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Comparative Analysis of Remote Sensing via Drone and On-the-Go Soil Sensing via Veris U3: A Dynamic Approach †

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Abstract: The use of drones to gather remote data and soil sensors to collect ground information has become a powerful method for agricultural monitoring and analysis. However, integrating data from drone remote sensing and soil sensors in agricultural contexts can be problematic due to variations in spatial and temporal resolutions. Ensuring precise synchronization and calibration is crucial for accurate comparative analysis. The objective of this study was to investigate the strengths and limitations of drone-based remote sensing and on-the-go Veris U3 sensor in agricultural contexts and explore the potential for data fusion. Through a series of field trials, data from drone-based remote sensing and ground-based soil sensing were collected in parallel. This data encompassed a range of factors, including vegetation health (vegetation indices), soil properties such as EC, pH, and optical measurements. The study delves into the challenges of data synchronization, calibration, and validation between the two methodologies. We discuss the potential for synergy in building a more holistic understanding of agriculture by fusing data from drones and in situ soil sensors. The findings of this research have implications for environmental monitoring, agriculture, and ecosystem management, suggesting that the combination of aerial and ground sensing offers a multi-dimensional perspective that can enhance decision-making processes and our grasp of intricate environmental processes.

Keywords: agriculture, remote sensing, drone, soil, Veris, crop, sustainability

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1. Introduction

In recent years, the incorporation of cutting-edge technologies in the agricultural sector has completely transformed our understanding and management of agriculture [1–4]. With the emergence of advanced tools like drones for remote data collection and ground-based soil sensors for localized information retrieval, precision agriculture has become a powerful tool for optimizing farming efficiency [3,5].

The application of drone-based remote sensing brings the advantage of capturing high-resolution aerial imagery and multispectral data, allowing for the assessment of vegetation indices and land cover changes over large areas [5–8]. Conversely, ground-based soil sensors provide a direct and in-depth measurement of soil properties such as electrical conductivity (EC) [9–12], soil acidity (pH) [13–15], and optical parameters [12,16,17].

However, the integration of data from drone remote sensing and soil sensors poses challenges stemming from disparities in spatial and temporal resolutions [18–20]. Furthermore, exploring the potential for data fusion from these sources necessitates an understanding of the complementary nature of the information they provide, potentially yielding a more holistic perspective on agricultural landscapes [20–22].

The primary objective of this study is to investigate the strengths and limitations of drone-based remote sensing and on-the-go Veris U3 sensor in agricultural contexts. Through a series of field trials, data encompassing various parameters including vegetation index and soil properties were collected in parallel using both methodologies. As the same fertilizers have been consistently applied year after year, there arose a critical need to evaluate their ongoing necessity and effectiveness. To address this, the Veris soil sensor was deployed as a valuable tool in this study. The focus on utilizing Veris sensor and integrating its data with other sources like NDVI from drones will contribute to understanding of soil-plant interactions and enable data-driven decisions that can enhance crop productivity and sustainability.

2. Materials and Methods

The study was conducted in Muramatsu station of Niigata University, located in the Niigata Prefecture of Japan. The Muramatsu Field Center and the Laboratory of Bioproduction and Machinery of Niigata University worked together to conduct a series of experiments in the DX project called "Digital Transformation in Agriculture". The project aimed to explore the ways in which digital technology can be utilized to enhance agricultural practices. Muramatsu's experimental fields, which span across 19 hectares, are utilized for a wide range of purposes including the cultivation of various vegetables, grasses that are later used as livestock feed, soybeans, seedlings, and other plants that are related to the experiments conducted at the university. These fields serve as an integral part of the university's research and development efforts, enabling researchers to engage in experiments and studies related to various plant species and their growth patterns.

The observed crop in this study was soybean (*Glycine max*), a leguminous plant with wide-ranging applications in agriculture, food production, and industrial sectors [23,24]. Soybean crops are particularly sensitive to fluctuations in soil properties and nutrient availability [25]. Variations in soil EC and pH can influence nutrient uptake, and overall crop health [25,26], thereby affecting the soybean remote sensing index to assess vegetation health and vigor. In this study, compost and nitrogen-liming, following a pattern established in the previous year, were utilized as vital methods for enhancing soybean crop growth and soil quality. These methods were chosen to optimize soil conditions, nutrient availability, and soybean crop health and productivity.

