



Possibilities and Challenges of Estimating and Mapping Soil Exchangeable Cation Bases in Saline Rice Fields Based on Salinity and Soil Indices

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Abstract. *Soil exchangeable cation bases (SECB)—calcium (Ca^{2+}), magnesium (Mg^{2+}), sodium (Na^+), and potassium (K^+)—are key indicators of soil fertility in paddy fields, yet remote sensing approaches for SECB assessment remain underexplored because of soil heterogeneity and the complexity of paddy management. This study evaluates multispectral UAV imagery for SECB prediction in saline rice fields using the Normalized Difference Salinity Index (NDSI), Soil-Adjusted Vegetation Index (SAVI), Modified Soil-Adjusted Vegetation Index (MSAVI), and Optimized Soil-Adjusted Vegetation Index (OSAVI). NDSI is a salinity index, while SAVI, MSAVI, and OSAVI are soil-adjusted vegetation indices used as complementary spectral proxies. Field sampling was conducted at 17 transect points in Jabon District, Sidoarjo Regency, East Java, Indonesia, with the sampling design determined by the spatial extent of the study area and UAV flight coverage. NDSI had the strongest correlation with SECB ($r = -0.55$ to -0.59). Univariate linear regression models for Ca, Mg, Na, and K produced moderate predictive accuracy ($R^2 = 0.31$ – 0.34), indicating that while spectral indices show potential for SECB estimation, their reliability is constrained by the managed nature of paddy fields. These findings highlight the challenges of using spectral indices in dynamic agroecosystems and point to the need for integrative approaches that combine remote sensing with advanced modeling. The results contribute to precision agriculture by refining soil fertility assessment in saline-affected paddy environments.*

Keywords: *exchangeable cation bases; UAV multispectral; saline paddy; precision agriculture; soil fertility mapping.*

Type of the Paper: Regular Article.



1. Introduction

Soil exchangeable cation bases (SECB), comprising calcium (Ca^{2+}), magnesium (Mg^{2+}), potassium (K^+), and sodium (Na^+), are fundamental to soil fertility and plant nutrition. These cations are adsorbed onto soil colloids and continually exchange with other ions in the soil solution, directly influencing nutrient availability, soil structure, and crop productivity [1]. A decline in base saturation reduces the soil's cation exchange capacity (CEC), leading to nutrient depletion and impaired plant growth [2]. While traditional soil fertility studies have focused on macronutrients like nitrogen (N) and phosphorus (P), the role of soil exchangeable cation bases (SECB) in saline environments remains underexplored. In paddy fields, where soil conditions shift

with irrigation and salinity intrusion, understanding SECB dynamics is critical for sustaining rice yields. Girdekar et al. [3] note, however, that the prevalence of low-activity clay colloids in these soils limits the retention of essential cations, worsening nutrient deficiencies and reducing rice productivity.

The physiological effects of SECB deficiency vary among cations. Calcium (Ca^{2+}) shortages causes chlorosis and root impairment, whereas magnesium (Mg^{2+}) deficiency disrupts chlorophyll synthesis, leading to leaf necrosis and poor grain quality [4]. In contrast, excessive sodium (Na^+) accumulation disrupts plant metabolism and soil structure by inducing sodicity, which degrades permeability and aeration [5]. Some studies, however, suggest that Na^+ can partially substitute for K^+ in maintaining turgor pressure and enhancing grain production under K-deficient conditions, particularly in rice [6]. These contrasting effects underscore the complexity of nutrient management in saline paddy fields, where both deficiencies and toxicities must be carefully balanced. Given the spatial variability of SECB across salinity gradients, conventional laboratory analyses—while precise—are labor-intensive and spatially restrictive, necessitating alternative methods that offer broader coverage and real-time insights.

Remote sensing, particularly UAV-based multispectral imaging, offers a promising alternative for SECB assessment by enabling the collection of high-resolution spectral data. Several spectral indices, such as NDSI, SAVI, MSAVI, and OSAVI, have commonly been used to evaluate macronutrient dynamics. Their potential for predicting SECB, however, has not yet been extensively explored. Despite this potential, UAV-based SECB assessment faces several challenges, including weak correlations between spectral reflectance and exchangeable cation concentrations, as well as spectral variability introduced by paddy field management practices. Unlike macronutrients, which show distinct spectral signatures due to their influence on vegetation, SECB interactions with soil properties are more complex and often confounded by external factors such as irrigation and fertilization. Therefore, while UAV imagery offers valuable spatial insights, its direct application for SECB quantification remains limited without complementary analytical approaches—a limitation that underscores the need for integrative predictive approaches.

Integrating UAV-based spectral data with machine learning algorithms or geostatistical models represents a promising direction for improving predictive accuracy in future studies. Current research demonstrates that while spectral indices can indicate salinity-induced variations in soil properties, their direct relationship with SECB is inconsistent. This highlights the need for a hybrid approach that combines remote sensing with soil sampling and advanced predictive modeling. Interdisciplinary efforts merging soil science, agronomy, and remote sensing will be crucial for refining SECB estimation methods in precision agriculture. By addressing these

challenges, UAV-based techniques can evolve into a viable tool for large-scale soil fertility monitoring, ultimately supporting sustainable rice production in saline-prone regions.

Despite the growing application of UAV-based remote sensing for soil property assessment, SECB estimation in saline paddy fields remains insufficiently explored. The complex interactions among salinity, soil physicochemical properties, and spectral responses create significant challenges for accurate SECB prediction using remote sensing data alone. This study therefore aims to evaluate the potential of UAV-based multispectral imagery for estimating SECB— Ca^{2+} , Mg^{2+} , K^{+} , and Na^{+} —in saline paddy fields. Specifically, the study seeks to (i) analyze the relationships between multispectral vegetation and salinity indices and SECB concentrations, (ii) identify the most informative spectral predictors for SECB estimation, and (iii) develop and evaluate predictive models for spatial assessment of SECB variability across salinity gradients. The findings are expected to support the development of efficient, non-destructive, and spatially explicit approaches for soil fertility monitoring and precision nutrient management in saline-prone rice-growing regions.

2. Materials and Methods

2.1. Study Area

The research was conducted in the paddy field area of Jabon District, Sidoarjo Regency, East Java (Fig. 1). Two observation locations were established within lowland rice ecosystems. Location 1 spans 112.721274° – 112.741195° E and 7.537748° – 7.545404° S, while Location 2 spans 112.739324° – 112.773098° E and 7.556630° – 7.566117° S.

