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Analysis and Prediction of Water Availability Criteria in Potato Using High-Resolution Aerial Photography

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ABSTRACT

Indonesia's potato fields are typically small and fragmented, making coarse resolution moisture products prone to spatial mismatch and limiting their usefulness for precision water management. This study developed plot scale, water based suitability information for potato by integrating UAV multispectral imagery with field measurements of soil water availability and plant height response. UAV imagery was processed into four vegetation indices, namely NDWI, SAVI, MSAVI, and SR, followed by geostatistical mapping. Relationships between indices and measured water availability were evaluated using correlation, linear regression, paired t test, and principal component analysis to examine inter index structure and redundancy. NDWI showed the most consistent performance, with a moderate positive correlation with measured water availability (r = 0.47), while SAVI and MSAVI were negatively correlated (r = −0.46) and SR showed the weakest association (r = −0.33). The NDWI based regression for water availability estimation was $y = 0.50x + 29.68$ with R^2 = 0.22. The paired t test indicated no significant difference between NDWI based estimates and field measurements, with mean values of 30.09 percent and 30.52 percent, respectively, across 17 observations. Water based land suitability classes were then refined using boundary line analysis linking water availability to plant height response, producing plot scale criteria suitable for precision zoning rather than landscape level evaluation

1. INTRODUCTION

Indonesia's potato production as reported by (BPS, 2019) increased by 10.31% in 2018 compared to 2017 (or from 1.16 million tons to 1.28 million tons). However, if viewed from the production pattern since 2015, potato production has decreased. Water availability is one of the limiting factors for potato production in highland agricultural areas of Indonesia. The availability of soil water may decline the production because potatoes are susceptible to lack of groundwater, and the crop needs available water between 83.38-86.28% (Broto *et al*., 2018).

The amount of water that must be provided for growing potatoes is very dependent on the availability of water in the soil. Soil water availability is commonly defined as the range between pF 2.54 (field capacity) and pF 4.25 (permanent wilting point), however this is a problem faced by most farmers because of the difficulties of measuring and expensive data. This limitation highlights the need for alternative approaches that are practical and spatially representative for agricultural management. Agricultural precision on water content can address their needs.

The use of the latest technology using UAVs which are supported by a vegetation index with high accuracy is expected to be able to help solve these problems so that the sustainability of productivity can be optimal. Ruwaimana *et al*. (2017) reported that UAV compared to mapping aircraft, are able to fly lower, so they have a more detailed image resolution and can reach below 1 cm.

The research of Benedetto *et al*. (2013) and Mohamed *et al*. (2019) show that a geostatistical method, namely kriging, allows researchers to get accurate results using a very small number of soil sampling offset by a much higher spatial resolution. The result showed that there was no significant difference between the actual groundwater content of the field measurements and the geostatistical estimation result using kriging. However, the data used were generally derived from medium-resolution imagery (approximately 30 m) even though agricultural land in Indonesia is generally fragmented and very narrow, so the potential for misalignment is high. Liu *et al*. (2020) reported that different resolutions will provide different information and impact the scale and result, and that decrease in spatial resolutions and gradually decrease in accuracy. Therefore, more accurate prediction of soil water content using high-resolution spatial data combined with geostatistical analysis is required, particularly for fragmented agricultural landscapes.

Prediction of soil water content with more accurate data using geostatistical analysis and utilization of aerial photographs has been carried out by researchers in 2019 using UAV with RGB cameras but has not succeeded in accurately predicting water availability (R2 11%) (Putra & Nita, 2020). Casamitjana *et al*. (2020) examined the use of 4 vegetation indexes (SAVI, NDVI, NDWI, and PDI) to measure the soil water content in various agricultural land uses (potato land, bare land, livestock) using a 3 m resolution UAV and concluded that the NDVI index showed a positive correlation and has a positive correlation to levels. Groundwater on bare soil, NDWI and PDI at a detailed scale. However, for potato land, NDWI was the best and significantly correlated with soil moisture content.

So, in this study, NDWI and SAVI were used and SR and MSAVI were addedas a comparison. Also, this study extends previous studies using UAV with a NIR band, geostatistical analysis and the development of water availability criteria related to potato production potential. Therefore, this study aims to (1) develop soil water availability criteria for potato crops based on high-resolution UAV imagery and geostatistical analysis, and (2) spatially predict soil water availability to support the assessment of potato production potential.

2. MATERIALS AND METHODS

2.1. UAV Flight and Research Location

Image recording started at 09:00 am on 29th February 2020 and was conducted in Bumiaji District, Batu City, East Java, Indonesia with a flight altitude of 40 m above ground level (agl). The study area is located at an elevation of approximately 900–1,200 m above sea level (asl). Bumiaji District is located at 7°53′4.35″ to 7°43′30.35″ S and 112°28′41.78″ to 112°35′16.35″ E with an area of 12,497.08 ha. Aerial photo recording run using the DJI Phantom 3 Pro Drone with visible and NIR camera (pixel size 9 cm^2), set up using a mission planner (Figure 1) to ensure the flight went well and covered approximately 3 ha of potato fields at 50 days after planting (DAP). The image acquisition at 50 days after planting was selected because this period corresponds to the second vegetative growth stage of potato plants, during which canopy development is optimal and leaf coverage is at its maximum, allowing vegetation indices to be more sensitive to soil water conditions (Mukiibi *et al*., 2025; Wang *et al*., 2025). In addition, UAV-based remote sensing has been widely used to assess crop water status and canopy/leaf water-related parameters through vegetation indices (Yang *et al*., 2025; Guo *et al*., 2024). This location has average temperature 22 °C and average rainfall 1,923 mm with 138 rainy days from November to April (BPS Kota Batu, 2017). The geological unit in Bumiaji District is Qvaw (Arjuno-Welirang Volcano Deposition), which originates from volcanic deposition processes. Based on the soil map of BBSDLP 1:25,000, the study area has Inceptisols with the Eutrudepts group.