The collected data were subjected to statistical analysis using R software [27,28] and QGIS tools [29,30]. Ground sensor data was interpolated by using the Kriging method. Comparative analysis, including correlation analysis and regression modeling, was conducted to assess the relationships between data from drone-based and ground-based sensing. A 1m-by-1m grid was established across the study area using QGIS. This grid facilitated systematic spatial analysis and comparison of datasets. The datasets, including NDVI derived from drone-based remote sensing and soil parameters obtained from the on-the-go Veris sensor, were compared within each grid cell by using zonal statistics tool.

2.1. Drone-Based Remote Sensing

A DJI Matrice 300 Real-Time Kinematic (RTK) drone equipped with a Micasense Rededge-P camera was utilized for aerial data acquisition. Drone flights were conducted at an altitude of 40 m with an overlap of 75% between adjacent images to ensure adequate coverage and resolution. Raw drone imagery underwent preprocessing and orthorectification using Agisoft Metashape software [31]. The use of Metashape software facilitated the transformation of raw drone imagery into georeferenced, radiometrically and geometrically corrected datasets suitable for quantitative analysis [31]. The high level of precision achieved through RTK GPS technology [32] and the software's processing capabilities [31] enhanced the reliability and accuracy of the drone-based remote sensing data, thereby enabling robust comparative analysis with ground-based soil sensing data.

2.2. On-the-Go Ground-Based Soil Sensing

An on-the-go Veris U3 sensor [15,33] was utilized to collect live soil data. The Veris sensor, mounted to a tractor Kubota, was driven across the study area as part of a continuous on-the-go data collection process. The U3 soil scanner was designed to measure three important soil properties EC, pH, and Soil Infrared (IR) sensing in the topsoil. The EC measurement was done by passing an electric current between two pairs of discs that were placed in the soil. This sensor, which measures bulk EC, differs from laboratory-measured soil EC methods, such as saturated paste extracts. Bulk EC sensors provide measurements that reflect the electrical conductivity of the entire soil matrix, capturing variations in soil properties at a larger scale. It should be noted that there can be variations in the EC values obtained through bulk measurements compared to laboratory methods due to differences in scale and scope. For measuring IR, the scanner used an optical sensor that worked in red and near-infrared wavelengths [13,33]. In our study, soil sensing utilizing the Veris sensor was conducted both before and after fertilization to evaluate soil parameters. By examining soil data at these time points, we gain insights into the impact of fertilization practices on soil health.

3. Results

In this section, we present the outcomes of a study that involved the comparative analysis of NDVI (distribution showed in Figure S1) and soil parameters, such as EC, pH, and IR sensing by using on-the-go Veris U3 sensor. The relationship between NDVI and EC underwent significant alterations following fertilization. Before fertilization, a negative correlation ($R = -0.39$) suggested that healthier soybean vegetation, indicated by higher NDVI values, was associated with lower soil EC. This correlation hinted at reduced soil salinity and dissolved salt content in areas with thriving soybean growth.

However, after fertilization, this relationship strengthened notably ($R = -0.55$). Fertilization induced changes, especially in areas with varying NDVI values. Soybean areas displaying healthier vegetation exhibited significantly reduced soil salinity levels after fertilization, reflecting the direct impact of this common agricultural practice on the soil's electrical conductivity (Figure 1). The interpolation by the Kriging method is shown in the Supplementary Materials (Figures S2 and S3).

