Available online at:
http://journal.unila.ac.id/index.php/tropicalsoil
DOI: 10.5400/jts.2025.v30i3.159-173

Integrating Soil Properties and Vegetation Indices for Modeling Potato Productivity

Sudarto[1], Aditya Nugraha Putra[1,2*], Dwi Christina Fauziah[1], Agung Nugroho[1], Adithya Riefanto Suryoprojo[1], Novandi Rizky Prasetya[3] and Michelle Talisia Sugiarto[4]

[1]*Department of Soil Science, Faculty of Agriculture, Brawijaya University, Malang 65145, Indonesia*
[2] *Department of Land and Water Resources Management, Faculty of Civil Engineering, Slovak University of Technology in Bratislava, Bratislava 81005, Slovakia*
[3]*Doctoral Program in Agricultural Science,* [4]*Soil and Water Management Study Program, Faculty of Agriculture, Brawijaya University, Veteran Street, Malang 65145, Indonesia*
**email: aditya.n.putra@ub.ac.id*

Received 18 June 2025 Revised 23 September 2025; Accepted 24 September 2025

ABSTRACT

Global potato production reached approximately 383 million metric tons in 2025, with Indonesia contributing around 1.22 million metric tons (0.32% of global output). However, the sustainability of Indonesia's potato production is increasingly threatened by soil quality degradation in key growing regions. Existing predictive studies have primarily focused on soil chemical properties, with limited incorporation of remote sensing technologies. This study investigates the potential of Unmanned Aerial Vehicle (UAV) as a high-resolution, non-destructive tool for estimating potato yield using vegetation index transformations. Utilizing a split-plot experimental design across elevation gradients, we integrated soil properties with UAV-derived vegetation indices—Visible Atmospherically Resistant Index (VARI), Green Leaf Index (GLI), and Normalized Green-Red Difference Index (NGRDI). Results reveal that total nitrogen, base saturation, and bulk density significantly influence yield variability, and can be accurately estimated using NGRDI, GLI, and a modified GLI (GLI CS), respectively. A multiple linear regression model was developed to predict potato yield = 24.22 + 7.26(NGRDI) + 9.87(GLI) + 28.42(GLI CS). This research demonstrates the efficacy of UAV-based spectral analysis in improving yield-prediction models, offering a scalable, precise approach for sustainable potato cultivation. Future work should incorporate machine learning to improve model robustness and assess applicability across varied agro-ecological contexts.

Keywords: Agriculture, geographic information system, remote sensing, soil fertility, staple food

INTRODUCTION

Potato (*Solanum tuberosum*) is a globally important crop, yet its production in Indonesia remains suboptimal despite the availability of vast agricultural land. While major producers like China and India yield tens of millions of tons annually, Indonesia's output lags significantly, highlighting inefficiencies in cultivation practices (FAOSTAT, 2019). This gap underscores the urgent need for innovative approaches to improve potato productivity.

Indonesia's increasing potato demand is not met by sufficient domestic production, leading to a reliance on imports. Between 2014 and 2017, national production declined from 1.35 million t to 1.16 million t, fulfilling only about 10% of total consumption (Statistic Indonesia, 2017). This decline is primarily due to soil degradation, erosion, and inefficient nutrient management, all of which reduce yield potential. Given these challenges, immediate interventions are required to enhance soil fertility, optimize nutrient input, and improve overall productivity.

By using UAV-derived vegetation indices—VARI, GLI, and NGRDI—alongside soil physical properties, this research aims to develop a high-accuracy model for yield potential estimation. Unlike conventional agronomic approaches, this method provides a data-driven framework for site-specific nutrient management, optimizing resources while improving sustainability. Recent studies have emphasized the advantages of UAV-based monitoring in agriculture, particularly in assessing soil conditions and crop health (Li et al., 2021; Njane et al., 2023). Geo-AI further reinforces these approaches, which integrate remote sensing indices and environmental covariates to accurately predict soil nitrogen status —a crucial factor for yield estimation (Prasetya et al., 2025). These technological advancements offer promising opportunities to bridge the productivity gap in Indonesia's potato sector.

Recent advances in remote sensing have demonstrated promising outcomes in estimating potato yield and growth traits. For example, Tatsumi & Usami (2024) successfully combined UAV-based RGB and hyperspectral imaging with machine learning to model above-ground biomass and yield (R^2 substantial). Moreover, Mukiibi et al. (2025) highlighted that vegetation indices strongly correlate with tuber yield, especially when measured during critical growth stages. Additionally, Li et al. (2021) improved yield prediction by integrating cultivar information with UAV multispectral data using machine learning, achieving validation R^2 values up to 0.79

Precision agriculture is rapidly transforming the global farming landscape. The adoption of UAV-based remote sensing allows for more accurate soil analysis and real-time monitoring of crop growth. In a recent study, UAV images were successfully used to predict potato yield and morphological quality, highlighting the technology's effectiveness in precision farming (Ccopi et al., 2024). Additionally, systematic reviews on vegetation indices for potato growth monitoring indicate that integrating remote sensing with traditional farming practices enhances decision-making and resource allocation (Mukiibi et al., 2025). These findings underscore the relevance of this study to modern agricultural challenges and solutions.

Despite these technological advances, a notable research gap persists in studies combining RGB-based vegetation indices (e.g., VARI, GLI, NGRDI) with soil physical properties to estimate potato yield. Most existing literature focuses on multispectral or hyperspectral indices (e.g., NDVI, NDRE, red-edge, GNDVI), which require more costly sensors. Our study addresses this gap by proposing a cost-effective, scalable, and field-friendly approach that uses widely accessible RGB imagery and key soil metrics.

By implementing advanced remote sensing technologies and precision agriculture approaches, this research aims to develop a practical, scalable model adaptable across regions and production systems to improve potato productivity in Indonesia. Future developments may include integrating machine learning algorithms to enhance predictive accuracy, thereby supporting data-driven decision-