2.2. Soil Sampling and Laboratory Analysis

The ground check was carried out by observing and collecting data such as production, land characteristics, and the suitability of water availability for mapping data validation. In this study, soil water content measured through laboratory analysis was used as the primary validation variable for spatial prediction, while crop production data were

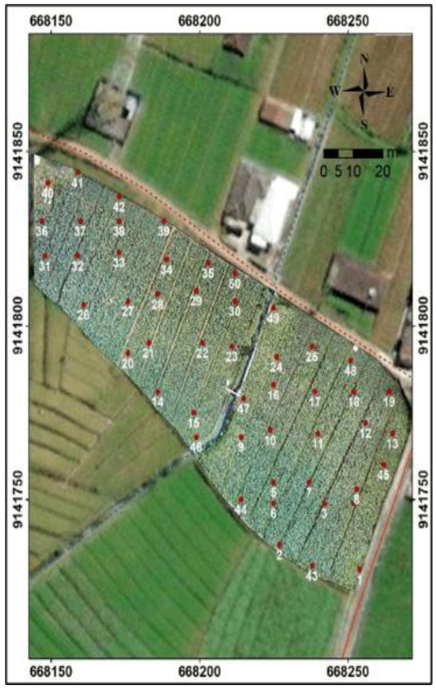

Figure 1. Point observation of flight planning in study area

used as supporting information. From the total field observation data, 70% of the samples were used for model development, while the remaining 30% of the field data were reserved for validation purposes.

Samples were taken based on predetermined patterns and distances (grid method) in a 13 m × 13 m grid with a total of 50 observation points. The grid size was selected to correspond with the spatial resolution of the UAV imagery and to ensure sufficient spatial representation within the 3 ha study area, while the number of sampling points was determined to balance spatial coverage and field sampling feasibility.

The technique of measuring soil water content is classified into two ways, direct and indirect (Dobriyal *et al*., 2012). Soil sampling was done on topsoil using undisturbed soil sampling method for analysis of soil physical properties and disturbed soil sampling for soil chemical analysis. The undisturbed soil sampling was carried out using a tube (ring) with a height of 4 cm, 7.93 cm outer diameter, and 7.63 cm as inner diameter. The disturbed soil sampling was carried out by taking soil from topsoil layers with a depth of 0–20 cm using pellets and then stored in plastic and without replication. Water content analysis is available using the gravimetric method (Gardner, 1986).

2.3. Preprocessing of Aerial Photography and Transformation Index

Aerial photo preprocessing followed by several steps (Brahmantara & Kustiyo, 2017), combining several photos into one image (orthomosaic) using Agisoft software, then change calculating vegetation indices such as Soil Adjusted Vegetation Index/SAVI (Huete, 1988), Modified Soil Adjusted Vegetation Index/MSAVI (Anurogo *et al*., 2018), Simple Ratio/SR (Meyer *et al*., 2019), Normalized Difference Water Index/NDWI (Serrano *et al*., 2019) (Table 1).

The aerial photographs were converted into a high-resolution Digital Elevation Model (DEM) then used to determine the general condition area to compose geology map, soil type (including characteristics), relief, land use considering soil sampling location plan.

This study also used data from the previous studies, pF 2.5 and 4.25, rainfall, and potential evapotranspiration. These variables were integrated as supporting environmental parameters and spatially interpolated using geostatistical analysis, while vegetation indices derived from UAV imagery served as the primary predictors of soil water availability. Then those data were analyzed using kriging geostatistical analysis (Equation 1) to obtain preliminary spatial maps of water availability. The resulting spatial maps were subsequently used as a reference for soil sampling design, as described in Section 2.2. Details of sampling point generation and field map preparation are provided in Section 2.2 to avoid repetition. The number of points adjusts to the land area, scale will be used, and the method of determining the number of points used (Sun *et al*., 2017).

Table 1. Utilization of various transformation indexes

No	Index	Formula(*)	References
1	SAVI (Soil Adjusted Vegetation Index)	$\frac{(\lambda NIR - \lambda Red)(L + 0.5)}{\lambda NIR + \lambda Red + L}$	(Huete, 1988)
2	MSAVI (Modified Soil Adjusted Vegetation Index)	*{2(NIR)+1-√{2(NIR)+1}²-8{(NIR) Red}/2*	(Anurogo *et al*., 2018)
3	SR (Simple Ratio)	$\frac{\lambda NIR}{\lambda Red}$	(Jordan, 1969)
4	NDWI (Normalized Difference Water Index)	$\frac{\lambda Green - \lambda NIR}{\lambda Green + \lambda NIR}$	(McFeeters, 1996)

2.4. Statistical Analysis

2.4.1. Correlation, Regression and T-test between the Vegetation Index and Soil Water Content

SPSS version 16.0 is used to analyze which vegetation indices (SR, SAVI, MSAVI and NDWI) are able to reflect the actual conditions of soil water content in the field through Pearson's correlation analysis (p value < 0.05), regression and t-test between the vegetation index and soil water content in the field.

2.4.2. Analysis and Modification Criteria Using Boundary Line Analysis

The development of site-specific land suitability criteria uses the boundary line method by creating a border at the upper envelope of the data distribution, where plant height is represented by the x-axis and soil water content is represented by the y-axis (Lamadi *et al*., 2025). The results of the boundary line analysis will later be able to produce a modified land suitability class for potato crops according to Djaenudin *et al*. (2011). The use of the boundary line method in modifying land suitability classes must have a positive interaction between parameters as indicated by the correlation and regression values between parameters (Sareh & Rayes, 2019).

