Probabilistic prediction of soil nitrogen supply potential of a corn field from electromagnetic induction

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Nitrogen (N) is an important nutrient in corn (Zea mays L.) production with both N deficiency and excess N having negative effects for crop yield and quality, and/or environment. Improving N rate determination to avoid over- or under-fertilization requires knowledge of the soil N supply potential through mineralization (Nsoil) of soil organic matter (SOM). The SOM content of soil is typically estimated by loss-on-ignition (LOI). This method does not take into account differences in N pools within SOM and it is thus not possible to accurately predict Nsoil across soils. The Illinois soil nitrogen test (ISNT) [Khan et al., 2001] was shown to provide a more accurate estimation of Nsoil for corn in New York [Klapwyk and Ketterings, 2006]. Testing for ISNT-N involves soil sampling and laboratory analyses that can be time-consuming, expensive, and limited in spatial resolution. Electromagnetic induction (EMI) has become increasing popular in precision agriculture due to its ability to rapidly and inexpensively provide spatially continuous soil characterization. EMI can capture bulk soil properties, such as soil salinity, texture, cation exchange capacity, organic carbon, etc. [Corwin et al., 2003]. Hence, EMI may offer an opportunity to rapidly and inexpensively predict Nsoil at high spatial resolution.

Figure 1: The EM38-MK2 instrument mounted in a custom-made cart for the electromagnetic induction survey.

In a New York Farm Viability Institute (NYFVI) funded project, we aim to estimate Nsoil from EMI soil characterization. Toward this end, we surveyed a corn field in Central NY using a Geonics EM38-MK2 instrument mounted in a custom-made cart (**Figure 1**) to measure soil apparent electrical conductivity (EC) and magnetic susceptibility (MS). The EM38-MK2 instrument has two receivers, the 0.5 and 1 m separation receivers, so at each measurement location, a set of two EC and MS were measured. For spatial cohesion in the observed EC and MS, we resampled the EMI data on a 10 x 10 m regular grid by assigning the average of all EMI measurements in a grid to that grid location. To obtain co-located EMI and ISNT-N measurements for the predictive modeling, we collected a total of 52 soil samples over a composite depth of 0-20 cm on a one acre regular grid. Samples were analyzed for ISNT-N and LOI at the Cornell University Nutrient Management Spear Program Laboratory. We performed correlation analyses of the co-located EMI and ISNT-N data and found the EC for the 0.5 m receiver and the MS for the 1 m receiver to have the highest correlation coefficients of 0.56 and -0.70 with ISNT-N, respectively. Figures 2A and 2B show, respectively, the EC and MS datasets with the highest correlations with ISNT-N used for the predictions. Ten of the 52 co-located data points were randomly selected for model validation (red star in Figure 2A) and the remaining 42 were used for the model calibration (black closed circles in **Figure 2A**).

We applied a linear mixed model (LMM) approach [e.g., Oliver, 2010] for the ISNT-N prediction. The LMM considers the prediction as a summation of two terms, the fixed and random effect terms. Specifically, the fixed effect term was modeled as a linear combination of the covariates (EC and MS) in a least-squares sense with parameters θ_fx. The random effect term was modeled as geostatistical random variables with parameters θ_rnd,