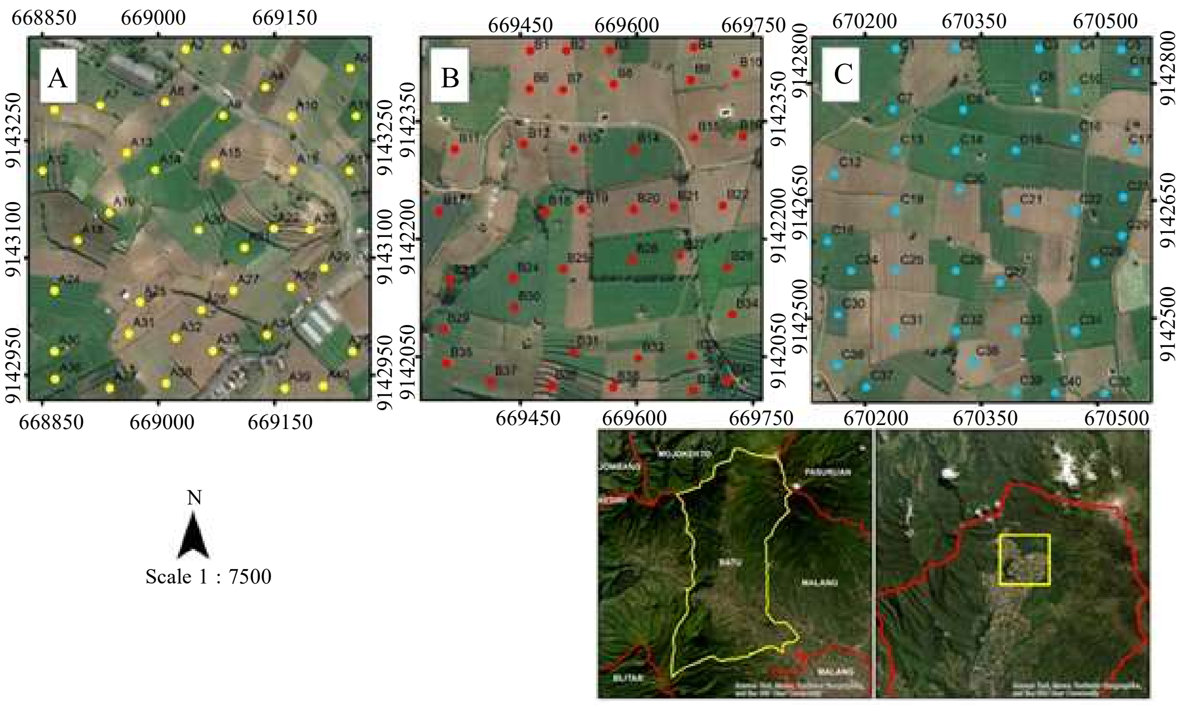

Figure 1. Research area in Sumber Brantas Village, Bumiaji Sub Districts, Batu City. : plot point, : plot point B, : plot point C.

making in agriculture. The findings from this study are expected to contribute significantly to sustainable farming practices, ensuring food security while minimizing environmental degradation. Furthermore, this approach could serve as a foundation for similar applications in other crops, reinforcing Indonesia's position in global agricultural innovation.

MATERIALS AND METHODS

Research Location and UAV Flight Information

The research was conducted in Sumber Brantas Village, Bumiaji Subdistrict, Batu City, East Java, an area known for being one of Indonesia's largest potato centers, as shown in Figure 1. Data was collected with precise observation points determined using a Garmin 78s GPS device. Aerial images were captured at 75 meters above sea level using a DJI Phantom 3 Pro drone with a 12 MP camera, which was set on a pre-programmed flight path. The region's climate, with average rainfall of 2,000 to 2,500 millimeters and temperatures between 18°C and 24°C, supports potato cultivation. The volcanic soils in the area are rich in nutrients, further enhancing the suitability for potato farming.

Experimental Design

This research employed a split-plot experimental design with an altitude-based factorial treatment pattern (Jones & Nachtsheim, 2009), consisting of three main altitude categories: <1800 m a.s.l., 1800-1900 m a.s.l., and >1900 m a.s.l. The selection of observation locations was based on the highest potato productivity in Bumiaji District (Statistics of Batu City, 2018). The sampling was conducted in 6.25 m² tile plots within each observation plot, as illustrated in Figure 2 (Statistic of Batu City, 2018), to assess potato crop production. Soil sampling was carried out using stratified random sampling (Rayes, 2006), with 120 sampling points established for crop assessment. The stratification was based on vegetation index values, which were divided into seven distinct classes ranging from Class 1 (very low vegetation, e.g., bare soil or poor crop cover), Class 2 (low vegetation, sparse or stressed crops), Class 3 (moderately low vegetation, below average crop growth), up to Class 7 (very high vegetation, representing dense and healthy crop cover). This classification ensured that the sampling represented the full spectrum of crop vigor conditions, thereby reducing bias and improving dataset representativeness.

Soil Characteristics Analysis

The soil characteristics assessed in this study included total nitrogen content (TN) using the Kjeldahl method (%) (Bremner & Mulvaney, 1982), and available phosphorus (Available-P) determined using the Bray I/II method (mg kg^{-1}) (Bray & Kurtz, 1945) and Olsen's method (Olsen, 1954). Exchangeable potassium (Exchangeable-K) was measured using 1N NH_4OAc at pH 7 (cmol kg^{-1}) (Soil Conservation Service, 1984). Organic carbon content (C-Organic) was determined following the methods outlined by Black et al. (1965) and Nelson & Sommers (1982). The cation exchange capacity (CEC) was evaluated through extraction with 1N NH_4OAc at pH 7 (cmol kg^{-1}), while the soil pH in water (pH H_2O) was measured using the method

Figure 2. Tile plots in each observation plot with a size of 6.25 m^2.

described by Peech (1965). Base saturation percentage was calculated based on the exchangeable concentrations of calcium (Exchangeable-Ca), magnesium (Exchangeable-Mg), and sodium (Exchangeable-Na), extracted with 1N NH,, OAc at pH 7 (cmol kg^{-1}) (Soil Conservation Service, 1984; Houba et al., 1988; Holmgren et al., 1977; Soil Survey Staff, 2014). Soil bulk density (g cm^{-3}) was determined following the procedures outlined by Blake and Hartge (1986), Klute (2018), and Soil Survey Staff (2014), while soil particle density was measured using a pycnometer (g cm^{-3}) (Black et al., 1965; Gee & Bauder, 1986). Soil porosity percentage was calculated following the method of Nimmo (2013), and soil penetration resistance was measured using a hand penetrometer (MPa) as outlined by Kees (2005).

Spatial Interpolation of Soil Properties

Point measurements (n = 120) were interpolated using ordinary kriging on a 10 m grid in ArcGIS 10.6. Experimental semivariograms were computed for each soil property, and spherical models were fitted after checking for normality. Both chemical (total nitrogen, available phosphorus, exchangeable potassium, base saturation, cation exchange capacity, pH, and organic carbon) and physical (soil penetration resistance, bulk density, and porosity) soil properties were mapped. Spatial mapping was carried out in ArcGIS 10.6 using UTM Zone 49S (EPSG:32749) coordinates.

Index Transformation

Agisoft was used to analyze aerial imagery, which involved stitching multiple photographs into a single orthomosaic (Zhang et al., 2023). The aerial photo taken on October 28, 2019 (Figure 3) was used as a visual reference to support field observations and spatial analysis Subsequently, vegetation index transformations were applied, including the Normalized Green-Red Difference Index (Li et al., 2021), Green Leaf Index (Nguy-Robertson et al., 2012), and Visible Atmospherically Resistant Index (Li et al., 2024). The calculation of these indices was performed using the following equations:

$$NGRDI = \frac{G - R}{G + R}$$

$$GLI = \frac{2G - R - B}{2G + R + B}$$

$$VARI = \frac{G - R}{G + R - B}$$

In this study, vegetation indices were calculated from reflectance values in UAV-derived imagery, where G, R, and B represent the reflectance values of the Green, Red, and Blue spectral bands, respectively.

