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Spatially explicit prediction of soil nutrients and characteristics in corn fields using soil electrical conductivity data and terrain attributes

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Abstract.

Site specific nutrient management (SSNM) in corn production environments can increase nutrient use efficiency and reduce gaseous and leaching losses. To implement SSNM plans, farmers need methods to monitor and map the spatial and temporal trends of soil nutrients. High resolution electrical conductivity (EC) mapping is becoming more available and affordable. The hypothesis for this study is that EC of the soil, in conjunction with detailed terrain and elevation attributes, can be used to map soil nutrients and characteristics. To test this, we have used an extensive data set of EC measurements (EM38, n = 14,199) and soil samplings (n = 522) conducted in 10 corn fields in Illinois, U.S. during the years 2000-2003. Detailed digital elevation model (5m resolution) was generated for each field using ground measurements, and was subsequently used to calculate multiple terrain attributes. The multiple fragmented layers were standardized and unified using Agmatix's Axiom platform. Here we focus on four soil micronutrients- Zn, Fe, Cu and Mn – and test the relative importance of terrain factors, elevation data and EC to serve as predictors.

A Random Forest algorithm was used to construct successive prediction models for the micronutrients using different combinations of predictors. The calibration model was established using 80% of the whole data, while the model was tested using the rest (20%) of data. The model was able to predict Zn, Fe, Cu and Mn with an RMSE of 0.23, 5.7, 0.21 and 4.3 ppm, respectively, and R2 of 0.82, 0.53, 0.71and 0.77, respectively. Terrain alone accounted for most of the prediction variability in Zn, and about half of the variability of all other three nutrients. Both elevation and EC alone were not good predictors of any of the nutrients. The best model to predict all nutrients was a model combining terrain, elevation and EC data. EC data is therefore found valuable as a complementary input for nutrient predictions. Further work is necessary to test the model on new fields not used for calibration.

Keywords.

EM38; micronutrients; machine learning; modeling; Zn; Fe; Cu; Mn; terrain; elevation; Agmatix

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1. Introduction

Site specific nutrient management can aid growers in optimizing crop production inputs, increase nutrient use efficiency, improve the return on investment, and reduce environmental pollution. There is a need to develop tools that aid farmers in understanding the spatial distribution of soil nutrients, to allow better planning and adjustment of inputs. Crops require supplemental input of nutrients to optimize crop growth and yield. Among these are macronutrients, such as potassium (K), phosphorous (P), sulfur (S), calcium (Ca) and magnesium (Mg), and micronutrients such as boron (B), copper (Cu), iron (Fe), manganese (Mn) or zinc (Zn). While soil macronutrients are frequently measured and monitored by farmers, micronutrients are in many times less monitored. Micronutrient deficiencies can hamper crop growth and contribute to potential yield loss (Alloway 2008).

Terrain attributes and the soil electrical conductivity (EC) are frequently used to map soil properties (Miao et al. 2006; Sudduth et al. 2005; Lund et al. 1999; Nawar et al. 2017; Nocco et al. 2019; Yan et al. 2007; Peralta & Costa 2013). Soil EC is an intrinsic prosperity of the soil, and as such EC readings can be useful to map spatial variability of soil properties (Lund et al. 1999). EC was found correlated to clay content, cation exchange capacity (CEC) and organic carbon (Sudduth et al. 2005). The correlation of EC to CEC supports the sensitivity of EC to the total amount of cations in the soil. It is of interest to test whether EC can be used to predict cations, particularly soil micronutrients.

The objective of this study is therefore to test the potential of soil EC and terrain data to directly predict soil micronutrients. The driving hypothesis is that EC data can increase the accuracy of soil micronutrients models compared to terrain data alone.

2. Methods

We utilize an extensive dataset, both tabular and GIS layers - of soil EC, terrain data and soil nutrients, collected in 10 corn fields during 2000-2003. All fields are located in the state of Illinois, US (Figure 1). All data were standardized and unified using Agmatix's standardization platform. The platform standardize data using GUARDS – Growing Universal Agronomic Research Data Standard – an extensive set of agronomic ontologies developed by Agmatix. Data from different files and layers is ingested through a semi-automatic procedure, where it is curated and assigned the correct GUARDS ontology. A quality assurance procedure ensures classification errors are identified and corrected. The raw data is not transformed or modified by the system. The end result is a unified database ready to be used for exploration and agronomic modeling. More information on the system can be found at www.agmatix.com.

