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Utilizing On-the-Go Soil Sensors to Explore Correlations between Electrical Conductivity, Soil Reflectance, Slope, and Elevation of Mississippi Farm Soils

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Abstract

Ten physical and environmental variables collected from an on-the-go soil sensor at two field sites (MF3E and MF11S) in Mississippi, USA, were analyzed to assess soil variability and the interrelationships among the measurements. At MF3E, moderate variability was observed in apparent electrical conductivity shallow (EC_{as}), slope, and EC_a ratio measurements, with coefficients of variation ranging from 20% to 27%. In contrast, MF11S exhibited higher variability, particularly in EC_{as} and EC_{ad} (deep) measurements, which exceeded 30% in their coefficient of variation values, indicating significant differences in soil composition and moisture content. Correlation analysis revealed strong positive relationships between the near-infrared-to-red ratio and red reflectance ($r = 0.897^{***}$) soil values at MF3E. MF11S demonstrated a strong negative correlation between EC_{as} and EC_{ad} readings with the x-coordinate ($r < -0.7^{***}$). Scatter plots and fitted models illustrated the complexity of relationships, with many showing nonlinear trends. These findings emphasize the need for continuous monitoring and advanced modeling to understand the dynamic nature of soil properties and their implications for agricultural practices. Future research should explore the underlying mechanisms driving variability in the soil characteristics to enhance soil management strategies at the study sites.

Keywords

Mobile Soil Sensors, Near-Infrared, Correlation, Nonlinear

1. Introduction

Soil health is fundamental to agricultural productivity, ecosystem sustainability, and environmental management [1]. Among these properties, apparent soil electrical conductivity (EC_a) and reflectance have garnered significant attention due to their potential as indicators of soil quality and health [2]. As agriculture increasingly relies on precision techniques, the need for efficient, accurate, and real-time soil assessments has become paramount, leading to the development of on-the-go soil sensors that can provide instantaneous readings of soil properties, thus enabling farmers and land managers to make informed decisions [3] [4].

Soil electrical conductivity is a measure of the ability of soil to conduct electrical current, which is influenced by factors such as soil moisture, salinity, and texture [5]-[7]. Numerous studies have demonstrated the utility of EC as a proxy for soil health, as it reflects variations in nutrient availability, soil texture, moisture content, and overall soil fertility [6] [8] [9]. Technological advancements have enabled the development of portable EC meters and on-the-go sensors, facilitating real-time data collection across vast areas. These devices allow for soil spatial variability assessments, enabling targeted management strategies to enhance crop yields and resource efficiency.

Soil reflectance, particularly in the visible and near-infrared wavelengths, has provided insights into soil properties such as moisture content, organic matter, and texture [10] [11]. Reflectance measurements have been employed to estimate soil characteristics non-invasively, reducing the need for extensive sampling. The relationship between soil reflectance and various soil properties has been well-documented [10]-[12]. Moreover, advances in sensor technology have allowed for the development of on-the-go reflectance sensors that can operate in conjunction with EC sensors, further enhancing the capacity for real-time soil assessment.

Geographical factors, including elevation and slope, significantly influence soil characteristics [13]. Changes in altitude can affect climate, vegetation, and soil formation processes, leading to variations in soil properties across different elevations [13]. Understanding these geographical influences is critical when interpreting soil data, as they provide context for the observed relationships between soil properties. Integrating geographic information systems (GIS) with soil data analysis has become a powerful tool for visualizing and interpreting spatial relationships. GIS allows researchers to overlay soil data with topographic maps, enabling a more comprehensive understanding of how elevation and slope affect soil dynamics. This approach can reveal obscure patterns, delivering valuable insights into soil management practices.

Despite the growing body of literature on apparent soil electrical conductivity and reflectance, significant gaps remain in understanding their interrelationships, particularly when considering the influence of geographical factors. While individual studies have examined these variables, few have integrated them within a unified framework utilizing on-the-go sensor technology. Moreover, the hypothesis that no statistically significant relationships exist among those variables presents an opportunity for further exploration, especially in Mississippi, where more information is needed on their relationships. This study investigated the correlations among soil EC_a, soil reflectance, and elevation based on measurements collected by an on-the-go soil sensor system. Ultimately, this research seeks to enhance our understanding of soil dynamics and variability, contributing to more effective agricultural practices and land management strategies.