Image Quality Improvement Scenario Results

A scenario aimed at improving image quality was implemented to reduce noise and opacity, and to prevent images from being either too dark or too bright during recording. This was particularly important for parameters that correlate with potato plant productivity. Several image enhancement methods were tested to address these issues and improve the quality of the data used for analysis.

Contrast stretching is a technique that creates a new image F0(x,y)F_0(x, y)F0 (x,y) with better

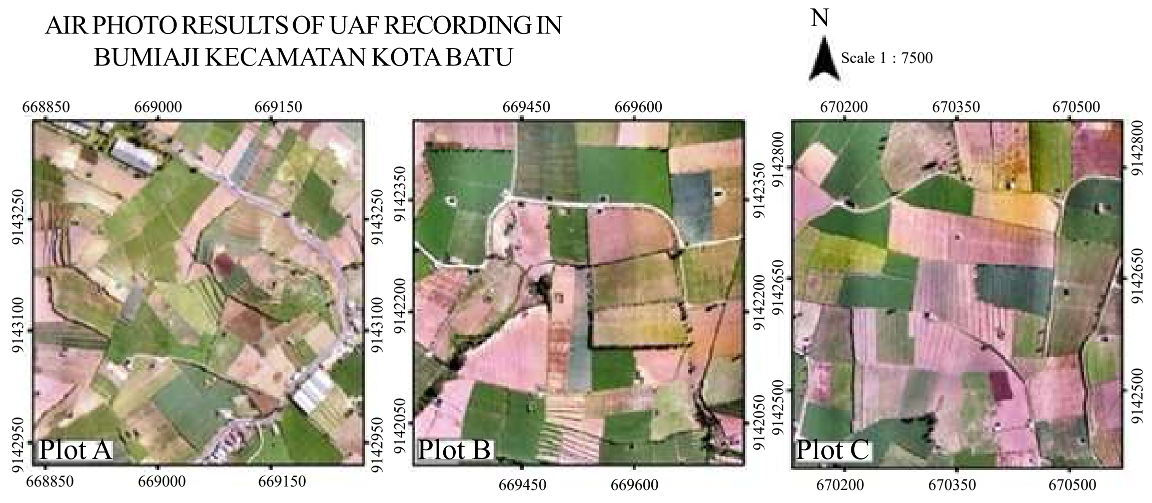

Figure 3. Aerial Photo Recording on October 28, 2019.

contrast than the original image F1(x,y)F_1(x, y)F1 (x,y) (Purba, 2017). For example, an input range of 55-255 was stretched to 0-255. Various methods were used for this enhancement, including linear, piecewise linear, Gaussian, equalization, and square root methods, all available in ENVI Classic 5.3. These results will be further explored in regression testing and model equation formulation.

Statistical Analysis

The vegetation index transformation results were subsequently subjected to correlation and regression statistical analysis using Genstat 10.4, with comparisons made to laboratory data correlating with potato crop production. Initially, laboratory results and the normality test for potato production were analyzed in Genstat 10.4 using the Anderson-Darling test (Anderson & Darling, 1954) to assess the distribution and sample data. The regression analysis was then performed, and the resulting equation was derived using the method outlined by Bewick et al. (2003). This equation was utilized to estimate potato crop production. Additionally, the resulting equation was further processed using map algebra in ArcMap 10.6 to produce a spatial distribution. The model estimation was validated using a paired t-test (Montolalu & Langi, 2018).

RESULTS AND DISCUSSION

Potato Productivity

The observed potato productivity in Bumiaji Sub-district ranged from 13.06 to 31.23 Mg ha^{-1}, with an overall average yield of 24.08 ± 4.78 Mg ha^{-1}. This figure is slightly lower than the reported average productivity of the Granola potato variety, which reaches 26.5 Mg ha^{-1} (Badan Litbang Pertanian, 2018). When comparing plots, Plot C recorded the highest productivity (25.73 ± 3.83 Mg ha^{-1}), followed by Plot B (24.33 ± 4.56 Mg ha^{-1}), while Plot A exhibited the lowest yield (22.19 ± 5.34 Mg ha^{-1}) and the most tremendous variability. These results indicate that productivity in Bumiaji fluctuates between plots, with environmental and management factors in Plot C likely contributing to its relatively higher and more stable yield performance. These discrepancies in yield can be attributed to a combination of factors, including but not limited to irrigation practices, soil type, soil compaction levels, nutrient availability from fertilizers, and the specific varieties planted. Additionally, environmental variability significantly influences the overall productivity of potato crops. As noted by recent studies (Xie et al., 2021), the interactions among these factors are complex and context-dependent, and thus a holistic approach to managing agricultural systems is critical for optimizing crop yields. It is essential to investigate these variables further, particularly irrigation and soil management practices, to identify potential avenues to improve productivity in this region. Moreover, despite the influence of environmental and agronomic factors, there remains a pressing need for more refined agricultural techniques and strategies to mitigate these challenges and enhance the sustainability of potato production in the face of climate change.

Spatial distribution of soil nutrients

The soil nutrient content at the observation site revealed an average TN of 0.33% (classified as medium), available phosphorus (Available-P) of 6.15 mg kg^{-1} (also medium), and exchangeable potassium (Exchangeable-K) of 0.40 me 100g{ ^{1} (moderate). These results provide important insight into soil fertility at the study location, indicating that the soil has a relatively balanced supply of essential nutrients for plant growth. However, improvements in nutrient management could be considered to optimize crop production.

The distribution of TN, Available-P, and Exchangeable-K data was classified based on nutrient status criteria provided by the Soil Research Institute (2009), and the spatial variation of these nutrients was visualized through interpolation methods as illustrated in Figure 4.1 (Nitrogen), Figure 4.2 (Phosphorus), and Figure 4.3 (Potassium). This approach not only highlights the spatial heterogeneity of soil nutrients but also underscores the importance of accounting for local nutrient conditions when managing agricultural practices, particularly for crops such as potatoes, which are highly sensitive to nutrient availability.

Moreover, while soil nutrient levels appear adequate for potato cultivation, it is essential to critically evaluate the dynamic interactions among soil properties, environmental factors, and crop requirements. Future research could further explore the mechanisms underlying nutrient uptake efficiency and its relationship with soil texture and organic matter content. Additionally, the findings underscore the need for tailored fertilization strategies to address potential imbalances, particularly phosphorus, which may influence potato yield and quality in the long term.