2.1 Availabel data layers

2.1.1 Soil EC measurments, elevation and terrain data

Soil EC measurements were measured using an EM38 instrument (Geonics Limited, Ontario, Canada), and elevation data were collected using a kinematic differential global position system (DGPS). Both datasets were collected at a 6X20 meter grid in each field, and interpolated to continuous 5m grids using IDW procedure in ArcGIS (ESRI, Redlands, CA, USA).

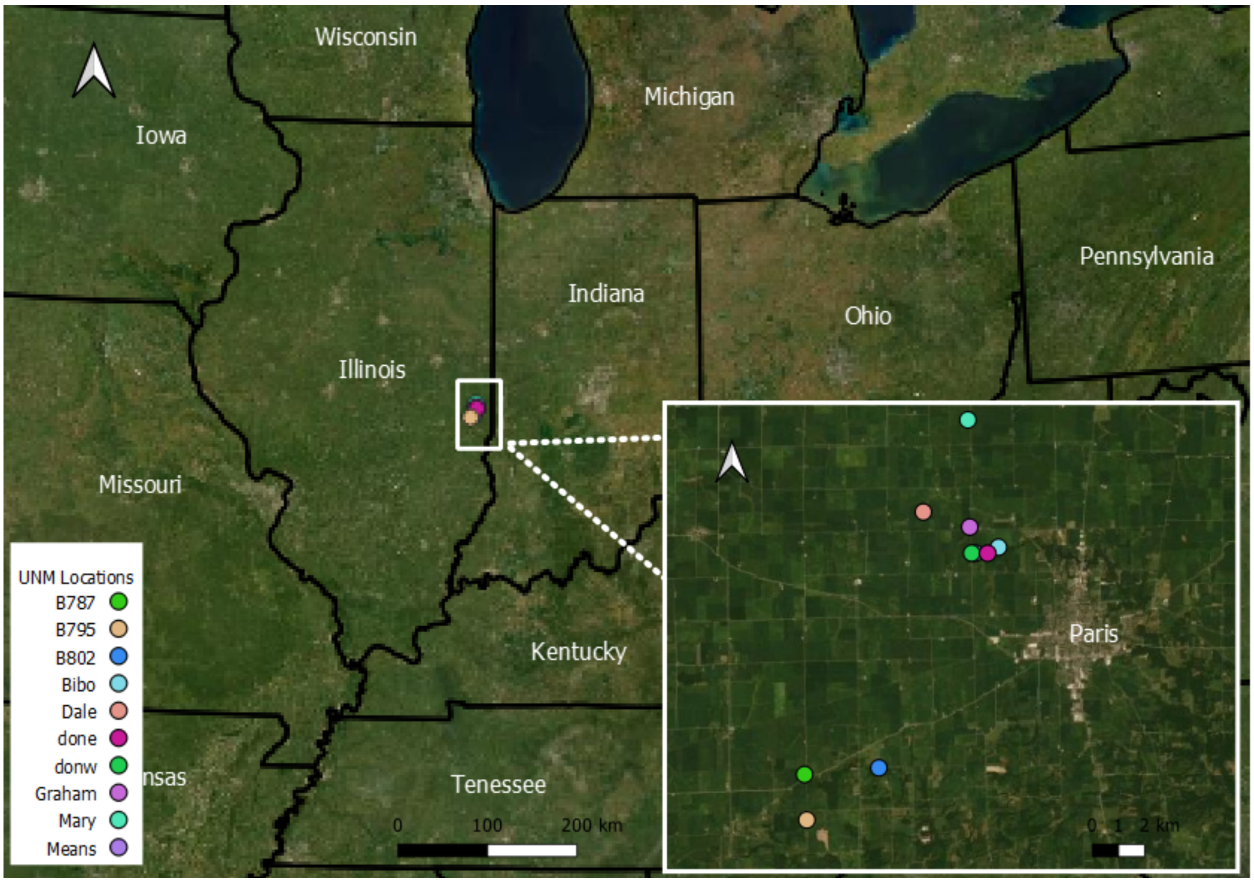

Figure 1. Location of the experimental trials at eastern part of the US state of IL.