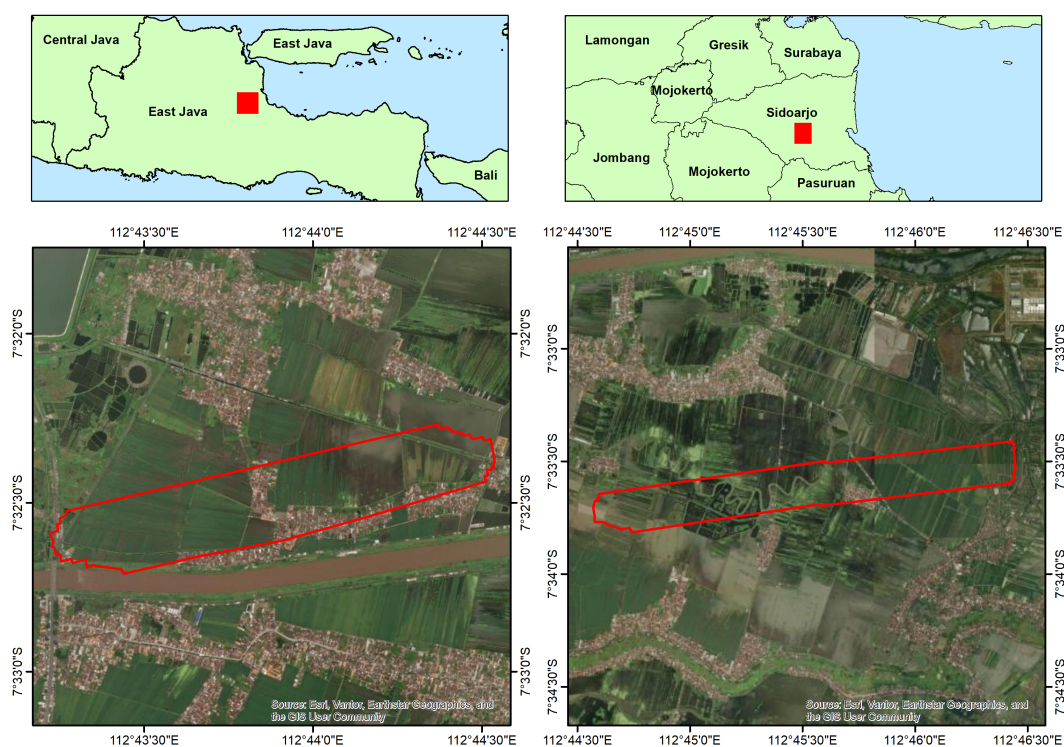


Fig. 1. Study area.

Jabon lies in the lower reaches of the Brantas River, the largest river in East Java. Rice is the primary crop, but salinity hampers production. Unlike areas along the North Coast, where salinity and rice production have been studied extensively, Jabon has received little research attention. Its landscape, however, forms a suitable transect for this study's objectives.

The topography is a coastal lowland shaped by fluvio-marine sedimentation and alluvial deposits [7]. The dominant soil types are Typic Endoaquents, Typic Fluvaquents, and Typic Hydraquents [8]. Paddy fields cover approximately 1,883.86 ha, or 23.05% of the district's total land area. Jabon District has two main landforms: alluvial and marine. The alluvial landform—an alluvial plain—occupies the western part of the district, covering about 2,417.01 ha (29.6%). The marine landform—a tidal plain—extends eastward toward the Java Sea, covering 5,756.34 ha (70.4%) [9]. These geomorphological features strongly influence soil properties and agricultural suitability in the region.

2.2. UAV Imagery Specification

UAV imagery was acquired at a flight altitude of 100 m above ground level [10] using a multispectral UAV platform equipped with a Parrot Sequoia camera. This sensor captures RGB imagery and four discrete multispectral bands (green, red, red edge, and near-infrared). These bands provided the spectral reflectance values needed to derive NDSI, SAVI, MSAVI, and OSAVI. The imagery had a ground sampling distance (GSD) of approximately 12 cm/pixel. The mapping covered two polygon areas totaling 208.25 ha, with flight lines programmed for a deployment distance of 3.5 km. Flights were conducted with 70% frontal and 70% side overlap, requiring an estimated 160 minutes of active flight time. Surveys were performed under clear weather conditions at approximately 10:00 local time (WIB). To ensure spatial accuracy, georeferencing used 15 ground control points (GCPs) distributed across the study area, resulting in a total of approximately 1,650 image trigger points that were captured and processed (Fig. 2).

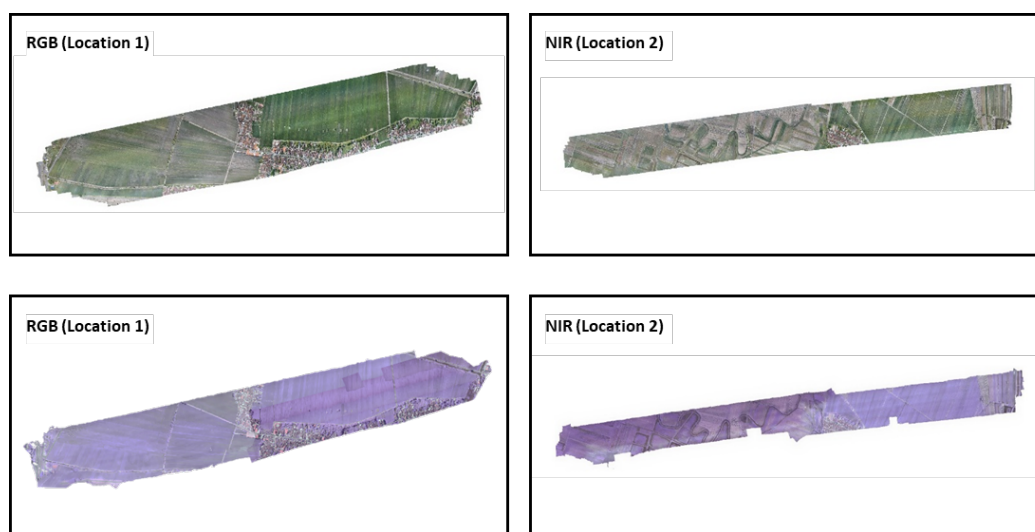


Fig. 2. UAV imagery in visible light (RGB) and NIR.

