik, Eric C. (2010). Soil health and productivity. *Soils, plant growth crop production, 1*, 106.

Doran, J. W., & Zeiss, M. R. (2000). Soil health and sustainability: managing the biotic component of soil quality. *Applied Soil Ecology, 15*(1), 3-11. doi: https://doi.org/10.1016/S0929-1393(00)00067-6

Haney, R. L., Haney, E. B., Smith, D. R., Harmel, R. D., & White, M. J. (2018). The soil health tool-Theory and initial broad-scale application. *Applied Soil Ecology, 125*, 162-168. doi: 10.1016/j.apsoil.2017.07.035

Kibblewhite, M.G, Ritz, K, & Swift, M.J. (2008). Soil health in agricultural systems. *363*(1492), 685-701. doi: doi:10.1098/rstb.2007.2178

Moebius-Clune, BN, Moebius-Clune, DJ, Gugino, BK, Idowu, OJ, Schindelbeck, RR, & Ristow, AJ. (2016). Comprehensive assessment of soil health: The Cornell Framework Manual, Edition 3.2. Ithaca, NY: Cornell University.

Parikh, Sanjai J, & James, Bruce R. (2012). Soil: the foundation of agriculture. *Nature Education Knowledge, 3*(10), 2.

R Development Core Team. (2008). R: A language and environment for statistical computing. Vienna, Austria: R Foundation for Statistical Computing. Retrieved from http://www.R-project.org

Soil Health Institute. (2018, 10/8/2018). North American Project to Evaluate Soil Health Measurements. Retrieved 07/10/2020, 2020, from https://soilhealthinstitute.org/north-american-project-to-evaluate-soil-health-measurements/

van Es, H. M., & Karlen, D. L. (2019). Reanalysis Validates Soil Health Indicator Sensitivity and Correlation with Long-term Crop Yields. *Soil Science Society of America Journal, 83*(3), 721-732. doi: 10.2136/sssaj2018.09.0338