Elevation data was used to generate 9 potential explanatory features:

i) Relative elevation [m], calculated for each field.

ii) Slope [degrees]

iii) Profile curvature [100 m^{-1}]

iv) Tangential curvature [100 m^{-1}]

v) Compound topographic index, also known as wetness index [unit less]

vi) Aspect [degrees]

vii) Planar Curvature [100 m^{-1}]

viii) Specific catchment area (SCA) [m^2/m]

ix) Stream power index [kg m^2/S^3], where S is the channel slope.

Detailed information on the calculation of each feature can be found in Miao et al. (2006).

2.1.2 Soil nutrients data

To test for spatial autocorrelation, a Moran's I test was performed for all the nutrient data of all fields. Fields that had no spatial autocorrelation were excluded from the analysis. Consequently, the number of fields used for each nutrient differs. For fields where spatial autocorrelation existed, nutrient point measurements were interpolated to 5m grid files using ordinary kriging procedure in ArcGIS (ESRI, Redlands, CA, USA).

2.1.3 Developing a database for model calibration and validation

To develop a dataset with ample amount of data points to be used in model development, in each field we have randomly generated 500 points, constraining the points to be at least 5 meter apart between each other. Within each field, the point layer was used to extract data from all raster layers (elevation, terrain, EC). Finally, nutrient data from all fields were joined altogether to create a comprehensive dataset and the nutrient-specific prediction models were developed (Table 1).

Table 1. Nutrient data points available for the analysis

Predicted variable	Number of spatially correlated fields	Number of data points used as input
Zn*	9	3305
Fe*	7	2812
Cu*	7	3000
Mn*	9	3810

*Total nutrient (ppm)

2.2 Modeling approach

For each nutrient, the data higher than three standard deviations from the mean outliers were removed as outliers. A Random Forest model, implemented using the scikit-learn package in python (Pedregosa et al. 2011), was used to predict soil micronutrients using EC, elevation and terrain attributes. To ensure good coverage of the nutrient parameter space, a stratified sampling approach was applied to split the data to training (80%) and testing (20%) datasets.

After the model was calibrated, it was validated using the independent test data set. Model efficiency was quantified using four indexes: i) R^2; ii) Mean Absolute Prediction Error (MAPE, [%]); iii) Root Mean Square Error (RMSE, [ppm]); and iv) Normalized RMSE (RMSE divided by the range of observations [%]).

3. Results and discussion

3.1 Descriptive statistics

Descriptive statistics for the four nutrients datasets are presented in Figure 2.