2.4.3. Geostatistical Analysis

The capacity of geostatistical analysis provides unbiased estimation of spatial variables and uncertainty involved is a key advantage of geostatistical approach (Manzione & Castrignanò, 2019). When estimating values in unknown areas, kriging is a geostatistical interpolation technique that considers both the distance and the degree of variance between known data points. Kriging is similar to IDW in that it assigns weights to the calculated values in the immediate vicinity while making a forecast (Venkatramanan *et al.*, 2019). According to Benedetto *et al*. (2013), Kriging estimator $\hat{z}(x_0)$ with x_0 is a linear combination of random variables, which can be seen in the withdrawal of as the following:

$$\hat{z}(x_0) - m = \sum_{i=1}^{k} \lambda_i [z(x_i) - m] \quad (1)$$

where m is mean (scalar constant), λ_i is weight $z(x_i)$ for location estimation x. The same $z(x_i)$ value will have different weight coefficients for estimations at a different location, x_i is a different location vector, k is lots of data sampled for estimation. The geostatistical analysis is used to distribute the available moisture content based on the modeling results. The analysis was performed by entering the available water content (model) into ArcMap's Geostatistical analysis.

A paired t-test (paired t-test) is one of the hypothesis testing methods where the data is characterized by the existence of relationship value in the same sample (paired). Vegetation indices that showed significant correlation and regression with soil water content were further tested using paired t-test. Paired t-test was used to compare two parameters, namely water available based on laboratory analysis and based on the model.

2.5. Potato Crops Productivity Analysis Methods

Delineation (a boundary line) was applied to analyze potato productivity by identifying the upper boundary of the relationship between soil water availability and potato yield. The boundary line was drawn by fitting the upper envelope of the scatter plot, where soil water availability was used as the independent variable and potato yield was used as the dependent variable, representing the maximum attainable productivity under given water conditions.

In determining land suitability criteria for productivity, productivity data are required. As a reference national average potato productivity in Indonesia (5–6 t/ha) was used as a general baseline. At the research location, potato varieties was Granola with production range from 20 to 32 t/ha. To determine the suitability level, land suitability classification based on productivity was applied. According to Suhairi *et al*. (2018), the productivity block with land suitability level N (unsuitable) is < 40% of the maximum yield, which is < 2.4 t/ha. Production suitability potential is grouped into four classes, namely S1 (> 80% productivity potential), S2 (60–80%), S3 (40–60%), and N (< 40%).

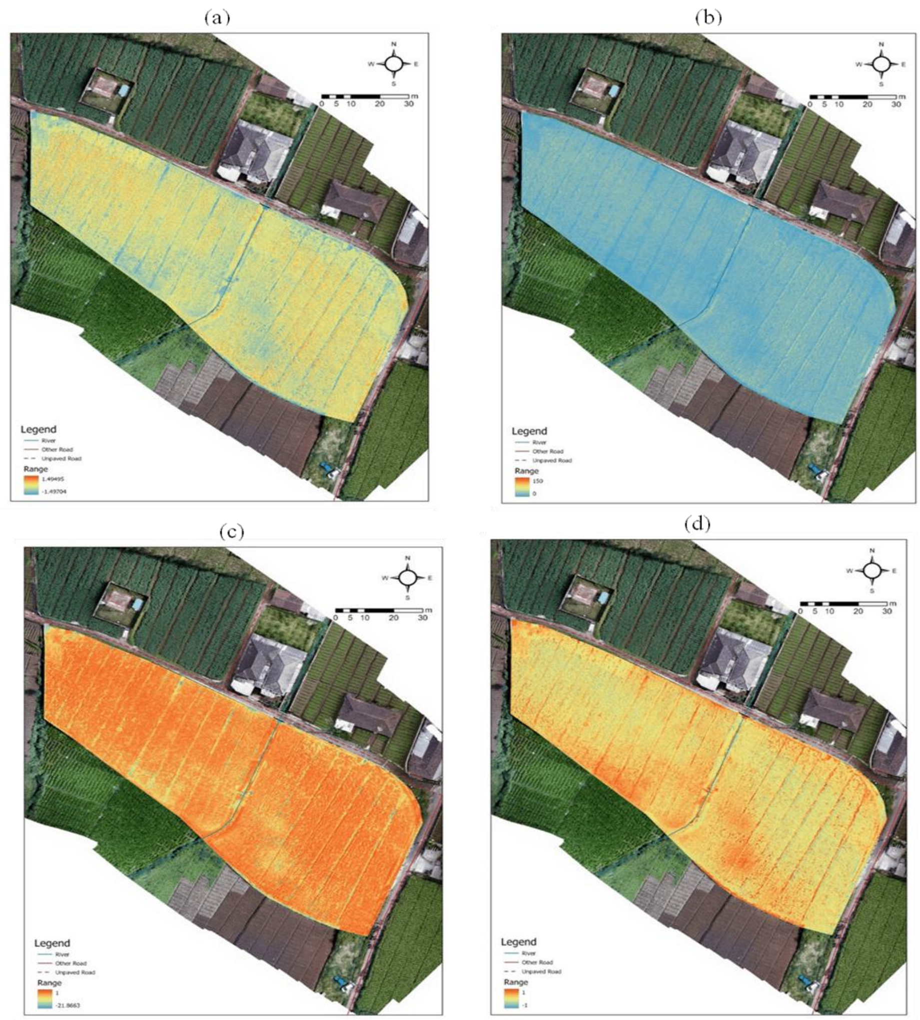

Figure 2. Vegetation index maps derived from UAV imagery (a) NDWI; (b) SR; (c) MSAVI; and (d) SAVI

3. RESULTS

3.1. Index Transformation Map

The transformation result map shown in Figure 2. NDWI is a sensitive remote sensing-based identification method to show the water level content in the soil and the moisture content in land cover. Based on the NDWI transformation map (Figure 2a), the lowest value range is –1.49, most of which is located in the irrigation channel between land plots. The highest value is approximately 1.49 in the middle of the land cover.

