A Practical Approach to the Evaluation of Proximal Soil Sensor Data Accuracy

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Introduction

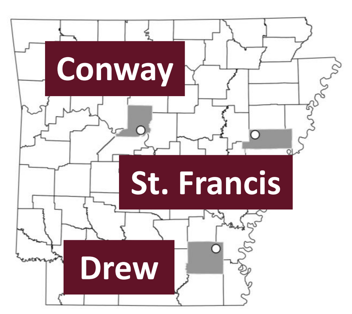
- Soil sampling is used to characterize spatial variability and inform soil fertility management.
- The **optimum sampling strategy** provides accurate, precise, and relevant representation of spatial variability. It may vary within a field or cropping system.

Can proximal soil sensing be used to inform soil sampling strategy in Arkansas?

Project Objective

Develop a method that evaluates proximal soil sensor data accuracy.

Experimental Setup



- 3 cropping systems
- 3 neighboring fields per system
- Field size from 10 to 20 ha
- Different management practices

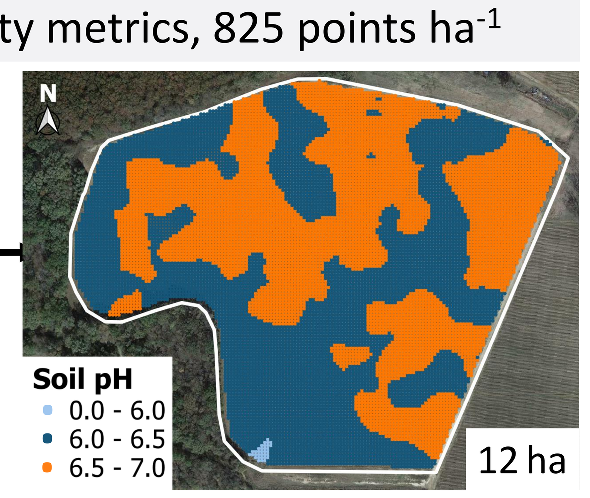
Data Collection

Figure 1: Sensor data collection setup

Ground-based mobile platform
GNSS receiver, RTK Accuracy
Gamma-ray spectrometer. 5 Hz sampling frequency, data collected along parallel passes (12m). Influence ≈ 2m wide x 15cm depth

Figure 2: Final sensor data product consisting of a point shapefile, specific soil fertility metrics, 825 points ha^{-1}

Data Processing:
- Calibration
- Interpolation



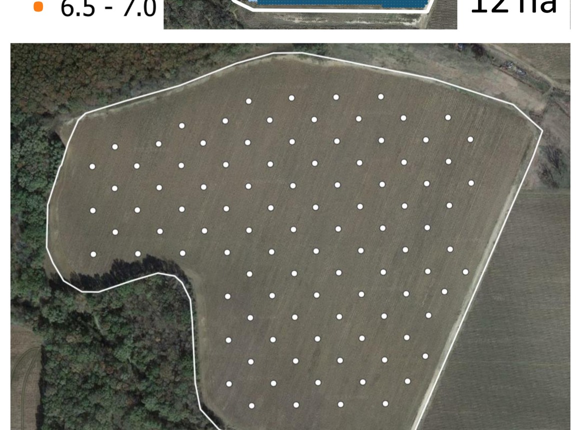


Figure 3: Soil sampling strategy for ground-truthing. In each field, 100 soil samples were collected at the 0-15.2 cm depth using diamond grid strategy.

Proposed Statistical Approach and Application to Collected Gamma-Ray Spectrometer and Soil Test pH Data