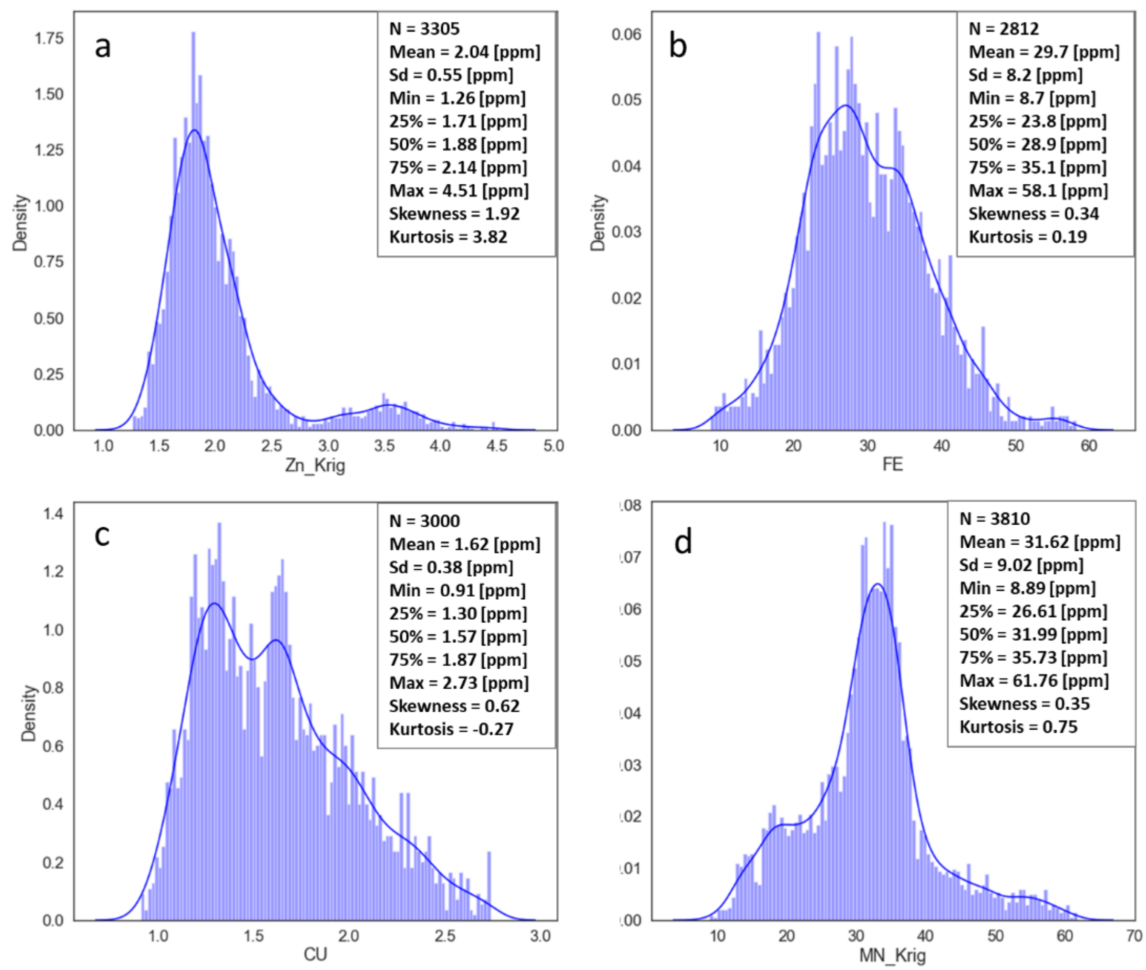

Figure 2. Histograms and descriptive data for Zinc (a), Fe (b), Cu (c), and Mn (d).

3.2 Zn prediction

Table 2 presents the efficiency of Zn prediction models produced with different input combinations. Relative elevation and EC alone were very weak predictors of Zn levels. The 8 terrain features, (referred hereafter collectively as “terrain”), were able to explain 72% of the Zn variability in the test data. Adding EC and relative elevation data to the terrain features improved prediction, and the best model was produced when all factors -terrain, relative elevation and EC data were accounted for (case 7 in Table 2, R^2 = 0.82, RMSE = 0.23 ppm, Figure 3).

Table 2. Efficiency indexes for different model inputs predicting Zn soil measurements (test data). *** for p< 0.001 ; ** for p>0.001 and p< 0.01 ; * for p>0.01 and p< 0.05; NS for p> 0.05

Case	Model inputs	R^2	MAPE(%)	RMSE(mg/kg)	NRMSE(%)
1	Relative elevation	0.00*	21.26	0.65	20.08
2	Terrain	0.72***	9.88	0.28	8.88
3	EC	0.07***	18.22	0.58	18.15
4	Relative elevation + terrain	0.76***	8.79	0.26	8.27
5	EC + terrain	0.78***	8.16	0.25	7.87
6	Relative elevation + EC	0.40***	13.63	0.42	13.02
7	Relative elevation + terrain + EC	0.82***	6.97	0.23	7.13