2. Materials and Methods

2.1. Study Sites

The study occurred at the United States Department of Agriculture, Agricultural Research Service Farm (Longitude: −90.872157, Latitude: 33.446486) near Stoneville, MS, USA. The area receives about 133 cm of precipitation annually, with an average temperature of 17.5˚C [14]. The research was conducted on two agricultural plots known as MF3E (May 5, 2015) and MF11S (April 26, 2016) (**Figure 1**). MF3E covers 1.8 ha and includes several soil map units: Commerce silty clay loam (0 to 2% slopes), Newellton silty clay (0 to 2% slopes, occasionally flooded), Sharkey clay (0.5 to 2% slopes), and Tunica clay (0 to 2% slopes). MF11S is 0.6 ha and consists of Commerce silty clay loam (0 to 2% slopes), Commerce very fine sandy loam (0 to 2% slopes), and Dowling soils (Sharkey) (0 to 2% slopes, occasionally flooded). Both plots were part of a continuous rotation of soybean (*Glycine max* L.) and corn (*Zea mays* L.) and were managed using standard agricultural practices in the region, including irrigation, weed control, and fertilization.

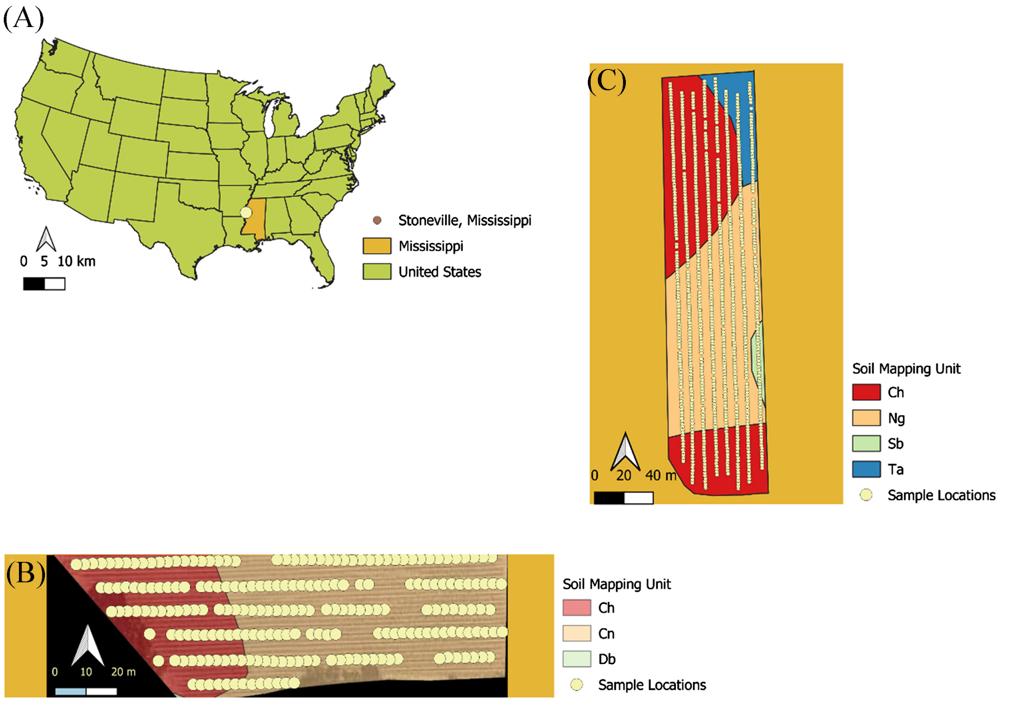

Figure 1. (A) General location of study sites; (B) MF11S field plot and sampling locations; (C) MF3 field plot and sampling locations. Soil map unit within each field: Commerce silty clay loam (Ch, 0 to 2% slopes), Commerce very fine sandy loam (Cn, 0 to 2% slopes), Dowling soils (Sharkey) (Db, 0 to 2% slopes, occasionally flooded), Newellton silty clay (Ng, 0 to 2% slopes, occasionally flooded), Sharkey clay (Sb, 0.5 to 2% slopes), and Tunica clay (Ta, 0 to 2% slopes).

2.2. Data Collection

The Veris MSP3 on-the-go soil mapping system was (Veris Technologies, Salina, KS, USA) employed to collect the soil data; the system acquired apparent electrical conductivity, near-infrared and red soil reflectance readings, latitude, longitude, and elevation as a tractor-pulled it across the fields. The EC_a readings were recorded at two separate depths: 0 - 30 cm (EC_{as}) and 0 - 90 cm (EC_{ad}). MF3E and MF11S data were collected on 8 and 6 predetermined transects, respectively.