Based on the map resulting from the SR (Simple Ratio) image transformation in Figure 2b, a range of values obtained between 0–150. The map shows range values close to 0 dominate most parts of the land, while the higher values are scattered in the middle. The Modified Soil Adjusted Vegetation Index (MSAVI) transformation in Figure 2c shows that it ranges between –21.87 to 1, where the highest value is close to 1, and has a dominant area on the plot of land. The SAVI (Soil Adjusted Vegetation Index) transformation in Figure 2d shows a range of values from thelowest (–1) to the highest with a value of 1, with values close to 1 dominating most of the cultivated area. Among the evaluated indices, NDWI exhibits clearer spatial contrasts related to irrigation channels and cultivated plots. However, the quantitative performance of each vegetation index in representing soil water content was further evaluated using correlation analysis (Table 4). Martiningrum (2017) explains that the SAVI and MSAVI values describe vegetation through satellite images by utilizing the reflectance value of the closest red and infrared channels with the soil brightness correction factor (L). This characteristic explains the more homogeneous spatial patterns observed in SAVI and MSAVI maps, where soil background effects are minimized, resulting in less contrast related to moisture variability.

3.2. Field Observations of Plant Height and Soil Water Content

The relationship between plant height (50-days after planting in cm) and water availability reveals a nonlinear growth response characterized by an initial stabilization phase followed by a pronounced increase at higher plant stature (Figure 3). At lower to intermediate heights, water availability remains relatively constant, indicating that early vegetative growth is sustained under moderate moisture conditions. Beyond this range, taller plants are consistently associated with higher water availability, suggesting that sufficient soil moisture becomes increasingly critical as vegetative demand intensifies. The polynomial regression captures this curvature effectively and explains a substantial proportion of the observed variation, as indicated by the coefficient of determination. This pattern reflects the physiological dependence of potato vegetative development on adequate water supply during advanced growth stages and supports the use of plant height as a reliable biological response variable for evaluating water based land suitability.

3.3. Regression Analysis for Soil Water Content Estimation

The regression assumption tests indicate that all vegetation indices (NDWI, SAVI, MSAVI, and SR) deviate from normality, as shown by Shapiro–Wilk statistics ranging from 0.638 to 0.669 with p-values < 0.001. However, the homoskedasticity assumption is satisfied for all models, with Breusch–Pagan p-values between 0.277 and 0.470. The violation of normality is common in high-resolution UAV-based remote sensing data due to spatial heterogeneity and non-linear spectral responses. Nevertheless, correlation and regression analyses remain valid in this study because the variance of residuals is stable, the sample size is sufficiently large to ensure robustness of parameter estimates, and the primary objective is predictive modeling rather than strict parametric inference. Therefore, regression analysis is considered appropriate for assessing and predicting water availability criteria in potato crops.

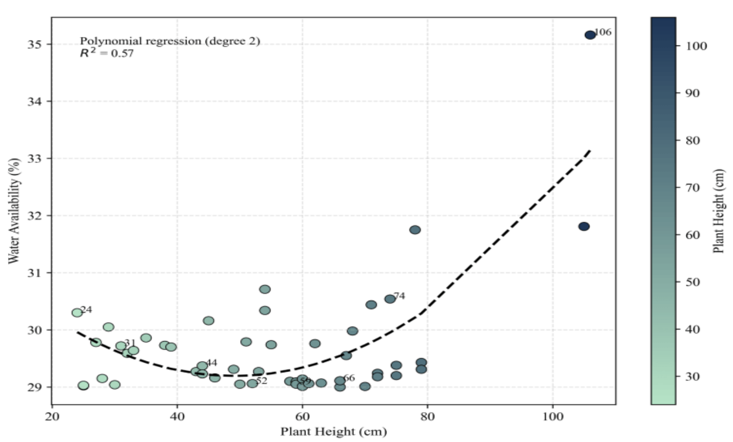

Figure 3. Polynomial relationship between plant height and water availability

Pearson's correlation analysis reveals distinct relationships between soil water availability and the evaluated vegetation indices. NDWI shows a moderate positive correlation with soil water content, with a correlation coefficient of 0.47 (*p* value < 0.05), indicating that higher NDWI values tend to be associated with increased water availability in the field. In contrast, SAVI and MSAVI exhibit moderate negative correlations with soil water content, both with coefficients of −0.46, suggesting that increases in these indices are not directly linked to higher soil moisture conditions. The Simple Ratio index also demonstrates a negative correlation with water availability, although with a lower magnitude of −0.33, indicating weaker sensitivity to soil water variability. Correlation strength was interpreted as weak to moderate when $|r| < 0.5$. The negative correlations observed for SAVI, MSAVI, and SR are likely related to canopy saturation and soil background effects during dense vegetative growth, whereas NDWI showed a positive correlation due to its specific sensitivity to vegetation and surface moisture conditions, as reported in previous studies.

Strong interrelationships are observed among the vegetation indices themselves, particularly between SAVI and MSAVI, which show a perfect positive correlation of 1.00, reflecting their similar formulation and response to vegetation and soil background conditions. Both indices also exhibit strong positive correlations with SR, with coefficients of 0.92, while NDWI shows strong negative correlations with SAVI and MSAVI, each with a value of −0.87, and with SR at −0.76. These contrasting patterns highlight the conceptual differences between moisture oriented indices and vegetation vigor based indices, and support the selection of NDWI as the most representative index for further spatial modeling of soil water availability in this study.

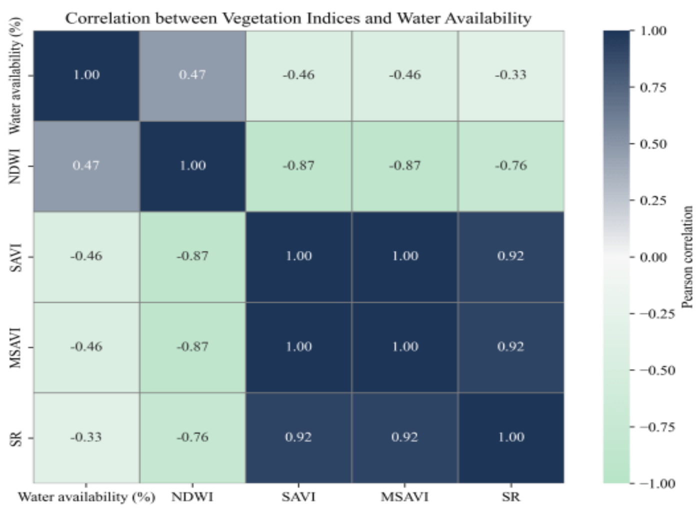

Figure 4. Correlation between vegetation indices and water availability for NDWI, SAVI, MSAVI, and SR

3.4. Regression Analysis for Soil Water Content Estimation

The relationships between vegetation indices and field measured water availability exhibit weak but distinguishable linear trends across all evaluated indices (Figure 5). NDWI shows a positive relationship with water availability, expressed by the regression equation $y = 29.68 + 0.50x$ with a coefficient of determination $R^2 = 0.22$. This indicates that increasing NDWI values are associated with a slight increase in water availability, although the explanatory power remains limited. The positive slope reflects the conceptual sensitivity of NDWI to moisture related spectral responses, particularly in agricultural fields with relatively uniform canopy cover.