2.3. Point Observation Distribution

The field survey followed two transects with different lengths. Transect 1 covered approximately 4 km, whereas Transect 2 extended for 3.4 km. A total of 17 observation points were established along the two transects, with spacing intervals of 316–817 m and 104–718 m, respectively. This sample size ($n = 17$) with irregular spacing represents a sparse network for spatial regression modeling, which may reduce statistical power and increase the risk of spatial autocorrelation bias; this constraint is acknowledged in the Discussion. The observation points were distributed using a free-grid sampling design adapted to the configuration of the lowland rice fields [11].

2.4. Soil Sampling and Analysis

Soil samples were collected as composites at each observation point at a depth of 0–20 cm to represent the rice rooting zone [12]. Soil samples were analyzed for exchangeable Ca, Mg, Na, and K. Exchangeable Ca, Mg, Na, and K were extracted and quantified using standard soil analytical procedures. Studies by Razzaghi et al. [13] and Liang et al. [14] provide relevant context on cation exchange capacity estimation and exchangeable cation dynamics in irrigated soils, respectively. A total of 17 soil samples were collected, matching the 17 UAV observation points used for spectral index extraction.

2.5. UAV Imagery Pre-processing

UAV imagery pre-processing involved stacking and mesh-building to combine layers from aerial photographs [15] using Agisoft Photoscan and ArcGIS 10.6. The stacked imagery then underwent radiometric calibration and correction. According to Daniels et al. [16], this step is essential for obtaining the camera distortion parameters required for image correction.

The processed UAV imagery was then transformed into a soil indices—NDSI [17], SAVI [18], MSAVI [19], and OSAVI [20]—using Quantum GIS 3.10 (Table 1). The index values were extracted at each observation point using the ‘Extract by Point’ function in ArcGIS 10.6.

Table 1. Soil index transformation and index number extraction.

Soil Index Transformation	Index Number Extraction	References
Normalized Difference Soil Index (NDSI)	$NDSI = \frac{Red - Red\ Edge}{Red + Red\ Edge}$	Voitik et al. [17]
Soil-Adjusted Vegetation Index (SAVI)	$SAVI = \frac{(NIR - Red)}{(NIR + Red)} \times (1 + L)$	Zhen et al. [18]
Modified Soil-Adjusted Vegetation Index (MSAVI)	$MSAVI = 0.5 \times (2NIR + 1 - \sqrt{(2NIR + 1)^2 - 8(NIR - Red)})$	Wiratmoko et al. [19]
Optimized Soil Adjusted Vegetation Index (OSAVI)	$OSAVI = \frac{(NIR - Red)}{(NIR + Red + 0.16)}$	Binte Mostafiz et al. [20]

2.6. Statistical Analysis

Statistical analysis included correlation, regression, and validation tests performed in R Studio [10]. Correlation analysis assessed the relationship between exchangeable bases and index

values. Regression analysis was then performed using the index with the highest correlation value.

2.7. Algorithm Building and Map Creating

Algorithm development were developed from regression equations in the form $y = a + bx$, where y is the exchangeable base and x is the index value [10]. These algorithms were then applied to create a spatial distribution map of exchangeable bases using the 'Map Algebra' function in ArcGIS 10.6.

2.8. Accuracy Assessment

To evaluate the predictive performance of the equations, root mean square error (RMSE) and mean absolute error (MAE) were calculated. A paired t-test was conducted between the laboratory-analyzed exchangeable bases and the estimated values derived from the spectral index. While RMSE and MAE specifically quantify the predictive accuracy and precision of the models, the paired t-test was retained to assess whether a systematic mean bias exists between the predicted and observed values. All statistical analyses were carried out using the statistical software R Studio [21].

3. Results and Discussion

3.1. Soil Exchangeable Bases Laboratory Analysis

Exchangeable calcium (Ca^{2+}) at the study sites ranged from 4.0 to 7.3 cmol kg^{-1} (Fig. 3), notably higher than the other base cations, which all remained below 2.0 cmol kg^{-1} . Magnesium (Mg^{2+}) and potassium (K^{+}) ranged from 0.6 to 1.65 cmol kg^{-1} and 0.3 to 1.1 cmol kg^{-1} , respectively. Sodium (Na^{+}) showed the lowest overall concentration, ranging from 0.2 to 1.0 cmol kg^{-1} .

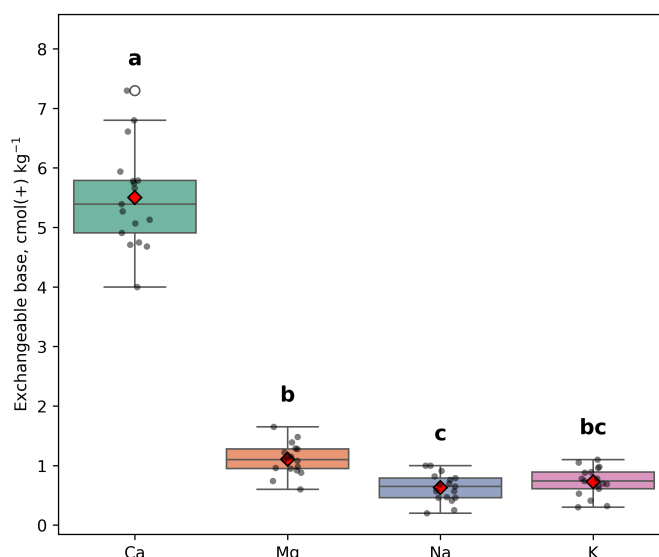


Fig. 3. Boxplot of soil cation base (Ca^{2+} , Mg^{2+} , Na^{+} and K^{+}).

Alkaline elements, encompassing potassium (K), sodium (Na), calcium (Ca), and magnesium (Mg), are fundamental to plant metabolism, particularly in enzyme activation and osmotic regulation [22]. The availability in soil varies considerably: Ca and Mg are often classified

as low to moderate, whereas K and Na frequently fall within the very low to low range [23]. Potassium deserves particular attention because of its essential role in plant physiology and its relatively high requirement in crop nutrition [24]. Beyond promoting enzymatic activity, K contributes to drought tolerance and structural integrity. In the Jabon transects, K ranged narrowly from 0.3 to 1.1 cmol kg⁻¹, a low-to-moderate level consistent with the very-low-to-low classification typical of salinity-affected, low-activity clay colloids in this coastal fluviomarine setting.