Spatial distribution of soil chemical properties

The soil pH analysis revealed an average value of 5.43, indicating an acidic soil environment. In

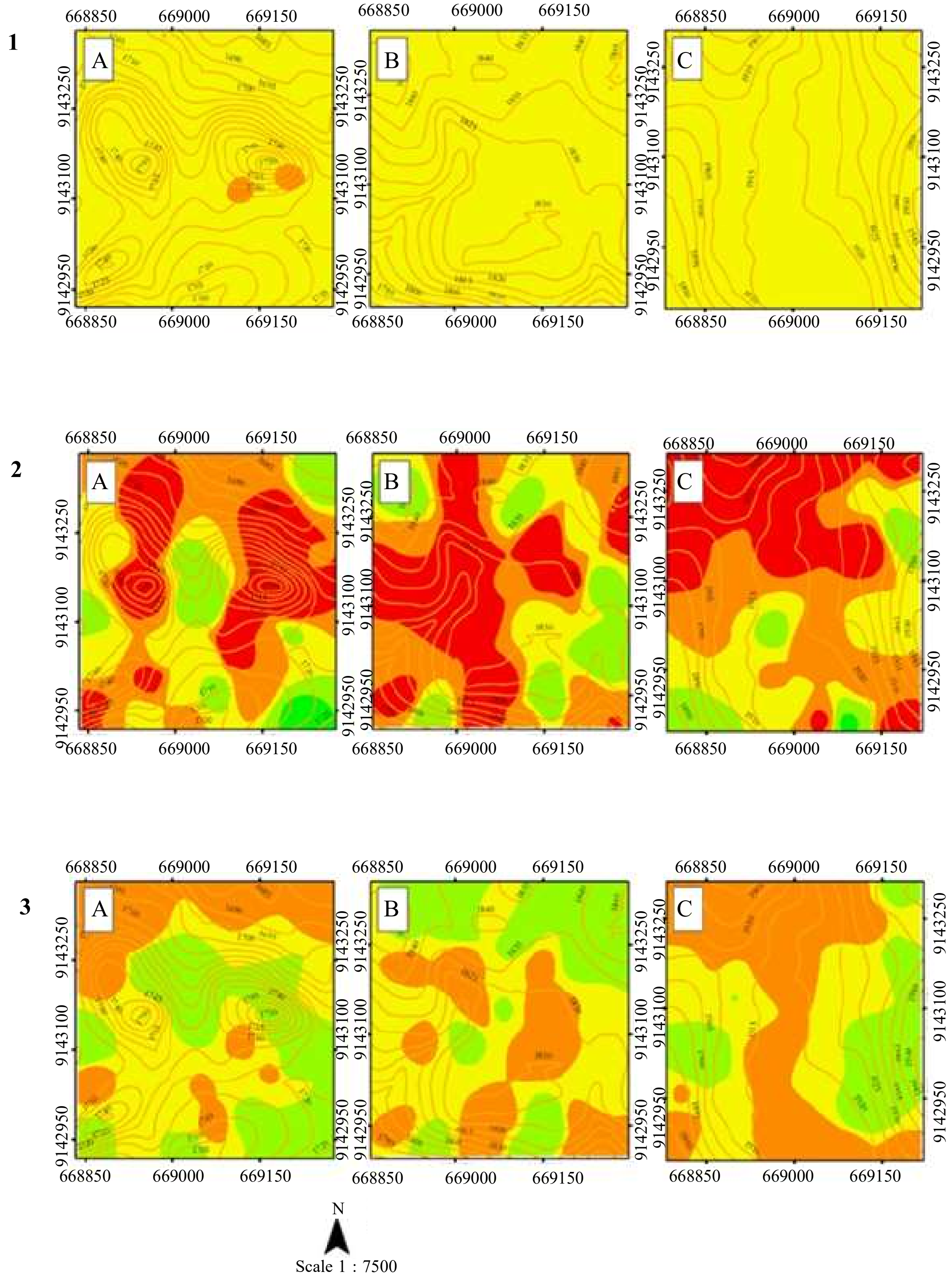

Figure 4. Spatial distribution of soil nutrients: 3.1 Total nitrogen (%), 3.2 Available phosphorus (mg kg^{-1}), and 3.3 Exchangeable potassium (me 100g^{-1}). 1. : contour 5m, : low (0.1-0.2%), : medium (0.21-0.5%). 2. : contour 5m, : lowest (<4 mg kg^{-1}), : low (5-7 mg kg^{-1}), : medium (8-10 mg kg^{-1}), : high (11-15 mg kg^{-1}), : highest (>15 mg kg^{-1}). 3. : contour 5m, : low (0.1-0.3 me 100 g^{-1}), : medium (0.4-0.5 me 100 g^{-1}), : high (0.6-1 me 100 g^{-1}).