The near-infrared and red soil reflectance values recorded by the on-the-go system were not recorded in a format available for quantitative analysis. The user must upload the data to the Field Fusion data site to obtain the reflectance values. Veris customer support will convert the near-infrared and red digital count data to a readable format. The customer support staff will also clean the raw data (removing outliers and noise) and provide additional information such as the EC_a ratio, and slope.

2.3. Data Analysis

Post-processing of the data included assigning each measurement an identification number (ID), and changing the longitude and latitude coordinate information to the Universal Transverse Mercator (UTM) coordinate system (UTM 15N WGS84). ID assignment and coordinate conversion were accomplished with QGIS (version 3.30.3-'s-Hertogenbosch [15]. The sample number for MF3E and MF11S were 1063 and 217, respectively.

Descriptive statistics (mean, standard deviation, range, and coefficient of variation [16] [17]) were calculated for EC_a, reflectance, elevation, and slope measurements. Pearson correlation coefficients [16]-[18] were computed to assess the strength and direction of relationships among the variables, providing insights into potential associations. Scatter plots were also used qualitatively to evaluate the relationships between variables; ggplot2 smooth and linear regression options were employed to provide a general understanding of nonlinear and linear relationships among the variables. Descriptive statistics, correlation, and scatter plot data were completed with the R software [19].

3. Results

Ten variables were analyzed, encompassing various physical and environmental factors collected by an on-the-go soil sensor at two study sites consisting of different soil map units. The descriptive statistics for both sites are summarized in **Table 1**. At MF3E, the mean values of variables such as EC_{as}, slope, and EC ratio exhibited moderate variability; the coefficient of variation ranged from 20% to 27%. The lowest variability was observed for elevation (2%). The maximum range for any variable was observed for the near-infrared readings. A general comparison of the EC_a readings at MF3E indicated that the EC_{as} readings were more variable than the EC_{ad} readings. The variability between the red and near-infrared values was similar.

Table 1. Descriptive statistics of field study sites.

Study Site	Variable	Mean	Standard Deviation	Range	CV (%)
MF3E	EC_{as} (mS/m)	62.7	14.2	21.7 - 94.3	23
	EC_{ad} (mS/m)	73.6	12.5	32.5 - 148.7	17
	EC ratio	1.21	0.2	0.93 - 3.01	20
	Red	339	23	308 - 427	7
	Near-infrared	765	61	652 - 966	8
	NIR:R	2.26	0.1	1.95 - 2.48	3
	Elevation (m)	40.3	0.7	39.0 - 42.0	2
	Slope	0.81	0.22	0.35 - 1.54	27
MF11S	EC_{as} (mS/m)	35.4	12.6	16.9 - 65.9	36
	EC_{ad} (mS/m)	50.2	17.2	27.8 - 93.6	34
	EC ratio	1.44	0.3	1.1 - 2.3	17
	Red	383	8.3	372 - 407	2
	Near-infrared	912	24.5	879 - 991	3
	NIR:R	2.37	0.03	2.31 - 2.45	1
	Elevation (m)	42.7	0.47	42.0 - 44.0	1
	Slope	0.49	0.16	0.27 - 0.82	32

Coefficient of variation—CV, near-infrared:red—NIR:R, EC—apparent electrical conductivity.

Similar results were observed for the soil variables measured at MF11S (**Table 1**). The highest variability was measured for EC_{as}, EC_{ad}, and the slope with values greater than 30%. The lowest variability was observed for the near-infrared to red ratio and elevation. A similar trend was observed for the EC_{as} and EC_{ad} readings in that the lower variability occurred for the EC_{ad} measurements. The red and near-infrared reflectance measurements had similar variability, which meant consistency throughout the field for those measurements.

Correlation analysis examined relationships among the data collected/derived from the on-the-go sensors. The Pearson correlation coefficients for each variable pair are summarized in **Figure 2** and **Figure 3**. At MF3E, strong positive correlations occurred between the near-infrared and red reflectance ($r = 0.897^{***}$), EC_{as} and EC_{ad} readings ($r = 0.781^{***}$), and EC_{as} and the y coordinate ($r = 0.784^{***}$). For the most part, the correlations ranged from moderate to no correlation.