Sodium (Na), though not essential macronutrient, has variable effects on plant growth, depending on its concentration and the species. At low concentrations, Na can partially substitute for K in certain physiological functions, such as maintaining cell turgor and enhancing potassium availability. Excessive Na accumulation, however, creates significant agronomic challenges: it raises osmotic potential, disrupts cellular homeostasis, and induces plasmolysis, ultimately impairing water and nutrient uptake [25]. From a soil physicochemical perspective, high Na concentrations contribute to sodicity, leading to structural degradation, reduced permeability, and compaction, which in turn limit root penetration and gaseous exchange. Although some halophytic and C4 species tolerate Na to a degree, its widespread presence in agricultural soils remains a concern, underscoring the need for integrated management to alleviate constraints on soil fertility and ensure stable crop production.

Calcium (Ca²⁺), despite its relatively low exchangeable content in many soils, rarely causes deficiency symptoms unless concentrations fall below a critical threshold of 1 cmol kg⁻¹. In rice cultivation, Ca plays a pivotal role in root system development, enhancing structural stability and mitigating susceptibility to iron toxicity. It has also been linked to stronger plant resistance against bacterial leaf blight, a prevalent disease affecting rice yields in many regions [26]. Conventional soil fertility assessments, however, often overlook Ca's role in stress mitigation, focusing instead on its contributions to structural integrity and nutrient transport. This narrow perspective underscores the need for more holistic approaches in soil nutrient diagnostics, particularly in intensively cultivated paddy ecosystems where Ca availability can fluctuate due to irrigation-induced leaching and soil acidification.

Magnesium (Mg), another critical alkaline nutrient, is the central component of the chlorophyll molecule and directly influences photosynthetic efficiency. Soils with Mg concentrations below 1 cmol kg⁻¹ are considered deficient, whereas levels exceeding 3 cmol kg⁻¹ are generally adequate for rice cultivation [27]. Mg deficiency initially manifests in older leaves as interveinal chlorosis. In the Jabon transects, Mg (0.6–1.65 cmol kg⁻¹) and Na (0.2–1.0 cmol kg⁻¹) fell within the low-to-moderate range typical of saline coastal soils affected by fluviomarine sedimentation and tidal intrusion from the Java Sea, consistent with the low-activity clay colloids

described for similar saline paddy systems [3]. While conventional fertilization practices often emphasize macronutrient supplementation, neglecting Mg can inadvertently compromise plant vigor and yield potential, highlighting the necessity of balanced nutrient management strategies.

3.2. Transformation of NDSI, SAVI, MSAVI, and OSAVI Index Values

The vegetation indices (SAVI, MSAVI, and OSAVI) ranged positively from 0.10 to 0.55 (Fig. 4 and Fig. 5). In contrast, NDSI showed a notably lower and strictly negative range, -0.52 to -0.08 . Among the vegetation indices, SAVI had the highest maximum value (0.55), followed by OSAVI (0.50) and MSAVI (0.45).

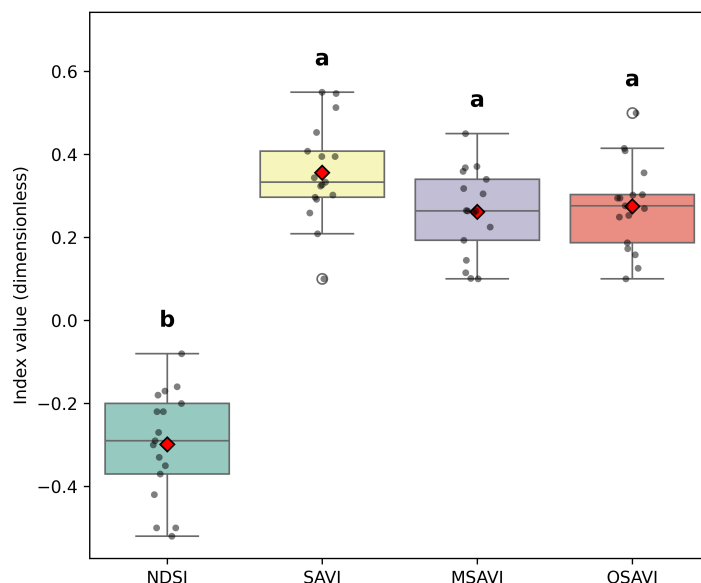


Fig. 4. Bloxplot of soil indices (NDSI, SAVI, MSAVI and OSAVI).

Beniaich et al. [28] demonstrated the potential of UAV-based vegetation monitoring for evaluating vegetation cover and its relationship with soil erosion dynamics in olive orchards. Their study showed that vegetation indices and cover indices derived from UAV imagery could effectively estimate the cover-management factor (C-factor) and predict soil loss under natural rainfall conditions. The total cover index exhibited the best performance for predicting soil loss and C-factor, highlighting the importance of minimizing soil exposure in agricultural landscapes. Similarly, vegetation indices such as SAVI, OSAVI, and MSAVI were developed to reduce the influence of soil background reflectance on vegetation assessment. Among these indices, MSAVI has been widely recognized for its enhanced capability to suppress excessive soil reflectance, making it particularly suitable for sparsely vegetated agricultural areas where soil interference can distort spectral-based estimations of plant biophysical properties, including nitrogen content. SAVI was specifically designed to compensate for soil-induced variations in reflectance by incorporating a canopy background adjustment factor, denoted as L . This factor is not a fixed value but rather a function of vegetation density, necessitating prior knowledge of vegetation coverage for optimal application. The determination of an appropriate L value is pivotal, as it directly

influences the extent to which soil optical properties are accounted for in spectral calculations. Zhen et al. [18] found that an L adjustment factor of 0.5 yielded consistent results across varying vegetation densities and soil types, suggesting its potential as a standardized parameter. However, while this adjustment improves SAVI's applicability, it remains inherently constrained by the requirement for predefined vegetation cover information, limiting its adaptability in dynamic or heterogeneous landscapes.