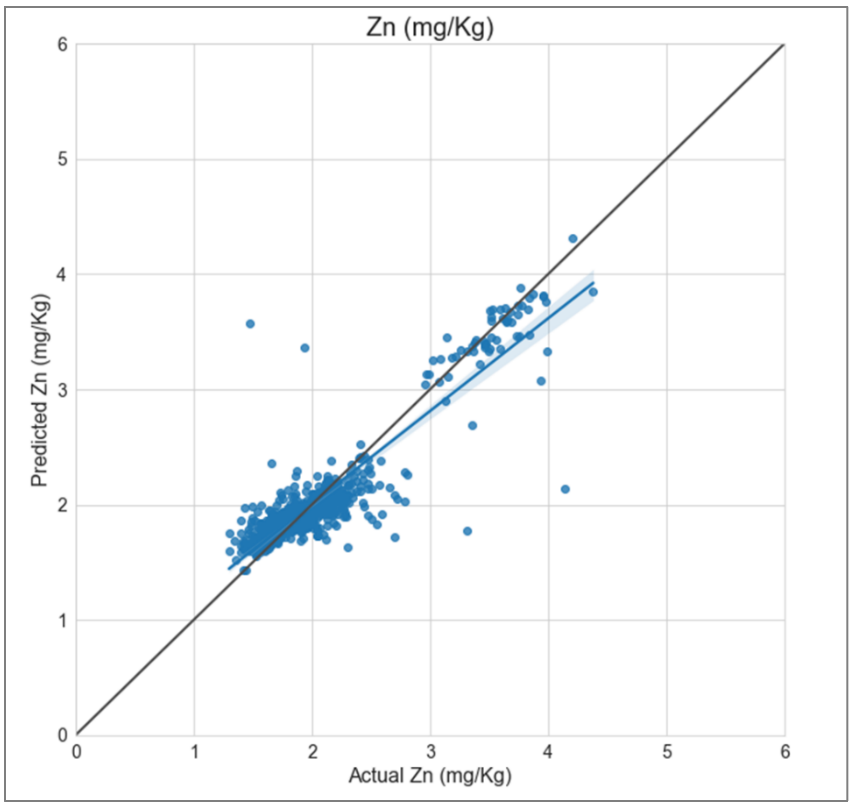

Figure 3. Predicted versus measured soil Zn values [ppm] for model #7 (test data)

3.3 Fe prediction

Table 3 presents the efficiency of Fe prediction models produced with different input combinations. Relative elevation and EC alone were very weak predictors of Fe levels. The eight terrain features were able to explain only a modest 31% of variability. Adding relative elevation increased the model R^2 to 0.49, and including all data increased it further only marginally. The best model (case 7) was able to predict Fe levels with an RMSE of 5.68 ppm, or 16% of error (Figure 4).

Table 3. Efficiency indexes for different model inputs predicting Fe soil measurements (test data). * for p< 0.001 ; ** for p>0.001 and p< 0.01 ; * for p>0.01 and p< 0.05 ; NS for p> 0.05**

Case	Model inputs	R^2	MAPE(%)	RMSE (mg/kg)	NRMSE(%)
1	Relative elevation	0.00**	28.08	9.40	19.02
2	Terrain	0.31***	19.24	6.83	13.82
3	EC	0.00 NS	29.86	9.90	20.03
4	Relative elevation + terrain	0.49***	16.41	5.93	12.01
5	EC + terrain	0.32***	18.85	6.64	13.45
6	Relative elevation + EC	0.21***	21.82	7.34	14.85
7	Relative elevation + terrain + EC	0.53***	15.57	5.68	11.50