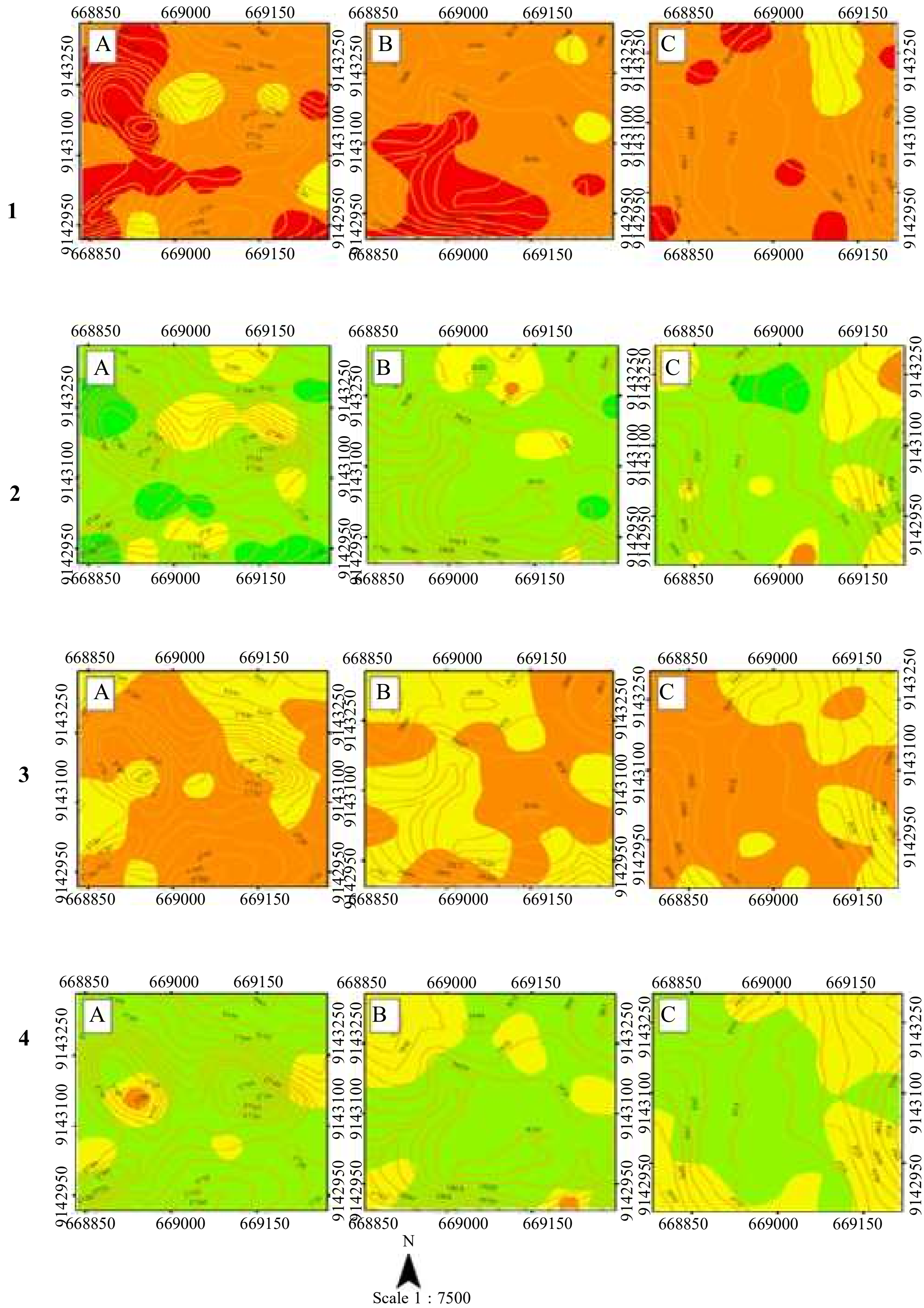

Figure 5. Spatial distribution of soil chemical properties: 4.1 Base saturation (%); 4.2 Cation exchange capacity (me 100 g^{-1}); 4.3 pH; 4.4 Organic carbon (%). 1. : contour 5m, : lowest (<20%), : low (20-40%), : medium (41-60%). 2. : contour 5m, : low (5-16 me 100 g^{-1}), : medium (17-24 me 100 g^{-1}), : high (24-40 me 100 g^{-1}), : highest (>40 me 100 g^{-1}). 3. : contour 5m, : medium acid (4.5-5.5), : slightly acid (5.5-6.5). 4. : contour 5m, : low (1-2%), : medium (2-3%), : high (3-5%).

contrast, the organic carbon content (C-Organic) was measured at an impressive 3.24%, which is considered high, alongside a cation exchange capacity (CEC) of 29.14 me 100g^{-1}, also categorized as high. However, land base saturation was relatively low, averaging 27.66%. These results suggest that while the soil's capacity for nutrient retention, as indicated by C-Organic and CEC, supports the potential for productive crop growth, the low base saturation may limit the soil's ability to maintain optimal nutrient availability over time.

However, while the retention of C-organic and CEC are vital factors influencing crop suitability, the pH and base saturation did not meet optimal thresholds for ideal potato growth, necessitating further investigation into soil management strategies to enhance these characteristics.

Nutrient retention data were classified according to the criteria provided by the Soil Research Institute (2009), and the results were interpolated and visualized in Figures 5.1 (Base Saturation), 5.2 (CEC), 5.3 (pH), and 5.4 (C-Organic). These figures illustrate the spatial variability and distribution of soil properties, which are crucial for understanding the broader implications for agricultural practices. It is important to note that although C-Organic and CEC are positively correlated with soil fertility and crop yield, the current low base saturation could pose challenges to nutrient balance, potentially affecting long-term sustainability in potato production. This highlights the need for targeted soil amendments and management practices to address these deficiencies and improve overall soil health.

As such, these findings present a clear opportunity to explore more effective soil conditioning techniques, such as lime or organic amendments, to correct pH and improve base saturation. Additionally, future research should focus on the interaction between these soil properties and crop performance under different management regimes, in order to further refine soil fertility models and optimize potato cultivation in this region.

Spatial distribution of soil physical properties

Field observations and laboratory analyses were conducted to examine various soil characteristics, including soil density parameters. The results indicated an average penetration value of 0.29 MP, suggesting moderate soil resistance to penetration. Soil bulk density was recorded at 0.86 g cm^{-3}, while soil particle density was measured at 2.13 g cm^{-3}, indicating a mineral soil composition. The soil's porosity was found to be 59.42%, highlighting the significant potential for water retention and root growth.

In terms of soil density distribution, the data was classified following the criteria established by the (Soil Survey Staff, 2022). The results were then interpolated to produce visual representations of the penetration, bulk density, and porosity variations across the study area, as shown in Figures 6.1 (Penetration), Figures 6.2 (Bulk Density), and Figures 6.3 (Porosity). This interpolation is crucial for understanding the spatial variability of these properties, which are directly linked to soil health and crop productivity. However, it is essential to recognize that soil density alone does not provide a complete picture of soil fertility or its suitability for specific crops; thus, it should be considered alongside other agronomic and environmental factors. Further investigation into the interactions between these soil properties and climatic conditions could offer deeper insights into optimizing agricultural practices in this region.

Vegetation Indices Value Extraction

The UAV imagery was processed to compute the vegetation indices (NGRDI, GLI, and VARI) based on reflectance values. The nominal range for the red spectrum varied from 73 to 254, while the green spectrum spanned from 94 to 247, and the blue spectrum had a nominal range of 70 to 249. All index transformation values followed a similar pattern, ranging from -1 to 1. In a related study using RGB UAV imagery to classify the number of flowers for oilseed extraction, the vegetation indices employed were NGDRI, GLI, and VARI (Ribeiro et al., 2023). The correlation analysis revealed a strong positive relationship between the NGRDI and VARI indices, with a correlation coefficient of $r = 0.99$. Conversely, NGRDI and GLI showed a negative correlation of $r = -0.64$, while VARI and GLI exhibited an even stronger negative correlation, with $r = -0.7$. These findings underscore the variable predictive capabilities of the indices, with VARI proving the most effective at estimating flower production, achieving an R^2 of 0.88 and a Root Mean Square Error of Prediction (RMSEP) of 19.78, followed by NGRDI and GLI (Ribeiro et al., 2023).

Correlation Between Potato Productivity and Parameter Observation

The analysis of the correlation between potato plant productivity and various soil parameters revealed significant positive relationships with TN, BS, soil penetration resistance, and BD (Table 1). The correlation coefficient (r) values exceeded the