In contrast, SAVI and MSAVI display negative linear relationships with water availability. SAVI follows the regression $y = 29.68 - 0.34x$ with $R^2 = 0.21$, while MSAVI exhibits $y = 29.68 - 1.03x$ with $R^2 = 0.21$. These negative trends suggest that higher SAVI and MSAVI values do not necessarily correspond to higher soil water availability in the study area. This behavior can be attributed to the design of soil adjusted indices, which prioritize vegetation vigor and soil background correction rather than direct sensitivity to surface or near surface moisture conditions. The low coefficients of determination indicate that these indices capture only a small proportion of the spatial variability in water availability.

The Simple Ratio index shows the weakest relationship with water availability, with the regression y = 29.79 − 0.08x and R^2 = 0.11. The near horizontal regression line and minimal explanatory power suggest that SR is largely insensitive to variations in water availability under the observed conditions. Overall, although all indices demonstrate limited statistical strength, NDWI consistently shows the most coherent directional response to water availability among the evaluated indices, supporting its subsequent use in spatial modeling and suitability analysis.

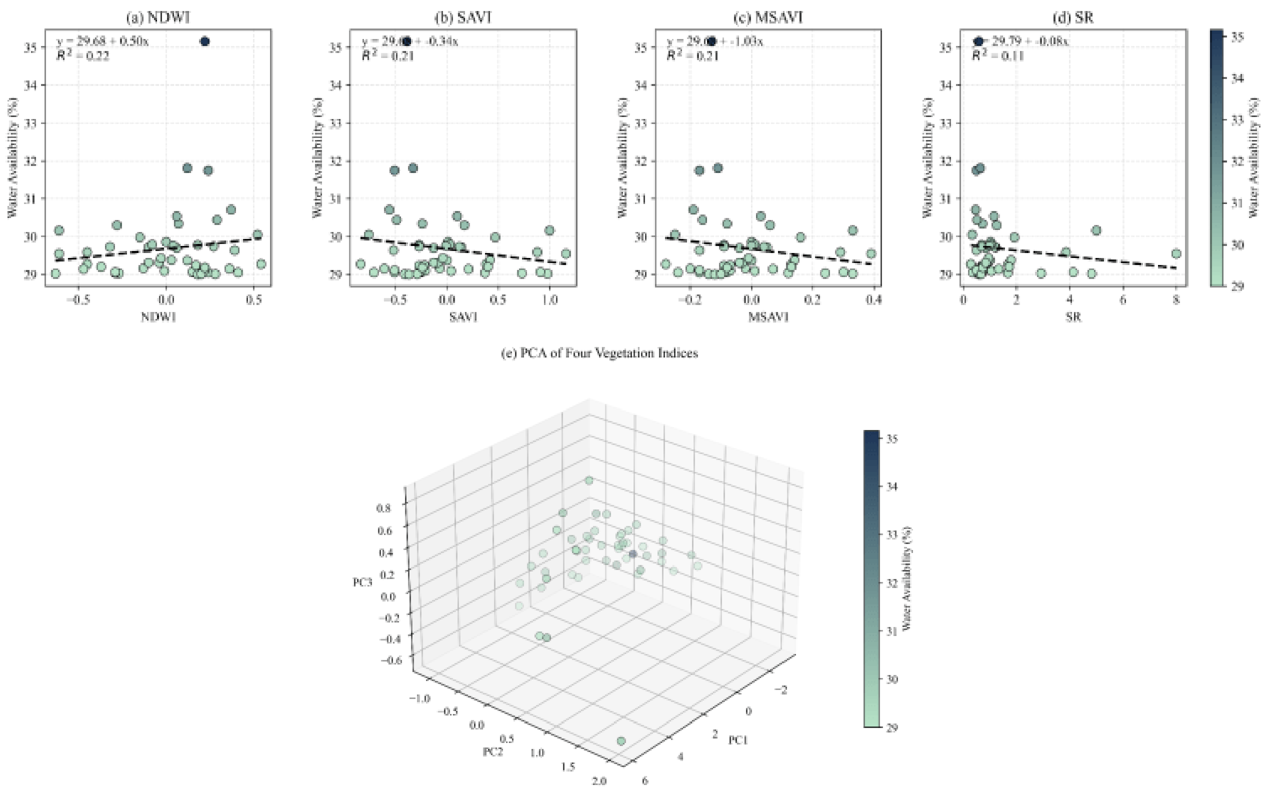

Figure 5. Linear relationships between vegetation indices and water availability for (a) NDWI, (b) SAVI, (c) MSAVI, and (d) SR, along with a three dimensional principal component analysis of the four vegetation indices (e).

The principal component analysis provides an integrated view of the relationships among NDWI, SAVI, MSAVI, and SR in representing soil water availability. The three dimensional PCA space shows that most observations cluster tightly, indicating strong redundancy among vegetation indices that share similar spectral responses, particularly SAVI and MSAVI, which load closely due to their common soil background adjustment mechanism. NDWI exhibits a more distinct orientation in the PCA space, reflecting its different sensitivity to canopy and surface moisture conditions and supporting its relatively stronger association with measured water availability observed in the regression and correlation analyses. The dispersion of points along the first principal component suggests that the dominant source of variability is driven by moisture related spectral contrast rather than vegetation density alone, while the second and third components capture more subtle variations linked to index formulation differences and local heterogeneity. Overall, the PCA confirms that NDWI contributes unique explanatory information compared to the other indices, whereas SAVI, MSAVI, and SR largely represent overlapping spectral information, reinforcing the selection of NDWI as the most informative index for plot scale estimation of soil water availability in this study.