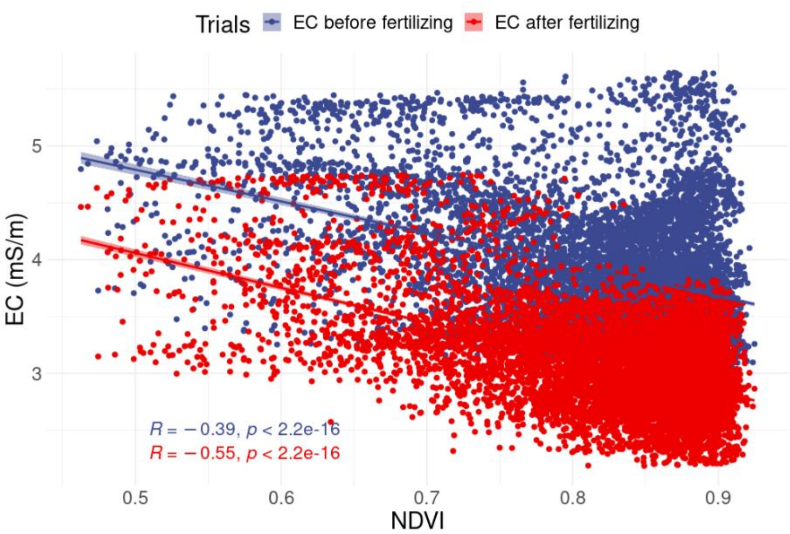

Figure 1. The relationship between drone-based remote sensing NDVI data and on-the-go ground-based soil sensing EC data before and after fertilization.

The evaluation of EC before and after fertilization through compost and nitrogen-liming applications reveals significant insights into soil dynamics. Prior to fertilization, EC levels indicate the baseline soil salinity and nutrient availability. Post-fertilization, a noticeable shift in EC levels becomes evident, reflecting alterations in soil ionic concentrations due to nutrient additions. Compost contributes to increased EC through the release of nutrients, while nitrogen-liming can also influence EC by affecting pH levels.

The relationship between NDVI and soil pH also evolved significantly in response to fertilization. Before fertilization, the correlation was relatively weak (R = 0.2). After fertilization, the correlation between NDVI and soil pH strengthened notably (R = 0.51). This change highlighted the influence of fertilization on the relationship between soybean vegetation health, as indicated by NDVI, and soil pH. Areas with thriving soybean growth exhibited a more pronounced tendency toward alkaline soil conditions after fertilization, suggesting that fertilization played a role in altering soil pH in this study (Figure 2). The interpolation by the Kriging method is shown in the Supplementary Materials (Figures S4 and S5).

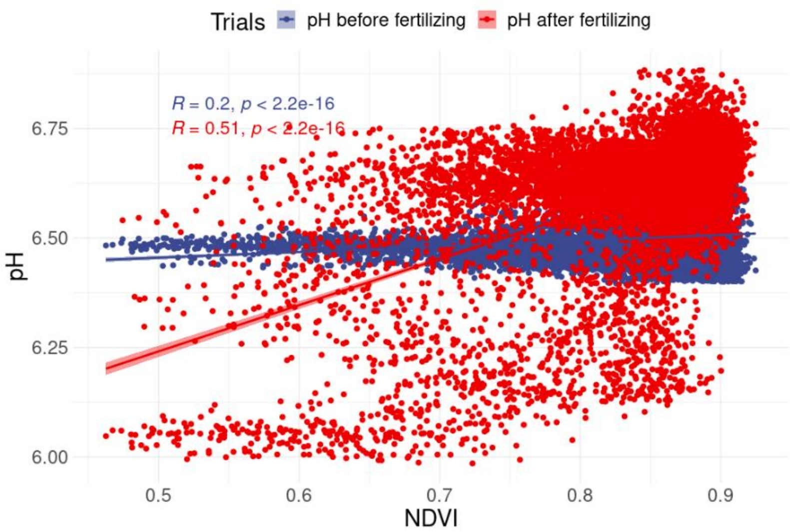

Figure 2. The relationship between drone-based remote sensing NDVI data and on-the-go ground-based soil sensing pH data before and after fertilization.

The assessment of pH levels before and after fertilization through compost and nitrogen-liming applications reveals that pH remained relatively stable throughout the study, maintaining a consistent level from 6 to 6.8. While compost applications may have the potential to influence pH due to their alkaline nature, the soil's inherent buffering capacity likely mitigated significant pH fluctuations. Nitrogen-liming, which can affect pH, also seemed to have a modest impact, given the soil's resilience to rapid pH changes. It should be noted that soil sensing occurred at one-month intervals between each other.