To address these limitations, researchers refined SAVI by developing MSAVI, an improved vegetation index that incorporates a self-adjusting L factor, eliminating the need for prior knowledge of vegetation density [19]. This refinement is particularly advantageous in areas with sparse vegetation, where bare soil significantly influences spectral reflectance. By dynamically adjusting to soil and vegetation conditions, MSAVI improves the accuracy of biomass and nutrient estimation in environments with substantial soil exposure. Despite these advancements, the effectiveness of MSAVI across different agroecosystems remains under investigation, as soil texture, moisture content, and organic matter variability can still introduce uncertainties in spectral measurements.

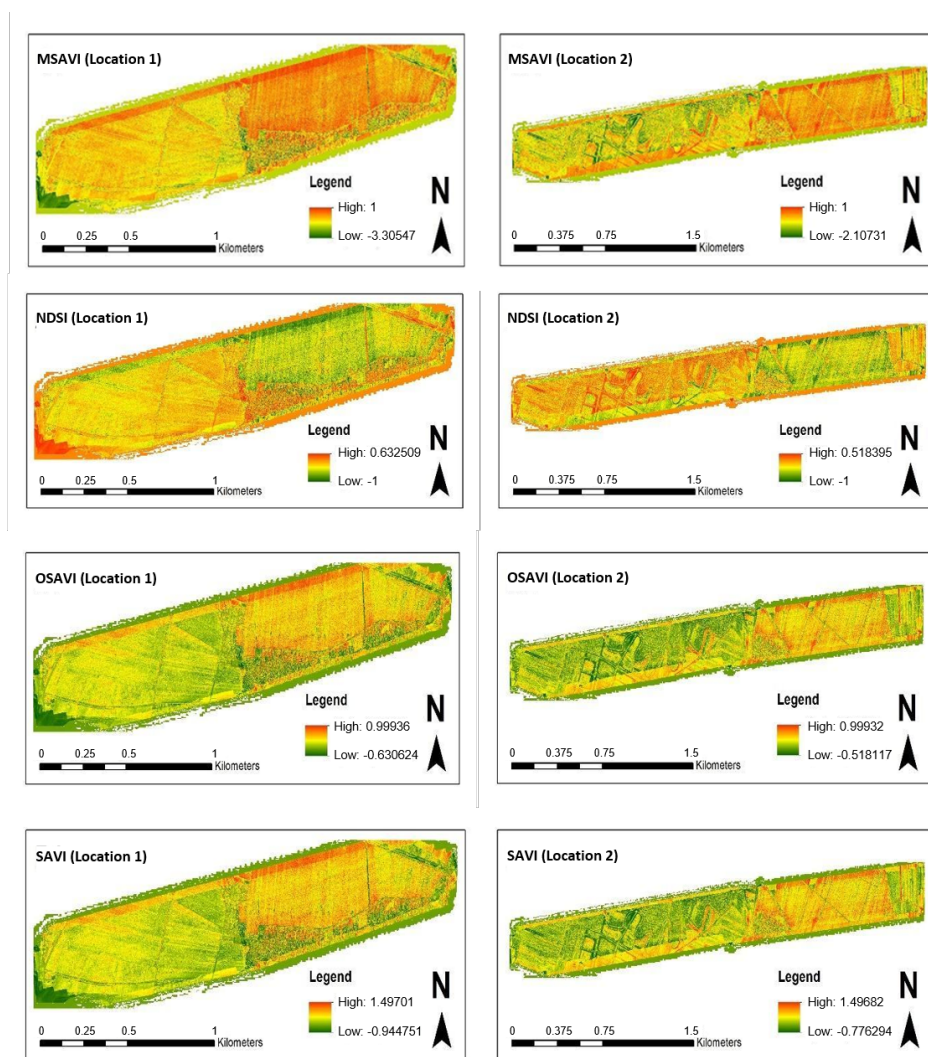


Fig. 5. Mapping of soil indices (MSAVI, NDSI, OSAVI and SAVI).

Fundamentally, the utility of vegetation indices such as SAVI, OSAVI, and MSAVI depends on the spectral characteristics of the near-infrared (NIR) and red bands, which are integral to assessing plant health and productivity [17]. While MSAVI offers a notable improvement in soil-adjusted vegetation assessments, its broader applicability necessitates further validation across diverse ecological settings. Future research should refine these indices by integrating machine learning techniques and hyperspectral data to enhance predictive accuracy and robustness. Such advances would allow vegetation indices to become more precise tools for monitoring plant nutrient status, particularly in precision agriculture and environmental monitoring.

3.3. Correlation between Exchangeable Bases and Soil Indices

Correlation analysis showed that almost all indices were significantly correlated with exchangeable base cations at the 0.05 significance level (Fig. 6). The correlations between exchangeable bases (Ca, Mg, Na, and K) and the NDSI, SAVI, MSAVI, and OSAVI indices are presented in Fig. 6, with asterisks (*) indicating significant correlations at the 0.05 level. Ca was positively correlated with the soil indices, except for NDSI, which showed a negative correlation of -0.55 . Although OSAVI had the highest correlation with Ca, NDSI was selected as the primary predictive index because it demonstrated consistently high correlations across all four cation bases (Ca, Mg, Na, and K), making it the most universally applicable index for multi-cation SECB estimation. K also showed a negative correlation with NDSI ($r = -0.58$). Overall, NDSI was the most suitable index for estimating exchangeable base cations.

Remote sensing offers a cost-effective approach for obtaining soil information with greater spatial coverage and faster processing. In soil studies, remote sensing data can generally be used to derive three types of information: soil properties inferred from spectral reflectance and image products, the influence of surface conditions on reflected radiation, and spatial patterns that support the mapping of soil variability [29].

According to Hopmans et al. [30], in saline environments, signal intensity is mainly associated with the concentration of soluble salts. Under non-saline conditions, in contrast, variations in soil electrical conductivity are primarily influenced by organic matter content, texture, moisture status, and cation exchange capacity. Silvero et al. [31], analyzing digital numbers, showed that ETM⁺ images have excellent potential for evaluating soil properties in areas with homogeneous features. The best indices in this research uses NDSI and DVI with values of 0.2000 and 0.2100, respectively. The findings provide practical information to support the development of appropriate soil management programs in the study area. However, differentiating soil properties using remote sensing data remains challenging because soil spectral responses are often complex and influenced by multiple interacting factors. According to Zhou et al. [32], the Normalized Difference Soil Index (NDSI) is focused on examining the soil's spectral condition.