Correlation analysis for MF11S showed a strong negative relationship between EC_{as} and EC_{ad} versus the x-coordinate ($r = -0.844^{***}$, $r = -0.777^{***}$) and the near-infrared to red ratio and the EC_{ad} readings ($r = -0.747^{***}$); strong positive correlation occurred between the EC_{as} and EC_{ad} ($r = 0.895^{***}$) measurements, red versus near-infrared reflectance ($r = 0.870^{***}$) measurements, near-infrared to red ratio and the slope ($r = 0.709^{***}$) readings, and near-infrared to red ratio and the x-coordinate ($r = 0.742^{***}$) measurements. There were other statistically significant correlations, but they were moderate to low. Also, some of the relationships were not statistically significant at all.

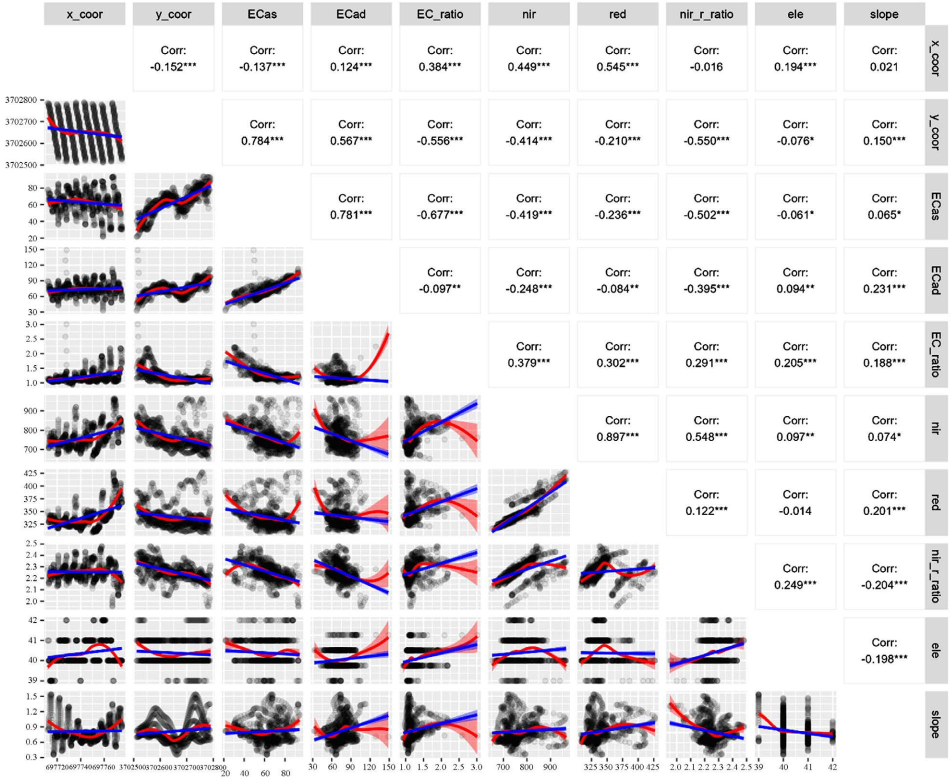

Figure 2. Correlation (Corr:) matrix (upper) and simulated models (lower) showing relationships between variables collected with an on-the-go soil system at field MF3E. $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. x_coor—x coordinate, y_coor—y coordinate, EC$_{as}$—apparent electrical conductivity shallow, EC$_{ad}$—apparent electrical conductivity deep, EC_ratio—apparent electrical conductivity ratio, NIR—near-infrared, NIR_R ratio—near-infrared to red ratio, and ele—elevation.

Scatter plots and a simulated linear model and nonlinear model fit were created for each variable, using ggplot2 plot tools of the R software to help further understand the relationships (Figure 2 and Figure 3). In most cases, the relationship between the collected soil data was not linear for the scatter plots. At MF3E, the best case for a linear relationship was observed between the red versus near-infrared and EC$_{as}$ and EC$_{ad}$. The same could be said for a linear relationship between EC$_{as}$ and EC$_{ad}$ at MF11S.

4. Discussion

Analyzing the ten physical and environmental variables collected from on-the-go soil sensors at two study sites, MF3E and MF11S in Mississippi, provided valuable insights into soil characteristics and their variability (Table 1; Figure 2 and Figure 3). The findings revealed notable patterns in variability, correlations, and the nature of relationships among the variables, which have implications for soil management.