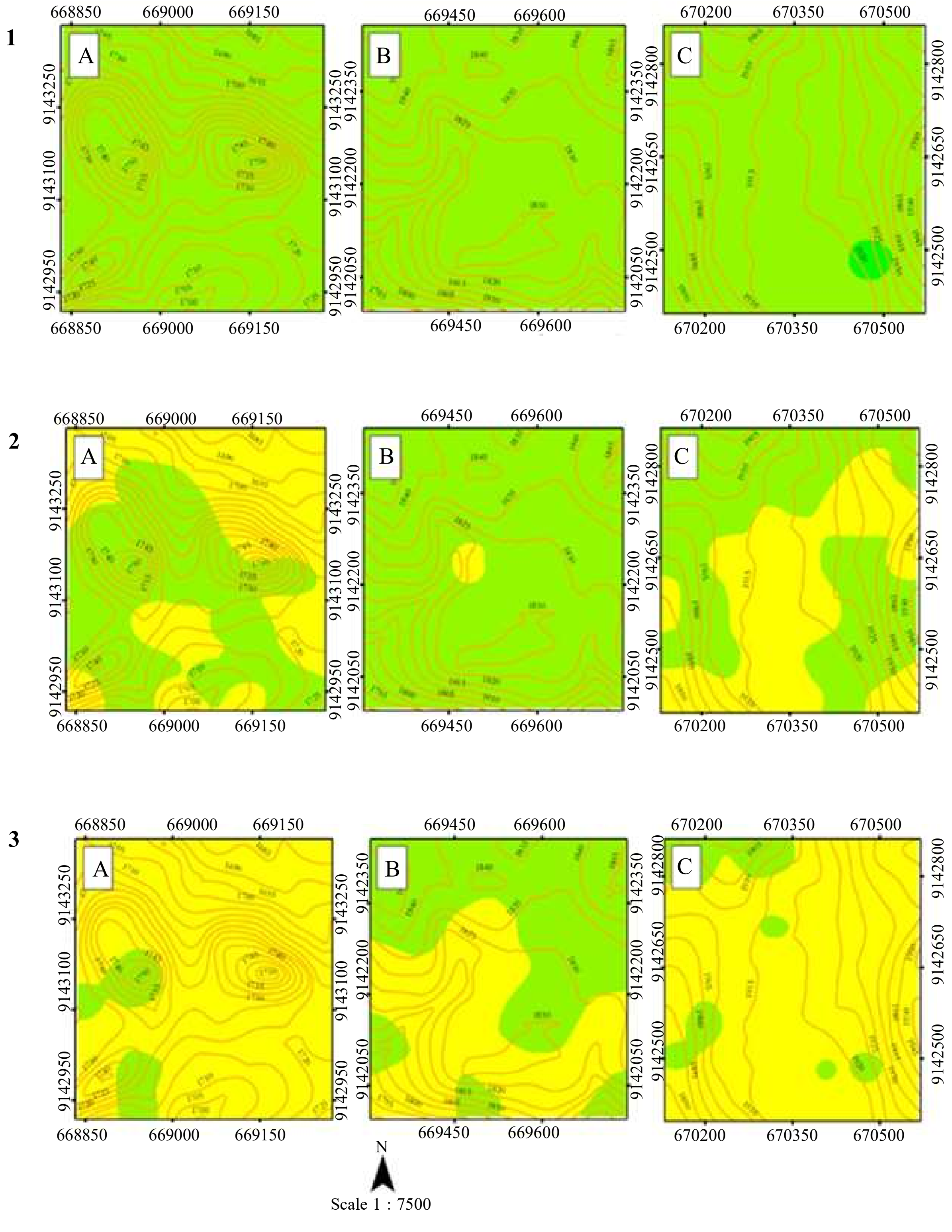

Figure 6. Spatial distribution of soil properties: (a) soil density penetration (MPa), (b) soil bulk density (g cm^{-3}), and (c) soil porosity (%). 1. : contour 5m, : lowest (< -0.1 MPa), : low (0.1-1 MPa). 2. : contour 5m, : low (< 0.9 g cm^{-3}), : medium (0.9-1.2 g cm^{-3}). 3. : contour 5m, : medium (31-63%), : high (> 63%).

critical value of the r-table (0.37), confirming the strength of these associations.

These findings emphasize the crucial roles of soil properties and plant nutrient content in determining potato plant productivity. However, it is important to consider the potential influence of unmeasured factors, such as environmental variables and management practices, which may also contribute to observed variations in crop yield. Moreover, while soil fertility and nutrient availability, particularly nitrogen, appear to influence potato growth significantly, the complexity of nutrient interactions and the roles of other micronutrients warrant further exploration in future studies to deepen our understanding of their combined effects on agricultural productivity.

Correlation Between the Index Transformation and Potato Plant Productivity

The parameter observations showed a correlation with potato plant productivity, prompting further testing to explore more advanced correlations with vegetation indices. The correlation tests showed that only three parameters were significantly related to the land indices. Specifically, TN showed the highest correlation with the Normalized Green-Red Difference Index (NGRDI) at 0.37; BS was most strongly correlated with the Green Leaf Index (GLI) at 0.22; and BD correlated with GLI at -0.25 (Table 2). These results suggest that soil properties such as nitrogen content, base saturation, and bulk density influence the vegetative indices associated with land productivity.

Several factors may account for these lower correlations, such as limitations in the quality of the UAV images or unmeasured environmental influences. To address this, a re-capture of UAV images is planned, with an emphasis on improving the image quality. It is anticipated that improving UAV imagery will yield more accurate data, thereby