The relationship between NDVI and IR Sensing, which captures properties related to soil moisture and organic matter content, showed limited correlation both before and after fertilization. Before fertilization, the correlation was weak and slightly negative (R = −0.13). After fertilization, the correlation remained weak and slightly negative (R = −0.16), with no substantial change in the relationship between NDVI and soil IR Sensing. This suggests that the infrared properties of the soil experienced limited alterations concerning NDVI values in soybean areas after fertilization (Figure 3). The interpolation by the Kriging method is shown in the Supplementary Materials (Figures S6 and S7).

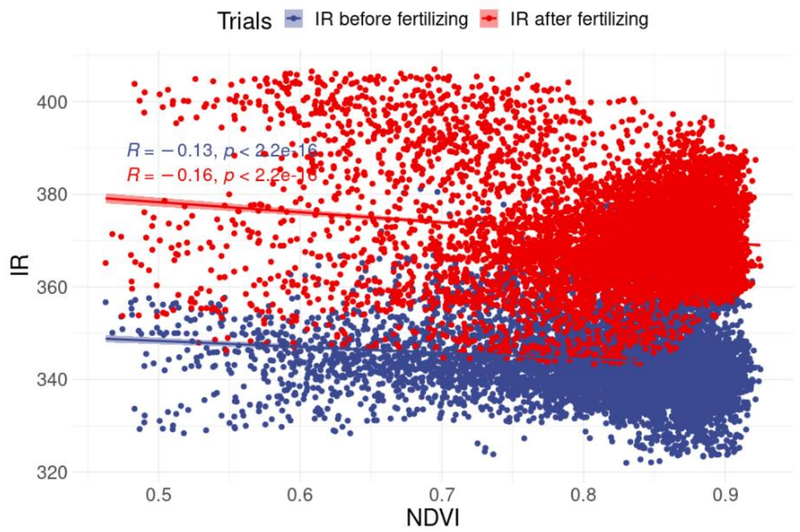

Figure 3. The relationship between drone-based remote sensing NDVI data and on-the-go ground-based soil sensing IR data before and after fertilization.

While other parameters such as EC and pH exhibited changes, IR sensing revealed that certain soil properties remained consistent, highlighting the importance of comprehensive data collection for understanding of soil responses to fertilization practices in agricultural contexts. Additionally, environmental factors such as temperature and lighting conditions can impact the accuracy of IR data. Hence, while IR sensing offers valuable insights, its use should be complemented with other sensing technologies and laboratory analyses to create a comprehensive understanding of soil behavior in future studies.

4. Conclusions

By providing real-time, on-the-go soil data, it offers insights into crucial soil properties such as pH, OM, and electrical conductivity. This data serves as a dynamic snapshot of the soil's current condition, which can change from year to year due to various factors, including crop uptake and environmental conditions. Indeed, the observed improvement in correlation after fertilization aligns with the known effects of fertilizer application on soil properties and crop health. In summary, the comparative analysis before and after fertilization revealed notable shifts in the relationships between NDVI and key soil parameters using on-the-go Veris U3 sensor. Fertilization played a significant role in influencing these relationships. The results underscore the importance of considering the effects of common agricultural practices on soybean crop health and soil conditions. The enhanced correlations post-fertilization highlight the dynamic nature of these interactions and emphasize the need for precision agricultural approaches that consider both vegetation and soil responses to management practices.

It is important to note that while NDVI provides valuable insights into vegetation health, its correlation with specific soil properties, such as those captured by Soil IR sensing, may be limited. Additional factors and data sources may be necessary to fully understand the complexities of soil-vegetation interactions. Our research is advancing into a more comprehensive phase, expanding our study to include a wider range of soil parameters. We're incorporating advanced laboratory analyses to delve deeper into factors such as nutrient content and soil texture. In parallel, we're expanding our analysis by incorporating additional vegetation indices such as NDRE (Normalized Difference Red Edge) and EVI (Enhanced Vegetation Index).

Supplementary Materials: The following supporting information can be viewed at: https://www.agr.niigata-u.ac.jp/~bpm/remote_sensing.html, Figures S1–S7.

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