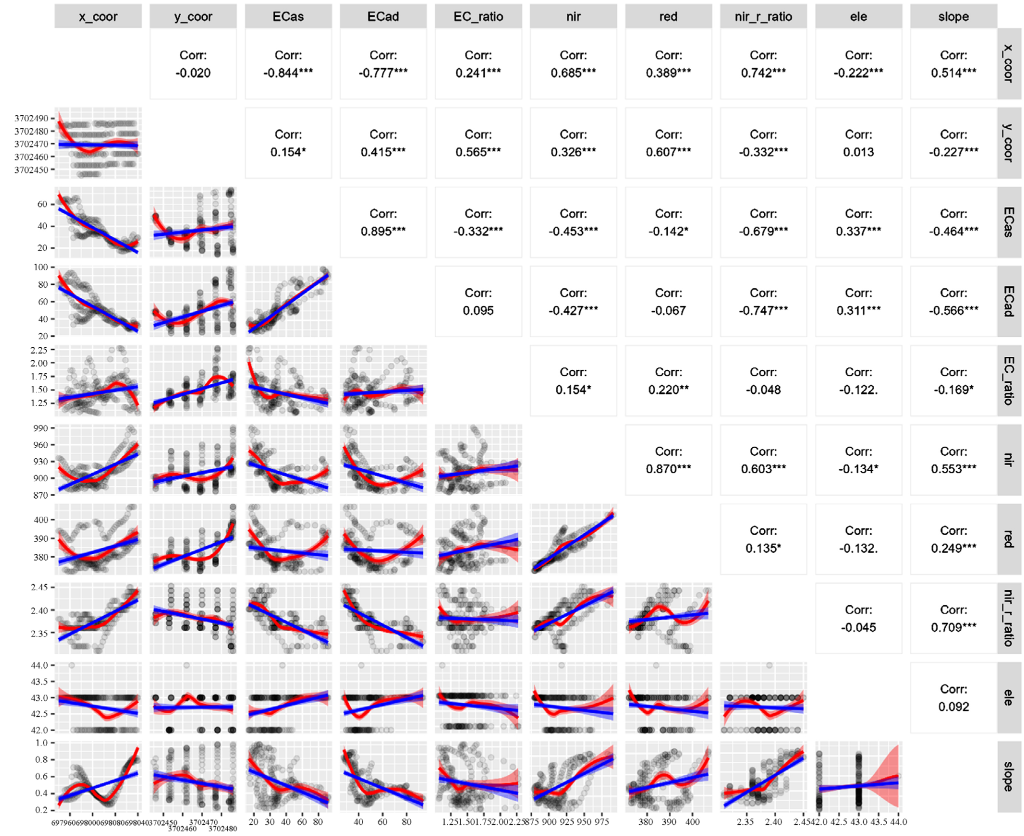

Figure 3. Correlation (Corr:) matrix (upper) and simulated models (lower) showing relationships between variables collected with an on-the-go soil system at field MF11S. $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. x_coor—x coordinate, y_coor—y coordinate, EC_{as}—apparent electrical conductivity shallow, EC_{ad}—apparent electrical conductivity deep, EC_a—apparent electrical conductivity ratio, NIR—near-infrared, NIR_R ratio—near-infrared to red ratio, and ele—elevation.

The results indicated moderate variability in key variables such as electrical conductivity, slope, and EC ratio at MF3E, with coefficients of variation ranging from 20% to 27%, suggesting that these factors can significantly influence soil properties and, consequently, plant growth. In contrast, the low variability observed in elevation (2%) implies that this variable is relatively stable across the study site, potentially serving as a reliable reference point for understanding how other factors interact with topography.

At MF11S, the observed variability was even more pronounced, particularly for EC_{as} and EC_{ad}, with coefficients of variation exceeding 30%. The higher variability in these conductivity readings indicated potential differences in soil composition and moisture content, which are critical for assessing soil health and fertility. Higher variability in EC_{as} has been observed in other fields on this farm [20] [21], and researchers have reported moderate to high variability of EC_a in agricultural fields [2].

The correlation analysis further explained relationships among the variables. At MF3E, strong positive correlations between the near-infrared and red reflectance ($r = 0.897^{***}$) highlighted the consistency in spectral measurements, indicating that as one increases, so does the other. Similarly, the strong correlation between EC_{as} and EC_{ad} ($r = 0.781^{***}$) suggested that these two conductivity measures were closely linked, potentially reflecting the same underlying soil properties.