1. Ground-Truth Characterization of Variability

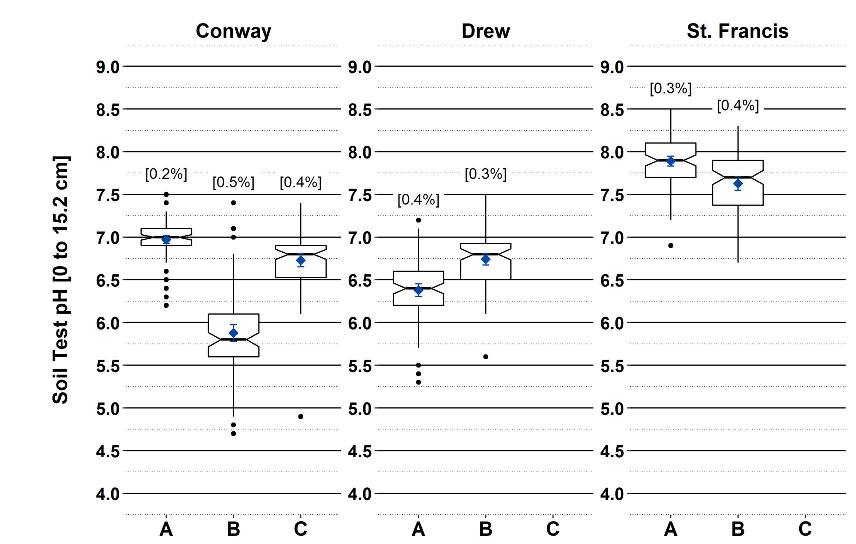


Figure 4: Distribution of soil test pH by field and cropping system.

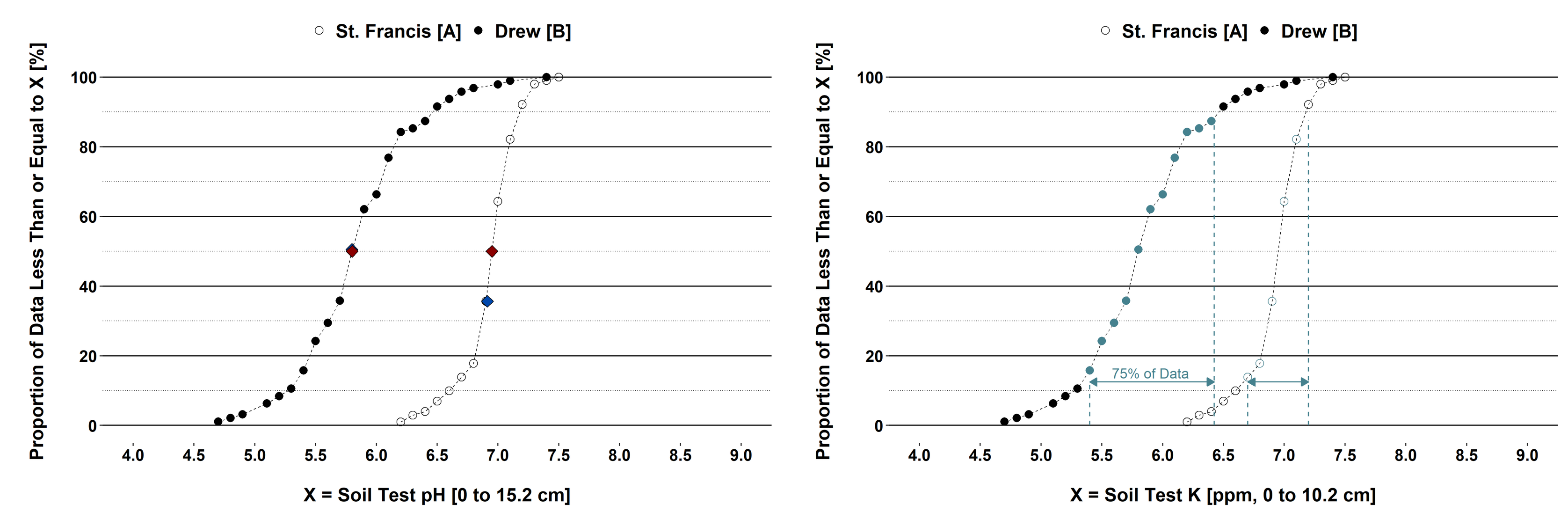


Figure 5: Characterization of the empirical distribution of soil pH. Different metrics were created to capture differences in central tendency, skew, and variability.