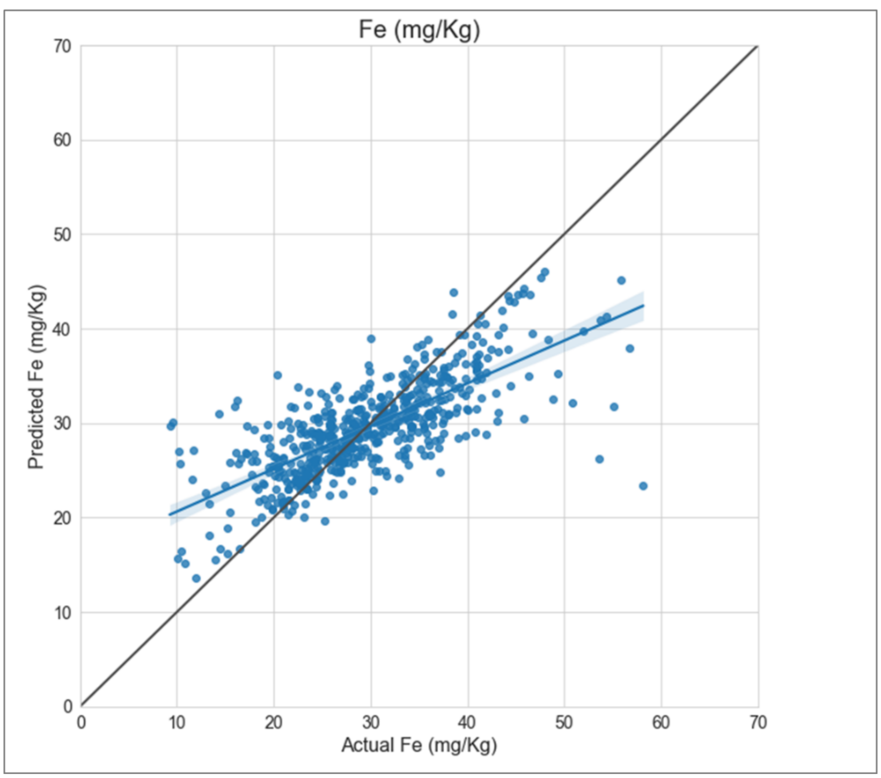

Figure 4. Predicted versus measured soil Fe values [ppm] for model #7 (test data)

3.4 Cu predictions

Table 4 presents the efficiency of Cu prediction models produced with different input combinations. Relative elevation, EC and terrain alone were weak predictors. Interestingly, adding either EC or relative elevation to the terrain substantially increased the prediction efficiency. The best model (case 7) was able to predict Cu levels with an RMSE of 0.21 ppm, or 12% of error (Figure 5).

Table 4. Efficiency indexes for different model inputs predicting Cu soil measurements (test data). * for p< 0.001 ; ** for p>0.001 and p< 0.01 ; * for p>0.01 and p< 0.05 ; NS for p> 0.05**

Case	Model inputs	R^2	MAPE(%)	RMSE(mg/kg)	NRMSE(%)
1	Relative elevation	0.10***	19.27	0.40	22.00
2	Terrain	0.22***	16.67	0.34	18.98
3	EC	0.10***	20.3	0.40	22.20
4	Relative elevation + terrain	0.54***	11.84	0.26	14.53
5	EC + terrain	0.53***	12.87	0.27	14.80
6	Relative elevation + EC	0.51***	12.88	0.27	15.05
7	Relative elevation + terrain + EC	0.71***	9.12	0.21	11.50