3.5. Spatial Distribution of Estimated Water Content

The spatial estimation of soil water availability derived from vegetation indices is presented in Figure 3 for SAVI, NDWI, and MSAVI (Figure 6). The estimated water availability across the study area ranges from approximately 24.67% to 40%, represented by red, yellow, and blue color gradients. SAVI and NDWI maps are dominated by yellow tones, indicating relatively uniform water availability conditions across most of the potato field, with limited spatial contrast. This pattern reflects the moderate sensitivity of both indices to variations in soil and canopy moisture under dense vegetation cover, as also indicated by their moderate correlations with measured water availability.

In contrast, the MSAVI based map exhibits a more heterogeneous spatial pattern, characterized by a wider range of colors from red to blue. Areas with lower estimated water availability around 24.67% are clearly distinguished from zones reaching values close to 40%. This enhanced spatial variability suggests that MSAVI is more responsive to subtle changes in soil moisture conditions, particularly in areas where soil background influence remains significant. The Simple Ratio index was not used for spatial estimation due to its weak correlation and very low coefficient of determination with measured water availability, indicating limited reliability for representing soil moisture conditions in this study area.

(a) (b) (c)

Figure 6. Estimating water soil content map (a) SAVI; (b) NDWI; and (c) MSAVI

3.6. Model Accuracy Assessment

The accuracy assessment results indicate that the Normalized Difference Water Index demonstrates the closest agreement with field measured soil water availability among the evaluated vegetation indices. The mean estimated water availability derived from NDWI is 30.09%, which is very close to the observed field mean of 30.52%, while also exhibiting the lowest variance at 1.16 compared to SAVI and MSAVI. This lower variance suggests that NDWI produces more stable and less dispersed estimates across the sampling points. In contrast, SAVI and MSAVI show slightly lower mean values and higher variances, indicating greater uncertainty and reduced consistency in representing spatial soil moisture conditions (Table 2).

Table 2. T-paired test between water available prediction and laboratory analysis

Statistical Parameter	NDWI	SAVI	MSAVI	Water Content (%)
Mean	30.09	29.88	29.76	30.52
Variance	1.16	2.45	3.12	6.01
Observations	17	17	17	17
Pearson Correlation (r)	-0.32	-0.21	-0.18	–
Hypothesized Mean Difference	0	0	0	–
Degrees of Freedom (df)	16	16	16	–
t Stat	-0.59	-0.38	-0.29	–
P(T≤t) one-tail	0.28	0.36	0.39	–
t Critical one-tail	1.75	1.75	1.75	–
P(T≤t) two-tail	0.56	0.72	0.78	–
t Critical two-tail	2.12	2.12	2.12	–

Statistical testing further confirms the relative robustness of NDWI. The Pearson correlation coefficient between NDWI based estimates and field measurements is −0.32, which is stronger than those obtained for SAVI and MSAVI. Although the paired t test results show no statistically significant difference between estimated and observed values for all indices at the 95% confidence level, NDWI yields the smallest absolute t statistic and the lowest variance among the indices. These results suggest that NDWI provides the most reliable approximation of soil water availability under the study conditions, supporting its selection as the primary index for spatial modeling and subsequent land suitability analysis.

The prediction accuracy assessment shows that all vegetation indices produced comparable error levels when estimating water availability. RMSE values ranged from 0.994 to 1.001, while MAE values were consistently low and stable (0.613–0.615), indicating that the average prediction error was close to 0.6% water content across all models. The bias values were effectively zero (-7.4×10^{-15} to 8.7×10^{-15}), suggesting no systematic overestimation or underestimation of water availability by any vegetation index. These results indicate that the developed regression models provide unbiased and reliable predictions of water availability, with small and consistent errors suitable for practical application in high-resolution UAV-based agricultural monitoring.

3.7. Boundary Line Analysis and Water-Based Land Suitability Criteria

The boundary line analysis in panel (a) (Figure 7) illustrates a nonlinear response of plant height to water availability, where the fitted polynomial curve captures the gradual increase in plant height with increasing soil water content.

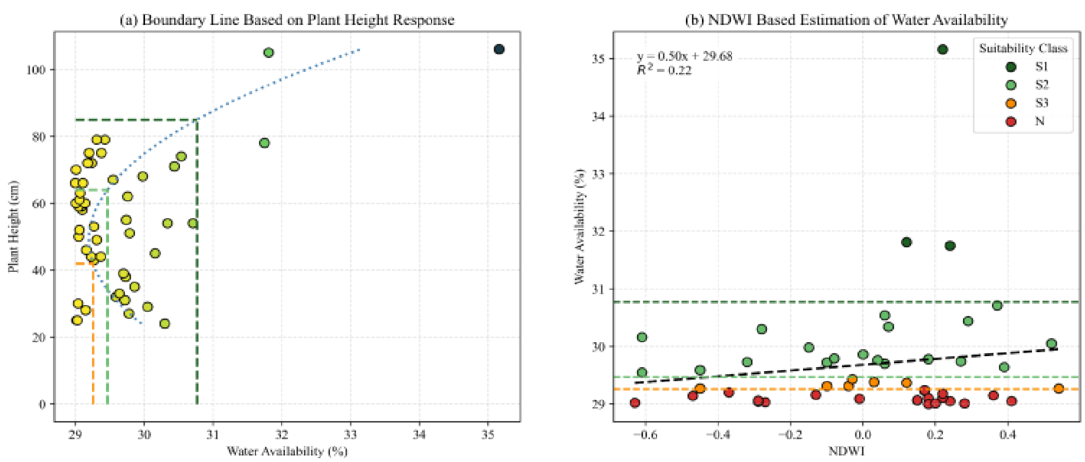

Figure 6. Boundary line analysis based on plant height response and NDWI-based estimation of soil water availability for land suitability classification

Using the observed maximum plant height of 106 cm as a reference, land suitability classes were delineated based on proportional thresholds of plant height response. The S1 class corresponds to plant heights above 85 cm or approximately more than 80 percent of the maximum response, which intersects the curve at water availability values slightly above 30.8 percent. The S2 class spans plant heights between 64 and 85 cm, associated with water availability ranging roughly from 29.5 to 30.8 percent. The S3 class covers plant heights between 42 and 64 cm, corresponding to water availability values of about 29.2 to 29.5 percent, while the N class represents plant heights below 42 cm and water availability lower than approximately 29.2 percent. This approach emphasizes plant height as an integrated biological response to soil water conditions rather than relying solely on linear assumptions.