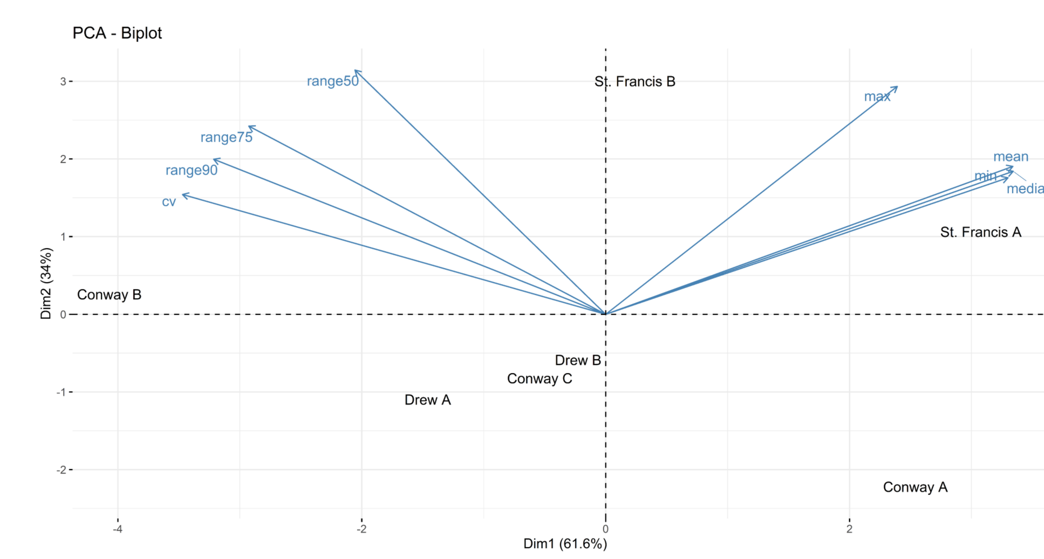


Figure 6: Field and cropping system classification of soil pH using principal component analysis.

2. Sensor (Non-Spatial) Data Distribution Accuracy

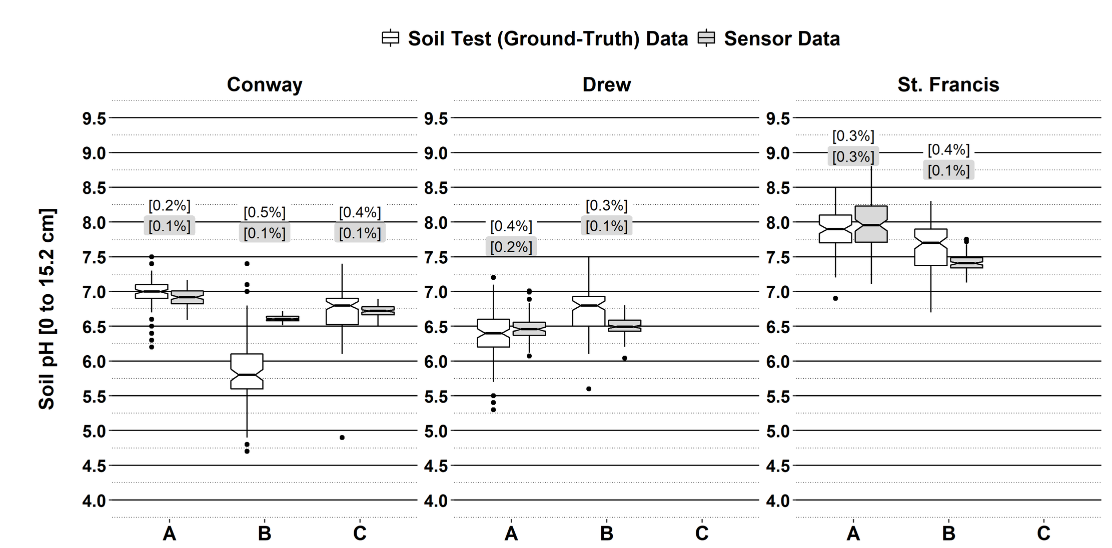


Figure 7: Side-by-side comparison of sensor and soil test pH data.