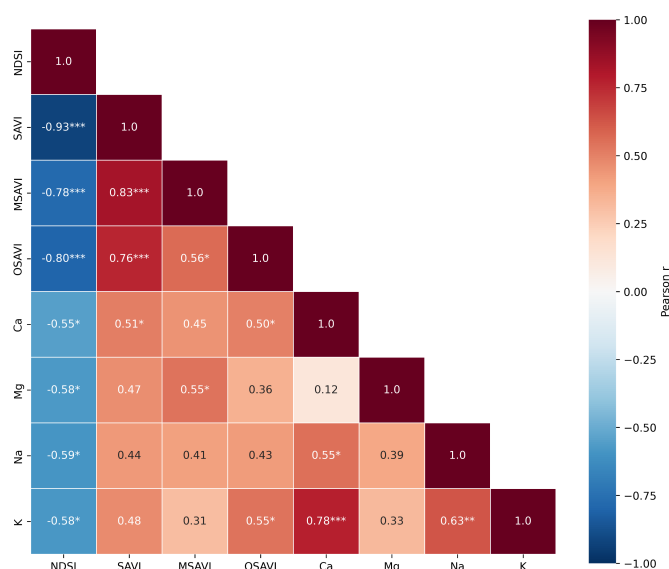


Fig. 6. Correlation test between soil indices from UAV imagery and soil cation bases.

3.4. NDSI and Exchangeable Bases Regression Analysis Result

After selecting NDSI as the best index for estimating exchangeable base cations, regression analysis was performed between NDSI and the exchangeable base cations (Fig. 7). The results of regression analysis show that Ca can be estimated using the formula $-3.5807x + 4.4318$ ($R^2 = 0.31$), Mg with the formula $-1.1756x + 0.7552$ ($R^2 = 0.33$), Na with the formula $-1.0661x + 0.3108$ ($R^2 = 0.34$), and K with the formula $-1.0693x + 0.4087$ ($R^2 = 0.34$) (Fig. 7).

In exploratory remote sensing studies of soil physicochemical properties, R^2 values between 0.20 and 0.50 have been reported as informative for spatial trend identification at field scales [30,31], supporting the interpretation of the present results as indicative rather than predictive.

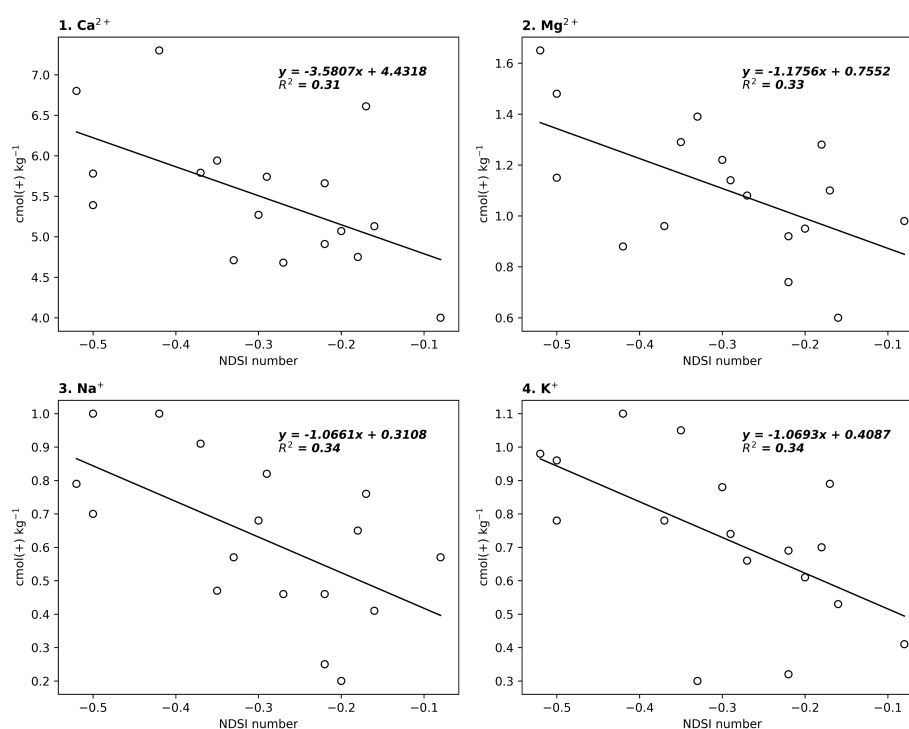


Fig. 7. Regression analysis between the Normalized Difference Salinity Index (NDSI) and soil exchangeable bases (1: Ca^{2+} , 2: Mg^{2+} , 3: Na^+ and 4: K^+).

3.5. Algorithm Building

Algorithms for predicting exchangeable base cations were developed from the regression equations:

$$\text{Ca} = -3.5807(\text{NDSI}) + 4.4318$$

$$\text{Mg} = -1.1756(\text{NDSI}) + 0.7552$$

$$\text{Na} = -1.0661(\text{NDSI}) + 0.3108$$

$$\text{K} = -1.0693(\text{NDSI}) + 0.4087.$$

3.6. Spatial Distribution Mapping of Estimated Exchangeable Bases

Based on the compiled maps, the estimated values ranged from 1.5827 to 8.3269 for Ca, 0.22821 to 1.6095 for K, 0.0449 to 2.2249 for Mg, and 0.33404 to 1.4017 for Na (Fig. 8).

The spatial distribution maps derived from the regression models revealed considerable variability in SECB across the study transects. Ca estimates ranged from 1.58 to 8.33 cmol kg^{-1} , reflecting proximity-driven gradients from marine salinity sources. The wider range of Ca compared to Mg, Na, and K is consistent with Ca's role as the dominant exchangeable cation in coastal alluvial soils [30]. The mapped distributions suggest that NDSI-based models can capture broad spatial patterns of SECB, although localized hotspots of cation accumulation may require higher sampling density for accurate delineation.