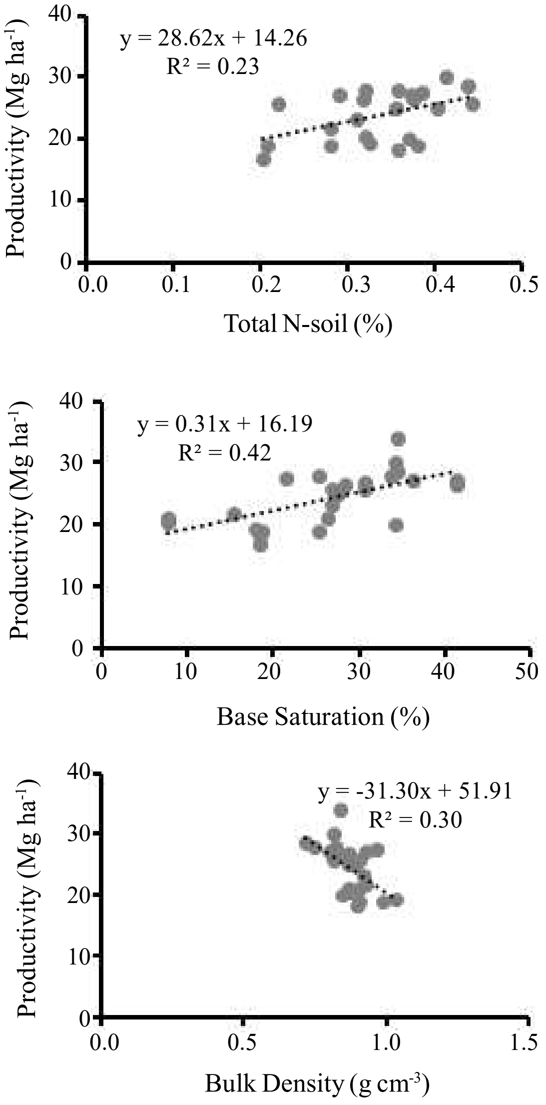

Figure 7. Regression analysis between soil properties and potato productivity

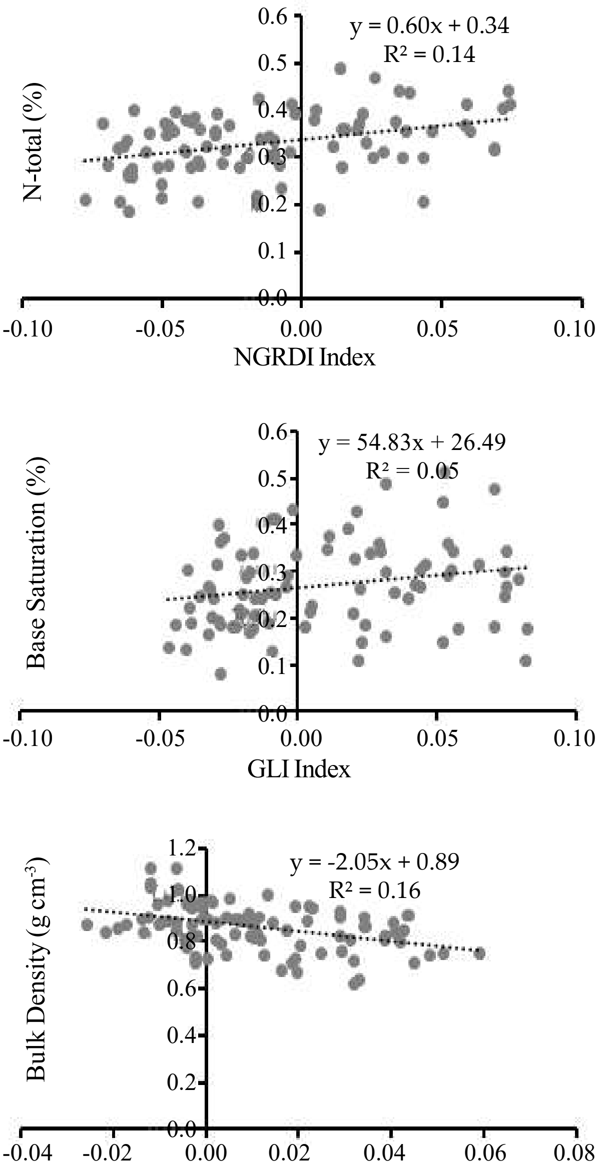

Figure 8. Regression analysis between soil properties and potato productivity.

increasing correlation values and enabling a more robust analysis of the relationship between plant productivity and remote sensing indices.

The Role of Soil Characteristics in Potato Productivity

Potato productivity is strongly influenced by soil characteristics, which directly and indirectly affect vegetative growth, tuber development, and final yield. Based on regression analysis, several soil properties exhibit significant relationships with potato productivity (Figure 7). BS demonstrates a moderately strong positive correlation with productivity (R^2 = 0.42, RMSE = 0.76 Mg ha^{-1}, nRMSE = 18.3%), indicating that increased base saturation—reflecting the availability of basic cations such as $Ca^{2}z$, $Mg^{2}z$, Kz , and Naz —plays an important role in supporting optimal potato growth. These cations help neutralize soil acidity and improve the availability of essential nutrients. Conversely, BD shows a negative correlation with productivity (R^2 = 0.30, RMSE = 0.89 Mg ha^{-1}, nRMSE = 21.4%). Higher bulk density is associated with compacted soils that limit root penetration, water movement, and air diffusion. Such conditions restrict the plant's ability to access water and nutrients efficiently, ultimately reducing tuber formation and yield potential. TN also exhibits a positive relationship with productivity (R^2 = 0.23, RMSE = 1.02 Mg ha^{-1}, nRMSE = 24.5%), underscoring the importance of nitrogen availability for vegetative growth and tuber development. However, this correlation is weaker than that of base saturation, possibly due to variations in nitrogen uptake efficiency or interactions with other limiting factors such as water availability and soil physical condition. Vegetation indices such as the Normalized Green-Red Difference Index (NGRDI) and the Green Leaf Index (GLI) are used as indicators of crop canopy vigor. NGRDI shows a weak positive correlation with TN (R^2 = 0.14, RMSE = 1.15 Mg ha^{-1}, nRMSE = 27.8%), while GLI has a very weak relationship with BS (R^2 = 0.05, RMSE = 1.28 Mg ha^{-1}, nRMSE = 31.0%) and a slightly negative correlation with BD (R^2 = 0.16, RMSE = 1.11 Mg ha^{-1}, nRMSE = 26.3%) (Figure 8). These findings suggest that vegetation indices may be less sensitive in detecting variation in soil chemical and physical properties, and are likely influenced by multiple interacting factors beyond soil fertility alone.

Compilation of Formulas Obtained

This section will explain the formula used to prepare the estimation model map. The estimates of potato crop productivity based on TN, BS, and BD are shown in the figure, ranging from red to green, while the white-to-gray areas are not potato fields (Figure 9). The green color indicated areas with high production values. The range of productivity of potato plants produced is from 9 Mg ha^{-1} to 40 Mg ha^{-1}.

The regression results for potato plant productivity and the parameters were combined with the equations obtained from the parameter indices. The results of the equation were Potato Plant Productivity = 27.80 + 12.10 [0.60 (NGRDI) + 0.34] + 0.18 [54,83 (GLI) + 26,49] – 14.00 [-2.03 (GLI CS) + 0.89], and then it was simplified to Potato Plant Productivity = 24.22 + 7.26 (NGRDI) + 9.87 (GLI) + 28.42 (GLI CS). The equation obtained a coefficient of determination (R^2 = 0.508) and a Root Mean Square Error (RMSE = 4.25 Mg ha^{-1}). This

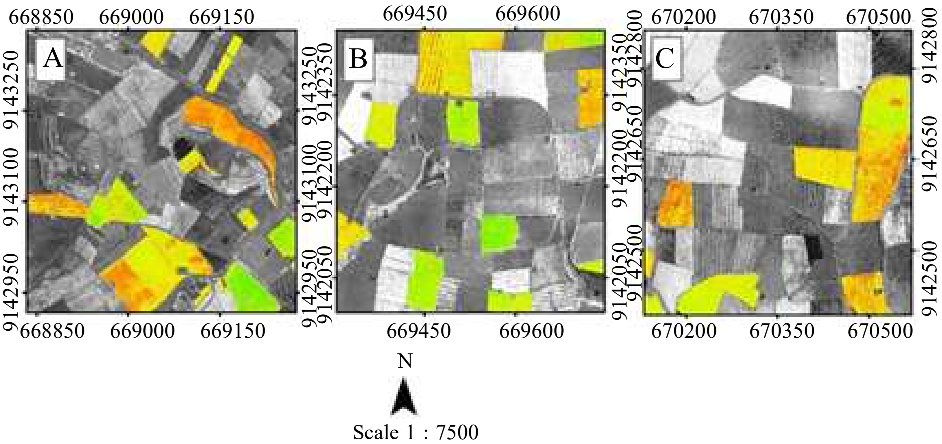

Figure 9. Estimation of potato plant productivity. Productivity (Mg ha^{-1}): High: 40 Low: 9

indicates that the model explains about 51% of the variation in potato productivity, with an average prediction error of approximately 4.25 Mg ha^{-1}.