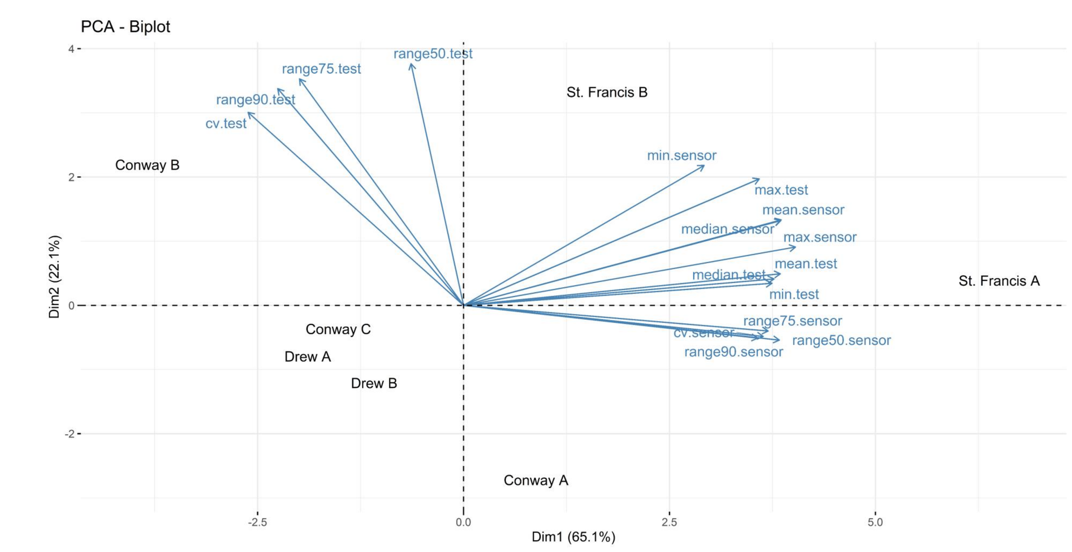


Figure 8: Field and cropping system classification of sensor performance for soil pH using principal component analysis.

3. Site-Specific (Spatial) Sensor Data Accuracy

Table 1: Summary of regression analysis computed to estimate sensor pH as a function of soil test pH and best model selection (in orange).

System	Field	Global Moran's I		Regression Model AICc* values			
		Statistic	P_{Moran}†	Intercept	OLS	Spatial Lag	Spatial Error
Conway	A	0.49	0.001	-140.6	-147.7	-163.2	-170.1
Conway	C	0.55	0.001	-205.8	-204.3	-222.3	-222.3
Drew	A	0.64	0.001	-57.19	-61.1	-100.7	-100.3
St. Francis	A	0.46	0.001	74.6	64.7	48.6	51.0

- * AICc = Aikaike's Information Criterion.
- † P_{Moran} = Significance level for the Global Moran's I statistic.
- If P ≤ 0.05 and Statistic > 0, the model residuals are significantly clustered.

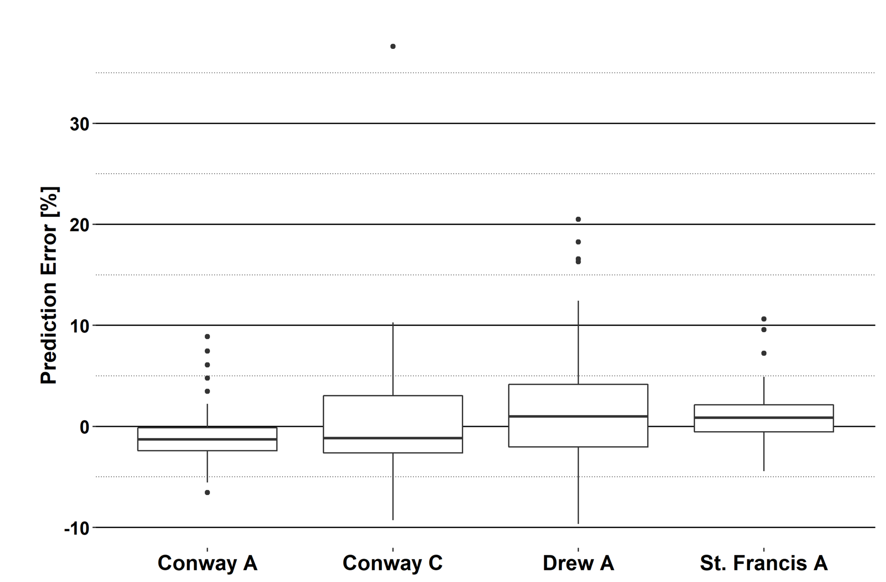


Figure 9: Variability of soil pH prediction error using the best model by field.

Key Findings

1. Different distributions of soil test pH were observed between fields. Greater soil pH values were found in the St. Francis fields. Smaller variability was observed in Conway A. Greater between-field variability was observed in the Conway system.

2. Differences in the non-spatial sensor performance were observed between fields. The sensor underestimated soil pH variability in all fields except St. Francis B. The sensor failed to capture the field distribution of soil pH in Conway B, Drew B, and St. Francis B. These fields were not used to assess site-specific data accuracy.

3. Spatial dependencies (clustering) were found in all fields. Output from the spatial lag and spatial error model provided an acceptable assessment of site-specific soil pH variability (within +/-10%).

Next Steps

- Automate data analysis
- Algorithm development to find the optimum sampling strategy from accurate sensor data
- Web-tool development

Practical Implications

- There are different ways to define and evaluate sensor performance
- Approach could be applied to other sensors
- Limitations to sensing of specific parameters

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