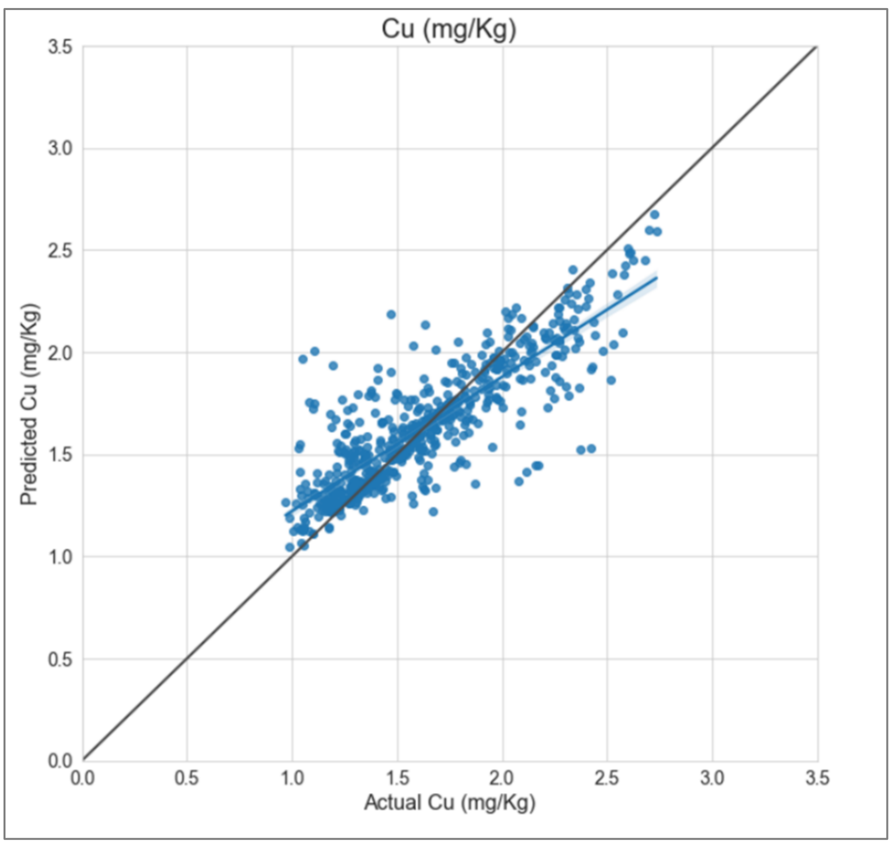

Figure 5. Predicted versus measured soil Cu values [ppm] for model #7 (test data)

3.5 Mn predictions

Table 5 presents the efficiency of Mn prediction models produced with different input combinations. Relative elevation, EC and terrain alone were weak predictors of Mn levels. Similar to the case of Mn, adding either EC or relative elevation to the terrain substantially increased the prediction efficiency. The best model (case 7) was able to predict Mn levels with an RMSE of 4.34 ppm, or 8.2% of error (Figure 6).

Table 5. Efficiency indexes for different model inputs predicting Mn soil measurements (test data). * for p< 0.001 ; ** for p>0.001 and p< 0.01 ; * for p>0.01 and p< 0.05 ; NS for p> 0.05**

Case	Model inputs	R^2	MAPE(%)	RMSE(mg/kg)	NRMSE(%)
1	Relative elevation	0.10***	27.14	9.40	17.84
2	Terrain	0.36***	21.23	7.30	13.80
3	EC	0.03***	27.57	10.14	19.18
4	Relative elevation + terrain	0.59***	16.85	5.75	10.93
5	EC + terrain	0.56***	16.46	5.99	11.34
6	Relative elevation + EC	0.49***	17.19	6.51	12.33
7	Relative elevation + terrain + EC	0.77***	11.68	4.34	8.22