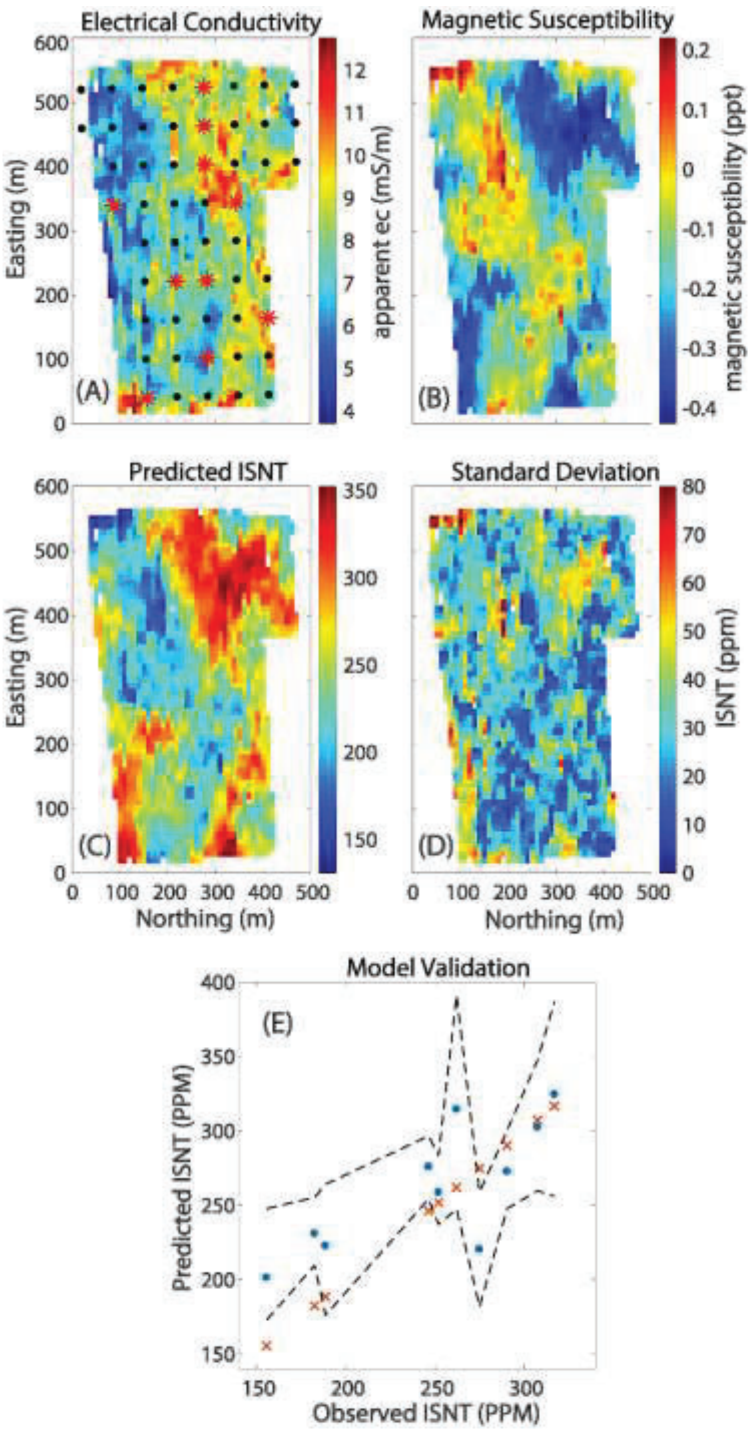

Figure 2: Observed apparent electrical conductivity (A), observed magnetic susceptibility (B), posterior mean (C) and standard deviation (D) of ISNT; scatter plot of observed vs predicted ISNT (E). The black filled circles and red stars in A show locations of the model calibration and validation data points, respectively. The black broken lines in E define the 95% confidence interval of the mean. The orange cross marks represent the one-to-one plot of the observed ISNT-N.

which are simply the parameters of a variogram (correlation length, sill and nugget variances) [e.g., Deutsch and Journel, 1998]. We first performed exploratory multivariate regression analyses of the 42 model calibration data points to find an appropriate model structure (linear here) for the fixed effect term. We also performed exploratory variogram analyses to find an appropriate variogram model (exponential here) and appropriate ranges of θ_rnd. We then applied a Bayesian Markov chain Monte Carlo (Bayesian-McMC) sampling [e.g., Oware et al., 2019] for the model (θ_fx) calibration. Precisely, for each Bayesian-McMC iteration, we sampled uniformly over the ranges of θ_rnd to estimate a covariance matrix to weigh the least-squares estimation of θ_fx to propose a model. We also considered measurement errors in the random effect term (covariance matrix). We ran the chain for 100,000 iterations and retained the last 50,000 models as posterior samples.

For the model prediction, we applied the EC and MS (**Figures 2A and 2B**) to estimate ISNT-N for the entire field. Particularly, we predicted ISNT-N for the entire field for each set of the 50,000 posterior samples of θ_fx. **Figures 2C and 2D** show, respectively, the posterior mean and standard deviations of the 50,000 ISNT-N predictions. Compared to the EC, the MS (**Figure 2B**) shows a stronger footprint on the spatial structure of the predicted mean ISNT-N, with negative MS values corresponding to high ISNT-N, and vice versa. Figure 2D shows the spatial distribution of uncertainty in the mean ISNT-N prediction, with mean and maximum uncertainty of 30 and 95 ppm, respectively. The model validation of the 10 independent ISNT-N measurements (**Figure 2E**) indicate that most of the validation data (orange cross marks in **Figure 2E**) were captured within the 95% confidence interval of the mean, which reposes confidence in the predicted ISNT-N for the entire field.

In summary, N fertilization guidelines for corn require knowledge of the amount of N that can be supplied by the soil, through soil mineralization. Knowing ISNT-N and LOI, can help identify where additional N is not needed. Here, we demonstrated the potential application of electromagnetic induction to rapidly and no-invasively estimate high resolution soil N supply potential. The results for the field in this study look promising. Data from additional fields are currently being evaluated. If EMI can accurately predict soil N supply potential at a much finer resolution and cheaper than can be done currently through analyses of soils for ISNT and LOI, it will have significant implications for guiding N use for corn.

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