Panel (b) translates these plant height based suitability thresholds into the NDWI domain through a linear regression between NDWI and water availability, expressed by the equation $y = 0.50x + 29.68$ with an R^2 value of 0.22. Although the coefficient of determination indicates a moderate explanatory power, the regression provides a practical linkage between remotely sensed NDWI values and field based water availability measurements. By projecting the water availability thresholds derived from panel (a) onto the NDWI axis, each suitability class can be inferred directly from NDWI values. Higher NDWI values are generally associated with the S1 and S2 classes, while lower NDWI values correspond predominantly to S3 and N classes. This confirms that NDWI, despite its limited R^2, remains the most consistent spectral index in representing relative variations in soil water availability and supports its application for spatial land suitability assessment when calibrated against field derived plant response data.

4. DISCUSSION

4.1. 4Performance of Vegetation Indices in Representing Soil Water Content

Soil water content is widely recognized as a sensitive and spatially variable driver of crop performance, yet optical remote sensing indices often respond to a mixture of canopy water status, canopy structure, and soil background, especially at plot scale. Recent work confirms that multispectral platforms, including UAV systems, can capture meaningful soil moisture patterns when the signal is sufficiently strong and when calibration data represent the full range of moisture conditions (Guan & Grote, 2023; Khose & Mailapalli, 2024). In our dataset, NDWI performed comparatively better than SR, SAVI, and MSAVI in representing measured water availability, which is consistent with the conceptual basis of NDWI as a moisture sensitive index. However, the relationship remained modest, reflecting the limited dynamic range of measured water availability in the field and the fact that reflectance based indices have shallow sensitivity and can saturate or become confounded under partial canopy cover.

The weak explanatory power observed across indices can be interpreted through two interacting mechanisms. First, the four indices share strong interdependence, as indicated by high absolute correlations among indices, which implies that they encode overlapping information and reduce the distinctiveness of each predictor. Second, when moisture variation is relatively small, minor differences in canopy density, illumination, or soil brightness corrections can dominate the spectral response and obscure a direct moisture signal. This limitation is frequently highlighted in recent literature, where optical indices alone can be effective under certain surface conditions but often benefit from complementary variables such as thermal information, ancillary meteorological data, or learning based fusion approaches to improve robustness (Imtiaz *et al*., 2024; Teixeira *et al*., 2025). In this context, the negative correlations of SAVI and MSAVI with water availability do not necessarily contradict plant physiology, but instead indicate that vegetation greenness and soil adjusted brightness corrections are not uniquely sensitive to water availability in the observed range and acquisition conditions.

Despite these constraints, NDWI remains a defensible operational choice for mapping relative moisture patterns in the study area because it outperformed the other indices and provides a consistent spatial contrast that can be translated into water availability estimates for site specific interpretation. The practical implication is not that NDWI perfectly measures soil water availability, but that NDWI can serve as a first order proxy for moisture related variability, particularly when the goal is to support field scale zoning and subsequent criteria development. This aligns with recent advances that frame optical indices as useful components in a broader estimation workflow, rather than standalone predictors, with best performance achieved when they are tied to carefully designed validation schemes and, when possible, combined with additional sensing modalities (Guan & Grote, 2023; Khose & Mailapalli, 2024; Teixeira *et al*., 2025).

4.2. Implications of Soil Water Availability on Potato Vegetative Growth

Soil water availability exerts a profound influence on the vegetative growth of potato crops and this influence extends beyond simplistic associations between moisture levels and height measurements to encompass physiological processes that govern plant development. Evidence from in situ studies and crop modelling has shown that variations in soil moisture during key phenological stages coincide with changes in leaf area index and biomass accumulation, indicating that plant water status is integrally linked with vegetative vigor and yield potential (Wang *et al*., 2025). In our study, this relationship manifests as a discernible boundary line response, where increased soil water availability corresponds with enhanced plant height, particularly within the S1 and S2 suitability classes that reflect higher moisture conditions. These observations concur with broader agronomic research showing that moderate water deficits can constrain vegetative growth, reducing canopy expansion and thereby limiting the crop’s ability to intercept light and accumulate biomass effectively (Peng *et al*., 2026).

The mechanistic importance of water availability is further highlighted by the dynamic interplay between soil moisture depletion and plant growth through the season. During rapid vegetative growth phases, soil water is rapidly extracted from the root zone and this drawdown aligns with peaks in leaf area and transpiration demand, creating a feedback loop in which water stress can quickly translate into reduced vegetative performance (Wang *et al*., 2025). As a result, even relatively modest spatial variations in water availability across a field, as captured through NDWI gradients, can give rise to measurable differences in plant response. The use of boundary line analysis to delineate suitability classes based on plant height response parlays this intrinsic sensitivity into an actionable framework that aligns with physiological thresholds of water limitation and growth suppression. This reinforces the perspective that soil water availability is not merely a background environmental variable but a primary driver of vegetative growth dynamics in potato cropping systems.