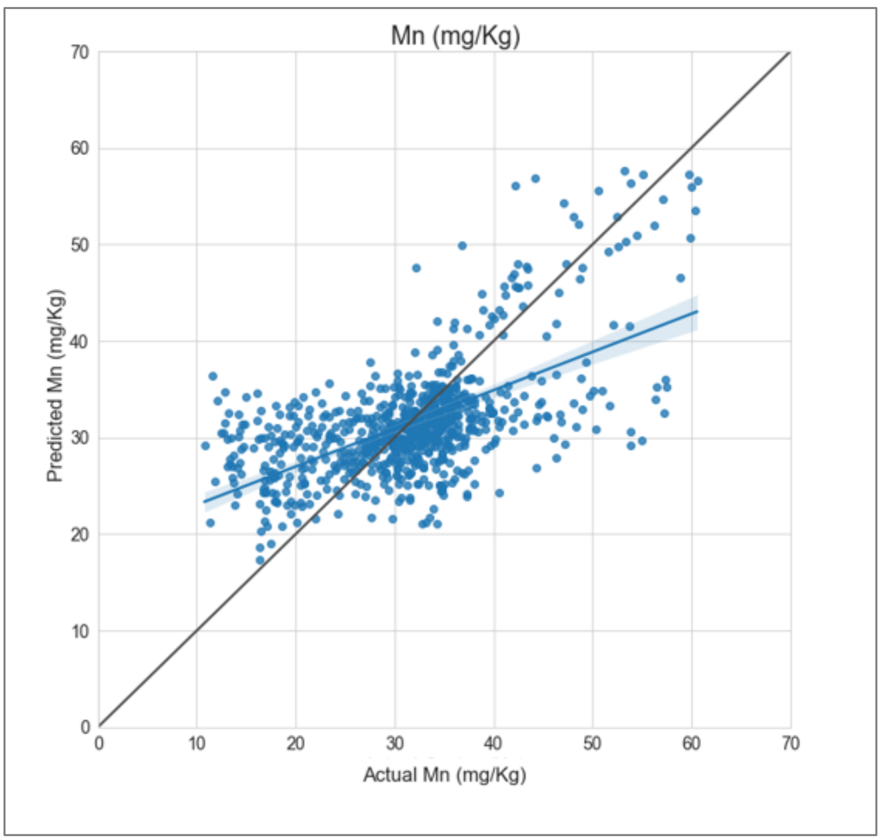

Figure 6. Predicted versus measured soil Mn values [ppm] for model #7 (test data)

4. Summary

To aid in site specific nutrient management, models for the prediction of four micronutrients were developed, and the relative importance of elevation, terrain and EC data was compared. The results suggested that terrain data alone could be good predictors only for Zn. For Cu and Mn, a combination of terrain, elevation and EC was needed to reach a reasonable prediction efficiency. For Fe, even an all-inclusive model was not able to adequately predict the nutrient level.

Our results suggested that EC alone was not a good predictor of nutrients. EC data were measured in all fields for the construction of management zones, and to study the spatial variability of soil. Thus, EC data is therefore found valuable as a complementary input to improve the prediction accuracy for soil micronutrients. Further work is necessary to develop a useful prediction model for Fe and test all the models on new fields.

5. References

Alloway, B. J. (2008). Micronutrients and Crop Production: An Introduction. *Micronutrient Deficiencies in Global Crop Production*, 1–39. doi:10.1007/978-1-4020-6860-7_1

Lund, E.D., Christy, C.D. & Drummond, P.E. (1999). Practical applications of soil electrical conductivity mapping. *Proceedings of the 2nd European Conference on Precision Agriculture*.

Miao, Y., Mulla, D.J. & Robert, P.C. (2006). Identifying important factors *influencing corn yield and grain quality variability using artificial neural networks. Precision* Agriculture, 7, 117–135. https://doi.org/10.1007/s11119-006-9004-y

Nawar, S., Corstanje, R., Halcro, G., Mulla, D. & Mouazen, A. M. (2017). Delineation of soil management zones for variable-rate fertilization: A review, *Advances in Agronomy*, 143. https://doi.org/10.1016/bs.agron.2017.01.003

Nocco, M.A., Ruark, M. D. & Kucharik, C.J. (2019). Apparent electrical conductivity predicts physical properties of coarse soils, *Geoderma* 335, 1-11. https://doi.org/10.1016/j.geoderma.2018.07.047

Pedregosa. F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B. Grisel, O. et al. (2011), Scikit-learn: Machine Learning in {P}ython. *Journal of Machine Learning Research, 12, 2825-2830.*

Peralta, N.R & Costa, J.L. (2013). Delineation of management zones with soil apparent electrical conductivity to improve nutrient management, *Computers and Electronics in Agriculture*, 99, 218-226. https://doi.org/10.1016/j.compag.2013.09.014

Sudduth, K.A., Kitchen, N.R., Wiebold, W.J., Batchelor, W.D., Bollero, G.A., Bullock, D.G., Clay, D.E., Palm, H.L., Pierce, F.J., Schuler, R.T. & Thelen, K.D. (2005), Relating apparent electrical conductivity to soil properties across the north-central USA, *Computers and Electronics in Agriculture*, 46, 263-283. https://doi.org/10.1016/j.compag.2004.11.010

Yan, L., Zhou. S., Feng, L. & Hong-Yi, L. (2007), Delineation of site-specific management zones using fuzzy clustering analysis in a coastal saline land, *Computers and Electronics in Agriculture*, 56, 174–186. https://doi.org/10.1016/j.compag.2007.01.013