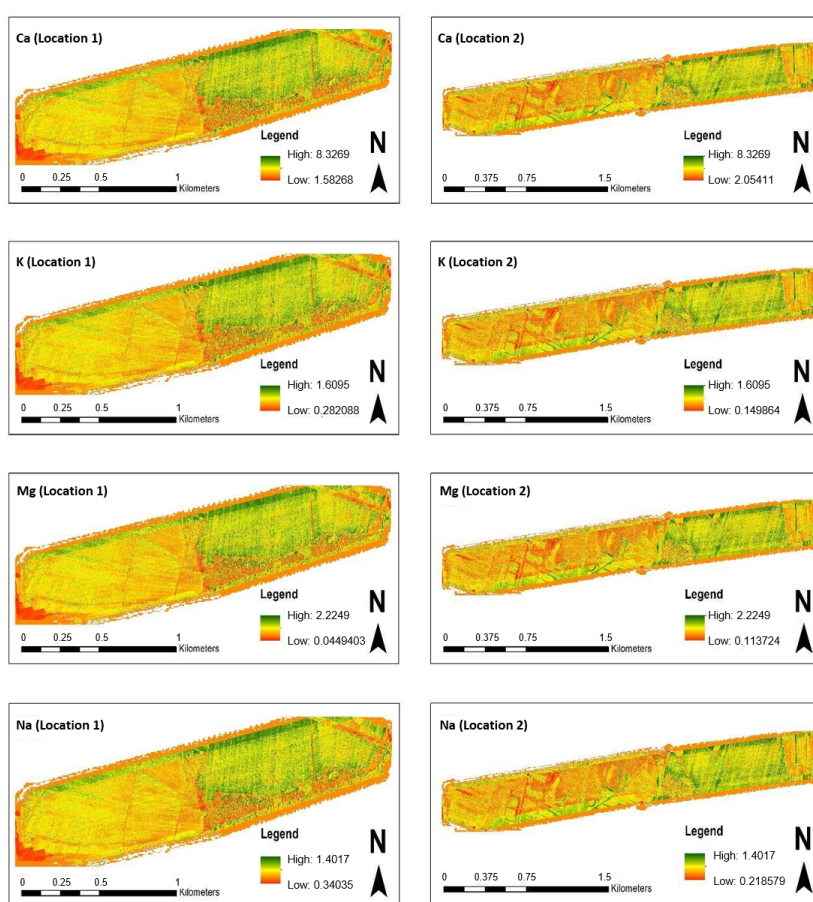


Fig. 8. Distribution mapping of estimated exchangeable bases (1: Ca^{2+} , 2: Mg^{2+} , 3: Na^{+} and 4: K^{+}).

3.7. Accuracy Assessment

Accuracy assessment was performed to determine whether the resulting equations could predict exchangeable soil bases in Jabon District, Sidoarjo. To quantify predictive accuracy, root mean square error (RMSE), mean absolute error (MAE), and leave-one-out cross-validation (LOOCV) R^2 were computed to compare the soil index results and exchangeable soil bases. The analysis yielded the following validation metrics for each exchangeable base: Ca (RMSE = 0.6830, MAE = 0.5370, LOOCV R^2 = 0.0817), Mg (RMSE = 0.2108, MAE = 0.1816, LOOCV R^2 = 0.1167), Na (RMSE = 0.1871, MAE = 0.1695, LOOCV R^2 = 0.1675), and K (RMSE = 0.1897, MAE = 0.1361, LOOCV R^2 = 0.1990). A paired *t*-test was then used to check for systematic mean bias between observed and predicted values. The results (Ca: t = -0.0002, p = 0.9998; Mg: t = -0.0005, p = 0.9996; Na: t = 0.0008, p = 0.9994; K: t = 0.0001, p = 0.9999; df = 16) showed no significant difference between the estimated laboratory-measured exchangeable bases.

3.8. Soil Morphology

The soil index cannot differentiate object variations when analyzed using image clustering techniques (Table 2). This limitation can be addressed by integrating of multiple soil indices through a multiple regression approach combined with multi-temporal aerial imagery. Such an approach would improve the precision of soil classification and improve the detection of spatial variability. For SECB, post-transformation differentiation was problematic, leading to reduced accuracy in delineating soil properties. To mitigate this issue, a more comprehensive sampling strategy is recommended, incorporating additional observation points within a structured grid system. Extending the observation distance from saline sources could also improve the accuracy of SECB identification, thereby refining soil classification models.

Table 2. Identified threats and alternative solutions in soil analysis and SECB transformation.

No.	Parameter	Threat	Alternative Solution
1	Soil Index	Inability to differentiate object variations through image clustering	Using a combination of soil indices (multiple regression) and multitemporal aerial imagery
2	SECB	Difficulty in differentiating soil properties after transformation into SECB estimates	1. Increase the number of observation points using a grid-based sampling design
3	Accuracy	Reliable but with limited predictive accuracy	2. Extend the observation distance from the saline source
4	Soil Characteristics	Soils converted into rice fields exhibit relatively homogeneous conditions that may not represent the actual spatial variability of SECB.	

Regarding accuracy, while current methods are reliable, their precision remains suboptimal. Further refinement of measurement techniques and the incorporation of advanced statistical models may be necessary to improve soil assessments. Finally, soil characteristics become homogeneous after conversion to rice fields, failing to reflect the inherent heterogeneity of SECB.

This homogenization effect suggests the need for advanced soil characterization techniques that capture spatial and temporal variability more effectively (Fig. 9). Integrating high-resolution remote sensing data, geostatistical modeling, and *in situ* soil analysis could improve the representation of soil variability and strengthen soil classification frameworks. These findings emphasize the need for methodological advancements in soil assessment to improve differentiation, classification accuracy, and overall reliability in agricultural and environmental applications.

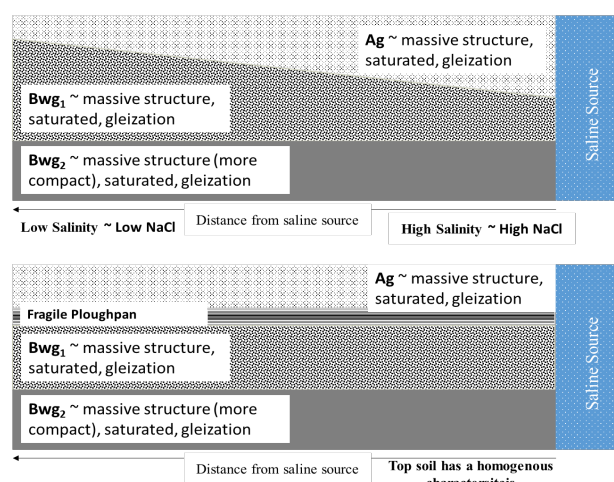


Fig. 9. Soil transformation profiles across distance from saline source.