Understanding the implications of soil water availability on vegetative growth also informs practical management. Irrigation scheduling and water resource allocation decisions need to consider not just gross soil moisture levels but the specific ranges in which water availability translates into meaningful gains in canopy development and, ultimately, yield potential. The mapping of NDWI to water availability and subsequently to plant response classes equips growers with a spatially explicit tool for identifying zones of relative moisture limitation, thereby facilitating targeted interventions that enhance overall crop performance. This approach is consistent with emerging precision agriculture paradigms that integrate remote sensing metrics with physiological insights, enabling growers to move beyond uniform management toward zone-specific strategies that optimize water use efficiency and vegetative growth outcomes (Mukiibi *et al*., 2025).

4.3. Advantages and Limitations of UAV-Based High-Resolution Mapping

Soil water monitoring with UAV-based high-resolution mapping offers compelling strengths that address critical gaps in traditional field assessment and remote sensing platforms. Unmanned aerial vehicles equipped with multispectral and thermal sensors provide fine spatial details that are unattainable with most satellite-based systems, enabling precise capture of crop canopy characteristics, soil surface conditions, and moisture gradients at field scales that are relevant to agronomic decision making. These capabilities have been shown to support timely and accurate assessments of crop water status, nutrient distribution, and plant health across varied agricultural scenarios, and can be rapidly deployed to capture data throughout the growing season, providing actionable insight for water management and site-specific interventions that improve resource use efficiency and crop performance (Zhang *et al*., 2025; Yang *et al*., 2025). By delivering high-resolution imagery on demand, UAV systems significantly reduce the latency between data acquisition and analysis, empowering researchers and farmers with a nuanced understanding of within-field variability that supports precision agriculture objectives.

Despite these advantages, UAV-based high-resolution mapping also faces substantive limitations that constrain its broader operational use and interpretative reliability. The intricate data processing workflow required for radiometric correction, mosaicking, and spectral index computation remains labor-intensive and often depends on manual intervention, which introduces challenges for scalability and real-time analysis in large agricultural landscapes. Moreover, environmental variables such as illumination conditions, atmospheric effects, and varying canopy structures can influence spectral responses and compromise inversion accuracy, necessitating careful calibration and validation against ground truth measurements (Yang *et al*., 2025). Practical constraints including limited flight duration due to battery capacity, regulatory restrictions on flight paths, and the need for specialized technical expertise further limit accessibility, particularly for smallholder farmers and resource-constrained operations. As UAV payload, sensor, and algorithm technologies continue to evolve, addressing these bottlenecks remains essential to fully realizing the potential of UAV-based high-resolution mapping in precision agriculture and soil water monitoring.

4.4. Comparison with Existing Land Suitability Criteria

Existing land suitability frameworks often integrate multi-criteria evaluations to classify land potential for crop production, with water availability typically considered alongside other key biophysical parameters such as soil texture, climate variables, topography, and land cover. For example, the integrated Analytic Hierarchy Process (AHP) and Geographic Information System (GIS) methodology produces spatially explicit suitability classes by weighting individual criteria and combining them into composite suitability maps, which has been demonstrated to enhance precision and accommodate heterogeneous data sources in arid regions (AbdelRahman *et al*., 2025). Similarly, comprehensive evaluations of land capability and crop water requirements, grounded in models such as FAO-CROPWAT, emphasize the importance of water budgets and climatic constraints in defining highly suitable (S1), moderately suitable (S2), marginally suitable (S3), and unsuitable classes for diverse crops (Selmy *et al*., 2024). These conventional approaches provide robust planning support at broad geographic scales, yet they most often rely on static parameter layers and expert-driven weight assignments that can dilute localized patterns of water stress and vegetative response.

In contrast, the suitability assessment developed in this study leverages high-resolution UAV imagery linked with field-measured water availability and vegetative response, offering a data-driven, crop-specific criterion anchored in physiological response rather than fixed biophysical thresholds alone. By deriving suitability classes from the quantitative relationship between soil water availability and potato plant height, and then projecting these classes through NDWI proxies, our approach aligns more directly with the actual moisture responses observed in the crop, thereby addressing limitations of generalized weighted overlay methods. This method enhances temporal and spatial sensitivity, particularly where micro-variability in soil moisture dictates within-field differences in crop performance, and complements existing criteria by providing field-scale refinement of suitability classes that can be integrated with broader AHP/GIS frameworks for strategic planning and precision agriculture applications. Such integration underscores the evolving landscape of land suitability assessment in which remote sensing and physiological calibration expand the interpretive power of classical multi-criteria models.

5. CONCLUSION

This study demonstrates that UAV based high resolution multispectral imagery, when calibrated with field measurements and interpreted through crop response analysis, can effectively support the assessment of soil water availability for potato cultivation at the plot scale. Among the evaluated vegetation indices, NDWI showed the most consistent performance in representing relative variations in soil water availability, although the strength of the relationship with measured water content remained moderate. These findings confirm that NDWI should not be interpreted as a direct estimator of absolute soil water content, but rather as a spatial proxy that captures moisture related variability when properly validated with ground observations.

The principal contribution of this research lies in the development of water based land suitability criteria derived from the observed relationship between soil water availability and potato vegetative growth, expressed through plant height response. Using boundary line analysis, suitability classes were delineated based on proportional plant height thresholds relative to the observed maximum growth, and subsequently translated into corresponding ranges of water availability. This approach refines existing land suitability criteria that rely primarily on climatic indicators by incorporating soil water availability as a spatially explicit and biologically grounded parameter. Although the resulting suitability thresholds are closely spaced, they reflect the high sensitivity of potato vegetative growth to small variations in soil moisture under the studied conditions. Consequently, the proposed criteria are most appropriate for plot scale applications, where high resolution UAV data can capture micro spatial variability, and should be integrated with broader scale assessments for regional planning.

AUTHOR CONTRIBUTION STATEMENT

Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
IN	✓		✓	✓	✓				✓	✓			✓	
ANP	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓		✓
SRN									✓					
MTS										✓				
NRP										✓				

C: Conceptualization	Fo: Formal Analysis	O: Writing - Original Draft	Fu: Funding Acquisition
M: Methodology	I: Investigation	E: Writing - Review & Editing	P: Project Administration
So: Software	D: Data Curation	Vi: Visualization	
Va: Validation	R: Resources	Su: Supervision	

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