Model Validation Test

The validation test was conducted to determine whether the model's estimate was obtained. The validation test was completed using a paired t-test to compare the field-average productivity with the model results. The average potato plant productivity in the area was 24.85 Mg ha^{-1}. The model's average estimate based on TN, BS, and BD was 25.12 Mg ha-1, with a t-test result of 0.29 and a t-table value of 2.26. The test results indicated that the t-count was less than the t-table value. It means the estimation model results were not much different from field conditions. Therefore, the estimation model equation could be used to estimate potato plant productivity.

Best Formula Model

The best formula to estimate potato plant productivity is soil total nitrogen (ground with NGRDI), base saturation (GLI), and bulk density (GLI CS). The resulting R^2 is relatively low, at 5% to 51%. One factor that affected the results was the uneven distribution of data on potato plant productivity, as farmers grew various commodities, including potatoes, cabbage, carrots, and others. There were disastrous local whirlwinds on June 19 and October 20, 2019, which caused crop failure among farmers. The windstorm disaster lifted the topsoil (Richa, 2019). Other factors that do not affect the maximum include environmental factors, aerial photography, and other unpredictable factors. In the opinion of Kelcey and Lucieer (2012), several factors affect the analysis results. Topography, landforms, and the degree of solar radiation influence environmental factors. Factors influenced by the UAV's image capture lens aperture, exposure settings, and the amount of reflection spectral response obtained on the lens. The differences in spectral response were caused by varying levels of brightness and color balance, resulting in a base color and contrast that were not sharp (Niethammer et al., 2012).

Moreover, estimates based on RGB-based UAVs to transform into NGRDI, GLI, and VARI are not widely used for prediction because they rely on 660 nm reflectance, which corresponds only to the Red component (Shofiyanti, 2011). The index commonly used for estimation models is a Near Infra-Red (NIR) index with an electromagnetic wavelength of 780-2500 nm (Nicolaï et al., 2007). The NIR components had higher wavelengths than the RGB bands; the higher the wavelength, the better the soil reflectance. Another factor influencing the land's reflectance characteristics in the aerial photo is the presence of organic material, soil moisture levels, soil iron oxide content, and soil surface structure (Huete & Glenn, 2011). Soil conditions and differences in altitude affected the vegetation index that was generated. These field conditions qualitatively indicate that land surface factors and topography can cause disturbances (Wiratmoko, 2015). Soil conditions in Bumiaji are pretty varied, with farmers' different cultivation and land management practices leading to changes in soil conditions across the area. The diverse topography and elevation also influenced the results at 1700, 1800, and 1900 m a.s.l. The estimation model, tested for validity, can be applied in the field despite a relatively low coefficient of determination.

Relationship Between Productivity Potato and Parameters

Potato productivity was not significantly correlated with any of the observation parameters. The only nutrient related to potato plant productivity was TN. This condition was due to the N function in the protein synthesis of potato crops to help improve yield growth. In contrast, P and K nutrients did not affect potatoes' increased production (Bagherzadeh et al., 2018). The high availability of nutrients does not necessarily influence the high or low productivity of potato plants, and not all available nutrients can increase the productivity of potato plants (Koch et al., 2020)

The nutrient retention that correlates with the productivity of potato plants was only BS, where if BS was higher, the soil would be more fertile (Jahan et al., 2016). Soils with low BS show more sorption complexes filled with acid cations such as Al and H; too many acid cations, especially Al, can cause toxicity to plants (Ghorbani et al., 2024). The use of lime on acid soils and the increase in BS have a positive effect on potato production because the addition of lime increases pH, which reduces Al phytotoxic levels' toxicity. While other variables such as pH, C-organic, CEC have a positive relationship with potato productivity but are not significantly related. This condition was not appropriate in several other studies. An increasing pH can reduce the toxicity of phytotoxic pH levels and increase production. Potato productivity with pH does not have a significant relationship, probably because the pH in the study area tends to be low and not suitable for potato plants (Nduwumuremyi et al., 2013).

Soil density, which has a relationship with potato productivity, is BD, but the relationship value obtained shows the opposite. This condition means that if the bulk density value increased, it would decrease productivity gains. This condition was appropriate because if the soil is getting congested, then the potato tuber formation would be inhibited. High soil density would result in the suboptimal quality of tubers (Stark et al., 2020). This condition is appropriate because if the soil is denser, the formation of potato tubers would be increasingly hampered. High soil density will cause the quality of the tubers produced to be less than optimal (Stark et al., 2020), and BD would affect the level of stability of soil aggregates where it would hamper the ability of the soil to pass water, which causes calm water. Flooding of water would cause the resulting tubers' quality to decrease (Richard et al., 2001).

Production Potential and Level of Reliability

Potato productivity in the District of Bumiaji based on measurements in the field obtained 24.85 t ha^{-1}. In contrast, the results obtained from the average estimation of the equation model are 24.19 t ha^{-1}. Results productivity estimates some results are inconsistent with productivity in the field, but this value is not much different from the average productivity of potato plants. Production potential by optimizing the process of cultivation of potato varieties of granola able to produce average productivity of 26.5 t ha^{-1} (Badan Litbang Pertanian, 2018). Meanwhile, the results of a national assessment of the potential productivity of 16.7 t ha^{-1} with the potential productivity in the province of East Java at 13.21 t ha^{-1} (Direktorat Jendral Hortikultura 2009) and the productivity of the potato crop in 2017 and 2018 amounted to 19.16 t ha^{-1} and 19.24 t ha^{-1} (Badan Pusat Statistik Kota Batu, 2018). Comparing the results of the potato crop productivity in Batu City can be said to be optimal on the national and regional scale.

The reliability estimation models tested showed that the model applied was not different from the conditions in the field as the result of t-counting was less than t-table. The equation model can be declared valid and consistent if used to estimate potato plants' productivity by N-total land, BS, and BD in Bumiaji, Batu.

CONCLUSIONS

The study identified that nutrient availability (soil N-total), nutrient retention (base saturation, BS), and soil density (bulk density, BD) are the key soil parameters influencing potato productivity. Among these, high bulk density negatively affects tuber growth due to restricted root development. Vegetation indices sensitive to these soil parameters and potato yield include NGRDI for soil N-total, GLI for BS, and GLI-CS for BD. The developed multiple regression model, Potato Plant Productivity = 24.22 + 7.26 (NGRDI) + 9.87 (GLI) + 28.42 (GLI-CS), achieved a coefficient of determination (R^2) of 0.51. This indicates that the model can moderately explain the variation in potato productivity. Statistical validation using the t-test further confirmed that the model is reliable and consistent for estimating potato yield in Bumiaji District, Batu City, soil total N.

ACKNOWLEDGEMENTS

This study was part of research funded by the PT. Indofood Sukses Makmur, Tbk in Indofood Research Nugraha program. Thank were delivered by top researchers who have awarded financial assistance to obtain these results.

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