3.9. Potential and Challenges

Remote sensing offers significant opportunities for advancing precision agriculture by assessing SECB in saline rice fields. Using multispectral UAV imagery, this study demonstrates the feasibility of applying soil indices such as NDSI, SAVI, MSAVI, and OSAVI to estimate SECB distribution. Correlation analysis indicates that NDSI has the strongest relationship with SECB, suggesting that spectral indices can serve as useful proxies for detecting salinity-induced variations in soil fertility. Mapping SECB remotely provides a scalable, cost-effective alternative to traditional laboratory-based soil analysis, enabling real-time monitoring and more efficient nutrient management. UAV-based assessments also allow high-resolution spatial analysis, which is particularly advantageous in heterogeneous agricultural landscapes where soil properties vary over short distances. These advances hold promise for improving soil health diagnostics and optimizing fertilizer application, ultimately enhancing crop productivity in saline-affected paddy ecosystems.

Despite these promising applications, several limitations constrain the reliability and accuracy of UAV-derived soil indices for SECB estimation. The moderate predictive accuracy ($R^2 = 0.31\text{--}0.34$) obtained in this study suggests that while spectral indices can capture general trends in SECB variation, their ability to provide precise quantitative measurements remains inadequate for field-scale implementation. A primary challenge is the managed nature of paddy fields, where

irrigation practices, soil amendments, and crop residue incorporation create complex interactions that obscure direct spectral relationships between soil properties and exchangeable cation concentrations. Unlike macronutrients such as nitrogen and phosphorus, which show strong spectral signatures through their influence on vegetation reflectance, SECB are less directly detectable by remote sensing because their distribution is mediated by soil texture, organic matter content, and salinity gradients. These factors introduce uncertainties that can diminish the effectiveness of purely spectral-based assessments, necessitating the integration of complementary data sources to improve model robustness.

Soil heterogeneity in paddy fields further complicates the development of universally applicable predictive models. Variability in soil texture, moisture content, and mineral composition can influence the spectral response of soil indices, leading to inconsistencies in SECB estimation across different environmental conditions. The effectiveness of UAV-based assessments also depends on external factors such as atmospheric interference, sensor calibration, and temporal changes in crop canopy reflectance, which can introduce additional noise into spectral analyses. While indices like NDSI show promise in detecting salinity-induced changes, their applicability to broader SECB assessments remains uncertain without further refinement. To address these challenges, future research should explore hybrid approaches that combine remote sensing with machine learning techniques, geostatistical modeling, and ground-based soil spectroscopy. Integrating multiple data streams could yield more accurate and adaptive models capable of capturing the nuanced interactions between soil properties and spectral reflectance patterns.

In conclusion, using UAV-derived soil indices for SECB assessment represents a significant step forward in agricultural remote sensing, offering valuable insights into soil fertility dynamics in saline paddy fields. However, the limitations highlighted in this study underscore the need for more sophisticated analytical frameworks that can account for the complexities of managed agroecosystems. Refining predictive models through interdisciplinary research—encompassing soil science, agronomy, and remote sensing—will be critical for enhancing the accuracy and applicability of spectral indices for SECB monitoring. While the potential of UAV-based assessments is undeniable, their practical implementation will require continued advances in data integration and model validation to ensure reliable decision-making in precision agriculture.

4. Conclusion

Integrating UAV-based spectral data offers a promising approach for assessing SECB in saline paddy fields, providing a scalable and cost-effective alternative to traditional laboratory methods. Multispectral imagery improves spatial resolution and enables mapping of spatial trends

in soil nutrient variability, although it does not provide precise quantitative diagnostics and may reduce reliance on time-consuming field sampling and testing. Spectral indices such as NDSI have shown strong potential for detecting salinity-induced changes in SECB, although predictive accuracy remains moderate ($R^2 = 0.31\text{--}0.34$), underscoring the need for further field-scale calibration. Beyond direct laboratory measurements, SECB can also be estimated using multispectral UAV-derived indices, offering a scalable alternative to laboratory testing alone. The NDSI index, in particular, had the highest correlation with exchangeable soil base parameters, highlighting its relevance to paddy productivity. Regression analysis identified NDSI as the primary spectral predictor of SECB variation, with consistent model coefficients across Ca, Mg, Na, and K, suggesting a shared salinity-driven mechanism underlying exchangeable cation distribution. Derived estimation models for exchangeable bases include: $\text{Ca} = -3.5807(\text{NDSI}) + 4.4318$, $\text{Mg} = -1.1756(\text{NDSI}) + 0.7552$, $\text{Na} = -1.0661(\text{NDSI}) + 0.3108$, and $\text{K} = -1.0693(\text{NDSI}) + 0.4087$. Nevertheless, significant challenges remain, particularly the high variability in soil properties, the influence of irrigation and crop residue, and atmospheric and seasonal effects on reflectance data. To address these limitations, hybrid modeling approaches that combine remote sensing, machine learning, and geostatistical methods are essential, though they require interdisciplinary collaboration and advanced data processing. Overall, remote sensing—especially when complemented by robust soil indices and predictive modeling—holds substantial potential for enhancing SECB assessment and supporting precision agriculture in managed paddy ecosystems.

Abbreviations

UAV	unmanned aerial vehicle
SECB	soil exchangeable cation bases
CEC	cation exchange capacity
NDSI	normalized difference salinity index
SAVI	soil-adjusted vegetation index
MSAVI	modified soil-adjusted vegetation index
OSAVI	optimized soil-adjusted vegetation index

Data Availability Statement

Data will be made available on request.

CRedit Authorship Contribution Statement

Aditya Nugraha Putra: Conceptualization, Methodology, Validation, Formal Analysis, Investigation, Resources, Data Curation, Writing-Original Draft, Writing-Review & Editing, Visualization, Supervision, Project Administration, Funding Acquisition. **Novandi Rizky Prasetya:** Formal Analysis, Investigation, Data Curation, Writing-Review & Editing, Visualization. **Michelle Talisia Sugiarto:** Writing-Review & Editing, Project Administration.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Declaration of Use of AI in the Writing Process

Nothing to disclose.

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