Conversely, at MF11S, the strong negative correlation between EC_{as} and EC_{ad} readings with the x-coordinate ($r = -0.844^{***}$, $r = -0.777^{***}$) raises intriguing questions about the spatial distribution that may relate to variations in soil texture or moisture levels. Soil salinity is not an issue in Mississippi agriculture, and thus, EC_a is probably related more to texture and moisture conditions.

Moreover, the presence of both strong positive and negative correlations at MF11S underscores the complexity of soil interactions in this area. The strong positive correlation between EC_{ad} and EC_{as} ($r = 0.895^{***}$) reinforces the relationship observed at MF3E, while correlations involving the near-infrared to red ratio and slope ($r = 0.709^{***}$) suggested that topographical features may influence spectral reflectance and, by extension, soil properties.

The use of scatter plots and fitting both linear and nonlinear models provided additional insights into the nature of the relationships among variables. The smooths generated in ggplot2 were primarily for visualization and did not directly provide a model or data that can be extracted for a report; nevertheless, they visually represent trends and relationships in the data. The observation that many relationships were not linear indicated the complexity of the soil systems and the influence of multiple factors on soil properties. At MF3E, the potential for linear relationships between the red versus near-infrared reflectance and EC_{as} and EC_{ad} suggested that simpler predictive models may be applicable under certain conditions. However, the predominance of nonlinear relationships calls for caution when interpreting the data and highlights the need for more sophisticated modeling approaches. At MF11S, the consistent linear relationship between EC_{as} and EC_{ad} supported the hypothesis that these variables are fundamentally linked, while also encouraging further exploration of the conditions under which linear relationships emerge.

Based on the Soilweb survey, which provides descriptions of various soil characteristics in the United States [22], two of the soil map units for the fields belong to the Commerce soil series. Soils classified in this series are somewhat poorly drained, moderately slowly permeable soils formed in loamy alluvial sediments and on level to undulating alluvial plains of the Mississippi River and its tributaries. One soil map unit was classified to the Newellton series, which consists of very deep, somewhat poorly drained, slowly permeable soils that formed in clayey over loamy alluvium and are developed on nearly level to gently sloping natural levee positions on the alluvial plain of the Mississippi River and its distributaries. The map unit belonging to the Tunica series consisted of deep, poorly drained soils formed in clayey alluvium and the underlying loamy alluvium. These soils were formed on the lower parts of natural levees on the younger meander belts of the Mississippi River and its tributaries of the Lower Mississippi Valley. Finally, the Sharkey map unit belongs to the Sharkey series, which consists of very deep, poorly and very poorly drained, very slowly permeable soils formed in clayey alluvium. These soils are on flood plains and low terraces of the Mississippi River. Several investigators have reported that external factors affect soil reflectance readings collected in fields [12] [23]. It was believed for the fields used in this study that a combination of where and how the soils were formed on the landscape and micro variability in external factors, such as soil moisture, roughness, aggregation, inclination, location of sensors on the ridge and furrow, and temperature affected the EC_a and reflectance readings and thus correlations among different sensor readings for the study sites. Also, as far as the spectral sensors, the readings were an average of what the sensor was in contact with within the upper 5 cm of the soil over a specific distance; for example, soil, decayed plant material from the previous crop, and maybe rocks, thus affecting the readings and the potential relationships with other readings. The findings from this analysis have practical implications for soil management and agricultural practices. The results also emphasize the importance of ongoing monitoring and data collection to understand the dynamic nature of soil properties better.

5. Conclusion

Using on-the-go soil sensors to analyze physical and environmental factors across the two study sites, MF3E and MF11S, has provided valuable insights into soil variability and the intricate relationships among key variables. The findings indicate a moderate to high variability in EC_a, suggesting a significant difference in soil properties that can impact agricultural practices. Strong positive and negative correlations highlight the complexity of soil dynamics, particularly concerning spatial variations across the study sites. The consistent relationships identified, especially between EC_{as} and EC_{ad}, point to the interconnected nature of soil properties, while the predominance of nonlinear relationships calls for a better understanding of the factors influencing soil behavior. Future research should aim to explore these relationships further and investigate the underlying mechanisms driving variability in the soil properties at the selected field locations.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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